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Inégalités et opinions professionnelles : une analyse sur la marché du travail européen

Maimouna Gaye

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Maimouna Gaye. Inégalités et opinions professionnelles : une analyse sur la marché du travail européen. Economies et finances. Normandie Université, 2023. Français. NNT : 2023NORMC012 . tel-04229481

HAL Id: tel-04229481

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Normandie Université

THÈSE

Pour obtenir le diplôme de doctorat

Spécialité SCIENCES ECONOMIQUES

Préparée au sein de l'Université de Caen Normandie

Inégalités et opinions professionnelles : une analyse sur la marché du travail européen.

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**Thèse soutenue le 16/06/2023
devant le jury composé de**

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UNIVERSITÉ
CAEN
NORMANDIE



Inégalités et opinions professionnelles: Une analyse sur le marché du travail européen

Thèse de Doctorat: Sciences Economiques

De

Maimouna GAYE

Sous la direction de:

Jean-Pascal GUIRONNET

16 Juin 2023

L'université n'entend donner aucune approbation ni improbation aux opinions émises dans cette thèse. Ces opinions doivent être considérées comme propres à l'auteur.

Cette thèse a été possible grâce à divers financements. Du 01 octobre 2019 au 31 août 2022, mes travaux de recherche ont été financés en entier grâce à un contrat doctoral d'établissement. Les conférences auxquelles j'ai assisté durant tout le déroulement de la thèse et l'école d'hiver qui a lieu à Aussois du 14 au 18 mars 2022 ont été financées par le laboratoire Centre de Recherche en Économie et Management (CREM). La mobilité internationale qui a eu lieu du 26 avril 2022 au 01 juillet 2022 en Italie (Université de Turin) a été financée par la bourse de mobilité ERASMUS et l'aide du laboratoire CREM.

Je dédie cette thèse,
À mon défunt père: Moustapha GAYE et à ma mère: Khady CISSE.
À mon époux Alioune Ndiaye DIOUF pour m'avoir soutenu tout au long de ce parcours.
À tous mes frères et toutes mes sœurs

Remerciements

Durant toute la durée de ma thèse, j'ai été incroyablement chanceux d'être entouré d'une multitude de personnes qui ont apporté leur soutien de différentes manières. Aujourd'hui, je saisis cette occasion pour exprimer ma profonde gratitude envers chacune d'entre elles. Je tiens en premier lieu à exprimer ma profonde gratitude envers mon directeur de thèse, Jean-Pascal Guironnet, pour son encadrement rigoureux, ses conseils avisés, son soutien indéfectible et sa patience infinie tout au long de cette recherche. Sa disponibilité et sa bienveillance m'ont permis de mener à bien ce travail dans les meilleures conditions.

Je tiens à exprimer ma profonde gratitude à l'ensemble des membres du jury: Isabelle Lebon, Dominique Meurs, Pascale Petit et Jean-François Giret. Leur acceptation de participer à cette thèse et leurs précieuses remarques et suggestions ont grandement contribué à l'amélioration de ce travail. Je leur suis profondément reconnaissante.

Mes sincères remerciements vont à l'endroit de Vincent Merlin, ex-directeur de l'école doctorale qui m'a permis de réaliser cette thèse dans de bonnes conditions, ainsi qu'à la nouvelle directrice, Fanny Simon-Lee. Je remercie également chaleureusement les membres de mon comité de suivi, Pr Jean-Sébastien Pentecôte et Pr Pierre Bergel, pour leur accompagnement attentif, leur soutien et leur expertise durant ces années de recherche.

Je souhaite également adresser mes sincères remerciements à l'ensemble de mon laboratoire de recherche, le CREM et la MRSH, pour l'environnement scientifique stimulant et bienveillant qu'ils offrent. Je voudrais particulièrement exprimer une fois de plus ma gratitude envers la Pr Isabelle Lebon, ancienne directrice adjointe du laboratoire CREM, et le Pr Jean-Sébastien Pentecôte, nouveau directeur adjoint du laboratoire CREM, pour leur soutien indéfectible tout au long de mon parcours doctoral. Leur bienveillance et leur expertise ont été d'une aide précieuse dans la réalisation de mes recherches.

Je remercie également Carole, Anne-Marie Lechevrel et Sandrine Maviel, pour leur précieuse aide administrative et leur soutien tout au long de cette aventure doctorale. Leur disponibilité et leur professionnalisme ont grandement facilité mes démarches et ont contribué à la réussite de ce projet de recherche. Par ailleurs, je tiens à exprimer mes sincères remerciements à l'UFR SEGGAT, l'IUT et l'UFR AES pour m'avoir offert l'opportunité d'enseigner dans leurs établissements. Cela a été une expérience extrêmement enrichissante pour moi et j'ai beaucoup appris en travaillant avec des étudiants et des enseignants aussi talentueux. Je suis reconnaissant envers les responsables de ces établissements pour leur confiance et leur soutien continu. Je remercie également l'ensemble du corps professoral d'économie pour leur enseignement de qualité et leurs précieux échanges lors des séminaires de recherche.

Je souhaite également exprimer ma gratitude envers Eva Coll-Martinez, Malia Kedjar et Kevin Fourrey, que j'ai eu le privilège de rencontrer dès mon entrée en thèse. Leurs conseils éclairés et leur soutien constant m'ont été d'une valeur inestimable. Je tiens à les remercier chaleureusement pour leur générosité et leur engagement envers mon parcours académique. Je tiens à remercier également tous mes collègues doctorants: Rodrigue Tido Takeng, Marin, Martin, William, Iverson, Etienne, et mes autres collègues de sciences humaines et sociales: Daphné et Léa, pour leur soutien et leur camaraderie. Je souhaite remercier chaleureusement Alseny Niare pour sa contribution technique inestimable. Je souhaite adresser mes remerciements à mon co-auteur, Nicolas Peypoch, pour sa contribution à ce travail. Sa participation a apporté une perspective supplémentaire et a enrichi notre projet commun.

Je tiens également à remercier Ambra Poggi, Professeure associée à l'Université de Turin, pour avoir accepté de m'accueillir dans son laboratoire pour une mobilité internationale. J'aimerais également remercier l'ensemble du personnel de l'Université de Turin pour leur accueil chaleureux tout au long de mon séjour. Cette expérience a été une opportunité unique et enrichissante, tant sur le plan professionnel que personnel, et je suis reconnaissante de l'avoir vécue. Je remercie le comité d'ERASMUS et le CREM qui ont contribué au financement de cette mobilité.

Je suis reconnaissante envers ma famille et ma belle-famille pour leur soutien inconditionnel et leur encouragement tout au long de ce parcours. Je souhaite particulièrement remercier ma mère pour son amour et son soutien indéfectible. Je tiens à remercier du fond du cœur mes amis, Natacha, Caroline, Yacine, Mame Cheikh, Insa Diop et Asma ben Haj Ali Guizani, pour leur soutien. Leurs encouragements, leur amitié et leur présence ont été un moteur essentiel pour moi, et ont rendu cette aventure encore plus riche et mémorable. Je tiens à exprimer ma profonde gratitude à mon époux Alioune Ndiaye Diouf, pour son amour, son soutien constant et sa patience durant ces années de thèse. Sa présence à mes côtés a été d'un réconfort inestimable et m'a permis de traverser les moments difficiles avec plus de sérénité. Je ne pourrais pas avoir réalisé cette thèse sans lui et je lui suis infiniment reconnaissante. Enfin, je voudrais exprimer ma profonde gratitude envers toutes les personnes qui ont participé de près ou de loin à la réalisation de cette thèse et qui ont contribué à ma formation de doctorante.

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Résumé Général

L'objectif de cette thèse est d'analyser les inégalités et les opinions professionnelles sur le marché du travail européen. Dans le premier chapitre, nous examinons la satisfaction des hommes et des femmes dans 35 pays européens. Nous utilisons une approche d'appariement exact pour échantillonner des hommes et des femmes ayant des caractéristiques similaires en raison de la ségrégation professionnelle existante. Les résultats montrent que les différences de satisfaction varient en fonction des caractéristiques individuelles et professionnelles entre les hommes et les femmes.

Le deuxième chapitre analyse les liens entre la satisfaction au travail et la productivité dans un cadre spatial représenté par les zones d'emploi (ZE) de résidence des travailleurs en utilisant des données sur des salariés français âgés de 20 à 42 ans. Après estimation, il apparaît que les critères de satisfaction ont un effet positif et significatif sur la productivité globale, mais varient en fonction des caractéristiques de la zone économique et du type de productivité. La satisfaction salariale et les perspectives professionnelles jouent un rôle crucial dans les variations de productivité dans certaines zones économiques. Les critères de satisfaction se révèlent également significatifs pour la variation d'efficacité des travailleurs.

Le troisième chapitre aborde la probabilité de démissionner en se concentrant sur les comparaisons interpersonnelles dans le contexte du marché du travail allemand. Les résultats montrent que les comparaisons interpersonnelles ont un impact sur la probabilité de démissionner, mais cela dépend également des caractéristiques du marché du travail et des compétences personnelles. Il y a une hétérogénéité dans les résultats en fonction des niveaux de salaires et des secteurs d'activité, ce qui suggère que les considérations de statut de l'emploi et l'aversion pour l'inégalité sont importantes.

Mots clés: Satisfaction au travail, Genre, Productivité, Démission, Inégalités, Europe.

General Abstract

The objective of this thesis is to analyze inequalities and professional opinions in the European labor market. In the first chapter, we examine the satisfaction levels of men and women in 35 European countries. We use an exact matching approach to sample men and women with similar characteristics due to existing occupational segregation. The results show that differences in satisfaction vary depending on individual and professional characteristics between men and women.

The second chapter analyzes the links between job satisfaction and productivity in a spatial framework represented by the employment areas (ZE) of workers' residence using data on French employees aged 20 to 42. After estimation, it appears that satisfaction criteria have a positive and significant effect on overall productivity, but vary depending on the characteristics of the economic zone and the type of productivity. Pay satisfaction and professional prospects play a crucial role in productivity variations in certain economic zones. Satisfaction criteria are also significant for worker efficiency variation.

The third chapter addresses the probability of quitting by focusing on interpersonal comparisons in the context of the German labor market. The results show that interpersonal comparisons have an impact on the probability of quitting, but this also depends on labor market characteristics and personal skills. There is heterogeneity in the results depending on pay levels and sectors of activity, which suggests that job status considerations and aversion to inequality are important.

Key words: Job satisfaction, Gender, Productivity, quit, Inequality, Europe.

Introduction Générale

LES inégalités sur le marché du travail peuvent prendre différentes formes, telles que la discrimination fondée sur le sexe, les écarts de salaire, l'accès inégal aux emplois ou la précarité de l'emploi. Les écarts de salaire sont un problème majeur sur le marché du travail, car les travailleurs appartenant à certains groupes, comme les femmes ou les minorités ethniques, peuvent être payés moins pour le même travail que les travailleurs appartenant à d'autres groupes. De même, l'accès inégal aux emplois est un fléau courant qui peut empêcher certaines personnes d'avoir accès à des emplois bien rémunérés ou prestigieux en raison de leur sexe, de leur race, de leur âge ou d'autres caractéristiques. Ces problèmes peuvent avoir des conséquences importantes sur la vie des travailleurs concernés, y compris leur niveau de pauvreté, leur capacité à subvenir à leurs besoins, leur motivation à fournir plus d'efforts au travail et leur aptitude à progresser dans leur carrière.

De plus, les opinions des employés sur leurs prestations de services peuvent être influencées par les inégalités qui existent sur le marché du travail, telles que les écarts salariaux, la précarité de l'emploi et les discriminations liées au genre, à l'âge ou à l'origine ethnique. Les travailleurs qui se sentent lésés dans leur rémunération ou dans leur accès à des emplois de qualité peuvent être moins motivés et engagés dans leur travail, ce qui peut avoir un impact négatif sur leur productivité et la qualité de leur travail qu'ils fournissent.

L'Europe est particulièrement touchée par ces situations qui révèlent des problèmes socio-économiques. Le marché du travail européen est confronté à plusieurs défis socio-économiques, tels que les inégalités de genre, les écarts salariaux, la précarité de l'emploi et le chômage élevé dans certains pays. Par exemple, les inégalités salariales persistent en Europe malgré les politiques de réduction des écarts de rémunération. Selon Eurostat (2020), l'écart de rémunération entre les hommes et les femmes en Europe était de 14.1% en 2020¹. De plus, environ 16% de la main-d'œuvre européenne sont des travailleurs à faible salaire, ce qui indique que de nombreux travailleurs ne sont pas rémunérés de manière équitable pour leur travail (Eurostat. 2020). La précarité de l'emploi est également un autre défi important pour le marché du travail européen. Selon Eurostat, le taux de travailleurs à temps partiel involontaire était de 6.4% en 2020². En

¹Eurostat. (2020). Annual data on average gross hourly earnings of men and women in the EU Member States, EEA and Switzerland. [Données annuelles sur les salaires horaires bruts moyens des hommes et des femmes dans les États membres de l'UE, de l'EEE et de la Suisse]. Récupéré de https://ec.europa.eu/eurostat/databrowser/view/earn_ses_pub2/default/table?lang=en.

²Eurostat. (2020). Household surveys in the EU Member States, the EEA and Switzerland. [Enquêtes auprès des

outre, en janvier 2022, le taux de chômage des jeunes dans l'Union Européenne était de 16.4%, soit plus du double du taux de chômage global³. Les travailleurs européens ont également une perception négative des conditions de travail. Selon une enquête de l'Agence européenne pour la sécurité et la santé au travail, 28% des travailleurs européens estiment que leur travail a un impact négatif sur leur santé et leur bien-être⁴.

Ces bouleversements ont un impact significatif sur la vie quotidienne des travailleurs européens. S'ils sont mal rémunérés ou travaillent dans des conditions précaires, ils peuvent être confrontés à des difficultés financières, des problèmes de santé mentale et physique, ainsi qu'à une insatisfaction globale à l'égard de leur vie professionnelle. Cela pourrait avoir des répercussions sur leur productivité et leur fidélité envers leur employeur. Ces situations ont un impact négatif sur la productivité et la compétitivité de l'économie européenne au niveau macroéconomique. Les travailleurs insatisfaits et mal rémunérés sont moins susceptibles de s'engager dans leur travail, ce qui peut réduire la productivité globale, augmenter les coûts de santé et réduire la participation à la main-d'œuvre, affectant ainsi la croissance économique à long terme (Oswald et al., 2015). De plus, les travailleurs insatisfaits peuvent être moins enclins à investir dans leur formation professionnelle ou à entreprendre des projets ambitieux, faire preuve de créativité et d'innovation, ce qui peut nuire à la capacité de l'économie à innover et à se développer (Bryson and Mackerron, 2017). C'est pourquoi il est important de mener une étude sur les opinions professionnelles dans le marché du travail européen. Les opinions professionnelles peuvent révéler des inégalités sur le marché du travail, telles que des écarts de rémunération, des différences dans les conditions de travail ou des obstacles à l'avancement professionnel pour certains groupes de travailleurs (Theodossiou, 1998). Cette étude est cruciale pour l'élaboration de politiques publiques efficaces et adaptées tout en prenant en compte les résidus de traitement des disparités. Les résultats de cette étude pourraient aider les décideurs politiques à comprendre les défis actuels et à concevoir des politiques qui favorisent la croissance économique, la création d'emplois et la réduction des inégalités. De plus, les inégalités et les opinions professionnelles peuvent avoir un impact important sur la vie quotidienne des individus. Cette étude pourrait donc aider à identifier les défis spécifiques auxquels sont confrontés les travailleurs européens et à proposer des solutions pour améliorer leur qualité de vie. En outre, l'étude des inégalités et des opinions professionnelles sur le marché du travail européen est importante pour promouvoir une économie plus inclusive et durable. En favorisant des conditions de travail équitables et en réduisant les inégalités salariales, les travailleurs européens pourraient être plus engagés et plus motivés dans leur travail, ce qui pourrait avoir un impact positif sur la société dans son ensemble.

ménages dans les États membres de l'UE, de l'EEE et de la Suisse]. <https://ec.europa.eu/eurostat/web/household-budget-surveys/data/database>.

³Eurostat. (2022). Monthly EU unemployment database. [Base de données mensuelle sur le chômage dans l'UE]. Récupéré de <https://ec.europa.eu/eurostat/web/labour-market/labour-market-statistics/monthly-unemployment>.

⁴European Agency for Safety and Health at Work (2020). Periodic survey on working conditions in the EU. [Enquête périodique sur les conditions de travail dans l'UE]. Récupéré de <https://osha.europa.eu/en/survey-results/periodic-survey-working-conditions-eu>.

Cette thèse de doctorat vise à améliorer la compréhension des facteurs qui influencent les opinions professionnelles des travailleurs dans un contexte d'inégalités professionnelles importantes en Europe, ainsi que les implications de ces opinions. Dans le cadre de cette analyse, nous avons étudié les écarts de satisfaction professionnelle entre les hommes et les femmes. Cette analyse est cruciale pour comprendre l'ampleur des inégalités de genre dans le monde du travail et comment les aborder. La satisfaction professionnelle est une mesure importante du bien-être au travail (Faragher et al., 2005), et les différences entre les sexes dans ce domaine peuvent révéler des inégalités de genre plus larges dans le monde du travail (Mottazi, 1986). Cette étude est particulièrement pertinente pour le marché du travail européen, car il existe de nombreuses inégalités de genre sur celui-ci. Les femmes sont plus susceptibles d'être confrontées à des obstacles professionnels tels que le plafond de verre et l'inégalité salariale, ce qui peut avoir un impact négatif sur leur satisfaction professionnelle. Selon une étude d'Eurostat de 2020, l'écart salarial entre les sexes en Europe était de 14.1%, ce qui signifie que les femmes gagnaient en moyenne 14.1% de moins que les hommes. En ce qui concerne le secteur d'emploi, les femmes sont souvent sous-représentées dans les postes de direction et les professions techniques. Selon Eurostat, en 2020, seulement 33.5% des postes de direction en Europe étaient occupés par des femmes. En outre, Selon une étude de l'Agence européenne pour la sécurité et la santé au travail, les femmes sont plus susceptibles de signaler des niveaux plus élevés de stress liés à l'intensité du travail, à la pression des délais, à la sécurité de l'emploi et à l'équilibre travail-vie personnelle que les hommes. En étudiant les écarts de satisfaction professionnelle entre les hommes et les femmes sur le marché du travail européen, il est possible d'identifier les domaines dans lesquels les femmes sont désavantagées par rapport aux hommes en matière de conditions de travail et d'opportunités professionnelles. Cela peut aider à comprendre les raisons pour lesquelles les femmes sont sous-représentées dans certaines professions ou occupent moins souvent des postes de direction. L'analyse des inégalités de satisfaction professionnelle peut également mettre en évidence les écarts salariaux entre les sexes, car la satisfaction professionnelle est souvent liée aux niveaux de rémunération. En comprenant mieux ces inégalités, les employeurs et les décideurs politiques peuvent prendre des mesures pour remédier aux écarts de rémunération et de traitement entre les sexes. De plus, la satisfaction professionnelle ne se limite pas seulement à une question de bien-être individuel, elle peut également avoir un impact sur la productivité au travail. C'est pourquoi notre étude examine également l'effet de la satisfaction professionnelle sur la productivité des travailleurs.

Cet objectif vise à mieux comprendre le fonctionnement du marché du travail en Europe, en mettant l'accent sur l'importance de la satisfaction professionnelle. En effet, la productivité des travailleurs est un élément clé pour la performance économique et la croissance (Gordon, 2000). Les travailleurs qui sont satisfaits de leur travail ont tendance à être plus productifs et plus engagés dans leur emploi (Judge et al., 2001). En analysant l'impact de la satisfaction au travail sur la productivité, on peut mieux comprendre comment les travailleurs heureux et satisfaits de leur travail peuvent contribuer à la performance économique. En outre, cette

analyse peut également aider à identifier les facteurs qui influencent la satisfaction au travail et qui peuvent donc être utilisés pour améliorer les conditions de travail et augmenter la productivité.

Dans le contexte de l'Europe, cette analyse est particulièrement pertinente en raison de la compétitivité économique accrue de la région, ainsi que des défis posés par les tendances démographiques telles que le vieillissement de la population active (Andreasen et al., 1995). Une main-d'œuvre plus heureuse et plus productive peut contribuer à relever ces défis et à renforcer la compétitivité économique de l'Europe sur la scène mondiale. Selon une étude de l'Institut Gallup (2021), les employés européens qui se sentent impliqués dans leur travail sont en moyenne 22 % plus productifs que ceux qui ne le sont pas. De même, les employés qui se sentent heureux et satisfaits de leur travail sont en moyenne 12 % plus productifs que ceux qui ne le sont pas⁵, ce qui souligne l'importance de la satisfaction au travail pour la productivité des travailleurs en Europe.

D'un autre côté, si un travailleur ne se sent pas satisfait de son travail, il peut être plus enclin à chercher un autre emploi. C'est pourquoi nous avons également examiné l'analyse de la probabilité de démission des travailleurs face aux comparaisons salariales et non salariales liées à la satisfaction à l'égard du temps de loisir et de la santé.

Cette analyse est importante pour mieux comprendre l'impact de la satisfaction professionnelle et des démissions sur le fonctionnement du marché du travail en Europe. En effet, lorsque les travailleurs sont satisfaits de leur travail, ils sont plus susceptibles de rester dans leur emploi. En revanche, lorsque les travailleurs ne sont pas satisfaits de leur travail, ils peuvent être plus enclins à chercher d'autres opportunités d'emploi et à démissionner (Spector, 1997; Pfeifer and Schneck, 2012; Anees et al., 2021). Cela peut avoir un impact négatif sur la performance économique, car la perte de travailleurs expérimentés et bien formés peut être coûteuse pour les employeurs (Par exemple, les coûts de recrutement, de formation et d'intégration d'un nouveau travailleur peuvent être élevés) (Pfeffer et al., 1998; Cappelli, 2008).

En analysant les facteurs qui influencent la décision de démissionner, on peut mieux comprendre les motivations des travailleurs et les raisons pour lesquelles ils quittent leur emploi. Les comparaisons salariales et les récompenses non-matérielles liées au temps de loisir et à la santé peuvent jouer un rôle important dans la décision de démissionner (Lévy-Garboua et al., 2007). Si un travailleur estime qu'il est relativement moins bien rémunéré que ses pairs, il peut se sentir frustré et insatisfait de son travail (Pfeifer and Schneck, 2012). De même, s'il estime que ses efforts ne sont pas reconnus ou que ses perspectives d'avancement sont limitées, il peut être plus enclin à chercher un autre emploi (d'Ambrosio et al., 2018).

En comprenant mieux les facteurs qui influencent la décision de démissionner, les employeurs et les décideurs peuvent mieux comprendre les attentes et les motivations des travailleurs, et

⁵Gallup Institute. (2021). Employee productivity in Europe. [Rapport]. <https://www.gallup.com/workplace/351562/employee-productivity-europe-2021.aspx>

prendre ainsi des mesures pour améliorer la satisfaction professionnelle de leurs employés et réduire le taux de rotation du personnel. Cela peut inclure l'augmentation des salaires, l'offre de récompenses non-matérielles attractives et la mise en place d'un environnement de travail favorable. De telles mesures peuvent également avoir des avantages économiques en réduisant les coûts liés au recrutement et à la formation de nouveaux employés, ainsi qu'en améliorant la productivité globale de l'entreprise.

Cette étude est particulièrement pertinente pour le marché du travail en Europe, car ce dernier est très compétitif et les travailleurs peuvent facilement changer d'employeur (Van, 2003). Les entreprises doivent donc être en mesure d'offrir des salaires et des avantages compétitifs pour retenir leurs employés les plus talentueux. De plus, l'Europe est une région qui connaît une forte mobilité des travailleurs, en particulier avec la libre circulation des travailleurs dans l'Union européenne. Les employeurs doivent donc être conscients des facteurs qui influencent les décisions de leurs employés de rester ou de partir. La concurrence pour les travailleurs hautement qualifiés étant intense en Europe, les entreprises doivent offrir des salaires et des avantages concurrentiels pour les attirer et les retenir. Si les travailleurs ne sont pas satisfaits de leur rémunération ou de leurs avantages, ils sont plus susceptibles de chercher un emploi ailleurs. Par conséquent, les entreprises doivent être conscientes de la façon dont les comparaisons salariales et non salariales peuvent affecter la satisfaction et la fidélité de leurs employés, afin de maintenir leur attractivité sur le marché du travail.

Afin de mieux comprendre les opinions professionnelles que nous étudions, nous allons maintenant décrire les différentes théories qui nous permettront d'analyser les comportements des travailleurs. Nous allons explorer trois théories clés: la théorie du rôle social, la théorie de l'échange social et la théorie de l'équité. En combinant ces approches théoriques, nous pourrions mieux comprendre les facteurs qui influencent les opinions et les attitudes professionnelles des travailleurs, ainsi que les implications de ces facteurs pour les inégalités sur le marché du travail européen.

Théorie du rôle social: La théorie du rôle social a contribué à expliquer comment les rôles de genre sont construits et maintenus dans la société (Gilbert and Malone, 1995). Selon cette théorie, les attentes sociales liées aux rôles de genre sont intériorisées dès le plus jeune âge à travers l'apprentissage des normes et des valeurs sociales de la société (Bussey and Bandura, 1999; Miller et al., 2006). Les individus sont socialisés pour se conformer aux attentes de leur sexe en adoptant des comportements, des attitudes et des croyances associés aux rôles de genre traditionnels (Eagly and Wood, 2012a). Les rôles professionnels et familiaux typiques des femmes et des hommes façonnent leurs comportements et déterminent les qualités perçues comme typiques des sexes (Eagly and Steffen, 1984; Eagly, 1987). Les femmes sont souvent observées dans des comportements domestiques tels que la garde des enfants, la cuisine et la couture (Tomaskovic-Devey et al., 2006), tandis que les hommes sont observés dans des activités commerciales rémunérées (Glick, 1991; Cejka and Eagly, 1999). Les rôles de genre

sont hiérarchisés, de sorte que les rôles féminins sont souvent considérés comme moins valorisés que les rôles masculins (Wood and Karten, 1986; Ridgeway and Bourg, 2004). Cette hiérarchie de genre est renforcée par des pratiques et des normes sociales qui découragent les femmes de poursuivre des carrières professionnelles ou qui les limitent dans leurs choix de métiers (Conway et al., 1996). Cependant, la théorie du rôle social a souligné que les rôles de genre ne sont pas statiques, mais qu'ils évoluent et se transforment au fil du temps en réponse aux changements sociaux et culturels. Des transformations économiques, politiques et culturelles ont permis des avancées significatives dans la promotion de l'égalité des genres, bien que des inégalités subsistent encore dans de nombreux domaines (Blau et al., 2006). Malgré cette diminution de la division du travail, il existe toujours des différences entre les sexes. Les femmes effectuent plus de travaux domestiques que les hommes et passent moins de temps dans un emploi rémunéré (Eagly and Wood, 2012b). De plus, même si la plupart des femmes ont un emploi, elles ont tendance à avoir des salaires inférieurs à ceux des hommes, à être concentrées dans certaines professions et à être sous-représentées aux plus hauts niveaux des entreprises et des gouvernements. Cette division du travail confère donc moins de pouvoir, de statut et de ressources aux femmes, ce qui maintient un certain degré de hiérarchie ou de patriarcat entre les sexes (Valian, 1998).

Il est vrai que la théorie du rôle social peut aider à mieux comprendre les comportements économiques des individus, en particulier dans le domaine du travail (Akerlof, 1982). Les attentes de la société envers les rôles de genre peuvent influencer les choix de carrière, les aspirations et les comportements au travail, ce qui peut conduire à des inégalités entre les sexes sur le marché du travail (Becker, 1981). En intégrant la théorie du rôle social dans l'étude des comportements économiques, il est possible de mieux comprendre les choix de carrière, les aspirations, les motivations et les attitudes des individus dans le cadre de leur travail (Granovetter, 2018). Cela peut aider à développer des politiques économiques plus adaptées et plus efficaces pour promouvoir l'égalité des chances et la réussite professionnelle pour tous. Cette théorie trouve son importance dans notre étude, car elle permet de montrer que les inégalités professionnelles entre les hommes et les femmes peuvent expliquer leurs disparités dans l'évaluation de leurs opinions vis-à-vis de leur emploi.

Théorie de l'échange social: Cette théorie se concentre sur les relations et les interactions sociales entre individus (Homans, 1961; Blau, 1964; Emerson, 1962, 1972). Elle postule que les interactions sociales sont basées sur un système d'échanges réciproques, où chaque individu cherche à maximiser ses avantages en minimisant ses coûts (Heath, 1976). Les avantages peuvent être tangibles ou intangibles (Homans, 1961), tandis que les coûts peuvent être physiques, financiers, temporels ou énergétiques (Emerson, 1972). Les individus sont également influencés par des normes sociales et des attentes en matière de comportement (Homans, 1974). La théorie de l'échange social peut être appliquée à divers domaines, notamment les relations de travail, les relations intergroupes et les interactions entre individus et la société en général.

L'application de la théorie de l'échange social dans le domaine de l'économie permet

de mieux comprendre les relations et les interactions entre les individus dans les échanges économiques (Molm et al., 2000). Selon cette théorie, les individus évaluent les coûts et les bénéfices de chaque échange et cherchent à maximiser leur gain net. Cette approche peut expliquer la coopération dans les échanges, les transactions à long terme et les phénomènes de réciprocité (Blau, 1986). Elle peut également aider à comprendre les dynamiques de pouvoir et d'influence entre les acteurs économiques et les motivations sous-jacentes aux choix économiques (Blau, 1964). La théorie de l'échange social peut être particulièrement pertinente pour comprendre les comportements économiques en situation d'incertitude ou d'asymétrie d'information, où les acteurs doivent faire confiance à leurs partenaires d'échange (Emerson, 1972). Ainsi, l'utilisation de la théorie de l'échange social peut aider à expliquer et à comprendre les interactions économiques entre les individus (Kelley and Thibaut, 1978).

L'utilisation de la théorie de l'échange social pour comprendre les relations entre les individus dans le milieu professionnel, notamment en ce qui concerne les inégalités et les opinions professionnelles, est également pertinente. Selon cette théorie, les relations sociales sont basées sur un échange de ressources entre les individus, qu'elles soient matérielles ou immatérielles. Les individus cherchent à maximiser les avantages qu'ils retirent de ces échanges tout en minimisant les coûts. Dans le contexte des inégalités et des opinions professionnelles, cette théorie permet d'expliquer comment les inégalités se développent et se maintiennent au sein d'une organisation. Les individus ayant accès à des ressources importantes peuvent les utiliser pour maintenir leur position de pouvoir et leur prestige, tandis que les autres peuvent être désavantagés. Cette théorie trouve son importance dans notre étude pour montrer comment les travailleurs peuvent se performer pour percevoir en retour le maximum d'avantages pécuniaires et non pécuniaire.

Théorie de l'équité: Cette théorie s'intéresse à la manière dont les individus perçoivent et évaluent l'équité dans les relations interpersonnelles. Elle a été développée dans les années 1960 par (Adams, 1963; Adam, 1965), Homans (1961), Jacques (1961) et Patchen (1961). Selon la théorie de l'équité, les individus évaluent leur relation avec les autres en comparant la quantité et la qualité des contributions qu'ils apportent à la relation avec ce qu'ils reçoivent en retour (Vroom, 1964). Si l'individu perçoit que la relation est équitable, c'est-à-dire que la quantité et la qualité de ce qu'il apporte est égale à ce qu'il reçoit en retour, alors il considère la relation comme satisfaisante et stable. En revanche, si l'individu perçoit que la relation est inéquitable, soit parce qu'il reçoit moins que ce qu'il apporte, soit parce qu'il reçoit plus que ce qu'il apporte, alors il ressentira un sentiment de tension et cherchera à rétablir l'équilibre Adam (1965). La théorie de l'équité s'intéresse également aux stratégies que les individus peuvent adopter pour rétablir l'équité dans une relation inéquitable. Selon Adams, les individus peuvent adopter différentes stratégies, telles que la modification de leur propre comportement, celle de l'autre, ou la rupture de la relation. Cette théorie a été appliquée à différents domaines tels que le travail, les relations interpersonnelles, la justice et l'éducation, et a permis de mieux comprendre les mécanismes psychologiques qui sous-tendent les relations interpersonnelles et les conséquences de l'inéquité sur la santé mentale et physique des individus.

Les notions d'équité et de justice sont importantes pour comprendre les comportements économiques des individus et des entreprises. Les individus ont souvent des préférences pour des résultats équitables, ce qui peut influencer leurs choix économiques (Clark, 1958). Par exemple, les salariés peuvent être insatisfaits de leur salaire même s'ils sont payés selon les standards du marché si leur rémunération n'est pas perçue comme équitable par rapport à celle de leurs collègues (Adams and Rosenbaum, 1962). De même, les entreprises qui adoptent des pratiques socialement responsables peuvent être perçues comme plus équitables et bénéficier d'une meilleure réputation et d'une plus grande fidélité des clients (Carrell and Dittrich, 1978).

Dans le cadre de cette étude, la théorie de l'équité peut aider à comprendre les comportements des travailleurs. Ces derniers évaluent les inégalités de rémunération, de traitement et de promotion par rapport à leurs collègues et à leur propre contribution au travail. S'ils perçoivent des inégalités dans les conditions de travail, ils peuvent se sentir démotivés et mécontents, ce qui peut nuire à leur performance au travail et les amener à vouloir quitter leur emploi. Ainsi, en examinant la perception de l'équité chez les travailleurs, il est possible de mieux comprendre comment les inégalités professionnelles affectent leur satisfaction au travail, leur motivation, leur performance et leur probabilité de démissionner de leur travail. Cela peut permettre de mieux cibler les politiques et les pratiques organisationnelles pour réduire les inégalités et améliorer la satisfaction et la performance des travailleurs et ainsi retenir les employés performants.

Après avoir présenté les trois théories clés essentielles pour comprendre les inégalités dans le monde du travail et leur influence sur les opinions professionnelles, nous interpréterons les résultats de cette thèse de doctorat au regard de ces trois intuitions théoriques.

La première partie de cette thèse se concentre sur l'analyse des inégalités de satisfaction professionnelle entre les hommes et les femmes. Cette étude a abouti à une publication dans la revue *Applied Economics* (Gaye, 2022). Nous avons utilisé plusieurs approches empiriques permettant de prendre en compte différents facteurs et de corriger les biais potentiels qui pourraient affecter les résultats. Nous avons commencé par décomposer l'écart de satisfaction en utilisant la méthode de décomposition de Fairlie (2005) pour identifier les facteurs les plus importants qui influencent cette différence, en utilisant un échantillon global et hétérogène. Cette méthode est importante car elle permet d'identifier les facteurs qui contribuent le plus à la différence de satisfaction professionnelle entre les hommes et les femmes, tels que la différence de salaire, le niveau d'éducation, l'âge, le temps de travail, la présence d'enfants, etc. La décomposition de Fairlie permet ainsi de quantifier la contribution de chaque facteur et de voir lequel est le plus important. Cependant, en raison de la ségrégation professionnelle entre les sexes, il peut y avoir des problèmes de spécification dans la décomposition de Fairlie. Par exemple, les emplois occupés par les femmes peuvent être différents de ceux occupés par les hommes en termes de responsabilités, de niveau de salaire, etc. Pour corriger ces problèmes, nous avons utilisé la méthode de CEM (*Coarsened Exact Matching*) (Iacus et al., 2011) pour appairer les

individus ayant des caractéristiques similaires, ce qui permet de comparer plus équitablement la satisfaction professionnelle entre les sexes. Nous avons également appliqué une régression par *probit* simple avec sélection d'échantillon (Van de Ven and Van Praag, 1981) pour analyser l'écart de satisfaction dans l'échantillon apparié. En utilisant cette méthode, nous pouvons corriger les problèmes de biais de sélection qui pourraient affecter les résultats. Par exemple, les femmes peuvent être plus susceptibles de quitter leur emploi si elles sont insatisfaites, ce qui peut biaiser les résultats. En utilisant cette méthode, on peut s'assurer que les résultats sont basés sur un échantillon représentatif. Nous avons ensuite croisé la variable binaire pour le genre avec différents indicateurs des attentes professionnelles pour vérifier l'hypothèse d'attente de Clark (1997). Cette hypothèse suggère que la satisfaction professionnelle dépend non seulement du niveau absolu de rémunération, mais également des attentes des individus quant à leur rémunération par rapport à celles de leurs pairs. Les résultats de cette analyse peuvent ainsi permettre de mieux comprendre comment les attentes professionnelles diffèrent entre les sexes et comment elles contribuent à la disparité de satisfaction professionnelle.

Nous avons utilisé les données de la sixième enquête européenne sur les conditions de travail (EWCS: *European Working Conditions Survey*) pour mener cette étude et avons considéré les salariés âgés de 15 à 65 ans. L'utilisation de cette base de données nous permet d'avoir une vue d'ensemble des conditions de travail en Europe, car cette enquête couvre un large éventail de questions liées au travail, telles que la qualité de l'emploi, la santé et la sécurité au travail, ainsi que la satisfaction au travail, entre autres. Ainsi, nous disposons de données fiables et comparables sur les conditions de travail dans différents pays européens, ce qui est important pour comprendre les différences entre les pays.

Nous avons utilisé cinq mesures de satisfaction, dont une mesure globale et quatre mesures spécifiques (salaire, perspectives de carrière, sécurité de l'emploi et relations entre collègues). L'utilisation de différentes mesures est importante, car elle nous permet d'analyser la satisfaction au travail de manière approfondie et nuancée. En effet, la satisfaction au travail est un concept multidimensionnel, et il est crucial de prendre en compte plusieurs aspects du travail pour comprendre la satisfaction des travailleurs. Les mesures spécifiques permettent de déterminer quels aspects du travail sont les plus importants pour la satisfaction des travailleurs, tandis que la mesure globale permet de synthétiser l'ensemble de ces aspects en une seule mesure.

Ce chapitre apporte deux contributions. Tout d'abord, nous avons inclus les perspectives d'évolution de carrière comme une mesure importante de la satisfaction, ce qui nous a permis de mieux comprendre la différence de perception entre hommes et femmes concernant leur progression professionnelle. Deuxièmement, nous avons appliqué la procédure du CEM afin d'avoir des caractéristiques équilibrées entre les groupes masculin et féminin, en contrôlant le déséquilibre maximal pour chaque variable considérée dans l'appariement. Cela garantit que les groupes sont comparables et que les différences observées dans les résultats de l'étude sont dues aux différences de genre plutôt qu'à des différences de caractéristiques individuelles. De plus,

cette méthode permet de manipuler une variable pour obtenir plus d'observations sans affecter le déséquilibre des autres variables, ce qui évite le processus laborieux de vérification de l'équilibre sur les covariables observé dans les autres méthodes d'appariement.

Ce travail de recherche a permis de mettre en évidence que les femmes expriment une satisfaction professionnelle plus élevée que les hommes, mais cela peut s'expliquer par une prise de conscience plus importante des inégalités auxquelles elles sont confrontées sur le marché du travail et leur nature plus sociale. Cependant, en termes de perspectives de carrière, les femmes se sentent moins optimistes vis-à-vis de leur carrière, ce qui pourrait s'expliquer par les stéréotypes de genre. Ces résultats soulignent l'importance de prendre des mesures pour réduire les inégalités de genre sur le lieu de travail en Europe. Ils soulignent également l'importance d'améliorer la satisfaction professionnelle, car cela peut affecter négativement la réalisation des tâches. Cela nous amène à notre prochaine partie, qui examine l'impact de la satisfaction au travail sur la productivité.

La deuxième partie de cette thèse de doctorat étudie le lien entre productivité et satisfaction (Gaye et al., 2023). Notre démarche empirique se divise en deux étapes. Premièrement, nous mesurons la productivité des travailleurs en utilisant la méthode DEA (Data Envelopment Analysis) et l'indice de Malmquist (Färe et al., 1994a; Tone, 1997). Cette méthode permet de décomposer la productivité globale en deux sous-indices: le changement d'efficacité et le changement technologique. En utilisant cette méthode, notre étude peut identifier les facteurs qui contribuent à la productivité globale, y compris le changement d'efficacité et le changement technologique. Cela permet de comprendre comment la satisfaction au travail peut influencer ces facteurs de productivité et, par conséquent, la productivité globale des travailleurs. Nous utilisons une structure hiérarchique basée sur le niveau d'éducation des travailleurs, en commençant par ceux qui ont le niveau d'éducation le plus faible et en remontant jusqu'au niveau de doctorat. En utilisant cette approche hiérarchique, notre étude peut identifier les facteurs qui contribuent le plus à la productivité dans chaque groupe de travailleurs. Cela permet de mieux comprendre comment la satisfaction au travail peut avoir un impact différent sur la productivité en fonction du niveau d'éducation des travailleurs. Les intrants (inputs) comprennent le niveau d'éducation, l'expérience professionnelle et l'ancienneté, tandis que le résultat (output) est le salaire déclaré. Deuxièmement, nous analysons la relation entre la satisfaction au travail et les indices de productivité, en utilisant la méthode multi-niveau et en considérant les zones d'emploi de résidence des travailleurs afin de capter la situation économique et sociale de l'espace de résidence et de travail de l'employé. Nous considérons principalement deux niveaux. Le niveau 1 étudie la relation simple entre les mesures de la satisfaction et les indices de productivité en contrôlant un ensemble de caractéristiques individuelles et professionnelles susceptibles d'avoir également un impact sur la productivité des travailleurs. Le niveau 2 décompose cet effet en croisant un ensemble de caractéristiques pertinentes des zones d'emploi, prenant en compte la richesse, la démographie et la spécialisation de l'activité économique. Cette méthode est importante, car elle permet d'analyser la relation entre la satisfaction au travail et la productivité tout en

prenant en compte les caractéristiques individuelles et professionnelles des travailleurs ainsi que les caractéristiques des zones d'emploi où ils travaillent. Cela permet de contrôler les facteurs qui pourraient également influencer la productivité, tels que l'âge, le niveau d'éducation, le type de contrat, etc., ainsi que les caractéristiques des zones d'emploi, telles que la richesse, la démographie et la spécialisation de l'activité économique.

Nous avons utilisé les données françaises de la Génération 2010, avec un échantillon de travailleurs âgés entre 20 et 42 ans, qui sont restés en emploi dans le secteur privé à temps complet entre 2013 et 2017. Nous avons également utilisé des données de l'Insee sur les caractéristiques économiques et sociales des zones d'emploi pendant cette période. Ces données nous ont permis d'analyser finement les facteurs qui influencent la satisfaction au travail et la productivité, en prenant en compte les caractéristiques économiques et sociales des zones d'emploi. En effet, les conditions de travail peuvent varier considérablement selon les régions et les secteurs d'activité, il est donc important de prendre en compte ces facteurs lors de l'analyse de l'impact de la satisfaction au travail sur la productivité. De plus, l'utilisation d'un échantillon de travailleurs relativement jeune et stable sur une période de quatre ans nous a permis d'examiner les effets à long terme de la satisfaction au travail sur la productivité, ce qui est particulièrement important pour les entreprises cherchant à améliorer la rétention et la productivité de leurs employés.

Nous avons considéré deux mesures de la satisfaction au travail: le salaire et les perspectives professionnelles. L'utilisation de ces deux mesures spécifiques nous a permis d'examiner l'impact de différents aspects de la satisfaction sur la productivité des travailleurs en France. La satisfaction salariale peut être considérée comme une mesure de la satisfaction financière, tandis que la satisfaction à l'égard des perspectives professionnelles peut refléter la satisfaction liée aux opportunités d'avancement et de développement de carrière. En étudiant l'effet de ces deux mesures de satisfaction sur la productivité des travailleurs, il est possible de comprendre comment différents aspects de la satisfaction influencent la performance des travailleurs et la manière dont ils se rapportent au travail. Cette information peut aider les employeurs à mieux comprendre les facteurs qui influencent la productivité de leurs employés et à mettre en place des politiques et des pratiques qui favorisent la satisfaction et la performance au travail.

Nos contributions dans ce chapitre se situent à deux niveaux. Tout d'abord, nous allons au-delà de l'analyse traditionnelle de la productivité globale pour examiner la relation entre la satisfaction professionnelle et trois indices de productivité distincts, à savoir la productivité globale, le changement d'efficience et le progrès technologique. Cette approche nous permet de clarifier la relation controversée entre la satisfaction professionnelle et la performance en termes de productivité. De plus, nous menons une analyse économétrique prenant en compte le cadre spatial pour déterminer si le lieu de résidence et de travail d'un travailleur influence sa performance, en fonction de sa perception de son salaire et de ses perspectives professionnelles. Ce chapitre a mis en évidence que les travailleurs qui sont satisfaits de leur travail ont tendance à être plus productifs et plus innovants. Cet effet est plus marqué lorsque le travailleur vit dans une

zone où la proportion de cadres est plus importante que celle des ouvriers, ou lorsque l'activité économique est dominée par l'industrie ou les services. En conséquence, il convient de favoriser la satisfaction professionnelle pour stimuler la productivité et la fidélisation des travailleurs. Cela nous amène à notre dernier chapitre, qui examine la probabilité de démission des travailleurs lorsque ces derniers ne sont pas satisfaits de leur salaire par rapport à la performance fournie ou lorsqu'ils s'intéressent davantage à des aspects non pécuniaires liés à leur temps de loisir ou à leur santé.

Ce projet a été initié lors de ma mobilité internationale à l'université de Turin, en Italie. Nous avons utilisé différentes approches empiriques, notamment la méthode de prédiction de salaires de référence externes pour chaque travailleur, en utilisant le GBRT (*Gradient Boosting Regression Tree*) (Friedman, 2001). Cette méthode de prédiction permet de déterminer le salaire typique que d'autres travailleurs sur le marché, ayant un profil similaire en termes de caractéristiques et de lieu géographique, reçoivent. Cette approche empirique est importante car elle prend en compte les comparaisons salariales entre les travailleurs, nous permettant ainsi de mesurer plus précisément l'effet de la satisfaction salariale sur la probabilité de démissionner.

Nous avons effectué une régression de la probabilité de démission en utilisant un modèle *probit* à effets aléatoires, en prenant en compte la satisfaction salariale ainsi que d'autres facteurs non monétaires. Cette approche nous permet de modéliser la relation entre la démission et divers facteurs tels que la satisfaction salariale et les facteurs non monétaires, tout en tenant compte de l'hétérogénéité non observée entre les individus qui peut influencer leur décision de démissionner. Nous avons mené des analyses sur l'échantillon global ainsi que sur les échantillons selon le salaire et les secteurs d'activité. Ces analyses sont importantes car elles nous permettent de détecter d'éventuelles différences dans les relations entre les variables pour différents groupes de travailleurs. De cette manière, nous pouvons mieux comprendre comment des facteurs tels que la satisfaction salariale, les comparaisons salariales et non salariales liées au temps libre et à la santé affectent la probabilité de démission, ainsi que la façon dont cela peut varier selon les caractéristiques des travailleurs et des secteurs d'activité.

Les données du panel socio-économique allemand (GSOEP: *German Socio-Economic Panel*) ont été utilisées pour cette étude, avec une base de données personnelles générée en fusionnant les données de plusieurs fichiers. Notre échantillon est composé de salariés âgés de 16 à 65 ans, entrés sur le marché de l'emploi à partir de 1998 et ayant renseigné leur salaire ainsi qu'une réponse sur les récompenses monétaires. Ces données sont pertinentes, car elles permettent d'étudier l'évolution de la probabilité de démission en fonction des comparaisons salariales sur une période de temps relativement longue. Elles permettent également d'étudier l'évolution de la probabilité de démission en fonction des comparaisons non salariales sur la même période de temps. Ceci peut permettre de mieux comprendre les tendances à long terme du marché du travail et les facteurs qui influencent la décision des travailleurs de quitter ou non leur emploi. En analysant les données sur une période de temps relativement longue, il est possible de repérer

des changements dans les comportements de démission des travailleurs, qui peuvent être liés à des évolutions économiques, sociales ou politiques. De plus, l'étude de l'évolution de la probabilité de démission peut également aider à identifier les facteurs qui ont le plus d'impact sur la décision des travailleurs de rester ou de quitter leur emploi, tels que les comparaisons salariales et non salariales, la satisfaction au travail, les conditions de travail, etc. En outre, les données personnelles générées en fusionnant les données de plusieurs fichiers nous permettent de prendre en compte un grand nombre de facteurs qui peuvent influencer la décision de démissionner, ainsi que d'utiliser des données précises sur les récompenses monétaires et non monétaires.

Ce travail présente trois contributions. Tout d'abord, une méthode basée sur le GBRT est utilisée pour prédire les salaires de référence externes, ce qui permet d'éviter les problèmes de la méthode de régression linéaire simple en présence de variables catégorielles, de relations non linéaires ou d'une dimension d'entrée élevée. Ensuite, deux mesures de satisfaction pertinentes pour les récompenses non monétaires sont utilisées, à savoir la satisfaction à l'égard du temps de loisir et la satisfaction à l'égard de la santé, pour mieux comprendre l'arbitrage entre les récompenses monétaires et non monétaires dans la décision de démissionner. Enfin, une analyse spécifique est menée en fonction du niveau de salaire et du secteur d'activité, ce qui permet de mieux comprendre comment l'arbitrage varie en fonction de ces profils. Cette recherche a permis de mettre en évidence que les travailleurs sous-payés sont plus susceptibles de quitter leur emploi. De plus, les considérations non financières, telles que les loisirs et les avantages sociaux, jouent également un rôle important dans la décision de démissionner des travailleurs à bas salaire. Ce travail souligne l'importance de rémunérer équitablement les travailleurs et de leur offrir plus de flexibilité, en particulier pour les rémunérations les plus faibles.

Chapter 1

Job satisfaction: Towards internalizing the feeling of inequality between men and women

Sommaire

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Résumé:

Ce chapitre analyse les raisons pour lesquelles les femmes ont tendance à être plus satisfaites de leur travail que les hommes, malgré des situations professionnelles moins favorables. L'étude utilise une méthode d'appariement innovante pour comparer des échantillons d'hommes et de femmes ayant des caractéristiques similaires. Une régression est ensuite effectuée pour évaluer la satisfaction au travail en fonction de cinq mesures différentes. Les données utilisées proviennent de l'enquête européenne sur les conditions de travail de 2015. L'analyse de la satisfaction professionnelle par sexe montre que les femmes sont plus satisfaites de la sécurité de l'emploi et des relations avec les collègues, mais moins satisfaites du salaire et des perspectives de carrière que les hommes. Ces différences disparaissent lorsque l'on tient compte des caractéristiques individuelles et professionnelles. Les femmes sont moins optimistes quant aux perspectives de carrière, et les attentes salariales et la satisfaction au travail sont affectées par des facteurs tels que l'âge, l'éducation, la position hiérarchique et l'environnement de travail. L'égalité des sexes a des effets limités sur la satisfaction au travail, et elle varie selon les dimensions et les pays. Il est essentiel de s'intéresser à l'inégalité entre les sexes et d'améliorer les conditions de travail afin de promouvoir la satisfaction professionnelle pour tous.

Abstract:

This chapter analyzes why women tend to be more satisfied with their jobs than men, despite less favorable work situations. The study uses an innovative matching method to compare samples of men and women with similar characteristics. A regression is then run to assess job satisfaction on five different measures. The data used are from the 2015 European Working Conditions Survey. Analysis of job satisfaction by gender shows that Women are more satisfied with job security and relationships with colleagues but less satisfied with pay and career prospects than men. These differences disappear when considering individual and professional characteristics. Women are less optimistic about career prospects, and pay expectations and job satisfaction are affected by factors such as age, education, hierarchical position, and work environment. Gender equality has limited effects on job satisfaction, and it varies across dimensions and countries. It is essential to address gender inequality and improve working conditions to promote job satisfaction for all.

Key words: Job satisfaction, Gender, Matching, Europe.

JEL Codes: J28, J16, C14.

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Status: Published in the journal "Applied Economics": Gaye, M. (2022). Job satisfaction: towards internalizing the feeling of inequality between men and women. *Applied Economics*, 54(33), 3823-3839.

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1.1 Introduction

Gender inequalities are particularly glaring in the professional sphere where women are in the majority in precarious and poorly paid jobs (Kim, 2005; Westover, 2009, 2012). Specifically, women are less likely than their male counterparts to work continuously after leaving school (Goldin and Katz, 2008). The anticipation of child-related work interruptions and the need to coordinate family responsibilities with work are likely to influence women's choice of occupation and type of industry (O'Neil, 2003). Thus, they are often led to make occupational choices with more flexible work hours. Part-time work is the most obvious manifestation of this adjustment (O'Neil, 2003). These occupational choices tend to reduce their earnings in the labor market compared to their male counterparts. In parallel to this less favorable job situation for women, many studies have suggested that women express either higher or equal job satisfaction compared to their male counterparts (Clark, 1997; Sloane and Williams, 2000; Sousa-Poza and Sousa-Poza, 2000; Bender et al., 2005; Carvajal et al., 2018; Eskildsen et al., 2004; Al-Ajmi, 2006; Redmond and McGuinness, 2020). A small number of studies have found higher satisfaction among men (Mora and Ferrer-i Carbonell, 2009; Hanebuth et al., 2012; García-Bernal et al., 2005).

These previous studies share a critical bias: they did not account for the non-comparability of men and women. If the covariates are very different between the sexes, the results of the regression analysis alone can be misleading. There are combinations of characteristics for which it is possible to find men but not women, and the opposite is also true. For example, considering occupations, women tend to be concentrated in certain occupations that require low-risk manual skills (e.g., elementary jobs, nurses, support staff, etc.), while men are more likely to work in hazardous or managerial occupations that require long hours of employment (See, Deutsch et al. (2002)). Hence, the comparison of satisfaction levels between men and women can lead to a misspecification of the model.

The aim of this chapter is to address a methodological flaw by ensuring balance between the characteristics of men and women prior to any regression analysis. This will be achieved using a matching method, such as the ones used by De Galdeano (2002) and Perugini and Vladislavljević (2019), to investigate if the disparity in job satisfaction between men and women can be attributed to their different individual and professional characteristics, or to differences in their expectations regarding their work. To accomplish this, we will employ a more recent matching procedure, Coarsened Exact Matching (CEM), which has been described by Iacus et al. (2011, 2012).

To the best of our knowledge, this will be the first study to apply this method in the literature on job satisfaction by gender. The CEM method is particularly advantageous for this study because it allows to avoid biases in the analysis by comparing groups that are balanced on important variables. It allows to determine the maximum degree of asymmetry of covariates between gender groups before matching individuals. This guarantees balance between the

characteristics of male and female groups in terms of covariates and ensures that any difference in job satisfaction between the two groups is due to differences in individual and professional characteristics rather than sampling biases. Additionally, the CEM method avoids measurement problems that can bias results and offers an alternative to the propensity score method, which can be laborious. In summary, CEM is an effective and precise method for measuring gender differences in job satisfaction while avoiding biases and distortions.

We use data from the fifth wave of the European Working Conditions Survey (EWCS) covering 35 European countries. This data is particularly relevant to our study because it provides recent and up-to-date information on working conditions in Europe. It also allows for comparisons with previous studies and a comparative analysis of working conditions in different national contexts, given the survey's coverage of a wide range of countries and sectors. The survey focuses on key themes such as employment, pay, working hours, workplace safety, and health and well-being, providing the relevant data we need. Additionally, the survey data is collected using a standardized protocol and rigorous methodology, ensuring data quality and reliability.

We consider five measures of job satisfaction: 1-overall job satisfaction, which assesses the overall level of satisfaction that workers experience towards their job as a whole; 2-satisfaction with pay, which assesses the level of satisfaction of workers towards their compensation, including their salary and benefits; 3-satisfaction with career development prospects, which assesses the level of satisfaction of workers regarding their opportunities for career progression and advancement, as well as their perception of the clarity of possible career paths and success criteria; 4-satisfaction with job security, which assesses the level of satisfaction of workers regarding job security. It may include aspects such as job stability, perception of future job security, likelihood of being laid off, etc.; and 5-satisfaction with relationships with colleagues, which assesses the level of satisfaction of workers regarding their relationships with colleagues and their work team. It may include aspects such as the level of collaboration and support from colleagues, the quality of social interactions, perception of the work atmosphere, etc.

Including career development prospects as a new measure in this literature allows us to account for satisfaction related to individualization and a sense of control over one's professional future, which are unequally shared by men and women due to their different professional trajectories (Testenoire, 2001). We include multiple measures of satisfaction because self-reported job satisfaction can be interpreted in different ways, depending on financial and non-financial assets. As such, individuals may have different perceptions of their level of job satisfaction (De Bustillo Llorente and Macias, 2005). Some may prioritize job-related aspects, while others may place less importance on them. Furthermore, some individuals may combine job-related aspects with other elements to assess their level of job satisfaction (Millán et al., 2013). This can make it difficult to determine what job satisfaction refers to and how it may differ between men and women, who often have different priorities. Men tend to prioritize extrinsic aspects of

work, such as pay and promotions, while women focus more on intrinsic aspects, such as social relationships and the work itself (Clark, 1997). This lack of understanding can be addressed by including multiple measures of satisfaction.

This chapter advances our understanding of the nature of the gender gap in job satisfaction. He describes a method (CEM) that allows measuring differences in job satisfaction between men and women while avoiding biases related to individual and professional characteristics. This can help to better understand differences in job satisfaction between genders and identify factors that contribute to these differences. The study also contributes to the existing literature on job satisfaction by adding a new measure of satisfaction related to career development prospects. In economics, understanding differences in job satisfaction between genders can help to better understand economic inequalities and the professional choices of men and women. Moreover, measuring job satisfaction can have important implications for productivity, worker motivation, and individuals' quality of life.

The remainder of this chapter is organized as follows. Section 1.2 discusses the literature related to the job satisfaction differential between men and women. Section 1.3 presents the data and summary statistics. Section 1.4 presents the econometric specification. Section 1.5 presents and discusses the results. Section 1.6 checks the robustness of the results. Section 1.7 concludes.

1.2 Theoretical foundations and Related literature

Job satisfaction is a non-financial utility indicator that has received considerable attention in previous studies (Millán et al., 2013). Locke (1976) defines job satisfaction as a positive or pleasant emotional state resulting from an individual's evaluation of their work or experiences at work. This area began to interest economists in the 1970s because of its impact on worker performance, turnover, and absenteeism (Freeman, 1978a; Clark, 1997). Economists consider job satisfaction as a utility function determined by pay, working hours, and a set of professional and individual characteristics, which are related in the following form:

$$S = u = u(w, h, j, i) \quad (1.1)$$

With w representing the pay that is assumed to increase job satisfaction. h are the hours worked that are supposed to decrease the level of job satisfaction. j and i are respectively, professional and individual characteristics.

Empirical studies have identified a set of common characteristics that are statistically correlated with job satisfaction responses. Factors related to individual and work characteristics such as age, gender, education, marital status, work location, relationships with colleagues, pay, working time, working conditions, perception of work value, autonomy, participation in decision making, staff development, company size in terms of number of employees, employment contract,

and awareness of work objectives are important determinants of job satisfaction (Clark, 1997; Bodur, 2002; Ghinetti, 2007). For example, research suggests that the age effect takes the form of a "U" shaped curve, representing a non-linear effect of age on satisfaction and suggesting that younger and older workers are more satisfied with their jobs (Clark, 1997; Ghinetti, 2007; Demoussis and Giannakopoulos, 2007). It is also documented that employees who have management responsibilities, who are not union members, who hold permanent positions, or who have opportunities for promotion are more satisfied with their jobs (Clark, 1997; Demoussis and Giannakopoulos, 2007; Ghinetti, 2007). On the other hand, it has been revealed that longer work hours, as well as time spent commuting to work, are associated with lower job satisfaction (Clark et al., 1996; Clark, 1997). Marital status is positively associated with higher job satisfaction (Gazioglu and Tansel, 2006), while the level of education has a negative effect once certain job-related characteristics (e.g., pay, occupation, etc.) are controlled for (Clark et al., 1996). Pay is positively associated with job satisfaction (Ghinetti, 2007). These investigations into the determinants of satisfaction have led to the study of a particular area, which is the analysis of the satisfaction differential according to gender.

The gender effect has received particular attention due to the different work situations experienced by men and women. Research has shown that women often experience more career failures than men, receive lower pay, and are less likely to benefit from training and social security (Kim, 2005; Westover, 2009, 2012). However, studies have found that women are more satisfied with their jobs than men (Clark, 1997; Sloane and Williams, 2000; Sousa-Poza and Sousa-Poza, 2000; Bender et al., 2005; Carvajal et al., 2018). This recurring result has been referred to as "the paradox of the satisfied worker" (Bender et al., 2005), since women's higher self-reported job satisfaction is at odds with their less favourable working conditions compared to men.

Empirical work has attempted to provide explanations for this paradox using a variety of data and samples. For instance, Clark (1997) investigated Great Britain using data from wave 1 of the British Household Panel Survey (BHPS) from September to December 1991. He considered eight measures of satisfaction: overall, promotion, pay, relationships, job security, initiative, work itself, and hours. He tested three possible explanations, one of which he chose as the main explanation for the different level of job satisfaction observed between men and women. First, he tested the effect of different individual and job characteristics in an ordered *probit* regression and found no difference in satisfaction due to these characteristic disparities. Second, he examined the effect of different participation levels between men and women by testing whether only happier women entered the workforce. Using the maximum likelihood estimation technique of the Heckman selection model, he found no evidence of selection bias in the female sample in the medium term. Finally, he tested the expectation explanation using regressions for men showing different profiles by age, education level, occupation status of the individual and his mother, and gender mix in the workplace. His conclusion validated the differential in satisfaction between men and women due to their different expectations of their jobs. He documented that women have lower expectations than men in the workplace due to their lower positions in the labor

market, which makes them satisfied with the little they have, hence their higher job satisfaction compared to men. This explanation of the differential in satisfaction between men and women based on different expectations has subsequently been validated in other studies. Sousa-Poza and Sousa-Poza (2003) tested whether this phenomenon of higher satisfaction among women related to their different expectations from men is a transitory or permanent phenomenon. They used the same database as Clark but with a longer time frame from 1991 to 2000. Using an ordered *probit* regression, they concluded that this expectation effect is just a transitory phenomenon and not permanent in Great Britain. Long (2005) and Kifle and Kler (2007) also tested this expectation and the hypothesis of the transitory phenomenon of the satisfaction gap between men and women developed by Sousa-Poza and Sousa-Poza in Australia with data from the first wave (2001--2004) of Household Income and Labour Dynamics in Australia (HILDA). They found that women enjoy higher levels of job satisfaction than men, with the exception of satisfaction with job flexibility, and suggested that the divergence in job satisfaction responses between the sexes is most evident for women and men with no further education and no qualifications and much less evident for those who are younger, childless, and with qualified education. They, therefore, accept Clark's hypothesis and conclude that the gender satisfaction gap is attributable to the different work expectations of men and women. However, they disagree with Sousa-Poza and Sousa-Poza's hypothesis regarding the transient phenomenon of the gender satisfaction gap for Australia. Their study shows that in Australia, the fact that women continue to choose a lifestyle where work is not their first priority means that differences in job satisfaction between men and women will persist over time.

Studies have tested the hypothesis using cross-national data. For example, Kaiser (2007) used data from the European Household Panel covering 14 EU member states (Denmark, Finland, the Netherlands, Austria, Belgium, France, Luxembourg, Germany, Greece, Italy, Portugal, Spain, the United Kingdom, and Ireland). Based on an ordinary regression model with ordered objectives, they found that the expectation hypothesis was accepted in 10 out of 14 countries, with women showing higher satisfaction rates, except in 4 countries: Denmark, Finland, the Netherlands, and Portugal. Furthermore, they found no significant difference in job satisfaction between men and women for Denmark, Finland, and the Netherlands. Indeed, it is documented that in Denmark and Finland, women's and men's employment opportunities are relatively equal, and this is also true for full-time positions. In the Netherlands, women's work arrangements are predominantly part-time. In contrast, in Portugal, women are less satisfied with their work than their male counterparts due to an extravagant state welfare regime and a labor market framework that does not favor women.

More recently, Perugini and Vladislavljević (2019) conducted a cross-national study using data from the 2013 EU-SILC module on subjective well-being to analyze adjusted gender gaps in job satisfaction across 32 European countries by relating them to cross-country differences in gender inequality. Their results provide extensive and robust evidence of a relationship between exposure to more gender-equal environments in the early stages of life and smaller gender

gaps in job satisfaction. Thus, they support the hypothesis that women who grew up in more gender-equal contexts have expectations that are increasingly aligned with those of their male counterparts. Furthermore, their results show that being employed in typically male occupations also enables this alignment, whereas higher levels of education do not have a similar effect.

Our study contributes to this literature by testing the validity of all explanations for the observed differential in job satisfaction between men and women. We also adopt a cross-national approach, which is rare in studies of this kind and is mostly descriptive. In contrast to previous studies by Kaiser (2007) and Perugini and Vladislavljević (2019), we use a more recent dataset - the Sixth European Working Conditions Survey (EWCS) from 2015 - and consider a larger sample of 35 European countries. Additionally, we examine several measures of satisfaction, including overall satisfaction, pay, career development prospects, job security, and co-worker relations. Before discussing our empirical strategy, we first describe the dataset, as it is crucial for obtaining reliable results.

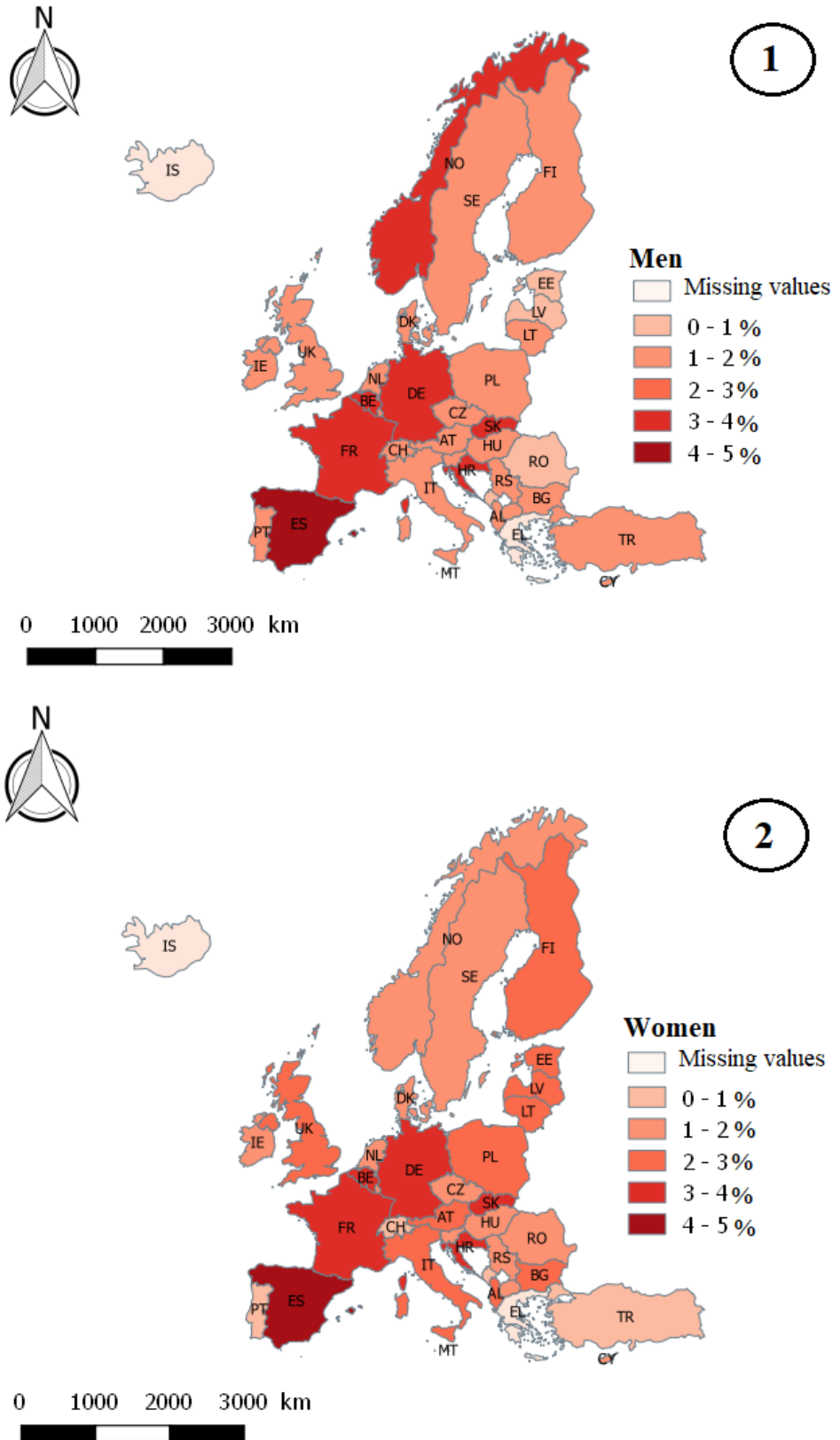
1.3 Data

The following section provides a detailed description of the data used in this study, as well as some descriptive statistics to help understand the characteristics of the sample. Specifically, this section will present information on the sample size, demographic characteristics, and key variables of interest. The aim is to provide a comprehensive overview of the data used for analysis, which will serve as the basis for the subsequent statistical analyses and interpretation of results.

1.3.1 Data Description

The data used in this study come from the European Working Conditions Survey (EWCS), produced by Eurofound (European Foundation for the Improvement of Living and Working Conditions). The EWCS is the main source of comparative information available on working conditions, job quality, well-being at work, and working life in Europe. It is a face-to-face survey that covers 35 European countries, 27 of which are members of the European Union. Launched in 1991, it is conducted once every 5 years. We use data from the 2015 survey, conducted from February to September, as it provides the most detailed information across countries for our study. Our total sample includes 43,850 workers aged 15 to 99, with 1,000 to 3,000 people per country. We retained only 28,483 individuals consisting of employees aged 15–65 years. We excluded employees over the age of 65, the self-employed, and those who did not respond regarding their level of satisfaction with the various measures and also their income level. We excluded people over the age of 65 to conform to International Labor Organization standards on the normal age range for employment. We excluded the self-employed because some of the questions used in the study are inapplicable, such as those referring to the size of the establishment or the number of hours worked per week, and differences in the determinants of job utility such as income and

Figure 1.1: Distribution of male and female employees in the sample by country



Note: Author's calculation based on data from EWCS (2015). These maps show the percentage of male employees (map 1) and female employees (map 2) in each European country (35), based on the sample used in this study. The percentages shown correspond to the proportion of employees from each gender in the sample for each country. The countries included in the sample are indicated on the map. This information is provided to illustrate the composition of the sample used in this study.

other working conditions (Blanchflower and Oswald, 1992; Clark, 1997).

Finally, approximately 31.5% of men and 33.9% of women are in our sample. Figure 1.1 shows the proportion of men and women in our sample for each of the 35 European countries included in our study. The legend shown provides information on the scales used for the graphical representation of data on the map. The different scales show the percentage distribution of male and female population in the various countries. The colors used on the map correspond to gradients that represent the representativeness of the male and female population of each country. Darker colors may indicate a higher representativeness, while lighter colors indicate a lower representativeness. Generally, there appears to be a slight predominance of women in our European sample, as the proportion of women is slightly higher than that of men in most countries. However, the proportion of men and women can vary considerably from one country to another. For example, in Spain, the proportion of men in our sample is about 3.8%, while the proportion of women is about 4.1%. In comparison, in Switzerland, the proportion of men is about 1.05% and the proportion of women is about 0.89%. The countries that show the most marked differences between the sexes are Turkey and Greece. In these countries, the proportion of men is significantly higher than the proportion of women in our sample. In some countries, the proportion of men and women in our sample is relatively similar. This is particularly the case in Norway, the Czech Republic, Slovenia, and Croatia.

These variations could reflect differences in the composition of the workforce and recruitment practices in different countries. For example, differences in the proportion of men and women could reflect differences in labor force participation rates, the sectoral structure of the economy, or gender pay gaps. In Spain, where the proportion of women is slightly higher than that of men, this could reflect a high level of female labor force participation, especially in traditionally female-dominated sectors such as services. In Switzerland, on the other hand, where the proportion of men is slightly higher than that of women, this could reflect a strong representation of men in traditionally male-dominated industries such as finance, technology, and construction. The marked differences between Turkey and Greece, where the proportion of men is significantly higher than that of women, could reflect recruitment practices that favor men in certain sectors, as well as differences in cultural and social norms that encourage or discourage women's participation in the labor force. The countries where the proportions of men and women in our sample are relatively similar, such as Norway, the Czech Republic, Slovenia, and Croatia, could reflect a more advanced culture and policy of gender equality, as well as relatively equal participation of men and women in the labor force.

In the questionnaire, the overall satisfaction was measured by the response on a four-point scale, ranging from 1 ("very satisfied") to 4 ("not at all satisfied"), to the question "In general, are you satisfied with the working conditions of your main paid job?" The remaining four measures were rated on a five-point scale, ranging from 1 ("strongly agree") to 5 ("strongly disagree"), in response to the question "How much do you agree or disagree with the following statements

describing some of the aspects of your job?" The statements were: 1) "I feel I am paid well for the effort I put in and the work I do," 2) "My job offers good prospects for career growth," 3) "I am not in danger of losing my job in the next six months," and 4) "I generally get along well with my co-workers." For each of these measures, a dummy variable was constructed, which is 1 if the respondent answers "strongly agree" or "agree" and 0 otherwise. To measure gender, we use a binary variable where 1 represents women and 0 represents men (Bertrand, 2013).

In addition to gender, we also considered individual and occupational characteristics to account for gender differences, such as age (including its quadratic term), level of education, whether the respondent is in a couple, presence of children in the household, health status, working time, net monthly pay received in the main job (including its logarithmic term), which corresponds to the income that an individual has after paying income taxes and social security contributions, type of contract, occupation, sector of activity, seniority, autonomy at work, and company size. The net monthly pay was corrected by Purchasing Power Parity to account for differences between countries. By taking into account these additional variables, the study can provide a more comprehensive understanding of the factors that contribute to differences in job satisfaction between genders. A detailed description of each of these variables is provided in Table 1.8.1 in the Appendix.

1.3.2 Descriptive Statistics

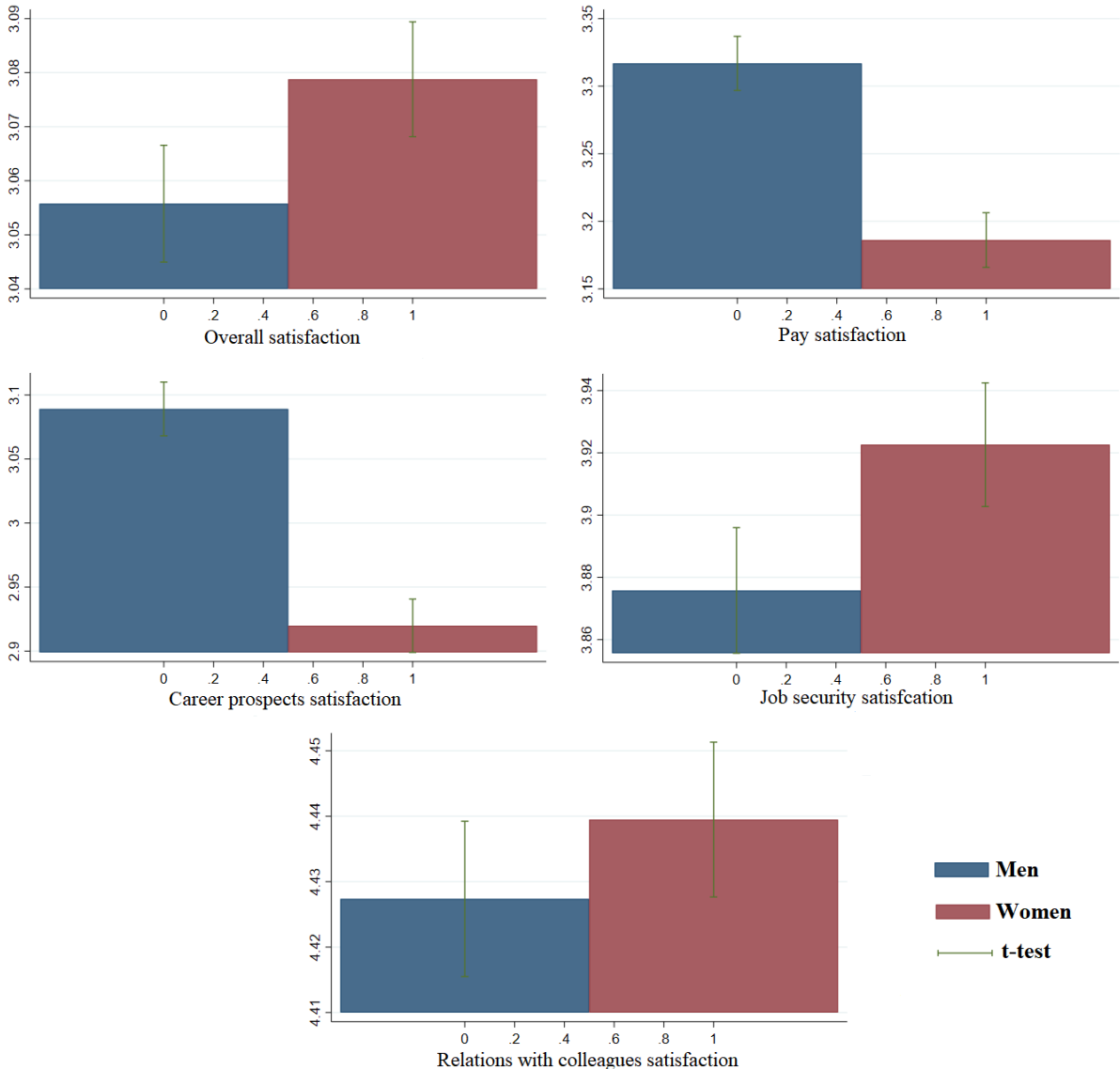
Figure 1.2 displays the average probability distributions of "very satisfied" and "strongly agree" among the men and women in our sample. The blue columns show the averages for men and the red columns for women. The t-test for the difference in mean proportions of job satisfaction between men and women is also presented. A closer examination of the response distributions for men and women reveals notable disparities in the various measures of job satisfaction. There is a clear indication of a satisfaction gap in overall satisfaction, job security, and co-worker relations (which is higher for women), as well as a satisfaction gap in terms of pay and career development prospects (which is lower for women). The tests of difference of proportions are significant for all gaps, indicating that they are not simply due to chance, but rather to gender-related factors. The results suggest that women may be disadvantaged compared to men regarding certain aspects of their work (for example, pay or career prospects).

Table 1.1 presents average comparisons of individual and occupational characteristics between men and women. The two samples show many significant differences in characteristics. Women have a higher level of education, even though they are recruited from lower socio-professional categories. Moreover, fewer women work full-time, and they earn less on average than men. Men are more likely to work in sectors such as agriculture, industry, construction, and transport, while women are more oriented towards sectors such as commerce and hospitality, financial services, education, and health.

These differences suggest that there may be systemic barriers and inequalities that affect

men and women differently in the workforce. Women’s higher level of education despite being recruited from lower socio-professional categories could indicate limited opportunities for career advancement and upward mobility. The differences in sectors of work may also reflect gendered stereotypes and biases that influence hiring practices and career paths. Overall, the findings highlight the need for further investigation into the underlying factors that contribute to these differences and their implications for gender equality in the workplace. The significant differences imply that satisfaction levels and the underlying mechanisms could operate differently for the two genders. To account for these differences, it is crucial to conduct an econometric analysis that includes a binary variable for gender as an explanatory variable and controls for individual and occupational characteristics.

Figure 1.2: Means satisfaction by gender and difference-in-mean proportions test



Notes: Author’s calculation based on data from EWCS (2015). The blue band corresponds to the average satisfaction of men and the red band to that of women.

Table 1.1: Differentiated characteristics of men and women

	Mean of Men	Mean of Women	Difference (ajusted for countries)	t-test
	(1)	(2)	(3)	(4)
Age (in years)	40.1	41.0	-0.5 (0.931)	-0.52
Age squared/100	17.5	18.1	-0.3 (0.763)	-0.44
Level of education				
Early childhood	0.003	0.003	0.000 (0.002)	0.12
Primary education	0.032	0.020	0.011 (0.015)	0.76
Lower secondary	0.129	0.097	0.031 (0.031)	1.00
Upper secondary	0.452	0.391	0.060 (0.029)	2.01
Post-secondary non-tertiary	0.067	0.078	-0.010 (0.034)	-0.31
Short cycle tertiary	0.086	0.120	-0.029 (0.031)	-1.22
Bachelor	0.127	0.164	-0.032 (0.031)	-1.22
Master	0.094	0.117	-0.020 (0.022)	-1.02
Doctorate	0.010	0.009	0.001 (0.003)	0.42
In a relationship	0.638	0.673	-0.031 (0.018)	1.74
Children	0.429	0.542	-0.069 (0.032)	2.17
Good health	0.878	0.882	-0.003 (0.004)	-0.73
Permanent contract	0.791	0.815	-0.013 (0.043)	-0.30
Full time	0.899	0.705	0.185 (0.052)	3.53
Net monthly pay (in euro)	1601.1	1293.7	221.5 (390.915)	1.08
Log net monthly pay	7.0	6.7	0.1 (0.285)	0.89
Tenure (in years)	9.9	9.7	0.1 (0.669)	0.37
Autonomy	0.508	0.496	0.009 (0.042)	2.94
Types of occupation				
Manager	0.052	0.039	0.012 (0.014)	1.29
professional	0.166	0.276	-0.094 (0.026)	-3.66
Technician	0.140	0.158	-0.008 (0.016)	-0.48
Clerical support workers	0.073	0.147	-0.067 (0.017)	-3.98
Service and sales workers	0.145	0.234	-0.087 (0.028)	-3.92
Craft workers	0.208	0.029	0.175 (0.032)	5.51
Plant and machine operators	0.143	0.034	0.101 (0.020)	4.98
Elementary occupations	0.074	0.083	-0.007 (0.011)	-1.53
Sectors of activity				
Industry	0.256	0.126	0.122 (0.029)	4.19
Construction	0.114	0.013	0.100 (0.018)	5.66
Commerce	0.181	0.214	-0.030 (0.023)	-2.24
Transport	0.097	0.027	0.070 (0.015)	4.72
Financial services	0.032	0.043	-0.001 (0.001)	-0.85
Public administration	0.069	0.064	0.001 (0.001)	1.32
Education	0.059	0.156	-0.089 (0.020)	-4.41
Health	0.040	0.194	-0.144 (0.036)	-4.03
Agriculture	0.930	0.870	0.02 (0.031)	3.54
Other services	0.151	0.161	-0.009 (0.012)	-1.51
Company size				
Small company	0.189	0.201	-0.011 (0.037)	-0.49
Medium company	0.448	0.448	0.000 (0.026)	0.07
Large company	0.363	0.351	0.009 (0.057)	0.45
Number of observations	13,811	14,672		

Notes: Author's calculation based on data from EWCS (2015). Values represent averages for men and women in the total sample. The difference between the means for men and women, adjusted for the country effect to account for heterogeneity presented in column 3 with estimated standard errors (in parentheses), clustered by country. The t-test for the difference between male and female means is presented in column 4.

1.4 Econometric specifications

Traditionally, the gender gap in job satisfaction has been examined using regressions on a heterogeneous sample of men and women (Clark, 1997; Sousa-Poza and Sousa-Poza, 2003). However, as discussed by Perugini and Vladislavljević (2019), among others, such procedures generally fail to recover the satisfaction gap unless the sample is homogeneous. Ignoring the comparability of empirical differences between the sexes, given established occupational and sectoral segregation, may lead to poor specifications (Perugini and Vladislavljević, 2019). Recent empirical work by Perugini and Vladislavljević (2019) has focused on balancing the characteristics of men and women using a matching method before running any regressions. Matching enables the creation of an observationally similar sample of men and women while minimizing the loss of observations (Rubin, 1974; Rosenbaum, 1983, 1985; Lyons and Zhang, 2017). In this study, we draw on this literature by using matching. However, prior to this, we began with a traditional analysis by running our regression on the overall heterogeneous sample of men and women. We utilized the Fairlie decomposition method (Fairlie, 2005), which decomposes the satisfaction gap into a part explained by observable personal and professional characteristics and another part explained by unobservable factors. This initial analysis allowed us to examine the overall size of the gap and to investigate how occupational inequalities between men and women impact their different perceptions of job aspects. Next, we will conduct analyses on a more homogeneous sample of men and women, using the relatively new Coarsened Exact Matching (CEM) method. Finally, we will specify the methodology for estimating the satisfaction gap in the homogeneous sample. This second analysis will enable us to better understand the gender differences in satisfaction, considering the factors that could influence this difference and isolating the specific role of gender. Such an analysis can be instrumental in identifying areas where gender inequalities in satisfaction exist, thus guiding policies and practices aimed at promoting gender equality in the workplace.

1.4.1 Fairlie's method for decomposing the job satisfaction gap between men and women

The Blinder-Oaxaca decomposition technique is commonly used to isolate and quantify the distinct contributions of group differences in characteristics to racial and gender disparities in outcomes. However, this technique may not be as effective when the outcome variable is nonlinear, as is the case in our study. To address this issue, we utilized the Fairlie decomposition method (Fairlie, 2005), which is better suited for our analysis. As our outcome variables are categorical and ordinal, we dichotomized them to align with Fairlie's approach. Specifically, we assigned a value of 1 if an individual reported being "very satisfied" (or "completely agree") and "satisfied" (or "agree"), and a value of 0 otherwise. For the specification, noting $g = (m, w)$ for the male and female groups, the decomposition is written:

$$\text{GAP} = \bar{y}_m - \bar{y}_w = \left[\sum_{i=1}^{N_m} \frac{A(x_m \hat{\beta}_w)}{N_m} - \sum_{i=1}^{N_w} \frac{A(x_w \hat{\beta}_w)}{N_w} \right] + \left[\sum_{i=1}^{N_m} \frac{A(x_m \hat{\beta}_m)}{N_m} - \sum_{i=1}^{N_m} \frac{A(x_m \hat{\beta}_w)}{N_m} \right] \quad (1.2)$$

Where, \bar{y}_m and \bar{y}_w , the average probabilities of the binary job satisfaction outcome for men and women, respectively. x_m and x_w are the vectors of the mean values of the independent variables for men and women, respectively (see Table 1.1). β_m and β_w represent the vectors of the estimated coefficients for men and women, respectively. N_m and N_w represent the sample sizes for men and women respectively. $A(\cdot)$ represents the cumulative distribution function from the standard normal distribution.

The first term enclosed in square brackets indicates the proportion of the job satisfaction gap that can be attributed to differences in the distributions of individual and job characteristics, which are clustered in the x vector, between men and women. On the other hand, the second term represents the proportion due to differences in group processes that determine job satisfaction levels. This second term also accounts for the portion of the gender gap that arises from differences in unobserved endowments between men and women. In this study, we focus solely on the portion "explained" by the observable characteristics to facilitate interpretation of the results. The unexplained portion of the Fairlie method is difficult to interpret as it represents differences in unobservable factors that contribute to the differential in job satisfaction between groups. These unobservable factors may include personality traits, cultural differences, individual preferences, or other hard-to-measure factors. Therefore, it is challenging to draw clear conclusions about why these differences exist, as it can be difficult to determine which combination of factors is responsible for the observed difference.

1.4.2 Matching for a homogeneous sample of men and women

We use a matching framework in which the satisfaction variable is considered an "attribute" that cannot be integrated into the matching procedure. Unlike previous studies (De Galdeano, 2002), we do not conduct matching on propensity scores but directly on the individuals' characteristics. To avoid a significant reduction in our sample, we employ the Coarsened Exact Matching (CEM) procedure instead of exact matching (Iacus et al., 2011, 2012). We utilize the *cem* command in Stata to implement the procedure (Blackwell et al., 2009).

The algorithm begins with a coarsening of the variables to be used in the matching. This recodes the categories of variables, such that those referring to the same information are grouped together and assigned a single numerical value. Then, strata are created based on this aggregated coding of coarsened values. Finally, the sample observations are assigned to these strata. At the end of this process the strata that contain at least one male and one female simultaneously are retained.

We use a set of individual and job characteristics that influence job satisfaction as the basis for our matching.² Incorporating these characteristics is especially important as they enable

²Previous studies have suggested considering variables that simultaneously affect the decision to participate in treatment and the outcome variable (Rosenbaum, 1983). Since we are not administering a treatment, we chose variables that impact job satisfaction.

us to control for potential confounding factors that could impact the satisfaction differential. Moreover, gender differences in satisfaction could be attributed not just to gender, but also to other personal and job characteristics like age, work experience, education, type of job, pay, and so on. Therefore, incorporating these factors into the matching process ensures that gender comparisons are fair and based on genuine gender differences, rather than differences attributable to other factors.

The literature (Hamermesh, 1977; Borjas, 1979; Clark, 1997) combined with the selection procedure discussed by (Fowler, 2012) allowed us to identify the variables to use. We entered several variables that were assumed to influence job satisfaction into a regression, where the gender variable was the first predictor, and other variables were considered as the second predictor. We included both the quadratic terms of the continuous variables and their interaction terms with the categorical variables, as well as the interaction terms between categorical variables. According to this method, we selected the variables that influenced all the variables to be explained. The final set of variables considered includes: net pay, full-time/part-time, permanent/temporary contract, occupation type (eight categories), industry (ten categories), company size (three categories), age, education level, marital status, presence of children in the household, and health status (see Table 1.8.1 in the Appendix). In addition, country dichotomous variables are included to account for geographic location. For all these variables, two coarsening techniques are used, depending on their nature. First, when the variable is categorical, we group categories that refer to the same information. Second, when the variable is continuous, we divide it into categories (Iacus et al., 2011). We do not perform coarsening on the dichotomous variables.

We first started with the basic procedure in which coarsening is performed automatically by the software. This step allows for quickly obtaining a first version of the comparison groups, which can be useful in identifying the variables that are most important in explaining differences in job satisfaction between men and women. Furthermore, automatic coarsening is a necessary first step for continuous variables to be compared with categorical variables, which is important because both continuous and categorical variables can be important determinants of job satisfaction. However, we recovered about 15% (i.e., 4,272 individuals) of our total sample. We then implemented a more precise manual coarsening strategy to obtain a larger number of observations and thus improve the quality of the study's results. For this approach, we grouped categories of some categorical variables that referred to the same information. This allowed us to simplify the analysis and make it more manageable by reducing the number of categories. It also allowed for easier comparison between the different levels of categories and facilitated the interpretation of the results. We also grouped information from some continuous variables. This is particularly relevant for several reasons. Firstly, it can facilitate the comparison between continuous and categorical variables, which is important as both types of variables can be important determinants of job satisfaction. Additionally, it can help avoid issues related to loss of precision when continuous variables are used in the matching process, which can be particularly important in empirical analyses. Finally, grouping continuous variables can reduce

the number of comparisons to be made, which can simplify the analysis and make the results more easily interpretable.

We grouped the categories of educational attainment based on the International Standard Classification of Education into three categories: "primary education" (Early childhood education, Primary education, and Lower secondary education), "secondary education" (Upper secondary education, Post-secondary non-tertiary education, and Short-cycle tertiary education), and "higher education" (Bachelor or equivalent, Master or equivalent, and Doctorate or equivalent). This grouping allows for the comparison of educational attainment across different countries and regions that use the same classification system, making it easier to conduct cross-national and cross-cultural research. These categories generally correspond to the standard classification of education categories. This coarsening provided about 21% more observations (i.e., 10,254 individuals). We next subdivided continuous variables. Age is grouped into five-year intervals that correspond to standard labor force categories. This grouping practice is commonly used in statistical analyses and facilitates comparison with other studies or demographic data (De Galdeano, 2002). There are eleven age intervals, ranging from ages 15 to 65, with each interval comprising a range of five years. Grouping age into intervals simplifies data analysis and allows for trends and patterns to be analyzed across different age groups. Additionally, the use of standard age intervals enables researchers to compare their findings with those of other studies that have used the same intervals, and follows an established methodology in statistical analysis. We introduce this variable into the algorithm by specifying in parentheses the cutoff points according to the thresholds of the intervals. This means that a variable is included in an algorithm and the thresholds for the intervals are determined by specifying the cutoff points in the variable. These cutoff points define the boundaries of the intervals and enable the algorithm to categorize observations based on the variable in question. By specifying the thresholds for the intervals, we can adjust the sensitivity of the algorithm to the distribution of the variable and obtain more accurate and meaningful results (Iacus et al., 2011). Pay is grouped into quintile groups (Perugini and Vladislavljević, 2019), dividing pays into five equal parts in terms of pay from lowest to highest. This grouping is particularly relevant because it allows for the variation in pays within each group to be taken into account, and ensures that the samples selected for each group have similar levels of remuneration. This helps to minimize the effects of pay on job satisfaction. We introduced this variable into the algorithm by indicating the variable representing pay and the number of groups into which it should be divided (in our case, 5). After matching, we obtained about 45% more matches.³ Finally, we obtained 2,598 strata with at least one male and one female match, including 18,676 employees out of 28,483 (with approximately 29% men and 36% women entering the new sample), which is about 66% of our initial sample.⁴

³We attempted more coarsening to obtain more matches (e.g., opting for 10-year age-gap intervals, etc.), but ended up with almost the same number of observations. As we do not want to delete any variables, since all of them are considered important, our coarsening strategy was therefore limited to this level, and we preferred to include the industry and occupation variables independently to avoid matching individuals in different types of jobs.

⁴Approximately 34% of employees are excluded from the sample. Of these individuals, 29% are women and 39% are men. Among the unmatched men and women, most do not match on pay (20% of men and 12% of women), followed by the type of occupation (11% of men and 13% of women), followed by sector of activity (5% of men

We assessed the success of the match between men and women by checking for balance. To do so, we utilized the multivariate imbalance measure (\mathcal{L}_1) developed by Iacus and colleagues.⁵ (See Table 1.8.2 in the Appendix for the results.) For each variable, the imbalance measure is either zero or very close to zero, and the initial overall imbalance is reduced by about 25%. This indicates that there is a perfect balance between men and women regarding their characteristics. After completing the matching procedure, we had a sample of comparable men and women that could be used to estimate the effect of job satisfaction. Thus, it is possible to reliably estimate the effect of job satisfaction using this matched sample.

1.4.3 Methodology for estimating gender differences in satisfaction at the homogeneous sample level

Simple *probit* regression is widely used to model binary outcomes. However, in the study of job satisfaction, there may still be a censoring problem since surveys do not provide job satisfaction data for respondents who are not employed (Clark, 1997; De Galdeano, 2002). In this case, unobserved factors that affect job satisfaction may be correlated with factors that affect employment status. This is particularly true when attempting to compare the level of job satisfaction between men and women, as different mechanisms may be involved in the selection of male and female samples. For instance, dissatisfied women may be more likely than dissatisfied men to prefer working from home because of different responsibilities (Perugini and Vladislavljević, 2019). Consequently, in job satisfaction surveys, men may be randomly selected since most of them work, which is not often the case for women, leading to selection bias. Therefore, direct estimation in the considered sample could yield inconsistent estimators. To address this issue, we assume that individuals can only report a level of job satisfaction if they are employed, and therefore, these individuals are likely to be a non-random subsample of all those who can express their level of satisfaction. In this case, we consider the probability of being employed as a selection equation and use the *probit* regression with sample selection introduced by (Van de Ven and Van Praag, 1981). We first consider the principal equation of job satisfaction described as follows:

$$y_i = 1(\beta W + x_i\theta + \mu_{1i}) \quad (1.3)$$

Where, y_i represents the dichotomous variable of job satisfaction. The indicator function $1(\cdot)$ is observed in the case where the individual is satisfied with his job, and 0 otherwise. W is the dichotomous variable for gender, which takes the value 1 if the individual is a woman and 0 otherwise. β is the coefficient to be estimated. It represents the difference in job satisfaction between women and men, *ceteris paribus*. Specifically, if $W = 1$ for women and $W = 0$ for men, then the coefficient β measures the average difference in job satisfaction between women

and 2% of women), while for the other variables used in the matching, the percentage does not exceed 0.5%.

⁵The multivariate imbalance measure is a relative quantity that depends on the variables used in the matching and the dataset. As the two distributions overlap, this measure decreases and approaches 0. It provides an overall measure of imbalance and a variable-specific measure (for more information, see Iacus et al. (2012)).

and men, after controlling for the effects of other explanatory variables (x_i). In economic terms, the coefficient β represents the *unexplained* difference in job satisfaction between women and men, i.e. the part of the difference that cannot be explained by the other explanatory variables included in the model. This unexplained difference could be due to factors such as gender discrimination, differences in cultural or job expectations, social roles, etc. x_i is the vector of explanatory variables that contains a set of control variables (this is the set of variables used in the matching but in an un-coarsened version) and other variables that may influence satisfaction (see Table 1.8.1 in Appendix for details of these variables); it also contains the constant. θ is the coefficient to be estimated. The error μ_{1i} is standard normal. In addition to this equation, there is the selection equation, which represents the probability of holding a salaried job, whose equation is written:

$$s_i = 1(z_i\alpha + \mu_{2i}) \quad (1.4)$$

With α a vector of unknown parameters to be estimated. z_i is a vector of predictors where some of them are not related to job satisfaction. Following the literature, we included a set of variables related to personal and household characteristics: age, age squared out of 100, education level, in a couple, number of hours worked by partner, number of children in the household (under 2, 2--6, and 7--14), number of elderly in the household, and household size (Clark, 1997; De Galdeano, 2002; Perugini and Vladislavljević, 2019). Each of the variables is then interacted with the dichotomous variable for gender (Clark, 1997; De Galdeano, 2002), allowing for differences in labor force participation behavior between men and women. The indicator function $1(\cdot)$ is observed if the respondent is working and 0, otherwise. The error μ_{2i} is standard normal. The errors μ_{1i} and μ_{2i} are assumed to be normal with:

$$\text{cor}(\mu_{1i} \text{ and } \mu_{2i}) = \rho \quad (1.5)$$

ρ allows us to analyze the relationship between the prediction errors of the satisfaction variables and the prediction errors of the selection variable. A positive correlation between the errors ($\rho > 0$) indicates that the errors in predicting the response variable and selection are positively correlated, i.e., if the model underestimates the probability of satisfaction for an individual, it also tends to underestimate the probability of selection for that individual. Similarly, if the model overestimates the probability of satisfaction for an individual, it also tends to overestimate the probability of selection for that individual. A negative correlation between the errors ($\rho < 0$) indicates an inverse relationship between the prediction errors of the response and selection variables. In this case, if the model underestimates the probability of satisfaction for an individual, it tends to overestimate the probability of selection for that individual, and conversely, if the model overestimates the probability of satisfaction for an individual, it tends to underestimate the probability of selection for that individual. In general, a high correlation between the errors (ρ close to 1 or -1) may indicate a strong interdependence between the selection and response processes, which may have important implications for the estimation and interpretation of the model coefficients.

Let N be the set of observations where satisfaction (y_i) is observed. The Log likelihood for the *probit* model with sample selection is:

$$\ln L = \sum_{i \in N} y_i \ln \Phi_2(\beta W + x_i \theta, z_i \alpha, \rho) + (1 - y_i) \ln \Phi_2(-(\beta W + x_i \theta), z_i \alpha, -\rho) + \sum_{i \in N} \ln(1 - \Phi_2(z_i \alpha)) \quad (1.6)$$

Φ_2 is the bivariate normal cumulative distribution function. $\ln L$ is used to evaluate the quality of the model's fit to the observed data. The higher the log-likelihood value, the better the fit of the model to the data.

After explaining our data and methodology, we now turn to the presentation of our main results, which provide important insights into our research question.

1.5 Empirical results

This section presents estimates of the decomposition of the satisfaction gap between men and women using the Fairlie method. We also examine the gender satisfaction gap on a sample of men and women with similar characteristics and take into account the selection bias problem. Finally, we test the hypothesis of different expectations between men and women.

1.5.1 Results of the gap decomposition by the Fairlie method

Table 1.2 presents the results of the decomposition analysis. The table displays the mean satisfaction levels for both men and women, the difference in satisfaction between the two groups, and the proportion of this difference in satisfaction that can be explained by measured and unmeasured factors. The column labeled "Details explained" shows the proportion of the difference in satisfaction explained by each measured factor, such as age, education, relationship status, parenthood, health, employment status, tenure, pay, company, occupation, sector, and country. The percentages indicate the share of the difference in satisfaction that can be explained by each factor.

The differences in satisfaction between men and women are statistically significant. The estimates show that women report higher levels of overall satisfaction, job security satisfaction, and social relationship satisfaction by 0.025, 0.022, and 0.013, respectively, compared to men. On the other hand, a higher percentage of women report lower levels of satisfaction with pay and career development prospects, with estimates of -0.031 and -0.039 , respectively (Clark, 1997).

The gaps in overall satisfaction and satisfaction with pay are mostly explained by the different individual and professional characteristics of men and women. The most influential factors for overall satisfaction are geographic location (35.3%), followed by sector of economic activity (26.5%), and having a permanent contract (14.5%). Regarding the gap related to pay, the number of hours worked (25.4%), followed by sector of activity (18.7%) and the pay received (15.1%) were the most influential factors for men's higher satisfaction. However, these results are not consistent with some previous studies (Clark, 1997; De Galdeano, 2002). Our results could be

explained by occupational segregation in the labor market, which has favored men in terms of pay rates and occupation by sector. Jobs in certain sectors (e.g., transport, construction, etc.) (see Table 1.1) are more commonly held by men than women, and provide higher than average pay levels.

The difference in satisfaction with job security appears to be explained by both observable and unobservable characteristics. The most influential observable effect is the sector of activity, which contributed 26.7%, followed by the position held with 21.7%, and having a permanent contract with 16.7%. This could be explained by the fact that women are more numerous in the service sector (see Table 1.1), which provides more permanent contracts subject to less strenuous work, and may provide them with a higher level of satisfaction through job security. For the remaining two measures, the gaps are largely unexplained. However, full-time employment, permanent contract, and company size each contributed 11% to the satisfaction gap, followed by tenure at 8% as observable factors. These elements can generally be compelling factors in an employee maintaining social contacts. In particular, among women, who are thought to be better at building relationships in the workplace and creating a friendly work environment (Burke, 2001).

Table 1.2: Fairlie decomposition gap of job satisfaction

	N	Overall	Pay	Prospects	Security	Colleagues
Mean satisfaction women	14,865	0.253	0.155	0.130	0.485	0.577
Mean satisfaction men	13,551	0.228	0.186	0.169	0.463	0.564
Satisfaction gap	28,483	0.025	-0.031	-0.039	0.022	0.013
Percentage explained		70.6%	-80.1%	-13.2%	50%	33.3%
Percentage unexplained		29.4%	-19.9%	-86.8%	50%	66.7%
Details explained						
Age		-2.9%	-0.2%	-1.5%	-6.7%	-11.1%
Education		0.0%	5.2%	3.8%	-10%	0.0%
Relationship		-1.9%	0.0%	-1.9%	0.0%	0.0%
Child		0.0%	-3.7%	-4.5%	-6.7%	3.2%
Good health		-5.9%	-1.5%	0.6%	1.7%	0.0%
Full time		0.0%	-25.4%	-5.1%	0.0%	11.1%
Permanent		14.5%	0.7%	0.6%	16.7%	11.1%
Tenure		0.0%	0.0%	0.0%	3.3%	8.1%
Autonomy		0.0%	0.0%	0.0%	0.0%	0.0%
Log pay		0.0%	-15.1%	-1.5%	-9.5%	-8.5%
Company		5.9%	4.5%	-0.6%	0.0%	11.1%
Occupation		0.0%	-11.2%	2.1%	21.7%	-5%
Sectors		26.5%	-18.7%	-3.1%	26.7%	6.1%
Countries		35.3%	-14.6%	-2.2%	12.7%	7.2%

Notes: Author's calculation based on data from European Working Condition Survey (2015). Fairlie's decomposition technique is based on simple *probit* regression with a pooled sample of men and women.

Regarding the gap related to career development prospects, the most significant factors are full-time work, childbearing, and sector of activity, explained respectively as 5.1%, 4.5%, and 3.1%. Career interruptions for women due to maternity can hinder their career development. In addition, this reflects the filling of jobs in sectors such as public works, construction, and

industry, where men predominate (see Table 1.1). These sectors generally react much more quickly when it comes to creating new jobs, while women are not able to adapt as easily to changing labor market demands due to child-bearing, maternity leave, and child-care.

However, it is possible that unmeasured factors such as differences in work experiences, skills, attitudes, or personal aspirations may influence the satisfaction gap between men and women. To better isolate the effects of the measured factors on satisfaction, it is important to reduce differences in the characteristics of the compared samples by conducting a more homogeneous analysis. To achieve this goal, we used a matching method to create a sample of comparable men and women, which will allow us to analyze the satisfaction differential with a new, more homogeneous sample.

1.5.2 Gender differences in job satisfaction among a homogeneous sample of men and women

In this section, we present the results of our analysis of job satisfaction determinants and gender-related differences among a homogeneous sample of men and women. First, we present the results of our analysis of the determinants of job satisfaction. We examine how each of these factors affects overall job satisfaction and satisfaction with specific job aspects. Next, we turn our attention to gender-related differences in job satisfaction within our sample. We examine whether there are any significant differences in job satisfaction levels between men and women, and if so, we explore the potential factors that may be contributing to these differences.

1.5.2.1 Determinants of job satisfaction

The determinants of satisfaction are analyzed on the basis of the control variables related to the individual and professional characteristics specified in Table 1.8.1 in the appendice and introduced into the different regressions of the differential of satisfaction according to gender in the Appendix. The interpretation of the results for these variables is based on the estimates obtained from the satisfaction equations with sample selection (see Table 1.8.5 in the appendix).

The coefficients of these controls indicate a non-linear relationship between age and all satisfaction measures, manifested as a "U" curve, as previously found by Clark (1997) and Gazioglu and Tansel (2006). According to Royuela (2013), this result is generally related to workers' expectations and goals in their professional careers. Younger workers tend to report higher job satisfaction due to success in finding a job, change of environment, improved pay, and change of status. However, job satisfaction tends to decrease as they gain more experience, probably because job expectations are not always met. This leads many workers to seek new employment opportunities with higher pay and better career plans. As workers gain more experience and age, they acquire a better understanding of the job market, allowing them to surpass the intrinsic values of a job, resulting in increased job satisfaction. The level of education is positively correlated with satisfaction in terms of pay, career development prospects, and job security, as previously

shown by O'Reilly III (1981) and Perugini and Vladislavljević (2019). However, the results of Clark et al. (1996) show a negative relationship between satisfaction and education, which is confirmed by Gazioglu and Tansel (2006), who found that workers with higher degrees are less satisfied than those with less education. The greatest dissatisfaction for highly educated workers is related to their sense of fulfillment with their work and its influence. According to Clark et al. (1996), although better-educated workers have better jobs, education is positively correlated with workers' expectations of the type of job they should have, leading to higher expectations that may not be met. Thus, the comparison effect associated with education seems to outweigh the positive effect associated with the type of job workers have. As a result, more workers report being dissatisfied with their jobs (Hackman, 1970). Relationship status and the presence of children in the household are only occasionally significant (Clark, 1997). Like Clark (1997), good health (as opposed to poor health) is positively correlated with all measures of job satisfaction. This positive effect is due to the fact that unhealthy workers tend to report low levels of satisfaction with all aspects of their lives or can only get relatively unsatisfying jobs (Clark, 1997).

Regarding job-related characteristics, manager, professional, technician, and clerical positions are all associated with higher job satisfaction compared to elementary occupations. The magnitude is higher for managers and professionals (Perugini and Vladislavljević, 2019). Working time has a negative effect on overall and pay satisfaction (Clark, 1997). Workers in the health sector are less satisfied with their pay compared to the industrial sector, while those in education and transport have lower satisfaction with their career development prospects. However, moving into sectors such as administration, education, and health is associated with higher satisfaction with job security. Workers in large firms express lower satisfaction with all measures compared to those in small firms. This is consistent with the results of Gazioglu and Tansel (2006) who studied the nature of this relationship and its link with overall satisfaction, pay, sense of accomplishment, and respect received from superiors. Smaller companies offer more conviviality and a better quality of life at work. They provide more responsibility through proximity, which allows for more effective communication and avoids information asymmetries linked to hierarchy. Furthermore, a large company has more entities giving more choice and access to senior positions, unlike a small company where management is not very broad and does not allow for rapid grading or horizontal progression to other positions. Employees on permanent contracts have higher levels of satisfaction on all measures compared to those on temporary contracts (Aleksynska, 2018). This is probably due to the security and stability of employment and the ease of taking out credit loans that this type of contract provides. Tenure is negatively related to satisfaction with pay and career development prospects and positively correlated with satisfaction in terms of job security and relationships with colleagues. Higher autonomy at work is associated with increased job satisfaction on all measures (Sousa-Poza and Sousa-Poza, 2000; De Galdeano, 2002). This is probably because the autonomous employee has the possibility to take initiatives without the advice of the superior in case of difficulties related to their work, to organize their work freely, and to make suggestions and give their opinion in certain situations. Thus, stress is less felt and the employee is more fulfilled in their work. High

pay positively affects employee satisfaction on all measures (Clark, 1997; De Galdeano, 2002; Gazioglu and Tansel, 2006; Card et al., 2012). However, Sell and Cleal (2011) consider that this positive relationship does not necessarily mean that the employee is happier at work, but that a higher pay increases overall utility by increasing opportunities for total spending.

We also consider the country pairs with the United Kingdom as the reference country.⁶ Our results showed that employees in Belgium, Denmark, Ireland, Luxembourg, the Netherlands, Austria, and Sweden were more likely to report higher levels of satisfaction on all measures. Conversely, employees in Greece, Italy, and Croatia reported levels of dissatisfaction on at least two measures.”

1.5.2.2 Differential by gender

Table 1.3 presents estimates from one-series *probit* models with and without sample selection for Generation 5, using the five measures of job satisfaction at the matched sample level. The models follow the specification in Equation (1.3) and include a dichotomous variable for gender, where women are assigned a value of 1 and men a value of 0. In this case, the satisfaction differential is captured by the level of satisfaction reported by women (in terms of sign and significance). Including a dichotomous variable for gender as a satisfaction gap allows us to directly account for the satisfaction gap between men and women in the regression model, without having to decompose the gap according to the different measures. This method is useful for studying the effect of gender on overall satisfaction, while controlling for other measured and unmeasured factors that might influence satisfaction.

The models are adjusted for sample selection using the job probability equation. The signs of the coefficients in the equation indicate that selection into paid employment is not random. The likelihood of being a dependent employee increases with education and childbearing. For women, being married and having children under the age of two decreases their likelihood of being a dependent employee. For men, being older, married, and having children increases their likelihood of being employed (see Table 1.8.3).

When considering the effects of job satisfaction by gender, we find, from the coefficients estimated using probit regression without correction for sample selection (Table 1.3), that differences in job satisfaction between men and women cannot be fully explained by differences in their individual and professional characteristics, such as work experience, skills, attitudes, or personal aspirations. Women have higher overall job satisfaction and job security, but lower pay satisfaction and career prospects than men. These results are consistent with previous studies, but differ with respect to satisfaction with relationships with colleagues, which is not significantly

⁶We chose to use the United Kingdom as our reference country for several reasons. Firstly, it is commonly used as a reference country in studies of Europe or English-speaking countries, making it easier to compare our results with other studies (e.g., Brug et al., 2008; Mackenbach et al., 2008; Maben et al., 2012). Additionally, if the goal of our analysis is to compare integrated European countries, the choice of reference country will not affect the results as long as the reference country is included in the sample.

Table 1.3: Coefficient for women: *probit* regression, and matched sample with CEM ($N = 18,676$)

Dependent variable	With interactions										ρ (for interactions)	ρ (for Dummy)	L.likelihood (for interactions)	L.likelihood (for Dummy)	L.likelihood (for interactions)
	Women	Women	Women	Women	Women	Women	Women	Women	Women	Women					
Overall (1)	0.041* (0.024)	0.039* (0.024)	-0.011 (0.021)	0.006 (0.024)	-0.001 (0.021)	0.006 (0.024)	0.006 (0.024)	0.006 (0.024)	0.006 (0.024)	0.006 (0.024)	-0.045** (0.024)	-0.378	-18,151.08	-17,141.01	
Overall (2)	0.039 (0.023)	0.038 (0.023)	-0.011 (0.021)	0.015 (0.023)	-0.006 (0.020)	0.015 (0.023)	0.015 (0.023)	0.015 (0.023)	0.015 (0.023)	0.015 (0.023)	-0.046** (0.022)	-0.393	-17,642.60	-17,393.45	
Pay (1)	-0.053* (0.028)	-0.051** (0.028)	0.015 (0.029)	0.016 (0.028)	0.037 (0.028)	0.016 (0.028)	0.016 (0.028)	0.016 (0.028)	0.016 (0.028)	0.016 (0.028)	-0.116** (0.025)	0.409	-17,863.70	-17,413.72	
Pay (2)	-0.033 (0.026)	-0.029 (0.025)	0.001 (0.028)	0.005 (0.031)	0.043* (0.024)	0.005 (0.031)	0.005 (0.031)	0.005 (0.031)	0.005 (0.031)	0.005 (0.031)	0.075** (0.024)	0.312	-16,740.25	-15,732.19	
Prospects (1)	-0.088** (0.029)	-0.086** (0.029)	0.094** (0.031)	-0.018 (0.025)	0.098** (0.026)	-0.018 (0.025)	-0.018 (0.025)	-0.018 (0.025)	-0.018 (0.025)	-0.018 (0.025)	0.010 (0.022)	0.538	-17,529.51	-17,482.08	
Prospects (2)	-0.075*** (0.028)	-0.077** (0.028)	0.074* (0.026)	-0.010 (0.023)	0.090** (0.023)	-0.010 (0.023)	-0.010 (0.023)	-0.010 (0.023)	-0.010 (0.023)	-0.010 (0.023)	0.003 (0.020)	0.532	-17,253.91	-17,166.43	
Job security (1)	0.063** (0.026)	0.063** (0.026)	-0.012 (0.024)	-0.018 (0.029)	-0.023 (0.026)	-0.018 (0.029)	-0.018 (0.029)	-0.018 (0.029)	-0.018 (0.029)	-0.018 (0.029)	-0.037* (0.021)	-0.026	-18,096.54	-18,075.52	
Job security (2)	0.062** (0.026)	0.060** (0.026)	-0.009 (0.025)	-0.019 (0.029)	0.020 (0.025)	-0.019 (0.029)	-0.019 (0.029)	-0.019 (0.029)	-0.019 (0.029)	-0.019 (0.029)	-0.032* (0.020)	-0.029	-18,069.26	-17,969.12	
Colleagues (1)	0.026 (0.025)	0.023 (0.025)	-0.008 (0.026)	-0.015 (0.025)	0.017 (0.023)	-0.015 (0.025)	-0.015 (0.025)	-0.015 (0.025)	-0.015 (0.025)	-0.015 (0.025)	-0.004 (0.020)	-0.017	-18,300.14	-18,257.98	
Colleagues (2)	0.025 (0.025)	0.024 (0.025)	-0.008 (0.021)	-0.016 (0.024)	0.016 (0.020)	-0.016 (0.024)	-0.016 (0.024)	-0.016 (0.024)	-0.016 (0.024)	-0.016 (0.024)	-0.004 (0.018)	-0.014	-18,066.11	-17,762.32	

Notes: Author's calculation based on data from EWCS (2015). The control variables specified in Table 1.8.1 in Appendix are included (Details of the results are presented in the tables 1.8.4 to 1.8.7). Country dummies (35) included. (1) is the regression result without sample correction and (2) is the counterpart with sample selection correction. The number of observations is obtained thanks to the option that allows us to have the total number of matched individuals. Robust standard errors are in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

different between men and women in this homogeneous sample. These findings are consistent with previous research (Clark, 1997; De Galdeano, 2002) regarding overall satisfaction.

Adjusting for sample selection has no impact on satisfaction with job security and relationships with colleagues, suggesting that these differences in satisfaction cannot be explained by sample selection. However, for overall satisfaction and pay satisfaction, the coefficients became insignificant after adjusting for sample selection, indicating that gender is a significant predictor of the likelihood of being employed, but once it is clear that the sample is composed only of employed people, the difference in overall satisfaction and pay satisfaction no longer seems to have the same significant importance. These results differ from previous studies (De Galdeano, 2002; Perugini and Vladislavljević, 2019). This could be explained by the use of the Coarsened Exact Matching (CEM) method, which guarantees a sample of men and women who are perfectly comparable in their characteristics. Additionally, it could be explained by the use of a more recent database including a larger number of European countries.

The results of this study suggest that there are differences in job satisfaction between men and women, even after controlling for individual and job characteristics. Specifically, women tend to be more satisfied with their job security and overall job satisfaction, but less satisfied with their pay and career prospects. This could suggest that women have a different appreciation of their work compared to men, or that they face specific obstacles in their careers that hinder their job satisfaction. The results of the study also show that controlling for sample selection did not have much of an impact on the differences in satisfaction between men and women with job security and relationships with colleagues. This suggests that women, once employed, are just as satisfied with their job security and relationships with colleagues as men. However, the differences in satisfaction between men and women in terms of overall satisfaction and pay satisfaction lost their significance after adjusting for sample selection. This indicates that the differences in satisfaction between men and women in these areas may be partly explained by differences in the job rather than by differences between the sexes themselves.

In terms of career prospects, the results show that men remained more satisfied despite controlling for confounding factors and sample selection. This result suggests that women feel less optimistic about their career prospects than men, even after controlling for confounding factors and sample selection. There are several reasons for this. First of all, there are gender stereotypes (Heilman, 2001). Women often face gender stereotypes in their working lives, which can limit their career progression. Employers and colleagues may have different expectations for men and women in terms of roles, behaviors, and skills, which may limit career opportunities for women. Secondly, there is the pay gap (Blau and Kahn, 2020). Women tend to earn less than men for the same work, which can affect their motivation and their perception of their career prospects. Pay differentials can also lead to a perception of unfairness and discrimination, which can limit women's confidence in their ability to progress in their careers. In addition, there is work-life balance. Women often face challenges in reconciling their work and personal lives,

such as childcare or caring for family members. This can limit their ability to work full-time, take on additional responsibilities or pursue career opportunities. Finally, there is the lack of female role models (Niederle and Vesterlund, 2007). The lack of female role models in leadership positions or traditionally male professions can limit women's perception of their own abilities to progress in their careers. Women may find it difficult to imagine themselves achieving leadership positions or ambitious careers if they do not have role models to compare themselves to.

However, it is important to note that the results may vary depending on different factors such as status, age, education, and sector of activity, which can all impact women's career expectations and prospects (Clark, 1997). For example, women in managerial positions or with a higher level of education may have different expectations and career prospects compared to those in junior positions or with a lower level of education. Similarly, women working in male-dominated sectors may face different challenges in terms of promotion and professional recognition. Therefore, further analysis has been conducted to determine whether these factors have an impact on the results observed in this study.

1.5.3 Analyzing the impact of expectation-indicating Variables on gender differences in job satisfaction

We also conducted an analysis of the interaction between the variable representing women and several other variables used in the estimations. This approach accounts for the limitations of using a dichotomous variable alone, which may not fully capture the differences in job satisfaction between men and women. As our analysis aims to explain the reasons for the observed differences in satisfaction levels, it is essential to consider expectation-indicating variables such as age, education level, position in the hierarchy, and working in male-dominated sectors.⁷ We dichotomized the age variable (*AGE*), which takes the value of 1 if the individual is aged between 15 and 24 years and 0 otherwise.⁸ The education level (*ED*) is dichotomized, with the value of 1 assigned to individuals who have completed higher education levels (bachelor's, master's, or doctorate), and 0 assigned to those who have not. For the good jobs variable (*GJ*), we coded managers, professionals, and technicians and associate professionals as 1 (consistent with Clark's reasoning (1997)), while all other occupations were coded as 0. For the male-dominated work sectors variable (*MDW*), we assigned a value of 1 for industries, construction, agriculture, and transport (in which men represent 65.7%, 90.38%, 65.4% and 77.54%, respectively), and 0 for all other sectors. To account for the effect of expectations, we estimate a modified version of equation (1.3), which includes the interaction between the expectation variables and the dichotomous variable for women, as follows:

$$y_i = 1(\beta W + \vartheta_1 \cdot W \times AGE + \vartheta_2 \cdot W \times ED + \vartheta_3 \cdot W \times GJ + \vartheta_4 \cdot W \times MDW + x_i \theta + \mu_{1i}) \quad (1.7)$$

⁷Clark (1997) argues that women who are younger, have completed higher levels of education, work in good jobs or male-dominated sectors, have similar work expectations as men, and therefore express lower levels of satisfaction with their work.

⁸According to the OECD, people between the ages of 15 and 24 are those who enter the labor market after completing their education.

The results are presented in Table 1.3, which highlights the impact of various factors on women's pay expectations. These factors include age, education level, hierarchical position, and work environment.

The results showed that women's pay expectations are influenced by different factors such as age, education level, hierarchical position, and work environment. Younger women, with higher education, in higher hierarchical positions, and working in male-dominated work environments have higher pay expectations, which may explain the pay satisfaction premium they express. As regards satisfaction with career development prospects, younger women and those in higher hierarchical positions expressed greater satisfaction. This may be due to the fact that they have not yet been confronted with social constraints such as household management, maternity leave, etc. Women in senior positions also express pride in their positions, perhaps because of their success in overcoming occupational segregation. With regard to overall satisfaction and satisfaction with job security, women working in male-dominated work environments expressed a decrease in satisfaction. This may be due to a revision of their expectations and an alignment of these with those of men (Perugini and Vladislavljević, 2019). Indeed, women working in male-dominated work environments may face different social norms and expectations compared to women working in female-dominated work environments.

The study's results appear to be consistent with theories of social role, social exchange, and equity. Firstly, social role theory suggests that individuals have roles and expectations associated with their gender, race, religion, etc. In this context, women have different salary expectations based on their age, education level, hierarchical position, and work environment, which can be influenced by social expectations associated with gender. Secondly, social exchange theory suggests that individuals evaluate their social relationships in terms of costs and benefits. Women have higher salary expectations in male-dominated work environments, which can be interpreted as an attempt to compensate for the additional costs associated with gender discrimination. Finally, equity theory suggests that individuals compare their contribution and reward with that of others to evaluate if they are being treated fairly. Women are less satisfied with their salary and career prospects than men, even after controlling for individual and job characteristics, which may be linked to a perception of imbalance between women's contribution and their reward, leading to a sense of injustice and dissatisfaction.

After presenting the results of a study, it is important to assess the robustness of these findings by examining their sensitivity to different specifications or methods. This allows to evaluate the strength and reliability of the results. Therefore, the next section will focus on the analysis of the robustness of the findings.

1.6 Robustness check

In this section, we aim to check the robustness of our results at five different levels. First, we will repeat the specifications by recoding the dichotomy of outcome variables related to various satisfaction measures. Second, we will apply the Oaxaca-Blinder decomposition method to validate the results obtained from the Fairlie decomposition. Third, we will test the robustness of our estimates at the level of a homogeneous sample of men and women by performing country-by-country estimates. Fourth, we will test the robustness of the Matching method using another matching approach, Propensity Score Matching (PSM), and subsequently test the regressions. Finally, we will check the robustness of our analysis of the expectations hypothesis by taking into account the different evolution of the context of gender inequalities in different countries.

1.6.1 Analyzing the robustness of job satisfaction measures through recoding of outcome variables

Our outcome variables, which are related to measures of job satisfaction, are measured using a Likert scale. However, we have observed that respondents tend to give the answer "satisfied" more frequently when asked to rate their level of satisfaction. This can result in a biased estimate of our coefficients if this answer is given arbitrarily, without reflecting the individual's true feelings. Therefore, we tested the robustness of our results by recoding our dependent dichotomous variables. Specifically, we coded the variable as 1 if the individual declared to be "very satisfied" or "completely agree," and 0 otherwise. We believe that individuals only declare to be "very satisfied" or "completely agree" if they truly feel that way, and therefore this recoding should result in a more accurate measure of job satisfaction.

Tables 1.4 and 1.5 present the results of the Fairlie decomposition and the estimation of the satisfaction differential at the matched sample level, respectively. For the second table, we plotted the results before and after adjusting for the selection effect, as we did in previous regressions. Overall, the results are quite similar in sign and significance to the previous regressions. According to the Fairlie decomposition results (Table 1.4), the direction of the gaps across different measures remains similar, suggesting that the previous estimates are robust. Women remain more satisfied with overall job security and relationships with colleagues, while men seem more satisfied with pay and career development prospects. Regarding overall satisfaction, differences in individual and professional characteristics explain the majority of the gap between men and women. In more detail, the most influential factors, in decreasing order, are differences according to the country (37.4%), sector of activity (30.1%), and permanent contract (18.5%). For satisfaction with job security and relations with colleagues, the differential in satisfaction is explained by unobservable effects. Satisfaction with job security differs slightly from the previous regressions, but the difference is not significant, especially since the differential is clearly in favor of women in the regressions. For measures related to pay and career development prospects, satisfaction appears to be higher among men. The pay satisfaction differential is mostly explained by observable characteristics. The most important observable elements concern

Table 1.4: Fairlie decomposition gap of job satisfaction after recoding the result variables

	N	Overall	Pay	Prospects	Security	Colleagues
Mean satisfaction women	14,865	0.351	0.178	0.125	0.479	0.575
Mean satisfaction men	13,551	0.218	0.195	0.178	0.461	0.560
Satisfaction gap	28,483	0.133	-0.017	-0.053	0.018	0.015
Percentage explained		85.4%	-88.5%	-12.9%	49.8%	33%
Percentage unexplained		14.6%	-11.5%	-87.1%	50.2%	67%
Details explained						
Age		-2.9%	-1.5%	-1.3%	-8.9%	-11.1%
Education		1.5%	7.8%	6.4%	-13.5%	0.0%
Relationship		-1.9%	3.3%	-1.9%	0.0%	0.0%
Child		0.3%	-3.7%	-6.9%	-7.2%	3.2%
Good health		-4.9%	-2.2%	0.6%	1.7%	0.0%
Full time		0.0%	-18.1%	-5.1%	0.0%	11.1%
Permanent		18.5%	1.0%	0.7%	17.7%	11.1%
tenure		0.0%	0.8%	0.2%	3.3%	10%
Autonomy		1.1%	0.9%	0.0%	0.4%	0.0%
Log income		0.2%	-27.5%	-1.8%	-12.5%	-9.5%
Company		5.9%	7.5%	-0.6%	0.0%	11.1%
Occupation		0.0%	-15.2%	2.3%	25.4%	-5%
Sectors		30.1%	-24.2%	-3.1%	29.1%	6.1%
Countries		37.4%	-17.5%	-2.5%	13.8%	7.2%

Notes: Author's calculation based on data from European Working Condition Survey (2015). Fairlie's decomposition technique is based on simple *probit* regression with a pooled sample of men and women.

monthly net pay (27.5%), sectors of activity (24.2%), full-time work (18.1%), countries (17.5%), and types of occupation (15.2%). According to the matched-sample regressions (Table 1.5), the results are also similar to previous estimates. The coefficients for overall satisfaction and pay satisfaction become insignificant once selection bias is taken into account. Women remain more satisfied with job security, while men appear more satisfied with career development opportunities. The effects remain significant despite the homogenization of the sample and the incorporation of selection bias. On the other hand, the difference in satisfaction with relationships with colleagues is not significant.

The fact that the results are similar even with different coding suggests that the results are robust and not heavily dependent on how the variables were coded. This also indicates that the results are reliable, and the conclusions are likely valid.

1.6.2 Beyond observable characteristics: A robustness analysis of the Fairlie decomposition results with the Oaxaca-Blinder decomposition method

In this study, we utilized the Fairlie decomposition method. However, this method does not identify factors that contribute to differences that cannot be explained by differences in characteristics between groups. Therefore, we employed the Oaxaca-Blinder decomposition method (Blinder, 1973; Oaxaca, 1973) to examine the robustness of the results. This method breaks down differences in outcomes between two groups into two parts: one that can be explained by

Table 1.5: Coefficient for women: *probit* regression after recoding the result variables, and matched sample with CEM ($N = 18,676$)

Dependent variable	With interactions										ρ (for Dummy)	ρ (for interactions)	L.likelihood (for Dummy)	L.likelihood (for interactions)
	Women	Women	Women	Women	Women	Women	Women	Women	Women	Women				
Overall (1)	0.043* (0.024)	0.040* (0.024)	-0.011 (0.021)	0.007 (0.024)	-0.004 (0.021)	-0.049** (0.024)	0.007 (0.024)	0.004 (0.024)	0.004 (0.024)	0.004 (0.024)	0.408	0.312	-18,151.05	-17,140.90
Overall (2)	0.038 (0.023)	0.038 (0.023)	-0.012 (0.021)	0.016 (0.023)	-0.007 (0.020)	-0.046** (0.022)	0.016 (0.023)	0.016 (0.023)	0.016 (0.023)	0.016 (0.023)	-0.377	-0.393	-17,642.61	-17,393.44
Pay (1)	-0.061** (0.028)	-0.052** (0.028)	0.015 (0.028)	0.016 (0.028)	0.035 (0.028)	-0.118** (0.025)	0.016 (0.028)	0.016 (0.028)	0.016 (0.028)	0.016 (0.028)	0.408	0.312	-17,862.91	-17,414.19
Pay (2)	-0.033 (0.026)	-0.028 (0.025)	0.001 (0.028)	0.004 (0.029)	0.044* (0.024)	0.075** (0.024)	0.004 (0.029)	0.004 (0.029)	0.004 (0.029)	0.004 (0.029)	0.408	0.312	-16,740.25	-15,732.19
Prospects (1)	-0.090** (0.028)	-0.087** (0.028)	0.098** (0.029)	-0.017 (0.025)	0.099** (0.026)	0.011 (0.022)	-0.017 (0.025)	-0.017 (0.025)	-0.017 (0.025)	-0.017 (0.025)	0.537	0.531	-17,529.45	-17,481.98
Prospects (2)	-0.081*** (0.027)	-0.089** (0.027)	0.078** (0.026)	-0.009 (0.023)	0.095** (0.023)	0.002 (0.020)	-0.009 (0.023)	-0.009 (0.023)	-0.009 (0.023)	-0.009 (0.023)	0.537	0.531	-17,252.88	-17,166.12
Job security (1)	0.063** (0.026)	0.063** (0.026)	-0.011 (0.024)	-0.016 (0.029)	-0.023 (0.026)	-0.038* (0.021)	-0.016 (0.029)	-0.016 (0.029)	-0.016 (0.029)	-0.016 (0.029)	-0.029	-0.026	-18,096.53	-18,075.52
Job security (2)	0.062** (0.026)	0.061** (0.026)	-0.009 (0.025)	-0.019 (0.029)	0.021 (0.025)	-0.033* (0.020)	-0.019 (0.029)	-0.019 (0.029)	-0.019 (0.029)	-0.019 (0.029)	-0.029	-0.026	-18,069.26	-17,969.11
Colleagues (1)	0.025 (0.025)	0.023 (0.025)	-0.009 (0.026)	-0.015 (0.025)	0.015 (0.023)	-0.004 (0.020)	-0.015 (0.025)	-0.015 (0.025)	-0.015 (0.025)	-0.015 (0.025)	-0.014	-0.014	-18,300.14	-18,257.96
Colleagues (2)	0.025 (0.025)	0.024 (0.025)	-0.006 (0.021)	-0.016 (0.024)	0.015 (0.020)	-0.004 (0.018)	-0.016 (0.024)	-0.016 (0.024)	-0.016 (0.024)	-0.016 (0.024)	-0.014	-0.014	-18,066.10	-17,762.31

Notes: Author's calculation based on data from EWCS (2015). The control variables specified in Table 1.8.1 in Appendix are included. Country dummies (35) included. (1) is the regression result without sample correction and (2) is the counterpart with sample selection correction. The number of observations is obtained thanks to the option that allows us to have the total number of matched individuals. Robust standard errors are in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

differences in group characteristics, and one that cannot be explained by these differences. The Oaxaca-Blinder decomposition method thus enables the identification of factors that contribute to gaps not explained by differences in characteristics, such as discrimination or differences in treatment in the labor market.

We followed the following steps for this method:

- (i) We estimated two separate regression models, one for men and one for women, using the Fairlie decomposition method. We included a set of individual and occupational characteristics as independent variables, and job satisfaction as the dependent variable. As job satisfaction is categorical and ordered, we used an ordered logistic regression approach to model this variable. Our dependent variable was thus modeled as a continuous latent variable related to the observed categories through thresholds.
- (ii) Next, we calculated the average of the coefficients for each independent variable in each group. These means represent the average effects of the independent variables on job satisfaction for each group (men and women).
- (iii) Then, we calculated the difference between the average effects of each variable for the two groups. This difference represents the average effect of each variable on the difference in job satisfaction between men and women.
- (iv) We estimated a third regression model that included a group variable (male or female) as well as all the independent variables used in the previous models. This regression was used to determine the extent to which observed differences in group characteristics explained the differences in job satisfaction between men and women.
- (v) Finally, we decomposed the difference in job satisfaction between men and women into two parts: a part that can be explained by differences in group characteristics (calculated in step 4) and a part that cannot be explained by these differences (calculated in step 3).

As such, this method provides insight into the extent to which differences in job satisfaction between men and women can be attributed to differences in group characteristics, and allows for the identification of factors that contribute to gaps not explained by differences in characteristics. Mathematically, the decomposition can be written as follows:

$$GAP = \bar{y}_i^w - \bar{y}_i^m = [\sum (\bar{X}_i^w - \bar{X}_i^m) \hat{\beta}_i^m] + [\sum \bar{X}_i^m (\hat{\beta}_i^w - \hat{\beta}_i^m)] \quad (1.8)$$

\bar{y}_i^m and \bar{y}_i^w represent respectively, the average satisfaction for men and women. \bar{X}_i^m and \bar{X}_i^w are the characteristics vectors for men and women respectively. $\hat{\beta}_i^m$ and $\hat{\beta}_i^w$ are the coefficient vectors for men and women respectively. \sum is the sum for all characteristics.

The results are presented in Table 1.6, which shows that the Fairlie method's decomposition results are robust. The Oaxaca-Blinder decomposition results also reveal that women's higher satisfaction, in aggregate terms, is mostly explained by differences in observable individual and job characteristics. Specifically, the results show a negative difference of 0.3%, 2.2%, and 1.2% in overall job satisfaction, satisfaction with job security, and satisfaction with relationships

between colleagues, respectively, between women and men. This means that, on average, women have slightly lower job satisfaction than men in these different measures. The explained percentage of 71.6% for overall satisfaction indicates that 71.6% of the difference in satisfaction between women and men can be explained by observed differences in characteristics such as age, education, and work experience, among others. Therefore, the differences in demographic and occupational characteristics between women and men are crucial factors contributing to the difference in job satisfaction between the two groups. However, there is still a significant portion (about 28.4%) of the difference in satisfaction that remains unexplained by these observed characteristics. This unexplained portion may be due to other factors such as discrimination, gender stereotypes, and pay inequalities. The gaps in satisfaction with job security and coworker relations of 0.022 and 0.012, respectively, with explained percentages of 49.8% and 33%, suggest that the differences in satisfaction between men and women in these two measures are partially explained by observed differences in their characteristics. Still, there remains a large portion of the difference that remains unexplained and may be due to unobservable factors.

Moreover, the results also show a pay satisfaction gap of 0.034 and a satisfaction with career prospects gap of 0.039, both in favor of men. This means that, on average, men are more satisfied with their pay and job prospects than women. The explained percentage of 82.1% indicates that the majority (82.1%) of this pay satisfaction difference can be explained by observed differences in group characteristics such as age, education, work experience, and hierarchical position. However, there remains a significant proportion of the difference in pay satisfaction (about 17.9%) that is unexplained by these observed characteristics and may be due to other unobservable factors. Similarly, the unexplained 86.7% of satisfaction with career prospects suggests that the majority of the satisfaction premium related to this measure among men is explained by unobservable effects.

Unobservable effects are factors that cannot be directly measured in data but could contribute to the differences in job satisfaction between men and women. Among these unobservable effects, we can find gender stereotypes that could influence how men and women are perceived and treated in the workplace (Kim, 2005). For example, men may be considered more competent or better suited to make important decisions, which could contribute to their satisfaction with career prospects and salary. Similarly, women may be considered better at teamwork and maintaining positive work relationships, which could contribute to their satisfaction with relationships with colleagues (Clark, 1997). Another factor could be individual preferences. Men and women may have different preferences regarding their work, which could influence their satisfaction. For instance, men may place more importance on pay and career prospects, while women may place more importance on overall satisfaction, job security, and relationships with colleagues (Clark, 1997). Another factor that could strongly play into these differences related to unobservable effects could be social expectations. Indeed, gender-related social expectations could influence the expectations of men and women regarding their work (Westover, 2009). For example, men may be more inclined to pursue ambitious careers and take risks to achieve high career goals,

while women may be more inclined to seek stable and secure jobs that allow them to better balance their professional and personal lives (Westover, 2012). Additionally, we can add the effect of different life experiences. Men and women may have different life experiences that influence their job satisfaction (O’Neil, 2003). For example, women are more likely to have family responsibilities that can affect their ability to pursue ambitious careers and obtain higher salaries, which could contribute to their satisfaction with job security and overall satisfaction.

Table 1.6: Oaxaca-Blinder decomposition gap of job satisfaction

	N	Overall	Pay	Prospects	Security	Colleagues
Mean satisfaction men	13,551	0.219	0.179	0.172	0.456	0.566
Mean satisfaction women	14,865	0.222	0.145	0.133	0.478	0.578
Satisfaction gap	28,483	-0.003	0.034	0.039	-0.022	-0.012
Percentage explained		-71.6%	82.1%	13.3%	-49.8%	-33%
Percentage unexplained		-28.4%	17.9%	86.7%	-50.2%	-67%

Notes: Author’s calculation based on data from European Working Condition Survey (2015).

1.6.3 Application of Propensity Score Matching (PSM) method for improved internal validity

We applied the Propensity Score Matching (PSM) method to compare the results obtained using different metrics with those of the CEM, which improves the internal validity of the study and increases confidence in the results. We utilized the nearest-neighbor matching method (De Galdeano, 2002), which involves matching each woman in the worker population to the men in the group who have the closest propensity score (see Imbens (2004)). The propensity score refers to the conditional probability of a woman being in the worker population, given the observable covariates (De Galdeano, 2002).⁹

From the estimated propensity scores, individuals were classified into a common support interval, which is defined as a range of probabilities resulting from the estimation of the propensity scores, and it is used to restrict the sample to individuals likely to be matched. This conforms to the CEM algorithm, which restricts the data through the formation of strata. Individuals who have a propensity score outside this range are excluded from the sample. This ensures that the matched sample is restricted to individuals who are most likely to be comparable, which improves the internal validity of the study. Since we are not estimating the job satisfaction gap as a treatment effect, but only restricting our sample to comparable men and women in terms of characteristics, the matching order is irrelevant. Therefore, we perform our matching by choosing a single nearest neighbor and using multiple observations as nearest neighbors. This means that for each individual in the treated (women) group, the algorithm identifies a single individual

⁹The propensity score is estimated through a logistic regression model with the following specification: $\Pr(\text{women dummy}=1)=F(\text{age, age-squared}/100, \text{education dummies, health dummy, relationship dummy, number of children in the household dummy, establishment size dummies, occupational category dummies, industry dummies, log income, full-time job dummy, permanent worker dummy, partner’s weekly hours of work dummies, household income dummies, and country dummies})$.

Table 1.7: Coefficient for women: *probit* regression, and matched sample with PSM ($N = 21,062$)

Dependent variable	With interactions										L.likelihood (for interactions)	L.likelihood (for Dummy)	ρ (for interactions)	ρ (for Dummy)	L.likelihood (for interactions)	L.likelihood (for Dummy)
	Women	Women	Women	Women × AGE	Women × ED	Women × GJ	Women × MDW	Women × ED	Women × GJ	Women × MDW						
Overall (1)	0.054** (0.026)	0.052** (0.026)	-0.036 (0.029)	-0.042 (0.036)	0.021 (0.026)	-0.076** (0.033)	0.526	-0.428	-20,906.30	-20,456.12						
Overall (2)	0.048 (0.025)	0.045 (0.025)	-0.033 (0.028)	0.039 (0.035)	-0.021 (0.025)	-0.066** (0.031)	-0.455	-0.428	-19,845.26	-19,656.35						
Pay (1)	-0.057** (0.030)	-0.056** (0.030)	0.022 (0.035)	-0.044 (0.035)	0.064*** (0.035)	-0.125*** (0.034)	0.526	-0.428	-19,911.91	-19,003.11						
Pay (2)	-0.049 (0.028)	-0.046 (0.028)	0.018 (0.029)	0.033 (0.033)	0.064** (0.034)	0.119*** (0.033)	0.526	0.489	-18,576.25	-18,004.32						
Prospects (1)	-0.105*** (0.031)	-0.102*** (0.031)	0.104** (0.036)	0.028 (0.028)	0.195*** (0.029)	0.016 (0.026)	0.599	0.575	-20,915.89	-19,752.16						
Prospects (2)	-0.091*** (0.030)	-0.088*** (0.029)	0.098* (0.030)	-0.025 (0.033)	-0.145*** (0.033)	0.035 (0.035)	0.599	0.575	-20,253.45	-20,094.55						
Job security (1)	0.083*** (0.029)	0.082*** (0.029)	-0.028 (0.031)	-0.029 (0.035)	-0.030 (0.033)	-0.063** (0.026)	-0.037	-0.033	-20,841.47	-20,526.87						
Job security (2)	0.082*** (0.029)	0.080*** (0.029)	-0.004 (0.028)	-0.014 (0.035)	0.042 (0.035)	-0.057* (0.031)	-0.037	-0.033	-20,759.36	-20,552.54						
Colleagues (1)	0.033 (0.028)	0.032 (0.028)	-0.028 (0.028)	-0.020 (0.028)	0.035 (0.026)	-0.016 (0.023)	-0.022	-0.020	-21,003.14	-20,996.28						
Colleagues (2)	0.033 (0.028)	0.036 (0.028)	-0.017 (0.026)	-0.037 (0.031)	0.029 (0.025)	-0.018 (0.028)	-0.022	-0.020	-20,966.11	-20,762.32						

Notes: Author's calculation based on data from EWCS (2015). The control variables specified in Table 1.8 in Appendix are included. Country dummies (35) included. (1) is the regression result without sample correction and (2) is the counterpart with sample selection correction. The number of observations is obtained thanks to the option that allows us to have the total number of matched individuals. Robust standard errors are in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

in the control (men) group who has the closest propensity score, and this is the individual that the algorithm matches with the woman. In other words, we identify the nearest data point for each observation using a distance measure (such as Euclidean distance), but instead of limiting ourselves to a single nearest neighbor, we consider several observations that are also very close (for example, within a given radius). This approach takes into account the variability of the data and reduces the impact of outliers or noisy data. We used the same variables and considered the same decompositions as the CEM method to ensure that our matching process is consistent and directly comparable to the original study. Matching was performed with the *"psmatch2"* command (Leuven and Sianesi, 2003). After propensity score matching, we were able to match 21,062 individuals, which represents approximately 74% of matched individuals (of which 34% were men and 36% were women entering the new sample). This is an 8% increase compared to the sample obtained by the CEM method.

In Table 1.7, we present the results of probit estimates with and without sample selection correction for the groups formed by the nearest-neighbor matching procedure. Overall, when comparing these results with those obtained using the CEM sample, we observe relatively similar coefficient signs (except for some non-significant coefficients), suggesting that the results are relatively robust. This demonstrates the balance between subjectivity and statistical objectivity. However, the level of significance of some coefficients differs from those obtained through CEM. In particular, the magnitude of the coefficients is relatively smaller in the results from the sample obtained by the CEM procedure, and some coefficients in the CEM sample are generally less significant for certain variables. This may be due to the individual reassessment of dissatisfaction in the sample obtained by the CEM procedure, where individuals are matched based on their characteristics, which may reduce the variance of the variables.

1.6.4 Country-by-country estimation for the robustness of the overall gender effect results

For this robustness analysis, we aim to investigate whether the effects observed in the matched sample are also observable by country. This analysis is particularly relevant as it highlights cultural, economic, and social differences between countries, and identifies national specificities in terms of gender equality and working conditions. Analyzing data country by country allows for the comparison of national policies and practices on gender equality and working conditions, as well as differences between industries, occupations, and age groups. Such analyses can help policymakers develop policies and measures to promote gender equality, improve working conditions, and enhance the quality of life of workers in Europe.

To conduct this analysis, we have run regressions separately for each country, as explained in section 1.5. In Figure 1.3, we present the adjusted country-by-country regressions for the female variable. A closer examination of this figure reveals that there is a roughly equal gap in overall satisfaction between women and men *ceteris paribus*. Specifically, we observe as

many countries where women would be more satisfied as countries where men would be more satisfied. However, in countries where women express higher overall satisfaction, the gap is only statistically significant for the Netherlands, Czech Republic, Italy, Estonia, Luxembourg, Sweden, and United Kingdom. For men, it is only significant for Denmark, Greece, Lithuania, Hungary, Malta, Austria, Portugal, Croatia, and Montenegro.

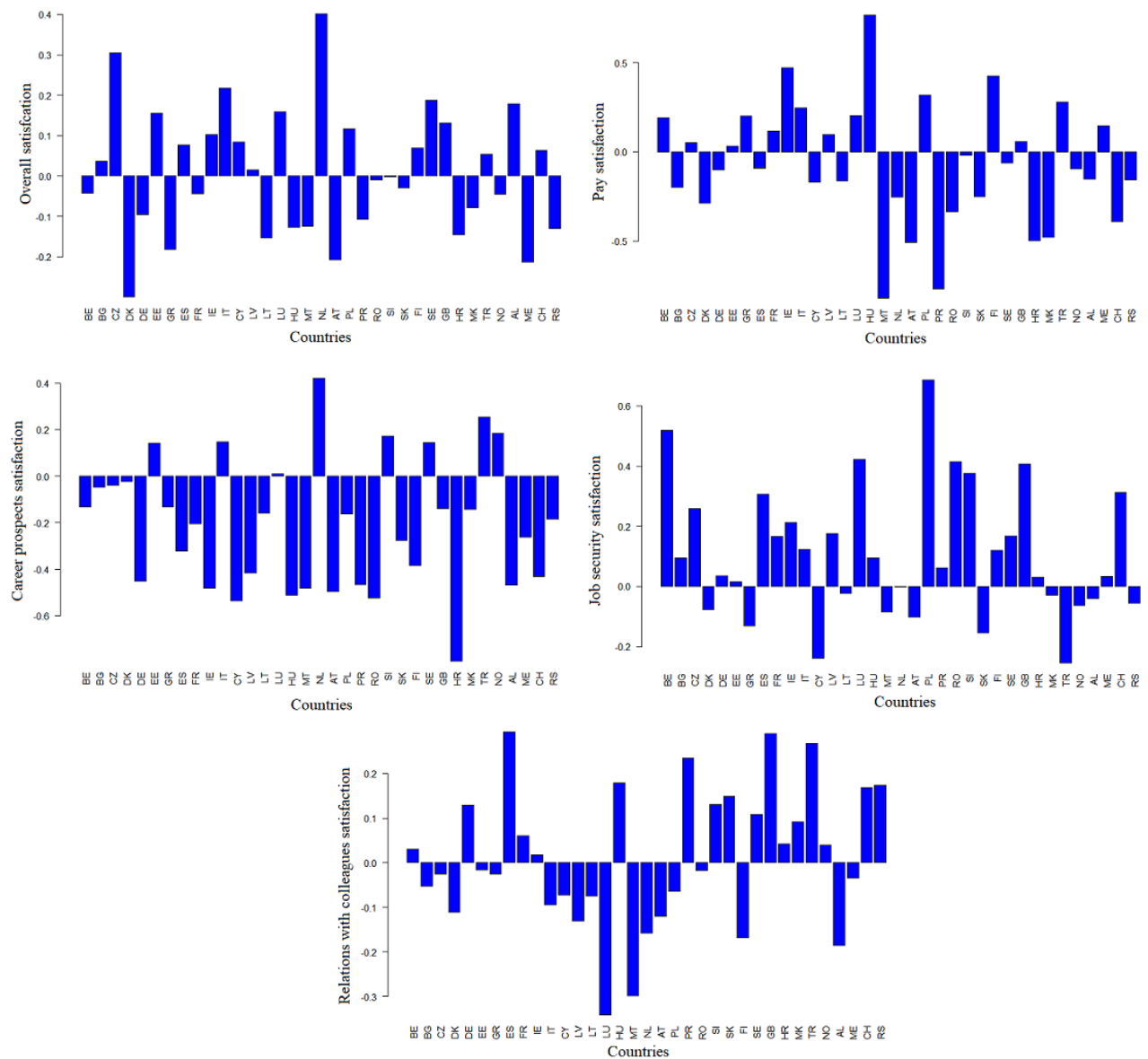
The satisfaction premium among women observed in some countries could be due to several reasons. First, these countries are known to have women-friendly labor policies, such as flexible working conditions, general maternity and paternity leave, and equal employment opportunities (ILO, 2014).¹⁰ Second, the culture in these countries promotes gender equality, and women tend to enjoy more equitable pays and career opportunities (OECD, 2022).¹¹ Finally, these countries value family and work-life balance, which may help reduce work-related stress and increase job satisfaction (Chan et al., 2016). In contrast, the higher satisfaction among men could be explained by their access to higher-paying jobs.

For job security, satisfaction is higher for women in the majority of countries. Men are more satisfied in only 12 countries, and among these countries, the effect is only statistically significant for Greece, Cyprus, Slovakia, and Turkey. This more favorable outcome for women in the vast majority of countries could be explained by more favorable employment protection policies for women, including anti-discrimination laws and gender equality policies. We note insignificant satisfaction gaps with regard to colleague relations for the vast majority of countries, with only Ireland, Italy, Luxembourg, Austria, and Albania showing statistical significance. As for satisfaction gaps in terms of pay, the differential is only significant for three countries: Malta and Portugal (with higher satisfaction among men) and Hungary (with higher satisfaction among women). However, for satisfaction with career development prospects, we observe lower satisfaction among women in most countries. Women expressed higher satisfaction in only eight countries: Netherlands, Turkey, Norway, Slovenia, Italy, Sweden, and Estonia. However, for these countries, the gap is only statistically significant for the Netherlands. This result could be explained by the culture of the Netherlands, which promotes gender equality, and women tend to have more career opportunities than in other countries (OECD, 2022).

¹⁰“Maternity and paternity at work: Law and practice across the world” by the International Labour Organization (ILO) provides information on the legal frameworks and practices related to maternity and paternity leave, flexible working arrangements, and other family-friendly policies in different countries around the world. Available at: https://www.ilo.org/global/topics/maternal-employment/publications/WCMS_242615/lang--en/index.htm.

¹¹“Gender Equality and Women’s Empowerment in OECD Countries” by the Organisation for Economic Co-operation and Development (OECD) provides comparative data and analysis on gender equality policies and outcomes in OECD countries, including information on gender pay gaps, gender segregation in occupations, and gender differences in employment rates and working conditions. Available at: <https://www.oecd.org/gender/data/gender-equality-and-women-s-empowerment-in-oecd-countries-9789264300282-en.htm>.

Figure 1.3: Adjusted gender gap in job satisfaction (job satisfaction of women compared to men) by country



Notes: Author's calculation based on data from EWCS (2015). Probit regression with sample selection correction is applied. The matched sample of men and women is considered. The control variables included in the previous estimates are also included

1.6.5 Taking into account the different evolution of the context of gender inequalities in the different countries

We have a database comprising several countries with different evolutions of gender equality over the years. An example of this evolution, represented for some countries, is shown in Figure 1.4 in the appendix. Thus, not accounting for these differences could lead to biased results. Individuals of similar ages and characteristics but who grew up in different countries may have experienced very different gender equality contexts during their early life. This highlights the importance of considering context and gender equality developments in the analyses to avoid biasing the results. Indeed, individuals' experiences can be strongly influenced by the context in which they grew up and lived, including the level of gender equality in their country of origin. Ignoring these differences could lead to erroneous conclusions about the factors that influence gender differences in job satisfaction.

To analyze the robustness of our results, we follow the approach of Perugini and Vladislavjević (2019) and "construct an indicator of early life exposure to gender equality (ELGE) as the average of the female/male participation ratio over the first 20 years of life of each respondent in her/his country" (p. 136). We obtain our activity ratio data from the World Bank, which starts from 1960. However, some years have missing information. To fill in these gaps, we use the linear interpolation method and additional sources such as (Chawla, 1990; Norwood, 1983; Sorrentino, 1983; Kinsella and Taeuber, 1993; Ashenfelter and Card, 2010; Loichinger, 2015; Praderie et al., 1964; Charalambis et al., 2004; Daune-Richard, 1993).¹² We follow a specific procedure in which we take the basic female-to-male activity ratio data from the World Bank and estimate missing values using the ratio from the previous or next year. For instance, if the activity ratio is 48.415% in 1962 in France, but missing in 1963, we estimate an activity ratio of 45.939% in 1962 and 49.007% in 1963 from our sources. The activity ratio in 1963 is calculated as $46.188 (= \frac{49.007 + 45.939}{2} \times 48.415)$. We repeat the procedure backward if the ratio value is missing in 1962 but not in 1963. This procedure allows us to obtain the correct level of the activity ratio indexed to the base year of the World Bank data. We perform these calculations using Excel. We then calculate an average of this ratio over the first 20 years of life for each individual in each country¹³.

The range of the index is from 0.332 to 0.975, indicating that there are significant differences in gender equality across countries. A lower index value suggests lower gender equality, while a higher index value indicates higher gender equality. The average index value is 0.745 suggesting that overall, gender equality is moderately high across the countries included in the study. However, it is important to note that this average value may mask significant variations in gender

¹²To supplement the missing information for all countries in our sample with additional sources, we consulted Perugini and Vladislavjević (2019)'s study as well as other supplementary sources, given that our sample includes a larger number of countries.

¹³Our sample comprises individuals born between 1950 and 1997. We have 5,182 individuals born before 1960, the year from which the female-to-male participation ratio is available. Therefore, we create our index using a smaller year range.

equality across individual countries. To account for these effects, we estimate a version of equation (1.7) that includes both the index and the interaction of the index and the dichotomous woman variable as follows:

$$y_i = 1(\beta W + \vartheta_1 \cdot W \times AGE + \vartheta_2 \cdot W \times ED + \vartheta_3 \cdot W \times GJ + \vartheta_4 \cdot W \times MDW + \vartheta_5 \cdot W \times ELGE + \alpha ELGE + x_i \theta + \mu_{1i}) \quad (1.9)$$

ELGE is the generational equality index and is normalized to zero.

The tables presenting the results of the probit models with and without sample selection obtained through the CEM procedure are listed in Tables 1.8, 1.9, 1.10, and 1.11. These tables display the results of two distinct probit models estimated, with the independent variables of interest being Women and the Gender Equality Index (ELGE), as well as their interaction term. The matched sample is used, and the same control variables used previously are incorporated.

In Table 1.8, the coefficients for the Women variable are positive and statistically significant in the overall job satisfaction and job security models, suggesting that women report higher levels of satisfaction in these areas. However, the coefficients for Women are negative and statistically significant in the pay satisfaction and career prospects satisfaction models, indicating that women report lower levels of satisfaction in these areas. The coefficient for the ELGE variable is negative but not statistically significant in any of the models. In Table 1.9, which includes sample selection and interaction terms, the coefficient for Women is positive and statistically significant only in the job security satisfaction model. The coefficient for ELGE is negative but not statistically significant in any of the models. The interaction term between Women and ELGE is negative and statistically significant in the pay satisfaction, career prospects satisfaction, and job security satisfaction models, indicating that the positive effect of being a woman on job satisfaction in these areas is weaker in countries with higher levels of gender equality.

Overall, the results suggest that the relationship between gender and job satisfaction is complex and varies across different dimensions of job satisfaction, and that gender equality has a limited effect on job satisfaction. Additionally, the findings indicate that individuals who have grown up in environments where gender inequalities are prevalent may be more likely to maintain gender stereotypes at work and engage in discriminatory behaviors or recruitment practices that discriminate against women. This may be due to the internalization of gender norms and values from an early age, which can be difficult to overcome even in the face of professional ethics or company policy.

Table 1.8: Results estimations with gender equality index: probit without sample selection and CEM sample

	Overall (1)	Pay (2)	Career Prospects (3)	Job security (4)	Relations with colleagues (5)
Women	0.050** (0.025)	-0.062* (0.031)	-0.104*** (0.037)	0.088*** (0.031)	0.031 (0.026)
GEI	-0.067 (0.076)	0.125*** (0.066)	0.126*** (0.066)	-0.067 (0.076)	-0.264*** (0.064)
Women × ELGE	-0.093 (0.072)	0.185*** (0.063)	0.660*** (0.077)	-0.120** (0.069)	0.012 (0.069)
Log likelihood	-17,883.88	-17,270.58	-17,418.55	-17,955.48	-18,248.50

Notes: Author's calculation based on 2015 EWCS data. All 5 measures are considered as dependent variables. The matched sample is considered. The *ELGE* index is normalized to the mean. The same control variables previously used are incorporated. Robust standard errors clustered at the country/gender level in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 1.9: Results estimations with gender equality index: probit with sample selection, CEM sample and interactions

	Overall (1)	Pay (2)	Career Prospects (3)	Job security (4)	Relations with colleagues (5)
Women	0.037 (0.024)	-0.042 (0.029)	-0.085*** (0.034)	0.074*** (0.029)	0.031 (0.026)
ELGE	-0.062 (0.077)	0.136*** (0.068)	0.157*** (0.066)	-0.055 (0.077)	-0.267*** (0.064)
Women × ELGE	-0.098 (0.073)	0.186*** (0.063)	0.663*** (0.077)	-0.122** (0.069)	0.010 (0.069)
ρ	-0.329	0.379	0.496	-0.021	-0.013
Log likelihood	-17,491.40	-16,110.13	-16,686.70	-17,730.61	-18,014.15

Notes: Author's calculation based on 2015 EWCS data. All 5 measures are considered as dependent variables. The matched sample is considered. The *ELGE* index is normalized to the mean. The same control variables previously used are incorporated. Robust standard errors clustered at the country/gender level in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 1.10: Results estimations with gender equality index: probit without sample selection, CEM sample and interactions

	Overall (1)	Pay (2)	Career Prospects (3)	Job security (4)	Relations with colleagues (5)
Women	0.051** (0.025)	-0.062* (0.031)	-0.102*** (0.037)	0.088*** (0.031)	0.032 (0.026)
Women × AGE	-0.004 (0.022)	0.003 (0.030)	0.078* (0.028)	-0.014 (0.028)	-0.017 (0.024)
Women × ED	0.018 (0.025)	0.009 (0.032)	-0.015 (0.024)	-0.021 (0.030)	-0.020 (0.025)
Women × GJ	-0.007 (0.021)	0.051* (0.025)	0.102** (0.025)	0.020 (0.025)	0.018 (0.022)
Women × MDW	-0.051** (0.024)	0.089** (0.026)	0.005 (0.021)	-0.035* (0.022)	-0.003 (0.020)
ELGE	-0.067 (0.076)	0.124*** (0.066)	0.123*** (0.066)	-0.067 (0.076)	-0.266*** (0.064)
Women × ELGE	-0.092 (0.072)	0.184*** (0.063)	0.660*** (0.077)	-0.119** (0.069)	0.012 (0.069)
Log likelihood	-17,067.55	-17,145.23	-17,287.75	-18,038.62	-18,146.24

Notes: Author's calculation based on 2015 EWCS data. All 5 measures are considered as dependent variables. The matched sample is considered. The *ELGE* index is normalized to the mean. The same control variables previously used are incorporated. Robust standard errors clustered at the country/gender level in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 1.11: Results estimations with gender equality index: probit with sample selection, CEM sample and interactions

	Overall (1)	Pay (2)	Career Prospects (3)	Job security (4)	Relations with colleagues (5)
Women	0.036 (0.024)	-0.040 (0.029)	-0.084*** (0.034)	0.074*** (0.029)	0.031 (0.026)
Women × AGE	-0.001 (0.021)	0.005 (0.030)	0.082** (0.029)	-0.018 (0.028)	-0.016 (0.024)
Women × ED	0.017 (0.025)	0.015 (0.033)	-0.022 (0.025)	-0.020 (0.030)	-0.020 (0.025)
Women × GJ	-0.007 (0.021)	0.050* (0.025)	0.128** (0.026)	0.017 (0.025)	0.018 (0.022)
Women × MDW	-0.063*** (0.025)	0.091** (0.026)	0.007 (0.022)	-0.044** (0.023)	-0.003 (0.021)
GEI	-0.061 (0.077)	0.136*** (0.068)	0.155*** (0.066)	-0.056 (0.077)	-0.267*** (0.064)
Women × ELGE	-0.098 (0.073)	0.185*** (0.063)	0.662*** (0.077)	-0.121** (0.069)	0.009 (0.069)
ρ	-0.315	0.292	0.488	-0.021	-0.011
Log likelihood	-17,359.75	-15,405.84	-16,735.89	-17,569.56	-17,751.47

Notes: Author's calculation based on 2015 EWCS data. All 5 measures are considered as dependent variables. The matched sample is considered. The *ELGE* index is normalized to the mean. The same control variables previously used are incorporated. Robust standard errors clustered at the country/gender level in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

1.7 Discussion and Conclusion

In this chapter, we analyze the differences in job satisfaction between men and women across five measures: overall job satisfaction, compensation, career development prospects, job security, and relationships between colleagues. We use data from the sixth European working conditions survey, which includes 35 European countries. Firstly, we apply Fairlie's method to the overall sample to decompose the satisfaction gap into a part that can be explained by individual and professional characteristics and an unexplained part. Next, we use a matching procedure, the CEM, to create a cohort of men and women who are comparable in terms of their characteristics. This helps us to avoid model misspecification that could arise due to unobserved heterogeneity between men and women. Finally, we run two regressions on the matched sample: a probit regression without sample selection correction and a probit regression with sample selection correction.

The analysis reveals significant gender disparities in job satisfaction, with women reporting higher satisfaction with job security and relationships with colleagues, but lower satisfaction with pay and career prospects compared to men. However, these differences disappear when individual and professional characteristics are taken into account. This indicates that the gender pay satisfaction gap and overall job satisfaction are not solely due to gender, but rather to other factors such as education, experience, and job responsibilities. The study also finds that women have less optimistic career prospects than men, even after controlling for confounding factors and sample selection. This suggests that gender inequality and bias may hinder women's career development and aspirations, resulting in lower satisfaction with career prospects. Moreover, the study shows that pay expectations and job satisfaction of women are influenced by various factors such as age, education, hierarchical position, and work environment. Younger women, those with higher education, or those in male-dominated fields adjust their expectations to match those of men, allowing them to react similarly to job satisfaction dimensions. Finally, the study indicates that gender equality has a limited effect on job satisfaction, and the relationship between gender and job satisfaction is complex, varying across dimensions and the level of gender equality in a given country. Overall, these findings emphasize the need to address gender inequality in the labor market and improve working conditions to promote job satisfaction for all workers.

The results have important implications. Firstly, gender differences in job satisfaction need to be considered in efforts to reduce gender inequalities in the labor market. Women tend to report higher satisfaction with job security and relationships with colleagues, but lower satisfaction with pay and career prospects. The persistence of gender differences in job satisfaction for job security and relationships with colleagues, even after controlling for individual and professional characteristics, suggests the need for further research on these dimensions of job satisfaction. Secondly, the findings emphasize the need for interventions to support women's career development and increase their confidence in career advancement, as women may have lower career optimism, even after obtaining paid employment. Addressing gender-based discrimination and biases in hiring and promotion practices is also crucial, as men report higher satisfaction with

career prospects despite controlling for confounding factors and selection bias. Thirdly, the study highlights that women's pay expectations and job satisfaction are influenced by several factors, including age, education level, hierarchical position, and work environment. Therefore, targeted policies and interventions are needed to address these factors and promote gender equality in the labor market. Lastly, the complex and varying relationship between gender and job satisfaction across different dimensions of job satisfaction and the level of gender equality in a given country, emphasizes the need for context-specific policies and interventions to address gender-based inequalities in the labor market.

The results of this analysis have several implications for public policies and businesses. Firstly, it is important to continue efforts to reduce gender inequalities in the labor market, particularly with regard to differences in pay and career prospects. Policies aimed at promoting gender equality in the areas of education, training, and professional advancement can help to reduce gender gaps in job satisfaction. Additionally, businesses should be encouraged to implement policies aimed at improving the job satisfaction of their female employees, particularly with respect to pay and career prospects. This could include pay transparency policies, mentorship programs for women in leadership positions, and merit-based promotion policies. It is also important to note that women's pay expectations and job satisfaction are affected by several factors, including age, education level, hierarchical position, and work environment. Policies should therefore be tailored to the specific needs of different groups of women, depending on their professional and personal situations. Lastly, the results highlight the complexity of the relationship between gender and job satisfaction, which varies across different dimensions of job satisfaction and the level of gender equality in a given country. Policies should therefore be designed to take this complexity into account and should be regularly evaluated to ensure they are effective and responsive to changing employee needs.

This study has several limitations. Firstly, the study is based on cross-sectional data, which means that causality cannot be inferred. Secondly, the study relies on self-reported measures of job satisfaction, which may be subject to biases and inaccuracies. Thirdly, the study is limited to the five measures of job satisfaction analyzed, and other dimensions of job satisfaction may be relevant for gender differences. Fourthly, the study is limited to the European context and may not be generalizable to other regions or countries. Lastly, the study is constrained by the available data and matching procedure used, which may not fully account for all relevant confounding factors and unobserved traits.

Acknowledgements

I would like to express my gratitude to Eurostat for providing the data necessary to conduct this study. I would also like to acknowledge the valuable feedback and support from Jean-Pascal Guironnet and Alioune Diouf, as well as the participants of the Journées de Microéconomie Appliquée (JMA, online conference, 2020), the CREM seminar in Caen, and the seminar in Turin, Italy. I am also grateful to the anonymous reviewers whose constructive comments helped

to improve the quality of this paper. This research was financially supported by the CREM laboratory. Any errors or omissions in this paper are solely my responsibility.

Appendix

1.8 Table

Table 1.8.1: Description of the control variables

variables	Description
<i>Age</i>	Age of the individual from 0 to 65 years
<i>Age²/100</i>	To take into account the non-linear effect of age
<i>Women</i>	1-women and 0-men
<i>Level of education</i>	The highest level of education that the employee has successfully completed according to the International Standard Classification of Education: 1-Primary education: for, early childhood education (ISCED 0), Primary education (ISCED 1) and Lower secondary education (ISCED 2). 2-Secondary education: for Upper secondary education (ISCED 3), Post-secondary non-tertiary education (ISCED 4) and Short-cycle tertiary education (ISCED 5) 3-Tertiary education: 1-Bachelor or equivalent (ISCED 6), Master or equivalent (ISCED 7) and Doctorate or equivalent (ISCED 8).
<i>Good health</i>	1-Good health (Very good and Good) and 0-Bad health (Fair, Bad and Very bad)
<i>Relationship</i>	1-In a relationship and 0-Single
<i>Child</i>	1-Has a child and 0-Otherwise
<i>Permanent</i>	1-An indefinite contract and 0-a fixed term contract, a temporary employment agency contract and an apprenticeship or other training scheme
<i>Full time</i>	1-Full time and 0-Part time
<i>Pay</i>	Monthly pay in euro
<i>Log Pay</i>	Pay in logarithmic form
<i>Tenure</i>	Number of years with the company
<i>Autonomy</i>	If the employee is able to change the order of his or her tasks or work methods or the pace or speed of work and 0-Otherwise
<i>Occupations</i>	According to the International Standard Classification of Occupations (ISCO): 1-Managers, 2-Professionals, 3-Technicians and associate professionals, 4-Clerical support workers, 5-Service and sales workers, 6-Skilled agricultural, forestry and fishery workers, 7-Craft and related trades workers 8-Plant and machine operators, and assemblers and 9-Elementary occupations
<i>Sectors</i>	According to the statistical nomenclature of economic activities in the European Community: 1-Agriculture, 2-Industry, 3-Construction, 4-Commerce and hospitality, 5-Transport, 6-Financial services, 7-Public administration and defence, 8-Education, 9-Health and 10-Other services
<i>Company</i>	Number of employees in the company: 1-Small: less than 9 employees, 2-Middle: between 10 and 249 employees and 3-Large: more than 250 employees

Table 1.8.2: Descriptive statistics after matching by CEM

Variables	(\mathcal{L}_1)	Men		Women		Difference	t-test
		Mean	SE	Mean	SE		
Before matching	0.981						
After matching	0.737						
Age	0.031	40.5	0.225	40.4	0.237	0.154	0.47
Education	0.000						
Primary		0.065	0.007	0.063	0.006	0.003	0.28
Secondary		0.647	0.013	0.645	0.013	0.001	0.08
High		0.288	0.013	0.292	0.012	-0.004	-0.23
Relationship	0.000	0.711	0.013	0.717	0.012	-0.006	-0.35
Child	0.000	0.548	0.014	0.561	0.013	-0.012	-0.64
Good health	0.000	0.914	0.003	0.918	0.003	-0.004	-1.15
Full time	0.000	0.882	0.009	0.873	0.009	0.009	0.74
Permanent	0.000	0.892	0.009	0.899	0.008	-0.008	-0.67
Pay	0.052	1704	15.11	1685.9	14.99	18.1	0.88
Occupation	0.000						
Manager		0.023	0.004	0.019	0.004	0.003	0.56
Professional		0.284	0.013	0.294	0.012	-0.010	-0.58
Technician		0.095	0.008	0.088	0.008	0.007	0.63
Clerical		0.070	0.007	0.071	0.007	-0.001	-0.06
Service		0.324	0.013	0.327	0.013	-0.003	-0.55
Trade		0.100	0.008	0.098	0.008	0.002	0.26
Plant		0.069	0.007	0.057	0.006	0.012	1.31
Elementary		0.034	0.005	0.040	0.005	-0.006	-0.83
Sectors	0.000						
Industry		0.010	0.003	0.007	0.002	0.003	0.81
Services		0.016	0.003	0.014	0.003	0.002	0.40
Education		0.156	0.010	0.176	0.010	-0.020	-1.40
Health		0.063	0.007	0.071	0.007	-0.008	-0.79

Notes: Author's calculation based on matched data from CEM. This table also includes descriptive statistics for the new sample of matched men and women based on the variables used in the matching. The t-test is also performed to conform to the imbalance measures of the other methods and the difference between males and females is non-significant. The values of the statistics are weighted by the weight generated by the CEM algorithm "cem_weights" (see, Iacus et al. (2012) for more details). In addition, the t-test of the differences in means are small and not significant for all variables. The covariate distributions are therefore perfectly balanced between men and women; the latter are therefore comparable on their individual and professional characteristics.

Table 1.8.3: Results of the estimation of the selection equation

Age	-0.057***
Age squared/100	0.006***
Education	
Primary	-0.575***
Secondary	-0.717***
High	-0.632***
Relationship	-0.218***
Child	
2 years old	-0.624***
2-6 years old	-0.218**
7-14 years old	-0.644***
15 years old and more	0.095**
Logarithm of the number of hours worked by the partner	-0.204***
Household size	
3 individuals in household	0.001
4 individuals in household	0.014
5 individuals in household	-0.012
6 and more individuals in household	-0.018
Age × Women	-0.086***
Age squared/100 × Women	0.009***
Education	
Primary × Women	-0.017
Secondary × Women	-0.010
High × Women	0.068*
Relationship × Women	-0.138**
Child	
2 years old × Women	-0.092**
2-6 years old × Women	-0.012
7-14 years old × Women	-0.015
15 years old and more × Women	0.054*
Number of hours worked by the partner × Women	0.027
Household size	
3 individuals in household × Women	0.011
4 individuals in household × Women	0.021
5 individuals in household × Women	0.007
6 and more individuals in household × Women	-0.002
Constante	0.522***

Notes: Author's calculation based on matched data from CEM. The dependent variable is the probability of being an employee.

Table 1.8.5: probit without sample selection correction in matched sample with CEM: all variables and interactions

Variables	Overall satisfaction (1)	Pay (2)	Career prospects (3)	Job security (4)	Colleagues relations (5)
Women	0.039*(0.024)	-0.051**(0.028)	-0.086**(0.029)	0.063**(0.026)	0.023(0.025)
Women * AGE	-0.011(0.021)	0.015(0.029)	0.094**(0.031)	-0.012(0.024)	-0.008(0.026)
Women * ED	0.006(0.024)	0.016(0.028)	-0.018(0.025)	-0.018(0.029)	-0.015(0.025)
Women * GJ	-0.001(0.021)	0.037(0.028)	0.098**(0.026)	-0.023(0.026)	0.017(0.023)
Women * MDW	-0.045**(0.024)	0.116**(0.025)	0.010(0.022)	-0.037*(0.021)	-0.004(0.020)
Age	-0.045**(0.010)	-0.048**(0.014)	-0.052**(0.017)	-0.048*** (0.013)	-0.024** (0.010)
Age ² /100	0.049** (0.015)	0.051** (0.017)	0.063** (0.021)	0.049*** (0.016)	0.033** (0.011)
<i>Education</i>					
Early (omitted)					
Primary	-0.146* (0.033)	0.402*** (0.035)	0.928*** (0.036)	0.512*** (0.033)	0.099* (0.033)
Lower	-0.130(0.029)	0.580*** (0.030)	0.935*** (0.033)	0.433*** (0.030)	-0.044(0.028)
Upper	-0.090(0.028)	0.575*** (0.030)	0.978*** (0.035)	0.389*** (0.030)	-0.118** (0.025)
Post-secondary	-0.082(0.033)	0.603*** (0.033)	0.980*** (0.035)	0.375*** (0.029)	-0.390*** (0.027)
Short-cycle	-0.275*** (0.035)	0.425*** (0.035)	0.935*** (0.036)	0.320*** (0.033)	-0.379*** (0.031)
Bachelor	-0.079(0.031)	0.535*** (0.033)	0.965*** (0.034)	0.248** (0.030)	-0.412*** (0.030)
Master	-0.065(0.030)	0.531*** (0.031)	1.002*** (0.033)	0.325*** (0.029)	-0.368*** (0.031)
Doctorate	-0.146* (0.034)	0.475*** (0.035)	0.986*** (0.035)	0.397** (0.035)	-0.645*** (0.033)
Relationship	0.033** (0.022)	0.016(0.025)	0.022(0.026)	-0.005(0.025)	0.019(0.020)
Child	0.018(0.020)	-0.022** (0.025)	-0.017(0.024)	0.149*** (0.024)	0.065** (0.021)
Good health	0.431*** (0.033)	0.485*** (0.035)	0.446*** (0.035)	0.433*** (0.030)	0.314*** (0.031)
Full time	-0.060** (0.022)	-0.224*** (0.028)	0.036(0.028)	0.030(0.025)	-0.028(0.023)
Permanent	0.067** (0.030)	0.093** (0.033)	0.170** (0.034)	0.427*** (0.033)	0.075** (0.031)
Log pay	0.188*** (0.028)	0.471*** (0.031)	0.361*** (0.033)	0.161*** (0.028)	0.031(0.028)
Tenure	-0.002(0.002)	-0.002* (0.002)	-0.009*** (0.002)	0.022*** (0.003)	0.008* (0.002)
Autonomy	0.276*** (0.025)	0.207*** (0.027)	0.219*** (0.028)	0.121** (0.024)	0.095*** (0.023)
<i>Occupations</i>					
Elementary (omitted)					
Manager	0.370*** (0.034)	0.257*** (0.038)	0.558** (0.042)	0.179(0.034)	0.280* (0.041)
Professional	0.345** (0.030)	0.264** (0.033)	0.597*** (0.035)	0.009(0.033)	0.462*** (0.031)
Technician	0.290*** (0.029)	0.151*** (0.034)	0.470*** (0.036)	-0.066(0.032)	0.275** (0.028)
Clerical	0.300*** (0.029)	0.233** (0.034)	0.552*** (0.031)	-0.024(0.032)	0.162* (0.028)
Service/sales	0.082(0.033)	0.042(0.035)	0.249** (0.034)	-0.044(0.030)	0.071(0.028)
Craft/trades	0.076(0.034)	-0.042(0.033)	0.026(0.031)	0.025(0.030)	0.152(0.031)
Plant/mach.op	-0.060(0.033)	-0.066(0.036)	-0.073(0.037)	-0.176(0.033)	0.122(0.033)
agricultural/fishery	0.200*** (0.028)	0.209*** (0.032)	0.500*** (0.033)	0.086(0.030)	-0.115(0.029)
<i>Sectors</i>					
Industry (omitted)					
Construction	-0.031(0.033)	-0.030(0.030)	0.065(0.032)	-0.087(0.035)	0.490*** (0.030)
Commerce	0.117(0.035)	-0.068(0.036)	-0.177(0.037)	0.068(0.036)	0.200(0.033)
Transport	0.089(0.036)	-0.175(0.040)	-0.480*** (0.041)	0.168* (0.033)	0.195(0.033)
Financial	0.115(0.035)	0.175(0.039)	0.106(0.041)	-0.021(0.036)	0.145(0.035)
Administration	0.286** (0.035)	0.062(0.041)	-0.057(0.044)	0.512*** (0.033)	0.142(0.035)
Education	0.033(0.035)	-0.167(0.039)	-0.233** (0.039)	0.317*** (0.035)	-0.018(0.030)
Health	-0.034(0.035)	-0.308*** (0.036)	-0.065(0.032)	0.456*** (0.035)	0.044(0.032)
Agriculture	0.055(0.031)	-0.016(0.039)	-0.041(0.036)	-0.188* (0.032)	-0.020(0.033)
Other	0.099(0.035)	0.054(0.041)	-0.066(0.039)	0.085(0.033)	0.150(0.031)
<i>Company</i>					
Small (omitted)					
Middle	-0.132*** (0.028)	-0.184*** (0.030)	0.040* (0.029)	-0.031(0.028)	-0.020(0.026)
Large	-0.212*** (0.029)	-0.332*** (0.029)	-0.057* (0.028)	-0.019(0.029)	0.046(0.025)
c	2.160*** (0.193)	1.458*** (0.269)	1.753(0.251)	2.466*** (0.276)	3.764*** (0.248)
Countries	yes	yes	yes	yes	yes
Log likelihood	-17,141.01	-17,413.72	-17,482.08	-18,075.52	-18,257.98
Pseudo R ²	0.0655	0.0763	0.0898	0.9112	0.0604
N	18,676	18,676	18,676	18,676	18,676

Notes: Author's calculation based on data from EWCS (2015). Country dummies (35) are included. The number of observations is obtained thanks to the option that allows us to have the total number of matched individuals. Robust standard errors are in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 1.8.6: probit with sample selection correction in matched sample with CEM: all variables

Variables	Overall satisfaction (1)	Pay (2)	Career prospects (3)	Job security (4)	Colleagues relations (5)
Women	0.039(0.023)	-0.033(0.026)	-0.075*** (0.028)	0.062** (0.026)	0.025(0.025)
Age	-0.044** (0.009)	-0.048** (0.015)	-0.044** (0.017)	-0.039*** (0.012)	-0.018** (0.009)
Age ² /100	0.048** (0.014)	0.040** (0.017)	0.034** (0.020)	0.040*** (0.015)	0.021** (0.010)
<i>Education</i>					
Early (omitted)					
Primary	-0.144(0.032)	0.389** (0.034)	0.907*** (0.035)	0.512** (0.033)	0.040(0.031)
Lower	-0.127(0.029)	0.577*** (0.030)	0.913*** (0.032)	0.429*** (0.030)	-0.042(0.028)
Upper	-0.098(0.029)	0.556*** (0.029)	0.945*** (0.030)	0.379*** (0.027)	-0.088* (0.024)
Post-secondary	-0.079(0.033)	0.569*** (0.031)	0.971*** (0.034)	0.331*** (0.028)	-0.385*** (0.027)
Short-cycle	-0.278*** (0.035)	0.412*** (0.035)	0.938*** (0.036)	0.312** (0.030)	-0.372*** (0.032)
Bachelor	-0.088(0.030)	0.536*** (0.033)	0.971*** (0.035)	0.227** (0.029)	-0.385*** (0.029)
Master	-0.077(0.031)	0.507*** (0.030)	0.998*** (0.033)	0.327*** (0.029)	-0.309*** (0.030)
Doctorate	-0.155(0.034)	0.436*** (0.033)	0.984*** (0.035)	0.353** (0.033)	-0.625*** (0.032)
Relationship	0.045** (0.021)	0.016(0.025)	0.012(0.024)	-0.002(0.025)	0.021(0.021)
Child	0.022(0.019)	-0.021(0.025)	-0.012(0.024)	0.080*** (0.024)	0.064** (0.021)
Good health	0.411*** (0.032)	0.487*** (0.035)	0.439*** (0.034)	0.378*** (0.028)	0.299*** (0.030)
Full time	-0.056* (0.021)	-0.178*** (0.027)	0.038(0.029)	0.032(0.026)	-0.031(0.024)
Permanent	0.056* (0.021)	0.090** (0.033)	0.169** (0.033)	0.418*** (0.033)	0.069** (0.024)
Log pay	0.184*** (0.028)	0.470*** (0.031)	0.366*** (0.033)	0.117*** (0.026)	0.031(0.028)
Tenure	-0.001(0.002)	-0.002(0.002)	-0.014*** (0.003)	0.019*** (0.003)	0.007* (0.002)
Autonomy	0.251*** (0.024)	0.208*** (0.027)	0.235*** (0.027)	0.084* (0.023)	0.093*** (0.023)
<i>Occupations</i>					
Elementary (omitted)					
Manager	0.325** (0.033)	0.277*** (0.039)	0.541** (0.041)	0.158(0.033)	0.262* (0.040)
Professional	0.342** (0.030)	0.257** (0.033)	0.577*** (0.033)	0.000(0.031)	0.459*** (0.031)
Technician	0.286*** (0.028)	0.133** (0.033)	0.417*** (0.035)	-0.053(0.031)	0.288** (0.033)
Clerical	0.289*** (0.028)	0.231** (0.033)	0.549*** (0.031)	-0.007(0.031)	0.151* (0.027)
Service/sales	0.079(0.033)	0.043(0.035)	0.249** (0.034)	-0.025(0.030)	0.071(0.028)
Craft/trades	0.070(0.034)	-0.036(0.032)	0.025(0.031)	0.024(0.030)	0.151(0.030)
Plant/mach.op	-0.064(0.033)	-0.066(0.036)	-0.072(0.037)	-0.153(0.031)	0.121(0.033)
agricultural/fishery	0.191** (0.027)	0.219*** (0.033)	0.498*** (0.033)	0.079(0.029)	-0.117(0.029)
<i>Sectors</i>					
Industry (omitted)					
Construction	-0.031(0.033)	-0.033(0.031)	0.062(0.032)	-0.058(0.033)	0.488*** (0.029)
Commerce	0.098(0.034)	-0.067(0.036)	-0.182(0.036)	0.052(0.035)	0.186(0.032)
Transport	0.089(0.036)	-0.158(0.039)	-0.447*** (0.040)	0.166(0.033)	0.191(0.033)
Financial	0.098(0.034)	0.171(0.039)	0.107(0.041)	-0.018(0.036)	0.142(0.035)
Administration	0.278** (0.034)	0.059(0.041)	-0.061(0.044)	0.489*** (0.034)	0.133(0.034)
Education	0.022(0.034)	-0.152(0.038)	-0.231** (0.039)	0.308*** (0.035)	-0.018(0.030)
Health	-0.036(0.035)	-0.309*** (0.036)	-0.062(0.032)	0.453*** (0.035)	0.043(0.032)
Agriculture	0.054(0.031)	-0.011(0.039)	-0.040(0.036)	-0.160(0.031)	-0.022(0.033)
Other	0.095(0.035)	0.047(0.040)	-0.058(0.038)	0.078(0.032)	0.148(0.031)
<i>Company</i>					
Small (omitted)					
Middle	-0.137** (0.028)	-0.179** (0.029)	0.023(0.028)	-0.039(0.028)	-0.020(0.026)
Large	-0.202*** (0.029)	-0.326*** (0.029)	-0.057* (0.028)	-0.015(0.029)	0.047(0.025)
c	2.158*** (0.195)	1.419*** (0.268)	1.778(0.248)	2.429*** (0.269)	3.758*** (0.249)
p	-0.378	0.409	0.538	-0.029	-0.017
Countries	yes	yes	yes	yes	yes
Log likelihood	-17,642.60	-16,740.25	-17,253.91	-18,069.26	-18,066.11
N	18,676	18,676	18,676	18,676	18,676

Notes: Author's calculation based on data from EWCS (2015). Country dummies (35) are included. The number of observations is obtained thanks to the option that allows us to have the total number of matched individuals. Robust standard errors are in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 1.8.7: probit with sample selection correction in matched sample with CEM: all variables with interactions

Variables	Overall satisfaction (1)	Pay (2)	Career prospects (3)	Job security (4)	Colleagues relations (5)
Women	0.038(0.023)	-0.029(0.025)	-0.086** (0.028)	0.060** (0.026)	0.024(0.025)
Women * AGE	-0.011(0.021)	0.001(0.028)	0.074* (0.026)	-0.009(0.025)	-0.008(0.021)
Women * ED	0.015(0.023)	0.005(0.031)	-0.010(0.023)	-0.019(0.029)	-0.016(0.024)
Women * GJ	-0.006(0.020)	0.043* (0.024)	0.090** (0.023)	0.020(0.025)	0.016(0.020)
Women * MDW	-0.046** (0.022)	0.075** (0.024)	0.003(0.020)	-0.032* (0.020)	-0.004(0.018)
Age	-0.043** (0.009)	-0.042** (0.014)	-0.039** (0.016)	-0.031*** (0.012)	-0.018** (0.009)
Age ² /100	0.046** (0.014)	0.040** (0.017)	0.033** (0.018)	0.035*** (0.014)	0.020** (0.010)
<i>Education</i>					
Early (omitted)					
Primary	-0.144(0.032)	0.388** (0.034)	0.905*** (0.035)	0.509** (0.033)	0.039(0.031)
Lower	-0.125(0.029)	0.575*** (0.030)	0.912*** (0.032)	0.425*** (0.030)	-0.041(0.028)
Upper	-0.098(0.029)	0.556*** (0.029)	0.944*** (0.030)	0.379*** (0.027)	-0.088* (0.024)
Post-secondary	-0.077(0.033)	0.568*** (0.031)	0.971*** (0.034)	0.330*** (0.028)	-0.385*** (0.027)
Short-cycle	-0.278*** (0.035)	0.412*** (0.035)	0.936*** (0.036)	0.310*** (0.030)	-0.371*** (0.032)
Bachelor	-0.088(0.030)	0.524*** (0.033)	0.971*** (0.035)	0.226** (0.029)	-0.383*** (0.029)
Master	-0.075(0.031)	0.507*** (0.030)	0.998*** (0.033)	0.327*** (0.029)	-0.308*** (0.030)
Doctorate	-0.155(0.034)	0.435*** (0.033)	0.982*** (0.035)	0.351** (0.033)	-0.624*** (0.032)
Relationship	0.044** (0.021)	0.015(0.025)	0.011(0.024)	-0.002(0.025)	0.019(0.021)
Child	0.019(0.019)	-0.020(0.025)	-0.012(0.024)	0.079*** (0.024)	0.063** (0.021)
Good health	0.409*** (0.032)	0.487*** (0.035)	0.438*** (0.034)	0.378*** (0.028)	0.299*** (0.030)
Full time	-0.056* (0.021)	-0.171*** (0.027)	0.032(0.029)	0.022(0.025)	-0.030(0.024)
Permanent	0.055* (0.021)	0.088** (0.033)	0.168** (0.033)	0.418*** (0.033)	0.069** (0.024)
Log pay	0.182*** (0.028)	0.465*** (0.030)	0.365*** (0.033)	0.115*** (0.026)	0.031(0.028)
Tenure	-0.001(0.002)	-0.001(0.002)	-0.014*** (0.003)	0.018*** (0.003)	0.006* (0.002)
Autonomy	0.250*** (0.024)	0.202*** (0.027)	0.235*** (0.027)	0.084* (0.023)	0.090*** (0.023)
<i>Occupations</i>					
Elementary (omitted)					
Manager	0.325** (0.033)	0.276*** (0.039)	0.540** (0.041)	0.158(0.033)	0.254* (0.039)
Professional	0.339** (0.030)	0.255** (0.033)	0.577*** (0.033)	0.000(0.031)	0.450*** (0.031)
Technician	0.286*** (0.028)	0.133** (0.033)	0.415*** (0.035)	-0.052(0.031)	0.288** (0.033)
Clerical	0.289*** (0.028)	0.229** (0.033)	0.549*** (0.031)	-0.006(0.031)	0.148* (0.027)
Service/sales	0.078(0.033)	0.043(0.035)	0.248** (0.034)	-0.024(0.030)	0.069(0.028)
Craft/trades	0.069(0.034)	-0.036(0.032)	0.024(0.031)	0.024(0.030)	0.151(0.033)
Plant/mach.op	-0.064(0.033)	-0.066(0.036)	-0.070(0.037)	-0.151(0.031)	0.119(0.033)
agricultural/fishery	0.189** (0.027)	0.218*** (0.033)	0.498*** (0.033)	0.078(0.029)	-0.117(0.029)
<i>Sectors</i>					
Industry (omitted)					
Construction	-0.029(0.033)	-0.031(0.031)	0.061(0.032)	-0.058(0.033)	0.485*** (0.029)
Commerce	0.098(0.034)	-0.066(0.036)	-0.182(0.036)	0.052(0.035)	0.174(0.031)
Transport	0.089(0.036)	-0.158(0.039)	-0.444*** (0.040)	0.164(0.033)	0.190(0.033)
Financial	0.098(0.034)	0.171(0.039)	0.106(0.041)	-0.017(0.036)	0.142(0.035)
Administration	0.277** (0.034)	0.057(0.041)	-0.059(0.044)	0.485*** (0.034)	0.133(0.034)
Education	0.021(0.034)	-0.151(0.038)	-0.231** (0.039)	0.306*** (0.035)	-0.015(0.030)
Health	-0.034(0.035)	-0.309*** (0.036)	-0.062(0.032)	0.453*** (0.035)	0.042(0.032)
Agriculture	0.054(0.031)	-0.010(0.039)	-0.039(0.036)	-0.158(0.031)	-0.022(0.033)
Other	0.095(0.035)	0.047(0.040)	-0.058(0.038)	0.077(0.032)	0.148(0.031)
<i>Company</i>					
Small (omitted)					
Middle	-0.127** (0.027)	-0.161** (0.028)	0.022(0.028)	-0.036(0.028)	-0.017(0.026)
Large	-0.201*** (0.029)	-0.322*** (0.029)	-0.057* (0.028)	-0.014(0.029)	0.039(0.024)
c	2.155*** (0.194)	1.406*** (0.266)	1.748(0.242)	2.404*** (0.266)	3.733*** (0.242)
ρ	-0.393	0.312	0.532	-0.026	-0.014
Countries	yes	yes	yes	yes	yes
Log likelihood	-17,393.45	-15,732.19	-17,166.43	-17,969.12	-17,762.32
N	18,676	18,676	18,676	18,676	18,676

Notes: Author's calculation based on data from EWCS (2015). Country dummies (35) are included. The number of observations is obtained thanks to the option that allows us to have the total number of matched individuals. Robust standard errors are in parentheses. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

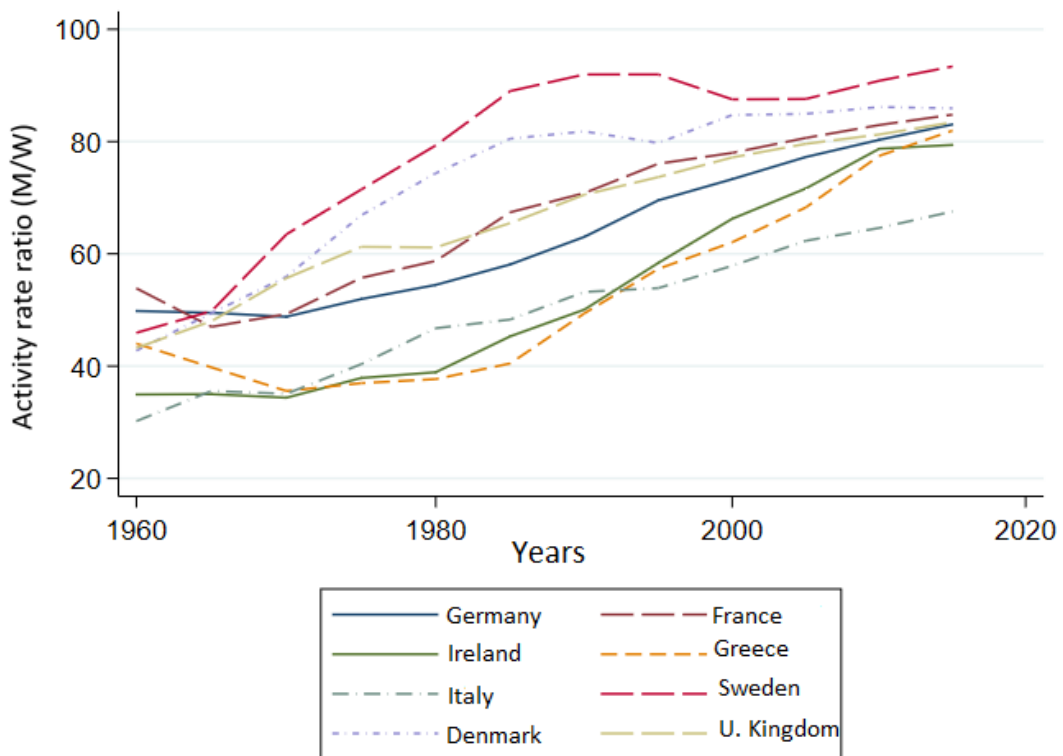


Figure 1.4: Ratio of women to men in selected countries

Note: Author based on data from the World Bank and other sources. M represents men and W women.

Chapter 2

Productivity at work and job satisfaction: A hierarchical and spatial examination

Sommaire

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Résumé:

Ce chapitre examine comment la satisfaction des travailleurs affecte leur productivité en utilisant des données de la Génération 2010 collectées en France en 2013 et 2017. Il utilise une méthode appelée DEA hiérarchique avec l'indice de Malmquist pour estimer la variation de la productivité des travailleurs en termes d'efficacité et de technologie, ainsi qu'une modélisation économétrique pour mesurer l'impact de la satisfaction des travailleurs sur leur productivité, dans un cadre spatial à travers les zones d'emploi de résidence des travailleurs et en fonction de deux mesures différentes de la satisfaction au travail. Les résultats montrent que la satisfaction salariale et la satisfaction à l'égard des perspectives professionnelles des travailleurs ont un impact positif significatif et robuste sur leur productivité, surtout pour les femmes, les jeunes et les employés de petites entreprises. La satisfaction salariale est particulièrement importante dans les zones d'emploi dominées par les cadres, ou celles spécialisées dans l'industrie ou le tertiaire. Les critères de satisfaction se révèlent également significatifs pour la variation d'efficacité des travailleurs. Cette étude met en évidence l'importance de la satisfaction des travailleurs pour améliorer leur productivité et souligne la nécessité pour les entreprises de prendre en compte ces facteurs dans leur gestion des ressources humaines.

Abstract:

This chapter analyzes the relationship between worker satisfaction and productivity, using data collected from the Generation 2010 survey in France in 2013 and 2017. The study employs a hierarchical Data Envelopment Analysis (DEA) with the Malmquist index to estimate variations in worker productivity in terms of efficiency and technology. Additionally, an econometric model is used to measure the impact of worker satisfaction on productivity, within a spatial framework that considers workers' residence employment areas. The study uses two different measures of job satisfaction to analyze the impact of worker satisfaction on productivity. The findings indicate that worker satisfaction with pay and career prospects has a significant and robust positive effect on their productivity, especially for women, young people, and employees of small businesses. Pay satisfaction is particularly important in employment areas dominated by managers or specialized in the industry or tertiary sectors. The study also finds that satisfaction criteria are significant for variations in worker efficiency. This study highlights the importance of worker satisfaction in improving their productivity and emphasizes the need for companies to take these factors into account in their human resource management.

Key words: Productivity, Job satisfaction, Hierarchical model, France.

JEL Codes: J01, J28, O47, O33.

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Status: Under review on *Revue d'Economie Politique*.

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2.1 Introduction

Despite numerous micro-econometric studies, the nature of the relationship between job satisfaction and worker productivity remains highly controversial. Proponents argue that job satisfaction has a positive effect on worker productivity (e.g., Petty et al., 1984; Miller and Monge, 1986; Spector, 1997; Thomas and Jex, 2002; Amabile et al., 2005; Piening et al., 2013). In contrast, others suggest that higher performance leads to greater worker satisfaction (e.g., Lawler III and Porter, 1967; Locke, 1970; Deci and Ryan, 1985; Gagné and Deci, 2005). Some previous empirical studies have questioned the extent to which employees' job satisfaction can significantly impact their performance (e.g., Greenberger et al., 1989), while other studies confirm the existence of a significant relationship between satisfaction and productivity, but with a causal relationship (e.g., Wanous, 1974; Locke, 1976). Moreover, some argue that the generally conflicting results regarding the link between worker satisfaction and productivity can be explained through various moderating factors. These factors include occupational group, job fit, level of supervision, production pressure, task difficulty, self-esteem, and need for accomplishment, among others, that can impact the correlation between these two factors (e.g., Petty et al., 1984; Judge et al., 2001).

These controversial findings have motivated our interest in investigating the nature of the relationship between job satisfaction and productivity. Studying this relationship is important for understanding the factors that influence worker productivity, improving worker well-being, supporting economic growth, and helping businesses maximize profitability (Maniadakis and Thanassoulis, 2004; Gummesson, 1998; Sels et al., 2006; Sharma and Sharma, 2014; Hanaysha, 2016). We use detailed data from two French surveys conducted in 2013 and 2017 with youth from the 2010 generation. We are interested in France for several reasons. Firstly, although French workers generally feel satisfied with their jobs, the productivity of French workers is relatively low compared to other countries. According to the Brameter report (Edenred-Ipsos, 2016)⁴, 67% of employees feel satisfied with their jobs. However, the productivity rate of French workers per year was only 0.9% between 2010 and 2016 (Insee, 2018).⁵ This raises questions about the real impact of job satisfaction on productivity, as low worker productivity can limit competitiveness and economic growth. Thus, understanding how job satisfaction can influence worker productivity can help identify ways to boost productivity and competitiveness in France.

Additionally, France has experienced an increase in unemployment rates in recent years. According to INSEE data, the unemployment rate was 7.8% in 2019, increased to 8.1% in 2020 due to the COVID-19 pandemic, and decreased to 7.4% in the fourth quarter of 2021, remaining almost stable at 7.3% in the third quarter of 2022. There are high levels of unemployment among young people and less qualified individuals. By improving worker job satisfaction, businesses

⁴Edenred-Ipsos Barometer (2016): Understand and improve the Wellbeing At Work. Available on https://www.ipsos.com/sites/default/files/2016-09/2016_Edenred-Ipsos_Barometer_wellbeing_at_work_19May2016.pdf

⁵Insee (2018): Slowdown in labour productivity and forecasting employment in France. Available on <https://www.insee.fr/en/statistiques/fichier/3593400/nc343dossier1.pdf>

can help reduce turnover rates and retain talent, which can be beneficial for the overall French economy. In addition, studying the relationship between job satisfaction and worker productivity can also inform government policies on labor and employment. By understanding factors that influence worker productivity, the government can develop policies that encourage the creation of quality jobs, professional training and career development, as well as other initiatives that improve job satisfaction and stimulate productivity. Finally, the results of previous studies on the relationship between job satisfaction and productivity are controversial and may vary according to national contexts. Thus, studying the relationship between job satisfaction and productivity in France can provide important information about the nature of this relationship in a specific context and help to understand the factors that influence the productivity of French workers.

In this study, we analyze the relationship between job well-being and productivity by considering two specific measures of job satisfaction: pay satisfaction and satisfaction with career prospects. Considering these two specific measures is particularly relevant because pay and career prospects are two of the main factors that influence employee job satisfaction (Di Tella et al., 2001; Judge et al., 2001). Workers who are satisfied with their pay and have clear career prospects are more likely to be happy and motivated in their work, which can lead to increased productivity (Blanchflower and Oswald, 2004). Additionally, pay and career prospects are key factors for talent retention and employee loyalty (Becker and Huselid, 2006). If employees are satisfied with their pay and career prospects, they are less likely to leave their job, which can reduce the costs associated with training and recruiting new employees. Finally, studying the relationship between pay satisfaction, satisfaction with career prospects, and productivity can help identify policies and practices that can improve worker well-being and productivity. The results of this study may be useful for employers and policymakers seeking to create healthier and more productive work environments.

Moreover, in France, pay and career prospects are two of the main factors that influence employee job satisfaction, as in many other countries (OECD, 2021).⁶ Additionally, the labor market in France is characterized by strong job protection, which makes pay and career prospects even more important for workers looking to advance and develop their careers (Cahuc et al., 2014). Therefore, studying the relationship between pay satisfaction, satisfaction with career prospects, and productivity is particularly relevant for understanding the factors that influence worker productivity in France and for identifying policies and practices that can improve workplace well-being and worker productivity in France. Furthermore, due to the low productivity of French workers compared to other countries, it is important to understand how job satisfaction can influence productivity and how companies can encourage job satisfaction to improve their competitiveness and economic growth.

The first part of our empirical analysis focuses on estimating worker productivity. Previous literature has used various proxies for worker productivity, such as sickness absence, quits,

⁶“How’s Life? 2021: France”

self-reported performance measures, and supervisory assessments of employee performance (see Judge et al., 2001; Zelenski et al., 2008). Experimental studies have also been used to determine worker productivity (e.g., Oswald et al., 2015). However, we aim to examine the effect of workers' self-reported satisfaction on their productivity at work. Using subjective measures for these factors makes it difficult to analyze this relationship. Thus, we adapt a conventional measure of worker productivity⁷ obtained from the DEA (Data Envelopment Analysis) efficiency scores and the Malmquist index (Lin et al., 2011; Färe et al., 1994a). This approach is particularly relevant to our study because traditional econometric methods, such as linear regressions, can be biased in the presence of inefficiency or unobservable latent variables (Fuentes and Lillo-Bañuls, 2015). The DEA method and the Malmquist index are non-parametric methods that can handle complex data and take multiple factors into account to estimate productivity (Färe et al., 1994b). Moreover, these methods are particularly suited for studies of productivity and efficiency in work environments where it is difficult to measure all relevant variables or to take into account all relevant factors that might influence worker performance (Grosskopf, 1993). Therefore, the use of these methods provides a better understanding of the relationship between job satisfaction and productivity while minimizing potential biases that could alter the results (Coelli, 1998). Furthermore, since we consider two different time periods (2013 and 2017), using the Malmquist index to compare productivity scores from 2013 and 2017 can help determine if job satisfaction had a positive impact on company productivity during this time period. This provides a better understanding of the relationship between job satisfaction and productivity in a temporal context and can help identify long-term trends. Moreover, by taking efficiency and technology into account, the method allows for a more comprehensive analysis of worker performance, which can then be used to identify the determinants of performance and propose avenues for improvement (Maniadakis and Thanassoulis, 2004). This approach is particularly relevant to this study as it provides a more nuanced and accurate view of worker performance and thus possible sources of inequalities and disparities in professional opinions that may affect performance.

We consider a hierarchical structure (Tone, 1997) of 2,716 individuals according to their education level because the positive correlation between education level and productivity is well established in the literature (Wise, 1975). Furthermore, taking into account the hierarchical structure of individuals according to their education level is a relevant approach for estimating productivity indices, as it better accounts for heterogeneity between individuals with different levels of education. Education levels can have an important influence on productivity, and by considering this hierarchical structure, it is possible to better model this influence and take into account differences between individuals in the same locality. Moreover, this approach allows for more accurate estimates of productivity indices by using granular data and considering individual worker characteristics. Productivity is estimated using Mincer (1974) type equations with monthly pay (which includes net monthly salary and bonuses) received by workers as the dependent variable. The choice of monthly pay as the dependent variable instead of hourly pay is

⁷Böckerman and Ilmakunnas (2012) also used a conventional measure to estimate the relationship between productivity and satisfaction, but unlike our study, they looked at the productivity of establishments rather than the individual level.

justified by the fact that in France, monthly pay is commonly used to describe a worker's level of compensation, while hourly pay is generally used to describe the compensation of a specific job over a given period. Furthermore, collective agreements, which often determine pays in France, generally set monthly pays rather than hourly pays. Therefore, using monthly pay received by workers as the dependent variable in a study in France is justifiable and may provide relevant results for understanding the relationship between productivity and worker compensation.

The second part of our empirical analysis focuses on the econometric estimation of the relationship between job satisfaction and worker productivity. This method is particularly relevant for our study as it allows us to take into account the hierarchical structure of the data, taking into account variations between individuals, groups, and organizations (Braun et al., 2013; Meneghel et al., 2016). By applying this method, we can consider variations in levels of satisfaction and productivity at different levels, such as individuals and their spatial framework. Additionally, the use of multilevel methods can help to better control for confounding variables by accounting for interindividual and intergroup differences, thereby improving the internal validity of the study.

In this study, our two specific measures, pay satisfaction and satisfaction with job prospects, are considered Level 1 independent variables that may potentially impact worker productivity (Di Tella et al., 2001; Blanchflower and Oswald, 2004; Compte and Postlewaite, 2004). Level 2 is composed of the characteristics of the employment areas (EAs) where individuals reside.

This chapter contributes to two strands of the literature on the relationship between job satisfaction and productivity. First, we contribute to the analysis of the productivity-job satisfaction relationship (e.g., Judge et al., 2001; Böckerman and Ilmakunnas, 2012) by studying the nature of the relationship between these two factors in terms of their influence on the level of overall productivity, as well as their influence on the productivities related to efficiency and technological changes, using the two components of the Malmquist index. This allows for a more refined and detailed analysis of the relationship between satisfaction and productivity. The findings of this study can help managers design more effective human resource management policies and practices to improve worker satisfaction and motivation, which can increase their productivity and performance. Furthermore, this study investigates how job satisfaction can influence efficiency and adaptation to technological change, which can contribute to the identification of strategies to help workers better adapt to technological change in a constantly changing economic environment.

Secondly, our study contributes to the literature on the relationship between job satisfaction and productivity by conducting a microeconomic analysis within a spatial framework using econometric estimation. We consider the EAs of residence of individuals as the spatial unit of analysis, as it is the space within which most of the working population resides and works. Our aim is to examine whether the EA of residence of an individual can influence the relationship between worker satisfaction and productivity. By introducing the EA as a dimension of analysis,

we can explore the interactions between living space and job performance in relation to the individual's well-being beyond their intrinsic characteristics. Additionally, it allows for a subjective evaluation of satisfaction according to the social group to which the individual belongs, leading to a better understanding of the factors that influence worker satisfaction and productivity. Moreover, spatial analysis can provide additional insights into the relationship between job satisfaction and productivity that would not be captured by non-spatial analysis. For instance, it can identify geographic differences in the association between these two factors, highlighting areas where job satisfaction is more strongly linked to productivity and those where it is less so. This information can be beneficial for businesses and policymakers seeking to target specific policies and interventions to improve worker productivity in particular geographic regions. Furthermore, our study uses the Malmquist index to explore how job satisfaction can affect a worker's performance in terms of efficiency and technological change, providing a more refined and detailed analysis of the relationship between satisfaction and productivity, which can help managers design more effective human resource management policies and practices to improve worker satisfaction and motivation, ultimately leading to increased productivity and performance.

The chapter proceeds as follows. In section 2.2, we describe the theoretical background and related literature. In Section 2.3, we present the data and some descriptive statistics. In Section 2.4, we discuss the empirical approach to productivity estimation and the econometric regression of the relationship between job satisfaction and productivity. In Section 2.5, we present the estimation results. In Section 2.6, we present robustness checks, and we conclude in Section 2.7.

2.2 Theoretical foundations and related literature

The topic of emotional states in the workplace has garnered increasing attention from researchers in recent years, with studies conducted by scholars such as Ewen (1964), Friedlander and Walton (1964), and Taylor and Weiss (1972) examining this variable. Scholars, such as Brief (2002), recognized the importance of this variable and its link to key organizational variables like work performance (Totterdell, 2000).

The relationship between job satisfaction and job productivity has been an ongoing topic of interest in organizational and social psychology literature (Judge et al., 2001). Several theories have been proposed to explain the phenomena of job satisfaction and productivity. One of the theories, Herzberg's motivation-hygiene theory (Herzberg et al., 1959; Herzberg, 1964, 1966), posits that factors related to the content of work contribute to job satisfaction, while factors related to the work context contribute to job dissatisfaction. Another theory, the adaptation-to-work theory (Weiss et al., 1967; Pallone et al., 1971), suggests that work personality and the work environment are linked and are the basis for explaining job satisfaction and productivity.

Numerous studies have been conducted based on these theories to elucidate the nature of the relationship between job satisfaction and job productivity. However, the nature of this

relationship remains unclear and gives rise to differing viewpoints. Some researchers propose a unidirectional relationship between job satisfaction and productivity (e.g., Fishbein, 1973; Olson and Zanna, 1993), while others consider a bidirectional relationship between these two factors (Wanous, 1974), and still others suggest no correlation between the two (e.g., Brief and Roberson, 1989; Greenberger et al., 1989).

The initial studies were based on the hypothesis that greater job satisfaction would lead to increased productivity among individuals (Gruneberg, 1979). This relationship was first explored in the human relations theory of the late 1920s with the Hawthorne studies, and then in the early 1930s with the Filley studies (McCue and Gianakis, 1997). According to Vroom (1964), the human relations movement assumed that job satisfaction was positively associated with job performance. This movement was an attempt to increase productivity by meeting the needs of employees (Judge et al., 2001).

Several studies have since investigated the correlation between job satisfaction and productivity, including studies by Brayfield and Crockett (1955), Vroom (1964), and Petty et al. (1984). Brayfield and Crockett (1955) conducted a narrative review of studies on this topic and found a positive mean correlation, which they considered to be minimal. However, their review was limited as only nine studies had been published at that time reporting a correlation between satisfaction and performance. In contrast, Vroom (1964) considered 20 studies and found a much higher correlation. Organ (1977) has criticized Vroom's study, suggesting that it might have been represented more pessimistically than it should have been, as only three of the 23 correlations he cited were negative. However, Petty et al. (1984) conducted a meta-analysis of 16 studies published between 1964 and 1983, and their results showed a similar correlation to that reported by Vroom, leading them to conclude that the relationship between job satisfaction and job productivity is stronger and more consistent than previously thought.

A more comprehensive meta-analysis was conducted by Iaffaldano and Muchinsky (1985), who included 217 correlations from 74 studies. They analyzed the effect of satisfaction on performance by examining the influence of specific measures of satisfaction, such as pay satisfaction, satisfaction with colleagues, and satisfaction with promotion, on performance. They then estimated the effect of overall satisfaction on performance by averaging these specific measure correlations. Their results were quite close to those of previous studies, such as that of Brayfield and Crockett (1955). However, some researchers have criticized this technique, arguing that it is limited because the effect of job satisfaction on performance is reduced when specific measures are considered, as the correlations of the facet measures are always lower than the correlations of overall satisfaction (Wanous et al., 1989). Nevertheless, studies have consistently shown that job satisfaction has a significant effect on job performance, particularly for people in supervisory and professional positions (Argyle, 1989). In these positions, performance depends less on external pressures such as pay incentives or assembly line speed, and more on motivation, creativity, and helpfulness (Bhagat, 1982). However, many researchers have questioned the nature of the

”happy worker is the productive worker” relationship (Locke, 1970) and have instead begun to focus on the strength and direction of the relationship between high satisfaction and high performance. Organ (1977) has suggested that the relationship deserves further exploration, as an inverse effect between satisfaction and productivity may exist. Some studies have even reversed the hypothetical causality, suggesting that performance leads to worker satisfaction (Judge et al., 2001).

The rationale for the nature of the relationship between job satisfaction and job productivity is based on theories of expectancy-based motivation and self-determination (Lawler III and Porter, 1967; Locke, 1970; Deci and Ryan, 1985; Gagné and Deci, 2005). These theories generally state that satisfaction is derived from the rewards produced by performance (Naylor et al., 2013). For example, based on the theory of motivation, Lawler III and Porter (1967) proposed a model in which the success of a task leads to satisfaction. According to this model, performance is related to satisfaction, and this relationship is moderated by the rewards for performance and the perceived fairness of those rewards. In particular, Lawler III and Porter (1967) showed that good performance can lead to rewards, which in turn lead to job satisfaction. The model thus implies that performance can lead to worker satisfaction if workers believe that they will be fairly rewarded for the work they do. Locke (1970) also proposed a theoretical framework to understand the relationship between job satisfaction and performance. He suggests that satisfaction results from performance, but in this case, satisfaction is seen as a function of goal-directed behavior to achieve a value. Deci and Ryan (1985) also based his theory on a theoretical framework, in particular, his theory of self-determination, and maintains that satisfaction results from the rewards that result from behavior. From this theory, it is suggested that when individuals are effective at work, they experience the satisfaction of basic psychological needs and have positive attitudes towards their work (Gagné and Deci, 2005). However, Deci and Ryan (1985) consider that when individuals are faced with external contingencies, their effective performance is less likely to result in high levels of job satisfaction.

These two ways of looking at the nature of the relationship between job satisfaction and job productivity have led some studies to assume that the relationship is more causal in nature (Wanous, 1974; Sheridan and Slocum Jr, 1975). In particular, this work considers that job satisfaction and job performance can impact each other, so the relationship can go both ways. However, Wanous (1974) considers that this causal relationship depends on the type of satisfaction. For extrinsic satisfaction (appreciation of the individual triggered by external circumstances), satisfaction impacts performance, whereas for intrinsic satisfaction (subjective appreciation of the individual), performance causes satisfaction. Contrary to these studies, a small number of studies found a non-significant correlation between job satisfaction and job performance (Greenberger et al., 1989). Researchers have argued that job satisfaction does not predict job performance because existing measures of job satisfaction reflect a cognitive assessment rather than an emotional tone (Brief and Roberson, 1989).

In the face of much controversy about the nature of the relationship between job satisfaction and productivity, a unified theory of this relationship has been presented by Judge et al. (2001), which is considered a seminal work in this area. To understand the inconsistencies, Judge and colleagues conducted a meta-analysis using a significantly larger sample size than previous meta-analyses, with 312 independent samples contained in 254 studies, for a total of 54,417. Satisfaction was measured overall (general perceptions of the job) and in reference to specific aspects of the work situation (supervision, colleagues, opportunities for advancement, etc.). From these specific measures, they constructed a composite indicator considered as general satisfaction from the correlations between the specific factors reported in each study. Their results indicate a positive correlation, which differs from zero, between satisfaction and performance. On the composite measure of overall satisfaction, the results also indicate a positive correlation of equal magnitude between these two factors. In addition, they found that job complexity has a much greater impact on this positive relationship than low or medium complexity jobs.

In this study, we aim to analyze the nature of the relationship between job satisfaction and worker productivity by examining specific measures of overall job satisfaction and various types of productivity. Specifically, we will consider pay satisfaction (e.g., Bretz and Thomas, 1992; Heneman and Judge, 2000; Currall et al., 2005) and satisfaction with job prospects (e.g., Stumpf and Rabinowitz, 1981; Nachbagauer and Riedl, 2002), and analyze their influence on workers' total productivity (Heneman et al., 1988; Heneman and Judge, 2000; Currall et al., 2005), as well as two components of productivity: efficiency changes and technological changes. To account for potential endogeneity, we will also explore the causal nature of the relationship between this measure of job satisfaction and job productivity. Next, we will describe the data used in our analysis.

2.3 Data and variables

The data used in this study comes from the 2013 and 2017 Generation 2010 surveys produced by Céreq (Centre d'étude et de recherches sur les qualifications). The surveys were conducted among first-time entrants to initial training for the period 2009--2010 and aim to analyze access to employment, career progression, as well as the training and life trajectories of these young people over several years. These are longitudinal surveys that allow the tracking of the evolution of young people's career and personal paths at different key moments in their professional and personal lives. The individuals surveyed in the "Generation 2010" surveys have the same level of seniority and experience on the job market since they are first-time entrants to initial training. This means that they left the education system at the same time and have not yet acquired significant professional experience at the time of the surveys. This could be advantageous for our study because by studying first-time entrants to initial training, we can evaluate the relationship between job satisfaction and work productivity among individuals with similar levels of seniority and professional experience. Indeed, studying this relationship among individuals with very different levels of seniority and professional experience can bias the results, as these factors

can influence job satisfaction and work productivity in different ways. By studying first-time entrants, we can also better understand the impact of first professional experiences on satisfaction and productivity, and identify the factors that promote or hinder their professional development. In addition, this can help better identify the needs of this specific population in terms of training and professional support to improve their satisfaction and productivity at work. In addition, the data is particularly relevant to this study because it provides detailed information on the personal and occupational characteristics of individuals, their geographic location, and the quality of their employment. Moreover, it provides information on workers' varying opinions about different aspects of their jobs. This information allows us to control for different individual characteristics in the regressions that may impact their level of productivity, take into account specific measures of job satisfaction, and perform a spatial analysis on precise geographical data.

The 2013 survey was conducted three years after the respondents' exit from the education system, with a sample size of 38,594 individuals. The 2017 survey was conducted seven years later on a sample of 13,707 individuals. To ensure consistency, we excluded individuals who did not respond to the 2017 questionnaire and kept only those who were employed in both 2013 and 2017, which makes an initial base sample of 13,707 individuals. In this base sample we excluded workers who were unemployed. We further excluded civil servants, part-time employees, and those who did not provide information on their opinion on employment or their pay and employment area in 2013 and 2017.

We made these exclusions for several reasons. First, selecting a sample of workers employed in both 2013 and 2017 allows us to focus on individuals with some professional stability and avoids cases where individuals are in the process of changing careers, which could skew the results. Second, excluding unemployed workers allows us to focus on individuals who have work experience, which is important for studying the relationship between job satisfaction and productivity. Third, excluding civil servants and part-time workers is justified by differences in pay and promotion systems in the public sector and differences in responsibility and involvement in part-time work. Finally, excluding individuals who did not provide information on their opinions regarding employment, salary, and employment area in 2013 and 2017 is necessary to ensure data quality and consistency of our analysis. Ultimately, our empirical strategy was applied to a sample of 2,716 workers aged between 20 and 42 years. Although the exclusions we made led to a loss of approximately 80% of the base sample, they are necessary to obtain a homogeneous and coherent sample that will allow us to draw reliable conclusions about the relationship between job satisfaction and productivity. However, the significant loss of our initial sample may have an impact on the validity of our results. That is why we conducted a variety of tests to analyze the robustness of our findings.

2.3.1 Variables

Table 2.8.1 in the Appendix summarizes all the definitions and sources of the variables. All variables used in this paper can be categorized as follows: input and output variables for the

first stage of the empirical approach to estimating productivity indices, variables measuring job satisfaction for the second stage of the empirical analysis, variables controlling for individual and occupational characteristics of workers for the second stage of the empirical approach, and key variables indicating the spatial setting. Table 2.3 presents the descriptive statistics of the full sample between 2013 and 2017.

The input and output variables were chosen based on information from the Mincer pay equations (Mincer, 1974). These variables are taken from the Generation 2010 database. The output is the net monthly pay (including bonuses) of individuals, while the inputs are education level, work experience, and tenure. Since the euro values for 2013 and 2017 are not directly comparable, the pays were adjusted with the 2013 constant price consumer price index to determine the equivalent value in 2017. In addition, the level of education is given in qualitative and categorical form in the database, according to the type of degree obtained upon leaving the education system. To evaluate an individual's productivity, we used the Malmquist method, which requires a quantitative variable for the level of education. To achieve this, we used the number of years of study corresponding to each degree declared by the individual based on the classification of the French education system. The distribution of categories is based on the duration of education in France starting from primary school. Each category is associated with a specific duration of education, ranging from 0 years for those without a diploma to 24 years for holders of a doctorate in health or in humanities, management, and law (see table 2.8.2 in the appendix). The correspondence between categories and durations of education was established based on degrees obtained at different levels of education (CAP-BEP-MC, vocational baccalaureate, technological baccalaureate, BTS-DUT, bachelor's degree, master's degree, business school, engineering degree, doctorate). Thus, for each individual in the sample, the duration of education was determined based on the highest degree they obtained, and the corresponding category was assigned to them.

For individuals without a diploma, we assigned a value of 0, but this does not mean that they are not educated. In reality, we estimated the number of years of education corresponding to the level they would have attained if they had obtained a diploma when entering the labor market. As for the numbers 15, 16, 18, 19, 20, 21, and 24, they represent the number of years of education required to obtain certain degrees in France. For example, to obtain a CAP-BEP in the industrial or tertiary field, two years of training are required after middle school, which corresponds to a total of 15 years of education. To obtain a doctorate in the health field, eight years of higher education are required after the baccalaureate, which corresponds to a total of 24 years of education. The intermediate numbers correspond to additional levels of education, such as the vocational baccalaureate, the technological baccalaureate, the bachelor's degree, the master's degree, and so on.

The descriptive statistics of these inputs and outputs presented in Table 2.3.1 show that the average pay in our sample is 2,007.55 euros, which is quite close to the average pay in France.

This may indicate that the individuals in the sample do not represent a particularly privileged or disadvantaged group in terms of economic status. The workers in our sample have relatively high levels of education, with an average of a university degree. This can be useful for understanding the skill level of the workers in the sample. In terms of work experience, these workers have acquired a certain level of competence in their task, with an average of 58 months of experience, which is just under 5 years and may be important for understanding their productivity at work. However, they have a shorter tenure with their employer, averaging about 33 months (2 years and 9 months) with their organization, indicating a significant number of job changes. This could be important for understanding their level of job satisfaction and their productivity at work.

Table 2.3.1: Descriptive statistics of the variables used for the period 2013--2017

	Mean (1)	Standard deviation (2)	Minimum (3)	Maximum (4)
<i>Output</i>				
Pay ^a	2,007.55	725.30	180	6,950
<i>Inputs</i>				
Level of education (in years)	19.14	3.83	0	24
Work experience (in months)	57.84	27.15	2	97
Tenure (in months)	32.69	3.18	28	45
<i>Job satisfaction measures</i>				
Pay satisfaction	0.152	0.359	0	1
Career prospects satisfaction	0.064	0.248	0	1
<i>Control variables</i>				
Gender (Men)	0.545	0.498	0	1
Age	29	3.076	20	42
Foreign origin	0.118	0.322	0	1
Father and/or mother manager	0.332	0.471	0	1
In relationship	0.592	0.491	0	1
Permanent contract	0.804	0.397	0	1
Geographic mobility between 2013--2017	0.152	0.359	0	1

^a Pay adjusted by the consumer price index.

Notes: Author's calculation from Generation 2010 data. The values represent the mean (column 1), standard deviation (column 2), minimum (column 3), and maximum (column 4) of the variables considered in the analysis, at the level of the overall sample. The values were weighted by the sampling weight.

In our study, we assess job satisfaction as the main independent variable through various specific measures aimed at capturing different dimensions of it (Judge et al., 2001). We selected two specific measures, pay satisfaction (e.g., Bretz and Thomas, 1992; Heneman and Judge, 2000; Currall et al., 2005) and satisfaction with career prospects (e.g., Stumpf and Rabinowitz, 1981; Nachbagauer and Riedl, 2002), following the information related to the job opinion provided by our database. We chose to focus on these two measures because they were identified as the most relevant for worker productivity in the empirical regressions we conducted later. Although other measures of worker opinions were available in the Génération 2010 database, these measures proved to be insignificant in our analyses. Therefore, we decided not to include these measures in our study. These two variables represent the main independent variables in the second stage of

the empirical approach.

Pay satisfaction was measured using the following question: "Would you say that you are": 1-"very well paid", 2-"somewhat well paid", 3-"somewhat badly paid", and 4-"very badly paid". Respondents could choose one of the four response categories. The second measure, satisfaction with career prospects, was assessed through the following question: "How do you see your future career?" Respondents could choose one of the following alternatives: 1-"You are rather worried", 2-"you are rather optimistic about your professional future", and 3-"Don't know". In Table 2.3.2, we report the distribution of responses to these questions among individuals in our analysis sample. In general, workers have a positive view of their career prospects and are relatively satisfied with their pay. However, almost a quarter of the individuals are still less satisfied with their pay. This suggests that the majority of workers in the sample have a positive perception of their career prospects and are generally satisfied with their pay. However, the fact that a quarter of individuals are less satisfied with their pay indicates that some workers may experience pay inequalities or have higher pay expectations.

Table 2.3.2: Proportion of responses from job satisfaction measures

		Very good	Fairly good	Fairly bad	Very bad
<i>Pay satisfaction</i>	2013	5.96	65.06	25.04	3.94
	2017	3.84	62.94	29.83	3.4
		Rather worried	Rather optimistic	Don't know	
<i>Career prospects</i>	2013	14.25	83.98	1.77	
	2017	18	82	0	

Notes: Author's calculation based on data from the 2010 Generation. This table presents the proportion of individuals who gave their opinion pay satisfaction and career prospects. The percentage of response given by workers in our sample for each possible response alternative based on the overall sample is represented for the years 2013 and 2017. The values were weighted by the sampling weight.

Our measures of job satisfaction have been designed to align with the job productivity index, which is determined as the change between 2013 and 2017. This simplifies the empirical analysis for estimating the influence of these measures on productivity. To measure the evolution of individuals' satisfaction between the two periods, we used a binary variable that takes the value 1 if the individual reported being more satisfied in 2017 compared to 2013 and 0 otherwise. For example, for satisfaction with pay, we used a Likert scale ranging from 1 to 4 to measure individuals' satisfaction in both 2013 and 2017. We then created the binary variable by comparing the ratings given by individuals in both periods. If an individual had a rating of 3 in 2013 and a rating of 2 in 2017, we coded their response as 1, indicating that they reported being more satisfied in 2017. If the individual reported the same rating or a decrease in rating between the two periods, we coded their response as 0. We proceeded in the same manner with responses related to satisfaction with career prospects. This method allows us to measure individuals' satisfaction evolution in a binary way and statistically analyze it later.

The descriptive statistics for these new variables are presented in Table 2.3.1. In general, the majority of workers reported either a decrease in their level of satisfaction or the same level of satisfaction with the measures. For those who reported an increase in their level of pay satisfaction, their share of the total population averaged just over fifteen percent between 2013 and 2017, while the share for career prospects was around 6%. These statistics may indicate that some workers are experiencing pay inequalities or have higher pay expectations that are not being met, leading to decreased job satisfaction. Additionally, the relatively low percentage of workers reporting an increase in satisfaction with career prospects may suggest that some workers may not see clear opportunities for career advancement or growth within their current organizations.

We considered a set of variables designed to control for differences in individual and occupational characteristics among workers that are expected to affect worker productivity. Following the literature, we included a set of individual and occupational characteristics such as gender (e.g., Guy, 1993; Azmat and Petrongolo, 2014; Ranganathan and Shivaram, 2021), age (e.g., Hellerstein and Neumark, 1995; Haltiwanger et al., 1999; Lallemand and Rycx, 2009; Mahlberg et al., 2013), origin (e.g., Fox, 2005), marital status (e.g., Fox, 2005), and employment contract (e.g., Wagenaar et al., 2015). We also added the employment status of the parents, which is likely to impact the employee's performance as having a father or mother who is an executive can increase the child's professional integration, allowing them to enter larger, more productive companies and potentially improve their productivity (Greenhaus and Powell, 2016).

Other relevant variables could include work experience, level of education, working hours, company size, perceived work-related stress, workload, and quality of interpersonal relationships at work. Since our main objective of our analysis is to understand the effect of satisfaction on productivity and we have included work experience and level of education in the estimation of productivity indices, we have already taken into account their potential effect on worker satisfaction and productivity. Working hours are not relevant in our case, as our sample consists only of full-time employees. Other variables have not been taken into account, as some could cause multicollinearity issues, while others are not provided in the database.

For the age, relationship, and employment contract variables, we considered the values in 2017 as there was a significant correlation with the values of these variables in 2013. This is because it allows for consistency and avoids potential measurement errors or biases that could arise if different values are used for the same variables across different time periods (Greene, 2012).

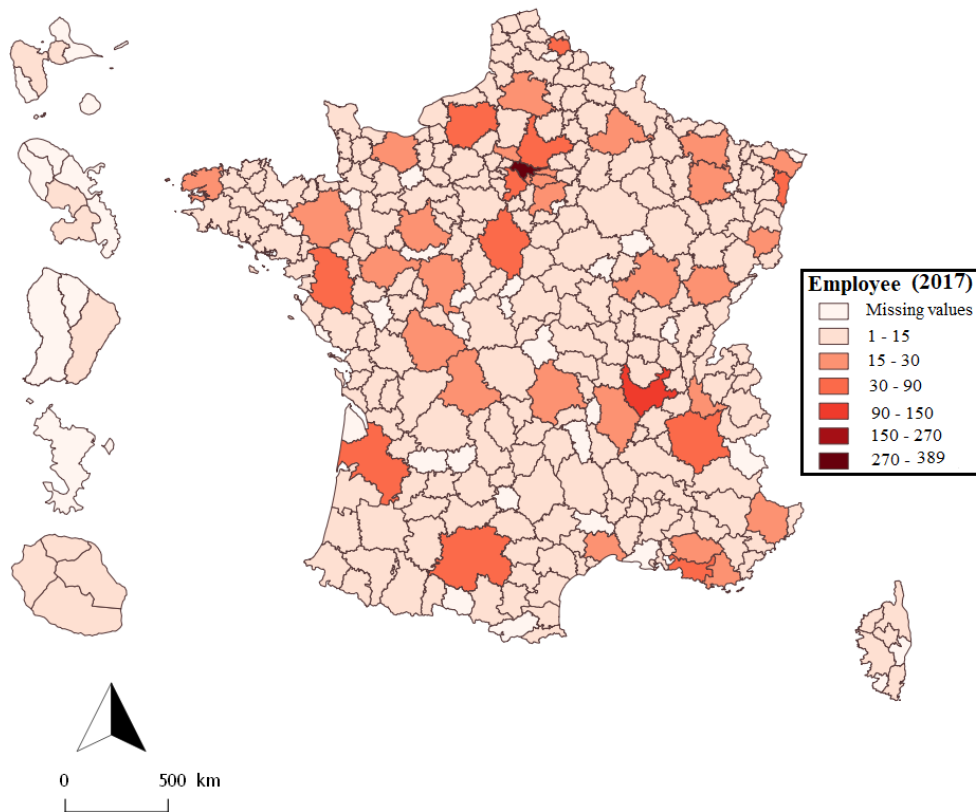
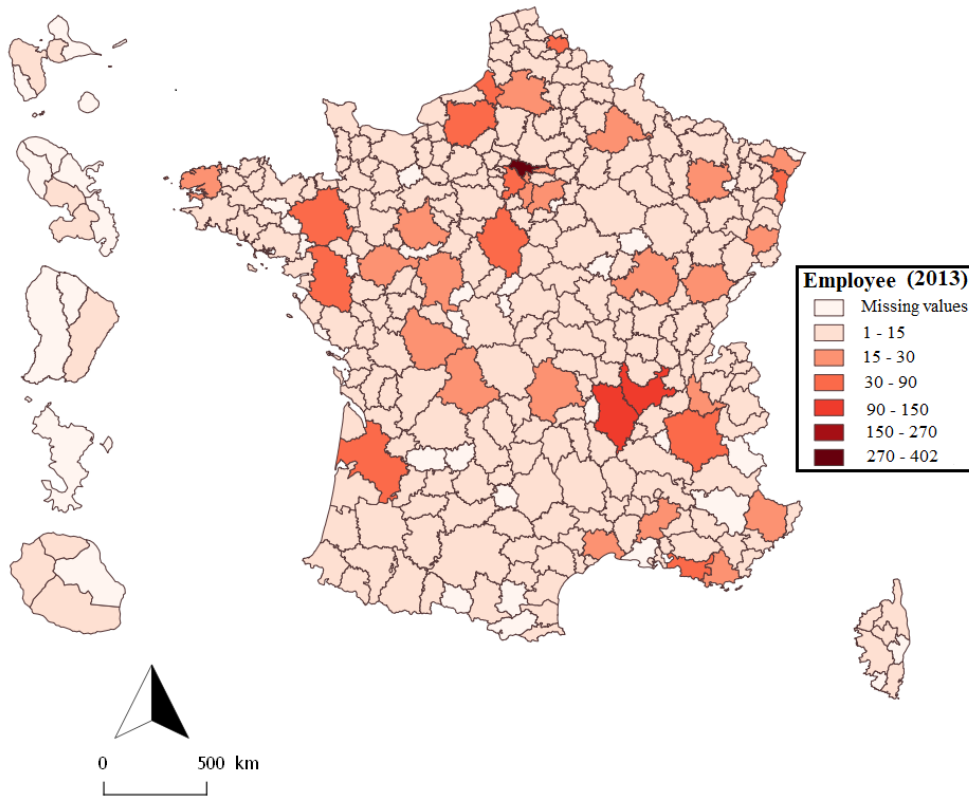
The descriptive statistics presented in Table 2.3.1 provide useful information on the characteristics of the studied sample. The average age of the sample is 29 years old, which suggests that most individuals are relatively young. Men are slightly more represented than women in the sample (54.5% versus 45.5%). This information may be useful for further analyses regarding

gender differences in the results. The vast majority of individuals in the sample (95.8%) have a degree, with nearly 60% having a university degree. This indicates that the sample is educated, which may have implications for the nature of jobs held and incomes earned. However, this may also mean that the job market is increasingly demanding in terms of qualifications, which can make it more difficult for people with lower levels of education to secure employment. Only 11.8% of individuals are of foreign origin, which suggests that the sample is mainly composed of French nationals. Approximately half of the workers in the sample reported being in a relationship in 2017, which may have implications for career choices, family responsibilities, and job satisfaction. Individuals in a relationship may have different job preferences compared to singles, seeking jobs that offer greater stability or more flexible schedules to better balance their professional and family lives. Nearly 80% of workers reported having a permanent contract in 2017, which may indicate some employment stability. This can be positive for workers as it provides them with some job security, but it may also have implications for the flexibility of the job market and the ability of companies to adapt to economic changes.

The spatial analysis framework was constructed using the workers' EA of residence for all urban areas in the French data set produced by Insee (Institut National de la Statistique et des Études Économiques) in 2010. These variables enabled us to distinguish between different types of urban amenities such as residential and workspaces, natural amenities, and cultural heritage. These workspaces also capture, to some extent, spatial heterogeneity in terms of working conditions among workers.

In total, we selected 280 EAs out of 322 based on our sampling criteria. Figure 2.1 illustrates the spatial distribution of workers in our analysis sample across the selected EAs in 2013 and 2017. The legend provides information on the scales used for the graphical representation of data on the map. The different scales show the distribution by number of the employed population in the 280 EA. The colors used on the map correspond to gradients that represent the representativeness of the employed population in our sample for each EA. Darker colors may indicate higher representativeness, while lighter colors indicate lower representativeness. We observe that the vast majority of workers in our sample reside in major metropolitan areas, particularly in the Paris EA, which accounted for approximately 15% and 14% of the sample in 2013 and 2017, respectively. This preponderance of workers in Paris could be attributed to the capital effect, which tends to offer a wider range of job opportunities, higher salaries, and better working conditions compared to smaller cities or rural areas. As a result, many workers are drawn to these urban areas in search of better career prospects. Large urban areas also benefit from agglomeration economies, which refer to the positive externalities that arise from the concentration of economic activity in a particular geographic area. For example, firms in a particular industry may cluster together in a particular city, leading to knowledge spillovers, lower transaction costs, and other benefits that make it easier and more profitable for firms to operate in that area. This, in turn, can attract more workers to the area. Major metropolitan areas like Paris tend to have better transportation infrastructure, making it easier for workers

Figure 2.1: Number of employees per EA (2013 and 2017)



Notes: Author's calculations, based from Generation 2010 data.

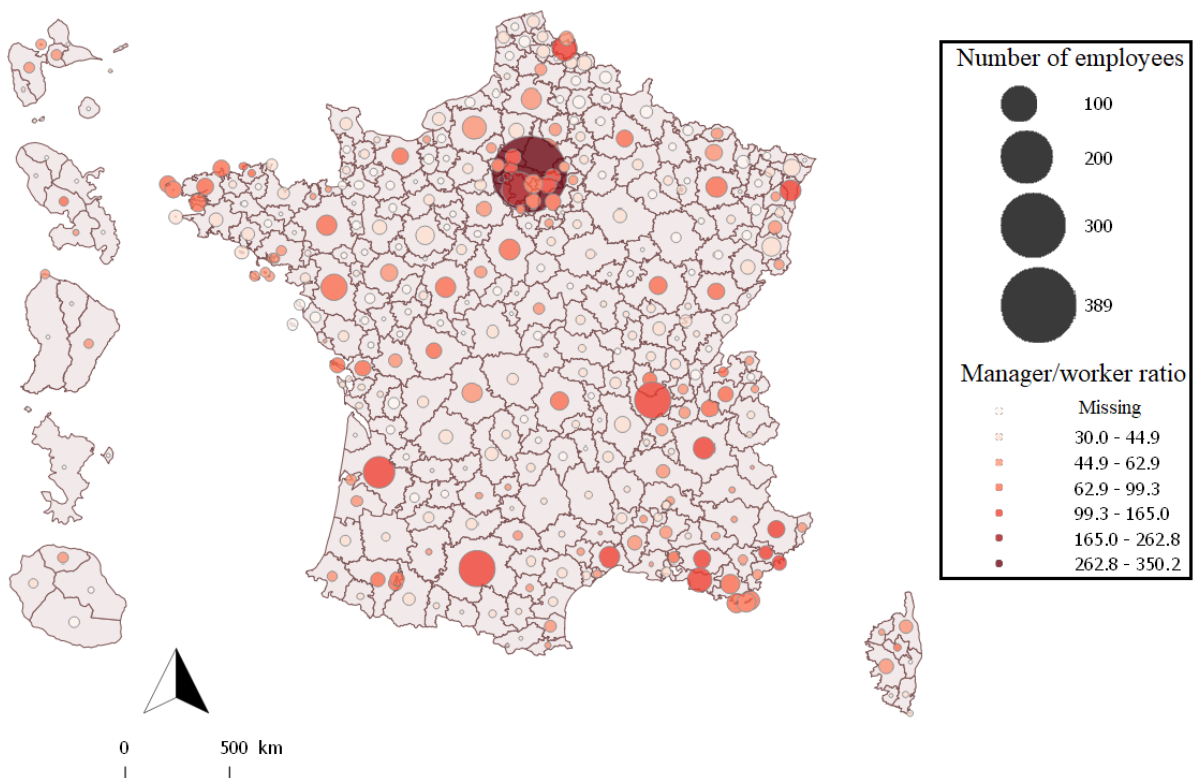
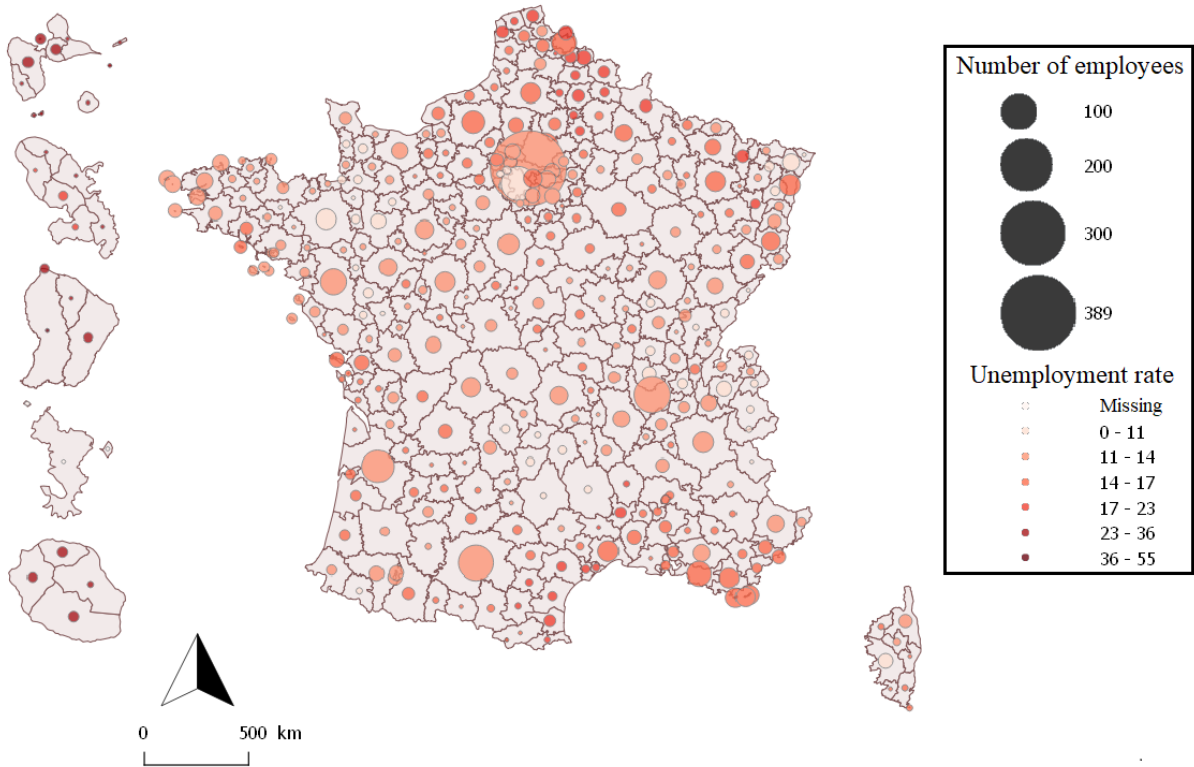
to commute to work from surrounding areas. This can also contribute to the concentration of workers in these urban areas.

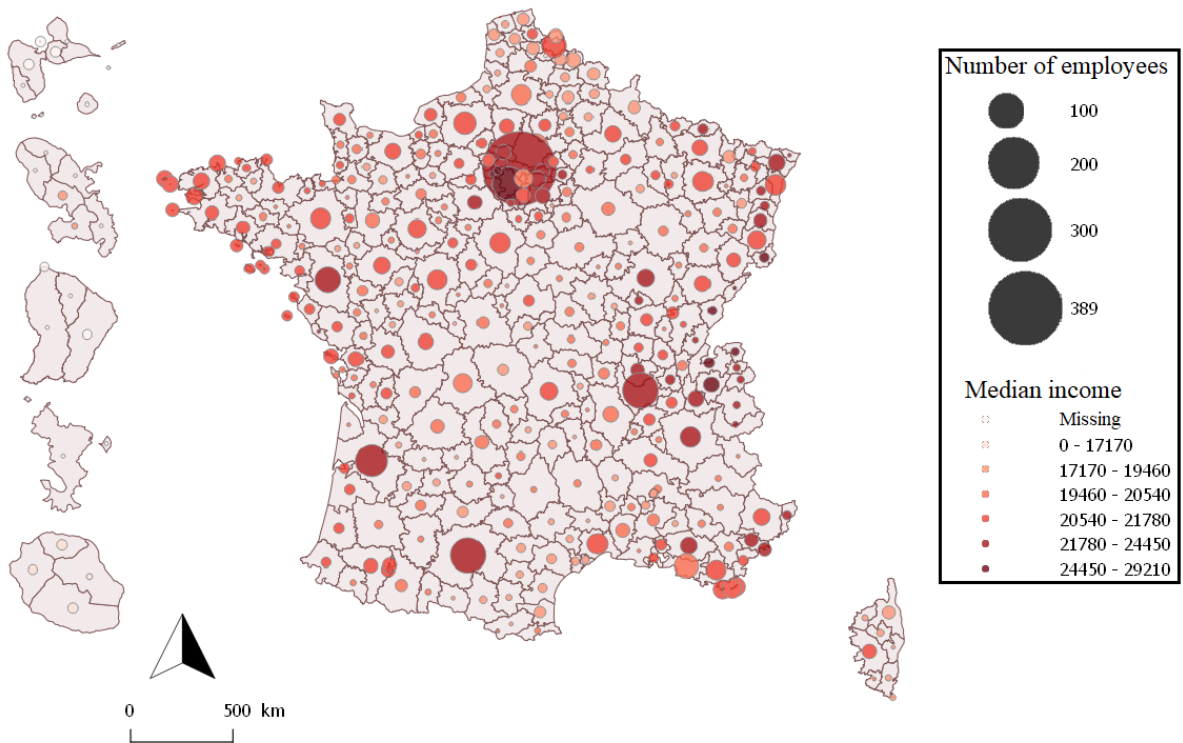
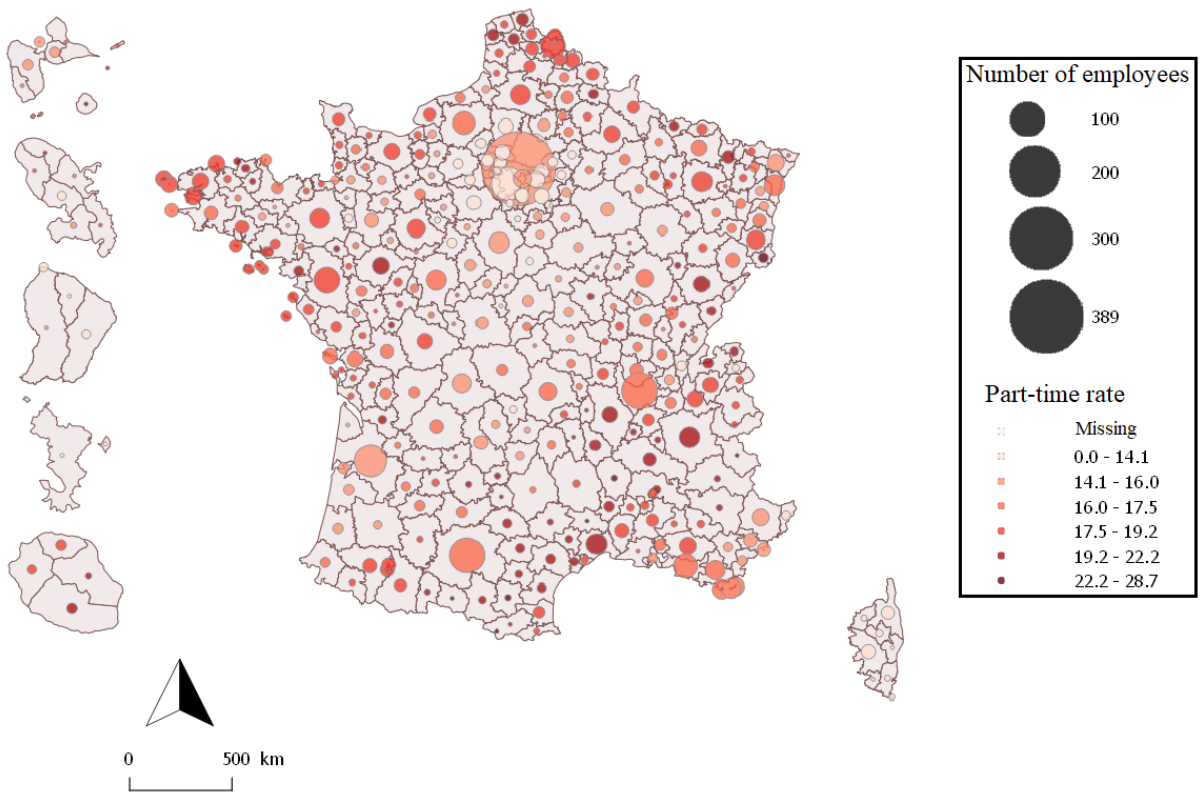
To capture the territorial context and labor market potential effects, we enriched each EA with economic indicators from Insee. We mainly considered the median household income, unemployment rate, share of part-time work, share of the agriculture sector, share of the industry sector, share of the tertiary sector, share of the construction sector, and the ratio of managers to workers. The choice of these indicators is particularly relevant as they are all important economic factors that can influence the labor market and professional opportunities in a given region. For example, the median household income can reflect the level of wealth and purchasing power in a region, while the unemployment rate can indicate the availability of jobs and competition in the labor market. The shares of different economic sectors can reflect the structure of the local economy and employment opportunities in each sector, while the ratio of managers to workers can give an indication of the level of hierarchy and quality of management in companies in the region. For each of these variables, we used the values from 2017 since we did not notice significant changes between 2013 and 2017. This also avoids strong correlations with the values in 2013. Additionally, we created a binary variable from the EA information that takes the value of 1 if the individual changed EAs between 2013 and 2017, and 0 otherwise. This variable allows us to capture the professional and residential mobility that could impact the worker's performance.

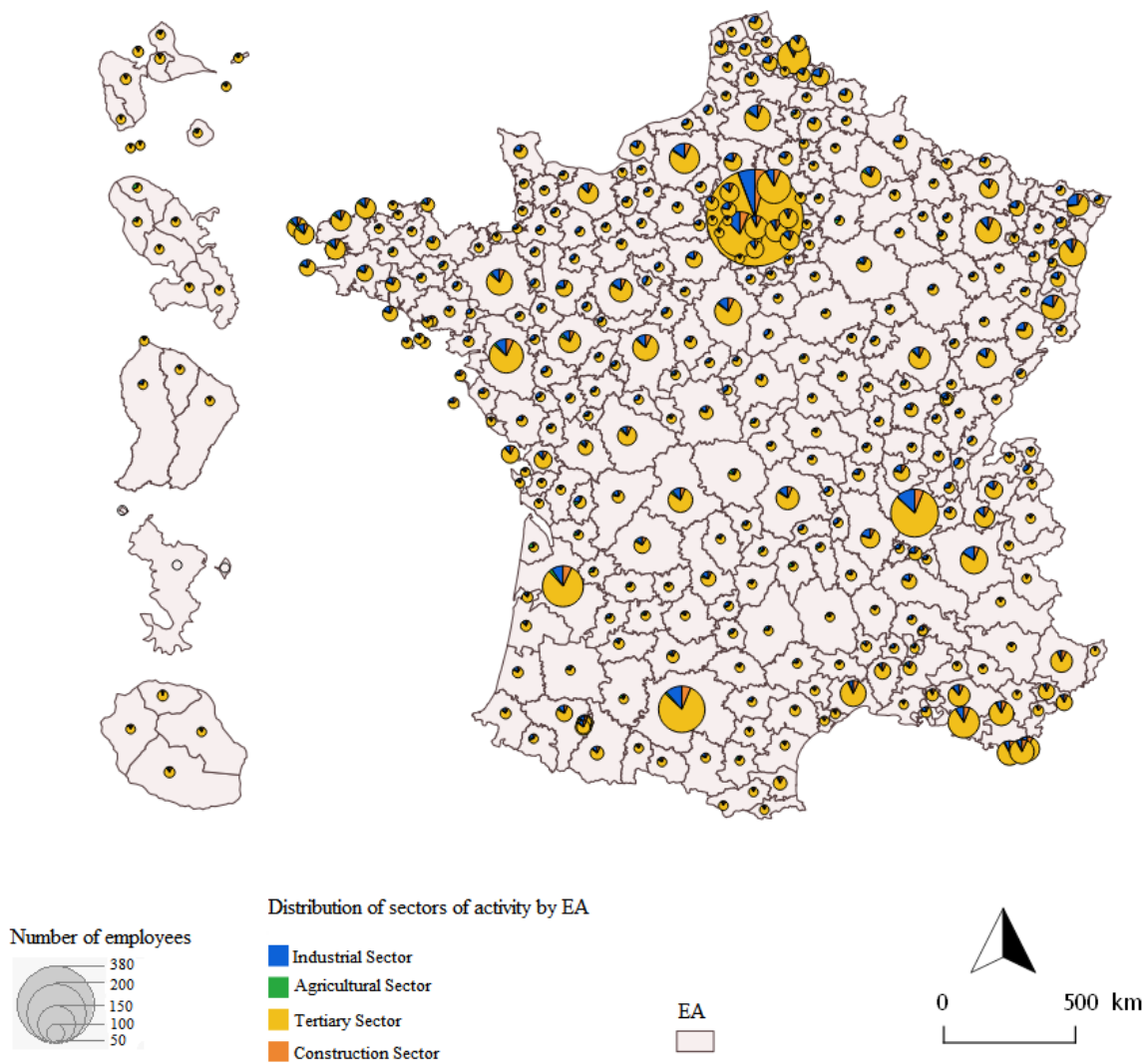
Figure 2.2 illustrates the distribution of workers according to EA characteristics. We created five maps to represent the representativeness of the employed population in our sample according to the characteristics of EAs. For this, we used a two-part legend on the first four maps. The first part uses gradient colors to show the EAs where the characteristics are more abundant in proportion to the unemployment rate, manager/worker ratio, part-time rate, and median income. The darker the color, the stronger the share for this characteristic, and the lighter the color, the weaker the share for this characteristic. The proportional circles associated with these representations of the characteristics for each EA show the number of employees in that EA. On the fifth map, we also used proportional circles to represent the number of employees in each EA. Inside these circles, we represented pie charts showing the share of the industrial, agricultural, tertiary, and construction sectors in the EA.

The graph suggests that workers tend to move to EAs with low unemployment rates, lower shares of part-time work, a higher ratio of managers to workers, and relatively high median incomes. In other words, workers predominantly move to areas where economic conditions are favorable. This trend can be attributed to various factors. Firstly, employees typically seek to maximize their employment opportunities and earning potential (Brunello and Langella, 2016). EAs with better economic conditions can provide more job opportunities in growing sectors, higher salaries, and better social benefits, making them more attractive for job seekers. Additionally, EAs with more favorable economic conditions can offer a better work environment and

Figure 2.2: Number of employees by EA characteristics







Notes: Author's calculations, based from Generation 2010 data.

more significant opportunities for professional growth (Blanchflower and Oswald, 1998; Green, 2006). Companies located in these areas may be more innovative and offer more training and career advancement opportunities (Freeman, 2008). Finally, employees may be drawn to more dynamic EAs that offer more modern infrastructure and more efficient public services (Glaeser and Gottlieb, 2008). EAs with better economic conditions can offer an overall higher standard of living, which can be an essential factor for employees when deciding where to live and work. This figure also highlights France's specialization in the service sector.

Now that we have explained our data and variables of interest, we move on to the empirical analysis. In the next section, we will explore the relationship between job satisfaction and worker productivity using various econometric techniques.

2.4 Empirical approach

This chapter adopts a two-step estimation strategy. We first estimate the indices of productivity change and decompose the change in the overall index into two sub-indexes including efficiency changes and technological changes. Next, we detail the econometric model with a multi-level hierarchical structure where we estimate the relationship between the variation of the different measures of job satisfaction and the variation of productivity indices at level 1. At level 2 we take into account the spatial location that is captured by the EA characteristics.

2.4.1 Method for estimating and decomposing productivity

Malmquist's productivity index (Färe et al., 1994a) is utilized in this paper using a hierarchical structure proposed by Tone (1997) in the framework of the DEA method (Data Envelopment Analysis). The Malmquist productivity index analyzes the change in total productivity between periods t and $t + 1$ (Malmquist, 1953). The Malmquist index can measure productivity growth in goal achievement for an individual business unit as an improvement in efficiency relative to the reference frontier (Chen and Ali, 2004). The index is based on the ratio of two distance functions used to measure productivity (Caves et al., 1982). Färe et al. (1994a) extended it to a productivity index based on the DEA method⁸ by using the geometric mean of two indices.

In this study, productivity will be estimated at the individual level as the selected individuals are identical between 2013 and 2017. Therefore, a hierarchy of increasing productivity based on the level of education of individuals is considered since research shows that productivity increases with the level of education (e.g., Becker, 1962; Rumberger, 1987; Middleton et al., 1993).⁹

⁸The DEA method is a non-parametric method that allows us to evaluate the performance of organizations or individuals (called *Decision-Making Units-textDMU_s*) that transform resources (inputs) into services (outputs) (Farrell, 1957; Charnes et al., 1978; Färe and Grosskopf, 1997; El-Mahgary and Lahdelma, 1995)

⁹The link between education level and productivity has been demonstrated by several studies. For example, a study conducted by (Psacharopoulos and Patrinos, 2018) revealed that each additional year of education results in an 8.8% increase in productivity in developed countries and a 10% increase in developing countries. Another study

Let $x = (x_1, \dots, x_m) \in \mathbb{R}^m_+$ denote inputs and $w = (w_1, \dots, w_s) \in \mathbb{R}^s_+$ denote outputs of a production technology. Building on the seminal work of Mincer (1974), we model the monthly pays as outputs (e.g., Lawler and Porter, 1966) that are determined by the following inputs: education level (e.g., Penzer, 1969), work experience (e.g., Chandler and Mccornach, 1963), and tenure (e.g., Grigsby and Burns, 1962) (see Table 2.3.1). In this study, hourly pays are not used to avoid the issue of using ratios in production technology that may lead to biased efficiency score estimates (Olesen et al., 2017). The production technology T at time t , denoted as T^t , can be expressed as:

$$T^t = \{(x_t, w_t) \in \mathbb{R}^{m+s}_+ : x_t \text{ can produce } w_t\} \quad (2.1)$$

We assume that the production technology satisfies the axioms of production frontier theory (Färe and Grosskopf, 1996). The characterization of a multi-input and multi-output production technology requires assuming a structure regarding returns to scale (CRS). Under the usual axiom of convexity of production technology, constant and variable returns to scale are the most commonly used. For this study, we choose a CRS structure (Guironnet and Peypoch, 2007) since we are in a finer spatial framework with more homogeneity. Moreover, this choice of CRS models is particularly relevant because they have higher discriminatory power and avoid the systematic bias present when calculating Malmquist-based productivity changes from variable returns to scale (VRS) models (Zhang et al., 2015). However, the hierarchical structure adopted in this article (Dong et al., 2020) takes into account the heterogeneity present at the level of individuals in the same locality. Nonetheless, we will later analyze the robustness of the results using VRS. The distance functions for computing the Malmquist productivity index are output-oriented. This choice is consistent with productivity studies in education economics (Guironnet and Peypoch, 2018) and is relevant to the data used to characterize the inputs and output of the production technology.

At period t , the distance function in output of Shephard (2015), $D_t^o : \mathbb{R}^m_+ \times \mathbb{R}^s_+ \rightarrow \mathbb{R}_+ \cup \{\infty\}$, is defined by:

$$D_t^o = \inf_{\theta} \left\{ \theta : \left(x_t, \frac{w_t}{\theta} \right) \in T^t \right\} \quad (2.2)$$

The output-oriented Malmquist productivity index (Färe et al., 1994a) is then defined by:

$$MI^o(x_t, w_t, x_{t+1}, w_{t+1}) = \left(\frac{D_{t+1}^o(x_{t+1}, w_{t+1})}{D_{t+1}^o(x_t, w_t)} \times \frac{D_t^o(x_{t+1}, w_{t+1})}{D_t^o(x_t, w_t)} \right)^{1/2} \quad (2.3)$$

Where $MI^o(x_t, w_t, x_{t+1}, w_{t+1})$ is the Malmquist's overall productivity index between the periods t and $t + 1$. The term $D_t^o(x_t, w_t)$ represents the observed distance function for the production technology at time t , while $D_{t+1}^o(x_{t+1}, w_{t+1})$ represents the observed distance function for the production technology at time $t + 1$. In this specification, efficiency improves if $MI^o(x_t, w_t, x_{t+1}, w_{t+1}) > 1$, remains at the same level if $MI^o(x_t, w_t, x_{t+1}, w_{t+1}) = 1$, and decreases

conducted by (Black et al., 1997) showed that workers with a university degree have 20% higher productivity than workers who have not completed their secondary education.

if $MI^o(x_t, w_t, x_{t+1}, w_{t+1}) < 1$. The change in technical efficiency (EFFCH) and technological change (TECH) appear respectively through the following decomposition:

$$MI^o(x_t, w_t, x_{t+1}, w_{t+1}) = \frac{D_{t+1}^o(x_{t+1}, w_{t+1})}{D_t^o(x_t, w_t)} \left(\frac{D_t^o(x_{t+1}, w_{t+1})}{D_{t+1}^o(x_{t+1}, w_{t+1})} \times \frac{D_t^o(x_t, w_t)}{D_{t+1}^o(x_t, w_t)} \right)^{1/2} \quad (2.4)$$

The first term represents the change in technical efficiency (EFFCH) over time. If the value of this term is greater than one, it implies that the individual has become more efficient over time, while if it is less than one, it implies that the individual has become less efficient over time. The second term represents the technological change (TECH) over time. If the value of this term is greater than one, it implies that the individual is more innovative over time, while if it is less than one, it implies that the individual is less innovative over time (Zhang et al., 2015).

The estimation of the Malmquist productivity index and its two components requires the calculation of four distance functions by linear programming, which depend on the time period of observation of the input-output vector and the time period of the reference technology. The technology is then characterized as non-parametric (Varian, 1984; Banker and Maindiratta, 1988):

$$T^t = \left\{ (x_t, w_t) \in \mathbb{R}_+^{m+s} : x_t \geq \sum_{i=1}^k \lambda_i x_{it}, w_t \leq \sum_{i=1}^k \lambda_i w_{it}, \lambda_i \geq 0, i = 1, \dots, k \right\} \quad (2.5)$$

Thus, for a given unit, the distance function $D_t^o(x_t, w_t)$ is then calculated by the following linear program:

$$\begin{aligned} D_t^o(x_t, w_t) &= \min_{\lambda, \theta} \theta \\ \text{s.t. } x_t &\geq \sum_{i=1}^k \lambda_i x_{it} \\ \frac{1}{\theta} y_t &\leq \sum_{i=1}^k \lambda_i w_{it} \\ \lambda_i &\geq 0, i = 1, \dots, k \end{aligned}$$

θ is the distance of the observed production technology from the production frontier, i.e., the measure of the technical inefficiency of the production unit. λ_i are the coefficients of the observed production technology, i.e., the weights assigned to each input to produce the observed outputs. x_t is the input vector for the production unit at time t . w_t is the output vector for the production unit at time t . y_t is a reference output vector for the reference technology at time t . The first set of constraints imposes that the observed technology produces at least the observed outputs from the observed inputs. The second set of constraints imposes that the observed technology does not produce more than the reference technology for all inputs.

The hierarchical structure of the Malmquist productivity index is characterized by 2,716 individuals grouped into 8 categories based on educational level (refer to Table 2.8.2 in the Appendix). The least advantaged group in terms of our problem consists of individuals with the lowest level of education (i.e., those who have not obtained a degree). Out of the 2,716 individuals, 43 individuals (corresponding to 43 units, where $k=43$) are compared only within

this category, and their productivity scores are extracted. Next, the second least advantaged group of individuals (those with 15 years of education) is added to the first category, and productivity scores are calculated on a sample of 268 units (43+225 units). The productivity scores of the second category are then extracted from this estimation for the individuals. This process is repeated for each successive category in the hierarchical structure until reaching the 555th category, which characterizes the most advantaged group.

2.4.2 Multilevel econometrics for estimating the relationship between job productivity and job satisfaction

We employed multilevel modeling for econometric analysis of productivity, similar to the hierarchical estimation method. Both approaches consider the hierarchical structure of the data, such as individuals grouped into clusters or variables grouped into factors (Snijders and Bosker, 2011). By using multilevel modeling, we can effectively model the relationship between productivity and explanatory variables while accounting for this data hierarchy (Goldstein, 2011). Specifically, we examined the productivity of French workers grouped by EA. Traditional OLS regression would require introducing 280 binary variables for this analysis, but this approach can result in specification bias. More specifically, introducing a large number of variables can lead to overfitting and specification bias, where the model may perform well on the data used for estimation but poorly on new data (Snijders and Bosker, 2011). Moreover, OLS regression does not account for the hierarchical structure of the data, which can result in biased estimates of coefficients and standard errors (Gelman and Hill, 2006).

Multilevel modeling provides a better alternative to address this issue because it takes into account the hierarchical structure of the data by modeling the variance at different levels of the data hierarchy (Goldstein, 2011). This approach allows us to estimate the effects of both individual-level and EA-level factors on the outcome of interest while avoiding overfitting and specification bias. By using multilevel modeling, we can obtain more reliable and accurate results.

In this approach, we can estimate a random effects model with a simple constant, which can be useful when dealing with data that have a hierarchical structure, such as individuals nested within groups or repeated measurements of the same individuals over time (Gelman and Hill, 2006). By estimating a random effects model with a simple constant, we can better model the impact of both individual-level and education-level factors on the outcome of interest. Our model estimation procedure is as follows:

$$\Delta y_{ij} = \beta_{0j} + \mu_{ij} \quad (2.6)$$

With Δy_{ij} representing the estimated productivity change of French workers between 2013 and 2017, according to the method presented in section 2.4.1. The subscript i denotes the workers and j denotes the group considered (EA). β_{0j} represents the average productivity in group j , and μ_{ij} represents the residuals. β_{0j} is assumed to be expressed as a linear combination of the

specific deviations ε of group j and a residual constant γ of group j , such that:

$$\beta_{0j} = \gamma_{00} + \varepsilon_{0j} \quad (2.7)$$

The term ε_{0j} is assumed to have a zero mean and independent of μ_{ij} . The variance can then be decomposed as follows:

$$\text{Var}(\Delta y_{ij}) = \text{Var}(\gamma_{00} + \varepsilon_{0j}) = \tau_{00} + \sigma_{0j} \quad (2.8)$$

With σ_{0j} the within-group variance of group j and τ_{00} , the between-group variance.

The intra-class correlation of this model is then written:

$$\rho_j = \frac{\tau_{00}}{\tau_{00} + \sigma_{0j}^2} \quad (2.9)$$

Following a relation (2.6), we can introduce the individual variable of the variation of job satisfaction ($\Delta satis$) such that:

$$\Delta y_{ij} = \beta_{0j} + \beta_{1j}(\Delta satis) + \alpha' x_{ij} + \eta IMR + \mu_{ij} \quad (2.10)$$

The vector $\Delta satis$ represents the change between 2013 and 2017 of the two measures of job satisfaction, namely pay satisfaction and satisfaction with career prospects. x_{ij} denotes the vector of control variables (refer to Table 2.3.2). We introduced IMR , the "Inverse Mills Ratio" from Heckman's model (Heckman, 1979), because we only selected employed individuals in our sample, which may lead to biased coefficients due to the characteristics of the non-employed population. In addition, it is possible that individuals with higher satisfaction are selected in the sample over those with lower satisfaction. The IMR is calculated from the estimation of employment determinants to account for the characteristics of non-employed individuals, who are not randomly selected from the population. A probit regression was performed using a set of individual and geographical characteristics, with the dichotomous variable of access to employment as the endogenous variable. Individual characteristics include gender, living with parents, foreign origin, number of children, field of study, education level, and time to first job access. Geographical characteristics include youth index, share of industry, share of service sector, share of construction, and unemployment rate of the EA.¹⁰

As an extension, it is also possible to explain the variations in β_{0j} and β_{1j} by the hierarchical structure, i.e., the level 2 variables representing the characteristics of the EAs specified in Section

¹⁰The results of this regression (refer to Table 2.8.4 in the appendix) indicate that individual and geographical characteristics have a significant impact on the probability of accessing employment. Specifically, individuals with long-term higher education degrees have a significantly higher probability of accessing employment than those with a lower level of education. Additionally, the youth index of the geographical area also has a significant positive impact on the probability of accessing employment, suggesting that areas with a young population are more likely to offer job opportunities. On the other hand, having children has a significant negative effect on the probability of accessing employment, which may reflect time and family responsibility constraints that can limit parents' ability to search for and accept employment.

2.3.1 as follows:

$$\begin{cases} \beta_{0j} = \gamma_{00} + \gamma_{01}U_j + \gamma_{02}RC_j + \gamma_{03}P_j + \gamma_{04}I_j + \gamma_{05}A_j + \gamma_{06}T_j + \gamma_{07}C_j + \gamma_{08}RM_j + \varepsilon_{0j} \\ \beta_{1j} = \gamma_{10} + \gamma_{11}U_j + \gamma_{12}RMW_j + \gamma_{13}PT_j + \gamma_{14}I_j + \gamma_{15}A_j + \gamma_{16}T_j + \gamma_{17}C_j + \gamma_{18}MI_j + \varepsilon_{1j} \end{cases} \quad (2.11)$$

Assuming that U is the unemployment rate, RMW is the ratio of managers to workers, PT is the share of part-time work, I is the share of the industrial sector, A is the share of the agricultural sector, T is the share of the tertiary sector, C is the share of the construction sector, and MI is the median income of the EA, it is assumed that γ does not vary between different j groups. However, this assumption can be relaxed by including variables that cross Level 1 and Level 2. Thus, the characteristics of the EAs can be used to explain the direct impact of β_{0j} and β_{1j} on the different productivity indices, and to test their intersection with each measure of job satisfaction on productivity. This allows us to assess whether the relationship between job satisfaction and productivity is more pronounced in areas with greater economic differences among workers. To ensure robust standard deviations based on our EA partitioning, we replicated our sample 1000 times. The next section presents the empirical results of our analysis, where we will examine the relationships between job satisfaction and worker productivity, taking into account various measures of job satisfaction and productivity.

2.5 Results

This section presents the main results. Firstly, we present the estimates of the productivity indices. Then, we discuss the econometric results of estimating the influence of job satisfaction measures on worker productivity, taking into account spatial heterogeneity through the characteristics of the workers' EAs of residence. The main objective is to determine whether an increase in worker satisfaction, as represented by specific measures, can improve their productivity at work. Additionally, we aim to observe whether membership in a specific EA has an effect on this relationship while controlling for other factors that may determine worker productivity.

2.5.1 Estimation results for productivity indices

Table 2.5.1 presents the summary results for the total productivity, Malmquist Index (MI), for all 2,716 individuals in our analysis sample. These results correspond to the MI estimation statistics defined in equation (2.3).

Upon examination of the table, it is clear that there was little growth in total worker productivity between 2013 and 2017, as evidenced by the average value of 0.767. Over the 2013--2017 period, almost all individuals (about 90% of workers in the overall sample) showed a significant decline in their total productivity level (MI below unity). This trend indicates that the largest majority of workers did not improve their overall efficiency levels between 2013 and 2017.

To investigate the sources of change in worker performance, the MI estimates were decomposed into their efficiency change (EFFCH) and technology change (TECH) components (the first term and second term of equation (2.4), respectively). Summary statistics for the estimates of these two components are also presented in Table 2.5.1.

The average efficiency change index (EFFCH) is about 0.704 in MI, which shows a decrease in the efficiency change of workers' performance. At the individual level, employees with EFFCH scores above one represent less than 1% of the overall sample. This result indicates that the movement of workers in our sample to the better production technology frontier is small over the study period and reflects the remoteness effect.

We found that the average technological change index (TECH) is about 1.096, indicating a 9.6% annual increase in the performance of workers in our sample due to technological change. This implies that the workers experienced technological growth over the period considered. At the individual level, slightly more than half of the individuals appear to have adopted new ways of working. This result suggests that highly educated individuals contributed to the influx of technological innovation over the study period (Bartel and Borjas, 1981).

The results indicate that the decrease in total worker productivity is attributed to the change in efficiency rather than technological change, as suggested by the very slight technological regression indicated by the average of the TECH component. This trend reveals that workers' ability to adopt technological innovations is a key factor in their performance.

Table 2.5.1: Statistics of estimated productivity indices

	Malmquist Index (MI) ^a (1)	Technical efficiency changes (EFFCH) (2)	Technological changes (TECH) (3)
Mean	0.767	0.704	1.096
Standard deviation	0.247	0.091	0.358
Minimum	0.110	0.279	0.275
Maximum	3.475	1.009	5.613

^a IM = EFFCH × TECH

Notes: Author's calculation using Generation 2010 data.

2.5.2 Results of the multilevel model estimations

In this subsection, we present the results of our multilevel methodology used to explain variations in total productivity and its components. The objective is to identify the factors that influence total worker productivity, as well as the components of productivity related to efficiency and technological changes, based on the main effects of pay satisfaction and satisfaction with job prospects. We estimate the models at two levels. Level 1 includes the variables composed of the main independent variables (pay satisfaction and satisfaction with career prospects) and a set of control variables related to the individual and professional characteristics of the individuals,

as specified in Table 2.3.1. Level 2 includes the variables incorporated in Level 1, as well as the characteristics of the EAs. At this level, we examine workers who are satisfied with their pay and career prospects in EAs where the overall unemployment rate, part-time work, the ratio of managers to workers, the share of economic sectors, or the median household income is high, and study the interactions of these observations on workers' performance. We first present results on the effect of pay satisfaction on total productivity, efficiency change, and technological change, followed by the results related to the effect of satisfaction with job prospects on these same productivity indices."

2.5.2.1 Effects of pay satisfaction

Table 2.5.2 presents the results for the main effect of pay satisfaction on overall productivity, on efficiency change and on technological change.

Estimates of the effect on overall productivity

Columns (1) and (2) present the estimated coefficients and standard deviations for the effect on overall productivity. Comparing the estimated constant between the OLS model and Level 1 of the multilevel model, we find a decrease in overall worker productivity between 2013 and 2017. Additionally, the variation in worker productivity appears somewhat heterogeneous across EAs, as indicated by the random effect estimate (EA), which accounts for 0.9% of the variation in overall productivity.

Based on the results of Level 1, we observe that an increase in a worker's pay satisfaction is positively associated with an improvement in their overall work productivity. This estimate remains robust after controlling for a variety of individual and professional characteristics. Furthermore, our results show that workers who are in a permanent contract or in a relationship tend to have higher overall productivity (Fox, 2005; Wagenaar et al., 2015). Men also appear to perform better in their jobs, likely due to higher pay (Azmat and Petrongolo, 2014; Ranganathan and Shivaram, 2021). In addition, employees with at least one manager parent also tend to perform better. In contrast, the individual's origin and whether they changed EA between 2013 and 2017 do not seem to significantly affect their overall productivity.

These findings are consistent with previous research on worker attitudes and effectiveness (Bartel and Borjas, 1981; Heneman et al., 1988; Bretz and Thomas, 1992; Heneman and Judge, 2000; Campbell and Im, 2019; Nugroho and Tanuwijaya, 2022), which suggest that pay dissatisfaction is related to reduced performance levels. Heneman et al. (1988) found a positive relationship between performance and overall satisfaction with pay, even after controlling for the effects of pay level, pay increases, performance appraisals, tenure, and promotions.

These results suggest that employees who feel well compensated are more likely to participate in the smooth running of their organization by putting in extra effort to complete their assigned tasks and improve their skills, as well as make better use of their organization's resources. Pay

satisfaction may also imply that workers can support themselves in terms of consumption and savings (Lazear, 2000), which could make them more enthusiastic about carrying out their tasks (Amabile et al., 2005). This increased energy and motivation, in turn, could encourage the worker to work more and avoid any form of labor disruption, such as strikes (Flaherty, 1987).

As an extension, we investigated the potential impact of EA characteristics on overall worker productivity. Our findings indicate that, irrespective of individual and professional characteristics, pay satisfaction has a greater positive effect on overall worker productivity in EAs with dynamic labor markets. Specifically, we found that workers satisfied with their pay exhibit higher overall job performance in EAs with a higher ratio of managers to workers. This result suggests that the greater proportion of managers in these EAs may indicate higher pay levels that could provide additional motivation for workers to maintain or improve their performance levels. Moreover, managers in these EAs can serve as mentors to enhance the performance of younger workers.

Additionally, we observed that workers who reported an improvement in their level of pay satisfaction are more likely to experience an increase in their overall work performance if they reside in EAs where the service or industry sector represents a larger share of economic activity. Conversely, for individuals satisfied with their pay, EAs with a higher unemployment rate appear to be less conducive to improving overall work productivity. These results suggest that the type of industry or sector in which a worker is employed may have an impact on their level of pay satisfaction and overall work performance. Specifically, workers who are employed in industries or sectors that represent a larger share of economic activity may be more likely to receive higher pay and have greater job satisfaction, which could lead to increased productivity. Conversely, workers in industries or sectors with lower economic activity may face lower pay and less job satisfaction, which could impact their overall work performance negatively. In contrast, a high unemployment rate may lead to lower pays, which could result in demotivation and decreased productivity among workers. Furthermore, EAs with a higher unemployment rate are less conducive to improving overall worker productivity, even if they are satisfied with their pay. Specifically, a high unemployment rate could create a competitive labor market where employers have more bargaining power and can afford to pay lower pays. This could reduce workers' motivation and level of performance, even if they are satisfied with their current pay (Lazear, 2000). Additionally, workers may face job-related pressures and uncertainties, which could reduce their engagement and motivation. Similarly, businesses located in EAs with a high unemployment rate may experience financial difficulties, which could limit their ability to invest in worker training or provide them with the necessary resources and tools to improve their performance (Amabile et al., 2005).

The advantage of estimating the change in productivity using the Malmquist productivity index is that it can be decomposed into efficiency and technological changes. The previous econometric reasoning is thus repeated for the efficiency component and the technology component of productivity change. The results are presented in the following sub-sections.

Estimates of effect on technological and efficiency change

The manifestation of the effect of pay satisfaction on technological change (columns (5) and (6)) is very similar to its effect on overall productivity. However, the constant shows an increase in technological variation among workers from 2013 to 2017. Again, technological variation depends on EA heterogeneity, with this factor explaining approximately 0.3 percentage points of individual differences. According to the level 1 results, an improvement in pay satisfaction, holding individual and professional characteristics constant, would increase the innovative capacity of workers. Additionally, the controlled characteristics indicate that the innovative capacity of individuals is higher with permanent contracts and for men, but decreases with age.

The statistically significant EA characteristics (Level 2) following the effect are very similar to the overall performance results. They reveal that the positive influence of pay satisfaction on the innovative capacity of workers seems to be explained by their presence in EAs where the share of managers is higher than that of workers or where economic activity is largely dominated by industry or the service sector. However, the innovativeness of the workers might experience a decline when the unemployment rate in the EA is high.

These results suggest that workers in EAs with a higher share of managers than workers may develop greater innovative capacities, possibly due to the influence of managers' proposals and the implementation of innovative ideas by employees. Additionally, satisfaction with compensation may act as an additional motivator for workers to participate in skill development training programs and improve their creativity. This effect may be particularly pronounced for workers in EAs dominated by the industry or service sectors, which are more likely to promote the development of innovative skills. However, the benefits of these innovations may not extend to all workers, particularly in EAs with declining labor demand and stagnant pay. In addition, High unemployment rates may lead to a more competitive job market, with workers focusing on job security rather than innovation. This could result in a decline in the overall motivation of workers to develop innovative skills and ideas. Additionally, employers may also be less willing to invest in research and development or new technologies during times of high unemployment, which could further hinder the innovative capacity of workers.

Contrary to the results observed for overall performance and technological variation, an increase in workers' pay satisfaction does not seem to have a significant effect on their technical variation (see columns (3) and (4) of Table 2.5.2). This may be due to several factors. Firstly, technical variation measures the ability of workers to produce goods or services with a given level of resources or time. It is possible that pay satisfaction is not directly related to this technical capacity. Additionally, it is possible that workers perceive pay as a less important element of their work compared to other factors such as recognition or job flexibility. It is also possible that other factors may be more important in determining workers' technical variation. Moreover, the results show that show that technical efficiency of individuals increases with age, relationship

status, and permanent contract, indicating that workers with more experience and stability may be more productive. Men appear to be statistically more efficient, as well as workers who have at least one parent in a managerial position. This suggests that social and cultural factors may also play a role in determining technical efficiency.

Table 2.5.2: Multi-level models and total productivity changes, efficiency changes, and technological changes: effect of pay satisfaction

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
OLS						
Δ SS ^a	0.107***	[0.013]	-0.009	[0.005]	0.171***	[0.019]
Constant	0.604***	[0.045]	0.579***	[0.016]	1.107***	[0.066]
IMR	-0.109	[0.069]	-0.188***	[0.024]	0.125	[0.101]
Multi-level						
<i>Level 1</i>						
Δ SS	0.108***	[0.022]	-0.009	[0.005]	0.171***	[0.032]
Age	0.001	[0.002]	0.005***	[0.001]	-0.007**	[0.003]
Men	0.028***	[0.010]	0.007*	[0.004]	0.031*	[0.015]
Origin	0.017	[0.018]	0.004	[0.007]	0.022	[0.026]
In relationship (2017)	0.026**	[0.010]	0.010**	[0.004]	0.021	[0.015]
Permanent contract (2017)	0.102***	[0.023]	0.030***	[0.011]	0.107***	[0.036]
Father/Mother manager	0.024**	[0.010]	0.010**	[0.004]	0.014	[0.015]
Geographical mobility	0.008	[0.015]	0.005	[0.006]	0.010	[0.023]
Constant	0.605***	[0.086]	0.580***	[0.029]	1.108***	[0.126]
IMR	-0.091	[0.086]	-0.181***	[0.031]	0.135	[0.131]
Random effect (EA)	0.022**	[0.005]	0.009*	[0.004]	0.020**	[0.007]
Residual variance	0.251***	[0.012]	0.088**	[0.003]	0.352***	[0.015]
<i>Level 2</i>						
Δ SS \times Unemployment rate	-0.022***	[0.008]	-0.003	[0.003]	-0.029***	[0.012]
Δ SS \times Manager/worker ratio	0.001***	[0.000]	-0.000	[0.000]	0.000**	[0.001]
Δ SS \times Partial time	0.005	[0.011]	0.001	[0.003]	0.005	[0.015]
Construction	Ref		Ref		Ref	
Δ SS \times Industry	0.034**	[0.022]	0.003	[0.008]	0.044**	[0.033]
Δ SS \times Agriculture	0.022	[0.024]	0.002	[0.008]	0.029	[0.038]
Δ SS \times Tertiary	0.032**	[0.023]	0.004	[0.008]	0.040**	[0.035]
Δ SS \times Median income	0.000	[0.000]	-0.000	[0.000]	0.000	[0.000]
Constant	0.718	[0.051]	0.482	[0.023]	1.383**	[0.051]
IMR	-0.066	[0.092]	-0.174***	[0.036]	0.154	[0.136]
Random effect (EA)	0.000	[0.000]	0.000	[0.000]	0.000	[0.000]
Residual variance	0.251***	[0.012]	0.088***	[0.003]	0.367***	[0.015]
Intra-EA correlation (level 1)	0.7%		1%		0.3%	
Intra-EA correlation (level 2)	0%		0%		0%	
AIC (level 1)	198.114		-4,291.947		1,826.628	
AIC (level 2)	201.462		-4,262.628		1,830.677	
Observations	2,716		2,716		2,716	

^a SS represents pay satisfaction

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

2.5.2.2 Effects of career prospects

The previous econometric analysis was repeated to examine the main impact of job prospects satisfaction. Table 2.5.3 shows the estimated coefficients and standard deviations for the effect on overall productivity, efficiency change, and technology change. We did not include Level 2 in these results as the coefficients were found to be statistically insignificant, despite the weakly significant impact of career prospects.

Effects on overall productivity

The results for the aggregate productivity effect are presented in columns (1) and (2) of the Table 2.5.3. In this effect, the variation in productivity is also influenced by the heterogeneity of the EAs, which explains 2.6 percent of the overall productivity variation. Consistent with the Level 1 results, we found that an increase in job prospects satisfaction among workers in our sample, while holding individual and job characteristics constant, leads to an increase in overall productivity.

This finding is in line with previous research (Stumpf and Rabinowitz, 1981; Nachbagauer and Riedl, 2002) that suggests workers may perform less effectively if they feel they have poor career prospects. For instance, Stumpf and Rabinowitz (1981) showed that individuals with a positive outlook on their career are more likely to develop skills, establish connections with colleagues, and take on additional responsibilities. Our results imply that workers who are content with their job prospects are likely to be more productive than those who are not. This increased productivity may be attributed to several factors, including higher motivation, commitment, and engagement among workers in their work. When workers have a clear and optimistic outlook on their work, they may be more inclined to invest more in their work and put in extra efforts to achieve their work goals, ultimately leading to greater efficiency and productivity.

Effects on technological variation and efficiency variation

The results for the Level 1 effect on technological change are comparable in significance to the findings for overall productivity. They demonstrate that an increase in job prospects satisfaction is associated with a positive change in technological variation. This implies that workers who are content with their career development tend to improve their skills to handle new responsibilities. Specifically, if a worker is satisfied with their job and career prospects, they are likely to be more motivated and engaged in their work, which can lead to innovative ideas and increased creativity. Moreover, workers who have a clear and positive career outlook are more likely to receive training and development opportunities in their field, which can further enhance their capacity for innovation. However, similar to pay satisfaction, an improvement in job prospects satisfaction does not seem to have a significant impact on the variation in worker efficiency.

Overall, the results of subsections 2.5.2.1 and 2.5.2.2 suggest that the spatial extent of individuals' residence is relevant for the study of the relationship between job satisfaction and job

performance. They also indicate that the positive impact of pay satisfaction or job prospects on performance is related to the higher share of managers in the workers' EA of residence or to economic activity dominated by industry or the service sector. Therefore, this type of relationship is likely to be more prominent in areas with large agglomerations, such as Paris, Toulouse, Lyon, Lille, Marseille, Grenoble, etc., which have a significant share of management jobs. In addition, residing in EAs such as Annecy could be beneficial in improving worker performance due to specialization in productive jobs, and Toulouse, which is specialized in high-tech industries.

Similarly, areas such as the Arve Valley, where the productive economy is highly specialized in screw-cutting, or Briançon or Ajaccio, where the residential economy has a strong tourist dimension, or Aix, Marseille, Strasbourg, Lille, or Paris, areas with a strong technopolitan dimension, could also benefit workers in their performance. Areas such as Mâcon, Colmar, or Epernay could also be included in this group thanks to the preponderance of food processing industries, wine trading, logistics, transport, and wine tourism. However, the results of these models should be interpreted with caution, as they appear to have poorer statistical quality (see the estimate of the residual variance), hence the interest in testing the robustness of the results in the next section.

Alternatively, the non-significant results on the change in efficiency may indicate that the relationships between these variables are not perfectly proportional or linear. The effect of pay satisfaction or job prospects on productivity may not be immediately apparent. It is also possible that the measure of efficiency change is not sensitive to small changes in pay satisfaction or job prospects, or that these variables are not the most important factors in explaining efficiency change.

Furthermore, it should be noted that the *IMR* is only significant for the effect of satisfaction measures on the variation in efficiency. There could be several reasons for this. Firstly, there is the issue of selection bias. It is possible that employees with low satisfaction with the measures have left the company, which may have created a selection bias in the sample. If the best performing employees were also the most satisfied with their pay or career prospects, this could explain why the *IMR* is significant only for efficiency variation. Secondly, there is the effect of pay satisfaction or prospects on motivation. These measures of satisfaction may have a greater effect on employees' motivation to perform their jobs effectively than on overall performance or technological change. Employees who are satisfied with their pay or career development may be more motivated to work hard to maintain their job, pay and development, which could lead to improved efficiency. Finally, there is the effect of these satisfaction measures on commitment. Satisfaction with pay or development could also have an effect on employees' commitment to their work. Employees who are satisfied with these measures may be more committed to their work and more likely to work effectively. This commitment could translate into increased employee efficiency. Additionally, the negative value of the correlation coefficient indicates a negative correlation between the residuals. This is consistent with the hypothesis that individuals differ in their willingness to wait for a well-paid job with the possibility of career advancement

(Heckman, 1979).

Table 2.5.3: Multi-level models and total productivity changes, efficiency changes, and technological changes: effect of career prospects

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
OLS						
Δ SP ^a	0.049**	[0.023]	-0.010	[0.008]	0.090***	[0.033]
Constant	0.630***	[0.078]	0.576***	[0.027]	1.149***	[0.115]
IMR	-0.122*	[0.069]	-0.188***	[0.024]	0.105	[0.102]
Multi-level						
<i>Level 1</i>						
Δ SP	0.050*	[0.032]	-0.010	[0.007]	0.089*	[0.048]
Age	0.001	[0.002]	0.005***	[0.001]	-0.008***	[0.003]
Men	0.031***	[0.011]	0.007*	[0.004]	0.035**	[0.015]
Origin	0.017	[0.019]	0.004	[0.007]	0.023	[0.027]
In relationship (2017)	0.026**	[0.011]	0.010**	[0.004]	0.021	[0.016]
Permanent contract (2017)	0.097***	[0.023]	0.030***	[0.011]	0.098***	[0.036]
Father/mother manager	0.024**	[0.012]	0.010**	[0.004]	0.015	[0.016]
Geographical mobility	0.008	[0.015]	0.005	[0.006]	0.011	[0.023]
Constant	0.632***	[0.052]	0.577***	[0.022]	1.150***	[0.055]
IMR	-0.105	[0.083]	-0.180***	[0.032]	0.112	[0.126]
Random effect (EA)	0.021**	[0.005]	0.009*	[0.004]	0.018**	[0.009]
Residual variance	0.254***	[0.012]	0.088***	[0.003]	0.373***	[0.018]
Intra-EA correlation	0.7%		1%		0.2%	
AIC	242.385		-4,290.835		1,877.146	
Observations	2,716		2,716		2,716	

^a SP represents satisfaction with career prospects.

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

These results are consistent with the theory of social exchange, which posits that individuals evaluate the costs and benefits of their social interactions (Blau, 1964). Workers who feel well-paid or optimistic about their career prospects may be more motivated to contribute to the success of their organization by providing extra effort to improve their skills and make better use of the organization's resources. This can be interpreted as a social role behavior, where workers contribute to the well-being of the organization in addition to fulfilling their main task (Katz and Kahn, 1978). Additionally, the results suggest that workers in more active economic sectors are more likely to receive higher pay and have greater job satisfaction, which can lead to increased productivity. This is consistent with the equity theory, which posits that individuals evaluate their pay based on perceived reward compared to others (Adams, 1965). Workers in more active economic sectors may be able to receive higher pay due to competition for skilled workers in those sectors. On the other hand, workers in less active economic sectors may receive lower pay, which can negatively affect their job satisfaction and productivity. Workers who perceive

their pay as unfair may be less motivated to engage in skill and creativity development activities, which can harm their productivity (Adams, 1965). Finally, the results suggest that workers in economic areas with a higher proportion of managers may be more inclined to develop their creativity and innovation capabilities, perhaps due to the influence of ideas proposed by managers and their implementation by employees. This can be interpreted as a social role behavior, where workers seek to contribute to their organization's innovation. However, the benefits of these innovations may not extend to all workers, especially in economic areas with declining labor demand and stagnant pay. Additionally, high unemployment rates can lead to a more competitive labor market, where workers focus on job security rather than innovation, which can harm workers' motivation to develop innovative skills and ideas (Blau, 1964).

Now that we have examined the results of our study, it is important to consider the robustness of these findings. In this next section, we will analyze the sensitivity of our results to various factors. By assessing the robustness of our results, we can determine the extent to which they hold up under different conditions and provide greater confidence in our conclusions.

2.6 Robustness check

Although we found evidence that an increase in a worker's pay satisfaction or satisfaction with their job prospects has a positive impact on improving their job performance, we cannot be sure that our results are not biased due to the potential causal relationship between satisfaction and productivity (Wanous, 1974; Locke, 1976; Lawler III and Porter, 1967), which may lead to an endogeneity bias problem. In our previous empirical specification, we used the multilevel method. However, in the context of multilevel modeling, endogeneity is more difficult to analyze. The random components of the different levels can be correlated with some predictors, which can lead to a bias in the estimated coefficients (Gui et al., 2020). For example, workers with a very high level of education are likely to be more productive, and therefore have higher levels of satisfaction. We generally assume that education increases the ability of individuals to perform tasks at work, which may provide greater recognition, rewards, and career opportunities leading to greater satisfaction. Similarly, one might also be concerned that in employment areas with more favorable economic characteristics, the most productive employees are also the most satisfied. As highlighted in the eleventh edition of the Labor Barometer, the most wealth-creating areas tend to reorient their human resource policies to make their productive workers more satisfied in their jobs (Edenred-Ipsos Barometer, 2016).

The identification assumption of equation 2.10 is that none of the variables in the model should be correlated with the random components, which is violated in the presence of endogeneity. We now test this hypothesis using a method appropriate for a hierarchical specification. In this perspective, we use the method developed by Kim and Frees (2007) namely, the GMM method with hierarchical structure to treat this potential endogeneity.¹¹ This method is particu-

¹¹The GMM method was first developed by Hansen (1982) and the application on hierarchical data was done by

larly useful for this study since we have hierarchical data grouped into EAs. The econometric specification of the GMM method with hierarchical structure is based on a model of simultaneous equations with endogenous and exogenous variables. Endogenous variables are modeled as linear functions of exogenous variables and errors. The errors themselves are modeled as linear combinations of errors from related equations and errors specific to each group. It relies on the estimation of generalized moments (GMM) for the parameters of the model. It uses instruments that are constructed from the variance-covariance of the errors, and that allow for efficient and consistent estimators of the parameters of the model. Furthermore, it allows for the inclusion of unobservable sources of variation, such as fixed effects or random effects, in the econometric model. These sources of variation can be specified at the equation level, the group level, or both. The advantage of the GMM method is that it does not require the use of external instrumental variables, which are often difficult to find and justify. However, when level 1 is affected by endogeneity, it is necessary to integrate one or more external instruments, as is the case here (see endogeneity tests below). The full explanation of the method is in section 2.8 in the Appendix.

2.6.1 Endogeneity test

We begin with the endogeneity test comparing the random-effect and fixed-effect estimators, the latter assuming that all variables are endogenous. Columns (1) to (6) of Table 2.6.1 present the results of the endogeneity tests for the total productivity, efficiency, and technology components. For total and technological productivity changes, non-significant probabilities are observed at levels 1 and 2. The null hypothesis that there is no endogeneity at these levels cannot be rejected. In contrast, the probabilities become significant at the one percent level for both levels of the efficiency change results. We can thus conclude that the results of columns (1) and (2) for overall productivity and columns (5) and (6) for technological change in Tables 2.5.2 and 2.5.3 are consistent. However, we may still perform estimations at this level to see the behavior of the estimated coefficients.

Table 2.6.1: Endogeneity test

	Total productivity		Efficiency changes		technological changes	
	t-statistics (1)	p-value (2)	t-statistics (3)	p-value (4)	t-statistics (5)	p-value (6)
<i>Pay satisfaction</i>						
Level 1	0.137	0.711	16.343	0.000	0.601	0.438
Level 2	9.124	0.167	25.378	0.000	6.505	0.353
<i>Professional prospects</i>						
Level 1	0.023	0.879	26.524	0.000	1.845	0.174
Level 2	4.265	0.641	22.053	0.001	4.341	0.631

Notes: Author's calculation based on Generation 2010 data. The endogeneity test is carried out through a comparison of the fixed effect and random effect results.

Because endogeneity is present at Level 1 for efficiency change due to the effects of pay

Kim and Frees (2007).

satisfaction and satisfaction with job prospects, we included external instruments. However, finding good instruments was a challenge as only a few studies have dealt with endogeneity, and those that have, were based on firm-level productivity (e.g., Böckerman and Ilmakunnas, 2012). Unfortunately, we could not use their instrument, which is satisfaction with housing, because we lacked information on this variable in our database. Therefore, we defined a good instrument as a variable that correlates with our job satisfaction measures but does not correlate with the job productivity indices. We eventually found the "internship performance" variable that led to the individual's employment (Table 2.8.3 in the Appendix tracks these correlations). In addition to being positively correlated with job satisfaction, this variable can be a good instrument because leaving an internship contract for a more attractive one can already give an employee satisfaction with the nature of the contract and the level of compensation (Le Saout and Coudin, 2015). This satisfaction can also lead to satisfaction with one's membership in the institution, one's career advancement, and one's colleagues' view of one's status (Platform et al., 2017). However, the nature of the internship contract cannot affect the employee's method of working and commitment to the achievement of objectives because of their responsibilities. The nature of the internship contract does not allow for demanding responsibilities to achieve objectives and therefore required performance (Chen et al., 2018). Our internship variable is measured using the question, "Did your internship help you find your current job?" Individuals can respond with "yes" or "no". We dichotomized this variable, taking the value of 1 if the response was yes and 0 otherwise.

Tables 2.6.2 and 2.6.3 present the estimation results of the GMM model for the effect of pay satisfaction and satisfaction with job prospects, respectively. Columns (1) and (2) present the results of the estimated coefficients and standard deviations for overall productivity. Columns (3) and (4) are for efficiency change, while columns (5) and (6) are for technological change.

2.6.2 Results of effects of pay satisfaction

Considering the results of Table 2.6.2 on the estimation of the effect of pay satisfaction on the indices of overall productivity and technological change, we observe that the coefficients linked to pay satisfaction and its interaction with the ratio of managers to workers and with the share of industry or services are not significantly modified relative to the results of Table 2.5.2. These coefficients remained positive and significant, which was expected following the previous result concerning the endogeneity test. On the other hand, the coefficients of levels 1 and 2 corresponding to the effect of pay satisfaction and its intersection with the unemployment rate and the ratio of managers to workers have changed significantly. The coefficients related to these variables that were insignificant in the first estimates (see Table 2.5.2) have become significant after treating for endogeneity bias. Thus, a negative relationship is observed between pay satisfaction and efficiency change. This effect is observed when the individual resides in an EA with a high unemployment rate. On the other hand, it tends to decrease in the case where the share of managers is higher than that of workers. This result indicates that pay development does not follow productivity.

This result can be interpreted in different ways from an economic perspective. On the one hand, this could suggest that workers who are more satisfied with their pay may be less motivated to work harder or improve their productivity, as they have less pressure to justify their pay. On the other hand, it could also indicate that workers who are less satisfied with their pay may be more motivated to improve their efficiency and performance, as they seek to be better rewarded. When the unemployment rate is high, workers may be more inclined to accept lower-paying jobs to avoid unemployment, which could decrease their motivation and efficiency at work. However, when the share of managers is higher than that of workers in the worker's residential employment zone, this may indicate that workers have access to better-paying jobs with higher career prospects, which can strengthen their motivation and efficiency at work. Overall, these results highlight the importance of considering the specific context of the employment zone in the analysis of the relationship between pay satisfaction and worker efficiency.

Table 2.6.2: Multi-level models and total productivity changes, efficiency changes, and technological changes: effect of pay satisfaction

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
<i>Level 1</i>						
Δ SP	0.114**	[0.023]	-0.019*	[0.017]	0.193***	[0.033]
Age	0.001	[0.002]	0.005***	[0.001]	-0.007**	[0.003]
Men	0.028**	[0.011]	0.007*	[0.004]	0.031*	[0.016]
Origin	0.023	[0.018]	0.006	[0.007]	0.026	[0.027]
In relationship (2017)	0.026**	[0.011]	0.010**	[0.004]	0.021	[0.016]
Permanent contract (2017)	0.104***	[0.023]	0.029***	[0.011]	0.109***	[0.035]
Father/mother manager	0.026**	[0.011]	0.011***	[0.004]	0.016	[0.016]
Geographical mobility	0.006	[0.015]	0.004	[0.006]	0.009	[0.024]
Constant	0.602***	[0.087]	0.581***	[0.028]	1.103***	[0.129]
IMR	-0.109	[0.088]	-0.189***	[0.030]	0.127	[0.134]
<i>Level 2</i>						
Δ SS \times Unemployment rate	-0.017**	[0.008]	-0.006	[0.004]	-0.017**	[0.011]
Δ SS \times Manager/worker ratio	0.000***	[0.001]	-0.000	[0.000]	0.001**	[0.001]
Δ SS \times Partial time	0.005	[0.011]	0.001	[0.004]	0.006	[0.015]
Construction	Ref		Ref		Ref	
Δ SS \times Industry	0.049**	[0.021]	0.009	[0.009]	0.056***	[0.032]
Δ SS \times Agriculture	0.017	[0.026]	0.003	[0.009]	0.033	[0.036]
Δ SS \times Tertiary	0.046**	[0.021]	0.006	[0.009]	0.067**	[0.036]
Δ SS \times Median income	0.000	[0.000]	-0.000	[0.000]	0.000	[0.000]
Constant	0.655***	[0.049]	0.903**	[0.035]	1.294***	[0.047]
IMR	-0.071	[0.089]	-0.171***	[0.037]	0.142	[0.137]
Observations	2,716		2,716		2,716	

^a SS represents pay satisfaction.

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

2.6.3 Results of the effect of satisfaction with job prospects

The analysis of the results in Table 2.6.3 regarding the effect of satisfaction with job prospects is generally consistent with the results for the influence of pay satisfaction. However, the results of level 2 remained non-significant, as was also the case in the previous results in Table 2.5.3. In particular, the coefficients related to the influence on overall productivity and technological change remain positive and significant. This result was predictable based on the previous results of the endogeneity test. Thus, the simultaneity bias of these global and technological components is not significant. On the other hand, the impact on the change in efficiency, which was previously insignificant, has become negative and significant. This result indicates that satisfaction with job prospects appears to be lower among individuals who are efficient in their jobs.

The interpretation of this result is that workers who are more satisfied with their career prospects may be less inclined to focus on the tasks required in their current job. They may be more likely to seek career opportunities elsewhere or focus on developing their skills to prepare for future jobs, rather than fully dedicating themselves to their current tasks. This can lead to a decrease in efficiency, which measures the optimal use of available resources to produce a given level of output. However, it is important to note that this interpretation is only a hypothesis and that other factors may also influence the relationship between job prospect satisfaction and changes in worker efficiency.

Table 2.6.3: Multi-level models and total productivity changes, efficiency changes, and technological changes: effect of career prospects satisfaction

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
<i>Level 1</i>						
Δ SP	0.054*	[0.026]	-0.227***	[0.023]	0.082**	[0.051]
Age	0.001	[0.002]	0.005***	[0.001]	-0.007**	[0.003]
Men	0.030***	[0.011]	0.006	[0.004]	0.035**	[0.016]
Origin	0.024	[0.019]	0.006	[0.007]	0.026	[0.027]
In relationship (2017)	0.025**	[0.018]	0.010**	[0.004]	0.021	[0.016]
Permanent contract (2017)	0.098***	[0.023]	0.030***	[0.011]	0.099***	[0.036]
Father/mother manager	0.025**	[0.012]	0.011**	[0.004]	0.016	[0.017]
Geographical mobility	0.007	[0.015]	0.004	[0.006]	0.010	[0.024]
Constant	0.628***	[0.085]	0.576***	[0.028]	1.149***	[0.056]
IMR	-0.121	[0.087]	-0.186***	[0.030]	0.105	[0.133]
Observations	2,716		2,716		2,716	

^a SP represents satisfaction with career prospects.

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

2.6.4 Instrument validity test

We then examine the validity of the instruments used in the estimates. This test consists of comparing the random effect and GMM estimators. Indeed, the GMM version assumes that a subset of the variables is exogenous while the random-effects estimator version assumes that all variables in the model are exogenous. Thus, the non-rejection of the null hypothesis for the tests indicates that the random-effects estimator is preferred and thus, that the instruments are valid. The results of this test are presented in Table 2.6.4.

Consistent with our identification assumption, the probabilities in Table 2.6.4 are all insignificant. The null hypothesis of non-endogeneity of the estimated coefficients is not rejected. The test shows that there is almost no significant difference between the coefficients of the different models. Endogeneity biases therefore appear to be largely reduced. Thus, the instruments used remain valid and the exogeneity of the individual and job characteristics variables and the dichotomous internship performance variable is valid. A few final considerations must be made regarding the external validity of the results.

Table 2.6.4: Validity of instruments

	Total productivity		Efficiency changes		Technological changes	
	t-statistics	p-value	t-statistics	p-value	t-statistics	p-value
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Pay satisfaction</i>						
Level 1	0.031	0.859	1.256	0.292	1.357	0.244
Level 2	0.303	0.859	1.315	0.195	1.850	0.396
<i>professional prospects</i>						
Level 1	0.034	0.853	1.224	0.269	0.385	0.535
Level 2	1.304	0.521	1.070	0.230	0.316	0.854

Notes: Author's calculation based on Generation 2010 data. The validity test of the instruments is carried out through a comparison of GMM and random effect results.

2.6.5 Use of the variable returns to scale (VRS) approach

We used the CRS approach to estimate productivity indices; however, the use of this approach can lead to some specification issues. In fact, the CRS approach assumes that all employees have the same optimal size, which may not be the case in reality. Additionally, this approach is less flexible in accounting for scale effects and economies of scale. We thus used the VRS approach to analyze the robustness of the results. The use of the VRS approach can allow us to account for variations in the size of production units, distinguish sources of productivity variation, and conduct more appropriate inter-individual comparisons. This can improve the accuracy of our estimates and help us better understand the relationship between job satisfaction and worker productivity.

Table 2.6.5 presents the summary statistics of the productivity indices estimated via VRS. Like the CRS version, the VRS approach also reveals a decrease in overall productivity and

efficiency variation, while an increase in technology variation is observed between 2013 and 2017. However, the effects of total productivity change and technological change are more pronounced in the VRS version than in the CRS approach, in contrast to the efficiency change. This result suggests that the decline in overall productivity or improvement in worker innovativeness is greater when we consider variations in production technology in their area of evolution.

Table 2.6.5: Statistics on productivity indices estimated via VRS

	Malmquist index (MI) ^a (1)	Efficiency changes (EFFCH) (2)	Technological changes (TECH) (3)
Mean	0.754	0.725	1.077
Standard deviation	0.206	0.131	0.406
Minimum	0.261	0.286	0.261
Maximum	2.712	1.452	6.593

$$^a \text{IM} = \text{EFFCH} \times \text{TECH}$$

Notes: Author's calculation based on Generation 2010 data. Mean, standard deviation, minimum and maximum of the Malmquist productivity index and its components in terms of the index technical change (EFFCH) and the index of technological change (TECH) estimated via VRS for the 2,716 individuals for the period 2013--2017 are shown in columns 1,2, and 3 respectively.

We then used the productivity indices estimated via VRS as dependent variables to replicate the specifications in section 2.4.2 that examine the influence of job satisfaction measures on these productivity variations. The results for the effect of pay satisfaction are shown in Table 2.6.6, and the effect of satisfaction with job prospects is shown in Table 2.6.7. When we look at these results, we see that the coefficients related to the influence on overall productivity and technological variation are not significantly altered compared to the results of the CRS version; they remained positive and statistically significant. However, the magnitude of the effect on overall performance decreased by about half. Additionally, the results of the cross-tabulation with EA characteristics reveal that only the cross-tabulation with the unemployment rate remained significant and negative; the sectors become insignificant. In contrast, the results for efficiency change due to the effect of pay satisfaction and satisfaction with job prospects changed significantly. Specifically, the effect of these two measures on efficiency changes becomes negative and significant.

One possible explanation for the difference in results between the CRS and VRS approaches could be the assumption of constant returns to scale made by the CRS approach. This assumption assumes that the size of the production unit is optimal and does not vary, and that any variation in productivity can be attributed solely to changes in technology or efficiency (Färe et al., 1994b). However, in reality, the size of the production unit (that is, the size of the company or organization in which the workers are employed) can vary, and this can affect the relationship between job satisfaction and productivity. The VRS approach allows for variable returns to scale (Färe and Grosskopf, 1996), which means that it can take into account variations in the size of the production unit and their impact on productivity. Therefore, when analyzing the robustness

Table 2.6.6: Multi-level models and total productivity changes, efficiency changes, and technological changes VRS version: effect of pay satisfaction

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
<i>Level 1</i>						
Δ SS	0.060***	[0.015]	-0.042***	[0.008]	0.176***	[0.036]
Age	-0.013***	[0.002]	-0.005***	[0.001]	-0.012***	[0.003]
Men	0.061***	[0.009]	0.026***	[0.006]	0.054***	[0.017]
Origin	0.017	[0.015]	0.008	[0.010]	0.019	[0.031]
In relationship (2017)	0.015	[0.009]	0.015**	[0.006]	0.003	[0.018]
Permanent contract (2017)	0.073***	[0.018]	0.009	[0.016]	0.098***	[0.038]
Father/mother manager	0.023***	[0.009]	0.013**	[0.006]	0.016	[0.019]
Geographical mobility	0.009	[0.013]	0.001	[0.009]	0.014	[0.026]
Constant	0.935***	[0.030]	0.801***	[0.024]	1.191***	[0.052]
IMR	0.211***	[0.064]	0.097**	[0.042]	0.268*	[0.144]
Random effect (EA)	0.027**	[0.005]	0.016**	[0.005]	0.015**	[0.013]
Residual variance	0.204***	[0.007]	0.129***	[0.003]	0.425***	[0.025]
<i>Level 2</i>						
Δ SS \times Unemployment rate	-0.012***	[0.005]	0.004	[0.003]	-0.032***	[0.012]
Δ SS \times Manager/worker ratio	-0.000	[0.000]	0.000	[0.000]	-0.001	[0.001]
Δ SS \times Partial time	-0.000	[0.006]	0.001	[0.004]	-0.001	[0.016]
Construction	Ref		Ref		Ref	
Δ SS \times Industry	0.004	[0.015]	-0.020**	[0.009]	0.046	[0.038]
Δ SS \times Agriculture	0.003	[0.017]	-0.019**	[0.010]	0.038	[0.044]
Δ SS \times Tertiary	0.005	[0.016]	-0.018**	[0.009]	0.046	[0.041]
Δ SS \times Median income	-0.000	[0.000]	0.000	[0.000]	-0.000	[0.000]
Constant	1.203***	[0.030]	0.031	[0.024]	2.677**	[0.054]
IMR	0.274***	[0.071]	0.170***	[0.047]	0.271	[0.155]
Random effect (EA)	0.000	[0.000]	0.000	[0.000]	0.000	[0.000]
Residual variance	0.205***	[0.007]	0.129***	[0.003]	0.424***	[0.024]
Intra-EA correlation (level 1)	1.7%		1.6%		0.1%	
Intra-EA correlation (level 2)	0%		0%		0%	
AIC (level 1)	-673.380		-2,622.425		2,437.517	
AIC (level 2)	-660.226		-2,620.53		2,443.367	
Observations	2,716		2,716		2,716	

^a SS represents pay satisfaction.

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

of results with the VRS approach, it is possible that the effect of job satisfaction on efficiency became negative and significant because the VRS approach took into account variable returns to scale and the impact of variations in the size of the production unit on productivity. This could explain the difference in results between the two approaches and support the use of the VRS approach for analyzing the robustness of results. However, it is important to note that we obtained overall worse AIC values with the VRS version, which may indicate that the model is more complex and less parsimonious. Nonetheless, this does not necessarily imply that the CRS approach is better, but rather that the VRS approach is more flexible in accounting for variations in production unit size, which may improve the accuracy of the estimates. However, this increased flexibility may also result in an increase in model complexity, which may require careful interpretation of the results.

Table 2.6.7: Multi-level models and total productivity changes, efficiency changes, and technological changes VRS version: effect of career prospects satisfaction

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
<i>Level 1</i>						
Δ SP	0.016	[0.021]	-0.034***	[0.012]	0.088*	[0.052]
Age	-0.013***	[0.002]	-0.004***	[0.001]	-0.012***	[0.003]
Men	0.062***	[0.009]	0.024***	[0.006]	0.058***	[0.018]
Origin	0.017	[0.015]	0.008	[0.010]	0.019	[0.032]
In relationship (2017)	0.015	[0.009]	0.015**	[0.006]	0.003	[0.019]
Permanent contract (2017)	0.069***	[0.018]	0.011	[0.017]	0.089***	[0.038]
Father/mother manager	0.023**	[0.010]	0.012**	[0.006]	0.016	[0.018]
Geographical mobility	0.008	[0.013]	0.001	[0.009]	0.015	[0.027]
Constant	0.950***	[0.030]	0.789***	[0.024]	1.235***	[0.055]
IMR	0.204***	[0.063]	0.103**	[0.044]	0.247*	[0.142]
Random effect (EA)	0.027**	[0.005]	0.016**	[0.004]	0.015**	[0.013]
Residual variance	0.205***	[0.007]	0.130***	[0.003]	0.429***	[0.025]
Intra-EA correlation	1.7%		1.5%		0.1%	
AIC	-651.135		-2,602.626		2,478.001	
Observations	2,716		2,716		2,716	

^a SP represents satisfaction with career prospects.

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

2.6.6 More heterogeneous analysis by gender, age and company size

Our sample comprises workers who may be in diverse work situations that could affect the direction of the effect of perceived aspects of their job on their performance differently. More precisely, the sample of workers in this study is likely to be diverse in terms of their work situations, and different aspects of their job could affect their performance in different ways. For example, women may face different challenges and have different priorities compared to men, which

could affect their job satisfaction and performance (Madden, 1987; O'Neil, 2003; Azmat and Petrongolo, 2014; Sin et al., 2022). Similarly, younger workers may have different expectations and motivations than older workers, which could affect how they respond to different aspects of their job (Feyrer, 2007; Mahlberg et al., 2013). The size of the company may also affect how workers perceive their job and their productivity levels. The theory and evidence support the conclusion that firms that grow to a large size create jobs (technology, equipment, work conditions, and organizations) that must be matched by more productive individuals (Idson and Oi, 1999). This motivates our analysis of heterogeneity by gender, age, and firm size.

We replicated the previous specifications from section 2.5.2 for men and women, workers aged 29 and under, and those over 29, as well as for workers in large and small firms.¹² Table 2.6.8 shows the results of the effect of pay satisfaction for the different groups for overall productivity, Table 2.6.9 for efficiency changes, and Table 2.6.10 for technological changes. The results of the effect of satisfaction with job prospects are presented in Tables 2.6.11, 2.6.12, and 2.6.13, respectively, for overall productivity change, efficiency change, and technology change. Columns (1), (2), (3), (4), (5), and (6) present the results for men, women, workers aged 29 or younger, workers over 29, employees in large firms, and those in small firms, respectively.

2.6.6.1 Effects of pay satisfaction

Effect on Global productivity

The results indicate that pay satisfaction has a significant impact on overall employee performance in small businesses comprised mainly of young workers. Additionally, the effects of pay satisfaction on overall performance are similar for both men and women. However, these effects are contingent on the characteristics of the EA, and the positive impact of pay satisfaction is more significant among young workers in EAs dominated by the industry or service sectors. This suggests that employers in these types of EAs can enhance the overall performance of young workers by offering satisfactory pay. However, when the unemployment rate is high in the EA, the positive impact of pay satisfaction on overall performance tends to decrease, implying that workers may be more sensitive to job availability during economic downturns.

Economically, these results suggest that pay satisfaction is an important factor in overall employee performance, especially in small businesses comprising young workers. Offering satisfactory pay can increase workers' motivation and commitment, leading to improved productivity and overall performance (Judge et al., 2001; Judge and Robbins, 2017). Additionally, these results highlight the importance of considering the characteristics of the EA in which businesses operate. EAs dominated by the industry or service sectors may offer specific economic benefits to young workers (Autor, 2001), and employers should be aware of these benefits when evaluating their compensation strategy. However, the decrease in the positive impact of pay satisfaction on

¹²We consider small enterprises as micro-enterprises (less than 10 employees) and small and medium enterprises (between 10 and 245 employees). Large enterprises are those that do not fall into this category, according to the European regulation on enterprise categories.

overall performance during an economic downturn suggests that workers are more sensitive to job availability during a crisis.

Furthermore, the similar impact on overall performance for men and women may indicate that pay satisfaction is an important factor for the performance of both genders, and employers should consider pay satisfaction as a motivation and retention strategy for all employees. This may also suggest that men and women can be motivated by the same factors at work, including compensation. It is important to note that gender pay gaps exist in many sectors and industries (O'Neil, 2003), and this can have an impact on pay satisfaction (Blau and Kahn, 2020). However, this result indicates that if employers offer equivalent pays for the same skills and performance, it can have a similar impact on workers' performance, whether they are men or women (Kahn, 2010).

Effect on Technological changes

Similar to previous findings, our results indicate that the effect of pay satisfaction on technological change is comparable to its impact on overall productivity. We do not observe a significant positive effect of pay satisfaction on workers' innovativeness, and this relationship does not vary significantly by gender. Interestingly, we find that the relationship between pay satisfaction and innovativeness is stronger among workers in small firms, particularly those composed of young workers, than in large firms. This may be due to the specific economic benefits offered to young workers in EA dominated by industry or the service sector. However, during periods of high unemployment in the EA, the positive effect of pay satisfaction on innovativeness tends to decrease.

These results suggest that validating and implementing new methods of application that are easier to implement in small firms than in large firms may foster more creativity among workers in small firms, particularly younger workers who have a greater capacity to adapt to changes. EAs dominated by industry or the service sector may have a greater influence on innovativeness due to the development of new working methods, such as artificial intelligence. However, the negative effect of economic downturns on pay satisfaction may decrease workers' motivation to be innovative, highlighting the importance of economic stability and job security in encouraging creativity and innovation in the workplace (Amabile et al., 2005; Bonnitcha et al., 2017).

Effect on Efficiency changes

The results indicate that the impact of pay satisfaction on workers' efficiency may vary based on their gender, the size of the firm they work for, and the characteristics of the employment area in which they reside. Specifically, the negative effect of pay satisfaction on worker efficiency is more prominent among men and workers in large firms when they reside in employment areas with high unemployment and a higher proportion of managers than workers. However, this negative effect seems to be counterbalanced when the economic activity of the employment area is dominated by the service sector.

Table 2.6.8: Multi-level models and variations in total productivity by gender, age, and firm size: effect of pay satisfaction

	Total productivity					
	Men	Women	Age ≤ 29	Age > 29	Large companies	Small companies
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Level 1</i>						
ΔSS	0.090*** [0.026]	0.110*** [0.041]	0.129*** [0.0336]	0.096*** [0.028]	0.072*** [0.028]	0.116*** [0.028]
Age	-0.002 [0.003]	0.007*** [0.004]	-0.007 [0.008]	0.005* [0.003]	0.003 [0.003]	0.001 [0.003]
Men	-	-	0.036** [0.015]	0.014 [0.012]	0.027 [0.016]	0.029** [0.014]
Origin	0.034 [0.023]	-0.029 [0.028]	-0.008 [0.034]	0.041*** [0.022]	0.023 [0.023]	0.021 [0.026]
In relationship (2017)	0.030* [0.014]	0.023* [0.015]	0.030* [0.016]	0.029* [0.014]	0.014 [0.017]	0.031** [0.013]
Permanent contract (2017)	0.084*** [0.033]	0.130*** [0.029]	0.082** [0.030]	0.152** [0.035]	0.003 [0.043]	0.135*** [0.027]
Father/mother manager	0.030** [0.015]	0.014 [0.016]	0.019 [0.018]	0.025* [0.013]	0.017 [0.016]	0.026* [0.014]
Mobility	0.010 [0.020]	0.002 [0.021]	0.035 [0.021]	-0.019 [0.020]	-0.013 [0.025]	0.008 [0.018]
Constant	0.713*** [0.056]	0.517*** [0.103]	0.799*** [0.083]	0.533*** [0.066]	0.710*** [0.046]	0.569*** [0.063]
IMR	-0.059 [0.103]	-0.165 [0.129]	-0.015 [0.148]	-0.387*** [0.096]	-0.331** [0.108]	-0.060 [0.106]
Random effect (EA)	0.028** [0.008]	0.000 [0.000]	0.000 [0.000]	0.022*** [0.006]	0.028** [0.018]	0.028*** [0.007]
Residual variance	0.256*** [0.014]	0.244*** [0.019]	0.259*** [0.019]	0.243*** [0.015]	0.197*** [0.008]	0.269*** [0.016]
<i>Level 2</i>						
ΔSS×Unemployment	-0.032*** [0.008]	-0.013 [0.008]	-0.040*** [0.013]	-0.010 [0.009]	-0.023** [0.013]	-0.022*** [0.010]
ΔSS×Manager/worker	-0.001** [0.000]	-0.000 [0.000]	-0.001* [0.001]	-0.000 [0.000]	0.000 [0.001]	-0.000 [0.001]
ΔSS×Partial time	-0.006 [0.009]	0.025 [0.009]	-0.005 [0.015]	0.024 [0.015]	0.001 [0.015]	0.004 [0.012]
Construction	Ref	Ref	Ref	Ref	Ref	Ref
ΔSS×Industry	0.039* [0.018]	0.034 [0.025]	0.048* [0.033]	0.027 [0.033]	0.055** [0.032]	0.020 [0.028]
ΔSS×Agriculture	0.009 [0.024]	0.036 [0.028]	0.034 [0.036]	0.006 [0.036]	0.046** [0.033]	0.007 [0.032]
ΔSS×Tertiary	0.035* [0.019]	0.032 [0.027]	0.046* [0.037]	0.024 [0.032]	0.59** [0.034]	0.021 [0.030]
ΔSS×Median income	-0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]
Constant	0.807*** [0.037]	0.638 [0.056]	1.363 [0.081]	0.498 [0.067]	-1.108 [0.045]	1.181 [0.063]
IMR	-0.067 [0.096]	-0.068 [0.098]	-0.073 [0.149]	-0.351*** [0.130]	-0.299*** [0.120]	-0.053 [0.107]
Random effect (EA)	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Residual variance	0.254*** [0.014]	0.243*** [0.019]	0.256*** [0.019]	0.242*** [0.015]	0.195*** [0.007]	0.269*** [0.012]
Intra-EA correlation (level 1)	1.1%	0%	0%	0.8%	2.5%	1.1%
Intra-EA correlation (level 2)	0%	0%	0%	0%	0%	0%
AIC (level 1)	170.011	37.297	156.224	42.693	-227.168	354.557
AIC (level 2)	165.227	55.277	160.961	54.643	-229.546	364.157
Observations	1,492	1,224	1,100	1,616	863	1,853

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013--2017. The dependent variable is changes in total productivity. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situation. For each group (men, women, young workers (≤ 29 years old), and older workers (> 29 years old)), the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

Table 2.6.9: Multi-level models and efficiency changes by gender, age, and firm size: effect of pay satisfaction

	Efficiency changes					
	Men	Women	Age ≤ 29	Age > 29	Large companies	Small companies
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Level 1</i>						
ΔSS	-0.018** [0.007]	0.004 [0.008]	-0.010 [0.010]	-0.007 [0.006]	-0.017** [0.009]	-0.003 [0.006]
Age	0.005*** [0.001]	0.004*** [0.001]	0.002 [0.003]	0.000 [0.001]	0.004*** [0.001]	0.005*** [0.001]
Men	-	-	0.007 [0.007]	0.004 [0.004]	0.011* [0.006]	0.005 [0.004]
Origin	-0.002 [0.009]	-0.013 [0.010]	-0.003 [0.013]	0.014 [0.006]	0.004 [0.010]	0.003 [0.007]
In relationship (2017)	0.014** [0.005]	0.005 [0.006]	0.014** [0.007]	0.008* [0.004]	0.008 [0.006]	0.012** [0.004]
Permanent contract (2017)	0.044*** [0.015]	0.007 [0.015]	0.030* [0.016]	0.035* [0.016]	0.004 [0.025]	0.039*** [0.005]
Father/mother manager	0.010* [0.006]	0.011* [0.006]	0.016* [0.009]	0.003 [0.004]	0.012* [0.007]	0.009 [0.005]
Mobility	-0.003 [0.008]	0.018** [0.009]	0.012 [0.009]	0.001 [0.007]	0.006 [0.011]	0.005 [0.006]
Constant	0.544*** [0.031]	0.633*** [0.034]	0.580*** [0.035]	0.783*** [0.036]	0.650*** [0.051]	0.480*** [0.033]
IMR	-0.144*** [0.045]	-0.235*** [0.040]	-0.014 [0.122]	-0.346*** [0.165]	-0.257*** [0.062]	-0.160*** [0.063]
Random effect (EA)	0.006* [0.006]	0.009* [0.005]	0.010* [0.011]	0.003 [0.003]	0.022*** [0.012]	0.018*** [0.011]
Residual variance	0.092*** [0.004]	0.082*** [0.003]	0.101*** [0.003]	0.070*** [0.003]	0.075*** [0.005]	0.092*** [0.003]
<i>Level 2</i>						
ΔSS×Unemployment	-0.007** [0.003]	-0.001 [0.005]	-0.006* [0.004]	-0.003 [0.004]	-0.008** [0.005]	-0.002 [0.003]
ΔSS×Manager/worker	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]	-0.000** [0.000]	-0.000 [0.000]
ΔSS×Partial time	-0.002 [0.005]	0.007 [0.005]	-0.001 [0.005]	0.005 [0.003]	0.001 [0.005]	0.000 [0.004]
Construction	Ref		Ref		Ref	
ΔSS×Industry	0.003 [0.011]	0.004 [0.011]	0.002 [0.013]	0.009 [0.009]	0.025*** [0.012]	-0.007 [0.010]
ΔSS×Agriculture	-0.001 [0.011]	0.004 [0.012]	0.003 [0.014]	0.008 [0.010]	0.026*** [0.013]	-0.007 [0.011]
ΔSS×Tertiary	0.003 [0.011]	0.006 [0.011]	0.005 [0.013]	0.008 [0.009]	0.026*** [0.013]	-0.006 [0.010]
ΔSS×Median income	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]
Constant	0.207 [0.031]	0.956** [0.035]	0.293 [0.034]	0.961*** [0.036]	-0.129 [0.052]	0.705** [0.027]
IMR	-0.104* [0.052]	-0.282*** [0.047]	0.035 [0.057]	-0.428*** [0.050]	-0.274*** [0.066]	-0.143*** [0.043]
Random effect (EA)	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Residual variance	0.091*** [0.003]	0.081*** [0.003]	0.101*** [0.003]	0.069*** [0.003]	0.076*** [0.005]	0.092*** [0.003]
Intra-EA correlation (level 1)	0.5%	1.3%	0.1%	0.1%	0.8%	1%
Intra-EA correlation (level 2)	0%	0%	0%	0%	0%	0%
AIC (level 1)	-2,362.328	-1,938.608	-1,668.532	-2,861.936	-1,448.392	-2,847.991
AIC (level 2)	-2,349.96	-1,915.889	-1,649.513	-2,849.373	-1,439.886	-2,836.588
Observations	1,492	1,224	1,100	1,616	863	1,853

Note: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013--2017. The dependent variable is efficiency change. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situation. For each group (men, women, young workers (≤ 29 years old), and older workers (> 29 years old)), the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

Table 2.6.10: Multi-level models and technological changes by gender, age, and firm size: effect of pay satisfaction

	Technological changes					
	Men	Women	Age ≤ 29	Age > 29	Large companies	Small companies
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Level 1</i>						
ΔSS	0.159*** [0.038]	0.194*** [0.057]	0.219*** [0.058]	0.141*** [0.039]	0.128*** [0.039]	0.180*** [0.040]
Age	-0.012*** [0.004]	-0.002 [0.005]	-0.010 [0.013]	0.004 [0.005]	-0.003 [0.004]	-0.008** [0.004]
Men	-	-	0.042 [0.024]	0.012 [0.021]	0.022 [0.022]	0.036* [0.021]
Origin	0.054 [0.037]	-0.017 [0.042]	-0.008 [0.051]	0.037 [0.032]	0.029 [0.034]	0.028 [0.037]
In relationship (2017)	0.021 [0.022]	0.026 [0.023]	0.024 [0.026]	0.027 [0.019]	0.005 [0.024]	0.028 [0.020]
Permanent contract (2017)	0.056 [0.053]	0.182*** [0.045]	0.074 [0.052]	0.164*** [0.048]	-0.005 [0.064]	0.141*** [0.042]
Father/mother manager	0.027 [0.022]	-0.006 [0.021]	0.006 [0.030]	0.025 [0.018]	0.004 [0.022]	0.020 [0.020]
Mobility	0.024 [0.031]	-0.016 [0.034]	0.044 [0.037]	-0.034 [0.027]	-0.025 [0.034]	0.012 [0.028]
Constant	0.882*** [0.055]	0.882*** [0.103]	1.29*** [0.082]	0.674*** [0.067]	1.155*** [0.041]	1.106*** [0.063]
IMR	0.103 [0.156]	-0.282*** [0.206]	-0.030 [0.227]	0.070 [0.147]	-0.084 [0.165]	-0.133 [0.159]
Random effect (EA)	0.000*** [0.000]	0.000 [0.000]	0.000 [0.000]	0.034*** [0.009]	0.000 [0.000]	0.038*** [0.014]
Residual variance	0.359*** [0.032]	0.343*** [0.026]	0.405*** [0.030]	0.328*** [0.020]	0.279*** [0.011]	0.398*** [0.023]
<i>Level 2</i>						
ΔSS×Unemployment	-0.039*** [0.014]	-0.019 [0.021]	-0.057*** [0.012]	-0.011 [0.013]	-0.022 [0.014]	-0.026** [0.007]
ΔSS×Manager/worker	-0.001 [0.001]	0.000 [0.001]	-0.001 [0.001]	-0.000 [0.001]	0.000 [0.001]	-0.001 [0.001]
ΔSS×Partial time	-0.004 [0.020]	0.022 [0.023]	-0.005 [0.022]	0.024 [0.019]	-0.003 [0.022]	-0.001 [0.017]
Construction	Ref	Ref	Ref	Ref	Ref	Ref
ΔSS×Industry	0.047* [0.034]	0.048 [0.055]	0.066* [0.051]	0.021 [0.046]	0.039 [0.043]	0.052 [0.045]
ΔSS×Agriculture	0.013 [0.042]	0.052 [0.064]	0.046 [0.059]	-0.007 [0.051]	0.048 [0.047]	0.035 [0.051]
ΔSS×Tertiary	0.043* [0.034]	0.044 [0.062]	0.060* [0.058]	0.020 [0.045]	0.026 [0.046]	0.053 [0.048]
ΔSS×Median income	0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]
Constant	1.884 [0.058]	0.624 [0.099]	2.578* [0.080]	0.196 [0.067]	-0.245 [0.043]	2.081** [0.065]
IMR	0.053 [0.148]	0.305 [0.240]	0.035 [0.238]	0.216 [0.193]	0.001 [0.194]	-0.143*** [0.171]
Random effect (EA)	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Residual variance	0.370*** [0.020]	0.358*** [0.031]	0.401*** [0.030]	0.329*** [0.020]	0.275*** [0.009]	0.380*** [0.020]
Intra-EA correlation (level 1)	0%	0%	0%	1%	0%	0.9%
Intra-EA correlation (level 2)	0%	0%	0%	0%	0%	0%
AIC (level 1)	1,093.79	740.051	1,032.979	744.469	208.353	1,521.948
AIC (level 2)	1,096.265	754.921	1,034.551	758.331	216.490	1,719.934
Observations	1,492	1,224	1,100	1,616	863	1,853

Note: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013--2017. The dependent variable is technological change. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situation. For each group (men, women, young workers (≤ 29 years old), and older workers (> 29 years old)), the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

The greater negative impact on men and workers in large companies can be attributed to several factors. Firstly, men and workers in large companies may have higher pay expectations than women or workers in small businesses, leading to greater disappointment in case of unsatisfactory pay. Therefore, an increase in pay satisfaction among these workers may have a greater impact on their motivation, productivity, and efficiency compared to other workers. Additionally, workers in large companies often have specialized roles and responsibilities, which can be demanding in terms of skills and concentration (Idson and Oi, 1999). If they are dissatisfied with their pay, it can lead to decreased motivation and engagement, resulting in decreased efficiency (Judge et al., 2001). Finally, workers in large companies may have fewer internal mobility opportunities, leading to reluctance to leave their job in case of unsatisfactory pay, further decreasing their motivation, engagement, and efficiency (Lee et al., 2004).

The negative effect of pay satisfaction on the variation in workers' efficiency may be more pronounced for men and workers in large companies residing in EA with high unemployment rates and where the share of executives is higher than that of workers. This could be due to their higher expectations in terms of pay and professional status, as there may be strong competition for jobs in these areas. Moreover, men and workers in large companies may have more important roles and responsibilities, which can increase their sensitivity to pay satisfaction (Judge et al., 2001). The fact that the share of executives is higher in these EA may also play a role, as executives may have higher expectations in terms of remuneration and status, making them more sensitive to pay satisfaction (A'yuninnisa and Saptoto, 2015). In contrast, workers may have more modest expectations in terms of pay, which can make them less sensitive to pay satisfaction. However, the negative effect is balanced when the economic activity of the EA is dominated by the service sector, possibly because workers in these sectors have different expectations in terms of remuneration and professional status, and may be more sensitive to other aspects of their work such as flexibility, quality of work-life, or professional development opportunities (Locke, 1976).¹³

2.6.6.2 Effects of satisfaction with job prospects

The results related to satisfaction with job prospects are presented in Tables 2.6.11 (for the effect on overall productivity), 2.6.12 (for the effect on efficiency change), and 2.6.13 (for the effect on technological change). Unlike the results for the overall sample, the results for the heterogeneous effect by gender, age, and firm size are not significant at level 2.

Effect on Global productivity

The results show that the previously observed positive effect of satisfaction with job prospects on changes in overall productivity is statistically significant for women and employees in small

¹³It should be noted that the negative effect of pay satisfaction on worker efficiency variation is moderate and does not apply to all workers. Additionally, other factors such as working conditions, training opportunities, and firm support may also influence worker efficiency.

firms, particularly those who are younger. The findings suggest that workers' satisfaction with their future prospects has a significant positive impact on changes in overall productivity, with this relationship being more pronounced among women and employees in small firms. This can be attributed to the fact that women and younger workers may have higher expectations in terms of career development and advancement, which can affect their motivation and commitment to work (Addison et al., 2014). Furthermore, workers in smaller firms, especially younger ones, may be more sensitive to the future of their company, as they have fewer opportunities for internal mobility and must therefore be more concerned about the financial health of their company (Ariely, 2016). Overall, these results suggest that job prospects are an important factor for worker motivation and productivity, particularly among women and employees in small firms. This finding supports the notion of the effect of expectations for women as discussed in Chapter 1 (section 1.5.3), where women are found to have higher expectations for professional development than men (Clark, 1997) due to their more favorable professional position (O'Neil, 2003; Westover, 2012).

Table 2.6.11: Multi-level models and total productivity by gender, age, and firm size: effect of satisfaction with career prospects

	Total productivity					
	Men	Women	Age ≤ 29	Age > 29	Large companies	Small companies
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Level 1</i>						
ΔSP	-0.021 [0.024]	0.123** [0.063]	0.111* [0.069]	0.021 [0.035]	-0.015 [0.036]	0.074** [0.043]
Age	-0.001 [0.003]	0.003 [0.003]	-0.009 [0.008]	0.005* [0.003]	0.003 [0.003]	0.003* [0.003]
Men	-	-	0.035** [0.016]	0.017 [0.015]	0.029* [0.016]	0.028** [0.013]
Origin	0.034 [0.025]	0.003 [0.027]	-0.002 [0.033]	0.038** [0.022]	0.026 [0.024]	-0.003 [0.027]
In relationship (2017)	0.029* [0.015]	0.020 [0.016]	0.028 [0.017]	0.030* [0.014]	0.011 [0.017]	0.036*** [0.013]
Permanent contract (2017)	0.079*** [0.036]	0.118*** [0.027]	0.083** [0.033]	0.140*** [0.036]	-0.009 [0.042]	0.032*** [0.025]
Father/mother manager	0.029** [0.015]	0.017 [0.016]	0.022 [0.019]	0.024 [0.014]	0.015 [0.017]	0.028** [0.014]
Mobility	0.012 [0.020]	0.001 [0.022]	0.035 [0.022]	-0.019 [0.021]	-0.018 [0.025]	0.006 [0.018]
Constant	0.727*** [0.058]	0.579*** [0.102]	0.887*** [0.085]	0.556*** [0.064]	0.742*** [0.047]	0.595*** [0.063]
IMR	-0.070 [0.102]	-0.185 [0.126]	-0.053 [0.142]	-0.368*** [0.097]	-0.357*** [0.111]	-0.143*** [0.103]
Random effect (EA)	0.027** [0.008]	0.000 [0.006]	0.000 [0.000]	0.020** [0.006]	0.027*** [0.019]	0.033*** [0.006]
Residual variance	0.258*** [0.014]	0.246*** [0.020]	0.262*** [0.020]	0.246*** [0.015]	0.199*** [0.009]	0.261*** [0.014]
Intra-EA correlation	1.1%	0%	0%	0.6%	1.8%	1.5%
AIC	189.349	55.850	177.509	65.255	-218.019	331.050
Observations	1,492	1,224	1,100	1,616	863	1,853

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013--2017. The dependent variable is changes in total productivity. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situation. For each group (men, women, young workers (≤ 29 years old), and older workers (> 29 years old)), the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

Effect on Technological changes

The results related to overall productivity and technological innovations show a similar effect of occupational prospects. Specifically, an increase in satisfaction with job prospects leads to an increase in innovativeness for women and employees in small firms. However, this effect is statistically insignificant for men and employees in large firms.

One possible interpretation is that women and employees of small businesses may be more motivated by the possibility of future career growth, which could enhance their innovation capacity. In contrast, men and employees of large businesses may have different motivations and incentives that are less related to future career prospects, which could explain the lack of statistical significance in their case (Kwon and Kim, 2020). It is also possible that women and employees of small businesses have less job security, and therefore they may be more motivated to innovate as a means of securing their future career prospects (Yang et al., 2022). Once again, this finding underscores the importance of professional prospects for women, as discussed in Chapter 1, section 1.5.2.2.

In addition, the result for small businesses suggests the "lead fish" effect, where small businesses, which often lack the resources and market power of larger competitors, may need to be more innovative to survive and thrive (Kelley, 2001). By creating new and innovative products or services, small businesses can differentiate themselves from competitors and attract the attention of larger businesses. This can lead to partnerships, collaborations, or even acquisition by larger companies (Granstrand and Sjölander, 1990).

These results suggest that companies should consider the specific needs and motivations of their employees when implementing strategies to increase innovation. Offering more opportunities for career growth and advancement may be particularly effective for women and employees of small businesses.

Effect on Efficiency changes

The impact of gender on efficiency changes was found to be statistically insignificant. This could be attributed to the fact that both men and women may face similar challenges in the workplace, such as job dissatisfaction, lack of advancement opportunities, or discrimination, which could affect their efficiency levels (Blau and Kahn, 2017). However, we found that an increase in job prospects satisfaction among older workers or employees of large firms results in a decrease in their efficiency capacity. This could be due to factors such as complacency, decreased motivation, or decreased commitment to work once job prospects are perceived as more secure (Kanfer and Ackerman, 2004).

It is important to note that this effect was not observed among employees of small firms, which may suggest that workers in small firms are more likely to focus on their current job, regardless of their long-term employment prospects (Baron and Tang, 2011). This highlights

Table 2.6.12: Multi-level models and efficiency changes by gender, age, and firm size: effect of satisfaction with career prospects

	Efficiency changes					
	Men	Women	Age ≤ 29	Age > 29	Large companies	Small companies
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Level 1</i>						
ΔSP	-0.003 [0.011]	-0.009 [0.009]	-0.000 [0.015]	-0.019* [0.008]	-0.023** [0.013]	-0.004 [0.009]
Age	0.005*** [0.001]	0.004*** [0.001]	0.002 [0.003]	0.000 [0.001]	0.004*** [0.001]	0.005*** [0.001]
Men	-	-	0.011 [0.007]	0.004 [0.004]	0.010* [0.006]	0.005 [0.005]
Origin	-0.002 [0.009]	0.013 [0.009]	-0.004 [0.013]	0.014 [0.006]	0.003 [0.010]	0.005 [0.009]
In relationship (2017)	0.014** [0.005]	0.005 [0.006]	0.014** [0.007]	0.007 [0.004]	0.008 [0.006]	0.011** [0.005]
Permanent contract (2017)	0.045*** [0.015]	0.007 [0.016]	0.030* [0.016]	0.035* [0.016]	0.004 [0.025]	0.038** [0.013]
Father/mother manager	0.011* [0.006]	0.010* [0.006]	0.016* [0.008]	0.002 [0.004]	0.011* [0.006]	0.009* [0.005]
Mobility	-0.004 [0.008]	0.017** [0.009]	0.012 [0.009]	0.001 [0.007]	0.006 [0.010]	0.003 [0.007]
Constant	0.541*** [0.031]	0.632*** [0.034]	0.573*** [0.034]	0.782*** [0.036]	0.646*** [0.052]	0.553*** [0.027]
IMR	-0.142*** [0.044]	-0.235*** [0.040]	-0.011 [0.048]	-0.344*** [0.044]	-0.252*** [0.046]	-0.160*** [0.037]
Random effect (EA)	0.007* [0.006]	0.008* [0.005]	0.009* [0.012]	0.003 [0.003]	0.024** [0.012]	0.000 [0.000]
Residual variance	0.092*** [0.004]	0.082*** [0.003]	0.102*** [0.003]	0.070*** [0.003]	0.075*** [0.005]	0.092*** [0.003]
Intra-EA correlation	0.5%	1.1%	0.9%	0.2%	0.9%	1%
AIC	-2,300.185	-1,940.266	-1,667.289	-2,866.415	-1,447.984	-1,587.625
Observations	1,492	1,224	1,100	1,616	863	1,853

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013--2017. The dependent variable is efficiency change. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situation. For each group (men, women, young workers (≤ 29 years old), and older workers (> 29 years old)), the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

the importance of considering contextual factors when analyzing the relationship between job satisfaction and worker performance.

Table 2.6.13: Multi-level models and technological changes by gender, age, and firm size: effect of satisfaction with career prospects

	Technological changes					
	Men	Women	Age ≤ 29	Age > 29	Large companies	Small companies
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Level 1</i>						
ΔSP	-0.020 [0.034]	0.205** [0.095]	0.176* [0.117]	0.056 [0.048]	0.011 [0.049]	0.126** [0.066]
Age	-0.012*** [0.004]	-0.003 [0.004]	-0.014 [0.012]	0.004 [0.004]	-0.003 [0.004]	-0.008** [0.004]
Men	-	-	0.041* [0.024]	0.018 [0.020]	0.027 [0.023]	0.040** [0.020]
Origin	0.054 [0.035]	-0.013 [0.041]	0.002 [0.051]	0.034 [0.031]	0.035 [0.034]	0.021 [0.039]
In relationship (2017)	0.020 [0.022]	0.022 [0.023]	0.020 [0.027]	0.029 [0.019]	-0.001 [0.024]	0.032 [0.020]
Permanent contract (2017)	0.049 [0.054]	0.166*** [0.047]	0.077* [0.054]	0.149** [0.048]	-0.022 [0.062]	0.134*** [0.043]
father/mother manager	0.024 [0.022]	0.000 [0.022]	0.011 [0.031]	0.024 [0.018]	0.001 [0.023]	0.022 [0.021]
Mobility	0.028 [0.031]	-0.017 [0.033]	0.046* [0.039]	-0.034 [0.027]	-0.033 [0.036]	0.013 [0.029]
Constant	1.349*** [0.056]	0.974*** [0.104]	1.444*** [0.086]	0.707*** [0.067]	1.206*** [0.043]	1.149*** [0.064]
IMR	0.116 [0.160]	0.074 [0.179]	-0.095 [0.220]	0.065 [0.161]	-0.122 [0.164]	0.118 [0.157]
Random effect (EA)	0.029*** [0.011]	0.000 [0.000]	0.000 [0.000]	0.029*** [0.009]	0.000 [0.000]	0.043*** [0.014]
Residual variance	0.377*** [0.021]	0.362*** [0.032]	0.410*** [0.031]	0.332*** [0.020]	0.282*** [0.011]	0.402*** [0.024]
Intra-EA correlation	0.6%	0%	0%	0.8%	0%	1.1%
AIC	1,122.87	751.936	1,059.03	769.619	223.372	1,553.274
Observations	1,492	1,224	1,100	1,616	863	1,853

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013--2017. The dependent variable is technological change. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situation. For each group (men, women, young workers (≤ 29 years old), and older workers (> 29 years old)), the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

2.6.7 Sensitivity analysis of the results to sample reduction through weighting

Our study is based on a database that underwent significant sample reduction due to exclusions. This sample loss may potentially affect the accuracy of our estimates and thus challenge the validity of our results. To address this issue, we used a weighting method to compensate for differences between the sample and the target population. To do so, we used the weights provided in the database and multiplied them by a normalization factor to adjust the distribution of these weights to match that of the target population. We calculated the normalization factor by taking the sum of weights w for each individual i in the sample, divided by the size of the total initial population. We then divided the adjusted weights by the mean weight of the sample to obtain the final weighting variable. This variable was included in our estimates to correct potential

biases introduced by sample loss and improve the accuracy of our results. We also performed a bootstrap analysis. We generated 1,000 bootstrap samples from our initial sample by resampling with replacement. For each bootstrap sample, we applied the same weighting method as for our initial sample. We then calculated the 95% confidence intervals of the bootstrap estimates to assess the robustness of our standard errors with respect to sample reduction.

The results of these multilevel models examining the effect of salary satisfaction and satisfaction with career prospects on changes in total productivity, efficiency changes, and technological changes using weighted data are presented in Tables 2.6.14 and 2.6.15. The coefficients and standard deviations are given for each explanatory variable.

2.6.7.1 Effect of satisfaction with pay

Comparing the results of the unweighted estimates to the weighted ones, we can notice that the results were quite similar and reveal a significant and positive effect on overall productivity and technological changes, but no significant effect on efficiency changes. The results at level 2 with the interaction of employment area characteristics are also similar in terms of coefficient significance. However, the magnitude of the coefficients seems higher in the case of weighted estimates. Indeed, with weighting, the coefficients of the effect on overall productivity and technological change would be higher (0.129 and 0.196 respectively) than in the case without weighting (0.108 and 0.171 respectively). The magnitude of the effects at level 2 also remains relatively higher. This indicates that the effect of salary satisfaction on overall productivity and innovation capability is likely underestimated in the unweighted model. Additionally, other independent variables also exhibit differences in regression coefficients between the two cases, but these differences are not significant in most cases.

Furthermore, the results with and without weighting show differences in the estimation of coefficients and residual variances. The estimated coefficients of the random effect (employment area) decreased with weighting in all three cases, while residual variances increased. These differences may be due to the impact of weighting on modeling random effects.

The differences in results between the two situations (without weighting and with weighting) for the Intra-Employment area correlation (level 1) and the Intra-Employment area correlation (level 2) are quite significant. In the situation without weighting, the correlations between individuals from the same employment area (level 1) are very low, ranging from 0.3% to 1%. This means that individuals from the same employment area have fairly different characteristics from each other. However, when weighting is taken into account, the correlations between individuals from the same employment area (level 1) increase significantly, ranging from 3.5% to 8.2%. This means that individuals from the same employment area have fairly similar characteristics to each other. Similarly, the Intra-Employment area correlation (level 2) also increases when weighting is taken into account, from 0% to 3.5% to 7%. This means that different employment areas also exhibit similarities in their characteristics when weighting is taken into account.

These results suggest that weighting seems to better highlight similarities between individuals and employment areas, which can be useful for better understanding employment and economic dynamics in a given region. However, the results with weighting have higher AIC values than the results without weighting. This indicates that the models with weighting have poorer fit than the models without weighting. This may be due to the complexity added by weighting.

Table 2.6.14: Multi-level models and total productivity changes, efficiency changes, and technological changes: effect of pay satisfaction-weighted sample

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
<i>Level 1</i>						
Δ SS	0.129***	[0.024]	-0.002	[0.004]	0.196***	[0.038]
Age	0.001	[0.002]	0.004***	[0.001]	-0.006	[0.004]
Men	0.035**	[0.015]	0.008*	[0.005]	0.036*	[0.020]
Origin	0.008	[0.020]	0.001	[0.009]	0.011	[0.026]
In relationship (2017)	0.029*	[0.018]	0.015***	[0.005]	0.021	[0.021]
Permanent contract (2017)	0.101***	[0.026]	0.031**	[0.012]	0.103***	[0.031]
Father/Mother manager	0.030**	[0.011]	0.004	[0.006]	0.030	[0.015]
Geographical mobility	0.022	[0.018]	0.009	[0.008]	0.024	[0.025]
Constant	0.548***	[0.123]	0.597***	[0.044]	1.015***	[0.197]
IMR	0.001	[0.139]	-0.197***	[0.055]	0.262	[0.213]
Random effect (EA)	0.050***	[0.012]	0.025**	[0.005]	0.086***	[0.022]
Residual variance	0.263***	[0.018]	0.084**	[0.004]	0.384***	[0.030]
<i>Level 2</i>						
Δ SS \times Unemployment rate	-0.025***	[0.009]	-0.003	[0.003]	-0.035**	[0.016]
Δ SS \times Manager/worker ratio	0.001***	[0.001]	-0.000	[0.000]	0.001***	[0.001]
Δ SS \times Partial time	0.001	[0.011]	-0.002	[0.007]	0.004	[0.018]
Construction	Ref		Ref		Ref	
Δ SS \times Industry	0.050**	[0.023]	0.000	[0.014]	0.067**	[0.035]
Δ SS \times Agriculture	0.041**	[0.025]	0.002	[0.014]	0.057**	[0.032]
Δ SS \times Tertiary	0.052**	[0.024]	0.003	[0.014]	0.070**	[0.037]
Δ SS \times Median income	-0.000	[0.000]	0.000	[0.000]	-0.000	[0.000]
Constant	1.156	[0.089]	0.531	[0.048]	1.716	[0.161]
IMR	0.016	[0.145]	-0.211***	[0.061]	0.294	[0.230]
Random effect (EA)	0.050**	[0.015]	0.023*	[0.006]	0.087**	[0.021]
Residual variance	0.261***	[0.018]	0.084***	[0.003]	0.382***	[0.029]
Intra-EA correlation (level 1)	3.5%		8.2%		4.8%	
Intra-EA correlation (level 2)	3.5%		7%		4.9%	
AIC (level 1)	342.325		-3,386.462		1,619.21	
AIC (level 2)	350.287		-3,367.006		1,623.618	
Observations	2,716		2,716		2,716	

^a SS represents pay satisfaction

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

2.6.7.2 Effect of satisfaction with career prospects

Comparing the results of the effect of satisfaction with job prospects in weighted and unweighted estimations, we can see that the regression coefficients differ between the two cases, although the significance remains similar. With weighting for the effect on overall and technological productivity, the coefficients are higher (0.103 and 0.166 respectively) than in the unweighted case (0.050 and 0.089 respectively). This indicates that the effect of satisfaction on overall productivity is likely underestimated in the unweighted model. Additionally, the other independent variables also exhibit differences in regression coefficients between the two cases, but these differences are not significant in most cases.

The introduction of weighting also led to an increase in the value of the coefficients for the random effects of employment area, suggesting an increased importance of the effect of employment on overall results. This may be due to the weighting taking into account differences in employment sizes between employment areas, which amplified the effect of employment on results. However, the residual variance also increased for the models with weighting, which may indicate a loss of precision in the estimations. This could be due to the addition of bias in the data due to the weighting used. As for the differences in intra-employment area correlation and AIC, it can be observed that the intra-employment area correlation is higher in the weighted model than in the unweighted model, which may indicate that the weighting takes into account differences in size between employment areas. On the other hand, the AIC is higher in the weighted model for overall and technological productivity, but lower for efficiency. This may indicate that the weighting improved the estimation precision for efficiency, but not for overall and technological productivity.

Table 2.6.15: Multi-level models and total productivity changes, efficiency changes, and technological changes: effect of career prospects-weighted sample

	Total		EFFCH		TECH	
	Coef (1)	SD (2)	Coef (3)	SD (4)	Coef (5)	SD (6)
<i>Level 1</i>						
Δ SP	0.103*	[0.032]	-0.008	[0.008]	0.166*	[0.038]
Age	0.001	[0.002]	0.004***	[0.001]	-0.007*	[0.003]
Men	0.037***	[0.011]	0.008*	[0.005]	0.041**	[0.015]
Origin	0.007	[0.019]	0.001	[0.007]	0.009	[0.027]
In relationship (2017)	0.028**	[0.011]	0.015***	[0.004]	0.019	[0.016]
Permanent contract (2017)	0.098***	[0.023]	0.031**	[0.012]	0.099***	[0.036]
Father/mother manager	0.033**	[0.012]	0.004	[0.006]	0.034*	[0.016]
Geographical mobility	0.020	[0.015]	0.012	[0.007]	0.022	[0.023]
Constant	0.589***	[0.052]	0.594***	[0.022]	1.082***	[0.055]
IMR	-0.016	[0.083]	-0.195***	[0.055]	0.234	[0.126]
Random effect (EA)	0.050**	[0.013]	0.025**	[0.005]	0.087**	[0.021]
Residual variance	0.265***	[0.018]	0.084***	[0.004]	0.388***	[0.030]
Intra-EA correlation	3.5%		8.3%		4.8%	
AIC	375.245		-3,387.134		1,653.19	
Observations	2,716		2,716		2,716	

^a SP represents satisfaction with career prospects.

Notes: Author's calculations are based on Generation 2010 data. The symbol Δ indicates the difference in the relevant variable between 2013 and 2017. The dependent variables are: changes in total productivity, efficiency, and technology over the period 2013--2017. In Level 2, the macroeconomic variables differentiate the EAs according to their economic situations. For each dependent variable, the first column (Coef) represents the estimated coefficients, and the second column (SD) represents the standard deviation. The standard deviations were estimated from 1,000 replications of the sample. Significances are denoted by * at the 10% threshold, ** at the 5% threshold, and *** at the 1% threshold.

2.7 Conclusion and discussion

The link between job satisfaction and productivity remains a complex relationship to study, with some studies showing a positive correlation between these two factors (Miller and Monge, 1986; Spector, 1997; Thomas and Jex, 2002; Piening et al., 2013), while other research fails to establish this relationship (Locke, 1970; Argyle, 1989; Deci and Ryan, 1985; Gagné and Deci, 2005).

The results of this study concur with the findings of the former, even after robust treatment of endogeneity bias, by showing positive and significant relationships between measures of satisfaction and overall job productivity (Stumpf and Rabinowitz, 1981; Bretz and Thomas, 1992; HG and TA., 2000; Nachbagauer and Riedl, 2002; Judge and Robbins, 2017; Campbell and Im, 2019; Nugroho and Tanuwijaya, 2022). In addition, this work contributes, compared to previous works, to extend the analysis of this phenomenon on three points: *(i)* First, it analyzes the traditional link between total productivity and worker satisfaction, but also examines this potential link with components related to efficiency changes and technological changes in productivity; *(ii)* Second, it explores the nature of these relationships in a spatial framework constituted by the EAs of residence of workers and retains a hierarchical structure in productivity and the satisfaction factor according to the individual's membership in an EA; *(iii)* Third, it examines these relationships by crossing the differences in characteristics between EAs with the worker satisfaction criterion.

Following these three innovative aspects, it is evident that the link between productivity and satisfaction needs to be analyzed according to multiple hierarchies. Analyzing this link according to various hierarchies allows for a better understanding of the underlying mechanisms that explain the relationship between these two variables, identification of the factors that most influence worker productivity, and the highlighting of potential interactions between the different levels. By analyzing the various aggregate characteristics and studying a component of productivity, we have highlighted different effects and contradictory behaviors based on the EA membership in this study. Therefore, the insignificance of the link between productivity and worker satisfaction may be due to overly aggregated analyses, where these opposing effects may offset each other. Secondly, methods to deal with the simultaneity bias between the satisfaction and productivity criteria must be considered to identify the direction of causality accurately.

Based on data from the 2010 Generation study of 2,716 French employees, this study found a positive, significant, and robust influence of pay satisfaction and satisfaction with professional prospects on the overall productivity of workers and their capacity for innovation. The decomposition of these influences by EA characteristics revealed that pay satisfaction primarily influenced overall productivity and technological change in EAs with a higher share of managers than blue-collar workers and with economic activity dominated by industry or the service sector. However, satisfaction with job prospects did not have a significant impact on workers' efficiency capacity in this decomposition.

However, the endogeneity treatment revealed that pay satisfaction and satisfaction with job

prospects did have a causal effect on efficiency capacity. The more satisfied the employee was with pay or job prospects, the less technically efficient they became on the job. Similarly, the more efficient the employee was, the less difficult it was to satisfy them in terms of pay or promotion. This result could suggest that employees desire a level of pay or position equivalent to their mastery of the job. If they already have a high pay or expected position, they may be less motivated.

More heterogeneous analyses by gender, age, and company size reveal differences in the effects observed between groups. The study finds no statistically significant gender effect of pay satisfaction on overall productivity improvement and innovative capacity. However, among workers in small firms (which are mostly young), pay satisfaction appears to be a factor that can improve their overall productivity and innovativeness. The theoretical implication of these findings is that the difference in overall productivity and innovative capacity between workers in small and large firms reflects the dynamism of young workers and their ability to adapt more easily to new changes. Moreover, they desire a higher pay and more comfortable standard of living due to their competence, which allows them to advance in their career and be promoted to positions of responsibility. Another argument is that the non-significant gender difference could indicate that pay satisfaction is an important factor in the performance of both sexes. Additionally, it may suggest that men and women may be motivated by the same factors at work, including pay. This reflects less discrimination in certain sectors, such as the service sector, where the positive link between pay satisfaction and productivity is stronger in EAs dominated by this type of sector.

Regarding career prospects, the study finds a stronger positive effect on overall productivity and technological change for women and workers in small firms. The increased differentiation between gender and company size could be due to the influence of inequalities in opportunities for success and career achievement between men and women or between workers in small and large companies.

The main economic policy implications of this study are as follows. Firstly, employers should consider the pay satisfaction and career prospects of their employees to improve their overall productivity and innovation capacity. Offering competitive pays and attractive career prospects can motivate employees to work more productively and innovatively. Secondly, pay satisfaction is a crucial factor for improving the overall productivity and innovation capacity of workers in employment areas dominated by executives and industries or the service sector. Employers in such areas should pay particular attention to their employees' pay satisfaction. Thirdly, the study finds that pay satisfaction does not significantly impact workers' efficiency capacity, and that highly paid workers may be less motivated to improve their efficiency. Employers should be aware of this and find ways to motivate highly paid workers. Finally, the study indicates that pay satisfaction is more important for improving the performance of workers in small businesses, especially young workers. Economic policies can focus on creating jobs in small businesses and improving career prospects and pays for young workers. In summary, this study highlights

the importance of pay satisfaction and career prospects in improving worker productivity and innovation capacity, and suggests that economic policies should take these factors into account.

However, this study has some limitations. Firstly, the results of this study are based on data from France, and therefore cannot be generalized to other countries or contexts, as economic conditions, organizational cultures, and employee expectations may differ across countries. Secondly, the study did not take into account other important factors, such as company culture, interpersonal relationships, mental health, training, and personal development, which could also have an impact on job satisfaction and productivity.

Acknowledgements

The article related to this chapter was co-written with Jean-Pascal Guironnet and Nicolas Peypoch, whom I thank for agreeing to work with me. The authors would like to thank the participants of the 17th annual TEPP (Theoretical and Policy Evaluation of Public Policies) conference at Université d'Évry - Université Paris-Saclay in October 2021, as well as the participants of the Caen seminar in July 2021 and those of the 38th JMA (Applied Microeconomics Days) in Rennes in June 2022 for their very useful comments and suggestions that helped improve this article. We would like to especially thank Professor Franck Portier (University College London) for his comments, advice, and suggestions, which were very helpful in improving the study. This research was financially supported by the CREM laboratory. Any errors or omissions in this paper are solely our responsibility.

Appendix

2.8 Explanation of the GMM hierarchical structure method

The convergent GMM estimators are constructed based on the orthogonality conditions, which assume no correlation between the instruments used and the error terms of the model (Wooldridge, 2001). To create the instrument vector, we followed this approach and exploited the hierarchical structure of the data, considering inter- and intra-group transformations for variables assumed to be exogenous. For variables assumed to be endogenous, we only performed the intra-group transformation. Therefore, for exogenous variables, we determined both the deviations from the mean and the means of these variables by individuals, while for endogenous variables, we only determined the deviations from the mean of these variables according to the group considered. Finally, we multiplied all variables (both endogenous and exogenous) by the deviation matrix (i.e., deviation from the mean), denoted by Q , and we used the matrix of means per group, denoted by P , for the variables considered as exogenous only.

We consider the variables related to the individual and occupational characteristics of individuals controlled in the previous estimations as exogenous variables. To these we added an

additional exogenous variable since level 1 is affected by endogeneity (see subsection 2.6.1). This variable corresponds to the performance of the internship that led to the individual's current job. The variables assumed to be endogenous are therefore the measures of job satisfaction, i.e. pay and career prospects, and the variables that cross-reference these measures with the characteristics of the EAs. Let X be the vector of all explanatory variables (assumed to be endogenous and exogenous) and X_E the vector of variables assumed to be exogenous only. We consider Z the vector of instruments. In this specific case, the instruments are constructed based on two types of transformations. For variables assumed to be exogenous, the instruments consist of PX_E , where P is a matrix of means per group considered for the variables considered as exogenous only. This means that we take the mean of each exogenous variable for each group, and then create a vector of instruments by multiplying these means by the corresponding indicator variables. For variables assumed to be both exogenous and endogenous, the instruments consist of QX , where Q is a deviation matrix that measures the deviation of each individual's value of each variable from the corresponding group mean. This means that we subtract the group mean from each individual value of each variable, and then create a vector of instruments by multiplying these deviations by the corresponding indicator variables. This approach allows us to create instruments that capture the variation within groups while controlling for the group-level effects.

Due to the additional orthogonality conditions related to the transformations by the P -matrix of the means, it is possible to observe overidentification. In this case, the convergence of the GMM estimator depends on the weight given to these additional conditions. More precisely, the estimator depends on the choice of the weighting matrix. Hansen (1982) considers that the optimal choice to have an efficient and convergent estimator is the one that minimizes the variance of the GMM estimator. In this perspective, Kim and Frees (2007) proposes a weight (which we denote W in this study) corresponding to the inverse of the square root of the variance-covariance matrix of all error terms of the model. By efficiency, we mean an estimator that is unbiased and has zero variance (Wooldridge, 2001).

The corresponding GMM estimator is thus obtained through a two-step procedure, in which the weighting matrix is obtained from the first step. First, we estimate the model using the weighting $W = I$ to obtain a consistent estimator (\hat{b}_{GMM1}). Second, we use this estimator to estimate the error terms in the model. We then compute the variance-covariance matrix, which we denote as \hat{V} , and the weight is determined as $\hat{W} = \hat{V}^{-1/2}$. Usually, in GMM methods, the weight is just the inverse of the weighting matrix ($W = \hat{V}^{-1/2}$), but using the weight in the form $W = \hat{V}^{-1/2}$ allows for the variance structure of hierarchical models. This weight will be used to find the GMM estimator in the second step. The GMM estimator is obtained by solving the moment conditions using the vector of predictors and the endogenous variables as follows:

$$\hat{b}_{GMM} = (X' \hat{V}^{-1/2} Z (Z' \hat{V}^{-1} Z)^{-1} Z' \hat{V}^{-1/2} X)^{-1} \times (X' \hat{V}^{-1/2} Z (Z' \hat{V}^{-1} Z)^{-1} Z' \hat{V}^{-1/2} y) \quad (2.12)$$

where \hat{b}_{GMM} is the vector of parameter estimates. X is the matrix of explanatory variables, which includes the satisfaction variables, their interaction variables with EZ characteristics, and the

control variables specified in Table 2.3.1. y the vector of dependent variables corresponding to the indices of overall productivity, efficiency change, and technological change. Z is the matrix of instruments.

Our standard deviations are calculated by taking the square root of the variance of the GMM estimator. The formula for the variance used is as follows:

$$\widehat{Var}_{b_{GMM}} = (X'AX)^{-1}X'Z(Z'Z)^{-1}(\sum Z'\varepsilon_{ij}\varepsilon'_{ij}Z)(Z'Z)^{-1}Z'X(X'AX)^{-1} \quad (2.13)$$

where ε_{ij} is the residual obtained from the GMM estimation and $\sum Z'\varepsilon_{ij}\varepsilon'_{ij}Z$ is the sum of the outer products of the residuals. The term $A = Z(Z'Z)^{-1}Z'$ is called the orthogonal projection matrix (or orthogonalization matrix). This matrix is used to project the exogenous variables X onto the vector space generated by the instrumental variables Z . In other words, the matrix A gives the regression coefficients of the exogenous variables X on the instrumental variables Z by minimizing the residuals.

The GMM estimator has the advantage of being flexible in terms of the choice of instrumental variables, which can be used to test the exogeneity of the variables. The robustness of the results and the exogeneity of the instrumental variables are validated by conducting statistical tests. The test used to compare the GMM estimator with the random-effects estimator (EA) is a likelihood ratio test, which is based on the difference in the log-likelihood of the two models. The null hypothesis is that the variables assumed to be endogenous in the model are exogenous, and the alternative hypothesis is that they are endogenous. If the null hypothesis is rejected, it suggests that the variables are endogenous and that the GMM estimator is more appropriate than the random-effects estimator.

Table 2.8.1: Description of variables and sources

Variables	Definition	Source
<i>Output variables</i>		
Net monthly pay	Net monthly earnings in euros, adjusted by the consumer price index	Own elaboration with Génération 2010 (2013-2017)
<i>Input variables</i>		
Educational level in years	Number of years of study corresponding to the highest level of degree obtained	Own elaboration with Génération 2010 (2013-2017)
Professional experience	Number of months in employment	Generation 2010 (2013-2017)
Tenure	Number of months in a job	Generation 2010 (2013-2017)
<i>Individual characteristics</i>		
Age	Age of the individual determined by the number of additional years compared to 2017 after leaving the school system in 2010, 7 years longer	Own elaboration with Génération 2010 (2013-2017)
Men	Dummy variable taking the value (1) if the individual is male	Own elaboration with Génération 2010 (2013-2017)
Origin	Dummy variable taking the value (1) if the individual is of foreign origin or (0) if it is of French origin	Own elaboration with Génération 2010 (2013-2017)
In relationship	Dummy variable taking the value (1) whether the individual lives with a spouse in 2017 or (0) if living alone or with parents	Own elaboration with Génération 2010 (2013-2017)
Father/mother manager	Dummy variable taking the value (1) if at least one of the parents is a manager or (0) if none of the parents is a manager	Own elaboration with Génération 2010 (2013-2017)
<i>Professional characteristics</i>		
Permanent contract	Dummy variable taking the value (1) if the individual is on permanent contract in 2017 or (0) if on a temporary contract	Own elaboration with Génération 2010 (2013-2017)
<i>Geographical informations</i>		
Employment area (EA) of residence	They indicate the space within which people live and work	Generation 2010 (2013-2017)
Geographical mobility	Dummy variable taking the value (1) if the individual changed employment area between 2013 and 2017 or (0) if he/she stayed in the same area	Own elaboration with Génération 2010 (2013-2017)
<i>EA characteristics</i>		
Median income	Median income of the EA	Insee-DGFIP-Cnaf-Cnav-CCMSA, Social and tax location file (Filosofi)
Unemployment rate	Unemployment rate of the EA	Insee-RP-historical data since 1968 (Employment areas (2010))
Partial time	Part-time share of the EA	Insee-RP-historical data since 1968 (Employment areas (2010))
Manager/worker ratio	Share of managerial/worker ratio of the EA	Insee-RP-historical data since 1968 (Employment areas (2010))
Agriculture	Share of the agricultural sector of the EA	Insee-RP-historical data since 1968 (Employment areas (2010))
Industry	Share of the industrial sector of the EA	Insee-RP-historical data since 1968 (Employment areas (2010))
Tertiary	Share of the tertiary sector of the EA	Insee-RP-historical data since 1968 (Employment areas (2010))
Construction	Share of the construction sector of the EA	Insee-RP-historical data since 1968 (Employment areas (2010))

Table 2.8.2: Distribution of individuals according to their level of education

Education level	Number of individuals	Proportion
0	43	1.58
15	225	8.28
16	442	16.27
18	326	12.00
19	497	18.30
20	49	1.80
21	579	21.32
24	555	20.43

Table 2.8.3: Correlations between productivity index-measures of satisfaction and external instrument

	Job obtained through the internship
Total productivity	0.08
Efficiency changes	0.06
Technological changes	-0.04
Pay satisfaction	0.31
Satisfaction with career prospects	0.27

Table 2.8.4: Determinants of employment: *Probit* regression

<i>Individual characteristics</i>	
Men	0.017***
Lives with parents	-0.169***
Foreign origin	-0.121***
Child(s)	-0.122***
Exact sciences	0.148***
Social sciences	0.060***
Bac	0.159***
Short higher education	0.355***
Long higher education	0.398***
Time to first job	-0.005***
<i>Characteristics of the geographical area</i>	
Youth index (2017)	0.001***
Industry share in % (2017)	0.022***
Service sector share in % (2017)	0.014***
Construction share in % (2017)	0.006***
Unemployment rate of the EZ (2017)	-0.022***
Constante	-0.653***
N	2,716
% concordant	61.1

Chapter 3

How different opportunities and advantages affect the decision to quit? Exploring the relationship between status, inequality aversion, and job retention

Sommaire

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Résumé:

Ce chapitre analyse la probabilité que les travailleurs démissionnent en réponse à des comparaisons salariales et non salariales liées au temps de loisirs et à la satisfaction à l'égard de la santé, en utilisant les données du panel socio-économique allemand de 1998 à 2019. L'étude montre que les travailleurs sont plus susceptibles de démissionner s'ils perçoivent un salaire inférieur aux taux du marché ou s'ils ne sont pas satisfaits de leur temps de loisirs, les hommes étant plus sensibles aux comparaisons salariales et les femmes à la satisfaction liée au temps de loisirs. Toutefois, les femmes qui perçoivent des salaires élevés ou qui travaillent dans des secteurs à prédominance masculine sont également influencées par les comparaisons salariales. Les résultats montrent également que les événements structurels tels que les crises et les récessions augmentent la probabilité que les travailleurs démissionnent, les travailleurs à salaire moyen étant les plus touchés en termes de congés et de santé, et les effets sur les salaires variant d'un secteur à l'autre. En outre, l'étude souligne l'importance des considérations de statut et de l'aversion pour l'inégalité dans la décision des travailleurs de quitter leur emploi.

Abstract:

This chapter analyzes the probability of workers quitting in response to pay and non-pay comparisons related to leisure time and health satisfaction, using data from the German Socio-Economic Panel from 1998 to 2019. The study finds that workers are more likely to quit if they receive pay below market rates or are dissatisfied with their leisure time, with men being more sensitive to pay comparisons and women to leisure time satisfaction. However, women with high pay or working in male-dominated sectors are also influenced by pay comparisons. The results also show that structural events such as crises and recessions increase the likelihood of workers quitting, with middle-pay workers being the most affected in terms of leave and health, and the effects on pays varying across different sectors. Additionally, the study highlights the importance of status considerations and aversion to inequality in workers' decisions to quit their jobs.

Key words: Quit, Pay comparison, Job satisfaction, Gender, Inequality, Panel data.

JEL Codes: J62, J31, J16, J28, D63.

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3.1 Introduction

IN Germany, since the grand coalition came to power in 1998, the labor market has become more dynamic, with a downward trend in the unemployment rate. However, despite reforms and policies to improve working conditions, notably with the Hartz reforms, the market has seen a significant quit movement. The reason for these quits may be that employees are increasingly looking for a better level of income, and a better working environment to finance their health, leisure and living expenses. These decisions are usually based on a cross-sectional comparison with their peers in the labor market.² When making the decision to quit their job, do employees primarily compare their pay to external opportunities? Or are they more affected by non-monetary aspects related to their well-being?

Motivated by these questions, this paper analyzes how job quits react to pay comparisons between own and external benchmark pays or other non-monetary aspects. Using panel data on a sample of employees in the German labor market drawn from the German Socio-Economic Panel (SOEP), we examine how quits are affected both by whether a worker receives a lower or higher pay than the external opportunities they would enjoy if they left their job, and by the effect of non-monetary rewards as alternatives to pay. We observe that job separations occur due to several reasons, but separations due to quits represent a much higher proportion compared to separations due to other reasons mentioned (see Figure 3.8 in the Appendix). Given that Germany is one of the economic engines of Europe and has the lowest quit rate but the highest separation due to quits, knowledge of the determinants of quits in Germany is particularly relevant (Lévy-Garboua et al., 2001).

This paper contributes to several strands of the literature on quitting. First, we contribute to the literature on predicting external pay³ (for example, see Clark et al., 1996; Pfeifer and Schneck, 2012). Previous literature has used the linear regression approach to predict reference pay.⁴ However, this approach assumes linear regression and low collinearity between the independent variables. This assumption seems strong when we consider that most of the explanatory variables for pay are categorical and collinear, and hence prediction by the regression approach may be

²According to the theoretical model, workers optimally search for and inform themselves about external job opportunities and accept any job with higher total compensation (Lévy-Garboua et al., 2007; Mohrenweiser and Pfeifer, 2019). The probability of receiving such an offer during a specified interval depends on the relative position of the individual in the distribution of total rewards and the degree of relaxation of total rewards in the labour market (Akerlof et al., 1988).

³In this study, we consider "pay" to refer to the total compensation after deduction of taxes and other mandatory deductions.

⁴Akerlof et al. (1988) and Viscusi (1980) predicted the reference pay from a regression on an extended group of characteristics. Clark et al. (1996) tested the hypothesis that utility depends on pay relative to a comparison or baseline on a set of 5,000 British workers. They determined the baseline pay by estimating a classical pay equation over the entire sample of employees and then using this regression equation to predict a pay level for each individual. These pay levels correspond to the pay of "typical" employees with given characteristics. Pfeifer and Schneck (2012) used a German employer-employee linked dataset to analyze the importance of relative pay positions in the context of individual quitting decisions. They used several comparison pay measures along an internal or external dimension, an earnings function is estimated for all individuals in all firms for each year, and then they predicted the external reference pay for each individual based on the results.

less accurate. Moreover, when the dimension of the model inputs becomes larger, as in our case, it becomes very difficult to model the relationship between pay and its determinants exogenously. In this study, we adopted the machine learning algorithm with the Decision Tree (DT) method approach, which is increasingly favored due to its efficiency and ability to solve practical prediction problems. Specifically, we predict our external pays using the Gradient Boosting Regression Tree (GBRT), which is unique in that it achieves predictive accuracy goals (Friedman, 2001) by constructing additional regression trees by minimizing the prediction residuals of the existing baseline models (Schapire, 2003). With the boosting approach, GBRT handles difficult cases by generating an optimal set of trees, which can not only capture the complex and nonlinear features of some determinants but also improve the overall prediction performance (Yang et al., 2020).

This paper also contributes to the literature that studies the impact of nonmonetary rewards on employee quit decisions (for example, see Clark et al. (1997); Clark and Georgellis (2004)). Previous works have examined the effect of job satisfaction.⁵ Thanks to the richness of our data, we have the advantage of examining the effect of two new measures, namely satisfaction with leisure time and satisfaction with health (Lévy-Garboua et al., 2001). These measures are very important in this study because they are directly related to the non-pay differentials between experienced jobs and external opportunities and represent the most consistent measures of non-monetary rewards (Lévy-Garboua et al., 2007); this allows us to measure the effect of the trade-off of monetary aspects for non-monetary rewards on the decision to quit.

Finally, our paper contributes to the quit literature by conducting analyses by pay levels and industries. Previous studies have examined different measures of pay on the decision to quit at the aggregate sample level (for example, see Godechot and Senik, 2015; d'Ambrosio et al., 2018). However, quit behavior may differ depending on whether the individual has low, medium, or high pay or whether the individual is in industries where working conditions are difficult. Thus, analysis of the determinants of quits that places all individuals in a single sample set may be less effective, as the effect of some of the more influential individuals may overshadow the effect of others. In this study, in addition to the analysis at the overall sample level, we will also subdivide our sample into different groups according to different pay levels and observe the effect of pay comparisons and non-monetary rewards on their decision to quit. Moreover, we will study quit intentions within the different sectors.

We begin by estimating the external reference pays. In our study, the reference pay is interpreted in an occupational sense, meaning it is the typical pay of people who share the employee's characteristics, skills, sector, productive position, and geographic area. This is because people with these same characteristics provide a natural benchmark for comparison (Senik, 2008). More

⁵Clark (1997) used subjective assessments of job satisfaction of German workers to predict their mobility. In their study, job satisfaction is implicitly assumed to reflect individuals' expectations of future pays and working conditions. Clark and Georgellis (2004) also contributed to the validation of job satisfaction scores by relating satisfaction at time t to the probability of quitting between time t and time $t+1$. They consider *ceteris paribus* that workers who report low levels of job satisfaction in period t would be more likely to leave their jobs in the period between t and $t+1$.

broadly, these predicted pays are interpreted as an expected external pay offer (Pfeifer and Schneck, 2012). To obtain accurate predicted pays, we used the GBRT algorithm and ran 1,000 iterations of the decision trees. We also applied a natural logarithmic transformation to the dependent variable of pay.

We subsequently estimated the response of quitting to pay comparisons and non-monetary rewards using a random-effects model with a dummy dependent variable. In this specification, the effect of pay differences is accounted for by incorporating the ratio of own pay to reference pay. Satisfaction with leisure and satisfaction with health are taken into account by considering the level of satisfaction that the individual declared before deciding to leave or not the following year. All time-varying regressors are lagged one year before observing the quit decision the following year. Using a one-year lag allows us to capture the effect of temporal variables that may influence the decision to quit. For example, if a worker has recently received a promotion or a pay raise, they may be less likely to quit even if they are currently dissatisfied with the job. By using a variable lagged one year, we can better predict the probability of quitting. Additionally, using a one-year lag can help reduce the effects of seasonality or short-term economic fluctuations that might influence the decision to quit.

Our estimates show that employees who are paid higher than the pays paid to other workers who fit their occupational profile in the market are less likely to quit their job. In addition, the likelihood of quitting decreases for those who express high satisfaction with leisure and increases for those who are satisfied with their health. These results indicate that employees may quit if they do not receive a higher pay than their peers in the market or if their job does not allow them to be satisfied with their leisure time. However, behavioral models consider that quits might be less important when the economic context is not favorable. For example, in the case of high unemployment, a worker might decide to stay in their job because of uncertainty about getting another better job.

To test the effect of unemployment, we included the unemployment rate and its square in our previous specification. The results indicate that quit behavior is not significantly affected by changes in the unemployment rate, suggesting that employees may make their decision to quit based on other factors, such as pay and leisure. The effect of pay is consistent with the status effect hypothesis (Clark et al., 2009). The standard estimates suggest that receiving a pay below the reference pay may be perceived as unfair and of low social status, which could increase the probability of quitting. Some studies have shown that low baseline pays are associated with lower quit rates (Galizzi and Lang, 1998; Pfeifer and Schneck, 2012). Card et al. (2012) find that employees with pays below the median of their unit report a significant increase in the likelihood of seeking a new job.⁶

⁶Other studies find a positive sign of the effect on quits, i.e., employees with lower pays have a lower propensity to quit from their jobs, which is the interpretation of the signal effect (e.g., see Clark et al., 2009). However, we cannot test the signaling hypothesis in this study as we only observe the effect of external pay comparisons due to the data limitations.

To test this status hypothesis more directly, we estimated a specification in which we split the effect of the ratio between the two pays into two effects depending on whether the ratio is strictly greater than one, i.e., the individual's own pay is strictly higher than the reference pay, and whether the ratio is strictly less than one, i.e., the individual's own pay is strictly below the reference pay. These results seem to confirm the status hypothesis. They show that employees who are paid higher pays than the reference pays are more likely to stay in their jobs, while those who are paid lower pays seem to have a higher probability of quitting.

Further analysis enables a better understanding of the reasons for separation by subdividing the individuals in our sample according to their pay level or sector of employment. These specifications allow us to identify the mechanisms that lead to quits, depending on whether the employee belongs to a low, medium, or high pay level or to sectors with working conditions that appear more challenging than others. The results reveal asymmetric responses in the probability of quitting.

The remainder of the paper is organized as follows. Section 3.2 describes the data, and Section 3.3 describes the empirical strategy. We begin with the GBRT approach to predicting external reference pays. We then estimate the probability of quitting by incorporating the predicted pays to account for pay comparisons. Section 3.4 presents the main results on the prediction of reference pays, the effect of monetary and non-monetary rewards on the probability of quitting, and analyzes these effects at different pay levels. Section 3.5 examines the robustness of the results. The final section reviews the estimates and discusses their implications.

3.2 Related Literature

Labor economics theory has produced some powerful predictions about job separation in job-matching models (Galizzi and Lang, 1998). These models suggest that workers acquire new information over time about external employment opportunities or their productivity in their current job (Burdett, 1978; Jovanovic, 1979a,b, 1984). As workers gain new information, they may move between firms in order to maximize their expected present value of lifetime wealth. Departures from their current job occur when the expected utility flow of an alternative job is greater than that of their current job, net of the costs of moving (Clark, 2001). The value of the current job depends on the pay trajectory, since workers can always quit in the case of a bad pay outcome, as well as on uncertainty, which may be a good thing rather than a bad thing, provided workers are not too risk-averse (Galizzi and Lang, 1998).

We can formalize the decision to quit by considering the lifetime utility maximization decision, in which a worker will choose to change jobs if the following condition is met (Lévy-Garboua et al., 2001):

$$E_{it}V_{it} - E_{it}V_{it}^* + C_{it} < 0 \quad (3.1)$$

With $E_{it}V_{it}$ the present value of pays or non-monetary work benefits expected by the worker i at time t ($t > 0$) if he stays with his employer. $E_{it}V_{it}^*$ is the corresponding value if he quits, and C_{it} is the cost of mobility. The total reward for work that determines the overall level of satisfaction achieved by a worker in a given job consists of two elements: the pay, or monetary reward, and a non-monetary reward (Akerlof et al., 1988).

Previous research has conclusively shown that voluntary labor mobility is strongly correlated with income comparisons (e.g., Akerlof et al., 1988), especially when individuals are interested in comparing their pay with others (Clark et al., 1996, 2009). In modern times, Adam (1965) discussed how low relative pay could be perceived as unfair. Further developments in the literature on comparison income were motivated by Hamermesh (1975), Frank (1985), and Akerlof et al. (1988). From an equity perspective, better outcomes for comparable workers at other firms could be interpreted as unfair pay by one's own firm, and this violation of equity could decrease utility and increase the likelihood of quitting Clark et al. (2009).

Empirical studies (Clark et al., 1996; Galizzi and Lang, 1998; Kim, 1999; Fairris, 2004; Godechot and Senik, 2015) and experimental studies (Card et al., 2012) generally consider pay comparisons to be crucial for studying the probability of workers quitting. For example, Card et al. (2012) found, in a field experiment on information processing among University of California employees, that workers who know they are earning a lower relative pay have a higher probability of seeking a new job. Previous studies using survey data (without information about workers within the same firm and, therefore, without internal pay structure variables) have reported evidence that perceived unfair pays, the gap between fair and actual salaries, and external benchmark pays are negatively correlated with job satisfaction and turnover intentions and positively correlated with actual quits (e.g., Clark et al., 1996; Von Felix and Pfeifer, 2013; d'Ambrosio et al., 2018). Using matched German employer-employee data, Pfeifer and Schneck (2012) found a nonlinear U-shaped effect with respect to relative position, as workers in relatively low-pay positions may quit because of their lower status and those in high relative-pay positions because of their low career advancement opportunities. In this case, an increase in income for one person may produce negative externalities for another person (Luttmer, 2005).

Previous work has highlighted the role of non-monetary factors in explaining voluntary labor mobility, such as in the studies by Gottschalk and Maloney (1985) and Borjas (1979). To illustrate, using data from the Study on Income Dynamics panel, Gottschalk and Maloney (1985) and David (1974) provided econometric evidence of the role of non-pecuniary factors in quit decisions. Previous studies have validated the importance of non-monetary rewards in predicting quitting behavior by linking job satisfaction at time t to the probability of quitting between time t and $t + 1$, beyond the effect of reported pay. For instance, Freeman (1978b) and Borjas (1979) conducted such a study using American data. Similarly, Clark et al. (1998) and Clark (2001) modeled this relationship using data from the German Socio-Economic Panel (GSOEP) and the British Household Panel Survey (BHPS), respectively. Lévy-Garboua et al. (2007) considered

non-monetary rewards such as leisure time satisfaction and health satisfaction in their study on Germany, using SOEP data. They tested the indirect effect of these factors on the probability of quitting by including the residuals of satisfaction with non-monetary and monetary rewards in their model. However, their results suggested that the residuals of satisfaction with non-monetary rewards did not significantly affect workers' probability of quitting.

In this section, we build on this literature to study workers' reasons for quitting in the case where individuals compare their pays to external monetary offers and in the case where workers are interested in the non-monetary rewards received in their jobs. External pays will be predicted with respect to workers with similar profiles. For non-monetary rewards, we follow Lévy-Garboua et al. (2007) and consider health satisfaction and leisure time satisfaction. Before moving on to the modeling strategy, it is appropriate to describe the data, as their nature is important and crucial to our approach.

3.3 Data and Descriptive Statistics

We aim to estimate the probability of quitting. However, since the factors that influence quitting are based on past experiences while quitting occurs in the future, our study requires individual panel data over a long period. To meet these prerequisites, we use data from the German Socio-Economic Panel (GSOEP), which is an annual survey conducted by the German Institute for Economic Research (DIW, Berlin) with a sample size of approximately 15,000 households or 30,000 individuals. The GSOEP is recognized by the scientific community, as evidenced by the existence of a large international and multidisciplinary research community (see for example, Lévy-Garboua et al., 2007; d'Ambrosio et al., 2018).

Our data are particularly well-suited for this study as the survey provides detailed information on respondents' biographies, employment, income, and measures of subjective well-being over time. We obtain our variables and sample by merging data from several GSOEP files. Specifically, we extract monthly net pay⁷, employment status, education level, and basic personal characteristics (such as age, gender, marital status, etc.) from the personal database generated by the GSOEP. We also incorporate additional variables on the region of residence of respondents and characteristics of their base household from the GSOEP household files. In addition, we link to these variables a dataset that covers information on subjective well-being and job changes from the detailed personal databases of the GSOEP survey and the job transition history.

The dataset used in this study is a non-cylindrical panel covering the period from 1984 to 2019. However, until 1984, the sample only included individuals living in West Germany. After the reunification of Germany in 1990, individuals who moved from West to East Germany were pursued and surveyed between 1990 and 1992, while the inhabitants of East Germany were not

⁷Monthly net pay refers to the total compensation that the worker receives for their work after deduction of taxes and other mandatory deductions.

yet included in the sample. It was only in 1993 that the inhabitants of the East were included in the survey. For this study, we have chosen the years 1998 to 2019, as it is in this interval that we have complete samples in both East and West Germany. Furthermore, we have chosen this interval due to methodological reasons - some control variables are left-censored before German unification in 1998. We consider individuals who entered the labor market from 1998 onwards and follow them throughout their careers to ensure homogeneity in the panel.⁸ Our sample is limited to employees of working age (16 to 65 years), as pensioners and self-employed individuals may behave differently from prime-age employees (Viscusi, 1980). The accuracy of our estimates depends on individuals having income from their main job and providing responses regarding satisfaction or quitting. Therefore, we have excluded workers for whom key information is missing, such as missing pay or satisfaction responses, or reasons for job termination.

We have observed inconsistencies in the reported incomes of some individuals, likely due to data entry errors. For example, we observed a payment of 60,000 euros for one individual, whereas their payment was about 2,000 euros in the previous year. We have excluded these payments from the sample. We also discarded payments that were very high but characterized only one person or a small proportion of individuals, as well as payments identified as outliers. However, removing these payments did not substantially affect our estimation results.

Table 3.9.1 in the appendix presents the characteristics of our sample. The final estimation sample consists of 247,349 employees. The sample is predominantly German (90.2%), educated (with an average of approximately 12 years of education), married (61.6%), and in very good health (72.2%). There are roughly equal proportions of men and women. Individuals are relatively old, with an average age of approximately 42 years. The employees in our sample earn on average 2,356.03 euros per month, work an average of 37 hours per week, and work mainly in medium-sized companies with between 20 and 200 employees (44.9%). They are mostly qualified (27.3%) and have relatively high tenure and work experience in full employment, with approximately 10 and 15 years, respectively. The table also highlights some sectoral differences, with firms in the manufacturing, services, and trade sectors employing on average more workers.

Our primary outcome of interest is the probability of quitting work. The data contain information on employment spells that begin or end during our sample period. With this information, we constructed the transitions from one job to another. In addition to the spells data, we observe the reasons for separation from each job. Based on this information, we define a quit of employment as a change of employment that was caused by the worker leaving his or her job voluntarily (i.e., by resigning) (d'Ambrosio et al., 2018). We thus created our dependent variable of probability of quitting, which represents a dummy variable for individuals who voluntarily quit their job.⁹ In

⁸Although we do not necessarily have the same individuals, we have taken this heterogeneity into account in our estimates. We will also provide year-by-year estimates.

⁹The pooled data statistics presented in Table 3.9.2 in the appendix show that nearly 15% of turnover in our sample, and about 31% of those who leave, indicate reasons related to quits that represent job-to-job transitions

this sense, employees who left their jobs for involuntary reasons such as redundancy, mutual dismissal, temporary jobs ending, and company closure, are excluded from the sample because, for these workers, the decision to quit is likely to have been the result of a choice by the employer or labor legislation. In addition, departures for personal reasons, e.g., retirement or old age pension, or departures to pursue studies, although considered as voluntary departures, are excluded from the sample, as these departures are not conditional on quit.¹⁰ However, workers who left for reasons of employer- or employee-induced transfers or for reasons of leave (sabbatical, maternity, and parental) are included in the sample of workers who remained in their jobs, as their absence from their jobs is considered temporary.

Figure 3.1 displays the distribution of job quits according to our definition of quitting. The data reveals that quit rates vary from year to year. Specifically, we note that the quit rates were low in 1998 and 1999, which could be attributed to the conservative economic policies introduced by the Christian liberal coalition from 1993 to 1997 (Clasen, 2000). These policies aimed to reduce public spending and tighten access to benefits, which may have made workers less likely to quit their jobs during this period. However, the high peak in quits observed in 2000 suggests that the 1998 reforms that gave employees more freedom to move to other job offers may have played a role. It's possible that these reforms made it easier for employees to leave their current jobs and seek better opportunities elsewhere. Moreover, the growing economy during this time may have created more job openings, further encouraging workers to explore different positions. Other policy changes or economic factors may have also influenced the high quit rate in 2000.

From 2010 to 2014, there was a significant increase in job quits, culminating in the highest peak. One explanation for this trend is the subprime crisis of 2007-2008 and the subsequent economic recovery, which led to labor market reforms such as the Hartz reforms in Germany (Kinderman, 2017). These reforms, particularly regarding dismissal and compensation, made it easier for workers to take up other job offers. The overall economic conditions during this period, including an increase in job opportunities and a decrease in unemployment, may have further incentivized workers to explore other employment options. Additionally, the increasing importance of work-life balance and employee satisfaction may have prompted workers to seek jobs that better align with their personal and professional goals.

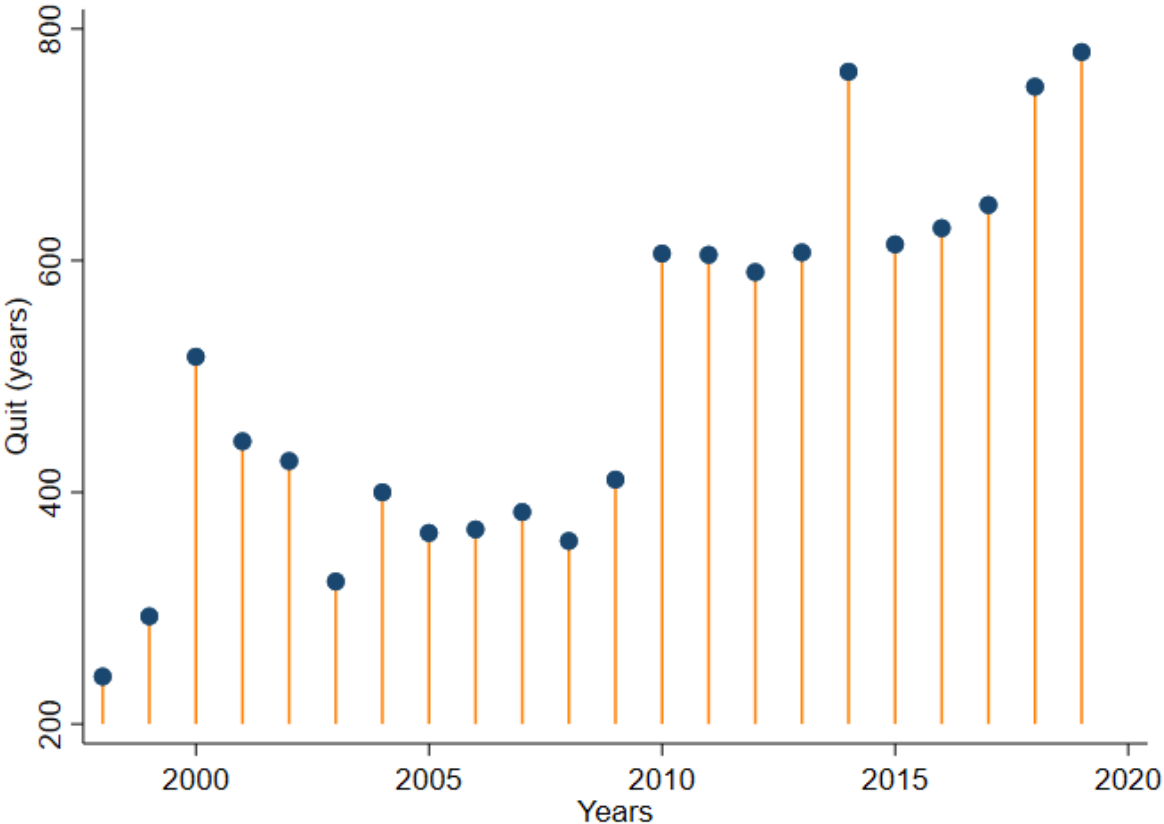
The trend in job quits sharply declined from 2015 before increasing again in 2018 and 2019. The decrease in 2015 could be attributed to the introduction of the minimum wage, which may have led to workers staying in their jobs rather than quitting (Garloff, 2019). However, the minimum wage also brought changes to the German labor market, resulting in the disappearance

as individuals quit to change jobs. Other reasons for leaving include layoff (12%), company closure (5%), end of test period (13%), return to school (0.1%), move or transfer to another company (0.2%), mutual termination (8%), retirement (0.8%), leave or temporary absence (1.7%), and ended self-employment (2.2%).

¹⁰These mobility events other than voluntary departures due to quit are included in the calculation of the comparison pays but are excluded only in the regression of the determinants of departures (Pfeifer and Schneck, 2012). However, the inclusion of these types of mobility in the propensity to quit regression has no impact on the results.

of mini jobs or part-time jobs in favor of more stable employment. As a consequence, we observed a peak in job quits from 2018 onwards.

Figure 3.1: Job quits by year



Notes: Author’s calculation based on data from GSOEP (1998--2019). The figure represents the number of individuals who quit their jobs by survey year using our definition of quits.

In our empirical analysis, we will consider the full range of economic conditions by including dummy variables for each year in our regression models. This will enable us to capture any effects that changes in economic conditions may have had on job quits. Additionally, we will perform robustness analyses by estimating the models with shorter time intervals. This will help to confirm the stability of our results with respect to the inclusion of these variables and provide further evidence for the relationships between the variables we are investigating. The next section will present the empirical specification of our analysis, where we will outline models used to investigate the probability of quit job.

3.4 Econometric Specification

This section begins with a description of the Gradient Boosting Regression Tree (GBRT) model that has been trained and validated to predict external comparison pays from a set of characteristics considered as pay determinants. We then discuss the procedure for estimating the determinants of workers’ job quit decisions.

3.4.1 Gradient Boosting Regression Tree (GBRT) model for pay comparison estimation

To predict external comparison pays, we used a Machine Learning algorithm called Gradient Boosting Regression Tree (GBRT), which is well-suited for categorical independent variables and can handle collinearity. GBRT is based on the decision tree model, which is popular in Machine Learning due to its ability to describe non-linear and complex relationships between input and output data, interpret input features, robustness to outliers, and higher prediction accuracy (Yang et al., 2020). Decision trees, also known as Classification and Regression Trees (CART), were described by Breiman et al. (1984) and Hastie et al. (2009). They work by dividing the feature space into regions using binary splits and fitting a different (linear) model to each region (Johnson et al., 2017). The split point is determined to minimize the residual sum (Friedman, 2001). This process results in a single tree structure that best describes the underlying relationships between variables in a dataset (Yang et al., 2020).

The GBRT model extends traditional decision tree modeling by incorporating a statistical technique called boosting (Johnson et al., 2017). Boosting methods combine weak learners by iteratively focusing on the errors resulting from each step until an appropriate strong learner is obtained as a sum of successive weak learners (Nie et al., 2021). Thus, with GBRT, decision trees are created sequentially using the residuals of the previous tree as input to the new tree. In this way, the model learns the relationship between features based on the errors in the previous tree (Johnson et al., 2017).¹¹

To optimize the performance of the model, it is necessary to adjust some parameters such as the number of trees, their depth, and the learning rate. The depth of the trees is particularly relevant, as it determines the degree of interaction between the features relevant for a prediction (Johnson et al., 2017). Shallow trees of the order of 4 to 6 are often preferred (Friedman, 2001). The learning rate is also important, as it determines the contribution of each tree to the model, and it is preferable to have the lowest possible value for a more accurate prediction (Li and Bai, 2016). The final model is a combination of all decision trees, and their contribution to the overall model is weighted by the learning rate (Johnson et al., 2017).

Our objective is to predict the pay of workers with the same profile in the job market. We have developed a spatio-temporal model that takes into account various characteristics, including time-varying and time-invariant factors, as determinants of pay. These include six continuous variables (work experience, number of hours worked per week, age, years of education, number of individuals in the household, and number of children) and seven categorical variables (level of qualification, marital status, nationality, size of the company, type of occupation, industry, and health status). We have created dummy variables for the categorical variables to avoid treating them as continuous variables. The spatial location across the 16 federal states (*Länders*) and the

¹¹This sequential model building process is a form of functional gradient descent that optimizes prediction by adding a new tree at each step that best reduces the loss function (Elith et al., 2008).

different survey years are also included as inputs. The output vector is the gross monthly pay received by employees in their jobs, and the predictions have been made based on these inputs.

We have divided the data into two parts: a training set (80% of the observations) to develop the model and a test set (20% of the observations) to validate the performance of the model. We have tuned several parameters, including the number of trees, tree depths, and learning rate, to optimize the model's performance. The model is trained and validated with different options until the most accurate pay prediction model is obtained¹² The prediction is made for each year and for each *Länders* considered, so that we can predict pay for each individual considering their place of residence and work, their characteristics, and the survey year considered. We have created the GBRT model using all explanatory variables to predict pay and finally performed predictions on the test data set to assess the generalizability of the model.¹³

We have found that absolute values of pay are too large for machine learning to handle accurately. Therefore, we have performed logarithmic transformations, which have given us more accurate results. After the prediction, we have done the inverse logarithm to find the true values of the prediction. We have evaluated the performance of the GBRT models using the coefficient of determination (R^2) and the root mean square error ($RMSE$). Higher R^2 coefficients and lower $RMSE$ indicate greater accuracy and precision of a pay prediction model.¹⁴ We have calculated R^2 and $RMSE$ after each annual prediction to assess how the performance of the model varies over time and whether the model is stable. We have also evaluated the overall performance of the model by representing the predicted values in the training and test data. The technical details of the model are provided in Section 3.10 (Subsection 3.10.1) of the Appendix.

3.4.2 Methodology for estimating the probability of quit

We aim to estimate the factors that explain employees' decision to quit, with a particular focus on the effect of pay comparisons with outside opportunities. Additionally, we investigate the impact of other non-monetary factors related to employee well-being on the likelihood of quitting. Explanatory variables that may vary over time are included with a one-year lag to account for the influence of time variables on the quitting decision and to mitigate the effects of seasonality or short-term economic fluctuations that could affect the decision to quit. We estimate the following model:

$$P(Q_{it} = 1) = a + \alpha T + \theta_1(w_{i,t-1}/\widehat{w}_{i,t-1}^{(M)}) + \theta_2 L_{i,t-1} + \theta_3 H_{i,t-1} + \tau U + \sum_k \pi' z + \lambda_R(i) + \eta_i + v_{it} \quad (3.2)$$

¹²Numbers of trees: 200--1000, Tree depths: 2--6, Learning rate: 0.005--0.500, and a maximum of split of 4.

¹³When we build a prediction model, we want it to be able to be applied to new data that was not used to train the model. The test set is used to simulate this scenario by providing a data set that was not used to fit the model parameters. By performing predictions on this data set, we can assess how well the model generalizes on new data and estimate its accuracy.

¹⁴GBRT was implemented using the Python package "Scikitlearn", version 17 (Pedregosa et al., 2011).

The left-hand side of the equation represents a dummy variable indicating whether individual i left their job to join another employer in period t . The vector $w_{i,t-1}$ represents individual pay, while $\widehat{w}_{i,t-1}^{(M)}$ denotes the external comparison pay estimated from GBRT. The ratio $w_{i,t-1}/\widehat{w}_{i,t-1}^{(M)}$ allows for comparisons of pays.¹⁵ $L_{i,t-1}$ and $H_{i,t-1}$ represent non-monetary rewards in terms of satisfaction with leisure time and satisfaction with health, respectively. We have chosen these two measures based on the work of (Lévy-Garboua et al., 2001, 2007), as they are directly related to non-pay differentials between experienced jobs and external opportunities and are also considered the most consistent measures of non-monetary rewards. As these variables were measured on a scale ranging from 0 to 10, we consider them as continuous variables in the regression to account for the incremental variation in these two non-monetary reward measures.¹⁶ z_{it} is the vector of individual characteristics such as age and gender. We did not include these characteristics with a one-year lag because we assumed that age generally does not change dramatically from year to year, and it is often considered a continuous rather than a discrete variable. In addition, we assumed that gender is a stable variable over time and does not have a clear temporal relationship with the probability of quitting.

If we consider the simple effect of these determinants, it is assumed that the errors are independent of them. However, we have a large panel of individuals, and if specific unobservable characteristics of individuals are not taken into account, the estimates will be biased upward. For example, more able and motivated individuals are more likely to find a good job in which they are more satisfied and less likely to quit (Gielen and Tatsiramos, 2012). Moreover, since the probability of leaving, which is the dependent variable, is a dummy variable, it only varies for individuals who move during the sample period. In this sense, the weight of mobile individuals is higher than in the other models, and these individuals are the most likely to move (Falch, 2011). In our specification, we control for this by including individual fixed effects (η_i) in the estimates. In addition, we take into account time fixed effects T to account for annual changes that are the same for all individuals. Because we consider external comparison pays, their effect on quits reflects variation across markets. In our specification, we control for heterogeneity across markets by using fixed effects for different regions of Germany (16 Länder) ($\lambda_R(i)$). We included these regions without delay because we assume that they are not a measure of the state of a variable over time but rather a characteristic of geographic location. We included the regional unemployment rate (U) in the regressions. Unemployment rates are derived from the German Federal Statistical Office: <https://www.destatis.de/EN/Home>. Behavioral models tend to view the quit factor as preeminent, and opportunity is viewed as a door that is more open during periods of relatively high employment than during periods of relatively high unemployment (Jovanovic, 1984). In particular, these considerations imply that quits should vary with the level of unemployment in the market. The rationale for including the unemployment

¹⁵Pay differentials are often considered in the literature (e.g., see d'Ambrosio et al., 2018). However, in our specification, we consider the ratio of the two pays, which has the same function as the differential. Only the ratio takes devaluation into account, and the interpretation with the ratio is more noticeable.

¹⁶In Figure 3.9 in the appendix, we report the distributions of responses for the measures of satisfaction with leisure and health among the individuals in our sample. Individuals in our sample are generally satisfied with leisure time and health. The largest proportion rated their level of satisfaction on both measures with a score of 8.

rate in the estimation of the probability of quitting is that the unemployment rate may influence the job search behavior of workers. When the unemployment rate is high, workers may be more likely to quit their current job because of greater confidence in their ability to find a new job quickly. Therefore, by including the unemployment rate in the estimate of the probability of quitting, the potential effect of the labor market on quitting decisions can be captured. We included this variable without a lag because it can be considered an exogenous variable that does not affect the probability of quitting with a delay. The unemployment square is also taken into account to test the non-linear effect and to observe low and high-level cycles in unemployment spells.

The coefficients of interest in (3.2) are θ_1 , θ_2 , and θ_3 . The coefficient θ_1 measures the effect of the difference between the actual pay and the predicted pay of the previous year on the probability of quitting. In other words, it measures how the difference between a worker's expected pay and actual pay in the previous year influences their decision to quit or not. If the coefficient θ_1 is positive, it means that the lower the actual pay is below the expected pay, the higher the probability of quitting. If the coefficient θ_1 is negative, it means that the higher the actual pay is above the expected pay, the lower the probability of quitting. If the coefficient θ_1 is close to zero, it indicates that the difference between the actual and expected pay has no significant effect on the probability of quitting. The coefficient θ_2 measures the impact of leisure on the probability of quitting, all else being equal, while the coefficient θ_3 measures the impact of health on the probability of quitting, all else being equal. A positive value for θ_2 indicates that the higher the level of leisure, the higher the probability of quitting, while a negative value indicates the opposite. Similarly, a positive value for θ_3 indicates that the higher the level of health, the higher the probability of quitting, while a negative value indicates the opposite.¹⁷ v_{it} represents the usual error term.

In the probability of quitting equation, the time fixed effects have been replaced by a specific year constant and the unemployment variable is taken at the current year. Thus, it is possible to use either a random effects model or a fixed effects model. However, fixed-effects models can be problematic with a non-cylindrical panel like in this case, as they require an additional identification variable to identify the fixed effects. Random effects models may be a more appropriate alternative as they estimate fixed effects using a probability distribution that captures heterogeneity among individuals (Wooldridge, 2010). Additionally, we have included time-invariant variables such as gender, and unobservable individual effects are likely to be correlated with these variables, further justifying the use of random-effects models. We have ensured that the assumptions for estimating random effects models were met, such as no time autocorrelation and no correlation of the random effects with the explanatory variables. We have also confirmed that the variables are correctly specified, and there are no missing or incorrect variables in the model.

¹⁷It is important to note that the coefficients θ_2 and θ_3 do not allow us to draw conclusions about causality, but rather about the association between these variables and the probability of quitting.

However, the predicted external reference pays included in the probability of quitting equation may contain prediction errors, which could propagate into the estimate of the probability of quitting and affect the precision of the coefficient estimates. We have therefore corrected for standard errors using the bootstrap method. We have estimated our regression model up to 1,000 replications using random samples of the dataset and calculated the standard deviations of the coefficients for each replication. We have used these standard deviations to calculate more precise confidence intervals for the coefficient estimates. After explaining the empirical specifications, the next section will present the results of the probability of worker quit analysis.

3.5 Predicted pay and quits: results

This section contains the first step of the empirical analysis. It first presents the results of the prediction of reference pays by the GBRT method. It then verifies our empirical strategy by showing that pay comparisons and non-monetary rewards are important determinants of employee quits. In this last specification, results at the overall sample level will be presented as well as more detailed results by pay level and industry.

3.5.1 Results of the GBRT algorithm

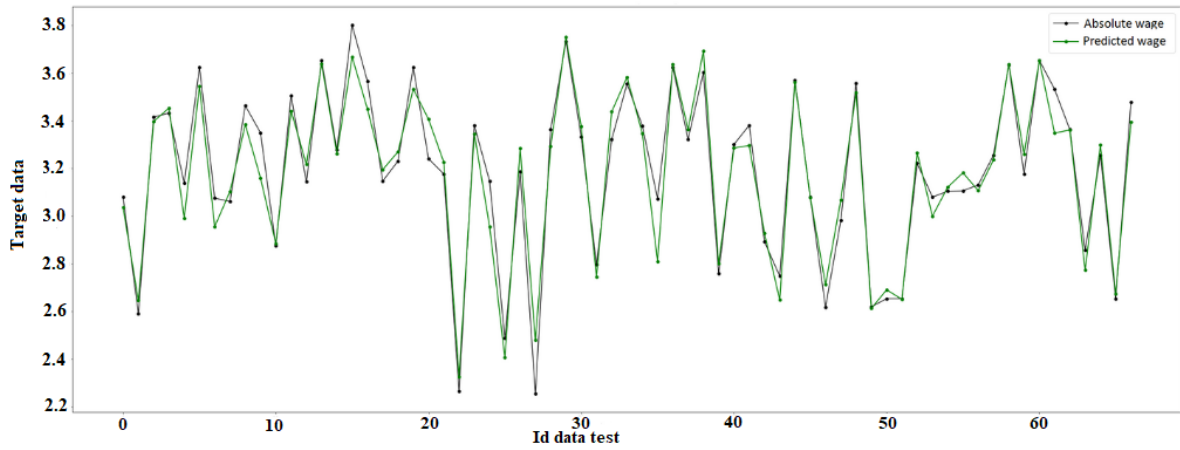
Table 3.5.1 presents the results of the external pays prediction performance over time, as measured by the coefficient of determination (R^2) and the root mean square error ($RMSE$). Overall, the results demonstrate that the prediction of external reference pays using the GBRT model is highly accurate, with high R^2 values and low $RMSE$ values. These findings suggest that the GBRT model is capable of effectively learning the necessary information from the training set, and thus, the predicted external reference pays may be a valuable variable to include in the probability of quitting regression. The strong predictive relationship between predicted external reference pays and employees' decisions to quit highlights the potential importance of this variable in understanding and predicting employee quit.

Table 3.5.1: Accuracy test results

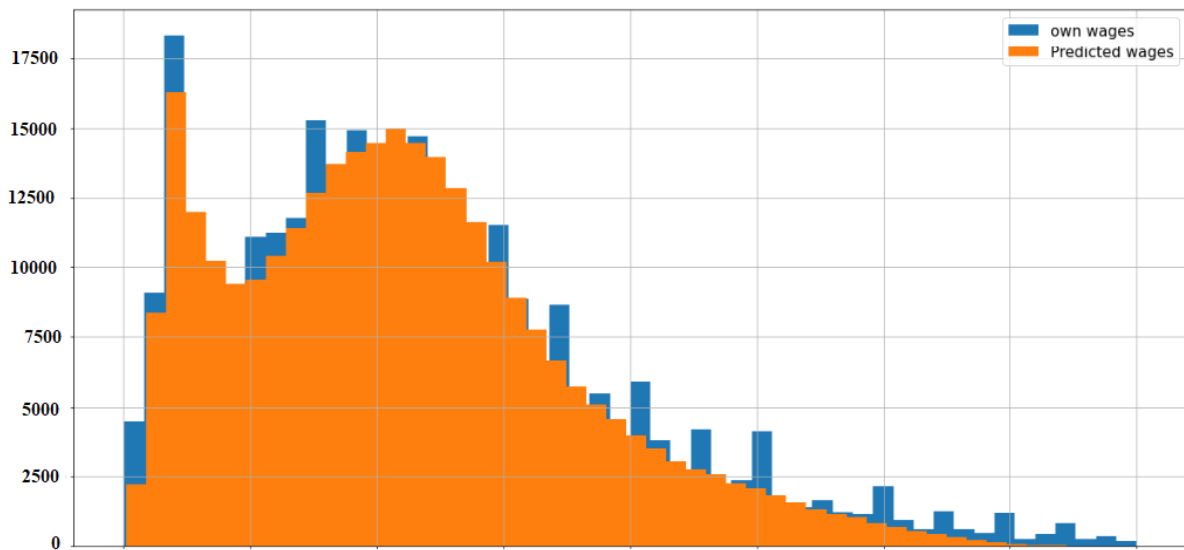
	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
R^2	0.92	0.92	0.93	0.92	0.92	0.91	0.92	0.90	0.92	0.92	0.92
RMSE	54.62	38.78	36.30	27.70	21.90	44.40	85.60	32.70	90.70	70.30	79
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
R^2	0.92	0.92	0.92	0.92	0.93	0.93	0.93	0.93	0.94	0.93	0.93
RMSE	56.90	80	40.80	70.80	97.90	40.90	49.60	56.50	84.50	85.90	56.80

Notes: Author's calculation based on data from GSOEP (1998--2019).

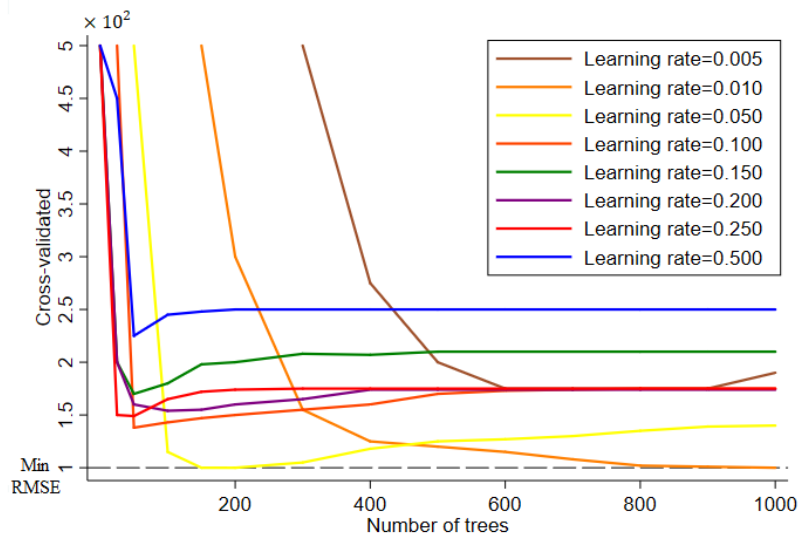
Figure 3.2: Precision test, pay distributions, and cross-validated



(a) Model accuracy test



(b) Own salary and reference salary distributions



(c) Cross-validated

Notes: Author's calculation based on data from GSOEP (1998--2019). In (a) we have plotted the test data on the x-axis and the target variable on the y-axis, which represent the individual pays. In black we have the individual own pays and in green we have the predicted external comparison pays. In (b), the blue color represents the distribution of own pays and the orange color the distribution of predicted reference pays. In (c) we have represented the cross-validation as a function of the number of trees

In part (a) of Figure 3.2, we plotted the actual pays (black) and predicted pays (green) of the training data against the test data to test the overall accuracy of the model. We obtained fairly close prediction curves, which suggests that the model has good generalization ability. In other words, the model is able to generalize well the relationships between the variables learned from the training data and apply them adequately to new data (test data) that it has never seen before. This also indicates that the model did not overfit the training data, i.e., it did not memorize the training data and fail to generalize on the test data. Overall, this suggests that the model is robust and reliable in making predictions on new data. Part (c) shows the cross-validated prediction performance as a function of the number of trees. We noticed that the cross-validated errors decreased with the number of trees. In addition, the prediction performance was obtained with fewer number of trees when we considered the maximum number of splits. The decrease in cross-validated errors with increasing number of trees suggests that prediction becomes more accurate as the model complexity increases.

Part (b) of Figure 3.2, shows the distributions of own pays (blue) and predicted pays (orange). We observe that the structure of the two pays is quite similar. This indicates that the GBRT model is able to capture important trends in the data, which is a good indicator of model validity. The graph shows that the majority of employees have pays between approximately 1,000 and 4,000 euros, while a small number have very low or very high pays. In this sense, if the model is biased towards certain pay ranges, this may lead to biased estimates for pay-related variables. Therefore, we subsequently estimated by pay categories to ensure that the estimates are reliable. However, we noted that GBRT had difficulty predicting high pays. This may indicate that these pays are influenced by factors that are not captured by the variables used in the model.

3.5.2 Estimates of the effect on quits

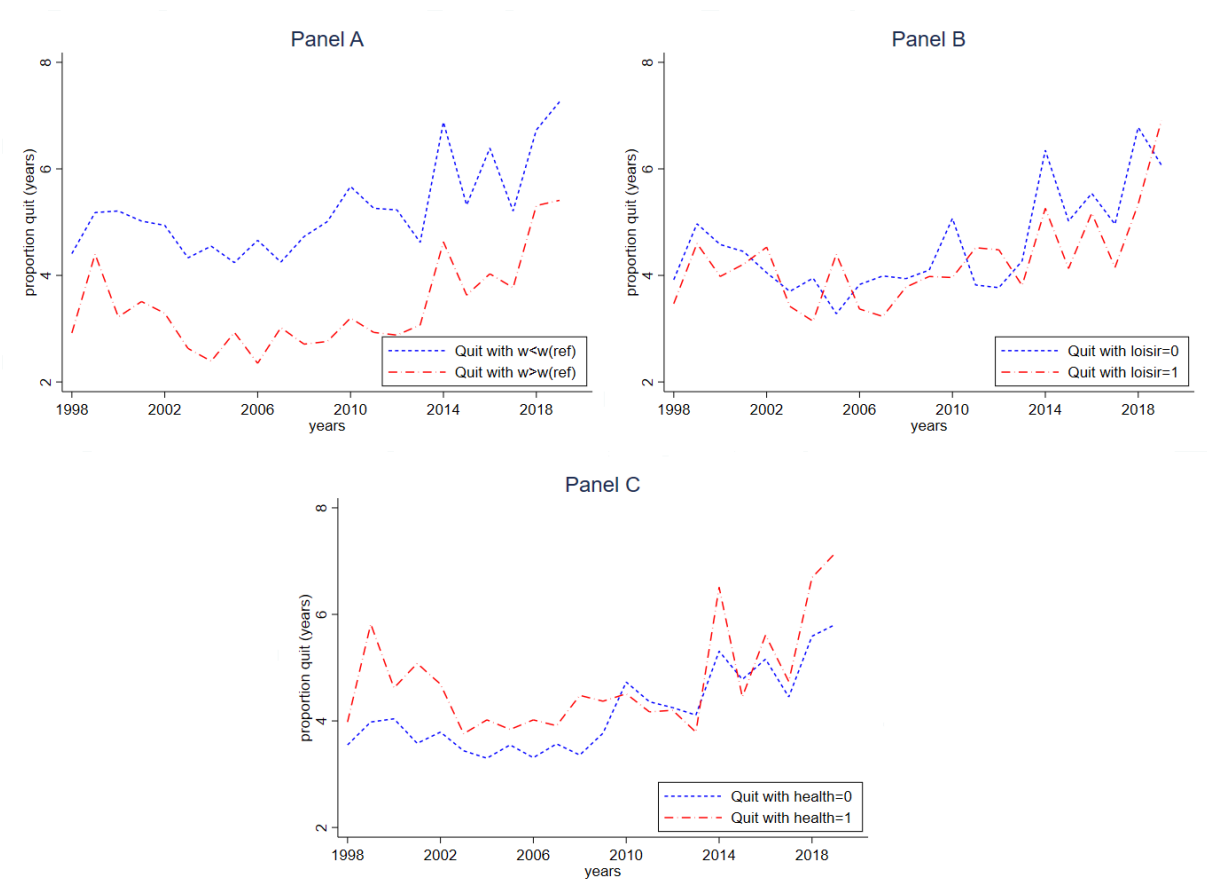
We examine now how workers' occupational quit decisions respond to external pay comparisons or to alterations in non-monetary rewards related to leisure time and health satisfaction. We compare the proportion of quits for workers whose pays are lower than external comparators or whose level of satisfaction in terms of leisure time and health is low (blue short dashed line) with workers who receive a higher pay in terms of leisure time and health (red dash-dotted line). Results are described in Parts A-C of Figure 3.3: Part A for pay, Part B for leisure time, and Part C for health.

The first graph (Part A) shows that the proportion of quits is higher among employees with below-market pay, and the difference between the proportion of workers quitting to more attractive offers versus those quitting with higher pay levels to external offers is statistically significant. These effects varied from year to year, and the proportion of quits peaked in 2014, possibly due to more favorable job opportunities as the German economy recovered from two years of recession. The subsequent large drop in 2015 could be explained by the implementation of the minimum wage, which increased pay for some employees, although not all workers were eligible.

The graphs representing leisure time (Part B) and health (Part C) do not show a statistically significant difference between employees who leave because of higher satisfaction with leisure time or health and those who leave because of a lack of such satisfaction. However, we can observe in Part B that the share of workers who leave because of a lack of satisfaction with non-work time is slightly higher than those who are satisfied, but this effect varies over the years, especially during the crisis and recession years. In contrast, for health, the proportion of quits is slightly higher among those who feel healthy.

We therefore observe a greater response to quit in the face of pay comparisons. This indicates the importance of pay in an employee’s career, as pay contributes to the possibility of having a better standard of living. We will next attempt to test whether these effects persist with a regression incorporating a set of controls related to individuals, location, time frame, and labor market supply situation.

Figure 3.3: Proportion of quit by pay comparisons, leisure time and health



Notes: Author’s calculation based on data from GSOEP (1998–2019). In part A we have plotted the proportion of employees who have quit and are paid a lower pay than the external comparators (blue dash line) against those who have received a higher pay (red long dash dot). Parts B and C represent similar representations for those who quit job and were dissatisfied with leisure and health compared to those who quit job and were satisfied.

Corresponding regression estimates of the effect on quits are provided in Table 3.5.2 and Figure 3.4 (for annual regressions). These show the estimated parameters from fitting Equation (3.2) to the data between 1998 and 2019. Each column reports a different model specification.

When considering only the pay ratio ($w_{i,t-1}/\widehat{w}^{(M)}_{i,t-1}$) with control of own pay and external comparison pay (column 1 and coefficient θ_1), we note a negative association with the propensity to quit, with a marginal effect of -0.044 ¹⁸. This means that a 1% increase in the ratio of own pay to predicted pay leads to a 0.044% decrease in the probability of leaving the job, *ceteris paribus*. In other words, the higher a worker's current pay relative to his or her predicted pay, the less likely he or she is to leave the job. This may suggest that employees who receive higher pays than those predicted by the model tend to stay in their current jobs rather than quitting to seek higher paying jobs. Our results are consistent with pay response estimates found in previous work (Von Felix and Pfeifer, 2013; Godechot and Senik, 2015). For example, Fairris (2004) found that workers in high-paying firms who already have a higher relative pay position than workers in other firms have less incentive to quit because they cannot earn much more. In their study on Germany, d'Ambrosio et al. (2018) found that a 1% increase in the gap between the individual's absolute income and the average income of the outside world leads to a 1.3 percentage point decrease in the probability of quitting. This result can be interpreted as an indicator of workers' satisfaction with and commitment to their employer. If a worker is paid more than he or she expected, he or she is likely to be satisfied with his or her job and compensation and less likely to leave. On the other hand, if a worker is paid less than they expected, they are less likely to be satisfied with their work and compensation and more likely to leave their job.

Column 2 considers non-monetary rewards only, with the same controls as in column 1. The results show that these variables also have a significant impact on the probability of leaving the job. Specifically, a 1-unit increase in the leisure variable (measured on a scale of 0 to 100) results in a 0.003% decrease in the probability of leaving the job, *ceteris paribus*. In contrast, a 1-unit increase in the health variable (measured on a scale of 0 to 100) results in a 0.003% increase in the probability of leaving the job, *ceteris paribus*. This suggests that workers with more free time (as measured by the leisure variable) are less likely to leave their jobs than those with less free time, even after controlling for other factors. In contrast, workers with better health (as measured by the health variable) are more likely to leave their jobs than those with poorer health, *ceteris paribus*. This can be interpreted as an indication of the importance of work-life balance and mental health on the decision to leave a job. Workers who have more free time for leisure activities tend to be more satisfied with their personal lives, which may translate into a lower propensity to leave a job. Healthier workers may be more willing to take risks and find other job opportunities or career paths, while less healthy workers may be more dependent on their current job for their livelihood. However, it should be noted that these marginal effects are relatively small compared to the pay effect.

Combining the results for monetary and non-monetary rewards in column 3 does not change the magnitude of their influence, and the impact of leisure and health remains small compared to the impact of pay. These results suggest that, even after controlling for leisure and health effects, the ratio of own pay to predicted pay remains the most important factor in predicting the

¹⁸The marginal effect of quitting on the coefficient θ_1 is given by $e_m = \frac{dQ}{d(w_{it}/\widehat{w}^{(M)})}$.

probability of leaving the job. This can be interpreted as an indication of the relative importance of pay compared to other factors such as health and leisure in workers' decisions to leave their jobs. However, the effects of leisure and health, although smaller, are still significant. This indicates that health and leisure are also important in the decision-making process of quitting a job.

The estimates are robust to the inclusion of time fixed effects, geographic location, and a set of additional controls that are considered determinants of the quit decision, such as age, gender, and household income, as shown in columns 4 to 7.¹⁹ The coefficients related to the pay ratio, leisure, and health did not change significantly after controlling for other variables in the model. This suggests that these variables continue to have an independent effect on the probability of leaving the job, even after controlling for other factors that may influence this probability. This implies that these variables are robust predictors of the probability of leaving the job.

Table 3.5.2: Estimates of the probability of quit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$w_{it}/\hat{w}^{(M)}$	-0.044*** (0.002)		-0.044*** (0.002)	-0.045*** (0.002)	-0.045*** (0.002)	-0.045*** (0.003)	-0.044*** (0.003)	
Leisure time		-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Health		0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
$w_{it}/\hat{w}^{(M)} \times (w_{it} < \hat{w}^{(M)})$								0.014*** (0.001)
$w_{it}/\hat{w}^{(M)} \times (w_{it} > \hat{w}^{(M)})$								-0.017*** (0.001)
Age						-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Female						0.000 (0.001)	0.000 (0.001)	0.002** (0.001)
Unemployment rate							-0.005*** (0.001)	
Squared unemployment rate							0.002** (0.000)	
Log likelihood	-22,269.641	-22,197.091	-21,975.9	-21,935.87	-21,928.175	-21,848.383	-21,769.198	-21,857.514
Dummies of years	No	No	No	Yes	Yes	Yes	No	Yes
Regions	No	No	No	No	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. The results in columns 1 to 7 are obtained from the estimation of equation 3.2 and those in column 8 from equation 3.3. Bootstrapped standard errors are in parentheses. The sample consists of workers who voluntarily quit their jobs during the period 1998--2019. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Full results with all variables are available on request.

As discussed earlier, individuals who are paid less than the market rate may consider their

¹⁹The results for personal characteristics and unemployment rate show that the probability of quitting appears to be lower for younger workers, probably due to lack of experience. Gender does not appear to have a statistically significant effect on the probability of quitting. A U-shaped relationship is observed between the probability of quitting and the unemployment rate. This relationship indicates that the probability of employees quitting is lower in periods of very high unemployment. This effect varies less significantly when the unemployment rate is low.

pay to be unfair and of low status, leading them to quit their jobs. We assume that the opposite is also true, and we test this hypothesis in column 8 of our model. To do so, we allow $w_{it}/\widehat{w}^{(M)}$ to vary depending on whether $w_{it} < \widehat{w}^{(M)}$ or $w_{it} > \widehat{w}^{(M)}$ (Card et al., 2012). In other words, we consider the ratio between an individual's own pay and the reference pay to be strictly less than one or strictly greater than one, respectively, as follow:

$$P(Q_{it} = 1) = a + \alpha T + \vartheta_1 \cdot (w_{i,t-1}/\widehat{w}_{i,t-1}^{(M)}) \cdot (w_{i,t-1} < \widehat{w}_{i,t-1}^{(M)}) + \vartheta_2 \cdot (w_{i,t-1}/\widehat{w}_{i,t-1}^{(M)}) \cdot (w_{i,t-1} > \widehat{w}_{i,t-1}^{(M)}) \\ + \theta_2 L_{i,t-1} + \theta_3 H_{i,t-1} + \tau U_{it} + \sum_k \pi' z_{it} + \lambda_R(i) + \eta_i + \nu_{it} \quad (3.3)$$

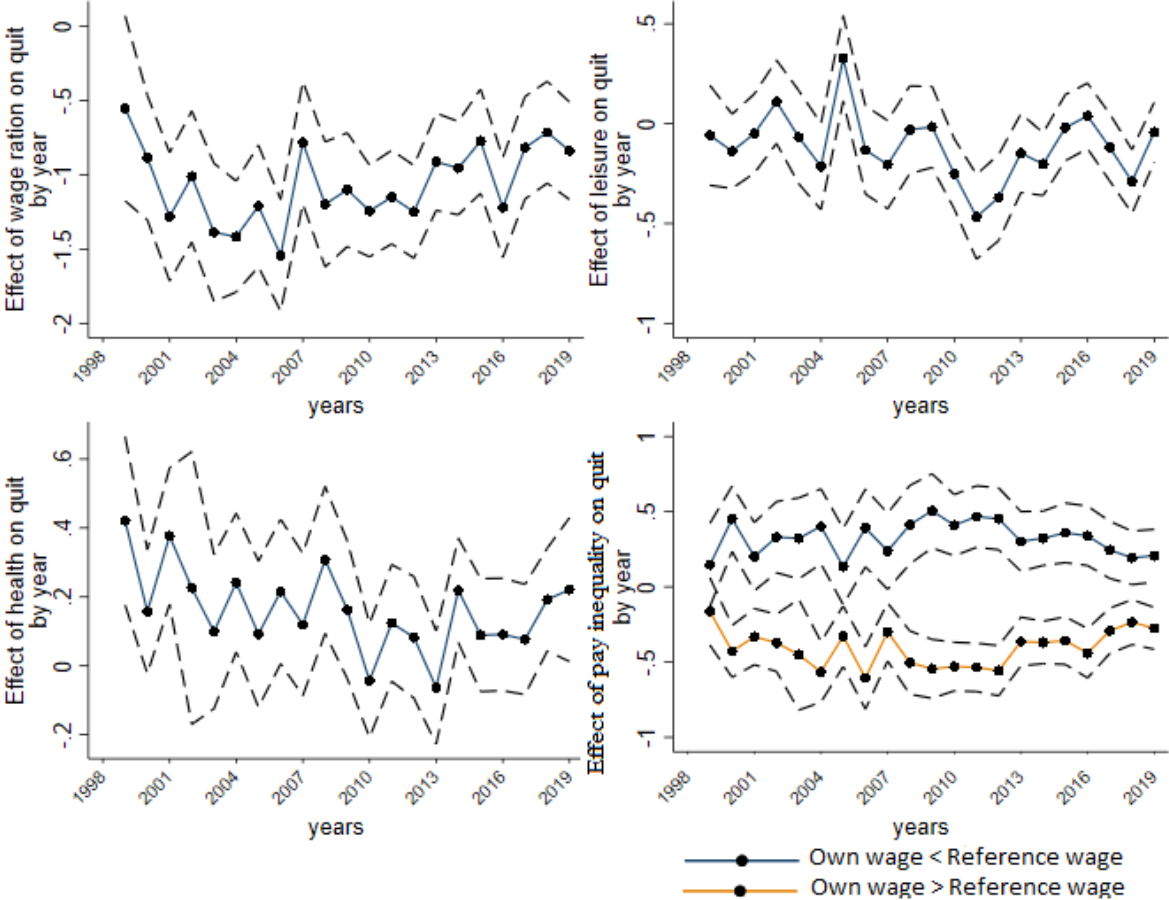
Our estimation results show that the effect of an individual's own pay versus predicted pay on the probability of quitting depends on their pay status. Specifically, when a worker's own pay is less than their predicted pay, the probability of quitting increases by 0.014%, *ceteris paribus*. This suggests that workers who are underpaid are more likely to quit their jobs, consistent with the notion that job satisfaction is closely related to pay. Conversely, when a worker's own pay is higher than their predicted pay, the probability of quitting decreases by 0.017%, *ceteris paribus*. This implies that workers who are overpaid relative to their predicted pay are less likely to quit their jobs, possibly because they are more satisfied with their pay or perceive their jobs as more secure than other available options. Our model also shows that other variables controlled in the model, such as time, health, and leisure, as well as individual and regional characteristics, unemployment, the unemployment rate, and other control variables, have a significant impact on the probability of quitting. Furthermore, the model accounts for individual-specific, regional, and unobservable effects.

We cannot reject the status effect when employees receive a pay that is lower than that of similar occupational profiles in the market (Clark et al., 2009). It is also likely that the status effect is observed with pay levels or sectors. For instance, it is possible that the effect of pay, health, and leisure on the likelihood of quitting varies across pay levels and industries. Workers in low-paying jobs may be more sensitive to health and leisure than those in high-paying jobs. Similarly, the effect of pay on the probability of quitting may differ across industries, as some industries may offer higher pays than others. Analyzing pay levels and industries separately can provide more precise information about the factors that influence the likelihood of quitting in each group. This can help decision-makers understand the needs and motivations of workers in different contexts and can be useful in setting up recruitment and retention policies.

In the case of the German labor market, decomposing pay levels can be justified by its specific characteristics. The German labor market has a system of collective bargaining and a statutory minimum pay, which may lead to pay rigidity. Additionally, Germany has a strong tradition of craft and industrial production, resulting in large pay disparities between different sectors. Dividing pay levels into categories can provide a better understanding of pay variations within different industries. Decomposing the analysis by industry is also relevant in labor market

analysis as market conditions and characteristics often vary across sectors. In Germany, key sectors such as manufacturing, finance, business services, and healthcare have different pay levels and unemployment rates. Moreover, the industrial sector in Germany has a strong tradition of cooperative work organization, characterized by collective bargaining, pay agreements, and governance structures that can affect labor market dynamics. Therefore, by decomposing the analysis by industry, we can better understand variations in labor market conditions and how they may affect workers' decisions regarding job mobility and quitting. We estimate these decompositions in the following section.

Figure 3.4: Effects of pay ratio, leisure time, health and pay inequality on quit by year



Notes: Author's calculation based on data from GSOEP (1998–2019). This figure represents the effect of monetary and non-monetary comparisons on the probability of quitting by year. The first three figures show the relationship between the ratio of own and reference pays and nonmonetary rewards in terms of leisure time and health (coefficients θ_1 , θ_2 , and θ_3 with (3.2)). The fourth figure represents the effects of pay comparisons when the individual's own pay is strictly below or strictly above the reference pays (coefficients ϑ_1 and ϑ_2 with (3.3)). Models estimated by simple logit with heterogeneity correction. The dashed lines are the 95 percent confidence intervals. The regressions include years, regions, personal characteristics, unemployment rate, and square of unemployment rate. Estimated reference pays using the GBRT method.

3.6 Heterogeneous responses to the probability of quitting by pay levels and sectors

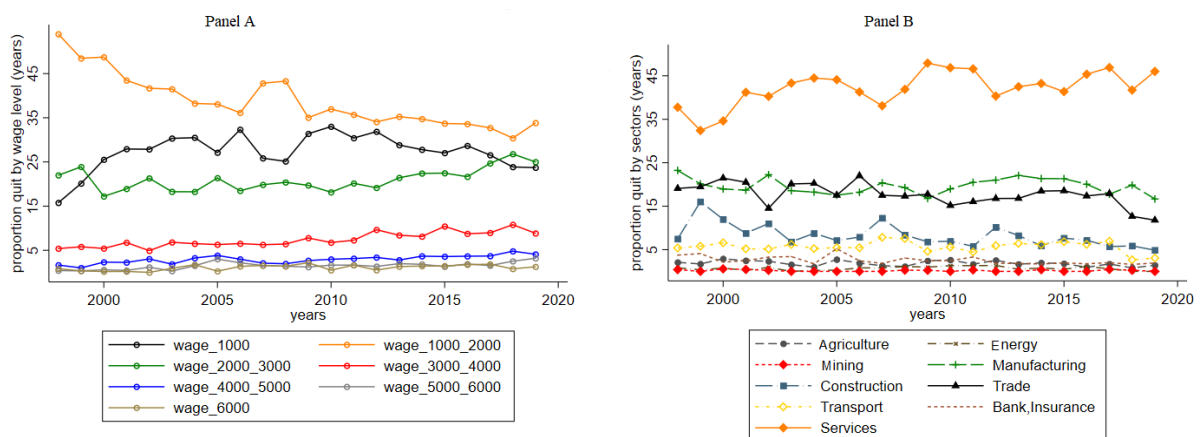
In this section, we first analyze the effects of pay comparisons when the individual receives a pay that is strictly lower than the reference pay or when he or she receives a strictly higher pay, and the effects of non-monetary rewards in terms of leisure time satisfaction and health satisfaction on quits. We then turn to an analysis of the effects on quits by industry.

3.6.1 By pay levels

We investigate the heterogeneity of responses to the effects of pay comparison, leisure, and health satisfaction for different pay levels. We divide the pay distribution into intervals of one thousand euros based on the size of the pay gap and the pay distribution in Figure 3.5. For pays above 5,000 euros, we group the effects together since the response to quits is similar, and there are fewer observations when we consider differences of 1,000 euros in these intervals. This decomposition also ensures that we have a sufficient number of observations in each category to obtain reliable coefficient estimates.

Part A of Figure 3.5 illustrates the distribution of quits by pay level and year. The proportion of quits is higher among individuals with low pays and those in the intermediate pay levels. The quit rate is higher among workers earning pays of 2,000 euros gross or less, with over 30% of workers quitting each year. For employees earning more than 2,000 euros but not more than 3,000 euros, the quit rate is lower than for others, but still exceeds 15% each year. For higher pay levels, the proportion of quits remains low, at just over 4%.

Figure 3.5: Proportion of quits by pay level, sectors and years



Notes: Author’s calculation based on data from GSOEP (1998--2019). In these figures, we have plotted the proportion of quits as a function of pay levels (Part A) and Sectors (Part B) for each year considered. Each color corresponds to quit rates by pay range and a difference of one thousand euros and by sectors over years.

Table 3.6.1 explores the heterogeneity of responses to pay comparisons and nonmonetary rewards on quits by pay levels, and the alternative results for each year are shown in Figure 3.6. We estimate the regression equation (3.3) separately for each of the pay categories. The results

reveal that for workers with pays up to 1,000 euros, the effect of the distance between their own pay and the reference pay on their decision to quit is constant as long as their own pay is below the reference pay. However, once their own pay exceeds the reference pay, the effect on quitting decreases by 0.023% and their probability of staying in their job is higher. In addition, workers with access to satisfying leisure have a lower propensity to quit. These results suggest that for low-pay workers, non-financial considerations such as leisure satisfaction have an important role to play in their decision to stay or leave their jobs.

Table 3.6.1: Effects on quits by pay categories

	$\leq 1,000$ (1)	$> 1,000--\leq 2,000$ (2)	$> 2,000--\leq 3,000$ (3)	$> 3,000--\leq 4,000$ (4)	$> 4,000--\leq 5,000$ (5)	$> 5,000$ (6)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.002 (0.007)	-0.003 (0.003)	0.010*** (0.002)	0.007*** (0.002)	0.001 (0.002)	0.001 (0.001)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.023*** (0.005)	-0.014*** (0.002)	-0.013*** (0.002)	-0.009*** (0.002)	-0.003 (0.002)	-0.000 (0.001)
Leisure	-0.012*** (0.003)	0.001 (0.002)	-0.002 (0.002)	-0.005** (0.002)	-0.004* (0.002)	-0.005** (0.002)
Health	0.000 (0.003)	0.002 (0.002)	0.004** (0.002)	0.005*** (0.002)	0.004* (0.002)	0.004** (0.002)
Age	-0.001*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Female	-0.007* (0.004)	-0.007* (0.003)	-0.003* (0.002)	0.005** (0.002)	-0.000 (0.002)	0.003 (0.003)
Log likelihood	-4,986.045	-7,520.018	-4,949.143	-2,028.297	-874.104	-665.998
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes

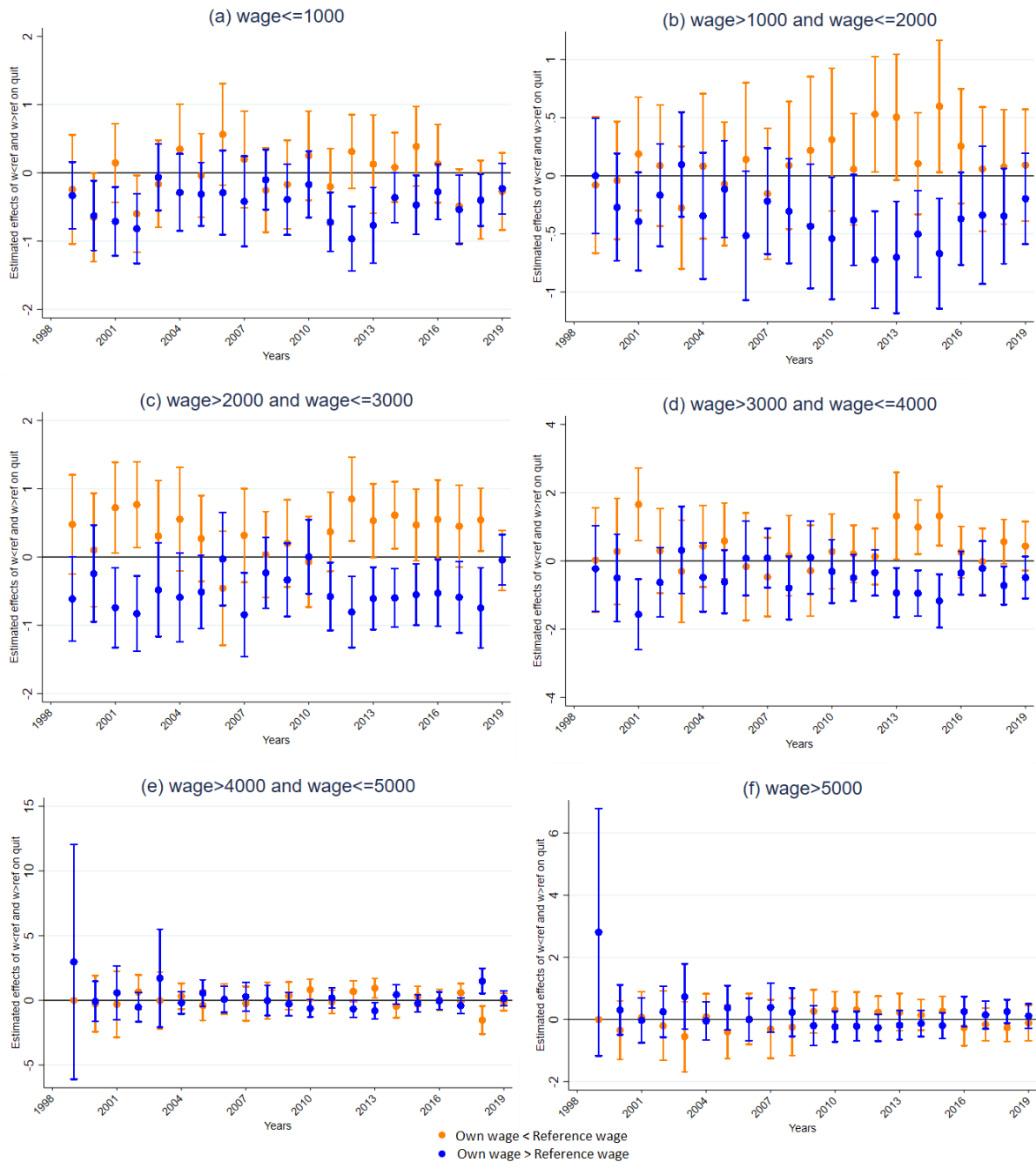
Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of workers who voluntarily quit their jobs during the period 1998--2019. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

For workers with pays between 1,000 and 2,000 euros, the significant factor in their decision to quit is their reaction to pay differences. In particular, workers have a low probability of quitting when they receive a pay higher than the market pay, while the effect of other aspects remains insignificant. These results suggest that for workers in this pay range, pay plays an important role in their decision to stay or quit their job.

For workers earning between 2,000 and 3,000 and between 3,000 and 4,000 euros, the effect of pay comparison is significant, and workers are more likely to quit when their own pays are lower than those of other workers with a similar labor market profile. This probability increases by 1% and 0.007%, respectively, for these two pay groups. In contrast, the probability of quitting decreases by 0.013% and 0.009%, respectively, when their pay is above the reference pay.

For workers whose pay is above 4,000 euros (columns 5 and 6), we do not observe a significant effect of the pay comparison. However, their probability of quitting may decrease by 0.004% when their job offers them satisfaction in terms of leisure or increase for the same probability when they feel healthy.

Figure 3.6: Estimated effects of pay comparisons by pay level and years



Notes: Author's calculation based on data from GSOEP (1998--2019). This figure shows the relationship between quits and pay comparisons by pay level when the individual earns a pay strictly below (in orange) or strictly above (in blue) the reference pays (ϑ_1 and ϑ_2 coefficients with (3.3)). Models estimated by simple logit with heterogeneity correction. Regressions include years, regions, and personal characteristics. Estimated reference pays using the GBRT method. The lines are the 95 percent confidence intervals.

These results suggest that the determinants of the decision to quit vary with workers' pay levels, and that non-financial considerations such as leisure and benefits may play an important role in the decision of low-pay workers. The latter appear willing to work even if they have health problems, but are more sensitive to the amount of free time available. This may have implications for public policies aimed at reducing unemployment in this pay bracket, particularly if workers face health problems that could prevent them from working.

For workers in the 2,000 to 4,000 euro pay levels, their greater sensitivity to pay comparisons may be explained by the fact that workers often have similar skills and qualifications, and thus can easily compare their pays with other workers. When they find that their pay is lower than that of their peers, it may affect their job satisfaction and commitment to their employer, which may ultimately lead them to seek other job opportunities that offer higher pays. On the other hand, if their own pay is higher than that of their peers, it may increase their job satisfaction and commitment, which may lead them to stay in their current job or seek opportunities for promotion or professional development within their current company.

These findings underscore the importance of pay comparison for workers in this pay range, and employers may want to pay attention to this to retain talented and skilled employees. For workers in the higher pay levels, their motivation to stay in their jobs may have more to do with quality of life and well-being considerations than with pay comparisons. This may be because these workers have already reached a certain income level and are therefore less sensitive to the effect of pay comparison than workers earning lower pays. However, they may be more sensitive to quality of life and health, as they likely have more resources to afford self-care and pursue activities that interest them outside of work. Overall, these results show that the propensity to quit depends on several factors that vary by pay level, and that the effect of status is not equally shared across pay levels.

3.6.2 By sectors

Panel B of Figure 3.5 depicts quit rates of workers by industry for different periods. The figure shows higher quit rates in the services sector, with quit rates exceeding 45% in some periods, followed by the manufacturing and trade sectors, where the quit proportions overlap over the years, and the rates sometimes approach 25%. However, for some sectors, quit rates barely exceed 5%, and other sectors such as agriculture, banking and insurance, and mining have quit rates that do not even reach this proportion. In the construction sector, quit rates sometimes exceed 10% in some years.

Table 3.6.2 and Figure 3.7 (for annual regression) also explore the heterogeneity of the effect of pay comparisons and nonmonetary rewards across different industries at the level of the overall sample and year by year. We estimate the (3.3) regression equation separately for each of the following sectors: agriculture, manufacturing, construction, trade, transportation, bank-insurance,

and services. The results show that the effects of pay comparisons and nonmonetary rewards on the likelihood of quitting vary across industries. In the agriculture sector, pay comparisons and nonmonetary rewards have no significant effect on the probability of quitting. In contrast, in the manufacturing, construction, trade, transportation, banking-insurance, and service sectors, workers with pays below the benchmark pays for their sector have a higher probability of quitting. The probability of leaving their job increases by 0.013%, 0.018%, 0.022%, 0.011%, and 0.013%, respectively. On the other hand, for those workers with pays above their reference pay, their probability of quitting may be low, with probabilities of 0.016%, 0.015%, 0.019%, 0.024%, 0.014%, and 0.017%, respectively. However, the response to pay comparisons is higher for workers in the transportation and construction sectors. In addition, other factors such as leisure or health may influence their decision to quit, especially for workers in the manufacturing or service sectors.

Table 3.6.2: Effects on quit by sectors

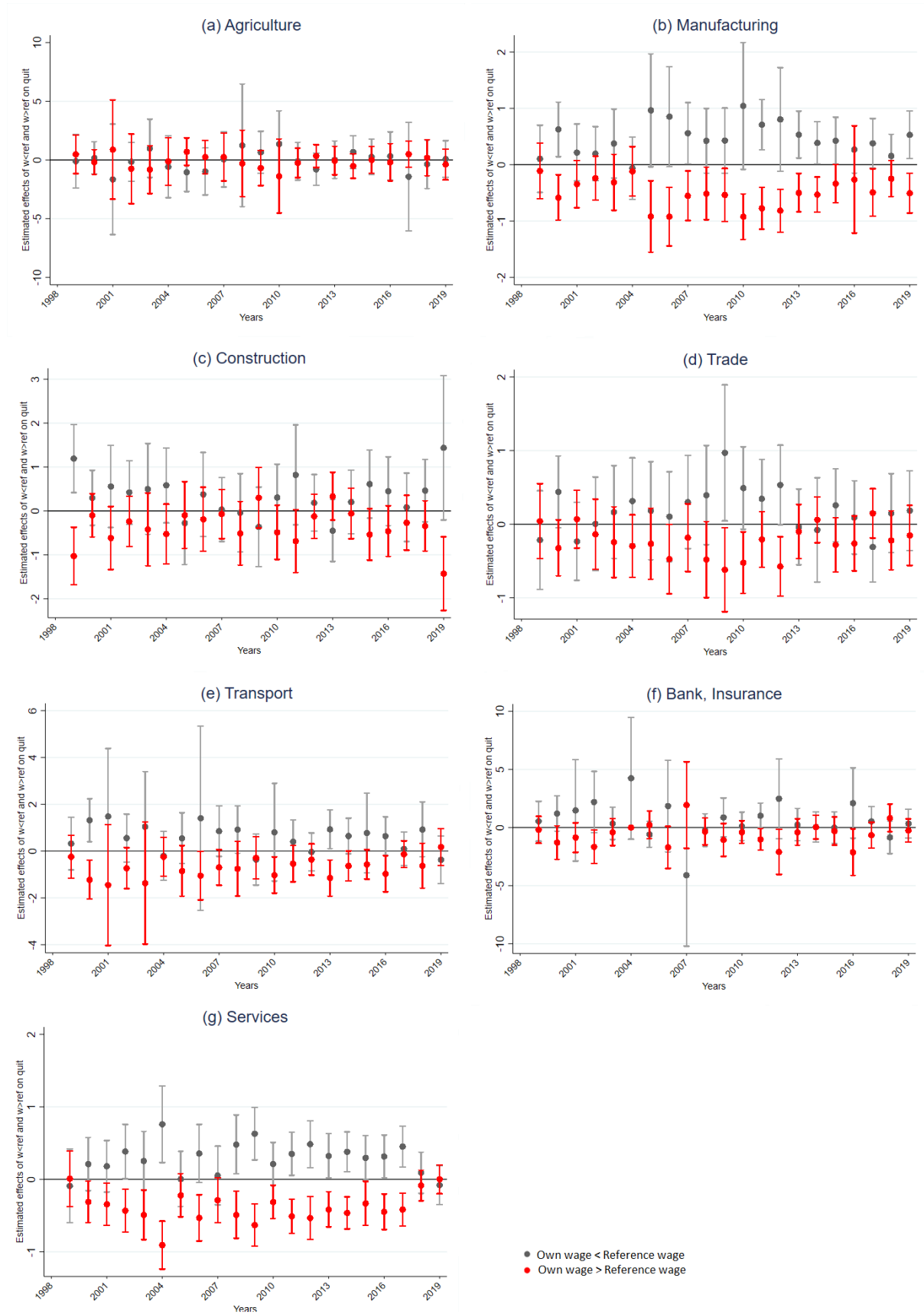
	Agriculture	Manufacturing	Construction	Trade	Transport	Bank Insurance	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.003 (0.010)	0.013*** (0.002)	0.018*** (0.006)	0.017*** (0.004)	0.022*** (0.006)	0.011** (0.004)	0.013*** (0.002)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.009 (0.009)	-0.016*** (0.002)	-0.015*** (0.004)	-0.019*** (0.003)	-0.024*** (0.005)	-0.014*** (0.004)	-0.017*** (0.002)
Leisure	-0.000 (0.008)	-0.003* (0.002)	0.005 (0.005)	-0.003 (0.003)	0.008 (0.005)	-0.000 (0.004)	-0.005*** (0.002)
Health	-0.004 (0.008)	0.006*** (0.002)	0.004 (0.005)	0.003 (0.003)	-0.004 (0.005)	0.005 (0.004)	0.003* (0.002)
Age	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Female	0.001 (0.002)	-0.007*** (0.002)	-0.001 (0.002)	-0.001 (0.003)	-0.008** (0.003)	-0.001 (0.004)	0.001 (0.002)
Log likelihood	-1,351.890	-4,375.264	-1,565.1971	-3,335.4861	-1,091.082	-2,547.611	-2,329.366
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of workers who voluntarily quit their jobs during the period 1998--2019. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

One possible explanation for these results is that the agricultural sector is generally dominated by family farms supported by the Länder, which may not encourage workers to seek other jobs for pay reasons.²⁰ Additionally, the sector employs seasonal workers who may be obligated to stay in their jobs to maintain their residency status. The significant effects of pay comparisons for workers in other sectors suggest that they pay attention to the pays of their peers and may be more likely to quit if their pays are not competitive. The magnitude of quits is particularly high in the transport and construction sectors, where job opportunities often exceed demand and where workers may have little chance for pay satisfaction due to poor advancement prospects

²⁰The German Federal Ministry of Food and Agriculture, in their report "Agriculture in Germany: Facts and Figures" (2021).

Figure 3.7: Estimated effects of pay comparisons by sector and years



Notes: Author's calculation based on data from GSOEP (1998–2019). This figure shows the relationship between quits and pay comparisons when the individual working in a given sector earns a pay strictly below (in gray) or strictly above (in red) the reference pays (ϑ_1 and ϑ_2 coefficients with (3.3)). Models estimated by simple logit with heterogeneity correction. Regressions include years, regions, and personal characteristics. Estimated reference pays using the GBRT method. The lines are the 95 percent confidence intervals.

and precarious employment conditions (Autor and Dorn, 2013; Haltiwanger et al., 2015). The probability of quitting is lower in the banking-insurance sector, possibly due to the numerous financial crises that have impacted this sector in Germany (Breuer, 2015). For workers in the manufacturing or service sectors, factors such as time away from work and good health may also play a role in their decision to quit, as the demanding nature of their jobs may leave them with a greater need for free time and good health may be an asset in pursuing more attractive opportunities outside of work (Green, 2011; Oshio et al., 2018).

Our results are consistent with the theories of social role, social exchange, and equity. The social role theory suggests that individuals are influenced by social expectations regarding their role, status, and professional identity (Eagly and Wood, 2012a). Our results indicate that low-paid workers are more likely to leave their jobs due to non-financial factors such as free time and social benefits, while high-income workers are more sensitive to factors such as equity of pay compared to their peers. This can be attributed to social expectations and professional role that workers perceive they should play based on their income status. Additionally, our results also support the social exchange theory, which states that interpersonal relationships are based on the principle of mutual exchange (Blau, 1964). Workers who perceive their pay as fair compared to their peers are more likely to stay in their job, while those who feel their pay is lower than that of their colleagues are more likely to quit. This reflects the principle of social exchange where workers expect fair retribution in return for their contribution to the company. Finally, our results are in line with the equity theory, which postulates that workers compare their pay to that of their peers and are influenced by their perception of the equity or injustice of their pay (Adam, 1965). Workers who believe their pay is fair compared to their colleagues are more likely to stay in their job, while those who consider their pay to be lower than that of their peers are more likely to quit. These results confirm that workers have a strong tendency to evaluate their pay based on that of their peers, which can have a significant impact on their decision to leave or stay in their job.

After analyzing the relationship between workers' pay and their decision to stay or leave their jobs, we now turn to examine the robustness of our findings. Specifically, we test the sensitivity of our results to different statistical specifications and samples, to ensure that our conclusions are not driven by a specific model or subset of data.

3.7 Robustness Analysis

The previous section established that individuals with higher pays than external benchmarks or those reporting higher levels of leisure satisfaction have a higher probability of quitting, while for health, the probability of quitting appears to be higher among those reporting lower levels of satisfaction, and the direct effect on quits when the employee receives a pay that is strictly lower than the reference pays depends on pay levels and sectors of employment. In this section, we aim to examine the robustness of our results by first repeating our regressions for male and female and East and West German sub-samples. Second, we will repeat the previous specifications using

shorter time periods to account for periods of economic change due to crises periods. Finally, we will consider further robustness tests by using an alternative measure of benchmark pay prediction by another machine learning method, namely the Random Forest (RF) algorithm.

3.7.1 Effects by gender and geographic location (East vs. West)

We conducted a study by gender and by Eastern and Western regions for several reasons. Firstly, it enables us to better understand how workers make decisions to quit in response to pressures related to compensation and quality of life in Germany. Secondly, it can help identify differences between men and women in their reactions to pay and non-pay pressures, as well as differences between East and West Germany in terms of labor market and professional culture. Finally, it can help develop policies and human resource management strategies that take these differences into account to improve worker satisfaction and retention.

Equations (3.2) and (3.3) were estimated separately for men and women on the one hand and for the West and East regions on the other. Given the less favorable working conditions for women and workers in East Germany, the determinants of the probability of quitting could vary between men and women and between workers in East and West Germany. The estimates at the aggregate level are presented in Table 3.7.1 for these different groups. The alternative estimations according to pay levels and sectors of activity are respectively presented in Tables 3.9.3 and 3.9.4 in the appendix.

3.7.1.1 According to gender

After controlling for years of experience, regions, individual characteristics, unemployment rate, and unemployment rate squared, we found that the pay effect is statistically significantly larger for men than for women. Specifically, men who earn a pay lower than their market benchmark have a 0.054% increase in the probability of quitting, an effect that is less than one time as large for women, whose probability of quitting is 0.038%. This result indicates that men are more likely to quit their jobs when they feel they are not well-compensated compared to external monetary opportunities. This result is consistent with previous studies' conclusions suggesting that men place greater value on external monetary opportunities than women, which explains their higher propensity to leave their job for another offer of a higher salary (Wozniak, 2017; Kuhn, 2018). However, for non-monetary rewards, women have a higher probability of quitting their job when it does not allow them to maintain a balance between work and personal life, while for men, the effect is statistically insignificant. On the other hand, men's probability of quitting may be higher when they feel healthy. These results suggest that women prefer to work in jobs that provide work-life balance, likely due to differences in family responsibilities compared to men. For men, the most important factor appears to be good health, enabling them to take advantage of outside opportunities to earn more. This is likely because men are more focused on monetary aspects in their jobs. These results are consistent with previous studies suggesting that women place more importance than men on work-life balance when it comes to job satisfaction

and the decision to quit their job, likely due to differences in family responsibilities. For men, good health appears to be a more important factor in their decision to quit their job (Michel et al., 2011; Shockley et al., 2017).

The results by pay levels reveal that both men and women in the middle pay range (2,000 to 4,000 euros) are more likely to be influenced by pay comparisons. Specifically, they are more likely to quit if they receive a pay below market offers and more likely to stay in their job if they feel well-paid. However, this effect is slightly stronger for women. This finding could be explained by the relatively high level of ambition of women in these pay ranges, as they have experience dealing with the various obstacles of occupational inequality. Additionally, these women typically have a fairly high level of education, which allows them to demand the same pay expectations as men. This result confirms our previous findings on the effect of gender expectations observed in Chapter 1 (Section 1.5.3). However, for both men and women in this pay range, leisure time and health appear to be equally important.

In contrast, when women are in low-paying jobs (less than 1,000 euros), they are only half as likely to leave their jobs as men when they feel well-paid in relation to market offers. Furthermore, for women in this category, leisure time appears to be statistically significant, whereas for men, the effect does not appear to be significant. This finding could suggest that, unlike women, men not only compare their pay level to their personal profile but also take into account their environment, such as their acquaintances. For women in these pay brackets, a job that allows them to find time for their family is more important. This is likely why they prefer to work part-time, especially since in Germany there is an abundant supply of part-time "mini-jobs," which affects women more than men. Moreover, family-work policies are less extensive in Germany, which leads to a greater recourse to part-time work among women, hence the need to hold a job that would leave them free time outside of work.

The results by sector show that, except for the agriculture and banking/insurance sectors, both men and women are more likely to quit if they receive a pay below market offers. However, in the construction sector, which is generally considered a male-dominated industry, women are more likely to quit in response to pay comparisons. Conversely, in tertiary sectors such as trade, transport, and banking/insurance, men are more responsive to pay comparisons.

In terms of non-monetary rewards, leisure time appears to be important for both men and women in the service sector. Their probability of quitting decreases if they have a job that allows them to enjoy non-work time, and there is no statistically significant difference between men and women in this regard. However, in the trade sector, leisure time is only statistically significant for women, while in the transport sector, it is men who respond significantly to the effect of leisure time.

These results suggest that women working in male-dominated sectors may feel the need

to demonstrate strength and technical proficiency to demand pays commensurate with their performance (Perugini and Vladislavljević, 2019). We observed the effect of sectoral expectations in Chapter 1 (Section 1.5.3). However, in sectors where they are used to working, such as tertiary sectors, they may not feel the same level of demand due to their habit of evolving and receiving low pays. Men may be more demanding on pays, as they are more sensitive to the financial argument (Kuhn, 2018). However, the complex and fast-paced nature of jobs in tertiary sectors may indicate the need for both men and women to have adequate time to engage in non-work activities to relieve stress. This is especially relevant during the current health crisis, where healthcare workers, for example, require more leisure time, even if it means leaving their jobs.

Table 3.7.1: Estimates of the probability of quit for Men, Women, West and East

	Men		Women		West		East	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$w_{it}/\widehat{w}^{(M)}$	-0.055*** (0.003)		-0.038*** (0.003)		-0.044*** (0.002)		-0.046*** (0.005)	
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$		0.014*** (0.002)		0.013*** (0.002)		0.014*** (0.001)		0.013*** (0.003)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$		-0.016*** (0.001)		-0.016*** (0.001)		-0.016*** (0.001)		-0.017*** (0.002)
Leisure time	-0.002 (0.001)	-0.001 (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.002*** (0.001)	-0.003*** (0.001)	-0.004* (0.002)	-0.003 (0.002)
Health	0.005*** (0.001)	0.005*** (0.001)	0.001 (0.001)	0.001 (0.001)	0.003*** (0.001)	0.003** (0.001)	0.004* (0.002)	0.004 (0.002)
Age	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Log likelihood	-10,720.849	-10,567.222	-10,941.315	-10,686.109	-16,305.47	-16,377.18	-5,192.701	-5,196.161
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of male workers who voluntarily quit their jobs during the period 1998--2019. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Full results with all variables are available on request.

3.7.1.2 According to workers in the East and in the West Germany

The regional results indicate that there is no statistically significant difference in the probability of quitting among workers in East and West Germany when they feel underpaid or well-paid or when they are satisfied or dissatisfied with their leisure time or health in comparison to the market offers. Similarly, the difference in quitting probability is not statistically significant when considering the results by pay levels. These findings may suggest that the likelihood of quitting is influenced more by personal needs, such as the desire for higher pays or non-monetary benefits related to physical and mental well-being, and the availability of free time outside of work rather than the economic situation of the geographical location.

Regarding sectoral effects, significant differences are observed between workers in the East and West in some sectors. In the construction sector, employees residing in the East exhibit a

stronger reaction to pay comparisons leading to quits. In contrast, workers in the West show a statistically greater response to pay comparisons when working in the tertiary sector, particularly in the trade and banking-insurance sectors.

These results could suggest that the observed pay inequalities in the construction sector between East and West German workers, with the latter being paid less than the former, may result in a stronger reaction in the need for higher pays among the East German workers, even if it means leaving their jobs for more attractive external offers. The greater reaction of western workers in the service sectors could be explained by the concentration of retail, banking, and insurance businesses in the West.

3.7.2 Effects of economic crises and downturns

The period of our analysis (1998--2019) covers economic crises and downturns, which may have impacted the results of our analysis to some extent. To address this, we estimated our previous specifications for different periods:

- (i) 1998--2001: This period was characterized by strong economic growth in Germany, with rising investment and household consumption. Additionally, in 1999, Germany adopted the euro as its national currency.
- (ii) 2002--2005: This period was marked by economic stagnation in Germany, with low GDP growth and rising unemployment.
- (iii) 2006--2009: This period was characterized by an economic recovery in Germany, with sustained GDP growth and a decline in the unemployment rate. However, in 2008, the global financial crisis hit Germany, resulting in an economic recession.
- (iv) 2010--2013: This period was marked by a gradual economic recovery in Germany, with GDP growth and falling unemployment. However, in 2011, Germany had to deal with a nuclear disaster in Japan, which led to a rethinking of German energy policy.
- (v) 2014--2017: This period was characterized by sustained economic growth in Germany, with falling unemployment and rising investment. However, in 2015, Germany faced a refugee crisis, which led to social and political tensions.
- (vi) 2018--2019: This period was marked by moderate economic growth in Germany, with a slight increase in unemployment.

The aggregate level results are presented in Tables 3.7.2 and 3.7.3. The alternative results by pay levels and sectors are presented respectively in Tables 3.9.5 and 3.9.6 in the Appendix. The results for the German crisis periods suggest that the marginal effect of an individual's own pay relative to the external reference pay on the probability of quitting is larger than in the aggregate estimation. Specifically, the marginal effect is -0.057 in the 1998--2001 period and gradually decreases to -0.054 in the 2018--2019 period, while the marginal effect in the overall estimation is -0.044 . Similarly, the results for leisure time and health also vary across crisis periods. For instance, the marginal effect of leisure time satisfaction on the probability of quitting

is larger in the 2002--2005 period (−0.004) than in the overall estimate (−0.003). In contrast, the marginal effect of health satisfaction on the probability of quitting is larger in the overall estimate (0.003) than in the 2002--2005 period (0.001). These results suggest that economic crisis periods may impact the relationship between the variables studied and the probability of quitting.

The more detailed analysis of the crisis periods shows that the effect of the pay relationship (own pay versus reference pay) on the results varies with the employee's position in the pay relationship. For employees with an own pay below the external reference pay, this effect is significantly positive, while for those with own pays above the external reference pay, the effect is significantly negative. Compared to the overall regressions, the estimates for the crisis periods show slightly smaller marginal effects for both groups of employees (0.017 versus 0.014 for employees with own pays below the reference pay and −0.020 versus −0.017 for employees with own pays above the reference pay). In terms of the effects on free time and health, the results are also different during crisis periods. Employees tend to have less free time during crisis periods, but this does not significantly affect their health. However, during crisis periods, employees whose own pay is higher than the external reference pay tend to have slightly better health, while employees whose own pay is lower than the external reference pay tend to have slightly worse health.

Table 3.7.2: Estimates of the probability of quit for different period intervals

	1998--2001	2002--2005	2006--2009	2010--2013	2014--2017	2018--2019
$w_{it}/\widehat{w}^{(M)}$	−0.057*** (0.006)	−0.042*** (0.004)	−0.038*** (0.004)	−0.041*** (0.004)	−0.048*** (0.004)	−0.054*** (0.007)
Leisure time	−0.003 (0.003)	−0.004** (0.002)	−0.002 (0.002)	−0.003 (0.002)	−0.003 (0.002)	−0.007** (0.003)
Health	0.005** (0.003)	0.003* (0.002)	0.005*** (0.002)	0.001 (0.002)	0.001 (0.002)	0.008*** (0.003)
Age	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)
Female	0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Log likelihood	−2,464.561	−4,641.335	−4,443.645	−5,507.864	−6,306.818	−2,930.251
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of workers who voluntarily quit their jobs during different time intervals. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Full results with all variables are available on request.

Decomposing the results according to different pay levels allows us to understand how the impact of the economic crisis was felt by different groups of workers in terms of pays, leisure

Table 3.7.3: Estimates of the probability of quit for different period intervals when $w_{it} < \hat{w}^{(M)}$ or $w_{it} > \hat{w}^{(M)}$

	1998--2001	2002--2005	2006--2009	2010--2013	2014--2017	2018--2019
$w_{it}/\hat{w}^{(M)} \times (w_{it} < \hat{w}^{(M)})$	0.017*** (0.003)	0.012*** (0.002)	0.007*** (0.002)	0.014*** (0.002)	0.016*** (0.002)	0.017*** (0.003)
$w_{it}/\hat{w}^{(M)} \times (w_{it} > \hat{w}^{(M)})$	-0.020*** (0.003)	-0.015*** (0.002)	-0.012*** (0.002)	-0.017*** (0.002)	-0.019*** (0.002)	-0.019*** (0.003)
Leisure time	-0.002 (0.002)	-0.003* (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.006** (0.003)
Health	0.005** (0.003)	0.002 (0.002)	0.005*** (0.002)	0.001 (0.002)	0.001 (0.002)	0.008** (0.003)
Age	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Female	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Log likelihood	-2,491.090	-4,682.516	-4,490.616	-5,549.990	-6,356.694	-2,947.021
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of workers who voluntarily quit their jobs during different time intervals. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Full results with all variables are available on request.

time, and health. The results show that for the period 1998--2001, workers earning between 2,000 and 4,000 euros experienced the greatest decline in leisure time, while workers earning more than 4,000 euros experienced the greatest decline in health. Workers earning less than 1,000 euros were relatively spared in terms of leisure time and health but saw their pays fall slightly. For the period 2002--2005, workers earning less than 2,000 euros experienced a decrease in leisure time, while workers earning between 2,000 and 3,000 euros saw their health deteriorate. Workers earning more than 5,000 euros were relatively spared. These results suggest that middle-pay workers were most affected by the economic crisis in terms of leisure time and health. This may be because these workers are often employed in less stable, lower-paying jobs than high-skilled workers but are also less likely to have job protection than low-pay workers. Highly skilled workers, on the other hand, may have been able to weather the crisis better because of their higher skill level and employment status.

The effects of economic crises on pays can also vary depending on how different sectors are affected. For instance, during the 1998--2001 crisis period, manufacturing and service workers who earned more than the median pay experienced a decline in their pays, while construction workers who earned less than the median pay saw an increase in their pays. This variation in the effects of economic crises on pays could be due to differences in how different sectors were impacted by the crisis. For example, a decrease in demand for manufactured goods or services may have had a more negative impact on higher-earning workers in those sectors. Additionally, the effects of health and leisure on pays may also differ by sector. For instance, during the

2002--2005 crisis period, an increase in health had a positive impact on pays in the banking and insurance sector, while a decrease in leisure had a negative impact on pays in the trade and transportation sectors. These differences in the effects of health and leisure on pays across different sectors could be due to variations in the types of jobs and the physical or mental demands of different sectors. For example, workers in banking and insurance may require good health to handle the stress and high responsibilities of their jobs, while workers in trade and transportation may be more susceptible to injury if they work long hours without adequate breaks.

In conclusion, these results suggest that competitive pay pressures during crisis periods may have varying effects depending on employees' external reference pay levels, with significant consequences for their working time and health.

3.7.3 Additional analyses

We also conducted an additional robustness analysis using an alternative method for predicting pays within the Machine Learning family of methods. The purpose of this analysis was to determine if we would obtain similar accuracy and pay levels using a different Machine Learning approach to avoid potential biases. We utilized the Random Forest (RF) method because it employs a different approach than GBRT, specifically the Bagging procedure. Further details on the model and prediction steps can be found in Section 3.10 (Subsection 3.10.2) of the Appendix.

The validity test and the comparison of predicted versus actual pays in Figure 3.10 (Parts (a) and (b)) demonstrate that the RF method produces similarly accurate predictions as the GBRT method, and the pay structures for both methods are very similar. Additionally, the results of replicating the regressions from Tables 3.5.2, 3.6.1, and 3.6.2 in Tables 3.10.1, 3.10.2, and 3.10.3 in the Appendix show almost identical magnitudes and signs. These findings indicate that the GBRT method is a good predictor of pays.

3.8 Discussion and Conclusion

Our study aimed to achieve three objectives: (a) to accurately predict external reference pays while accounting for the complex relationships between pays and their determinants; (b) to estimate the determinants of quitting by observing the impact of monetary rewards on pay comparisons, taking into consideration an individual's pay in relation to other workers with the same skills and profile in the market, as well as non-monetary aspects that contribute to individual well-being. In our analysis, we considered satisfaction with leisure time and health; (c) to estimate how much the response to quitting might vary across pay levels or industries depending on whether the employee is paid below or above the market benchmark pays.

Our estimates are based on three comprehensive database files drawn from the German Socio-Economic Panel (SOEP) spanning the period from 1998 to 2019. The SOEP provides

detailed information on individual and occupational characteristics of employees, employment history, and various aspects related to well-being. It is representative of all private households in Germany.

The empirical analysis involves two approaches. Firstly, we utilize a Machine Learning method, specifically the Gradient Boosting Regression Tree (Friedman, 2001), to accurately predict external benchmark pays. Secondly, we estimate the determinants of quits using the random-effects model (Pfeifer and Schneck, 2012). This model is used to examine how the response to quits varies based on pay comparisons and non-monetary rewards across employees of different pay levels or industries.

The primary findings of our study are as follows. We discovered that pay inequality is a significant factor in workers' decisions to quit their jobs. Specifically, our results indicate that the difference between an individual's own pay and their predicted pay has a significant impact on their likelihood of quitting, depending on their pay level. Underpaid workers are more likely to leave their jobs, while overpaid workers are less likely to quit, particularly those in the middle pay range of 2,000 to 4,000 euros. For workers earning over 4,000 euros, pay comparisons do not appear to affect their propensity to quit. Furthermore, our results suggest that non-monetary rewards, such as leisure time and health benefits, are more critical to these workers. Our findings are consistent with those of d'Ambrosio et al. (2018), who explored the impact of fair income levels on job abandonment and subjective well-being.

We also discovered that the factors affecting the decision to quit vary based on the employee's pay level. Low-pay workers place greater emphasis on non-financial considerations, such as leisure time and benefits, when deciding to quit their jobs. Furthermore, we observed that the effects of pay comparisons and non-monetary rewards on the likelihood of quitting differ by industry. For example, the response to quitting appears to be statistically insignificant in the agricultural sector, regardless of the impact of pay comparisons. In contrast, other sectors exhibit more significant responses to pay inequality, resulting in a higher probability of quitting when employees receive a lower pay than the market average, and a greater likelihood of staying when they receive a higher pay.

The results reveal differences in the reactions of men and women, as well as differences between workers in West and East Germany, to quitting across different sectors and pay levels in Germany. Specifically, the findings by gender and geographical location indicate that men are more likely to quit in search of higher pays, particularly when they are in good health. In contrast, women tend to value jobs that allow them to balance their personal and professional lives, but their pay expectations may become more prominent at higher pay levels or in male-dominated sectors, such as construction. This could be due to the fact that women have overcome occupational barriers and are as ambitious as men, as indicated by the test of the expectations hypothesis in Chapter 1.

Regarding workers in East and West Germany, we found that the reactions to quits for pays or non-monetary rewards were statistically similar. This suggests that the pursuit of more attractive career opportunities is more likely driven by a personal desire for a higher standard of living than by geographical location. However, structural events could have an important impact. In particular, we observe that the likelihood of quitting may be higher during times of crisis and recession. This could be due to the fact that, in such periods, firms generally care less about their employees, as they are also affected. Workers might therefore be more likely to quit. Nonetheless, the results suggest that during economic downturns, competitive pay pressures may affect workers differently depending on their external reference pay level. Workers who earn less than the benchmark tend to work more, be healthier, and accept a small pay cut, while those who earn more tend to work less, be less healthy, and accept a larger pay cut. Middle-pay workers have been the most affected in terms of time off and health. The effects on pays may also vary depending on the sectors affected by the crisis. During the 1998–2001 crisis, manufacturing and service workers experienced a decline in pays, while construction workers saw their pays increase.

Several implications can be drawn from these results. Firstly, the finding that workers who receive lower pays are more likely to quit is consistent with the employment status effect theory. If workers perceive their pays as unfair and low-status compared to other workers in the market, they may leave their jobs. This could lead to a migration of jobs from low-pay sectors to those with higher pays, creating an imbalance in the labor market. Additionally, it may be difficult for firms to recruit for low-pay jobs, putting them at a disadvantage. Conversely, well-paid workers may be less likely to quit as they may not find higher-paying external opportunities. The competitive nature of the labor market means that workers may react to even small differences in pay when comparing their pays to outside offers. The second implication of the results is related to non-monetary rewards. If workers find a good balance between their work and non-work activities, they may be less likely to quit as they are satisfied with their leisure time. This can create a sense of balance for employees both professionally and personally, retaining them in their jobs and avoiding job insecurity through quitting. However, health is an important factor in work, and healthier employees are often more productive. Therefore, they may be more likely to compare their pays to the market and may be more inclined to quit if they perceive their pays to be unfairly low compared to their peers.

The results have implications for policy. Firstly, as discussed above, workers may leave their jobs to find a firm with better pays. Human resource policies should implement action plans to improve workers' pay levels and constantly evaluate their impact. Moreover, given the findings on sectors, hiring policies must be tailored more to one sector or job type than another because of pay levels. Secondly, we found that workers with flexibility in work-life management were less likely to leave their jobs, unlike those satisfied with their health. Workplace wellness policies must take into account the weekly working time and, therefore, the hours outside of the employees' professional activities, proposing more telework and paid vacations. Employees who

are satisfied with their leisure time have achieved a perfect balance of their work and personal activities, which consequently reduces their propensity for quitting, implying lower turnover costs for companies. On the other hand, certain types of jobs, such as those in the manufacturing or service sectors, require physical strength for the most part, which makes it more likely that employees who are more satisfied with their health will meet the job requirements set by employers. Despite the recruitment quota for jobs recognized as disabled, the provision of work does not favor those recognized as disabled workers, which implies hidden discrimination in job offers. The findings suggest that policies are needed to address gender disparities, especially in terms of work-life balance and fair pays for women. Policies such as extended parental leave, flexible work schedules, and childcare policies should be implemented to support women in their careers. Similarly, policies are needed to create jobs in economically disadvantaged areas to provide better career opportunities for workers in those regions. These policies could include tax incentives for firms that locate in these areas and job training programs for local workers. During an economic crisis, it is important to have job protection policies in place to protect workers from the negative effects of the crisis, such as pay cuts and layoffs. Training and retraining programs, subsidies for firms that maintain their workforce during the crisis, and measures to encourage economic recovery in the hardest hit sectors can be helpful in this regard. The findings also suggest that economic diversification is necessary to reduce workers' vulnerability to economic crises. Policies that promote economic diversification could include subsidies for firms investing in emerging sectors, job training programs for workers seeking to transition into growth sectors, and policies to encourage innovation and job creation in new and promising sectors.

However, this study has some limitations. Firstly, the data used in this study are from Germany only, which limits the generalizability of the results to other countries. Additionally, the study does not account for cultural, economic, and institutional differences that may influence the results. Finally, the study only considers the impact of monetary and non-monetary aspects of the job on the decision to quit, and does not take into account other factors such as company culture or relationships with co-workers, which may also play a significant role in an employee's decision to leave their job.

Acknowledgements

This project would not have been possible without the unwavering support of Ambra Poggi, who graciously hosted me at the University of Turin for an international research position. The author is grateful for her invaluable advice, suggestions, and comments that significantly enhanced this research work. Additionally, the author would like to extend thanks to the ERASMUS committee for financing this international exchange, and to the CREM laboratory, particularly Jean-Sébastien Pentecôte, for providing financial support. The author would also like to express appreciation to the PhD students and attendees of the ESOMAS seminar in Italy for their welcoming nature, insightful comments, and constructive suggestions. Special thanks go to the participants of the CREM seminar in Caen, Jean-Pascal Guironnet, and Alioune Diouf, for their relevant comments and suggestions that helped to refine this work. Lastly, the author would

like to acknowledge Isabelle Lebon, with whom they discussed this project before commencing work, and whose advice greatly guided the purpose of this study.

Appendix

3.9 Appendix Tables and Figures

Table 3.9.1: Sample descriptive statistics in pooled data for the period of 1998--2019

	Mean	Standard deviation	Observations
Gender (Male)	0.507	0.499	247,349
Age (years)	42.33	11.28	247,349
Nationality (German)	0.902	0.297	274,135
<i>Education-degree level</i>			247,349
Secondary School Degree	0.234	0.424	
Intermediate School Degree	0.353	0.478	
Technical School Degree	0.065	0.247	
Upper Secondary Degree	0.240	0.427	
Other Degree	0.090	0.286	
Dropout, No School Degree	0.013	0.115	
No School Degree Yet	0.003	0.055	
No School Attended	0.001	0.028	
Years Education (years)	12.49	2.69	246,597
<i>Marital Status</i>			147,349
Married	0.616	0.486	
Married, But Separated	0.026	0.159	
Single	0.252	0.434	
Divorced	0.090	0.286	
Widow(er)	0.014	0.118	
Husband/wife abroad	0.001	0.031	
Registered Same-Sex Partnership, living together	0.002	0.041	
Registered Same-Sex Partnership, living separately	0.000	0.013	
<i>Health status</i>			274,136
Very good	0.088	0.283	
Good	0.357	0.479	
Satisfactory	0.277	0.447	
Less good	0.113	0.317	
Poor	0.029	0.168	
Family income (euros)	3123.70	2688.92	235,406
Number of individuals in the household (Number)	3	1.45	247,349
Number of children (Number)	1	1.22	247,349
Work hours (hours)	37.22	12.79	244,361
Experience full time (years)	15.21	11.65	241,102
Experience part time (years)	3.26	5.78	244,361
Tenure (years)	10.66	9.97	246,799
Own pay (euros)	2356.03	1514.17	247,349

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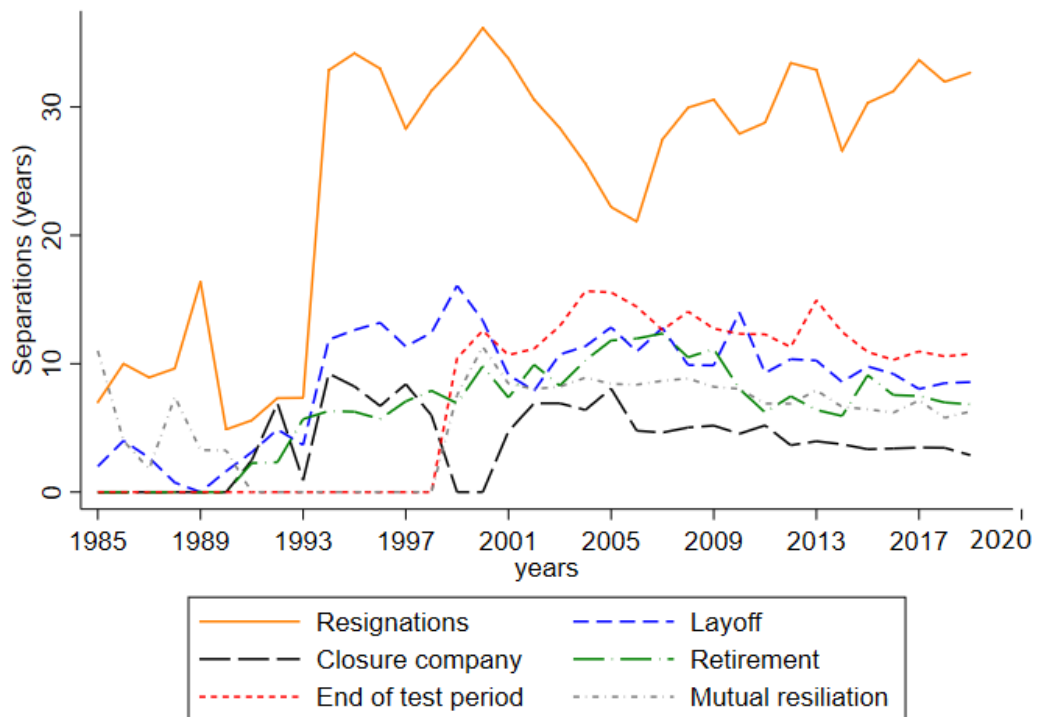
Table 3.9.1 – continued from previous page

	Mean	Standard deviation	
Pay predict (euros)	2393.90	1325.29	247,349
<i>Occupation</i>			232,856
Pensioner	0.002	0.045	
Apprentice trainee	0.002	0.049	
Apprentice trainee in industry	0.022	0.147	
Apprentice trainee in trade	0.013	0.114	
Student trainee	0.005	0.070	
Untrained worker	0.046	0.209	
Semi-trained worker	0.099	0.299	
Trained worker	0.111	0.314	
Foreman group leader	0.016	0.127	
Foreman	0.007	0.083	
Help in family business	0.002	0.047	
Industry or factory foreman	0.006	0.076	
Salaried unskilled with completed training	0.063	0.244	
Salaried unskilled without completed training	0.089	0.285	
Salaried employee, skilled	0.273	0.446	
Salaried employee, highly skilled	0.149	0.356	
Salaried with extensive	0.013	0.113	
Managing partner	0.000	0.011	
Civil servant, lower	0.002	0.044	
Civil servant, middle	0.019	0.136	
Civil servant, upper	0.036	0.186	
Civil servant, executive	0.022	0.146	
<i>Industry</i>			252,933
Agriculture	0.016	0.125	
Energy	0.010	0.098	
Mining	0.002	0.049	
Manufacturing	0.232	0.422	
Construction	0.060	0.238	
Trade	0.149	0.356	
Transport	0.050	0.218	
Bank, Insurance	0.038	0.191	
Services	0.425	0.494	
Other	0.018	0.133	
<i>Size of the company</i>			238,773
< 5	0.092	0.289	
5–20	0.171	0.377	
20–200	0.279	0.449	
200–2000	0.212	0.409	
> 2000	0.245	0.430	

Table 3.9.2: Proportion of turnover for different reasons

Proportions by reason for turnover	
Resignations	15%
Layoff	12%
Company closure	5%
End of test period	13%
Return to school	0.1%
Move or transfer to another company	0.2%
Mutual termination	8%
Retirement	0.8%
Leave or temporary absence	1.7%
Ended self-employed	2.2%

Figure 3.8: Fraction of job separations by different reasons by year



Notes: Author's calculation based on data from GSOEP (1998--2019).

Table 3.9.3: Effects on quits by pay level for Men, Women, West, and East

	$\leq 1,000$ (1)	$> 1,000--\leq 2,000$ (2)	$> 2,000--\leq 3,000$ (3)	$> 3,000--\leq 4,000$ (4)	$> 4,000--\leq 5,000$ (5)	$> 5,000$ (6)
Men						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.008 (0.013)	-0.010 (0.006)	0.007*** (0.002)	0.006*** (0.002)	-0.000 (0.003)	0.005 (0.005)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.018*** (0.009)	-0.001 (0.005)	-0.009*** (0.002)	-0.008*** (0.002)	-0.001 (0.002)	-0.004 (0.004)
Leisure	-0.002 (0.007)	0.007 (0.005)	-0.000 (0.002)	-0.006*** (0.002)	-0.004 (0.003)	-0.008* (0.005)
Health	-0.001 (0.008)	0.001 (0.005)	0.005** (0.002)	0.004** (0.002)	0.004 (0.002)	0.004 (0.004)
Women						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.006 (0.005)	-0.015*** (0.003)	0.012*** (0.003)	0.011*** (0.004)	0.007 (0.006)	0.002 (0.004)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.044*** (0.004)	-0.001 (0.005)	-0.009*** (0.002)	-0.014*** (0.003)	-0.009 (0.005)	-0.002 (0.004)
Leisure	-0.013*** (0.003)	-0.002 (0.003)	-0.005** (0.003)	-0.002 (0.004)	-0.003 (0.005)	-0.005** (0.003)
Health	-0.002 (0.003)	0.001 (0.003)	0.002 (0.003)	0.006** (0.003)	0.006 (0.005)	0.003 (0.003)
West						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.007 (0.006)	0.007* (0.003)	0.008** (0.004)	0.007*** (0.002)	0.002 (0.002)	0.006 (0.004)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.020*** (0.004)	-0.016*** (0.003)	-0.013*** (0.002)	-0.010** (0.004)	-0.004* (0.002)	-0.006 (0.004)
Leisure	-0.008** (0.003)	0.001 (0.003)	-0.003 (0.004)	-0.004* (0.002)	-0.003 (0.002)	-0.006 (0.004)
Health	-0.000 (0.003)	0.003 (0.003)	0.003 (0.004)	0.004** (0.002)	0.002 (0.002)	0.008* (0.004)
East						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.023* (0.013)	-0.004 (0.005)	0.011*** (0.002)	0.007*** (0.002)	-0.003 (0.003)	0.003 (0.002)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.030*** (0.010)	-0.009*** (0.004)	-0.012*** (0.003)	-0.009** (0.004)	0.001 (0.001)	-0.001 (0.002)
Leisure	-0.021*** (0.008)	0.002 (0.004)	-0.003 (0.004)	-0.005** (0.002)	-0.005 (0.002)	-0.005** (0.002)
Health	0.001 (0.008)	0.002 (0.004)	0.003 (0.004)	0.005*** (0.002)	0.008** (0.001)	0.004** (0.002)
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of male workers who voluntarily quit their jobs during the period 1998--2019. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. Additional individual characteristics included are age and gender. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 3.9.4: Effects on quits by sectors for Men, Women, West, and East

	Agriculture	Manufacturing	Construction	Trade	Transport	Bank Insurance	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Men							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.001 (0.013)	0.013*** (0.002)	0.018*** (0.006)	0.023*** (0.006)	0.025*** (0.007)	0.011* (0.006)	0.014*** (0.003)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.009 (0.010)	-0.015*** (0.002)	-0.015*** (0.005)	-0.025*** (0.005)	-0.027*** (0.006)	-0.016*** (0.006)	-0.018*** (0.002)
Leisure	-0.004 (0.013)	-0.002 (0.002)	0.005 (0.005)	-0.006 (0.005)	0.014** (0.007)	-0.000 (0.006)	-0.005* (0.003)
Health	-0.002 (0.012)	0.008*** (0.002)	0.004 (0.005)	0.001 (0.005)	-0.010 (0.007)	0.002 (0.006)	0.007*** (0.003)
Women							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.006 (0.012)	0.012** (0.005)	0.022*** (0.005)	0.013*** (0.006)	0.017*** (0.011)	0.010 (0.006)	0.014*** (0.002)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.004 (0.009)	-0.017*** (0.004)	-0.026*** (0.005)	-0.015*** (0.004)	-0.018** (0.009)	-0.010 (0.005)	-0.017*** (0.002)
Leisure	-0.002 (0.012)	-0.006 (0.004)	0.005 (0.005)	-0.010** (0.004)	-0.001 (0.009)	-0.002 (0.006)	-0.004** (0.002)
Health	0.002 (0.012)	0.001 (0.004)	0.005 (0.005)	0.004 (0.004)	-0.012 (0.009)	0.009 (0.005)	0.000 (0.002)
West							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.011 (0.014)	0.012*** (0.002)	0.014*** (0.006)	0.020*** (0.004)	0.022*** (0.007)	0.013** (0.005)	0.014*** (0.002)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.008 (0.011)	-0.015*** (0.002)	-0.012** (0.005)	-0.020*** (0.003)	-0.024*** (0.006)	-0.015*** (0.004)	-0.017*** (0.002)
Leisure	-0.006 (0.008)	-0.003 (0.002)	0.003 (0.006)	-0.002 (0.003)	0.007 (0.006)	-0.001 (0.004)	-0.004** (0.002)
Health	-0.005 (0.008)	0.006*** (0.002)	0.005 (0.006)	0.004 (0.003)	-0.012* (0.006)	0.006 (0.004)	0.002 (0.002)
East							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.014 (0.013)	0.013*** (0.007)	0.028** (0.012)	0.009 (0.009)	0.025*** (0.014)	0.005 (0.008)	0.013*** (0.004)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.010 (0.012)	-0.018*** (0.005)	-0.021** (0.009)	-0.015** (0.007)	-0.024*** (0.011)	-0.006 (0.007)	-0.017*** (0.003)
Leisure	-0.007 (0.008)	-0.003 (0.006)	0.001 (0.010)	-0.011 (0.007)	0.009 (0.011)	-0.007 (0.005)	-0.005 (0.004)
Health	-0.004 (0.008)	0.004 (0.005)	0.005 (0.009)	0.001 (0.007)	0.017* (0.011)	0.006 (0.005)	0.004 (0.003)
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of male workers who voluntarily quit their jobs during the period 1998--2019. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the GBRT algorithm. Additional individual characteristics included are age and gender. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 3.9.5: Effects on quits by pay level for different periods

	$\leq 1,000$ (1)	$> 1,000--\leq 2,000$ (2)	$> 2,000--\leq 3,000$ (3)	$> 3,000--\leq 4,000$ (4)	$> 4,000--\leq 5,000$ (5)	$> 5,000$ (6)
1998--2001						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.003 (0.014)	0.001 (0.006)	0.011*** (0.004)	0.017*** (0.006)	0.007 (0.010)	0.001 (0.008)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.004 (0.010)	-0.010* (0.005)	-0.012*** (0.003)	-0.016*** (0.005)	-0.005 (0.008)	-0.000 (0.007)
Leisure	-0.007 (0.008)	0.005 (0.005)	-0.005 (0.004)	-0.0014** (0.007)	-0.000 (0.008)	-0.001 (0.008)
Health	0.014* (0.008)	0.000 (0.005)	0.009** (0.004)	0.008 (0.006)	-0.004 (0.008)	0.004** (0.008)
2002--2005						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.006 (0.010)	-0.002 (0.005)	0.009*** (0.003)	0.003 (0.003)	-0.002 (0.006)	0.003 (0.007)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.013* (0.008)	-0.004 (0.004)	-0.011*** (0.003)	-0.004 (0.003)	0.001 (0.005)	-0.006 (0.006)
Leisure	-0.014** (0.006)	-0.003 (0.004)	-0.002 (0.003)	-0.005 (0.003)	-0.004 (0.004)	-0.003 (0.004)
Health	0.001 (0.006)	0.009** (0.004)	-0.000 (0.003)	0.002 (0.003)	-0.003 (0.005)	0.005 (0.004)
2006--2009						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.002 (0.005)	0.000 (0.006)	0.002 (0.004)	-0.002 (0.004)	0.003 (0.005)	0.005 (0.006)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.023*** (0.008)	-0.012** (0.005)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.004 (0.004)
Leisure	-0.012* (0.007)	0.003 (0.005)	0.001 (0.003)	-0.002 (0.004)	0.005 (0.005)	-0.008 (0.006)
Health	0.002 (0.006)	0.008* (0.005)	0.001 (0.003)	0.006 (0.003)	0.003 (0.005)	0.010* (0.006)
2010--2013						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.007 (0.010)	0.015** (0.006)	0.007* (0.004)	0.005 (0.004)	-0.004 (0.008)	0.009 (0.003)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.022*** (0.007)	-0.026*** (0.005)	-0.009*** (0.003)	-0.008*** (0.003)	0.002 (0.005)	-0.005 (0.003)
Leisure	-0.015** (0.006)	-0.000 (0.005)	-0.003 (0.004)	-0.003 (0.004)	-0.002 (0.005)	-0.005* (0.003)
Health	-0.009 (0.006)	-0.004 (0.005)	0.006* (0.003)	0.002 (0.003)	0.007 (0.005)	-0.004 (0.003)
2014--2017						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.010 (0.011)	0.007 (0.006)	0.014*** (0.004)	0.010*** (0.004)	0.005 (0.005)	0.005 (0.005)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.029*** (0.007)	-0.018*** (0.005)	-0.013*** (0.003)	-0.011*** (0.003)	-0.007 (0.004)	-0.006 (0.004)
Leisure	-0.005 (0.006)	-0.003 (0.006)	-0.003 (0.004)	-0.002 (0.003)	-0.006 (0.004)	-0.005 (0.004)
Health	0.000 (0.006)	0.004 (0.005)	0.005 (0.004)	0.005 (0.003)	0.002 (0.004)	0.001 (0.004)
2018--2019						
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.009 (0.007)	0.006 (0.010)	0.013*** (0.007)	0.011*** (0.006)	-0.005 (0.006)	0.008 (0.007)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.042*** (0.012)	-0.016** (0.008)	-0.015*** (0.005)	-0.013*** (0.005)	-0.005 (0.006)	-0.005 (0.006)
Leisure	-0.017** (0.009)	0.005 (0.008)	-0.010 (0.006)	-0.010* (0.005)	-0.013* (0.007)	0.001 (0.006)
Health	0.002 (0.010)	0.005 (0.008)	0.012** (0.006)	0.005 (0.005)	0.007 (0.007)	0.005 (0.006)
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes

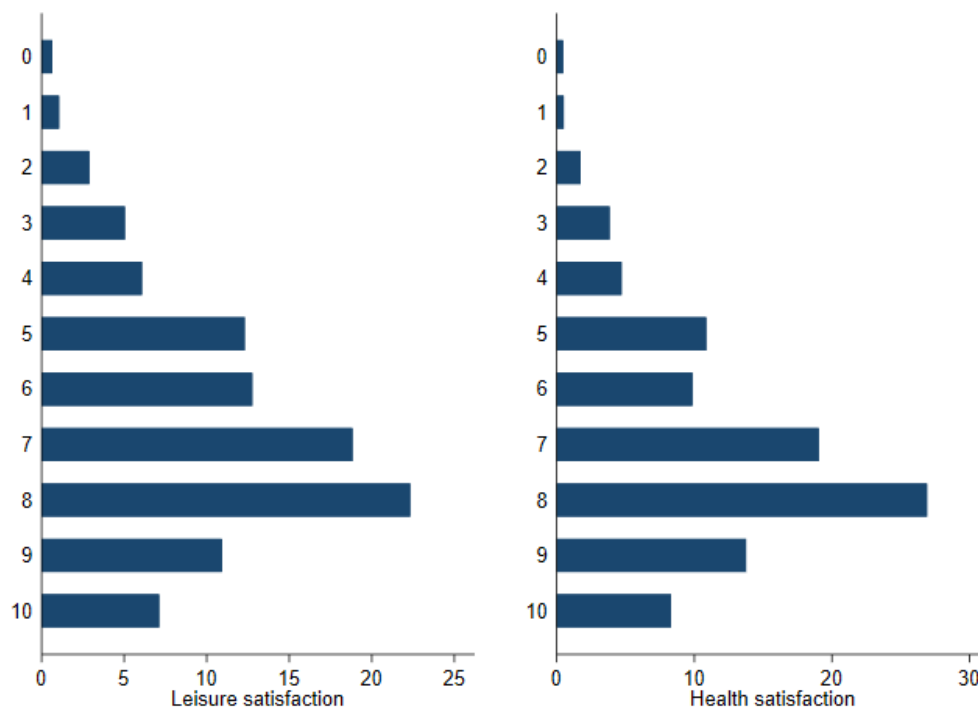
Notes: Author's calculation based on data from GSOEP (1998--2019).

Table 3.9.6: Effects on quits by sectors for different periods

	Agriculture	Manufacturing	Construction	Trade	Transport	Bank Insurance	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1998--2001							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.006 (0.006)	0.017*** (0.005)	0.008 (0.008)	0.007 (0.009)	0.028* (0.008)	0.009 (0.009)	0.020*** (0.005)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.007 (0.005)	-0.015*** (0.004)	-0.020** (0.010)	-0.012* (0.007)	-0.026** (0.009)	-0.006 (0.006)	-0.026*** (0.005)
Leisure	-0.006 (0.003)	-0.005 (0.004)	-0.007 (0.008)	0.009 (0.008)	-0.009 (0.007)	0.006 (0.006)	-0.005 (0.004)
Health	-0.006 (0.003)	0.010** (0.004)	0.012** (0.008)	0.000 (0.008)	-0.002 (0.007)	0.004 (0.006)	0.003 (0.004)
2002--2005							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.003 (0.011)	0.005 (0.004)	0.032*** (0.011)	0.012* (0.007)	0.005 (0.009)	0.009 (0.009)	0.012*** (0.004)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.007 (0.009)	-0.009*** (0.003)	-0.023*** (0.008)	-0.011** (0.005)	-0.009 (0.008)	-0.019*** (0.009)	-0.016*** (0.003)
Leisure	-0.003 (0.009)	-0.006* (0.004)	-0.003 (0.009)	-0.002 (0.006)	0.007 (0.008)	-0.005 (0.008)	-0.007** (0.003)
Health	0.004 (0.009)	0.004 (0.003)	-0.003 (0.009)	0.002 (0.006)	-0.007 (0.008)	0.020** (0.009)	0.003 (0.003)
2006--2009							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.007 (0.007)	0.006 (0.004)	-0.007 (0.009)	0.021*** (0.008)	0.004 (0.009)	0.003 (0.007)	0.007* (0.004)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	0.000 (0.008)	-0.012*** (0.004)	0.007 (0.009)	-0.020*** (0.006)	-0.010 (0.009)	-0.003 (0.006)	-0.014*** (0.003)
Leisure	0.004 (0.004)	-0.003 (0.004)	-0.001 (0.009)	-0.004 (0.006)	0.008 (0.005)	0.003 (0.006)	0.003 (0.003)
Health	0.001 (0.004)	0.008** (0.004)	-0.004 (0.009)	0.004 (0.006)	0.004 (0.005)	0.006 (0.007)	0.003 (0.003)
2010--2013							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.008 (0.008)	0.019*** (0.005)	0.009 (0.011)	0.016** (0.007)	0.034*** (0.010)	0.024** (0.010)	0.010*** (0.003)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.009 (0.008)	-0.021*** (0.004)	-0.012 (0.009)	-0.020*** (0.006)	-0.038*** (0.012)	-0.027*** (0.010)	-0.013*** (0.003)
Leisure	0.010 (0.007)	-0.006 (0.004)	0.008 (0.010)	-0.001 (0.006)	0.001 (0.008)	-0.004 (0.008)	-0.005* (0.003)
Health	-0.014* (0.006)	0.008** (0.004)	0.006 (0.009)	-0.000 (0.006)	-0.009 (0.008)	-0.009 (0.008)	-0.004 (0.003)
2014--2017							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.010 (0.008)	0.008** (0.004)	0.023*** (0.011)	0.017** (0.007)	0.025*** (0.011)	0.001 (0.009)	0.018*** (0.003)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.008 (0.009)	-0.013*** (0.004)	-0.020*** (0.009)	-0.021*** (0.005)	-0.027*** (0.009)	-0.006 (0.008)	-0.021*** (0.003)
Leisure	-0.008 (0.007)	-0.004 (0.004)	0.008 (0.010)	-0.005 (0.006)	0.007 (0.008)	0.003 (0.008)	-0.004 (0.003)
Health	-0.000 (0.008)	0.002 (0.004)	0.006 (0.009)	0.005 (0.006)	-0.001 (0.008)	-0.002 (0.008)	0.004 (0.003)
2018--2019							
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	-0.009 (0.008)	0.017*** (0.007)	0.008 (0.008)	0.026** (0.006)	0.008 (0.008)	0.004 (0.009)	0.017*** (0.006)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.003 (0.009)	-0.017*** (0.006)	-0.004 (0.009)	-0.024*** (0.009)	-0.008 (0.009)	0.004 (0.009)	-0.017*** (0.005)
Leisure	-0.000 (0.007)	-0.001 (0.006)	0.008 (0.005)	-0.004 (0.006)	0.010 (0.006)	-0.004 (0.008)	-0.013** (0.005)
Health	0.003 (0.009)	0.006 (0.006)	0.006 (0.005)	0.012* (0.005)	0.007 (0.006)	0.004 (0.007)	0.010* (0.005)
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019).

Figure 3.9: Satisfaction rate in terms of leisure and health by years



Notes: Author's calculation based on data from GSOEP (1998--2019).

3.10 Explanation of the GBRT and RF models

3.10.1 Appendix GBRT for estimation of reference pays

Let $x = \{x_i\}_{i=1}^N$ be the vector of all input variables and $w = \{w_i\}_{i=1}^N$ be the output vector. The model takes as input a set of fifteen characteristics considered as determinants of the pay.

The variables selected as inputs are fed into the GBRT model to form a good regression model. The inputs to the GBRT model include a set of training samples $D = \{(x_i, w_i)\}_{i=1}^N$, $x_i \in \mathbb{R}^D$, $w_i \in \mathbb{R}$. The objective with the GBRT is to find a predicted pay \hat{w} that associates x with w and, in the meantime, minimizes the expected value of a specified loss function $\psi(w_i, \hat{w})$ ²¹ on the distribution of x and w , i.e., minimizes the empirical risk (Li and Bai, 2016). The prediction process of our model is mainly summarized in three steps (Friedman, 2001): Step 1 is to initialize the base learner $\hat{w}^{(0)}$, which is usually a constant function, and the specific calculation is as follows:

$$\hat{w}^{(0)} = \arg \min_{\gamma_0} \sum_{i=1}^N \psi(w_i, \gamma_0) \quad (3.4)$$

Step 2 is the update of the weak model, which also includes 3 steps. First, the value of the

²¹The loss function measures the amount by which the predicted pays \hat{w} deviate from the individual pay variable, which can be the squared error, absolute error, Huber error, etc. (Yang et al., 2020).

negative gradient of the loss function is calculated as follows (Li and Bai, 2016):

$$r_{im} = - \left[\frac{\partial \psi(w_i, \hat{w})}{\partial \hat{w}} \right]_{\hat{w}=\hat{w}^{(m-1)}}, i = 1, \dots, N \quad (3.5)$$

Where $\hat{w}^{(m-1)}$ denotes the $(m-1)$ -th weak pay prediction, w_i is the real value of the i -th sample, and \hat{w} is the predicted pay value of the individual pays w . The data (x_i, r_{im}) can then be used to fit a regression tree and obtain its corresponding leaf node region R_{fm} where $f = 1, \dots, F$ and F is the number of leaf nodes in this regression tree. Second, for each node region, a predicted value γ_{fm} is obtained by minimizing the following equation:

$$\gamma_{fm} = \arg \min_{\gamma} \sum_{i \in R_{fm}} \psi(w_i, \hat{w}^{(m-1)} + \gamma) \quad (3.6)$$

γ_{fm} represent the best fit values of the f -th leaf node in the m -th regression tree, with $m = 1, \dots, M$ the number of regression trees. Third, the m -th regression tree $\hat{w}^{(m)}$, i.e., the updated model whose corresponding leaf node area is R_{fm} is obtained as follows (Bevilacqua et al., 2003):

$$\hat{w}^{(m)} = \hat{w}^{(m-1)} + \sum_{f=1}^F \gamma_{fm} I(x \in R_{fm}) \quad (3.7)$$

Where, $I = 1$ if $x \in R_{fm}$ and $I = 0$ otherwise.

For step 3, we repeated step 2 until the number of iterations was equal 1,000, with a maximum depth of 6, a maximum learning rate of 0.500, and a maximum of divisions of 4, which allowed us to obtain a very accurate prediction of the pays. We thus obtained our final predicted pay based on the weak pay prediction models as follows:

$$\hat{w}^{(M)} = \hat{w}^0 + \sum_{f=1}^F \sum_{m=1}^M \gamma_{fm} I(x \in R_{fm}) \quad (3.8)$$

The formula of R^2 and $RMSE$ calculated to validate the performance of the model are: $R^2 = 1 - \frac{\sum_{i=1}^N (w - \hat{w}^{(M)})^2}{\sum_{i=1}^N (w - \bar{w})^2}$ where \bar{w} is the average pay and $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (w - \hat{w}^{(M)})^2}$.

3.10.2 Appendix Random Forest regression for estimation of an alternative measure of reference pays

We also explore the use of benchmark pays predicted from an alternative GBRT measure to see if the results remain similar when we employ another machine learning algorithm that uses a different approach. We use the RF algorithm, which uses a different approach to GBRT boosting; in particular, it uses bagging to make the predictions.

A Random Forest (RF) regressor consists of a collection of a set of regression trees $\{T_b : b = 1, \dots, B\}$ that act as regression functions in their own right, where $b = 1, \dots, B$ is the number of

trees generated. The RF uses a basic b -tree structured classifier, $h(X, \Theta_b)$ where X is the input vector and Θ_b is a family of independent and identically distributed random vectors in each b tree (see Breiman et al. (1984) for more details). Trees are generated at the training stage using an algorithm called "bagging (or bootstrap aggregation)" (Breiman, 2001). The RF is thus constructed based on random sampling called bootstrapping where a sample is obtained by randomly selecting with replacement n observations from the training dataset and each observation has a $1/n$ probability of being selected (Li et al., 2018). Each decision tree consists of decision nodes and leaf nodes (Breiman, 1996). Each node is split using the best binary split among a subset of input variables (Adelabu et al., 2015; Alpaydin, 2020). The predicted value of an observation is calculated by averaging all outputs predicted by the decision trees (Breiman, 2001; Lawrence et al., 2006).

Our objective is to predict the pays of workers who have the same profile in the market. Let $x = \{x_i\}_{i=1}^N$ be the vector of all input variables and $w = \{w_i\}_{i=1}^N$ be the output vector. The model takes as input and output the same variables considered in the GBRT. We also subdivided the data with 80 percent in training data and 20 percent in test data which represent the out-of-bag (OOB) data. The inputs to the RF model include a set of training samples, which we denote D_n , and is composed of the set of all peer samples of X and w expressed as follows:

$$D_n = \{(x_i, w_i)\}_{i=1}^N, X \in \mathbb{R}^p (p \text{ is the number of predictors}), w \in \mathbb{R} \quad (3.9)$$

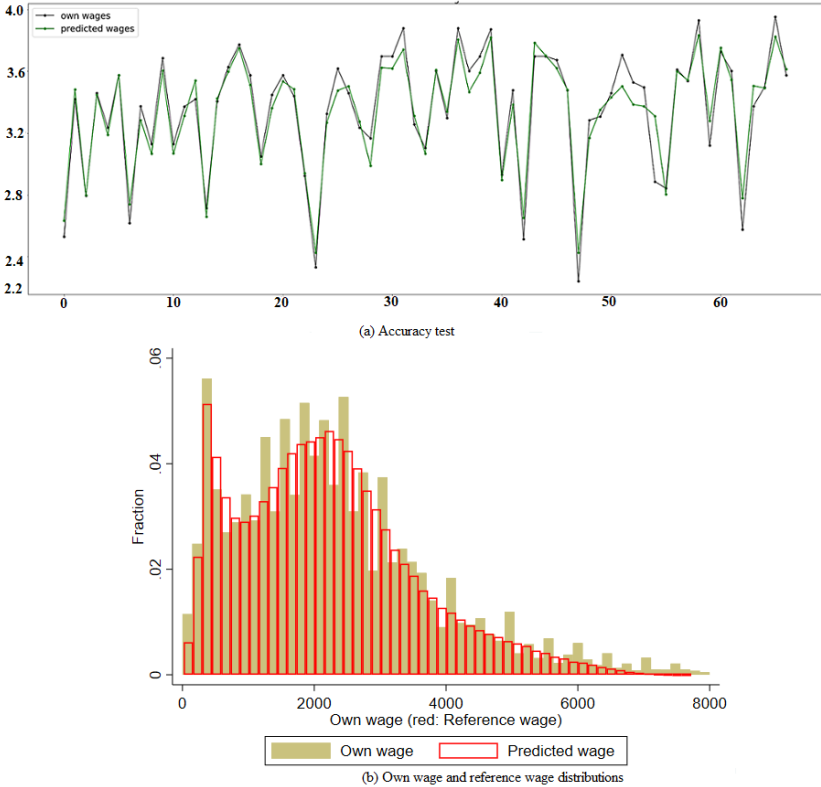
The prediction process of our model is mainly summarized in three steps. Step 1 consists of the bagging algorithm. During this step, the bagging algorithm selects several bootstrap samples ($D_n^{\Theta_1}, D_n^{\Theta_2}, \dots, D_n^{\Theta_B}$) from our training sample D_n . Step 2 is the node splitting process, which also includes 2 steps. First, the data sets are split at each node by the algorithm, so that the parameters of the splitting functions are optimized to fit the D_n set of our training data. Third, each node then performs its own split function to the new pay determinants it contains. For step 3, we repeated step 2 until the number of iterations was equal to 1,000, which allowed us to obtain a very accurate prediction of the pays. At the end of this process, each tree provided a pay prediction $\hat{w}_1 = \hat{h}(X, D_n^{\Theta_1}), \hat{w}_2 = \hat{h}(X, D_n^{\Theta_2}), \dots, \hat{w}_B = \hat{h}(X, D_n^{\Theta_B})$. The aggregation is done by averaging all the pays predicted by the different trees. We thus obtain our external reference pay for workers in the market as follows:

$$\hat{w}_{kBt} = \frac{1}{B} \sum_{b=1}^B \hat{w}_b = \frac{1}{B} \sum_{b=1}^B \hat{h}(X, D_n^{\Theta_b}) \quad (3.10)$$

Where, \hat{w}_{kBt} is the prediction of the pay in X using the b -th tree. For each step ntree values (number of trees) from 100 to 1,000 were tested with intervals of 100 (Hatfield and Prueger, 2010), and Mtry (number of variables) was tested from 3 to 10 to obtain an accurate model. We used the command *rforest* on stata for the regression algorithm (Zou and Schonlau, 2022). The validity test and the structure of predicted versus actual pays in Figure C.1, as well as the estimate of the probability of quitting in Table C.1, are quite similar from the GBRT. This is also

the case for the estimates by pay levels and by industry in tables C.2 and C.3 respectively.

Figure 3.10: Accuracy test and pay distributions



Notes: Figures plot the accuracy test of the RF algorithm’s prediction of external comparison pays (part (a)) and own pay, reference pay distributions. In (a) we have plotted the test data on the x-axis and the target variable on the y-axis, which represent the individual pays. In black we have the individual own pays and in green we have the predicted external comparison pays. In (b) the khaki color represents the distribution of own pays, and the red color the distribution of predicted reference pays.

Table 3.10.1: Estimates of the probability of quit: Estimated reference pays by RF

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$w_{it}/\widehat{w}^{(M)}$	-0.044*** (0.002)		-0.044*** (0.002)	-0.044*** (0.002)	-0.043*** (0.002)	-0.045*** (0.002)	-0.043*** (0.002)	
Leisure time		-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Health		0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$								0.016*** (0.001)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$								-0.015*** (0.001)
Age						-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Female						0.000 (0.001)	0.000 (0.001)	0.002** (0.001)
Unemployment rate							-0.005*** (0.001)	
Squared unemployment rate							0.002** (0.000)	
Log likelihood	-22,269.639	-22,197.091	-21,975.899	-21,935.87	-21,928.176	-21,848.379	-21,769.189	-21,257.516
Dummies of years	No	No	No	Yes	Yes	Yes	Yes	Yes
Regions	No	No	No	No	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The sample consists of workers who voluntarily quit their jobs during the period 1998--2019. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the RF algorithm. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Full results with all variables are available on request.

Table 3.10.2: Effects on quits by pay level: Estimated reference pays by RF

	$\leq 1,000$ (1)	$> 1,000--\leq 2,000$ (2)	$> 2,000--\leq 3,000$ (3)	$> 3,000--\leq 4,000$ (4)	$> 4,000--\leq 5,000$ (5)	$> 5,000$ (6)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.003 (0.006)	-0.003 (0.003)	0.011*** (0.002)	0.007*** (0.002)	0.001 (0.002)	0.002 (0.002)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.022*** (0.005)	-0.014*** (0.002)	-0.013*** (0.002)	-0.010*** (0.002)	-0.003 (0.002)	-0.001 (0.002)
Leisure	-0.012*** (0.003)	0.001 (0.002)	-0.001 (0.002)	-0.005** (0.002)	-0.004* (0.002)	-0.005** (0.002)
Health	0.002 (0.003)	0.002 (0.002)	0.004** (0.002)	0.005*** (0.002)	0.004* (0.002)	0.004** (0.002)
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the RF algorithm. Additional individual characteristics included are age and gender. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Table 3.10.3: Effects on quits by sectors: Estimated reference pays by RF

	Agriculture	Manufacturing	Construction	Trade	Transport	Bank Insurance	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} < \widehat{w}^{(M)})$	0.002 (0.009)	0.013*** (0.002)	0.018*** (0.006)	0.017*** (0.004)	0.021*** (0.006)	0.012** (0.004)	0.013*** (0.002)
$w_{it}/\widehat{w}^{(M)} \times (w_{it} > \widehat{w}^{(M)})$	-0.008 (0.008)	-0.016*** (0.002)	-0.015*** (0.004)	-0.019*** (0.003)	-0.024*** (0.005)	-0.014*** (0.004)	-0.017*** (0.002)
Leisure	-0.000 (0.008)	-0.003* (0.002)	0.005 (0.005)	-0.003 (0.003)	0.008 (0.005)	-0.001 (0.004)	-0.005*** (0.002)
Health	-0.004 (0.008)	0.006*** (0.002)	0.004 (0.005)	0.003 (0.003)	-0.004 (0.005)	0.004 (0.004)	0.003* (0.002)
Dummies of years	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Author's calculation based on data from GSOEP (1998--2019). Estimates of the random effects model with heterogeneity correction. The values represent marginal effects. Bootstrapped standard errors are in parentheses. The dependent variable is the dummy variable of the probability of quitting. Quits are defined as voluntary terminations induced by an employee's quit. The external comparison pay is predicted using the RF algorithm. Additional individual characteristics included are age and gender. * significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

Conclusion Générale

Les différents chapitres de cette thèse ont permis d'approfondir l'analyse de la satisfaction professionnelle et de son impact sur le marché du travail en Europe. Ils ont mis en évidence les disparités de genre ainsi que l'importance de la satisfaction professionnelle pour la performance économique et la rétention des travailleurs.

Le chapitre 1 utilise différentes mesures des opinions professionnelles, telles que la satisfaction globale, le salaire, les perspectives d'évolution de carrière, la sécurité de l'emploi et les relations entre collègues pour analyser les raisons pour lesquelles les femmes ont tendance à être plus satisfaites de leur travail que les hommes, malgré des situations professionnelles moins favorables. Une méthode d'appariement a été préalablement effectuée selon les caractéristiques individuelles et professionnelles des hommes et des femmes pour contrôler les facteurs confondants qui pourraient influencer le différentiel de satisfaction. Par la suite, une analyse par régression *probit* avec sélection de l'échantillon a été effectuée suivant les différentes mesures de la satisfaction au travail, sur un échantillon de 28 483 salariés âgés de 15 à 65 ans, dans 35 pays d'Europe en 2015.

Ce chapitre a permis de mettre en lumière qu'il existe des différences significatives entre les sexes en matière de satisfaction professionnelle. Les femmes se déclarent plus satisfaites de la sécurité de l'emploi et des relations avec les collègues, mais moins satisfaites du salaire et des perspectives de carrière que les hommes. Toutefois, ces différences disparaissent lorsque les caractéristiques individuelles et professionnelles sont prises en compte, ce qui indique que l'écart de rémunération entre les sexes et la satisfaction professionnelle globale ne sont pas uniquement dus au genre, mais plutôt à d'autres facteurs tels que l'éducation, l'expérience et les responsabilités professionnelles. En outre, l'étude met en évidence que les femmes sont moins optimistes que les hommes quant à leurs perspectives de carrière, même après avoir pris en compte les facteurs de confusion et la sélection de l'échantillon. Cela suggère que l'inégalité et les préjugés liés au genre peuvent affecter le développement de carrière et les aspirations des femmes, entraînant une moindre satisfaction quant à leurs perspectives de carrière. L'étude met également en lumière que les attentes salariales et la satisfaction professionnelle des femmes sont affectées par divers facteurs tels que l'âge, l'éducation, la position hiérarchique et l'environnement de travail. Les femmes plus jeunes, celles qui ont fait des études supérieures ou celles qui travaillent dans des domaines dominés par les hommes alignent leurs attentes sur celles des hommes, ce qui leur permet de réagir de manière similaire aux dimensions de la satisfaction professionnelle. Enfin,

l'étude permet de mettre en évidence que l'égalité des sexes a un effet limité sur la satisfaction au travail et que la relation entre le sexe et la satisfaction au travail est complexe, variant selon les dimensions et le niveau d'égalité des sexes dans un pays donné.

Ces résultats soulignent l'importance de s'intéresser davantage aux inégalités entre les sexes sur le marché du travail et d'améliorer les conditions de travail pour promouvoir la satisfaction au travail de tous les travailleurs. Maintenant que nous avons examiné les raisons pour lesquelles les femmes ont tendance à être plus satisfaites de leur travail que les hommes, nous allons nous pencher sur l'impact de la satisfaction des travailleurs sur leur productivité.

Le chapitre 2 examine comment la satisfaction des travailleurs affecte leur productivité en utilisant un échantillon de 2 716 salariés français provenant des enquêtes Génération 2010 de 2013 et 2017. Il utilise une méthode DEA avec l'indice de *Malmquist* hiérarchique pour estimer la variation de la productivité globale des travailleurs, qui est ensuite décomposée en termes d'efficience et de technologie. De plus, une modélisation économétrique est utilisée pour mesurer l'impact de la satisfaction des travailleurs sur leur productivité à l'aide de deux mesures des opinions professionnelles (salaires et perspectives professionnelles). Cette modélisation tient compte du cadre spatial représenté par la zone d'emploi de résidence des travailleurs, ainsi que d'un ensemble de caractéristiques individuelles et professionnelles susceptibles d'affecter leur performance.

Les résultats montrent que les employés qui se sentent bien rémunérés ou qui sont optimistes quant à leur avancement de carrière sont plus susceptibles de fournir un effort supplémentaire dans la réalisation de leurs tâches et d'améliorer leurs compétences en créativité. En revanche, les travailleurs plus satisfaits de leur salaire ou de leurs perspectives professionnelles ont tendance à être moins efficaces au travail. Les résultats ont également montré que ces relations peuvent varier selon différents facteurs, tels que le sexe, l'âge, la taille de l'entreprise et les caractéristiques de la zone d'emploi. En particulier, les effets positifs de la satisfaction salariale sur la performance des travailleurs sont plus importants pour les jeunes travailleurs dans des petites entreprises opérant dans des zones d'emploi dominées par l'industrie ou le secteur des services, où la part de cadres est plus importante par rapport aux ouvriers. De plus, la satisfaction salariale peut avoir des effets négatifs sur l'efficacité des travailleurs, en particulier pour les hommes et les travailleurs des grandes entreprises, en particulier lorsqu'ils résident dans des zones d'emploi à fort taux de chômage.

Ces résultats soulignent l'importance de considérer différents facteurs contextuels lors de l'évaluation de l'impact de la satisfaction au travail sur la performance des travailleurs. Les employeurs devraient tenir compte des caractéristiques du cadre spatial dans lequel ils opèrent, ainsi que des différentes caractéristiques de leurs travailleurs, lorsqu'ils conçoivent leur stratégie de rémunération. Cela est particulièrement important car la satisfaction d'un travailleur ne dépend pas seulement de ses propres conditions de travail, mais aussi de la comparaison de celles-ci

avec celles de son plus proche voisin. Par conséquent, les employeurs devraient également tenir compte de l'environnement social et relationnel des travailleurs pour concevoir des stratégies de rémunération qui maximisent la satisfaction et la performance des travailleurs dans leur contexte spécifique. Dans le chapitre suivant, nous nous intéresserons à la probabilité de démission d'un travailleur en réponse à des comparaisons salariales et non salariales liées à la satisfaction en matière de temps libre et de santé.

Le dernier chapitre examine la probabilité de démission d'un travailleur en réponse à des comparaisons salariales liées à son propre salaire et les salaires offerts aux autres travailleurs répondant à son profil sur le marché, et non salariales liées à la satisfaction en matière de temps libre hors activité professionnelle et de santé. Le salaire de référence externe d'un travailleur est prédit à partir de la procédure du GBRT pour tenir compte des relations souvent complexes entre le salaire et ses déterminants. Ensuite, une régression *probit* à effet aléatoire est effectuée pour estimer la probabilité de démission sur un échantillon de 247 349 employés allemands âgés de 16 à 65 ans, tiré des données de panel socio-économique allemand de 1998 à 2019.

Les résultats ont permis de mettre en lumière que l'inégalité salariale est fortement susceptible de conduire les travailleurs à démissionner. En particulier, les travailleurs sous-payés sont plus susceptibles de quitter leur emploi, tandis que les travailleurs surpayés par rapport à leur salaire prédit sont moins susceptibles de le faire, en particulier parmi les travailleurs des tranches de salaire moyennes (entre 2 000 et 4 000 euros). Les résultats ont également permis de mettre en évidence que les déterminants de la décision de démissionner varient selon les considérations non financières telles que les loisirs et les avantages sociaux jouant un rôle important dans la décision de démissionner des travailleurs à bas salaire. Les résultats ont également montré que les effets des comparaisons salariales et des récompenses non monétaires sur la probabilité de démissionner varient selon le secteur d'activité. En particulier, les réponses hétérogènes entre les secteurs soulignent que les réponses aux démissions semblent être statistiquement égales à zéro pour le secteur agricole, quel que soit l'effet des comparaisons de salaires. Les résultats ont également montré des différences entre les réactions des hommes et des femmes à la démission dans différents secteurs et niveaux de salaire en Allemagne. Particulièrement, les résultats selon le sexe révèlent que la probabilité de démissionner des hommes est davantage orientée vers la recherche de salaires plus élevés, ce qui est plus important lorsqu'ils sont en bonne santé. En revanche, pour les femmes, leur intérêt se porterait davantage sur les emplois qui leur permettent de concilier leur vie privée et leur vie professionnelle. Les résultats suggèrent également que la poursuite d'objectifs de carrière plus attrayants serait davantage orientée vers le désir personnel d'un niveau de vie plus élevé que vers la situation géographique.

Toutefois, les événements structurels pourraient avoir un impact important. En particulier, les résultats suggèrent qu'en période de crise économique, les pressions concurrentielles sur les salaires peuvent affecter les travailleurs différemment selon leur niveau de salaire de référence externe. Les travailleurs gagnant moins que ce niveau de référence ont tendance à travailler

d'avantage, à être en meilleure santé et à accepter une petite réduction de salaire, tandis que ceux qui gagnent plus ont tendance à travailler moins, à être en moins bonne santé et à accepter une plus grande réduction de salaire. Les travailleurs à salaire moyen ont été les plus touchés en termes de temps libre et de santé. Les effets sur les salaires peuvent également varier en fonction des secteurs touchés par la crise. Pendant la crise de 1998--2001, les travailleurs de l'industrie manufacturière et des services ont connu une baisse de salaire, tandis que les travailleurs de la construction ont vu leur salaire augmenter. Cela peut être interprété comme une réponse des employeurs aux pressions économiques pendant les périodes de crise en ajustant les salaires en fonction de la position de l'employé dans la relation salariale. Les employeurs peuvent réduire les salaires des employés dont le salaire est plus élevé que le salaire de référence externe pour maintenir leur compétitivité sur le marché, tandis que les employés dont le salaire est inférieur au salaire de référence externe peuvent voir une augmentation de leur salaire pour les retenir. Les employeurs devraient donc offrir de meilleurs salaires pour retenir les travailleurs, et les politiques de ressources humaines doivent constamment évaluer l'impact de ces plans d'action. Les politiques d'embauche doivent être plus adaptées à certains secteurs ou types d'emploi en raison des niveaux de salaire. Les politiques de bien-être au travail devraient prendre en compte le temps de travail hebdomadaire et proposer davantage de télétravail et de congés payés pour réduire les coûts de rotation pour les entreprises. Les travailleurs qui bénéficient d'une certaine souplesse dans la gestion de leur vie professionnelle et privée ont moins tendance à quitter leur emploi.

En somme, les différents chapitres de cette thèse ont permis de mieux comprendre l'importance de la satisfaction professionnelle pour le fonctionnement du marché du travail en Europe, ainsi que les implications économiques et sociales de la satisfaction professionnelle des travailleurs. L'analyse des inégalités de satisfaction professionnelle entre les hommes et les femmes a permis de mettre en évidence les disparités de genre sur le marché du travail, qui peuvent affecter la productivité des travailleurs et des entreprises. Lorsque les travailleurs ne sont pas satisfaits de leur travail, cela peut entraîner une baisse de la productivité, ce qui peut nuire à la performance des entreprises et, par conséquent, à l'économie en général. L'analyse de l'impact de la satisfaction au travail sur la productivité a permis de mieux comprendre comment la satisfaction des travailleurs est liée à la performance du travailleur et, par conséquent, de l'entreprise. En outre, cette analyse a également permis de montrer comment les politiques visant à améliorer la satisfaction professionnelle peuvent conduire à une meilleure performance économique. De plus, l'analyse de l'impact de la satisfaction au travail sur la productivité nous permet également de mieux comprendre les déterminants de la satisfaction professionnelle, qui sont étroitement liés à la probabilité de démission des salariés. Enfin, l'analyse de la probabilité de démission face aux comparaisons salariales et face à des récompenses non monétaires liées au temps de loisir et à la santé a permis de comprendre comment la satisfaction professionnelle est liée à la rétention des travailleurs. Lorsque les travailleurs ne sont pas satisfaits de leur travail, ils sont plus susceptibles de chercher des opportunités ailleurs, ce qui peut conduire à une perte de talent pour les entreprises. Cela peut également affecter la compétitivité des entreprises et, par conséquent, l'économie en général.

Pour conclure, nous abordons les limites et les perspectives futures des travaux issus de cette thèse de doctorat. Les travaux de cette thèse ont contribué à une meilleure compréhension de l'impact des inégalités professionnelles sur les opinions professionnelles des travailleurs, ainsi que sur leurs performances et leur probabilité de démission. Cependant, certaines limites peuvent être relevées, notamment en termes de généralisation des résultats à d'autres horizons et de la prise en compte de facteurs qui n'ont pas été inclus dans l'étude, tels que les différences culturelles et les aspects psychologiques. Dans cette thèse de doctorat nous nous sommes concentrés sur les relations entre la satisfaction professionnelle, la productivité au travail et la probabilité de démission qui pourraient affecter l'économie européenne. Cependant, d'autres recherches peuvent explorer les relations inverses. Par exemple, une croissance économique forte peut être associée à une demande accrue pour des biens et des services, ce qui peut entraîner une augmentation de la production, des investissements, et par conséquent, une augmentation des opportunités d'emploi. Cela peut conduire à une augmentation de la mobilité de la main-d'œuvre, car les travailleurs peuvent être plus enclins à chercher des emplois mieux rémunérés ou plus satisfaisants, ou même à créer leurs propres entreprises. En outre, lorsque la croissance économique est forte, les entreprises peuvent être plus enclines à embaucher rapidement des travailleurs supplémentaires pour répondre à la demande croissante, plutôt que d'investir dans la formation et le développement des compétences de leur personnel existant. Cela peut conduire à une baisse de la productivité des employés, car ils ne sont pas suffisamment formés ou équipés pour faire face aux nouveaux défis qui se présentent. Également, lorsque la croissance économique est forte, les travailleurs peuvent avoir des attentes plus élevées en termes de salaire et d'avantages, car ils ont plus d'options d'emploi. Si les employeurs ne peuvent pas répondre à ces attentes, cela peut conduire à une augmentation de la démission des employés insatisfaits, ce qui peut nuire à la productivité et à la stabilité de l'entreprise.

Cette thèse pourrait être prolongée par des travaux futurs en étendant l'étude à d'autres zones, étant donné la particularité des conditions de travail d'une zone à une autre. Elle pourrait également être prolongée en examinant les effets à long terme des inégalités professionnelles sur les carrières et la santé mentale des travailleurs. Cela permettrait de mieux comprendre les conséquences à long terme des inégalités professionnelles sur les individus, en particulier les femmes. Les inégalités professionnelles peuvent avoir des répercussions sur la santé mentale, l'estime de soi, la confiance en soi et la satisfaction au travail, ce qui peut affecter négativement les carrières des travailleurs. Comprendre ces effets à long terme permettrait de mettre en place des politiques et des pratiques pour atténuer ces effets négatifs. Les travaux pourraient également s'étendre à l'analyse de l'impact des inégalités sociales et économiques sur le marché du travail, en examinant l'interaction entre le statut socio-économique et l'ethnie du travailleur. Cela permettrait de mieux comprendre comment ces facteurs interagissent et influencent l'expérience des travailleurs. Par exemple, les travailleurs issus de milieux socio-économiques défavorisés ou les minorités raciales/ethniques peuvent faire face à des obstacles différents en matière d'accès à l'emploi, de progression de carrière et de rémunération équitable. En outre, cette thèse pourrait être prolongée en effectuant une analyse comparative entre les inégalités professionnelles dans

le secteur public et le secteur privé, ainsi qu'entre les travailleurs qualifiés et non qualifiés. En comparant les inégalités professionnelles dans le secteur public et le secteur privé, nous pourrions mieux comprendre les différences dans les politiques et les pratiques qui peuvent influencer l'expérience des travailleurs. Par exemple, le secteur public peut avoir des politiques plus strictes en matière de rémunération et de promotion, tandis que le secteur privé peut offrir des avantages tels que des actions en bourse ou des primes pour stimuler les performances des travailleurs. En comparant les inégalités professionnelles entre les travailleurs qualifiés et non qualifiés, nous pourrions mieux comprendre comment l'expérience des travailleurs varie en fonction de leur niveau de qualification et des opportunités de formation et de développement professionnel qui leur sont offertes. Enfin, des recherches pourraient être menées pour examiner l'impact des nouvelles technologies et des changements économiques sur les inégalités et les opinions professionnelles. Avec l'émergence de l'automatisation et de l'intelligence artificielle, de nombreuses tâches sont de plus en plus automatisées, ce qui peut affecter les types d'emplois disponibles et les compétences requises pour ces emplois. Il est important d'examiner comment ces changements affectent les inégalités en matière d'emploi et les opinions professionnelles pour les différentes catégories de travailleurs. De plus, les changements économiques, tels que les changements dans la demande des consommateurs, peuvent également avoir un impact important sur les inégalités et les opinions professionnelles. Il est donc crucial de comprendre comment ces changements économiques influencent les inégalités et les opinions professionnelles pour les différents groupes de travailleurs.

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