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Three essays on labour market polarization

Elliot Moiteaux

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Three essays on labour market polarization

présentée et soutenue publiquement par
Elliot Moiteaux

préparée sous la direction de Monsieur Paul MAAREK et Madame Thepthida
SOPRASEUTH

Composition du jury :

Sandra CAVACO	Maître de conférences, Université Paris II Panthéon Assas	Rapporteur
Jérôme HÉRICOURT	Professeur des Universités, Université de Lille 1	Examineur
Paul MAAREK	Professeur des Universités, Université Paris II Panthéon Assas	Directeur
Thepthida SOPRASEUTH	Professeure des Universités, CY Cergy Paris Université	Direcrice
Grégory VERDUGO	Professeur des Universités, Université d'Évry	Rapporteur



A Palette,

Table des matières

Remerciements	vi
Introduction générale	1
1 Polarization, employment, participation and the minimum wage: Evidence from European local labor markets	21
2 Routine-biased technological change and wages by education level: Occupational downgrading and displacement effects	71
3 The rise and fall of the medium-skill premium	112
Conclusion générale	181
Bibliographie	190
<i>Liste des tables</i>	194
<i>Liste des figures</i>	196

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Introduction générale

Contents

1	Objet d'étude et contexte	1
1.1	Le rôle du progrès technologique dans les récentes évolutions du marché du travail.	2
1.2	L'impact du commerce international et liens avec le progrès technologique	4
1.3	Conséquences sociales et politiques de ces phénomènes	5
2	Présentation de la littérature sur la polarisation du marché du travail	7
3	Présentation de la littérature sur l'automatisation et la robotisation	12
4	Explications alternatives aux évolutions récentes du marché de l'emploi	13
5	Contributions	15
6	Présentation des chapitres de thèse	17
6.1	Chapitre 1	17
6.2	Chapitre 2	18
6.3	Chapitre 3	19

1 Objet d'étude et contexte

Depuis plusieurs décennies, le marché du travail a connu de nombreuses évolutions, sous l'impulsion de deux phénomènes intrinsèquement liés et se nourrissant l'un et l'autre : la mondialisation et le progrès technologique. La mondialisation n'aurait pas pu se faire à un rythme si soutenu sans l'essor des nouvelles technologies de l'information et de la communication (NTIC), et ces innovations technologiques ne se seraient pas diffusées si rapidement si

les personnes, les capitaux et les idées ne se déplaçaient pas librement. Ces deux phénomènes ont eu un impact non-négligeable sur la manière dont la production de biens et services est réalisée.

1.1 Le rôle du progrès technologique dans les récentes évolutions du marché du travail.

Au cours de l'histoire, le progrès technologique a eu tendance à substituer le capital au travail. Dans un premier temps, avec l'invention de la machine à vapeur et de la machine à coudre, puis au travers des nombreuses innovations technologiques successives : l'électricité ainsi que l'utilisation du pétrole et de ses dérivés durant la seconde Révolution Industrielle, puis avec l'apparition d'Internet et des NTIC au cours des années 80, et enfin plus récemment avec la montée en puissance des algorithmes et des intelligences artificielles.

Chaque évolution technologique a eu tendance à supprimer des emplois peu ou moyennement qualifiés dans des industries sénescents dans un premier temps, puis à générer des créations d'emplois qualifiés dans des industries naissantes dans un second temps. Cette destruction créatrice au sens de Schumpeter va avoir diverses implications : elle va accroître la demande de travail pour les emplois nouvellement créés, elle va augmenter la productivité dans les emplois où elle a lieu et donc potentiellement réduire le prix des biens et services produits, mais elle va aussi réduire la demande de travail pour ces mêmes occupations. L'effet sur l'emploi total est donc ambigu d'un point de vue théorique : il dépend de la capacité des travailleurs à se réallouer, ainsi que de la magnitude de la croissance de l'emploi dans les industries naissantes relativement à la destruction des emplois dans les industries sénescents.

Dans les industries sénescents, le progrès technologique a eu deux effets distincts sur la manière dont les biens et les services sont produits : il a substitué directement du capital au travail à travers les gains de productivité des machines et des logiciels, et il a aussi permis de transférer des tâches du producteur au consommateur. Ce sont principalement les emplois historiques de la classe moyenne, c'est-à-dire les emplois peu ou moyennement qualifiés situés au milieu de la distribution des salaires qui ont été le plus affectés par ce phénomène ([Goos and Manning \(2007\)](#)). Par exemple en France, l'impact de ces deux effets est particulièrement visible dans le secteur bancaire : les gains de productivité dans la gestion des comptes client ainsi que l'apparition des applications de gestion de comptes ont réduit la demande pour les conseillers clientèle, ce qui a conduit à une réduction du nombre de personnes travaillant dans le secteur bancaire ainsi que du nombre d'agences. Il est important de noter que d'autres occupations au sein du secteur bancaire ont connu une augmentation,

comme les conseillers en gestion de patrimoine, qui sont caractérisés par des niveaux de qualifications et de rémunérations plus élevés que les conseillers clientèles. L'exemple du secteur bancaire est représentatif d'un phénomène plus large, la polarisation de l'emploi : une diminution des emplois situés au milieu de la distribution des salaires accompagnée d'une augmentation de l'emploi aux extrémités de cette distribution.

Par ailleurs, le progrès technologique n'a pas uniquement eu des effets sur la distribution de l'emploi, il a aussi eu des conséquences sur les niveaux de salaires. Comme pour l'emploi, il est nécessaire de distinguer les travailleurs qualifiés des non qualifiés. La première catégorie a bénéficié du progrès technologique. En effet, de nombreux auteurs ont constaté que ce type de travailleurs étaient complémentaires avec ces technologies, car il semblerait que le capital humain soit complémentaire avec les NTIC, ce qui a permis une croissance plus forte de leur salaire relativement au reste de la population, en dépit de l'accroissement de l'offre de travailleurs qualifiés ([Krueger \(1993\)](#), [Acemoglu \(1998\)](#) par exemple).

Dans le même temps, les conséquences en termes salariales semblent être négatives pour les travailleurs peu ou moyennement qualifiés ayant des occupations facilement substituables par du capital technologique, en raison d'une demande plus faible pour ce type de d'emplois malgré une offre de travail identique ([Autor and Dorn \(2013\)](#)). Par ailleurs, il existe une sous-catégorie de travailleurs non qualifiés qui n'ont pas connu de dégradations en termes de salaire, ceux qui sont situés en bas de la distribution des salaires, spécialisés dans les occupations dites de « services ». En effet, ces occupations ont connu une augmentation des salaires au cours de la période 1980-2005 ([Autor and Dorn \(2013\)](#)). L'argument avancé afin d'expliquer ce phénomène est le suivant : le progrès technologique a permis de réduire les coûts de production, et donc le prix de certains biens, générant une hausse du pouvoir d'achat. Comme les biens et les services sont complémentaires dans la consommation, et qu'il n'existe pas de substituts à la production de services, cela va engendrer un accroissement de la demande pour ce type de service, et donc de l'emploi et des salaires pour les travailleurs les produisant.

Cependant, il existe un autre mécanisme par lequel le progrès technologique modifie les salaires. Théorisé par [Acemoglu and Restrepo \(2018\)](#), « l'effet de déplacement » correspond à l'afflux de travailleurs venant d'occupations ayant été touchées par l'automatisation vers de nouvelles occupations. Cette réallocation a pour conséquence de générer une pression à la baisse des salaires dans ces occupations. L'effet sur les occupations de service est donc théoriquement ambigu : la demande pour ces occupations augmente, ce qui aurait tendance à faire augmenter le salaire de ces travailleurs, mais dans le même temps, l'offre de travail augmente aussi dû à la destruction d'emplois dans les industries sénescents. L'effet total

dépendra donc de la magnitude de ces deux effets (Michaels et al. (2014)).

Dès lors, il semble logique qu'une partie de l'accroissement des inégalités observées dans les pays développés, et particulièrement aux États-Unis, soit depuis longtemps attribué au progrès technologique. En effet, bien que le niveau des inégalités se soit maintenu jusqu'au début des années 1980 (Blinder (1980)), de nombreux auteurs ont montré que les inégalités avaient fortement augmenté sur la décennie suivante (Levy and Murnane (1992), Katz and Murphy (1992) parmi d'autres). Le consensus de la littérature à cette époque est que la principale cause de ce phénomène est le progrès technologique biaisé en faveur des travailleurs qualifiés, en raison de la forte croissance des salaires de ces travailleurs. Le fait que le marché de l'emploi se soit polarisé a pu masquer une partie de ces évolutions. En effet, historiquement la littérature s'est concentrée sur le rapport inter-décile $D9/D1$, or comme nous l'avons vu précédemment, les salaires ont augmenté en bas de la distribution, ce qui a contribué à limiter l'accroissement des inégalités, voir à les maintenir à leurs niveaux de 1980. Cependant, dans le même temps, les inégalités ont bel et bien augmenté si l'on regarde le rapport $D5/D1$, ce qui est cohérent avec les mécanismes mentionnés précédemment (Autor et al. (2008)).

Il est important de noter que l'hypothèse de progrès technologique biaisé en faveur des travailleurs qualifiés est incomplète, en raison de la stagnation des inégalités dans les années 90 en dépit de l'accélération de l'adoption du capital technologique. Comme nous le verrons dans la revue de littérature, d'autres théories existent afin d'expliquer ce phénomène, mais il est important de noter que toutes reposent sur l'hypothèse d'une complémentarité entre les travailleurs qualifiés et le progrès technologique, en particulier les NTIC.

1.2 L'impact du commerce international et liens avec le progrès technologique

Par ailleurs, un autre facteur a aussi eu un impact significatif sur l'emploi et les salaires : l'intensification des échanges internationaux. Initialement dans les années 1990, le commerce international était supposé n'avoir qu'un impact limité sur les économies développées en raison de la faible magnitude des importations en provenance des pays en voie de développement (Krugman (2000)). De plus, Aghion et al. (1999) avancent trois arguments supplémentaires. Tout d'abord, si le commerce international avait un effet important sur les économies développées, nous devrions observer une réallocation des travailleurs vers les industries peu qualifiées vers les industries qualifiées. Or, Berman et al. (1994) montrent que l'accroissement des travailleurs qualifiés provient surtout d'une croissance de leur nombre au sein des industries, ce qui correspond à une augmentation de la demande de travailleurs qualifiées en

raison d'un progrès technologique biaisé en leur faveur. De plus, si le commerce international était le principal facteur des récentes évolutions du marché du travail, nous devrions observer une diminution des prix relatifs des biens moins intensifs en travailleurs qualifiés relativement à ceux intensifs en travailleurs qualifiés, or il existe peu de résultats allant dans ce sens dans de nombreuses études empiriques. Enfin, on devrait pouvoir aussi observer une diminution du ratio des travailleurs qualifiés sur les travailleurs non qualifiés, en raison de la réallocation de ces derniers, mais une nouvelle fois, ce n'est pas observable empiriquement.

Dans un second temps, lorsque le commerce international s'est accru avec des pays à faibles salaires, notamment avec l'accession de la Chine à l'Organisation Mondiale du Commerce, les échanges internationaux ont commencé à être vu comme potentiellement disruptifs pour les pays développés. Une contribution importante à ce sujet est celle d'[Autor et al. \(2013\)](#). Dans cet article, ils montrent que le commerce international a eu des effets significatifs, notamment dans le secteur manufacturier : une hausse du chômage, une plus faible participation au marché du travail ainsi qu'une diminution du salaire dans les zones les plus exposées au commerce international, c'est-à-dire celle spécialisée dans des industries en compétition avec les importations venant d'autres pays. Le débat sur le rôle du commerce international et du progrès technologique porte principalement sur la magnitude des impacts de ceux-ci, en raison de la difficulté à séparer précisément leurs effets. Cependant, plus récemment, de nombreux articles soulignent la complémentarité de ces deux phénomènes. [Autor et al. \(2015\)](#) montrent que le commerce international et le progrès technologique ont eu des effets distincts. Tout d'abord, le progrès technologique n'a pas de conséquences sur l'emploi agrégé mais génère une recomposition de celui-ci, tandis que le commerce international a des effets négatifs sur l'emploi agrégé. De plus, ils soulignent un changement au cours du temps : l'impact du commerce international devient plus important au début des années 2000, en raison de l'intensification des importations, tandis que l'impact du progrès technologique semble se déplacer de l'automatisation de tâche dans les secteurs manufacturiers vers les secteurs non-manufacturiers.

1.3 Conséquences sociales et politiques de ces phénomènes

Par conséquent, bien que les effets positifs du progrès technologique et du commerce international soient indéniables à l'échelle d'un pays ou du monde, certains pans de la société ont quant à eux soufferts de ces évolutions. Les destructions d'emplois et le déclassement en termes de salaires ne sont pas neutres sur le plan économique, social et politique. Toutes les régions n'ont pas été affectées uniformément, générant un accroissement des inégalités au

sein des pays, créant des inquiétudes sur l'avenir pour les populations affectées. Ces préoccupations se retrouvent désormais dans le débat public. Depuis quelques années, on entend de nombreux partis politiques plaider pour un retour du protectionnisme afin d'endiguer les délocalisations, ainsi que de l'introduction d'une taxe technologique afin de ralentir le processus de substitution de capital au travail.

De plus, ces inquiétudes ont aussi contribué aux montées du populisme en Europe et aux Etats-Unis. [Dijkstra et al. \(2019\)](#) montrent que le vote pour des partis anti-européens est considérablement plus élevé dans les régions caractérisées par un déclin industriel. [Autor et al. \(2020a\)](#) ont mis en lumière des éléments confirmant cette hypothèse. Tout d'abord, ils montrent une forte corrélation entre l'exposition aux importations chinoises et l'adhésion à une idéologie qualifiée d'extrême-droite dans les zones ayant une forte population blanche. Selon eux, l'exposition au commerce international a contribué à la polarisation de la politique américaine au cours de ces dernières années. Le progrès technologique a lui aussi contribué à la polarisation du paysage politique. [Anelli et al. \(2019\)](#) montrent qu'en Europe, il existe un lien de causalité entre l'exposition des régions à l'automatisation et le vote pour des partis d'extrême-droite nationaliste. Les inquiétudes des « perdants » de la mondialisation et du progrès technologique ont donc des conséquences réelles sur le débat public.

Cependant, nous pouvons noter que ces craintes ne sont pas nouvelles. En effet, dès le début de la première révolution industrielle en Angleterre, des artisans spécialisés dans les métiers à bras se sont opposés à l'adoption des machines dans les manufactures et ont entrepris de détruire ces nouvelles machines, craignant pour la pérennité de leur activité. [Reshef and Toubal \(2018\)](#) notent que ce mouvement s'est aussi étendu à d'autres pays comme la France, et que ces exemples montrent que l'apparition de nouvelles technologies s'accompagnent toujours de craintes pour l'avenir des travailleurs.

Les conséquences du progrès technologiques sont donc nombreuses et affectent diverses dimensions du marché du travail et de notre société. Plusieurs questions restent cependant sans réponses. Est-ce que l'accroissement des inégalités de revenus observé dans les pays développés peut-il être attribué, en partie ou en totalité, au progrès technologique ? Est-ce que les institutions du marché du travail en Europe ont-elles générées des dynamiques différentes en termes d'emplois relativement aux États-Unis ? Est-ce que tous les types de travailleurs ont été impactés de la même façon au cours du temps ? Notamment, est-ce que l'avantage comparatif procuré par les diplômés a-t-il changé en réaction au progrès technologique ? Par ailleurs, est-ce que toutes les catégories d'âges sont affectées de la même façon ?

2 Présentation de la littérature sur la polarisation du marché du travail

Ces questions, ce sont des questions centrales de la littérature sur la polarisation du travail, sur laquelle porte ma thèse. La littérature sur la polarisation porte principalement sur l'impact du progrès technologique, mais aborde aussi les implications de la mondialisation.

Cette littérature est née à la suite d'un article majeur d'[Autor et al. \(2003\)](#). Dans cet article, ils explorent les implications de l'introduction des ordinateurs dans l'environnement de travail sur l'emploi. Leur analyse part du cadre classique où le progrès technologique est biaisé en faveur des travailleurs qualifiés (« skill-biased technological change », SBTC), ce qui a pour conséquence d'accroître la demande de l'emploi qualifié relativement à l'emploi non qualifié, sans pour autant expliquer quel mécanisme est à l'œuvre, pour aller vers un cadre où le progrès technologie est biaisé conduisant à l'automatisation des tâches routinières.

Tout d'abord, il est important de noter que l'hypothèse selon laquelle le progrès technologique est biaisé en faveur des travailleurs qualifiés s'est développée afin d'expliquer la croissance des inégalités salariales. En effet, de nombreux chercheurs ont observé une croissance du ratio entre le salaire moyen des travailleurs qualifiés relativement au salaire moyen des non qualifiés, ainsi qu'entre le haut de la distribution des salaires relativement au milieu et au bas de la distribution des salaires. Ce fait stylisé est paradoxal dans le cadre d'un modèle économique classique, puisque l'on assiste à une croissance du prix d'un facteur de production alors que l'offre de ce facteur augmente. Cette hypothèse de progrès technologique biaisé en faveur des travailleurs qualifiés était la plus populaire durant les années 1990 pour expliquer ces dynamiques salariales et repose sur deux observations. La première fait référence au timing. En effet, il a été observé que les inégalités salariales ont commencé à augmenter au début des années 1980, quelques années après l'invention et l'adoption massive des ordinateurs personnels par le grand public et les entreprises ([Katz and Autor \(1999\)](#)). Par ailleurs, [Krueger \(1993\)](#) observa que les travailleurs qualifiés étaient plus susceptibles d'utiliser des ordinateurs dans leur emplois, suggérant que le capital humain qu'ils avaient accumulés durant leur formation était complémentaire avec le progrès technologique. [Acemoglu \(2002\)](#) proposa lui un modèle pour expliquer cette complémentarité : le progrès technologique n'est pas biaisé en faveur des travailleurs qualifiés par nature, ce sont les innovations qui sont destinées à compléter les travailleurs qualifiés. L'idée est que si les travailleurs qualifiés sont plus nombreux, il est plus profitable pour un innovateur de se concentrer sur la création d'inventions qui vont leur profiter, i.e. accroître leur productivité.

Dès lors, un consensus apparut dans la littérature : la demande pour les travailleurs qualifiés s'est accrue, augmentant les inégalités salariales par conséquence. Cependant, cette explication ne permet pas de comprendre quels sont réellement les mécanismes à l'œuvre. L'innovation dans [Autor et al. \(2003\)](#) réside dans une vision plus nuancée du progrès technologique : ici, les auteurs se concentrent sur le contenu en termes de tâches des emplois. Ils abandonnent la vision selon laquelle ce sont les compétences ou le capital humain accumulé qui sont complémentaires ou substituables avec le progrès technologique, et adoptent une approche plus fine, en considérant qu'un emploi est caractérisé par une somme de tâches. Cette innovation permet d'avoir une analyse plus précise, et surtout permet d'explicitier les mécanismes à l'œuvre derrière les dernières évolutions du marché de l'emploi. Selon eux, certaines tâches sont complémentaires avec les NTIC tandis que d'autres sont substituables. Plus précisément, ces tâches substituables sont celles qui sont « routinières », c'est-à-dire nécessitant un portefeuille de compétences limité et défini, et qui peuvent être exécutées en suivant des règles explicites. A contrario, ils définissent des tâches « non-routinières », nécessitant de la dextérité, de communiquer et interagir avec d'autres personnes, de résoudre des problèmes complexes ou de raisonner de manière abstraite, et qui sont soit non-substituables soit complémentaires avec le progrès technologique. De plus, toute tâche, qu'elle soit routinière ou non-routinière, est qualifiée de « manuelle » ou de « cognitive ». Ici, les auteurs considèrent un progrès technique biaisé conduisant à l'automatisation des tâches routinières. (« routine-biased technological change », RBTC), dans le sens où comme conséquence principale de faire disparaître des tâches, voir des emplois routiniers.

Les auteurs concluent que les industries, occupations ou régions utilisant les tâches routinières de manière intensives vont investir relativement plus dans les NTIC au fur et à mesure que le coût de ces nouvelles technologies diminue. Cela aura pour conséquence de substituer le travail non qualifié utilisé dans les tâches routinières par du capital technologique, et d'augmenter la demande pour les travailleurs qualifiés exécutant des tâches non-routinières, qui sont complémentaires avec les NTIC. Le passage d'un cadre théorique reposant sur l'hypothèse de progrès technologique biaisé en faveur des travailleurs qualifiés à un cadre théorique supposant un progrès technique biaisé conduisant à l'automatisation des tâches routinières a permis de mieux comprendre les dynamiques de salaires pour les différents groupes d'édu-cations ou d'occupations. Cependant, la polarisation du marché du travail n'avait pas été encore démontrée.

Le second article majeur de cette littérature est celui publié par [Goos and Manning \(2007\)](#). Dans cet article, les auteurs montrent que le marché du travail s'est polarisé : depuis le milieu des années 1970 au Royaume-Uni, on assiste à une croissance de l'emploi en haut et en bas

de la distribution des salaires, ainsi qu'à une diminution de l'emploi au milieu de la distribution. Cette découverte a contribué à remettre en cause l'hypothèse traditionnelle de progrès technologique biaisé en faveur des travailleurs qualifiés et a donné un poids supplémentaire à l'hypothèse d'[Autor et al. \(2003\)](#). En effet, bien que le modèle de progrès technologique biaisé en faveur des travailleurs qualifiés permet d'expliquer les dynamiques en haut de la distribution des salaires, celui-ci ne permet pas d'expliquer les dynamiques se produisant en bas (et au milieu) de cette distribution, c'est-à-dire à la fois la croissance (diminution) de l'emploi et des salaires, contrairement au modèle de progrès technique biaisé conduisant à l'automatisation des tâches routinières. Ici, l'hypothèse que les auteurs souhaitent tester est la suivante : en raison des caractéristiques des emplois routiniers, ceux-ci n'étaient jamais les emplois les moins bien payés, et avaient plutôt tendance à se situer au milieu de la distribution des salaires. Leur disparition a eu pour conséquence de forcer la réallocation des travailleurs vers des tâches non-routinières : les plus qualifiés essayant de réallouer leur force de travail dans des emplois intensifs en tâches abstraites, situés en haut de la distribution des salaires, complémentaires avec les NTIC, tandis que les moins qualifiés se sont réalloués vers des occupations intensives en tâches manuelles, qui ne sont pour le moment pas automatisable ou facilement substituables, généralement situés en bas de la distribution des salaires. Les auteurs démontrent que cette hypothèse est bel et bien vérifiée, et notent qu'il est possible que cet effet soit potentiellement renforcé par le processus de mondialisation, vu que les tâches routinières semblent être des tâches facilement délocalisables car extrêmement standardisées.

Par ailleurs, il est important de noter que ces prédictions n'ont pas seulement été vérifiées au niveau agrégé, mais aussi au niveau individuel. [Cortes \(2016\)](#) montre que le principal facteur déterminant dans quelles catégories vont se réallouer les personnes ayant perdu un emploi routinier est la compétence.¹ Il montre qu'au sein d'une catégorie occupationnelle en déclin, ceux situés aux extrémités de la distribution des compétences ont plus de chance de se réallouer, vers des occupations manuelles pour ceux situés en bas de la distribution ou à l'inverse vers des occupations abstraites pour ceux situés en haut de la distribution.

Enfin, le troisième article majeur de cette littérature est l'article d'[Autor and Dorn \(2013\)](#). Cet article montre que la polarisation du marché du travail est aussi observable aux États-Unis, confirmant ainsi les découvertes de [Goos and Manning \(2007\)](#) au Royaume-Uni. La principale contribution de cet article est de mettre en lumière quels sont les mécanismes à l'œuvre derrière la croissance des emplois en bas de la distribution des salaires. Les auteurs distinguent deux catégories au sein des occupations manuelles : les occupations de services à

1. Approximé par la distribution des salaires.

la personne et les autres occupations. Selon eux, l'accroissement des occupations manuelles est entièrement lié aux services à la personne, et notent que les autres occupations de type manuelles ont connu une réduction au cours de la période 1980 à 2005.

Dans cet article, deux autres résultats importants sont présents : la croissance des emplois de services n'est pas la conséquence directe de l'augmentation des revenus des personnes occupant un emploi intensif en tâches abstraites, et l'exposition au commerce international n'est pas la cause de l'accroissement de l'emploi de service.

En effet, concernant le premier résultat, il aurait été raisonnable de penser que l'augmentation de l'emploi à dominante cognitive non-routinière, qui est caractérisé par de hauts revenus et ayant augmenté le taux de participation des femmes, aurait induit une plus grande demande de services à la personne, car ceux-ci sont des substituts à la production domestique, qui a baissé du fait de l'augmentation de la participation des femmes au marché du travail. Cependant, ils montrent que l'augmentation des salaires en haut de la distribution, bien que plus importante dans les zones précédemment spécialisées dans les occupations à dominantes routinières, ne permet pas d'expliquer les variations dans l'emploi manuel au niveau local. Leur argument théorique est le suivant : si l'élasticité de substitution entre les NTIC et le travail routinier est plus importante que l'élasticité de substitution entre les biens (produits grâce à des tâches routinières) et les services (produits grâce à des tâches manuelles), la réduction du coût de ces technologies finira par rendre le salaire dans les tâches manuelles supérieur au salaire dans les tâches routinières. Dès lors, les travailleurs n'ayant pas d'avantages comparatifs dans les tâches routinières se réalloueront dans les tâches manuelles, générant une polarisation de l'emploi.

Concernant le lien possible entre exposition au commerce international et l'accroissement de l'emploi de service, de nombreux auteurs montrent que les tâches qui sont délocalisées sont celles ne nécessitant pas d'être en contacts avec les clients ou localisés sur des sites spécifiques (Firpo et al. (2011) et Blinder and Krueger (2013) parmi d'autres). De nombreuses occupations routinières semblent donc correspondre à cette définition. En revanche, les emplois de services nécessitent d'être en contact direct avec les clients ou d'être sur un site précis, par exemple dans un salon de coiffure ou à domicile, et ne sont donc pas délocalisables. Dès lors, le commerce international pourrait-être la cause de l'augmentation observée dans l'emploi de service. Cet argument n'est cependant pas supporté dans les données : l'exposition au commerce international ne permet pas de prédire les changements de l'emploi de service.

Que ce soit pour mesurer l'exposition au changement technologique ou au commerce international, la dimension locale est extrêmement importante. En effet, conformément avec l'article initial d'Autor et al. (2003), la spécialisation initiale des zones joue un rôle détermi-

nant dans l'adoption du progrès technologique permettant de substituer du capital aux tâches routinières. Cela va avoir pour conséquence de générer des trajectoires très différentes pour les travailleurs en fonction du bassin d'emploi auxquels ils appartiennent. Par exemple, aux États-Unis, nous pouvons voir que les zones les plus exposés au changement occupationnel, c'est-à-dire les zones qui comptaient initialement la plus grande concentration d'occupations à dominante routinières, sont principalement concentrées à l'intérieur de la « Rust Belt », qui a été durement affecté par le progrès technologique et les délocalisations.

Cependant, jusqu'à récemment, une caractéristique importante des marchés du travail locaux n'avait pas été prise en compte dans l'analyse du processus de polarisation : la densité de ceux-ci, et plus exactement, la différence entre les marchés du travail ruraux et urbains. [Autor \(2020\)](#) met en lumière ce lien : une partie de l'impact de la polarisation en termes de salaires pour les peu qualifiés est lié à une dégradation d'un premium urbain pour les personnes occupant des emplois routiniers au cours du temps.² Selon lui, entre la fin de la Seconde Guerre mondiale et le début des années 1970, les personnes n'ayant pas terminé l'université occupant des emplois routiniers (manuel ou cognitif) bénéficiaient d'un premium à habiter en ville, car ils étaient complémentaires avec les personnes occupant des emplois qualifiés. Cependant, ce premium s'est progressivement érodé, en raison de la montée en puissance de l'automatisation et du commerce international qui réduisit la demande pour ce type d'occupations. Dès lors, ces personnes se sont réallouées dans des occupations moins qualifiées que précédemment, créant une pression à la baisse des salaires. Par ailleurs, il montre que cet effet est plus prononcé pour les travailleurs noirs et hispaniques, et en particulier les hommes. Cet ensemble de fait stylisé démontre que l'effet d'ascenseur social qu'offrait les zones urbaines précédemment disparaît progressivement. Par ailleurs, il semblerait que la polarisation ait commencé plus tôt que suggéré par les premières contributions, et qu'elle ne soit pas seulement occupationnelle mais aussi industrielle. Selon [Barany and Siegel \(2018\)](#), le processus de polarisation a commencé dès les années 1950-1960, et est directement relié au déclin de l'emploi manufacturier. En effet, en développant un modèle de marché du travail avec des travailleurs hétérogènes inspiré de celui de [Roy \(1951\)](#), ils parviennent à répliquer de nombreux faits stylés de la littérature. Leur modèle prédit que le progrès technologique biaisé en faveur des travailleurs qualifiés génère de la réallocation entre les secteurs, ce qui correspond à un phénomène de polarisation de l'emploi, et affecte aussi les salaires positivement au sein des industries, ce qui génère de la polarisation de la distribution des salaires.

Cependant, il existe aussi d'autres mécanismes qui contribuent, de manières moins importantes, à la polarisation. Jusqu'ici, j'ai souligné l'importance du progrès technologiques et du

2. Relativement à un travailleur rural, toutes choses égales par ailleurs.

commerce international dans les grandes évolutions du marché du travail au cours des dernières décennies, mais d'autres facteurs ont aussi contribué aux transformations du marché du travail. Tout d'abord, nous pouvons noter que la structure par âge d'une économie a des conséquences sur la polarisation. En effet, une économie dont la population tend à vieillir sera une économie qui aura plus recours aux services à la personne, créant un choc de demande supplémentaire pour les emplois de types manuels ([Moreno-Galbis and Sopraseuth \(2014\)](#)). Par ailleurs, selon [Autor and Dorn \(2009\)](#), l'âge joue aussi un rôle dans les réallocations des travailleurs affectés par ce phénomène. En effet, il semblerait que seuls les travailleurs les plus jeunes arrivent à se réallouer dans des occupations situées plus haut dans la distribution des salaires lorsqu'ils perdent leurs emplois routiniers, tandis que pour les autres catégories d'âges, les réallocations se font quasiment exclusivement vers le bas de la distribution.

3 Présentation de la littérature sur l'automatisation et la robotisation

Nous pouvons aussi noter qu'il existe une littérature connexe à la littérature sur la polarisation qui se concentre uniquement sur l'automatisation, avec notamment une série d'articles ([Acemoglu and Restrepo, 2017, 2020a](#)). Ces contributions sont principalement théoriques, bien que récemment l'effort se soit concentré sur l'estimation de ces conséquences sur le marché du travail en termes d'emploi et de salaire.

Dans le premier article, ils développent un cadre théorique permettant de modéliser l'automatisation pour plusieurs types de qualifications, où les machines sont en concurrence avec des travailleurs qualifiés et non qualifiés. Lorsque les machines peuvent réaliser plus de tâches dans un type d'emploi que précédemment, cela réduit le salaire des travailleurs occupant ce type d'emplois, mais cela augmente le salaire de l'autre type de travailleur, à travers un effet positif de productivité. Cependant, ce même phénomène a aussi pour effet de réduire le salaire des catégories de travailleurs non-affectés par le progrès technologique, car il génère un afflux de main-d'œuvre dans les occupations restantes, créant une pression à la baisse. Cet effet est qualifié d'effet de déplacement. Par conséquent, si l'effet de déplacement est supérieur à l'effet de productivité, les salaires en bas de la distribution vont diminuer. Ce résultat n'est cependant pas incompatible avec la polarisation, puisque si l'effet de productivité est supérieur à l'effet de déplacement, une croissance des salaires en bas de la distribution est possible. Dans le second article, ils estiment l'impact de l'adoption de robots, qu'ils distinguent des autres types de capital technologiques, sur l'emploi. Ils montrent que les zones les plus exposées

à l'automatisation du fait de leur spécialisation ont vu leurs taux d'emploi et leur salaire moyen diminuer le plus fortement. Ces résultats viennent valider une partie des prédictions théoriques de l'article mentionné précédemment.

Enfin, [Acemoglu and Restrepo \(2020b\)](#) s'intéressent à l'impact spécifique des intelligences artificielles. Ils montrent que les établissements les plus exposés à l'intelligence artificielle ont réduit leur emploi dans les occupations qui ne sont pas liées à l'intelligence artificielle. Cependant, cet effet n'est pas visible au niveau occupationnel ou industriel. Ils en concluent que malgré le fait que l'impact de l'intelligence artificielle est réel car se substituant aux travailleurs dans certaines tâches, elles ne sont pas encore suffisamment répandues pour avoir un effet significatif sur l'emploi agrégé.

Cette littérature peut être vue comme une généralisation théorique de la littérature sur la polarisation. En effet, nous pouvons retrouver les prédictions théoriques des modèles de polarisation du marché du travail en fixant certaines hypothèses, tel que la catégorie de qualification affectés par le progrès technologique.

4 Explications alternatives aux évolutions récentes du marché de l'emploi

Enfin, il est aussi important de noter que certains auteurs apportent des nuances concernant le processus de polarisation, notamment car la théorie associée ne permet pas d'expliquer la dynamique des salaires pour les personnes qualifiées. En effet, le premium à détenir un diplôme du supérieur aux Etats-Unis stagne depuis le début des années 2000, ce qui ne peut pas être expliqué par le processus de polarisation : si la demande pour les emplois à dominante abstraites est en constante augmentation dû à sa complémentarité avec les NTIC, le premium des personnes qualifiées devrait normalement augmenter, ce qui n'est pourtant pas le cas. [Beaudry et al. \(2016\)](#) s'intéressent à cette question, et développent un modèle d'expansion-récession (« boom and bust » en anglais.) afin d'expliquer ce phénomène. Selon eux, la demande pour les personnes qualifiées aurait augmenté jusqu'au début des années 2000, puis aurait commencé à diminuer, comme dans un modèle expansion-récession. Ici le stock considéré correspond aux tâches cognitives. Elles ne sont plus vues comme un flux mais comme un stock servant à accumuler le capital. Lorsque suffisamment de capital a été accumulé, la demande diminue, de sorte que les travailleurs qualifiés produisent suffisamment de stock de tâches cognitives afin de compenser la dépréciation du capital technologique. Selon eux, la phase de récession (« bust ») a commencé au début des années 2000, ce qui expli-

querait pourquoi le premium associé au diplôme du supérieur a diminué : il y a désormais un excès d'offre de travail qualifiés, forçant ceux n'ayant pas trouvé un emploi adapté à se réallouer plus bas dans la distribution du salaire.

Cette diminution de la demande de travailleurs qualifiés n'est pour autant pas totalement contradictoire avec le reste de la littérature sur la polarisation. En effet, [Valletta \(2018\)](#) montre que la polarisation et ce phénomène ne sont pas incompatibles, et jouent tous les deux un rôle. Pour ce faire, il décompose la variation du premium à être aller à l'université en deux termes. Le premier correspond au processus de réallocation des travailleurs à travers les occupations, qu'il associe au phénomène de polarisation de l'emploi. Le second correspond à la diminution du premium à être allé à l'université au sein des occupations, ce qu'il associe au ralentissement de la demande pour les travailleurs qualifiés décrit par [Beaudry et al. \(2016\)](#). Cette décomposition lui permet d'observer une augmentation du nombre de personnes qualifiées occupant des emplois routiniers sur la période récente, ce qui diminue le salaire moyen des travailleurs qualifiés car se réallouant dans occupations moins bien rémunérés, ce qui correspond au phénomène de polarisation. De plus, il note que le salaire des travailleurs qualifiés relativement au salaire des travailleurs non qualifiés au sein de groupes occupationnels a diminué au cours de la décennie 2010, ce qui suggère que l'avantage comparatif des travailleurs qualifiés relativement aux non qualifiés diminue au cours du temps, ce qui cohérent avec l'hypothèse de [Beaudry et al. \(2016\)](#). Il conclue que la croissance du premium à être diplômé a été limité par la réallocation des travailleurs sur la période 2000-2010, donc par le processus de polarisation, puis que c'est le ralentissement de la demande pour les travailleurs qualifiés qui a joué le rôle le plus important sur la dynamique des salaires relatifs depuis les années 2010.

[Hunt and Nunn \(2019\)](#) apportent aussi un éclairage différent sur les récentes évolutions du marché du travail. Selon eux, le progrès technologique ne serait pas responsable de la polarisation de l'emploi depuis les années 1970. De plus, ils remettent en cause les méthodologies employées dans la littérature concernant l'accroissement des inégalités de salaire. Afin de conduire leur analyse, ils affectent chaque travailleur à une catégorie représentant un intervalle de salaire horaire, intervalle restant constant au cours du temps afin de capturer les évolutions de salaire réel. Grâce à cette méthodologie, ils observent que la part des travailleurs appartenant à la catégorie la plus faible en termes de rémunération diminue, hormis pour la période récente (2002-2012). Ce fait stylisé n'est pas cohérent avec le récit traditionnel de la polarisation. De plus, selon eux, l'accroissement des emplois manuels précédemment était uniquement dû à un problème de classification. Par ailleurs, ils insistent sur les défauts d'aborder les questions d'inégalités salariales à travers le salaire moyen ou médian au sein

des occupations, même finement définies. Ils montrent qu’au sein d’une occupation il existe une dispersion des salaires importante, et que la plupart de l’accroissement des inégalités a lieu au sein des occupations.

5 Contributions

Cette littérature étant relativement jeune, il existe encore de nombreuses zones d’ombres concernant les effets de la polarisation. Tout d’abord, peu de contributions dans cette littérature se sont intéressées aux effets sur l’emploi total. Or, il est possible que le processus de créations d’emplois dans des industries naissantes prennent du temps, et que par conséquent, cela se traduise par une diminution du taux d’emploi ou du taux de participation.

Par ailleurs, comme mentionné précédemment, les personnes qui perdent leurs emplois routinier ne sont pas celles qui retrouve un emploi dans une de ces nouvelles occupations ou industries. Ces emplois attirent principalement des jeunes, et les occupations routinières sont principalement occupées par des personnes plus âgées. Comme mentionné précédemment, [Autor and Dorn \(2009\)](#) montre que seuls les plus jeunes arrivent à se réallouer dans des emplois plus qualifiés et plus rémunérateurs après avoir occupé un emploi routinier, tandis que pour les autres catégories d’âges, la réallocation se fait uniquement vers le bas de la distribution des salaires. Il est donc possible que certains individus préfèrent ne plus participer au marché de l’emploi dans ces conditions ([Beaudry et al. \(2016\)](#)). Il est donc possible que la polarisation n’ait pas un effet neutre sur l’emploi.

Les quelques contributions de la littérature à ce sujet n’ont pas permis d’aboutir à un consensus. Tout d’abord, [Jaimovich and Siu \(2020\)](#) montrent que les reprises de l’activité économiques après une récession ne s’accompagnent pas forcément d’une reprise de l’emploi. Ils appellent cela des « reprises sans-emplois » (« jobless recoveries » en anglais.). Selon eux, ce fait est directement lié au processus de polarisation : la majorité des emplois détruits sont des emplois à dominante routinière, et il n’y a pas un rebond suffisant de l’emploi pour compenser cette diminution.

Enfin, nous pouvons aussi noter que le processus de polarisation a eu pour conséquence d’augmenter la participation des femmes au marché du travail. En effet, [Verdugo and Allègre \(2020\)](#) montre que dans les zones les plus affectées par la destruction d’emplois routiniers, le taux de participation des femmes a augmenté de manière très importante. Le mécanisme sous-jacent est le suivant : les hommes occupaient principalement des occupations routinières, tandis que les femmes principalement des occupations manuelles et abstraites, et ont donc plus bénéficiées de la croissance des salaires dans ces occupations, ce qui a agi comme une

incitation à intégrer le marché de l'emploi. Afin d'apporter de nouveaux éléments à ce débat, je vais dans mon premier chapitre de thèse explorer les implications de la polarisation et du progrès technologique sur l'emploi agrégé. La littérature sur la polarisation s'est principalement concentrée sur le marché du travail américain et la plupart des modèles, comme celui d'[Acemoglu and Autor \(2011\)](#) ou [Acemoglu and Restrepo \(2020a\)](#). Le premier montre que la polarisation n'a pas eu d'effets sur l'emploi agrégé et a simplement provoqué une réallocation des travailleurs à travers les occupations, tandis que le second montre que les effets sur l'emploi du progrès technologique sont très limités lorsque l'on s'intéresse à l'emploi agrégé. Cependant, ces modèles supposent des salaires flexibles.

Or, en Europe, le salaire minimum et les institutions du marché du travail créent des frictions qui peuvent modifier les conclusions de ces modèles : il est possible que ces rigidités empêchent la création de suffisamment d'emplois manuels en bas de la distribution des salaires afin de compenser la diminution de l'emploi routinier.

Un autre écueil de cette littérature est qu'il est courant d'approximer les compétences par le salaire moyen au sein d'une occupation. Cette approche pose deux problèmes. Tout d'abord, elle ignore la dispersion importante des salaires au sein des occupations. Les occupations sont des regroupements d'emplois partageant des caractéristiques similaires, mais dont chaque emploi qui les constitue sont marginalement différents en termes de compétences et de salaires. Par ailleurs, cette approche ignore la dimension de l'éducation. Les compétences d'un travailleur sont à la fois capturées par l'expérience qu'il possède dans une occupation donnée, mais aussi par son éducation. On observe d'ailleurs des premiums à être diplômé au sein même d'une occupation.

Une littérature proche de ces questions est celle qui étudie l'inadéquation entre le niveau d'éducation d'un travailleur et celui requis pour exercer son emploi (« educational mismatch » en anglais). Il existe deux types de décalages : les inadéquations verticales (ou inadéquation des compétences ou des qualifications) et les inadéquations horizontales (ou inadéquation du domaine d'études). La première catégorie correspond à la situation où un travailleur est sur-éduqué ou sous-éduqué pour le poste qu'il occupe. On observe de plus en plus de décalages verticaux, et ce sont majoritairement des cas où les personnes sont sur-éduquées. Le second type fait référence au fait que certains travailleurs occupent une occupation qui correspond à leur niveau d'éducation, mais dont les compétences et connaissances acquises durant la formation ne sont pas utilisées car appartenant à un champ différent. Il existe plusieurs explications à ce phénomène. Tout d'abord, l'augmentation très importantes du nombre de diplômés du supérieur a excédé la demande pour ce type de travailleur dans certains secteurs, forçant ceux n'ayant pas trouvé un emploi correspondant à leur formation.

Le progrès technologique est aussi en partie responsable de ce phénomène à travers deux effets distincts. Le premier canal que nous pouvons distinguer est l'obsolescence des compétences : au gré des évolutions technologiques, certaines compétences se retrouvent obsolètes.

Dès lors, les personnes possédant ce type de compétences vont devoir se réallouer dans d'autres types d'occupations, générant de l'inadéquation entre les compétences possédées et celles requises pour exercer l'emploi. Le second canal est lié à la polarisation du marché de l'emploi : le progrès technologique ayant tendance à substituer du capital au travail dans les emplois routiniers, ceux possédant des emplois routiniers et ayant des compétences adaptées vont devoir se réallouer, principalement dans des occupations manuelles comme vu précédemment, ce qui va aussi participer à ce décalage entre les compétences acquises et requises. Cela a pour conséquence de réduire les salaires des personnes concernées, à la fois car se réallouant dans des occupations moins rémunératrices, et aussi car perdant le premium associé à l'expérience, qui est bien souvent spécifique à une occupation.

C'est pour cela que dans les Chapitre X et Chapitre Y, j'explore les implications de la polarisation sur les différentes catégories d'éducation en terme salarial. Dans le Chapitre Y, nous tentons d'estimer l'impact de la polarisation en termes de salaire.

Plus précisément, nous cherchons à déterminer, pour chaque catégorie d'éducation, si la variation de salaire observée est principalement dû à un effet de déplacement, c'est-à-dire la pression à la baisse sur les salaires générées par l'augmentation de l'offre de travail dans des occupations, à travers la réallocation de travailleurs ayant perdu leurs emplois plus haut dans la distribution, ou à la polarisation du marché du travail, qui est un effet de composition.

6 Présentation des chapitres de thèse

6.1 Chapitre 1

Dans ce premier chapitre, l'objectif est d'analyser l'impact du processus de polarisation sur l'emploi, au travers du taux d'emploi et du taux de participation. La littérature s'est principalement concentrée sur les dynamiques en termes de composition de l'emploi, mais n'a que peu exploré les implications sur l'emploi total. La question est de savoir si, l'existence d'un salaire minimum modifie la forme prise par la polarisation, et plus particulièrement s'il peut prévenir la création d'emplois manuels. En effet, ces emplois étant situé en bas de la distribution des salaires, il est possible que les frictions introduites par le salaire minimum empêchent la création de suffisamment d'emploi manuel afin de compenser la disparition de l'emploi routinier.

Pour réaliser cette analyse qui porte sur 8 des 15 membres fondateurs de l'Union Européenne, j'ai utilisé les données de l'Enquête Emploi Européenne (ou European Labor Force Survey ELFS). Conformément aux travaux existants, je capture le processus de polarisation à travers la part de routine au sein d'un marché du travail local, ici approximé par les zones NUTS (Nomenclature des unités territoriales statistiques). Afin d'avoir une interprétation causale, je mets en place une stratégie d'estimation par variable instrumentale, en instrumentant la variation de la routine par un instrument capturant les investissements dans les NTIC.

Mes résultats indiquent que le processus de polarisation a des conséquences hétérogènes sur l'emploi en fonction du salaire minimum. Dans les pays à haut salaire minimum, les zones ayant connues des destructions importantes d'emplois routiniers ont vu leurs taux d'emplois et de participation diminuer. Je montre que cet effet est principalement dû à une augmentation insuffisante des emplois manuels afin de compenser la destruction des emplois routiniers dans les pays à haut salaire minimum.

De plus, je montre que cet effet n'est pas dû à d'autres institutions du marché de l'emploi, mais bel et bien au salaire minimum en lui-même. Enfin, je m'assure que le salaire minimum n'est pas endogène, dans le sens où ses variations au cours du temps serait lié au processus de polarisation.

6.2 Chapitre 2

Dans ce second chapitre, l'objectif est de regarder l'impact du processus de polarisation en fonction du niveau d'éducation. En particulier, je me concentre sur une catégorie qui a été en partie ignoré par la littérature en dépit de sa place de plus en plus importante : les personnes moyennement qualifiées, c'est-à-dire, celles étant allé à l'université mais n'ont pas validé un diplôme en 4 ans, ce qui est la norme pour être considéré comme qualifiés aux Etats-Unis. S'intéresser à cette catégorie est d'autant plus important que de nos jours, cette catégorie représente environ 30% de l'emploi aux Etats-Unis. Dans un contexte où le coût de l'enseignement supérieur ne cesse de croître aux Etats-Unis, il me semble important de savoir si un niveau d'éducation moyen permettait d'être protégé du processus de polarisation, c'est-à-dire si un niveau moyen d'éducation permet de se réallouer dans des occupations mieux payées que les occupations qui ont disparue ou si le fait de détenir ce niveau d'éducation permet de préserver son salaire dans des occupations routinières. Ici, l'objectif n'est pas de finement calculer des rendements de l'éducation, mais plus de regarder comment se comporte ce groupe de travailleurs.

Pour faire cela, je définis trois catégories d'éducation : ceux ayant un diplôme équivalent au niveau lycée ou moins, ceux étant allé à l'université mais n'ayant pas validé diplôme de 4^{-ème} année, et enfin ceux ayant obtenu au moins un diplôme du supérieur. Ces trois catégories seront respectivement les peu qualifiés, les moyennement qualifiés et les hautement qualifiés. Cette nomenclature possède l'avantage d'être utilisable sur une longue période temporelle. Afin d'estimer l'impact de la polarisation sur les différentes catégories d'éducatons, j'ai utilisé les données du recensement aux Etats-Unis entre 1970 et 2017 (US Census (1970-2000) et American Community Survey (ACS, 2005-2017)). J'adopte une approche en termes de marché locaux de l'emploi (« Commuting Zones »), en utilisant toujours la proportion d'emplois routines au niveau local comme mesure de la polarisation. Les salaires sont tout d'abord purgés des caractéristiques individuelles dans une première étape, car je soupçonne la présence de tri spatial concernant l'allocation des travailleurs sur le territoire. Ces résidus sont ensuite agrégés au niveau local par groupe de compétences. Ensuite, j'utilise une méthode d'estimation par variable instrumentale, grâce à un instrument de type Bartik. Je fournis de nombreux tests de robustesses concernant cet instrument, en accord avec la littérature la plus récente concernant les instruments de ce type.

Mes résultats indiquent que la polarisation a un impact négatif sur la catégorie des peu qualifiés, mais aussi que ce phénomène semble impacter, dans la même mesure, les personnes moyennement qualifiés. En décomposant le coefficient, je montre que l'effet de composition, i.e. la réallocation des travailleurs à vers des occupations et des industries moins rémunératrices ne compte que pour 10 à 20% de l'effet total, le reste étant dû à la diminution des salaires à l'intérieur des industries et des occupations. Ces résultats sont cohérents avec l'effet de déplacement décrit dans la littérature théorique, dans laquelle la réallocation des personnes occupant des emplois routiniers génère une pression à la baisse des salaires dans les occupations dans lesquels ils se réallouent, à travers une augmentation massive de l'offre de travail dans ces catégories.

6.3 Chapitre 3

Dans ce troisième chapitre, j'analyse les dynamiques des salaires relatives entre les travailleurs peu qualifiés et ceux moyennement qualifiés. En effet, le premium à être moyennement qualifié relativement à être peu qualifié a augmenté entre 1980 et le début des années 2000, au même rythme que le premium à être hautement qualifié relativement à être peu qualifié. Cependant, le premium à être moyennement qualifié à fortement diminué depuis, et l'objectif de ce chapitre est de comprendre les mécanismes à l'œuvre derrière cette baisse peu

étudiée dans la littérature.

Dans ce chapitre, qui est une extension du précédent, je réutilise les mêmes données ainsi que les mêmes catégories d'éducatons que celles utilisées dans le second chapitre. Ce chapitre est structuré autour de deux parties : une première, descriptive, au niveau national, montrant les dynamiques récentes en termes de salaires et de structure occupationnelle, par groupe d'éducation et par groupe d'âge. Ces faits stylisés sont accompagnés d'exercices de décompositions afin de déterminer quel est le rôle de chaque dimension envisagée dans les variations récentes du premium à être moyennement qualifié. Dans un second temps, j'adopte une stratégie similaire au second chapitre, c'est à dire en termes de marché du travail locaux. J'adopte donc aussi une stratégie semblable en termes de salaires : je purge les salaires des caractéristiques individuelles et les agrège au niveau local par groupe d'éducation, toujours afin de contrôler pour le phénomène de tri spatial, puis je calcule le premium comme étant le rapport des salaires moyens purgés.

Les résultats montrent que cette baisse est principalement concentrée au sein des jeunes travailleurs, et qu'une part importante de cette baisse du premium a lieu au sein des occupations. En effet, durant la période récente, les jeunes travailleurs moyennement qualifiés entrent relativement moins dans des occupations routinières (et plus récemment dans les occupations abstraites), et plus dans des occupations manuelles, en raison de la plus grand compétition avec les travailleurs qualifiés pour ce type d'occupations. Ce changement d'opportunité a été plus important que pour les peu qualifiés, car il y a eu plus de destructions d'emplois routiniers à dominante cognitive relativement aux emplois routiniers à dominante manuelle, or ces emplois routiniers cognitifs étaient majoritairement occupés par des travailleurs moyennement qualifiés. Cet afflux de travailleur vers les occupations manuelles a eu un impact négatif sur les salaires des moyennement qualifiés en raison de l'effet de déplacement mentionné précédemment.

Chapter 1

Polarization, employment, participation and the minimum wage: Evidence from European local labor markets

Summary of the chapter

The labor market is becoming increasingly polarized as routine jobs disappear. In the flexible US labor market, this has had a limited impact on employment due to the strong employment growth in low-paying manual occupations for workers who are not able to reallocate to high-paying abstract occupations. This may not be the case in some rigid wage European economies, which are capable of creating fewer low-paying manual jobs. We study the effect of a decrease in the proportion of routine jobs on employment and participation rates, conditional on the level of the minimum wage, in European local labor markets. Our OLS and IV estimates show that the polarization process has a negative impact on labor market outcomes in high minimum wage countries only.

Co-authorship

This chapter is taken from "Polarization, employment, participation and the minimum wage: Evidence from European local labor markets", co-authored with Paul Maarek

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Contents

1.1	Introduction	23
1.2	Data and stylized facts	28
1.3	Empirical strategy	36
1.4	Baseline Results	40
1.5	Some evidence on the mechanisms	46
1.6	The role of other labor market institutions	49
1.7	Conclusion	53
1.A	Data	54
1.B	Additional graphs	54
1.C	Robustness	56
1.D	Additional result: Correlation between the share of routine and the instrument	69
1.E	Additional result: The role of other labor market institutions	69

1.1 Introduction

The polarization of the labor market is now a well-documented phenomenon in the US (Autor et al. (2003) Autor et al. (2006)) and Europe (Goos and Manning (2007), Goos et al. (2014), Dustmann et al. (2009)), beginning in the mid-1980s and accelerating in the 1990s. It corresponds to a strong increase in the share of employment in high-paying abstract occupations and low-paying manual occupations, relative to the share of routine occupations in the middle of the wage distribution. Routine occupations are indeed easier to automate using information technologies, as they contain a large share of repetitive tasks. This has led researchers to reconsider the canonical model of skill-biased technological change toward a more subtle understanding of the labor in terms of tasks. Technology can substitute for workers in a subset of tasks (Acemoglu and Autor (2011)). This process has led to a dramatic deterioration of economic opportunities for low-skilled non-college-educated workers and particularly males (see Acemoglu and Autor (2011), Autor (2019) or Verdugo and Allègre (2020)). First, workers with low ability who lose their relatively well-paid routine occupations tend to reallocate to manual occupations that pay less on average, as they have no comparative advantage in abstract occupations (Cortes (2016) or Autor (2019)). Second, this creates a “displacement effect”, which lowers the demand for this factor and creates downward pressure on wages for

both workers in the occupation that disappeared and occupations to which a share of the workers from the middling occupations reallocate. (Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2017)). We argue that, in a context in which labor market institutions do not allow wages to fully adjust, this process could lead to lower employment.

Surprisingly, the impact of this process in terms of aggregate employment has received limited attention (with some notable exceptions, however – see the literature review). The conventional wisdom is that this process has limited implications in terms of aggregate labor market performance. The destruction of routine occupations is accompanied by the massive creation of abstract occupations, mainly for high-skilled workers, and manual jobs for low-skilled workers, especially in the service sectors (Autor and Dorn (2013)). Autor et al. (2015) document an extremely limited impact of technology shocks implying routine job destruction on aggregate employment at the local labor market level in the US. Trade shocks have been argued to be much more costly in terms of aggregate employment (Autor and Dorn (2013)) but seem to be weakly related to polarization (see Goos et al. (2014) and Autor et al. (2015)). In the context of task-biased technological change, Acemoglu and Restrepo (2017) and Acemoglu and Restrepo (2020a) provide a framework in which wages adjust, allowing the lower occupations to absorb the excess labor supply from the occupations (or tasks) that disappeared at the cost of a downward wage adjustment. We argue that the polarization process could have had a very different impact from that in the US in certain European countries, given the higher minimum wage in place in the latter. In a rigid wage environment, wages do not necessarily adjust to clear the labor market, especially in the left tail of the wage distribution, where the minimum wage plays a crucial role in the wage determination process. This may prevent the creation of a sufficient number of low-paying jobs for low-skilled workers, who cannot reallocate to abstract occupations, to compensate for the destruction of routine jobs, which has been observed in every European country. The United States also has a national minimum wage, but relative to the median wage, it is much lower in many European countries. In France, for instance, in which a significant share of workers (approximately 13% in 2019 according to Garnero (2019)) are paid the minimum wage, Catherine et al. (2015) and Cahuc and Debonneuil (2004) document a strong deficit in manual job creation in the service sector relative to the US economy and relate this difference to the high minimum wage. We argue that, in such an environment, the destruction of routine jobs could have severe consequences in terms of aggregate employment, as routine jobs are often occupied by low-skilled workers, who cannot reallocate to abstract, high-paying jobs.

In this paper, we use the European Union Labor Force Survey (EULFS hereafter), which provides detailed information about the economic situation of a sample of workers from

1983 to 2014 at the subnational level (i.e., on local labor markets). The survey contains comprehensive information on occupations, allowing us to measure the polarization process (i.e., the evolution of the proportion of routine jobs) for each area within a country, which we define as a local labor market (Goos and Manning (2007) and Goos et al. (2014) use the same data). The cross-country dimension of the dataset, with important heterogeneity in minimum wage levels, enables us to measure the heterogeneity in the impact of the decrease in routine jobs on employment and participation rates in a particular local labor market within a country, depending on the level of the minimum wage. Retaining only countries with a national legal minimum wage (8 countries from the 14-country sample of Goos et al. (2014)), we ultimately have a panel of 86 local labor markets within our sample, as defined by the EULFS. There exists considerable heterogeneity in the levels of national minimum wages, ranging from 0.278 to 0.585 as a percentage of the mean wage of full-time workers. This allows us to identify the role of minimum wages in the impact of increasing job market polarization on labor market performance. Our identification relies on two sources of variation. First, we are able to compare the impacts of different degrees of routine job destruction within the same institutional setting. For instance, the local labor markets within a given country have not experienced the same degree of routine job destruction. Second, we are able to compare some local labor markets with roughly similar degrees of routine job destruction located in different countries and subjected to different institutional settings. The EULFS also contains many socioeconomic characteristics that allow us to control for key variables that plausibly affect both the polarization process and the labor market outcome variable that we seek to explain (e.g., age structure, skill supply, industry composition). First, using fixed effects (local labor market and time) regressions in level, we show that the decrease in the number of routine jobs in a given local labor market has no impact, or a very limited positive one in a local labor market characterized by a low minimum wage, but it is strongly negatively correlated with the employment and participation rates in a local labor market characterized by a strong minimum wage. This outcome is consistent with Autor et al. (2015), who find a very weak effect of polarization on the employment rate for the US economy. This result holds for European countries characterized by a low minimum wage. The very modest increase observed in some specifications is consistent with the results of Verdugo and Allègre (2020), who show an increase in the participation rate of women associated with the polarization process, which they interpret as an intra-household response to the decreasing economic opportunities of men. For flexible wage labor markets, this effect should translate into an increase in the overall participation rate. For rigid wage labor markets, however, it is likely that the overall decrease in employment opportunities for males translates into a

decrease in participation for this category of workers, which could more than compensate for the increase in women's participation.

We then provide more detailed evidence for the mechanisms. Consistent with our narrative, we show that a high minimum wage is associated with less creation of low-paying manual jobs following a decrease in the proportion of routine jobs, which we interpret as evidence of the mechanism that we have in mind to explain the effect of employment polarization in terms of aggregate labor market performance. Some of the workers who have no comparative advantage in abstract occupations and who suffer from the destruction of their routine jobs are unable to reallocate to manual occupations due to the presence of a high minimum wage that prevents the creation of low-paying occupations. Second, we focus on France, the highest minimum wage country in our sample for which we have detailed data on wage and occupations. We show that i) minimum wage workers are disproportionately concentrated in manual occupations and to a lesser extent in routine occupations and that ii) the proportion of minimum wage earners sharply increased in manual jobs and to a lesser extent in routine occupations despite a stagnation of the ratio of the minimum wage to the mean wage over the period. This pattern is consistent with the idea that the displacement effect and the downward wage pressure induced by the destruction of routine jobs render the minimum wage more binding. Finally, we also include alternative labor market institutions, such as employment protection, and their interactions with the proportion of routine to understand whether the impact of minimum wage does not capture the effects of other labor market institutions, which may be correlated with the minimum wage. We show that labor market institutions are only weakly correlated with the level of the minimum wage in our sample. In addition, we find that, even when not controlling for minimum wage level, labor market institutions do not explain much of the dynamics in terms of employment in a context of routine job destruction.

We address the possible endogeneity of the proportion of routine jobs using an instrumental variable (IV) strategy. Despite our inclusion of numerous fixed effects and other controls, we cannot completely exclude the possibility of reverse causality, although the decrease in routine jobs is generally considered a demand shock (related to technology shocks). We follow the logic of the instrumental strategy of [Karabarbounis and Neiman \(2013\)](#) and use the shocks in ICT investment prices (from the KLEMS dataset) that occurred in the 1990s and that are recognized in the literature as having been among the major factors responsible for the decrease in the proportion of routine jobs (see [Autor and Dorn \(2013\)](#) or [Michaels et al. \(2014\)](#)). The massive adoption of computers and IT technologies substitute for workers (mostly low skilled) in performing routine tasks—such as bookkeeping, clerical work, and

repetitive production and monitoring activities—which are readily automatized because they follow precise and well-defined procedures. Specifically, to capture the extent to which a local labor market has been affected by a substantial decline in the price of new technology investments, we rely on a Bartik-type instrument and use the initial sector specialization of the local labor market and the initial ICT capital intensity of sectors, under the assumption that sectors (and local labor markets specialized in these sectors) that use ICT more intensively should be more affected by price shocks in ICT. This assumption allows us to construct the degree of exposure of each local labor market to the (exogenous) technological shocks, explaining the decrease in the proportion of routine jobs. These results are qualitatively similar to those obtained with OLS but are larger in magnitude.

Our results suggest that the impact of the minimum wage may depend on the economic context and, more particularly, the rates at which routine jobs are destroyed and the labor market is experiencing structural transformation. In such a context, more flexible institutional arrangements, such as minimum wages negotiated at the sector or firm level, could be much more efficient (as in countries such as Germany and Sweden). Another possibility that might lead to efficiency gains in such an environment is to fix the minimum wage at a sub-national level because local labor markets have very different exposures to global technology shocks.

We are not the first to question the impact of polarization on aggregate employment and participation rates. [Autor et al. \(2015\)](#) find little evidence that technology shocks that destroy routine jobs have a sizable aggregate impact on employment for the US economy. We show that this conclusion does not necessarily hold in countries with more rigid wages, due to their poor ability to create low-paying jobs. Two papers are very closely related to the mechanisms that we have in mind to explain the potential cost of routine job destruction in term of aggregate employment. First, [Bock \(2017\)](#) uses a calibrated general equilibrium model and find that labor market polarization, by displacing unskilled workers from routine to manual jobs, could explain the strong decline in employment for this category of workers given its substantial labor costs. Using a similar calibration strategy, [Albertini et al. \(2016\)](#) compare the labor market performance of two economies with very different institutional settings (France and the US) in a context in which technology shocks destroy routine jobs. [Nellas et al. \(2011\)](#) also used a theoretical model to compare the employment consequences of the destruction of routine jobs between the US and the UK, which have flexible labor markets, and continental European countries. We directly use data at the local labor market level, which allows us to empirically compare the employment response to polarization across different institutional settings. [Jaimovich and Siu \(2020\)](#) show that the process of polarization

may have been responsible for the jobless recovery after the Great Recession of 2008 in the US, given the acceleration of the destruction of routine jobs during this period, which did not recover following the recession. We focus on the long-term impact of labor market polarization on and the role of labor market institutions in this outcome.

Finally, in a very recent paper related to ours, [Lordan and Neumark \(2018\)](#) use the inflows and outflows of employment across the US states and show that workers who have lost their routine jobs are less likely to find a new job in states with a high minimum wage. Our results are in line with their findings, but our paper is distinct from theirs in several respects. First, we focus on aggregate equilibrium labor market performance instead of labor flows. Second, we analyze the effects on both employment and participation rates. Third, using data on European local labor markets allows us to compare very different institutional settings and heterogeneous minimum wage levels and to compare the impacts of very different labor market shocks within the same institutional setting. Finally, we use an IV strategy, which permits a causal interpretation of our results.

The remainder of this paper is organized as follows. We first present the data that we employ throughout the paper and some basic stylized facts. Then, we present our empirical strategy. Finally, we present our results and conclude the paper.

1.2 Data and stylized facts

1.2.1 Data

In this section, we present the main data sources that we use in this paper. We first present the EULFS, from which we derive our main polarization variable and the control variables.

The EULFS contains data on 28 European countries at the national level.¹ One of the main advantages of this dataset is that it is available for many countries over a relatively long time period and has a large sample size of approximately 200,000 annual observations per country each year. We limit our analyses to the fifteen countries that composed the European Union before the 2004 enlargement as in [Goos et al. \(2014\)](#). These countries have the most complete datasets, and they should be very similar in terms of exposure to technology shocks, relative to the newest EU members. Of these fifteen countries, only 8 have a national

1. Then, the data are processed centrally by Eurostat, which harmonizes them with the same set of characteristics for each country, common classifications and definitions.

minimum wage, making institutions and labor costs for low-skilled workers comparable across them. These countries are Belgium, Spain, France, Greece, Ireland, the Netherlands, Portugal and the United Kingdom. We ultimately have a total of 86 local labor markets within these 8 countries.² Occupations are coded using the two-digit 1988 International Standard Classification for Occupations (ISCO1988) and industries with the Nomenclature Statistique des Activités Economiques dans la Communauté Européenne (NACE) revision 1. These classifications include 39 occupations, 23 industries before 2008 and 22 industries after 2008.

The version of the EULFS that we use ranges from 1983 to 2013. As there is no information on the occupations of workers before 1992, we only use data from 1992 onward. Our baseline sample stops in 2007 to avoid the effect of the 2008 crisis on the labor market. Additionally, during this period, the NACE and ISCO classifications changed in 2008 and 2010, respectively, making use of the EULFS sample very difficult for years after 2010 (see below). Nevertheless, as a robustness test, we also consider a sample including post-crisis years until 2010.³

Table 1.1 displays some summary statistics for the variables that we use in this analysis. First, there is important variation in the proportion of routine occupations within and between local labor markets. We mostly use within variation in the proportion of routine occupations in our empirical analysis, as we introduce local labor market fixed effects in most specifications. Moreover, the between-country standard deviation in the minimum wage is much greater than the within-country component, which means that the minimum wage is relatively stable in a given country and differs little relative to the institutional differences across countries.⁴ The set of control variables displays standard values, giving us confidence

2. Using the 7 other countries with no national minimum wage using an alternative measure for possible downward rigidities would render comparisons difficult. For instance, in countries with no national minimum wage but an industry minimum wage, the lower bound for the wage can adjust more easily in industries with an excess supply of labor. We could consider the wage level of the lower wage decile compared to the mean wage in the population as an alternative measure for these countries. However, a high wage at the bottom of the wage distribution can be the result of a low supply of low skilled workers, as in the Scandinavian countries, for instance. For these reasons, it seems preferable to retain only countries with a national minimum wage to measure properly the impact of such an institution.

3. To address the change in the NACE classification in 2008, we use the methodology of [Verdugo and Allègre \(2020\)](#). They manually created a crosswalk to convert the classification from NCAE Rev. 1 to NACE Rev. 2, and to have consistent industries over time, they aggregated D (Electricity) with E (Water supply), H (Transportation) with J (Information) and L (Real Estate) and M (Professional activities) with N (Administrative and support service activities). Concerning the change in the ISCO classification in 2010, we use an existing crosswalk. The crosswalk was provided by the Institute for Structural Research and Faculty of Economics of the University of Warsaw. However, we observe a structural break in the data after using this crosswalk, so we do not use data from years after 2010, as argued in [Breemersch et al. \(2017\)](#). In our version of the EULFS, we had data until 2013, so we dropped 2011, 2012 and 2013. Note that our results are robust regardless of whether we consider data until 2007 or 2010 (see Tables 1.10 and 1.11).

4. As we use interaction terms to measure the effect of within country variation in routine on employment

Table 1.1 – Summary statistics

	N	Mean	Min	Max	S.D.	Between S.D.	Within S.D.
Sh. of middling occ.	1137	0.422	0.230	0.602	0.060	0.055	0.029
Avg. minimum wage	1137	0.402	0.278	0.541	0.086	0.081	0.022
Sh. of low-skill	1134	0.533	0.230	0.890	0.141	0.145	0.051
Sh. of medium-skill	1134	0.297	0.073	0.476	0.102	0.103	0.027
Sh. of high-skill	1134	0.170	0.029	0.389	0.069	0.066	0.031
Sh. of male	1137	0.494	0.447	0.528	0.009	0.007	0.005
Sh. of ≤ 27 y.o.	1137	0.268	0.131	0.378	0.031	0.027	0.017
Sh. of 28-37 y.o.	1137	0.196	0.128	0.291	0.017	0.013	0.011
Sh. of 38-47 y.o.	1137	0.185	0.123	0.225	0.015	0.010	0.011
Sh. of 48-57 y.o.	1137	0.155	0.106	0.241	0.020	0.013	0.016
Sh. of 58-67 y.o.	1137	0.136	0.093	0.233	0.022	0.019	0.011

Source: EULFS dataset for years 1992-2007. The data used include all working individuals aged 17-72.

in the representativeness of our sample.

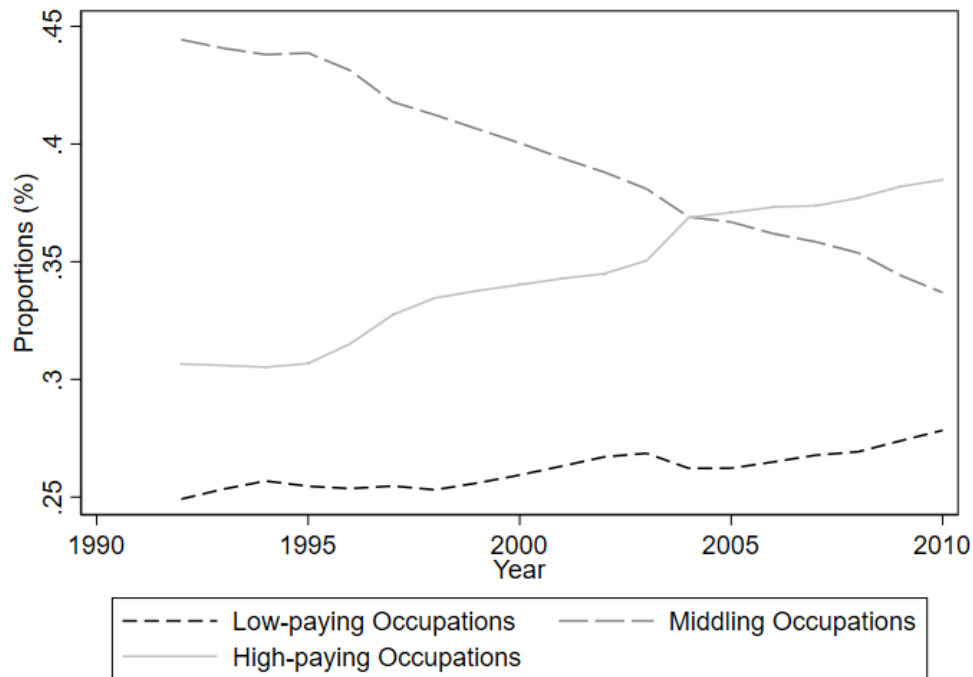
Measure of routineness

To measure the evolution of middling occupations, we follow [Verdugo and Allègre \(2020\)](#) and [Goos et al. \(2014\)](#). There are several approaches in the literature to measuring labor market polarization. One approach is to consider the skill content of each occupation using the Dictionary of Occupational Titles (DOT, 1968) and classifying occupations according to their intensity in terms of routine tasks (see [Autor et al. \(2003\)](#), [Autor and Dorn \(2013\)](#) or [Goos et al. \(2014\)](#), specifically the second part of the paper). This approach has the merit of focusing directly on the skill content of each occupation. However, there are two main drawbacks of this approach. First, the US occupation classification differs substantially from the EULFS classification, and mapping occupations from the DOT to occupations in the EULFS necessitates the use of several correspondence tables with highly imperfect mapping at each step, requiring some random assignment (see [Goos et al. \(2014\)](#)). Second, the DOT provides a classification based on the task content of occupations in 1968, which may have evolved substantially since then (see [Spitz-Oener \(2006\)](#)).

As a result, we prefer to use a more direct approach. We follow [Verdugo and Allègre \(2020\)](#), [Acemoglu and Autor \(2011\)](#) and [Goos et al. \(2014\)](#) in the first part of their paper by directly considering the occupations in the middle of the wage distribution (middling occupations). [Goos et al. \(2014\)](#) show that these occupations correspond to the routine

outcomes conditionally on the level of the minimum wage, our heterogeneous effect should be driven mostly by the between country variation in the minimum wage. As explained later, we use the initial level of the minimum wage at the beginning of the period as the minimum wage could be affected by the variation in routine.

Figure 1.1 – Evolution of occupations’ shares



Source: EULFS dataset for years 1992-2010. The data used include all working individuals aged 17-72.

occupations defined by Autor et al. (2003). We also define the corresponding categories for low-paying jobs (manual) and high-paying jobs (abstract).⁵ We define the proportion of each category of occupations as its proportion of total employment. In the remainder of the paper, we refer to middling occupations rather than routine occupations as defined using the position of an occupation in the wage distribution. In addition, we refer to low-paying and high-paying occupations when considering manual and abstract occupations, respectively.

We can see in Figure 1.1 that the proportion of middling occupations clearly exhibits a sharp and continuous decrease over the period covered by our dataset. Conversely, we observe

5. Specifically, as in Goos et al. (2014, Table 1, p. 2512 and Appendix Table A3), low-paying occupations include the occupations “51: Personal and protective service workers”, “52: Models, salespersons, and demonstrators”, “91: Sales and service elementary occupations” and “93: Laborers in mining, construction, manufacturing, and transport”. Middling occupations include “42: Customer service clerks”, “71: Extraction and building trades workers”, “72: Metal, machinery, and related trade work”, “73: Precision, handicraft, craft printing, and related trade workers”, “74: Other craft and related trade workers”, “81: Stationary plant and related operators”, “82: Machine operators and assemblers”, and “83: Drivers and mobile plant operators.” High-paying occupations include “12: Corporate managers”, “13: Managers of small enterprises”, “21: Physical, mathematical, and engineering professionals”, “22: Life science and health professionals”, “24: Other professionals”, “31: Physical, mathematical, and engineering associate”, “32: Life science and health associate professionals” and “34: Other associate professionals”.

a clear increase in the proportion of high-paying jobs. However, the evidence is less clear-cut for the proportion of low-paying jobs. We observe an increase, but it seems to be much less important than that in the US labor market, as documented in the literature. We argue that at least part of this specific pattern could be related to European labor institutions, which may have prevented a massive creation of low-paying jobs at the expense of a decrease in employment and labor market participation.

Labor market outcomes

The employment rate in a local labor market is defined as the ratio of the employed to the working age population. The participation rate is defined as the ratio of employed and unemployed to the working age population.⁶

Share of high-skilled and low-skilled workers

Skill levels are coded using the information on education available in the dataset. The EULFS contains some detailed, harmonized data on educational attainment in the categories of low education, medium education and high education.⁷

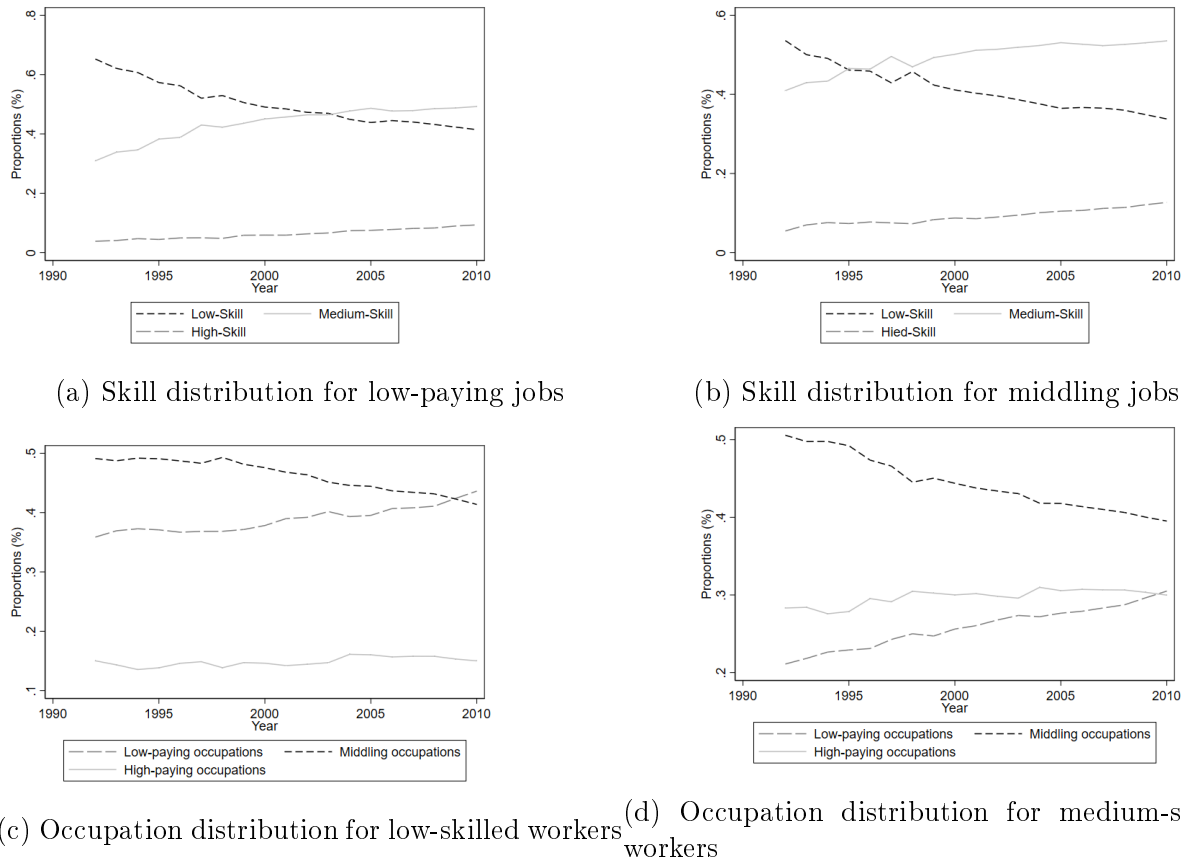
It is important to control for the educational attainment of the workforce in our regressions. Generally, the polarization process can be seen as driven by demand or supply factors. The most discussed factor in the literature is the introduction of new technologies (computers) that are substitutes for workers in some occupations and have modified labor demand. IT technologies are seen as the main driver behind the sharp decrease in the proportion of middling occupations. However, the polarization process can also be driven by supply shocks as a general increase in the skills of the labor force, making firms create more complex occupations with cognitive tasks. Generally, the literature regards polarization process as being driven by demand factors (see [Autor et al. \(2003\)](#), [Autor and Dorn \(2013\)](#), [Goos et al. \(2014\)](#), [Acemoglu and Autor \(2011\)](#) or [Acemoglu and Restrepo \(2020a\)](#)), but we cannot exclude the possibility that part of it is driven by the global increase in skill supply observed in Europe in the 1990s, which could have also impacted labor market outcomes.

Regarding the skill composition of the workforce, we can derive several interesting pat-

6. In the EULFS, we do not have the exact age of each person; we only know to which 5-year age band an individual belongs (e.g., 0-4, 5-9). In our analysis, the working age population is defined as the number of individuals older than 17 and younger than 72. We also considered a lower threshold, i.e., younger than 67 years old, and our results are not affected by such a modification, mainly because we control for the age structure of the population.

7. These levels are defined following the International Standard Classification of Education of 1997 (ISCED 1997). In the EULFS, “low education” refers to lower secondary or the second stage of basic education (ISCED 0 to ISCED 2), “medium education” corresponds to upper secondary education (ISCED 3 and ISCED 4), and “high education” represents tertiary education or post-secondary education (ISCED 5 and ISCED 6). Throughout the paper, we approximate skill by education, so low-skill refers to low-education and high-skill to high-education.

Figure 1.2 – Evolution of labor market opportunities



Source: See Figure 1.1.

terms. First, we compute the proportion of low-paying and middling occupations that are occupied by low-skilled and medium-skilled workers, respectively. These results are displayed in Figure 1.2. We also compute the proportion of low-skilled and medium-skilled workers occupying low-paying and middling occupations. These results are also displayed in Figure 1.2.

Two important facts emerge. First, the proportion of low-skilled workers in low-paying and middling occupations tends to decrease sharply. The proportion of medium-skilled workers increased sharply not only in middling occupations but also in low-paying occupations. Second, the probability of a low-skilled worker having a low-paying occupation increased substantially over the period considered, consistent with Cortes (2016), who shows that workers with low ability move more often from routine (middling) to manual (low-paying) occupations relative to workers of higher ability. Moreover, there appears to be some skill downgrading: medium-skilled workers occupy less-qualified jobs than previously, given their

increasing share among low-paying occupations. More generally, this is consistent with the “displacement effect” highlighted in [Acemoglu and Restrepo \(2018\)](#) and [Acemoglu and Restrepo \(2017\)](#), whereby part of the workers whose (middling) occupations have been destroyed are driven down in the occupational ladder and now compete with workers in occupations that have not been destroyed. Overall, this pattern is consistent with the view that labor market polarization has deteriorated the economic opportunities of low-skilled workers. The disappearance of middling occupations seems to be associated with an increase in the proportion of low-skilled workers with low-paying occupations and a sharp decrease in the proportion of low-skilled workers who have a middling occupation. This sorting process does not favor low-skilled workers (and to some extent, medium-skilled workers) who cannot reallocate to high-paying, abstract jobs. The question that we ask is related to the ability of an economy to create a sufficient number of low-paying jobs for low-skilled workers, whose employment opportunities decreased sharply in middling occupations and cannot reallocate to high-paying occupations.

Local labor markets

Local labor markets are coded using the Nomenclature des Unités Territoriales Statistiques at the two-digit level (NUTS). The NUTS data in the EULFS are unbalanced : we have only one region for the Netherlands, i.e., the entire country, while we have 22 regions for France.⁸

The minimum wage

To obtain information on the national minimum wage in each country, we use a dataset from the OECD. Here, the minimum wage is expressed as the proportion of the average wages of full-time workers. Only 8 countries are available in this dataset: Belgium, Spain, France, Greece, Ireland, the Netherlands, Portugal and the United Kingdom. This is explained by the fact that many countries, such as Germany, do not have a national minimum wage but several sectoral minimum wages. As a consequence, our analysis of the impact of the national minimum wage on the shape of the polarization of the labor market is restricted to countries that have a national minimum wage to ensure that labor market institutions and minimum wage levels are comparable across countries.

8. Moreover, to perform our analysis, we must have a consistent definition of a local labor market over time. However, there are several changes in classification for some countries over time. To address this problem, we retain only those regions that are comparable over time. In essence, we aggregate areas when necessary and drop areas when they disappear from the classification to ensure that the definition of a given local labor market is the same throughout the period considered. Further details are available in the Appendix. Our results are not sensitive to this modification in the classification of local labor markets or to the exclusion of the Netherlands.

9. For Ireland, we decided to use the minimum wage in 2001 instead of 2000, as its level changed from

Table 1.2 – Summary statistics: Minimum Wage (new)

Country	Available since	Initial level	Mean
Belgium	1992	0.490	0.460
France	1992	0.492	0.505
Greece	1992	0.420	0.369
Ireland	2000	0.441 ⁹	0.459
Netherlands	1992	0.498	0.455
Portugal	1998	0.313	0.328
Spain	1992	0.321	0.301
United-Kingdom	1999	0.356	0.358

Note: OECD dataset on minimum wages.

Table 1.2 displays the first year of data on the national minimum wage in each country, its initial level and its mean over the period. First, we observe substantial heterogeneity in the levels of the minimum wage between countries, and as a result, we should have sufficient variation to identify the role of the minimum wage in the impact of polarization on the labor market. However, one caveat is that our panel is unbalanced: we only have five countries since the beginning of our sample in 1992, due to the absence, at this time, of a national minimum wage in the other three countries. In Appendix Figure 1.6, we also provide a graph displaying the evolution of the minimum wage for each country of the sample.

Additional controls

In addition to skill levels, we control for other characteristics in our regressions. These controls are the proportion of males in the working age population of the local labor market, the age structure of the population using detailed age categories and the industry shares in terms of employment (13 industries).¹⁰ These controls are necessary to control for the heterogeneity of the labor force since these populations have different job opportunities, and these characteristics may affect the shape of labor market polarization. For instance, the age structure of the population is likely to influence the rate of destruction of middling occupations ([Autor and Dorn \(2009\)](#)). Also, structural change, such as the decrease in manufacturing, may affect the degree of job market polarization, as shown by [Barany and Siegel \(2018\)](#), and could also affect labor market outcomes.

ICT investment price data and technology shocks

We use the price index of ICT capital and the ICT capital stock for the US, which are 0.59 to 0.44 in 2001 and didn't change much afterwards. This choice doesn't affect our results and our results are unaffected by using the minimum wage level of 2000.

10. Younger than or 27 years old, between 28 and 37, between 38 and 47, between 48 and 57 and finally between 58 and 67

available at the sector level (NACE Rev. 1) in the KLEMS dataset.¹¹ For the exclusion restriction to be satisfied, the price shock variable should not affect the labor market outcomes through channels other than the destruction of middling occupations.¹² The price shock variable should affect labor market outcomes only through the destruction of middling occupations. We believe that this should be the case. In the recent literature, it is now widely accepted that ICT, such as the massive diffusion of computers in many industries, is task-biased rather than skill-biased and is the main factor behind the massive destruction of middling occupations (Autor et al. (2003), Acemoglu and Autor (2011), Autor and Dorn (2013)).

1.3 Empirical strategy

Baseline specifications

We first estimate an OLS specification to highlight the relationship between the variation in the share of middling occupations (MSH) and our labor market outcome (LMO) variables, which correspond to the employment rate and the participation rate, respectively. Formally, we estimate for each outcome:

$$LMO_{a,t} = \alpha_1 MSH_{a,t-1} + \alpha_2 (MSH \times \overline{MW})_{a,t-1} + \beta X_{a,t-1} + \gamma_a + \delta_t + u_{a,t} \quad (1.1)$$

where γ_a , δ_t , and $u_{a,t}$ correspond to a local labor market fixed-effect, a time fixed-effect and the error term that captures all other factors not correlated with our controls, respectively, which may also explain our $MSH_{a,t-1}$ variable and the $LMO_{a,t}$ variables, with $E(u_{a,t}) = 0$. In Equation 1.1, $X_{a,t-1}$ is a vector of the control variables described above. \overline{MW}_a corresponds to the initial minimum wage in local labor market a . Our $MSH_{a,t-1}$ variable is interacted with the initial level of the minimum wage at the beginning of the period. The impact of the share of middling jobs on labor market outcomes corresponds to $\alpha_1 + \alpha_2 \times MW$; thus, it is conditional on the level of the minimum wage. In OLS estimates, all of the variables are one period lagged. Using a fixed level of the minimum wage in the interaction seems preferable

11. Sectors in the KLEMS dataset are defined according to the NACE Rev. 2 classification. As we have regrouped the sectors in the EULFS to have consistent sector definitions over the period considered, we must do the same for the KLEMS dataset. When sectors are merged in the KLEMS dataset to match those in the EULFS, they are weighted by their relative GDP.

12. We use US capital stock and prices, as they should better satisfy the exogeneity conditions with respect to the evolution in European labor markets.

since the minimum wage policy could react to labor market outcomes or the destruction rate of middling jobs.

This specification relies on the between variation only to estimate a conditional effect.¹³ Note that the between variation of the minimum wage is much greater than the within variation of the minimum wage. Alternatively we also estimate a dynamic specification including the lag of $LMO_{a,t}$ as a regressor. Labor market adjustments can take time, and a dynamic specification could capture this process more accurately.¹⁴

Also, instead of using a continuous variable for the minimum wage in the interaction, we also estimate specification using dummies for high and low minimum wage countries. The high minimum wage countries are France (0.50), Belgium (0.46), Ireland (0.45) and the Netherlands (0.46), and the low minimum wage countries are Greece (0.37), the United-Kingdom (0.36), Portugal (0.33) and Spain (0.30).

Instrumental Variable Strategy

We then turn to the IV strategy. The correlation that we observe may be due to an omitted variable that is correlated with both labor market outcomes and the occupational composition of the workforce. We cannot exclude this possibility despite all of the controls and fixed effects that we introduce in our regressions.¹⁵ Second, poor labor market conditions and economic outcomes could affect the decision to destroy middling occupations and thus accelerate the diffusion of technologies. Our estimates could capture such reverse causality. In our IV strategy, we thus attempt to isolate a technology shock that will affect labor demand through its impact on the destruction of middling jobs using a shift-share setting. The disappearance of middling occupations is explained primarily by the diffusion of information technologies (see [Goos et al. \(2014\)](#) or [Autor and Dorn \(2013\)](#)). In the spirit of [Karabarbounis and Neiman \(2013\)](#), we use the investment price of ICT capital, which decreased sharply over the period that we study and explains the massive diffusion of ICT capital, such as computers in the economy. To identify how each local labor market has been exposed to such a price

13. In Appendix Tables 1.12 and 1.13, we also estimate a model using the time-varying level of the minimum wage in the interaction and also as a regressor. The results are unchanged, suggesting that the between component of the minimum wage is the key driver of our identification of heterogenous effects of the proportion of middling jobs. In addition, in Tables 1.14 and 1.15, we also estimate a model using the mean minimum wage level over the period, and our results are also unchanged

14. Estimating a dynamic model with a lagged dependent variable as a regressor may suffer from the so-called dynamic panel bias ([Nickell \(1981\)](#)). We note, however, that the size of the bias ($1/T$) decreases with T ([Judson and Owen \(1999\)](#)) and should not be a first-order concern given the time period that we consider.

15. For instance, polarization could be related to a global increase in skill supply, which will affect the occupational composition of the workforce but does not correspond to a shock affecting labor demand, which is what we assume is at work. We control for the most obvious factors, such as the skill supply, demographic factors, industry composition and area and time fixed-effects, to account for unobserved heterogeneity, but some omitted variables may nevertheless bias our estimates.

shock, we use the initial industrial specialization of each local labor market and the ICT capital use intensity of each sector at the national level from KLEMS.¹⁶ Our regression sample is smaller in IV than in OLS because ICT data are only available since 1998 in the KLEMS dataset. More formally, our instrument for $MSH_{a,t-1}$ is written as:

$$Exposure_{at} = \sum_s \left(\frac{L_{s,a,2000}}{L_{a,2000}} \times P_{s,t}^{ICT} \times \frac{K_{s,2000}^{ICT}}{L_{s,2000}} \right) \quad (1.2)$$

where s , a and t correspond to sector, local labor market and year, respectively. $P_{s,t}^{ICT}$ corresponds to the price of ICT capital for sector s in year t in the US economy. $K_{s,2000}^{ICT}$ and $L_{s,2000}$ correspond to ICT capital stock and employment, respectively, in sector s in the year 2000. $L_{s,a,2000}$ and $L_{a,2000}$ correspond to employment in sector s in local labor market a and to employment in area a , respectively. In this equation, $(L_{s,a,2000}/L_{a,2000})$ is the industrial specialization in 2000, and $(K_{s,2000}^{ICT}/L_{s,2000})$ corresponds to the ICT capital stock per worker in sector s in the US in 2000. Here, the idea is that the exposure of a local labor market to price shocks in ICT should depend on its intensity of ICT capital use, which is defined as each sector's share of total employment times the ICT capital stock per worker in 2000 in this sector. We use 2000 as a reference year because data are available for all local labor markets on this date. In other words, our instrument is local labor market specific, given that the intensity of ICT use $(\frac{L_{s,a,2000}}{L_{a,2000}} \times \frac{K_{s,2000}^{ICT}}{L_{s,2000}})$ is local labor market specific. Our instrument varies over time due to our ICT price variable, which is industry-year specific.

We instrument our interaction term $MSH_{a,t} \times \overline{MW}_a$ using the interaction of our instrument with the initial level of the minimum wage $Exposure_{a,t-1} \times \overline{MW}_a$ as [Woolridge \(2000\)](#) suggests for estimating a model with interaction terms in which one regressor is endogenous.

An important literature on the shift-share Bartik instrument emerged recently. [Goldsmith-Pinkham et al. \(2020\)](#) discuss the identification assumption underlying Bartik instruments and the conditions under which the instruments should be valid. An important question is whether the identification relies on industry share (in our case, initial industry composition multiplied by initial ICT capital intensity of each industry) or shocks (in our case, ICT capital price in each sector). In most papers reviewed in [Goldsmith-Pinkham et al. \(2020\)](#), identification mostly relies on shares rather than shocks. Our setting makes no exception. Appendix Figure 1.7 shows the evolution of ICT capital prices in each sector, and we can see that they evolve very similarly across all sectors. This outcome suggests that changes

16. The instrument's construction follows the same Bartik logic of [Autor and Dorn \(2013\)](#) for trade shocks, exploiting nationwide variation in trade at the sector level (ICT prices in our case) with the initial specialization of the area or [Acemoglu and Restrepo \(2020a\)](#) for robots.

in ICT prices are a global shock that cheapened ICT capital for all sectors of the economy. The heterogeneity of the exposure of each local labor market is due to differences in initial specialization (and sector-specific intensity in ICT use, rather than heterogenous shocks across sectors).¹⁷ When identification relies on industry shares, it is important to ensure that initial industry shares are exogenous to local labor market future developments and do not affect labor market outcomes through other channels than destruction of middling jobs (i.e., the exclusion restrictions are satisfied). We control for many factors in our regressions, which could be affected by the initial industry shares in a local labor market and which could affect labor market outcomes. An important factor to control, which is recommended by [Goldsmith-Pinkham et al. \(2020\)](#), is the current industry share at time t . It is quite plausible that initial industry shares determine the evolution of industry shares in a local labor market, which could affect labor market outcomes in many ways. For instance, an important initial manufacturing sector is a good predictor of the future decrease in the manufacturing sector share over time in a local labor market. [Autor and Dorn \(2013\)](#) control for the manufacturing sector share. We control for broad industry shares (i.e., primary, secondary and tertiary sectors), but we also use the more detailed classification NACE rev 1, which we use for the Bartik instrument.

Investigation of Mechanisms

We finally provide a preliminary investigation of the mechanisms for the role of the minimum wage in shaping the relationship between destruction of middling jobs and employment. First, we investigate the role of other labor market institutions that may be correlated with the degree of minimum wage. We include an interaction between our *MSH* variable and other labor market institutions, such as the EPL from OECD, in the regression, with and without controlling for the interaction with the minimum wage. We expect a null coefficient for other labor market institutions, which would suggest a specific role for the minimum wage. Second, we estimate the impact of the variation in the proportion of middling occupations on the proportion of low-paying manual jobs in a local labor market. The mechanism that we have in mind is that the presence of a strong minimum wage prevents the creation of low-paid jobs at the bottom of the wage distribution to provide sufficient jobs for low-skilled workers who lost their middling occupations and cannot reallocate to high-paying occupations due to skill mismatch. As a result, in the presence of a high minimum wage, we should observe a smaller increase in the proportion of low-paying occupations following a decrease in the

17. [Goldsmith-Pinkham et al. \(2020\)](#) developed a methodology based on the Rotemberg weights to understand the part of the identification for the IV coefficient that is related to shocks and the part that is related to industry shares. Unfortunately, the methodology that they developed allows for only one endogenous regressor.

proportion of middling occupations. Finally, we focus on France, which is characterized by the highest minimum wage level of our sample and for which we have detailed information on wages and occupations provided by the French labor force survey. The mechanism that we have in mind implies that we should observe a sharp increase in the proportion of workers paid the minimum wage concentrated on manual jobs, suggesting that the wage constraint is binding.¹⁸ The minimum wage did not increase during the period that we study, and a change in the proportion of individual paid at the minimum wage cannot be attributed to a change in regulation as a result.

1.4 Baseline Results

This section presents the results for our OLS and IV specifications.

1.4.1 Labor market outcomes, OLS results

The estimated coefficients of Equation 1.1 are presented in Table 1.3 considering the employment rate and in Table 1.4 considering the participation rate as the LMO variables. Both tables have the same presentation: the first two columns display simple regressions of the proportion of middling occupations in a local labor market on the outcome variable. The second columns include our standard set of control variables: gender, skill and age composition of the population, as defined previously. Columns 3 and 4 reproduce columns 1 and 2, respectively, including lag of $LMO_{a,t}$ (which are also included in columns 5 and 6). In columns 5 and 6, we estimate specifications using dummies for high and low instead of the continuous minimum wage variable (with and without our set of controls). Local labor market and time fixed effects are included in all regressions. Standard errors are clustered at the local labor market level. For regressions in columns 1 to 4, we compute the threshold value of the minimum wage such that the marginal effect of MSH equals zero ($\alpha_1 + \alpha_2 \times MW = 0$). If $\alpha_1 < 0$ and $\alpha_2 > 0$, as we expect, the marginal impact of a decrease in MSH is negative for values of the minimum wage higher than this threshold.

Focusing first on Table 1.3, the coefficients are significant in all specifications. The threshold values for the minimum wage decrease as we add control variables. In the most complete specification using the level of the minimum wage in column 4, the threshold value is equal

18. This should also be observed to a lesser extent on middling occupations. We will show that a significant proportion of individuals in middling occupation are paid the minimum wage, but this proportion remains substantially smaller than in manual occupations. The displacement effect should exert downward pressure on middling occupations too and increase the proportion of individuals paid the minimum wage as a result.

to 0.367, meaning that, when the national minimum wage level, calculated as a fraction of the average wages of full-time workers, exceeds 0.367, a reduction in the proportion of middling occupations has a negative effect on employment according to our estimation (i.e., the marginal impact of $MSH \alpha_1 + \alpha_2 \times MW$ is positive). Then, looking at columns 5 and 6, we can see that a decrease in MSH has a negative impact on labor market outcomes only for high minimum wage countries and no impact for low minimum wage countries. Indeed, in columns 5 and 6, the coefficient associated with the share of middling is statistically insignificant, indicating that the average effect when considering the bottom half of the minimum wage distribution is null.

Table 1.3 – OLS regressions: Employment rate

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.884 ^a (0.263)	-0.953 ^a (0.194)	-0.548 ^a (0.078)	-0.488 ^a (0.088)	-0.023 (0.027)	0.012 (0.025)
- X Minimum Wage ₀	4.297 ^a (0.617)	2.454 ^a (0.448)	1.326 ^a (0.176)	1.330 ^a (0.219)		
- X Up. half MW ₀					0.079 ^a (0.030)	0.130 ^a (0.034)
Sh. male ₋₁		0.084 (0.248)		-0.038 (0.121)		-0.000 (0.134)
Sh. high-skill ₋₁		0.538 ^a (0.083)		0.173 ^a (0.038)		0.209 ^a (0.037)
Sh. low-skill ₋₁		0.057 (0.059)		0.037 (0.026)		0.081 ^a (0.022)
Emp. rate ₋₁			0.817 ^a (0.026)	0.727 ^a (0.029)	0.865 ^a (0.026)	0.761 ^a (0.025)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.91	0.95	0.97	0.97	0.97	0.97
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.438	.389	.413	.367	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

If we consider the impact on the participation rate in Table 1.4, the results are almost identical. When considering columns 1 to 4, all of the coefficients are significant, and the threshold value decreases as we add controls, although it is slightly lower than for the previous estimates for the employment rate. When the minimum wage becomes sufficiently high, the diminution of the proportion of middling occupations decreases the participation rate. When looking at the specifications using minimum wage dummies (column 5 and 6), the results are also similar to the previous ones: the minimum wages level plays a role in the labor market impacts of the polarization only in high minimum wage countries.

Figure 1.3 provides a visualization of the conditional marginal effects estimated in column

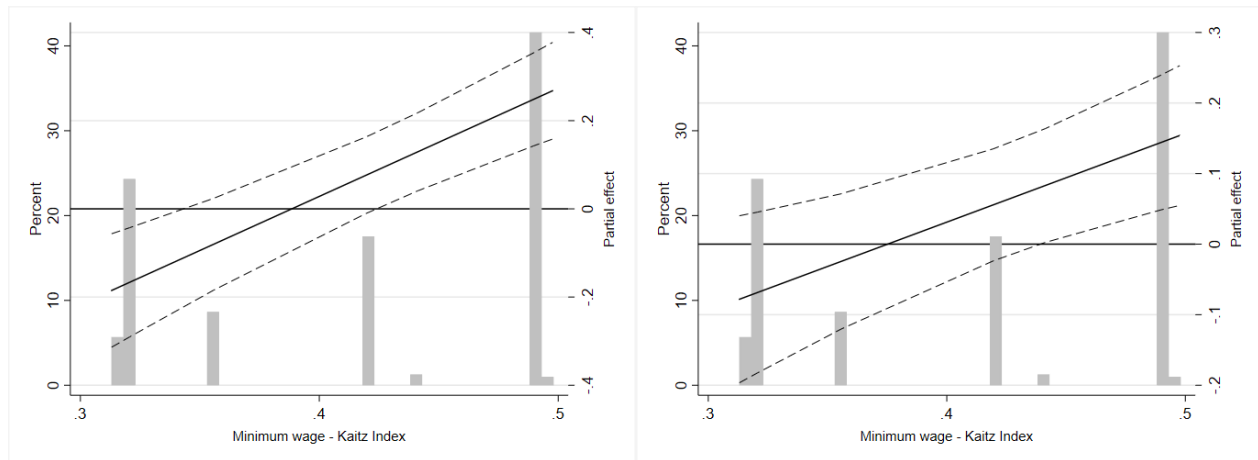
Table 1.4 – OLS regressions: Participation rate

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.019 ^a (0.183)	-0.472 ^a (0.177)	-0.427 ^a (0.083)	-0.284 ^b (0.111)	0.009 (0.030)	0.042 (0.036)
- X Minimum Wage ₀	2.389 ^a (0.419)	1.257 ^a (0.407)	1.117 ^a (0.192)	0.870 ^a (0.264)		
- X Up. half MW ₀					0.082 ^b (0.032)	0.090 ^b (0.043)
Sh. male ₋₁		0.289 ^c (0.164)		0.148 (0.102)		0.174 ^c (0.103)
Sh. high-skill ₋₁		0.243 ^a (0.058)		0.093 ^b (0.040)		0.129 ^a (0.035)
Sh. low-skill ₋₁		0.017 (0.052)		0.007 (0.033)		0.044 ^c (0.025)
Part. rate ₋₁			0.653 ^a (0.041)	0.590 ^a (0.037)	0.700 ^a (0.043)	0.614 ^a (0.037)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.92	0.94	0.95	0.96	0.95	0.96
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.427	.375	.382	.326	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

2 of Tables 1.3 and 1.4, i.e., on the employment rate and participation rate, respectively. The plotted line shows the effect of a marginal increase in the proportion of middling occupations on the labor market outcomes ($\alpha_1 + \alpha_2 \times MW$). The plot is superimposed over a histogram of the distribution of initial minimum wage levels over local labor markets to provide a sense of the empirical relevance of the range of minimum wage levels for which the effect of the reduction in the proportion of middling occupations is statistically significant. The left panel of Figure 1.3 shows that the marginal effect of a decrease in the proportion of middling occupations on the employment rate is negative and significant ($\alpha_1 + \alpha_2 \times MW > 0$) for sufficiently high values of the minimum wage (above 0.43) and very marginally positive and significant ($\alpha_1 + \alpha_2 \times MW < 0$) for sufficiently low values of the minimum wage (below 0.33). The impact of the polarization phenomenon is thus negative on employment when the minimum wage is high, which we interpret as the poor ability of such economies to create a sufficient number of low-paying occupations for workers who do not reallocate to abstract, high-paying occupations. The right panel of Figure 1.3 demonstrates that the marginal effect of a decrease in the proportion of middling occupations on the participation rate is negative and significant ($\alpha_1 + \alpha_2 \times MW > 0$) for high levels of the minimum wage (above 0.43) and positive but never significant ($\alpha_1 + \alpha_2 \times MW < 0$) for low values (less than 0.37). This finding is consistent with our findings on the employment rate. When the minimum wage

Figure 1.3 – Marginal effect of the proportion of routine occupations on labor market outcomes, conditional on the value of the minimum wage.



(a) Employment rate

(b) Participation rate

Notes: The figure is based on regression estimates from column 2 of Tables 1.3 and 1.4. Dashed lines represent 95% confidence intervals.

is high, the decrease in employment rate translates into a decrease in participation. Many people exit the labor market due to skill mismatch and poor employment prospects. When the minimum wage is low, the economy is able to create a number of low-paying jobs in the service sector, translating into an increase in the participation rate. Over the period of 1992-2010, the proportion of middling occupations decreased by approximately ten percentage points, and this shock had a heterogeneous impact. According to our estimates (Table 1.3 and Table 1.4, column 2), the employment rate decreases by 2.49 percentage points in France, which is characterized by a high-level minimum wage over the period considered (0.49). In contrast, over the same period in the United Kingdom, a country with a low minimum wage of 0.36, it triggered a 0.69 percentage point increase in the employment rate. However, the effect is not significant. Concerning the participation rate, when the proportion of middling occupations declines by 10 percentage points, polarization leads to a 1.43 percentage point decrease in France. For the United Kingdom, it leads to a 0.19 percentage point increase in the participation rate, but here again, the effect is not significant. These effects are economically sizable for high minimum wage countries. Several robustness checks are provided in the Appendix: using data until 2010 instead of 2007 in Tables 1.10 and 1.11, using the time-varying minimum wage in Tables 1.12 and 1.13, using the mean minimum wage over the period in Tables 1.14 and 1.15, including controls for 3 industry shares in Tables 1.16 and 1.17, including controls for 16 industry shares in Tables 1.18 and 1.19 and finally using a jackknife estimator in Tables 1.20 and 1.21.

1.4.2 Labor market outcomes, IV results

To address the endogeneity issue mentioned above, we re-estimate Equation 1.1 using an IV strategy. Results concerning employment and participation rate are respectively displayed in Tables 1.5 and 1.6. As we cluster standard errors at the local labor market level, we provide the cluster-robust Kleibergen-Paap Wald rk F-statistic to determine whether our instrument is strong. We also display the standard F-statistic.¹⁹ All IV estimations contain local labor market and time fixed effects.²⁰

It is worth noting that the F-statistics in our specifications are around the rule-of-thumb threshold of 10 but are sometime slightly less than this threshold. However, as noted in [Andrews et al. \(2019\)](#), the factr that instruments are weak is not a problem in itself since it may “unnecessarily eliminates specifications of potential economic interest”. As a consequence and as they recommend, we also evaluate the joint significance of the instrumented endogenous variables in the second stage regression with the p-value of the Anderson-Rubin Wald statistic, which provides valid inference when instrument are weak.

Table 1.5 – IV regressions: Employment rate

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling	-3.195 ^a (0.973)	-3.719 ^a (0.855)	-0.630 ^c (0.377)	-1.121 ^a (0.417)	-1.185 ^a (0.397)	-1.097 ^a (0.401)
- X Minimum Wage ₀	6.505 ^a (1.672)	7.479 ^a (1.648)	1.420 ^b (0.625)	2.658 ^a (0.799)	2.523 ^a (0.763)	2.470 ^a (0.794)
Sh. male ₋₁		-0.068 (0.221)		-0.204 (0.182)	-0.153 (0.154)	-0.221 (0.185)
Sh. high-skill ₋₁		0.302 ^a (0.084)		0.107 ^c (0.059)	0.123 ^b (0.055)	0.125 (0.078)
Sh. low-skill ₋₁		0.164 ^a (0.059)		0.099 ^c (0.051)	0.092 ^c (0.052)	0.056 (0.035)
Emp. rate ₋₁			0.722 ^a (0.037)	0.684 ^a (0.052)	0.658 ^a (0.056)	0.629 ^a (0.052)
Sh. age cat. ₋₁	no	yes	no	yes	yes	yes
Sh. ind. ₋₁	no	no	no	no	3 posts	16 posts
Observations	823	823	823	823	823	823
F	12	12	12	11	8	8
F K-P	9	10	9	9	10	8
A-R Wald χ^2 (p-value)	0.000	0.000	0.003	0.000	0.000	0.000
Threshold value	.491	.497	.444	.422	.47	.444

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

19. [Andrews et al. \(2019\)](#) argue that there is “no theoretical justification for the use of either the standard or cluster robust F-statistic to gauge instrument strength in non-homoskedastic settings”. We thus report both to provide all of the information to the reader.

20. First-stage results are available in the Appendix Tables 1.22 and 1.23.

Table 1.6 – IV regressions: Participation rate

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling	-2.117 ^a	-2.555 ^a	-0.979 ^b	-1.454 ^a	-1.183 ^a	-0.897 ^b
	(0.770)	(0.618)	(0.431)	(0.388)	(0.330)	(0.372)
- X Minimum Wage ₀	4.541 ^a	5.259 ^a	2.175 ^a	3.349 ^a	2.902 ^a	2.430 ^a
	(1.272)	(1.250)	(0.692)	(0.790)	(0.724)	(0.689)
Sh. male ₋₁		0.041		-0.058	-0.029	-0.079
		(0.181)		(0.135)	(0.136)	(0.168)
Sh. high-skill ₋₁		0.205 ^a		0.094 ^b	0.118 ^b	0.113 ^b
		(0.072)		(0.047)	(0.047)	(0.053)
Sh. low-skill ₋₁		0.134 ^b		0.102 ^b	0.086	0.043
		(0.056)		(0.043)	(0.052)	(0.039)
Part. rate ₋₁			0.569 ^a	0.514 ^a	0.498 ^a	0.455 ^a
			(0.040)	(0.049)	(0.049)	(0.044)
Sh. age cat. ₋₁	no	yes	no	yes	yes	yes
Sh. ind. ₋₁	no	no	no	no	3 posts	16 posts
Observations	823	823	823	823	823	823
F	12	12	13	11	8	8
F K-P	9	10	9	10	10	8
A-R Wald χ^2 (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Threshold value	.466	.486	.45	.434	.408	.369

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

We also provide some more tests to convince the reader that the instrument is exogenous and that the exclusion restrictions are likely to be satisfied. First, as explained earlier, in columns 5 and 6, following the recommendations of [Goldsmith-Pinkham et al. \(2020\)](#), we include industry shares as a control (aggregated 3 industries and more detailed 16 industries classifications respectively). In addition, we show in Appendix Table 1.24 that the past share of middling occupations does not predict future values of the instrument (conditional on past values of the instrument).²¹ In all specifications of Tables 1.5 and 1.6, we observe that all of the coefficients are statistically significant. The Anderson-Rubin Wald statistics indicate that, for all specifications, the endogenous regressors are jointly significant. Threshold values and the magnitudes of the coefficients are higher than in OLS specifications, but our results remain qualitatively unchanged. The minimum wage level plays a role in the impact of the destruction of middling occupations on labor market outcomes.

21. More specifically, we regress the value of the instrument on the one year lagged value of the instrument and the one year lagged share of middling occupation, including all of the controls of the IV estimates. We expect that the past value of middling occupation does not explain contemporaneous values of our instrument.

1.5 Some evidence on the mechanisms

1.5.1 The number of low-paying occupations

We now examine more specifically the mechanism that we have in mind by which the minimum wage prevents the creation of sufficient low-paying jobs to compensate for the decrease in the number of middling occupations and thus reduces the employment rate when the number of middling occupations decreases. We slightly modify Equation 1.1: instead of focusing on one of our LMO variables, we now estimate the effect of the proportion of middling occupations on the number of low-paying occupations.²² The results are displayed in Table 1.7. In columns 1 and 2, we estimate our standard specification with the continuous minimum wage variable, while in columns 3 and 4, we use dummies for minimum wage groups as in our baseline OLS specifications in Tables 1.3 and 1.4. Controls for industry shares are included in all regressions.

Table 1.7 – OLS regressions: Low-paying in numbers (log)

	(1)	(2)	(3)	(4)
Sh. middling ₋₁	-8.687 ^a (2.829)	-7.358 ^b (3.353)	-2.250 ^a (0.746)	-2.050 ^b (0.913)
- X Minimum Wage ₀	19.191 ^a (6.587)	16.629 ^b (7.679)		
- X Up. half MW ₀			3.270 ^a (0.929)	3.489 ^a (1.100)
Sh. male ₋₁		-2.005 (3.601)		-2.714 (3.439)
Sh. high-skill ₋₁		2.010 (1.641)		1.577 (1.453)
Sh. low-skill ₋₁		0.505 (1.077)		-0.073 (0.815)
Sh. age cat. ₋₁	no	yes	no	yes
R ²	0.88	0.88	0.88	0.88
Observations	1137	1111	1177	1137
Threshold value	.453	.442	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007. All regressions include control for 16 industry shares.

The mechanism that we have previously highlighted seems to be confirmed. All of the coefficients are highly significant. When the proportion of middling occupations decreases, the number of low-paying occupation occupations increases, but this increase is conditional

22. We express the number of low-paying jobs in log to prevent the largest local labor markets from driving all of our results.

on the level of the minimum wage; the higher that the minimum wage is, the smaller that the resulting increase in the proportion of manual low-paying occupations is.

According to the estimates in column 2, in a low minimum wage country, such as the United Kingdom, a 1 percentage point decrease in the share of middling occupations increases by 1.38% the number of low-paying jobs compared to other local labor markets. In contrast, for a high minimum wage country such as France, a 1 percentage point decrease in the share of middling occupations decreases by 0.78% the number of low-paying jobs compared to other local labor markets. Our results show that the impact of the decrease in the proportion of middling occupations on employment in low-paying occupations is thus very different across low and high minimum wage countries.

1.5.2 Individual paid at the minimum wage by occupations: The case of France

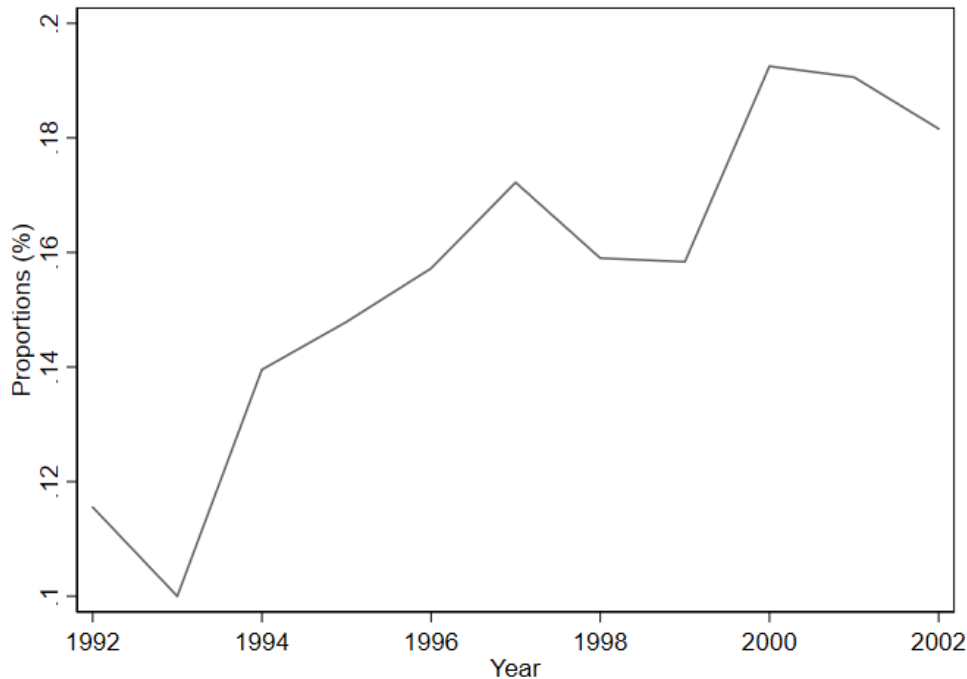
We document how the minimum wage became more constraining over time for wage determination, especially for low-paying occupations, focusing on France, a high minimum wage country.

Consistent with the mechanism that we have in mind, we should observe more individuals paid at the minimum wage at the bottom of the wage distribution, in low-paying occupations. As middling occupations disappear, workers reallocate from middling to low-paying occupations, creating a downward wage pressure in occupations in which workers are displaced. The proportion of individuals paid at the minimum wage at the bottom of the wage distribution should increase as a result.

We use the *Enquête Emploi en Continue* (the French labor force survey). One caveat of this dataset is that the wage data are very noisy, especially when considering hourly wage data. To identify workers paid the minimum wage, we consider a 10% halo around the value of the minimum wage. Indeed, there are many observations in which the hourly wage is less than the minimum wage. Observations with an hourly wage inferior to 90% of the minimum wage are dropped. In addition, there is a structural break in the data in 2003, so we only use data from 1992 to 2002. However, there is no reason to expect that the dynamic drastically change after 2002. We are confident in the relevance of our strategy to identify workers paid the minimum wage since our numbers correspond to proportions estimated by [Garnero \(2019\)](#).

Looking at Figure 1.4, we can see that the share of workers earning the minimum wage among the low-paying occupations is growing over time, going from approximately 10% at

Figure 1.4 – Evolution of minimum wage workers’ shares, low-paying occupations only

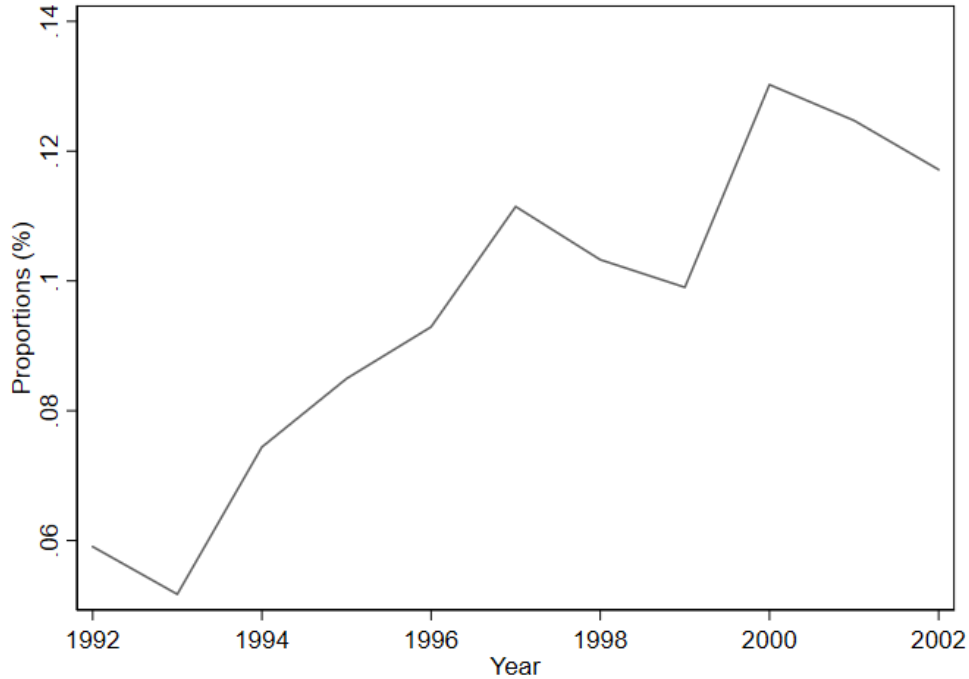


Source: Enquête Emploi en Continu (EEC) from 1992 to 2002. Share of workers paid at the minimum wage calculated using a 10% halo around the minimum wage value due to data limitations.

the beginning of the 1990s to nearly 20% at the beginning of the 2000s. Looking at Figure 1.5, we observe the same dynamic for workers occupying middling occupations. Although fewer workers are paid the minimum wage in these occupations, the share goes from 6% at the beginning of the 1990s to nearly 12% at the beginning of the 2000s.²³ This pattern should not be related to institutional change since the minimum wage as a proportion of the mean wage was quite stable over this period in France, going from 0.492 in 1992 to 0.510 in 2002. This pattern is consistent with the displacement effect in an environment in which wages at the lower bound of the distribution are rigid. Displaced workers create a downward wage pressure such that more workers meet the minimum wage threshold. The effect is also observed for middling occupations since a significant share of workers (but fewer than for low-paying occupations) are paid the minimum wage. This displacement effect should also concern these occupations.

23. This pattern is also observed when considering different halo sizes, ranging from 1 to 10%.

Figure 1.5 – Evolution of minimum wage workers' shares, middling occupations only



Source: Enquête Emploi en Continu (EEC) from 1992 to 2002. Share of workers paid at the minimum wage calculated using a 10% halo around the minimum wage value due to data limitations.

1.6 The role of other labor market institutions

One concern that could arise regarding the preceding analysis is the role played by other labor market institutions. It is possible that, through the level of the national minimum wage, we are capturing the impact of other labor market institutions because a high minimum wage is often correlated with strong labor market institutions. Note, however, that this assumption is not systematically true, as we will see. As a consequence of possible correlation between the minimum wage and other labor market institutions, our interaction coefficient $((MSH \times MW)_{a,t})$ could capture some other institutional factors, leading to incorrect inferences about the role of the minimum wage in driving the shape of polarization and its impact on labor market outcomes. Specifically, the other labor market institutions could create frictions at the bottom of the wage distribution that inhibit the creation of manual low-paying jobs and, as a consequence, negatively affect labor market outcomes in the context of the destruction of middling occupations. More generally, strong labor market institutions provide workers with some bargaining power and affect the wage determination process. However,

in our opinion, labor market institutions and the level of the minimum wage do not affect wages in the same way. The national minimum wage acts as a lower bound on wages, creating important downward nominal wage rigidity for lower wages. This increases the wages of workers in low-paying occupations relative to other workers. Conversely, labor market institutions give bargaining power to all workers, but the bargaining power of low-paid workers should not increase much, mainly because they are easily substitutable in a context of high unemployment and because they often have temporary jobs, which offer less protection. As a result, other labor market institutions, unlike the minimum wage, should not increase the relative wages of low-paid workers. The mechanism that we have in mind to explain the impact of the massive destruction of middling occupations on employment is thus specific to the minimum wage.

To capture the other labor market institutions, we use several indicators. Most of these indicators come from the OECD Indicators of Employment Protection Legislation (EPL) dataset. First, we employ the most aggregated indicator of labor market institutions, the EPRC index, which captures regulations on “Regular contracts, including additional provision for collective dismissals”. This indicator consists of several variables representing the numerous dimensions of labor market institutions. In addition, we consider the EPT index, which reflects regulations on "Temporary employment". Finally, we also use the Gross Replacement Rate (GRR), also provided by the OECD. Those variables should allow us to capture the various dimensions of the labor market institutions in each country that are different from the minimum wage.

Table 1.8 – Correlation table: Minimum wage and EPL indexes

	Minimum Wage	EPRC	EPT	GRR
Minimum Wage	1.00			
EPRC	-0.31	1.00		
EPT	-0.04	0.31	1.00	
GRR	0.38	0.26	-0.25	1.00

Notes: Data from OECD Employment Protection Legislation, OECD minimum wage and OECD Gross replacement rate for years 1992-2007.

We first display in Table 1.8 correlations between the minimum wage and the various labor market institutions variables mentioned before. We can see that, for our sample of countries, the level of the minimum wage is not strongly correlated with either the aggregated indicators of employment protection or the gross replacement rate. This suggests that the minimum wage should not systematically capture the effect of other labor market institutions, but it plays a specific role by making the wages of low-paying occupations difficult to adjust after

the displacement effect generated by labor market polarization. In the Appendix Table 1.25, we also provide the average of these variables for each country of our sample. As we can see, in Spain, for example, many strong labor market institutions (regarding regular and temporary contracts, for instance) coexist with a very low minimum wage. We then perform a statistical analysis to confirm the specific role of the minimum wage. To do so, we estimate the same specification as in the rest of the paper, and we simply sequentially add several labor market institution variables and their interactions with the level of middling occupations at the local labor market level. Given the weak correlation between the minimum wage and other labor market institutions shown in Table 1.8, this outcome should allow for estimating the specific role of both types of institutions. Specifically, we estimate the following equation for each outcome:

$$LMO_{a,t} = \alpha_1 MSH_{a,t} + \alpha_2 (MSH \times MW)_{a,t} + \alpha_3 (MSH \times LMI)_{a,t} + \beta X_{a,t} + \gamma_a + \delta_t + u_{a,t} \quad (1.3)$$

All of the variables in this equation are the same as before except for LMI, which stands for “labor market institutions”. Similar to the minimum wage, we fix the LMI variables to their initial levels since changes in labor market institutions may be correlated with the polarization of the labor market. If the mechanism that we have in mind is the one at work, most of the effect will go through the minimum wage variable, and the labor market institutions, interacted with the level of middling occupations, should not have a significant, positive impact on labor market outcomes.

Alternatively, we also estimate a slightly different specification, in which we only include the other labor market institutions and their interactions with *MSH* without the minimum wage.

These specifications are available in the Appendix in Table 1.26. We do not expect the coefficient related to LMI and its interaction with *MSH* to be significant and positive. Such an outcome would confirm the specific role of the minimum wage, rather than other labor market institutions.

The estimated coefficients of Equation 1.3 are presented in Table 1.9 for both the employment and participation rates. Local labor market and time fixed effects are included in all of the regressions. As before, standard errors are clustered at the local labor market level. In columns 1 and 5, we display the coefficients from our baseline specification for both

Table 1.9 – OLS regressions: EPL

	Employment rate				Participation rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh. middling ₋₁	-0.953 ^a (0.194)	-1.348 ^a (0.289)	-0.930 ^a (0.190)	-0.821 ^a (0.178)	-0.472 ^a (0.177)	-0.347 (0.221)	-0.407 ^b (0.156)	-0.345 ^b (0.163)
- X Minimum Wage ₀	2.454 ^d (0.448)	2.936 ^a (0.442)	2.668 ^a (0.487)	2.804 ^a (0.518)	1.257 ^a (0.407)	1.105 ^a (0.406)	1.862 ^a (0.412)	1.592 ^a (0.416)
- X EPRCv1 ₀		0.076 (0.060)				-0.024 (0.036)		
- X EPTv1 ₀			-0.030 (0.022)				-0.084 ^a (0.021)	
- X GRR APW ₀				-0.900 ^b (0.365)				-0.862 ^a (0.308)
Sh. male ₋₁	0.084 (0.248)	0.061 (0.256)	0.087 (0.245)	0.098 (0.235)	0.289 ^c (0.164)	0.297 ^c (0.163)	0.298 ^c (0.160)	0.302 ^c (0.155)
Sh. high-skill ₋₁	0.538 ^a (0.083)	0.552 ^a (0.084)	0.530 ^a (0.084)	0.486 ^a (0.086)	0.243 ^a (0.058)	0.238 ^a (0.057)	0.221 ^a (0.057)	0.194 ^a (0.057)
Sh. low-skill ₋₁	0.057 (0.059)	0.057 (0.060)	0.061 (0.059)	0.034 (0.057)	0.017 (0.052)	0.017 (0.052)	0.029 (0.049)	-0.005 (0.049)
R ²	0.95	0.95	0.95	0.95	0.94	0.94	0.94	0.94
Observations	1111	1111	1111	1111	1111	1111	1111	1111

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007. Share of age categories included in all regressions.

the employment and the participation rates from Tables 1.3 and 1.3, column 2, to ease the comparison.

Looking at Table 1.9, we can see that the interaction coefficient $(MSH \times MW)_{a,t}$ for the minimum wage is still positive and highly significant in all specifications. The magnitude of the coefficients does not significantly change when controlling more broadly for many dimensions of labor market institutions, which are distinct from the minimum wage. We observe that the coefficients associated with the labor market institutions, interacted with the proportion of middling occupations in a local labor market, are not significant or are statistically significant but negative. This finding confirms that our effect works only through the minimum wage level and its specific impact on the degree of wage rigidity at the bottom of the wage distribution, and it does not capture the effect of other labor market institutions.²⁴

24. Appendix Table 1.26 displays results when we do not include the minimum wage and its interaction. We observe that the coefficient associated with $MSH_{a,t}$ is positive, and the interaction with the labor market institutions is negative or insignificant, providing additional evidence for the mechanism that we have in mind. Other labor market institutions do not seem to play a similar role and do not capture the impact of the minimum wage. Those results are in line with the results in Table 1.9, and they can be seen as a falsification test.

1.7 Conclusion

In recent years, a growing body of literature has focused on the causes of labor market polarization, but little attention has been paid to its possible impact on labor market outcomes. Our hypothesis is that the minimum wage level changed the shape taken by polarization by preventing the creation of low-paying jobs at the bottom of the skill distribution, thereby affecting the participation and employment rates. Using the European Union Labor Force Survey, we estimated the impact of a reduction in the proportion of middling occupations on labor market outcomes, such as participation and employment rates. Our estimates show that the minimum wage level plays a crucial role in the impact of the destruction of routine occupations on labor market outcomes: economies characterized by high minimum wages saw their employment decrease as the proportion of middling occupations decreased, while no impact was observed for low minimum wage countries. In addition, we demonstrated that these results are consistent with our preferred explanation: a high minimum wage seems to prevent the creation of low-paying jobs. Our estimates indicate that the proportion of manual jobs does not increase in response to the reduction in middling occupations when the minimum wage is high.

Our results suggest that the costs of the minimum wage could be magnified in an environment in which middling occupations are destroyed. These jobs provided good wage opportunities for low-skilled (and some medium-skilled) workers, and employment opportunities for this category of workers deteriorated as a result. In this environment, in which many low-skilled workers cannot reallocate to abstract, well-paid occupations, the ability of an economy to create manual low-paying jobs is necessary to maintain a constant employment rate. This ability could be limited in high minimum wage countries, and the displacement effect documented theoretically in [Acemoglu and Restrepo \(2017\)](#) should generate a decrease in employment in such an environment. Given the higher cost of a nationwide minimum wage in the context of rapid, task-biased technological change that destroys middling occupations at a rapid rate, alternative policy interventions could be attractive to prevent such a pervasive impact on local labor markets affected by polarization shocks. For instance, employment subsidies could be a credible alternative because they do not modify the relative labor costs of low- and high-skilled workers. Another alternative for such countries would be to allow the minimum wage to be set at the sector level (as in Sweden and Germany, for example) or even at the local labor market level, to make labor market institutions more flexible in response to technological shocks, which have heterogeneous impacts across local labor markets.

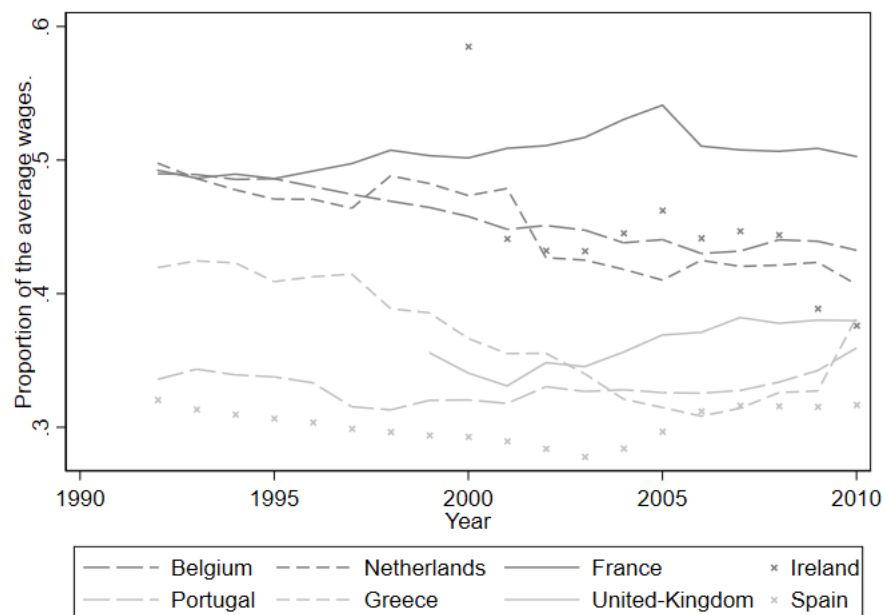
1.A Data

1.A.1 NUTS Classification

As mentioned before, we had to delete and modify some areas in the EULFS in order to have a consistent coding over time. Here, we will detail those modifications. Concerning Belgium, for years prior to 1996, we have deleted area "BE12", and modified the code of "BE11" to "BE21", "BE24" to "BE33", "BE13" to "BE24", "BE22" to "BE31", "BE15" to "BE22", "BE19" to "BE25", "BE23" to "BE32", "BE18" to "BE23", "BE26" to "BE34", "BE27" to "BE35" and "BE30" to "BE10". For Spain, we only had to recode one area, from "ES64" to "ES63". Concerning Portugal and Ireland, we had to drop years before 1998, as the classification completely change afterwards for those two countries. Finally, we had to drop all the years before 1997, for the same reason as before, classification completely change and information is too aggregated to use a crosswalk.

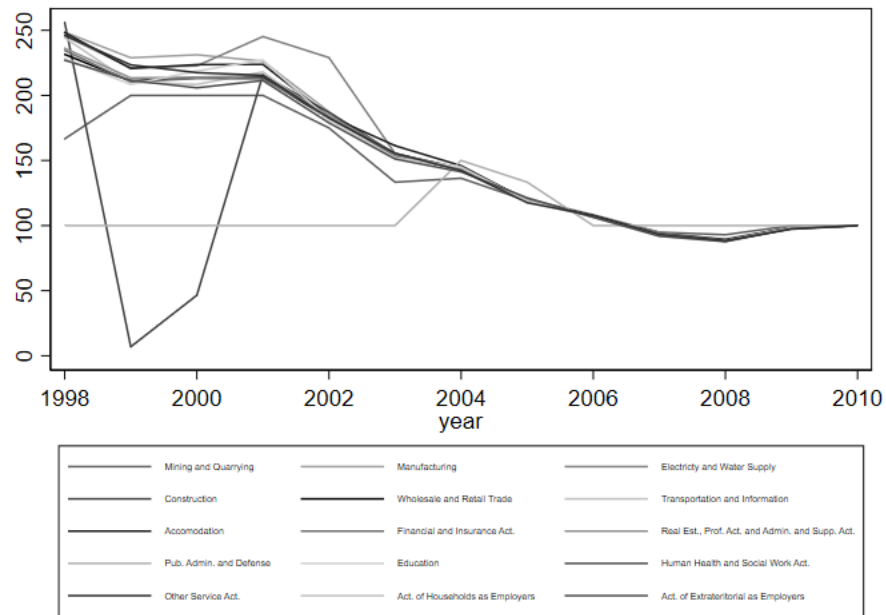
1.B Additional graphs

Figure 1.6 – Evolution of the levels of the minimum wage



Source: OECD dataset on minimum wages.

Figure 1.7 – Evolution of the price indices of ICT Capital per industry in the US



Source: Klems dataset. Merged industries weighted by their relative GDP.

1.C Robustness

1.C.1 OLS until 2010

Table 1.10 – OLS regressions: Employment rate, *with sample stopping in 2010 instead of 2007*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.400 ^a (0.229)	-0.610 ^a (0.189)	-0.185 ^a (0.058)	-0.227 ^a (0.067)	0.013 (0.023)	0.042 ^c (0.024)
- X Minimum Wage ₀	3.133 ^a (0.527)	1.646 ^a (0.422)	0.466 ^a (0.131)	0.706 ^a (0.162)		
- X Up. half MW ₀					0.002 (0.020)	0.056 ^b (0.027)
Sh. male ₋₁		0.113 (0.183)		-0.047 (0.081)		-0.016 (0.086)
Sh. high-skill ₋₁		0.560 ^a (0.087)		0.134 ^a (0.039)		0.150 ^a (0.040)
Sh. low-skill ₋₁		0.029 (0.052)		0.035 (0.023)		0.060 ^a (0.020)
Emp. rate ₋₁			0.800 ^a (0.019)	0.790 ^a (0.025)	0.826 ^a (0.018)	0.810 ^a (0.025)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.90	0.93	0.97	0.97	0.97	0.97
Observations	1395	1369	1395	1369	1435	1395
Threshold value	.447	.371	.397	.321	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2010.

Table 1.11 – OLS regressions: Participation rate, *with sample stopping in 2010 instead of 2007*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.162 ^a (0.171)	-0.515 ^a (0.160)	-0.358 ^a (0.071)	-0.242 ^b (0.097)	0.016 (0.026)	0.051 ^c (0.031)
- X Minimum Wage ₀	2.741 ^a (0.400)	1.382 ^a (0.377)	0.970 ^a (0.171)	0.784 ^a (0.244)		
- X Up. half MW ₀					0.078 ^a (0.026)	0.079 ^b (0.038)
Sh. male ₋₁		0.313 ^b (0.135)		0.157 ^c (0.080)		0.179 ^b (0.080)
Sh. high-skill ₋₁		0.241 ^a (0.055)		0.081 ^b (0.036)		0.106 ^a (0.034)
Sh. low-skill ₋₁		-0.007 (0.043)		-0.003 (0.024)		0.024 (0.020)
Part. rate ₋₁			0.694 ^a (0.038)	0.626 ^a (0.035)	0.743 ^a (0.037)	0.653 ^a (0.033)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.91	0.94	0.96	0.96	0.96	0.96
Observations	1395	1369	1395	1369	1435	1395
Threshold value	.424	.373	.369	.309	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2010.

1.C.2 Time-varying minimum wage

Table 1.12 – OLS regressions *using time-varying minimum wage*: Employment rate

	(1)	(2)	(3)	(4)
Sh. middling ₋₁	-1.843 ^a (0.229)	-0.731 ^a (0.159)	-0.517 ^a (0.084)	-0.370 ^a (0.082)
- X Minimum Wage ₋₁	4.305 ^a (0.550)	1.986 ^a (0.373)	1.276 ^a (0.191)	1.076 ^a (0.196)
Minimum Wage ₋₁	-1.557 ^a (0.222)	-0.615 ^a (0.166)	-0.485 ^a (0.081)	-0.414 ^a (0.089)
Sh. male ₋₁		0.170 (0.249)		-0.009 (0.127)
Sh. high-skill ₋₁		0.491 ^a (0.078)		0.161 ^a (0.038)
Sh. low-skill ₋₁		-0.015 (0.052)		0.018 (0.026)
Emp. rate ₋₁			0.798 ^a (0.026)	0.725 ^a (0.030)
Sh. age cat. ₋₁	no	yes	no	yes
R ²	0.92	0.95	0.97	0.97
Observations	1137	1111	1137	1111
Threshold value	.428	.368	.405	.344

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

Table 1.13 – OLS regressions *using time-varying minimum wage*: Participation rate

	(1)	(2)	(3)	(4)
Sh. middling ₋₁	-1.023 ^a (0.155)	-0.458 ^a (0.130)	-0.448 ^a (0.075)	-0.290 ^a (0.087)
- X Minimum Wage ₋₁	2.457 ^a (0.357)	1.258 ^a (0.296)	1.192 ^a (0.167)	0.906 ^a (0.197)
Minimum Wage ₋₁	-0.969 ^a (0.143)	-0.438 ^a (0.130)	-0.456 ^a (0.069)	-0.337 ^a (0.089)
Sh. male ₋₁		0.326 ^b (0.163)		0.171 (0.104)
Sh. high-skill ₋₁		0.213 ^a (0.056)		0.076 ^c (0.040)
Sh. low-skill ₋₁		-0.013 (0.048)		-0.009 (0.032)
Part. rate ₋₁			0.636 ^a (0.038)	0.582 ^a (0.036)
Sh. age cat. ₋₁	no	yes	no	yes
R ²	0.92	0.94	0.95	0.96
Observations	1137	1111	1137	1111
Threshold value	.416	.364	.376	.32

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

1.C.3 Mean minimum wage over the period considered

Table 1.14 – OLS regressions *using mean minimum wage*: Employment rate

	(1)	(2)	(3)	(4)
Sh. middling ₋₁	-1.377 ^a	-0.804 ^a	-0.361 ^a	-0.416 ^a
	(0.258)	(0.164)	(0.071)	(0.075)
- X Mean Minimum Wage	3.292 ^a	2.206 ^a	0.935 ^a	1.211 ^a
	(0.621)	(0.389)	(0.159)	(0.188)
Sh. male ₋₁		0.175		-0.013
		(0.276)		(0.135)
Sh. high-skill ₋₁		0.613 ^a		0.194 ^a
		(0.078)		(0.036)
Sh. low-skill ₋₁		0.179 ^a		0.086 ^a
		(0.049)		(0.022)
Emp. rate ₋₁			0.841 ^a	0.745 ^a
			(0.025)	(0.026)
Sh. age cat. ₋₁	no	yes	no	yes
R ²	0.91	0.95	0.97	0.97
Observations	1177	1137	1177	1137
Threshold value	.418	.364	.386	.343

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

Table 1.15 – OLS regressions *using mean minimum wage*: Participation rate

	(1)	(2)	(3)	(4)
Sh. middling ₋₁	-0.786 ^a	-0.467 ^a	-0.318 ^a	-0.292 ^a
	(0.177)	(0.154)	(0.074)	(0.098)
- X Mean Minimum Wage	1.971 ^a	1.314 ^a	0.911 ^a	0.933 ^a
	(0.409)	(0.364)	(0.169)	(0.240)
Sh. male ₋₁		0.347 ^c		0.164
		(0.180)		(0.104)
Sh. high-skill ₋₁		0.293 ^a		0.114 ^a
		(0.053)		(0.035)
Sh. low-skill ₋₁		0.107 ^b		0.049 ^b
		(0.041)		(0.025)
Part. rate ₋₁			0.675 ^a	0.600 ^a
			(0.041)	(0.037)
Sh. age cat. ₋₁	no	yes	no	yes
R ²	0.92	0.94	0.95	0.96
Observations	1177	1137	1177	1137
Threshold value	.399	.356	.349	.313

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

1.C.4 Including controls for industry share

3 industries

Table 1.16 – OLS regressions: Employment rate, *controlling for 3 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.954 ^a (0.244)	-0.864 ^a (0.173)	-0.567 ^a (0.086)	-0.482 ^a (0.085)	-0.054 ^c (0.028)	-0.018 (0.026)
- X Minimum Wage ₀	4.404 ^a (0.580)	2.085 ^a (0.412)	1.316 ^a (0.200)	1.249 ^a (0.214)		
- X Up. half MW ₀					0.076 ^b (0.032)	0.121 ^a (0.033)
Sh. male ₋₁		0.258 (0.215)		-0.016 (0.127)		0.011 (0.137)
Sh. high-skill ₋₁		0.481 ^a (0.079)		0.179 ^a (0.038)		0.210 ^a (0.038)
Sh. low-skill ₋₁		-0.025 (0.053)		0.034 (0.029)		0.076 ^a (0.022)
Emp. rate ₋₁			0.800 ^a (0.024)	0.713 ^a (0.036)	0.850 ^a (0.023)	0.748 ^a (0.032)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.92	0.95	0.97	0.97	0.97	0.97
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.444	.414	.43	.386	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

Table 1.17 – OLS regressions: Participation rate, *controlling for 3 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.073 ^a (0.171)	-0.430 ^b (0.170)	-0.448 ^a (0.087)	-0.281 ^b (0.113)	-0.007 (0.030)	0.034 (0.036)
- X Minimum Wage ₀	2.546 ^a (0.408)	1.154 ^a (0.393)	1.159 ^a (0.215)	0.853 ^a (0.280)		
- X Up. half MW ₀					0.090 ^a (0.033)	0.088 ^b (0.043)
Sh. male ₋₁		0.390 ^b (0.163)		0.177 ^c (0.106)		0.200 ^c (0.107)
Sh. high-skill ₋₁		0.202 ^a (0.057)		0.090 ^b (0.041)		0.126 ^a (0.035)
Sh. low-skill ₋₁		-0.042 (0.046)		-0.006 (0.032)		0.037 (0.024)
Part. rate ₋₁			0.640 ^a (0.037)	0.568 ^a (0.037)	0.690 ^a (0.038)	0.599 ^a (0.037)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.92	0.94	0.95	0.96	0.95	0.96
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.421	.373	.387	.329	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

16 industries

Table 1.18 – OLS regressions: Employment rate, *controlling for 16 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.695 ^a (0.247)	-0.651 ^a (0.166)	-0.525 ^a (0.086)	-0.421 ^a (0.084)	-0.051 ^c (0.026)	-0.010 (0.027)
- X Minimum Wage ₀	3.824 ^a (0.572)	1.645 ^a (0.394)	1.199 ^a (0.201)	1.101 ^a (0.211)		
- X Up. half MW ₀					0.066 ^b (0.032)	0.103 ^a (0.031)
Sh. male ₋₁		0.158 (0.195)		-0.044 (0.132)		-0.001 (0.138)
Sh. high-skill ₋₁		0.489 ^a (0.070)		0.174 ^a (0.048)		0.201 ^a (0.047)
Sh. low-skill ₋₁		-0.087 ^c (0.048)		0.007 (0.028)		0.065 ^a (0.023)
Emp. rate ₋₁			0.761 ^a (0.028)	0.669 ^a (0.039)	0.807 ^a (0.028)	0.707 ^a (0.033)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.94	0.96	0.97	0.97	0.97	0.97
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.443	.396	.438	.382	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

Table 1.19 – OLS regressions: Participation rate, *controlling for 16 industry shares*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-0.882 ^a (0.162)	-0.259 (0.156)	-0.343 ^a (0.097)	-0.167 (0.114)	0.021 (0.034)	0.061 (0.042)
- X Minimum Wage ₀	2.175 ^a (0.384)	0.822 ^b (0.350)	0.952 ^a (0.229)	0.611 ^b (0.264)		
- X Up. half MW ₀					0.075 ^b (0.036)	0.060 (0.042)
Sh. male ₋₁		0.377 ^b (0.149)		0.196 ^c (0.102)		0.219 ^b (0.102)
Sh. high-skill ₋₁		0.180 ^a (0.050)		0.079 ^c (0.041)		0.110 ^a (0.037)
Sh. low-skill ₋₁		-0.080 (0.050)		-0.023 (0.034)		0.023 (0.024)
Part. rate ₋₁			0.609 ^a (0.039)	0.524 ^a (0.034)	0.648 ^a (0.039)	0.555 ^a (0.031)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.93	0.95	0.95	0.96	0.96	0.96
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.405	.315	.361	.273	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

1.C.5 Jackknife resampling

Table 1.20 – OLS regressions: Employment rate, *jackknife resampling*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.884 ^a (0.273)	-0.953 ^a (0.207)	-0.548 ^a (0.080)	-0.488 ^a (0.093)	-0.023 (0.028)	0.012 (0.026)
- X Minimum Wage ₀	4.297 ^a (0.639)	2.454 ^a (0.481)	1.326 ^a (0.181)	1.330 ^a (0.233)		
- X Up. half MW ₀					0.079 ^b (0.030)	0.130 ^a (0.037)
Sh. male ₋₁		0.084 (0.294)		-0.038 (0.134)		-0.000 (0.156)
Sh. high-skill ₋₁		0.538 ^a (0.089)		0.173 ^a (0.040)		0.209 ^a (0.039)
Sh. low-skill ₋₁		0.057 (0.067)		0.037 (0.028)		0.081 ^a (0.023)
Emp. rate ₋₁			0.817 ^a (0.027)	0.727 ^a (0.030)	0.865 ^a (0.027)	0.761 ^a (0.026)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.66	0.80	0.88	0.89	0.87	0.89
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.438	.389	.413	.367	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

Table 1.21 – OLS regressions: Participation rate, *jackknife resampling*

	(1)	(2)	(3)	(4)	(5)	(6)
Sh. middling ₋₁	-1.019 ^a (0.192)	-0.472 ^b (0.192)	-0.264 ^c (0.136)	-0.191 (0.179)	0.021 (0.042)	0.035 (0.055)
- X Minimum Wage ₀	2.389 ^a (0.438)	1.257 ^a (0.446)	0.711 ^b (0.282)	0.578 (0.385)		
- X Up. half MW ₀					0.052 (0.039)	0.042 (0.058)
Sh. male ₋₁		0.289 (0.189)		0.215 ^c (0.119)		0.245 ^c (0.125)
Sh. high-skill ₋₁		0.243 ^a (0.063)		0.023 (0.045)		0.048 (0.042)
Sh. low-skill ₋₁		0.017 (0.061)		0.005 (0.039)		0.041 (0.031)
Emp. rate ₋₁			0.462 ^a (0.034)	0.439 ^a (0.040)	0.493 ^a (0.032)	0.460 ^a (0.040)
Sh. age cat. ₋₁	no	yes	no	yes	no	yes
R ²	0.65	0.73	0.78	0.80	0.78	0.79
Observations	1137	1111	1137	1111	1177	1137
Threshold value	.427	.375	.372	.33	-	-

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

1.C.6 Instrumental Variables - First-Stage

Those two tables present the first-stage regressions from Table 1.5 and Table 1.6. The first two columns of each table corresponds to the first two columns of Table 1.5 and 1.6. Columns 3 to 6 corresponds to columns 3 to 6 of Table 1.5 and columns 7 to 10 of Table 1.6.

Table 1.22 – First-stage regressions from Table 1.5 and Table 1.6: share of middling occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Instrument ₋₁	0.004 (0.003)	0.005 ^c (0.003)	0.002 (0.003)	0.004 (0.003)	0.006 ^c (0.003)	0.005 (0.003)	0.003 (0.003)	0.004 ^c (0.003)	0.007 ^b (0.003)	0.006 ^b (0.003)
- X Minimum Wage ₀	0.011 ^b (0.004)	0.009 ^c (0.005)	0.014 ^a (0.004)	0.010 ^c (0.006)	0.009 (0.005)	0.009 (0.006)	0.013 ^a (0.004)	0.009 ^c (0.005)	0.007 (0.005)	0.007 (0.005)
Sh. male ₋₁		0.204 (0.222)		0.217 (0.216)	0.274 (0.218)	0.204 (0.225)		0.212 (0.217)	0.262 (0.221)	0.193 (0.228)
Sh. high-skill ₋₁		-0.074 (0.064)		-0.053 (0.070)	-0.021 (0.072)	-0.040 (0.070)		-0.061 (0.067)	-0.038 (0.068)	-0.063 (0.066)
Sh. low-skill ₋₁		-0.039 (0.075)		-0.035 (0.077)	-0.059 (0.074)	-0.055 (0.062)		-0.036 (0.077)	-0.060 (0.075)	-0.052 (0.063)
Emp. rate ₋₁			-0.092 (0.058)		-0.099 (0.077)	-0.079 (0.077)				
Part. rate ₋₁							-0.081 (0.059)	-0.047 (0.072)	-0.079 (0.075)	-0.032 (0.080)
Sh. age cat. ₋₁	no 0.91	yes 0.91	no 0.91	yes 0.91	yes 0.91	yes 0.91	no 0.91	yes 0.91	yes 0.91	yes 0.91
R ²										
Sh. ind. ₋₁	no 823	no 823	no 823	no 823	3 posts 823	16 posts 823	no 823	no 823	3 posts 823	16 posts 823
Observations										

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

Table 1.23 – First-stage regressions from Table 1.5 and Table 1.6: share of middling occupations interacted with initial minimum wage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Instrument ₋₁	-0.001 (0.001)	-0.000 (0.001)	-0.002 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
- X Minimum Wage ₀	0.011 ^a (0.002)	0.009 ^a (0.002)	0.012 ^a (0.002)	0.010 ^a (0.002)	0.009 ^a (0.002)	0.009 ^a (0.002)	0.011 ^a (0.002)	0.009 ^a (0.002)	0.008 ^a (0.002)	0.008 ^a (0.002)
Sh. male ₋₁	0.114 (0.098)	0.114 (0.098)	0.122 (0.096)	0.122 (0.096)	0.144 (0.097)	0.112 (0.101)	0.117 (0.097)	0.136 (0.098)	0.104 (0.102)	0.104 (0.102)
Sh. high-skill ₋₁	-0.025 (0.028)	-0.025 (0.028)	-0.012 (0.031)	-0.012 (0.031)	-0.000 (0.032)	-0.007 (0.030)	-0.021 (0.029)	-0.012 (0.030)	-0.022 (0.029)	-0.022 (0.029)
Sh. low-skill ₋₁	-0.023 (0.035)	-0.023 (0.035)	-0.020 (0.035)	-0.020 (0.035)	-0.030 (0.035)	-0.026 (0.027)	-0.022 (0.035)	-0.031 (0.035)	-0.025 (0.027)	-0.025 (0.027)
Emp. rate ₋₁			-0.046 ^b (0.023)	-0.034 (0.030)	-0.051 (0.032)	-0.041 (0.032)				
Part. rate ₋₁										
Sh. age cat. ₋₁	no 0.96	yes 0.96	no 0.96	yes 0.96	yes 0.96	yes 0.97	no 0.96	yes 0.96	yes 0.96	yes 0.97
R ²										
Sh. ind. ₋₁	no 823	no 823	no 823	no 823	3 posts 823	16 posts 823	no 823	no 823	3 posts 823	16 posts 823
Observations										

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

1.D Additional result: Correlation between the share of routine and the instrument

Table 1.24 – OLS Regressions: Share of middling occupations, controlling for 16 industry shares

	(1)	(2)	(3)	(4)
Instrument ₋₁	0.842 ^a (0.024)	0.838 ^a (0.024)	0.815 ^a (0.025)	0.816 ^a (0.027)
Sh. middling ₋₁	0.523 (0.419)	0.521 (0.419)	0.344 (0.403)	0.360 (1.607)
Sh. male ₋₁		-4.923 ^a (1.546)	-5.115 ^a (1.199)	-4.898 ^a (1.335)
Sh. high-skill ₋₁		-0.742 (0.468)	-1.731 ^a (0.560)	-1.634 ^b (0.633)
Sh. low-skill ₋₁		-0.680 (0.447)	-0.984 ^b (0.448)	-0.795 (0.700)
- X Minimum Wage ₀				-0.026 (3.399)
Sh. age cat. ₋₁	no	no	yes	yes
R ²	1.00	1.00	1.00	1.00
Observations	851	837	837	823

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Sample stops in 2007.

1.E Additional result: The role of other labor market institutions

Table 1.25 – Summary statistics: Average minimum wage and EPL Indexes by country

Country	Minimum wage	GRR	EPRC	EPT
Belgium	0.46	1.87	3.13	0.40
France	0.51	2.38	3.63	0.39
Greece	0.37	2.80	4.25	0.14
Ireland	0.46	1.39	0.44	0.31
Netherlands	0.46	2.89	1.13	0.51
Portugal	0.32	4.52	2.71	0.41
Spain	0.30	2.58	3.33	0.35
United-Kingdom	0.36	1.24	0.32	0.16

Notes: Data from OECD Employment Protection Legislation, OECD minimum wage and OECD Gross replacement rate for years 1992-2007.

Table 1.26 – OLS regressions: EPL, without minimum wage

	Employment rate				Participation rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh. middling ₋₁	-0.953 ^a (0.194)	0.440 ^a (0.145)	0.092 (0.109)	0.236 ^b (0.089)	-0.472 ^a (0.177)	0.352 ^a (0.106)	0.247 ^b (0.094)	0.259 ^a (0.085)
- X Minimum Wage ₀	2.454 ^a (0.448)				1.257 ^a (0.407)			
- X EPRCv1 ₀		-0.142 ^b (0.056)				-0.116 ^a (0.037)		
- X EPTv1 ₀			-0.002 (0.024)				-0.049 ^b (0.020)	
- X GRR APW ₀				-0.487 ^c (0.257)				-0.639 ^a (0.223)
Sh. male ₋₁	0.084 (0.248)	0.220 (0.246)	0.228 (0.275)	0.230 (0.262)	0.289 ^c (0.164)	0.372 ^b (0.159)	0.365 ^b (0.169)	0.381 ^b (0.166)
Sh. high-skill ₋₁	0.538 ^a (0.083)	0.583 ^a (0.087)	0.651 ^a (0.087)	0.623 ^a (0.085)	0.243 ^a (0.058)	0.260 ^a (0.055)	0.296 ^a (0.059)	0.278 ^a (0.056)
Sh. low-skill ₋₁	0.057 (0.059)	0.104 ^b (0.046)	0.124 ^b (0.055)	0.101 ^b (0.048)	0.017 (0.052)	0.058 (0.039)	0.050 (0.046)	0.042 (0.041)
R ²	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.94
Observations	1111	1137	1137	1137	1111	1137	1137	1137

^a, ^b, ^c represent significance at the 0.01 / 0.05 / 0.10 levels, respectively. Robust standard errors clustered by local labor markets are in parentheses. Age categories' share included in all regressions. Sample stops in 2007.

Chapter 2

Routine-biased technological change and wages by education level: Occupational downgrading and displacement effects

Summary of the chapter

Taking advantage of geographic (and time) variation in the proportion of routine occupations in the US, we study the impact of this variation on the wage rate of workers by educational group. Using individual data and a Bartik-type IV strategy, we show that not only non-college-educated workers but also, in the same proportion, workers with fewer than four years of college are negatively impacted by this routine-biased technological change. The latter skill group currently represents 30% of the US population. We show that only 10% to 20% of the impact on both educational groups is related to occupational and industrial downgrading (the composition effect) and that most of the wage impact occurs within industries and occupations, including manual service occupations. This is consistent with the displacement effect described in the theoretical literature on task-biased technological change and automation.

Co-authorship

This chapter is taken from "Routine-biased technological change and wages by education level: Occupational downgrading and displacement effects", co-authored with Clement Bosquet and Paul Maarek

Classification

JEL Codes: I24, J23, J24, J31, O33

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Contents

2.1	Introduction	73
2.2	Data and stylized facts	78
2.3	Identification strategy	83
2.4	Results	88
2.5	Conclusion	98
2.A	Discussion on the Bartik instrument	100
2.B	Additional results	105
2.C	Individual-level regressions	109

2.1 Introduction

In recent decades, the labor market has become increasingly polarized. Technological progress and globalization have progressively made routine occupations disappear. Technology has substituted human labor in routine tasks such as bookkeeping. The corresponding jobs require some skills and are not the lowest paid in the labor market but are rather intermediate-pay jobs (Goos and Manning, 2007). The proportion of routine occupations in the US went from 42.9% in 1970 to 26.1% in 2017.¹

These intermediate occupations in the wage distribution have been replaced by less well-paid manual occupations, and, at the top of the distribution, abstract occupations. Many employees in these routine jobs have moved into manual occupations. Cortes (2016) shows that the least able workers tend to reallocate to manual occupations. Competition to reallocate toward abstract occupations is very high, especially for less able workers. Alongside the strong increase in the number of abstract occupations, the number of college graduate workers has drastically increased in the United States during the same period. Autor (2019) shows that many non-college-educated workers have moved from intermediate (routine) occupations requiring specific skills to low-paid occupations requiring generic skills. This has decreased the proportion of non-college-educated workers who hold intermediate-skill occupations.

We study how this process has impacted the wages of US workers by education/skill group over the period 1970-2010.² The literature generally distinguishes between college graduates

1. The literature uses the terms ‘job polarization’, ‘routine-biased technological change’ or ‘task-biased technological change’ to describe this phenomenon.

2. Like Michaels et al. (2014), “we follow the literature by referring to ‘education’ and ‘skills’ interchangeably; thus, ‘high skilled’ refers to ‘highly educated’, ‘middle skilled’ refers to those with intermediate levels

(those with at least four years of college) and non-college-educated workers, and routine-biased technological change seems clearly unfavorable to the latter (Acemoglu and Autor, 2011; Autor, 2019). We distinguish not only low-skilled individuals without a college degree but also two different types of college-educated workers: those who went to college for three years or fewer and possibly obtained a diploma (middle skilled) and those who completed college, generally in four years or more (high skilled). Middle-skilled individuals are an important group of the US working-age population, with this group's share increasing from 9.9% in 1970 to 28.7% in 2017. Some of them occupy routine jobs and do not necessarily have the capacity to reallocate into abstract occupations: 45.1% of middle-skilled workers held a routine occupation in 1970 against only 32.8% in 2017. Conversely, only 18.8% of middle-skilled workers held a manual occupation in 1970 against 32.5% today. The proportion of middle-skilled workers holding an abstract occupation even decreased slightly during the period (from 36.1% to 34.6%), despite the strong increase in the proportion of abstract occupations (from 25.8% to 43.1%) among all jobs. The latter are mainly held by high-skilled individuals. It is thus very likely that the disappearance of routine jobs also affected medium-skilled workers. On the other hand, approximately 80% of high-skilled workers hold an abstract occupation, and this proportion has been very stable over time. Our intuition is that compared to medium-skilled workers, high-skilled workers should not be affected by routine-biased technological change given that the occupations that they overwhelmingly hold have tended to expand rather than decrease.

Using a local labor market approach and an instrumental variable strategy, we show that this current occupational change in the labor market has significantly decreased the wage rate of individuals with low and medium skills over the long run (1970-2010). Individuals with a four-year degree or more do not seem affected by the change in occupational structure, which is consistent with the job polarization literature. The (abstract) occupations that they occupy are not affected by automation. The decline of routine jobs affects low-skilled workers in similar proportion to middle-skilled workers.

The use of individual data on wages and occupations allows us to disentangle the mechanisms behind the impact of occupational change on the wage structure: the average wage of an occupation in a given industry can remain constant, but low- and medium-skilled individuals may experience some occupational downgrading or/and industry switches (composition effects). Many workers whose routine occupation disappeared have reallocated into manual occupations that are characterized by lower wages. This occupational downgrading is high-

of education, and 'low skilled' refers to those with lower levels of education." For more details on how the variables are constructed, see section 2.2.

lighted by Autor (2019) for low-skilled workers and corresponds to the composition effects in the task-biased workhorse model of Acemoglu and Restrepo (2019). This composition effect should also hold for medium-skilled workers, as argued earlier, since such workers largely hold routine occupations and do not reallocate into abstract jobs. This effect is very important in the narrative in the job polarization literature explaining the decrease in economic opportunities of low-skilled workers (see, for instance, Autor, 2019). Alternatively, wages can change within occupations for a skill group (general equilibrium effect) due to a displacement effect as in Acemoglu and Restrepo (2018)'s task-biased model of technological change. The workers occupying the jobs that disappeared and who are reallocated into existing occupations create downward wage pressure within those occupations, in which there is an overflow of labor supply. Even workers who do not experience occupational downgrading are affected. In the case of medium-skilled workers who cannot reallocate into abstract jobs and therefore compete with low-skilled workers for manual jobs (and the remaining routine jobs), they should experience a decrease in wages relative to their productivity within their (manual and routine) occupations, as low-skilled workers. If the displacement effect is sufficiently high, the wages of medium-skilled workers may even decrease in absolute terms. This is an important implication of recent works on task-biased technological change and automation: workers are not only affected because they reallocate to some occupations that pay less (the composition or between effect) but also because the displacement effect and overflow of labor supply imply a decrease in wages within occupations.³

In our empirical strategy, using a Bartik shift-share instrument, we identify local labor market (commuting zone or CZ) shocks that alter the occupational structure of these areas. In the same spirit as Autor and Dorn (2013) or Acemoglu and Restrepo (2020a), we use the evolution of the proportion of routine jobs by sector at the national level to measure how each sector is affected by job polarization. We then interact those proportions with the initial specialization of the areas (sector shares), which allows us to determine how exposed each zone is, according to its initial specialization, to a global technological progress shock that eliminates routine occupations. Identifying an exogenous shock is crucial given that (i) many variables simultaneously influence the proportion of routine jobs as well as local wages

3. The polarization process may also be related to or result in structural change. In Goos and Manning (2007), routine-biased technological change implies that some workers move between industries when changing occupations (the between component of job polarization). In Barany and Siegel (2018), some sector-level asymmetric productivity shocks (not task biased) that affect routine-intensive industries and lead to reallocation across industries generate structural change and job polarization between industries. This implies that workers also reallocate across industries. The wage impact for workers should be partly captured by an occupation-specific composition effect (occupational downgrading), but wages could also be affected by an industry effect. Occupations do not necessarily have the same wage rate across industries.

and (ii) a change in the sectoral and occupational structure may be the consequence of wage changes. Next, we take into account the concerns raised by [Goldsmith-Pinkham et al. \(2020\)](#) to verify that it is not only a few industries that drive the variation in the instrument and provide several robustness tests and discussions of our results.

Our results suggest that both low- and medium-skilled workers are negatively affected in similar proportions by the disappearance of routine occupations. Consistent with theoretical priors, we find no effect (or only a very reduced effect) on the high-skilled group. The effects on the low- and medium-skilled groups are economically sizeable: a 5.7 percentage point increase in the initial proportion of routine occupations in the CZ, which corresponds to one standard deviation in the distribution observed in local labor markets over the 1970-2010 period, implies a decrease in average wages of 3.3% for the low-skilled group and 2.5% for the medium-skilled group over a 10-year period.

Our results also suggest that the two channels mentioned above are both important in explaining the wage impact of job polarization for the different skill groups. However, the within effect related to the displacement effect seems to be dominant since it explains more than 80% (90%) of the wage impact for medium-skilled (low-skilled) workers. This result is in line with the recent findings of [Hunt and Nunn \(2019\)](#), who argue that wage inequalities are only weakly related to occupations. Wage dispersion within occupations is much more important than that between occupations. We show that the routine occupation wage premium (relative to the wage in manual occupations) for low- and medium-skilled workers is indeed very low. It is thus not surprising that the wage impact of the disappearance of routine jobs does not occur through the composition effect. This contradicts the traditional narrative in the job polarization literature positing (i) that wage distributions are highly related to occupations and (ii) that automation has been detrimental to low-skilled workers because it replaced well-paid routine occupations with low-paid manual ones. Instead, we show that routine-biased technological change has impacted low-skilled (and medium-skilled) workers mainly through the downward wage pressure it implies within occupations.

Furthermore, we show that the negative effects for low- and medium-skilled workers is observed for individuals in routine or manual occupations, including low-skilled (manual) service occupations. This is at odds with the traditional narrative on job polarization, according to which the highest wage growth should be observed at the top and bottom of the wage distribution. According to [Autor and Dorn \(2013\)](#), this is especially true for manual low-skilled service occupations, in which wages should increase due to strong complementarities with abstract high-paid occupations. We show that the disappearance of routine jobs decreases wages for both low- and medium-skilled workers in all manual occupations,

including low-skilled manual service occupations. This finding is more consistent with the displacement effect of [Acemoglu and Restrepo \(2019\)](#) discussed earlier.⁴

Moreover, we find that the negative effects are more important for young workers, which is not surprising, as they face fewer job opportunities when they enter the labor market. Older low- and medium-skilled workers had the opportunity to climb the occupational ladder when they entered the labor market, at a time when more opportunities existed.

Our results may explain part of the wage and income stagnation recently observed in the data. (Since the 1980s, real income has not increased for around half of the American population.) We show that job polarization creates downward wage pressure for an important part of the population. (The low- and middle-skilled groups represented 70% of the US population in 2017.)

Our paper is related to several strands of the literature. It is first connected to the literature on polarization and task-biased technological change. In a seminal contribution [Autor et al. \(2003\)](#) and then [Acemoglu and Autor \(2011\)](#), [Autor and Dorn \(2013\)](#), [Goos and Manning \(2007\)](#), [Goos et al. \(2009\)](#), and [Dustmann et al. \(2009\)](#) show that middle-pay (routine) occupations tend to disappear and that this decline is related to ICT diffusion. Traditionally, the literature on polarization has examined the evolution of intermediate wages by looking at the middle of the wage distribution, sometimes referred to as the medium-skill segment. However, this does not tell who medium-wage individuals are and how different educational groups are affected by the disappearance of routine jobs. Generally, this disappearance is seen as detrimental for low-skilled workers who have not been to college, as they tend to hold routine occupations. (see, for instance, [Acemoglu and Autor, 2011](#); [Autor, 2019](#)). We show that many workers with some college (fewer than four years) are also strongly affected by this process and that manual workers, including those in service occupations, also suffer from the disappearance of routine jobs, consistent with the literature on automation and task-biased technological change. The impact on wages occurs within occupations rather than between occupations. This casts some doubt on the hypothesis that wage inequality and the wage impact of occupational change are mostly driven by individual occupational switches (the composition effect).

Several other papers distinguish multiple classes of college workers. First, [Valletta \(2018\)](#) tries to explain the stagnation in the high-skill premium since 2000. He distinguishes between high-skilled workers (those with four-years degrees) and very high-skilled workers (those with

4. [Hunt and Nunn \(2019\)](#), among others, also note that the positive effect on manual service occupations in [Autor and Dorn \(2013\)](#) could be offset by an excess supply of labor in those occupations, which could create downward wage pressure. We show that the displacement effect clearly does offset the positive complementarity effect.

postgraduate degrees). and looks at national-level factors, including polarization, to explain the slowdown in demand for cognitive skills.⁵ Another important exception that is closely related to our paper is [Michaels et al. \(2014\)](#), who look at how ICT diffusion at the sector level has polarized skill demand. More specifically, they look at the wage share of high-skilled (college graduates), medium-skilled (some college) and low-skilled (no college) workers. in the total wage bill at the industry level for 11 countries and find a clear negative impact of ICT diffusion on the wage share of medium-skilled individuals. Our approach differs significantly. We make use of geographical disparities in industry specialization and the destruction of routine jobs within industries at the national level to identify task-biased technological shocks at the local level. We focus on individual-level data, which allows us to study the sources of wage variation (within versus between occupations and industries) among groups with different levels of education.

The rest of the paper is organized as follows. Section 2.2 presents the data and some stylized facts regarding the evolution of the skill supply (education) and occupational structure over time. The empirical/identification strategy is developed in section 2.3, while section 2.4 displays our results. Section 2.5 concludes.

2.2 Data and stylized facts

Census/American Community Survey

The main data source we use in this paper is the Census/American Community Survey from IPUMS. We mostly use the 1960, 1970, 1980, 1990, 2000 and 2010 waves for regressions and the harmonized variables provided by IPUMS, which are consistently coded across years.⁶ We construct three samples for the different exercises. For all of them, we restrict the dataset to nonmilitary individuals aged between 16 and 64 years old, following [Acemoglu and Autor \(2011\)](#).⁷ Skill shares, for instance, are calculated with this working-age population. To

5. [Lindley and Machin \(2016\)](#) also distinguish two types of college educated workers: graduates and postgraduates. They document a rise in the postgraduate relative to the graduate wage premium.

6. We also use the 1950 and annual waves from 2005 to 2017 in our discussion of the stylized facts below. IPUMS provides two different samples for 1970: the state sample and the metro sample. We use the state sample for the stylized facts below due to its very slightly higher number of observations, but the two datasets are so similar that the statistics are exactly the same if we use the metro sample. We also use the state sample for the robustness regressions at the state level, and we use the metro sample for the regressions at the commuting zone level, as the smallest identifiable area in the state sample is the state. Both samples are composed of two forms each. We combine both forms for each sample and divide the weights by two for each observation.

7. As a robustness test, we also consider the sample of workers aged 25-64 years old, as in [Valletta \(2018\)](#). Results are qualitatively and quantitatively similar. (See the online appendix.)

calculate industry and occupational shares at the sectoral or geographical level, we also drop nonworking individuals.⁸ Finally, again following [Acemoglu and Autor \(2011\)](#), we also exclude self-employed, part-time and part-year workers from the regression sample.⁹ Our wage variable is the annual labor income of workers during the previous year.¹⁰ Following [Autor and Dorn \(2013\)](#)'s methodology, we create local labor markets at the CZ level. This method uses probabilistic matching to map substate geographic units in the US Census to CZs. Each observation in each CZ is then weighted according to the fraction of the county group/Public Use Microdata Area (PUMA) that maps to the given CZ. There are 722 CZs in the mainland USA and 741 when Alaska and Hawaii are included.¹¹ Finally, to interact industry shares at the CZ level with industry routine shares at the national level for each census year, we need to have a consistent industry classification over time. Based on the major industry categories, we unify the classification and end up with 34 industries. Following [Goldsmith-Pinkham et al. \(2020\)](#), we separate industries with a high Rotemberg weight in the overall instrument and end up with 43 industries. (See Appendix 2.A for a detailed discussion on the Bartik shift-share instrument.)¹² Finally, we also complement the census data with the IPUMS March Current Population Survey, mainly to derive the stylized facts documented below.¹³

Measure of routineness

There are two methods generally found in the literature to classify occupations according to their degree of routineness. The first method is to proxy for job tasks by directly working with broad occupational categories (see [Acemoglu and Autor \(2011\)](#) or [Verdugo and Allègre \(2020\)](#) among others). Another standard method, used, for instance, by [Autor and Dorn \(2013\)](#), is to use data from the Dictionary of Occupational Titles (DOT) or Occupational Information Network (O*NET).¹⁴

8. Our results are robust to calculating the local shares of routine workers over the full working-age population. (See the online appendix.)

9. Our results are robust to the inclusion of part-time, part-year or self-employed workers. (See the online appendix.)

10. According to IPUMS, this income is composed of “wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer. Payments-in-kind or reimbursements for business expenses are not included”.

11. To construct CZs for 1960, we use a similar methodology to that provided by [Rose \(2018\)](#).

12. Our results are robust to using the original classification with 34 industries. (See the online appendix.)

13. A description of this dataset is presented in the online appendix.

14. These databases give the task content of each occupation. Each task of each occupation receives a score between 0 and 5 depending on its importance for the occupation. Then, those task scores are aggregated by occupation into three categories: routine, manual and abstract. Next, for each occupation, a routine

As our main measure of routineness, we rely on the first method and use the broad occupational groupings defined by [Acemoglu and Autor \(2011\)](#): managerial, professional and technical occupations are specialized in abstract, nonroutine cognitive tasks; sales, clerical and administrative support occupations are specialized in routine cognitive tasks; production, craft, repair, and operative occupations are specialized in routine manual tasks; and service occupations are specialized in nonroutine manual tasks. As is usually done in the literature, we group the routine manual and routine cognitive occupations into a single category. The main advantage of this measure is that it does not rely on a rigid task-based classification of occupations made in 1968, as is the case for the DOT. It is very likely that the task content of occupations was very different at that time from what it is today. Relying on the DOT also requires adopting criteria to weight the different task scores of each occupation. Nevertheless, in several robustness checks, we also use the classification of occupations based on the DOT using the criteria of [Autor and Dorn \(2013\)](#).¹⁵

Skills

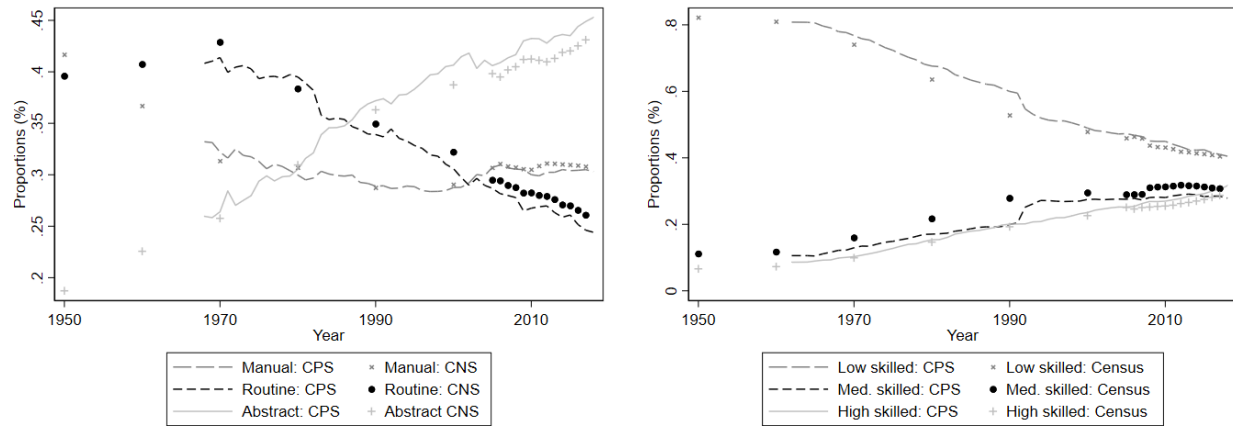
Skill levels are coded using the education information available in the database. Educational attainment is measured by the highest year of school or degree completed. In this paper, the low-skilled category refers to individuals who have completed or dropped out before completing high school. The medium-skilled category corresponds to individuals who went to college but completed fewer than four years. Finally, the high-skilled category corresponds to individuals who have at least a four-year college degree. Overall, in 2017, the three skill groups represented a sizable share of the population: the medium- and high-skilled groups represented 30.8% and 28.7% of the working-age population, respectively. For a more detailed analysis, we also divide each skill group into two categories and end up with six categories: lower low-skilled workers, who do not have a high school degree; upper low-skilled workers, who have a high school degree; lower medium-skilled workers, who have completed fewer than three years of college; upper medium-skilled workers, who have completed three years of college; lower high-skilled workers, who have completed four years of college; and upper high-skilled workers, who have completed more than four years of college.¹⁶

task intensity measure, equal to $\ln(\text{Routine score}) - \ln(\text{Manual score}) - \ln(\text{Abstract score})$, is computed. Finally, routine occupations are defined as occupations belonging in the top third of the routine task intensity distribution. [Goos et al. \(2014\)](#) show that the two measures are highly correlated.

15. We directly use the data from [Autor and Dorn \(2013\)](#), which classify each occupation as routine, manual or abstract and are available on the AEA website.

16. These categories correspond to IPUMS codes 1 to 50, 60 to 64, 65 to 71, 80 to 90, 100 to 101 and 110 to 116, respectively.

Figure 2.1 – Evolution of workers’ occupations and educational attainment for the overall population



(a) Occupations (workers only)

(b) Educational attainment (full pop.)

Sources: March CPS data for years 1963-2017, Census IPUMS 5% samples for 1950, 1960, 1980, 1990 and 2000, Census IPUMS 1% state sample for 1970 and Census American Community Survey for 2005-2017. The data used in figure (b) include all persons aged 16-64, excluding those employed by the military. In figure (a), non-working individuals are also excluded.

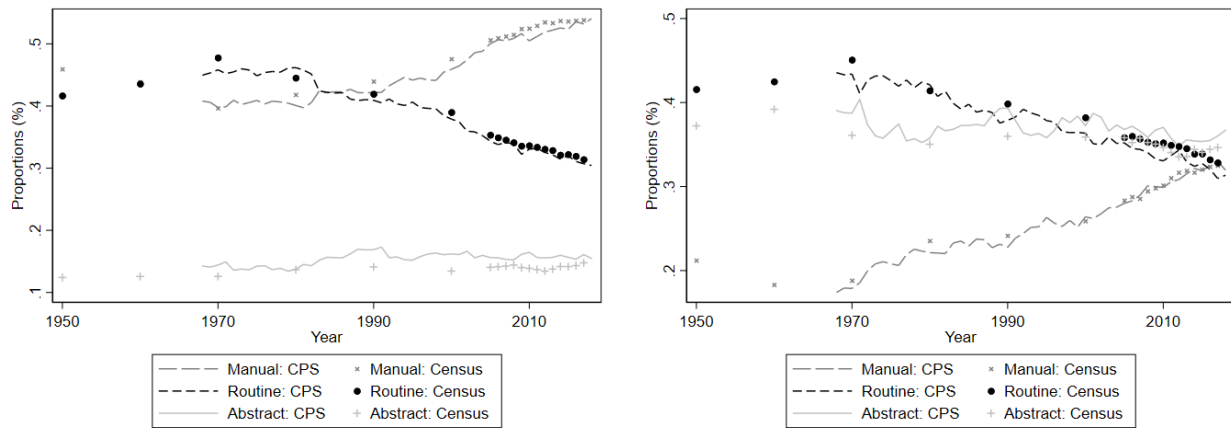
Stylized facts: occupations and skills

In this section, we document both the global evolution of occupations and skills (Figure 2.1) and the evolution of occupations for workers in each skill group (Figure 2.2).

The evolution of workers’ broad occupations is depicted in Figure 2.1a. As is well known in the literature, the proportion of routine occupations has sharply decreased. In the US, it went from 42.9% in 1970 to 26.1% in 2017. These occupations have been replaced by abstract occupations and, to a lesser extent, by manual ones. Another important well-known fact is the sharp increase in the share of the working-age population that has been to college, as shown in Figure 2.1b. This share goes from 25.9% in 1970 to 59.5% in 2017. More precisely, the proportion of individuals who have completed a four-year program (high skilled) rose from 9.9% in 1970 to 28.7% in 2017, and the proportion of individuals with fewer than four years of college education (medium skilled) went from 15.9% in 1970 to 30.8% in 2017.

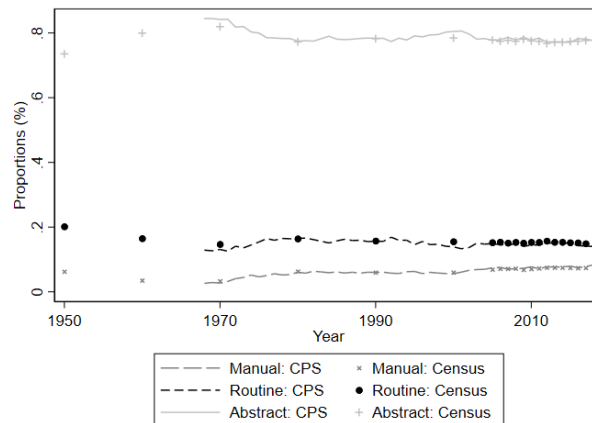
To clarify the reallocation pattern for individuals working in routine occupations in the 1970s, we next show that the share of low- and medium-skilled workers in routine jobs substantially decreased over the 1970-2017 period. First, Figure 2.2 shows that 45.1% (47.8%) of medium-skilled (low-skilled) workers had a routine occupation in 1970 but only 32.8% (31.4%) did so in 2017. Second, the share of abstract occupation holders did not increase in this group (and even slightly decreased from 36.1% in 1970 to 34.6% in 2017 for medium-

Figure 2.2 – Evolution of occupations’ shares for low, medium, and high-skilled workers



(a) Low-skilled workers

(b) Med. skilled workers



(c) High-skilled workers

Sources: See Figure 2.1(a).

skilled workers) despite the strong increase in the proportion of abstract jobs in the economy. Conversely, the share of manual occupation holders among these individuals rose substantially, from 18.8% in 1970 to 32.5% in 2017 for medium-skilled workers and from 39.7% to 53.8% for low-skilled workers, suggesting an occupational downgrading pattern for those skill groups.¹⁷ At the same time, the occupational structure of high-skilled workers has been very stable over time: approximately 80% of these individuals hold abstract jobs.¹⁸

These stylized facts indicate that due to the sharp increase in the supply of high-skilled workers, competition for abstract jobs has increased. As a consequence, medium-skilled

17. In the online appendix, we also provide graphs of the evolution of broad occupation shares among the full working-age population.

18. In the online appendix, we also provide graphs that display the shares of each skill group within each occupational category.

workers who have lost their routine jobs have tended to reallocate into manual occupations and have been unable to reallocate into abstract jobs. Given those patterns, we expect this change in the occupational structure to have negatively affected low- and medium-skilled workers, first, because of occupational (and possibly industry) downgrading, which pushes low- and medium-skilled workers into lower-ranked occupations (and industries), and second, because of the general equilibrium effect, which should affect wages within the remaining occupations.

2.3 Identification strategy

To estimate the impact of the decrease in the proportion of routine occupations on the wages of low-, medium- and high-skilled workers, we adopt a local labor market approach. As Census data are individual level data whereas our variable of interest is at the CZ level, we proceed in two steps. In the first step, we regress individual annual log wages ω_i on individual demographic characteristics for each year y and education group g separately:

$$\omega_{i \in gy} = X_i \beta_{gy} + \epsilon_i \quad (2.1)$$

where X_i includes age and its square, gender and race dummies.¹⁹

In a second step, we use the average residual over each CZ c for each year and education group $w_c = \frac{1}{N_c} \sum_{i \in c} \hat{\epsilon}_i$.²⁰ Variations in w_c reflect local variations in average wages net of individual characteristics to take into account both the spatial sorting of workers and the sampling of IPUMS. We regress these variations $\Delta w_{ct} = w_{ct_1} - w_{ct_0}$ on the initial share of routine jobs in the CZ for each skill group separately:

$$\Delta w_{ct} = \gamma \text{Routine}_{ct_0} + \Delta Z_{ct} \theta + \lambda_t + \varepsilon_{ct} \quad (2.2)$$

where Routine_{ct_0} is the share of routine jobs in CZ c at date t_0 , Z_{ct} is a vector of time-varying area controls such as the shares of the different skills and other local labor market variables,

19. Thus, we allow the return of individual characteristics to vary over time and across education groups. Those returns are provided in the online appendix. We weight these first stage regressions by the Census weights (i.e. how many persons in the US population are represented by a given person in an IPUMS sample) in order to ensure their representativeness with respect to the US population.

20. To compute these average residualized wages, each observation is weighted by its Census weight multiplied by the CZ specific weight (i.e. the fraction of the county group/PUMA that maps to this given CZ, as mentioned in section 2.2). This ensures that the local variations in average wages for the IPUMS sample reflect the variations for the US workers in each CZ.

and λ_t is a time fixed effect.

As standard in this literature, we first estimate the model in stacked differences over 10-year periods (see [Verdugo and Allègre, 2020](#); [Autor and Dorn, 2013](#); [Acemoglu and Restrepo, 2020b](#)). Thus, t refers to decades 70's 80's 90's and 00's and Δw_{ct} correspond to wage variations over the decades. We also consider long run differences over the 1970-2010 period or stacked differences over 20-year periods. As in [Verdugo and Allègre \(2020\)](#) or [Autor and Dorn \(2013\)](#), we consider as our main regressor the initial share of routine jobs in t_0 of each decade t , which is a very strong predictor of the decrease in routine jobs over the period. It can be interpreted as the exposition of a CZ to task-biased technological change and to the decrease in routine occupations.²¹

γ , our main coefficient of interest, is then identified with the time variations of the local shares of routine jobs. The variations in the proportions of medium- and high-skilled individuals at the local level are introduced to control for the supply factors of skills as it could affect the local equilibrium wages of the different skill groups and the occupational structure of the workforce. As often done in the literature, we also control for the variations in the proportion of foreign-born individuals in a CZ as those individuals may have lower bargaining power and often work in the manual service sector (see [Autor and Dorn, 2013](#)).

Despite the introduction of individual and local control variables in the first- and second-stage regressions, respectively, the initial share of routine occupations might still be endogenous. For instance, the rate of routine job destruction and then the proportion of routine jobs could respond to the wage adjustment. If wages sufficiently adjust downward, this could limit the technology induced destruction of routine jobs and our OLS coefficient could be downward biased. Also, it is still possible that an unobserved/omitted variable affects simultaneously wages and occupation composition at the local level.²² As a consequence, we instrument the initial proportion of routine jobs in the CZ ($Routine_{ct_0}$) by the following arguably exogenous measure of exposure to task-biased technological change, based on the past industrial specialization of each CZ:

$$Exposure_{ct} = \sum_{j=1}^N \varphi_{cj} Routine_{jt-1} \quad (2.3)$$

where φ_{cj} is the employment share of sector j in area c in 1960 and $Routine_{jt-1}$ is the 10-

21. As a robustness, we also directly consider the variation in the share of routine occupations as our main regressor. Results are qualitatively similar across specifications.

22. For instance, a tax policy which affects more routine intensive sector than other sectors.

year lag of period t initial share of routine occupations at the national level in sector j .²³ $Routine_{jt_{-1}}$ summarizes a variety of shocks that affect the proportion of routine jobs at the sector level and which should be only marginally related to what happens in a given area. This should be the result of task-biased technological change or the possibility to offshore some tasks abroad. φ_{cj} summarizes how those shocks at the national level translate into shocks at the local level. We follow the literature (see for instance [Verdugo and Allègre, 2020](#); [Autor and Dorn, 2013](#)) and consider the employment shares φ_{cj} ten years before the start of our first period as it should better satisfy their exogeneity with respect to the evolution of wages.²⁴ For the national sector shares of routine occupations, we consider a 10-year lag of period t initial shares (t_{-1}) as [Autor and Dorn \(2013\)](#).²⁵

Following [Goldsmith-Pinkham et al. \(2020\)](#), we discuss extensively the variations that drive the identification of our coefficient of interest and the exogeneity of the instrument in Appendix 2.A. As in most empirical settings using Bartik shift-share instruments, our identification relies on the industry shares rather than on specific shocks at the sector level given that automation and ICT affected many sectors at the same time.²⁶ It is thus important that the initial industry shares are exogenous to the local development of CZ that affects the wage rate of individuals. In some IV regressions, we then control for the variations in the shares of the broad manufacturing and service sectors, as suggested by [Goldsmith-Pinkham et al. \(2020\)](#), given that the initial industry shares in our instrument could be endogenous to the variations in the aggregate sectoral composition in CZ which could affect the wage rate. [Autor and Dorn \(2013\)](#) also control for the share of the manufacturing sector. Results are robust to the inclusion of these local variations of aggregate shares as additional controls.^{27 28}

Figure 2.3 plots $Exposure_{ct}$ for 1970, the beginning of our estimation period. We can see that CZs had very different expositions to shocks that lead to a decrease in the proportion

23. Alternatively, we estimate a reduced form model using our exposure variable directly as a regressor: $\Delta w_{ct} = \gamma Exposure_{ct} + Z_{ct} \theta + \lambda_t + \varepsilon_{ct}$, for each skill group separately.

24. Note however that many papers that use shift-share (Bartik) instrument consider the shares at the initial period of their sample. In our case, it would imply to use the local sector shares of 1970. We provide estimates using the 1970 shares in the online appendix. Results are unchanged.

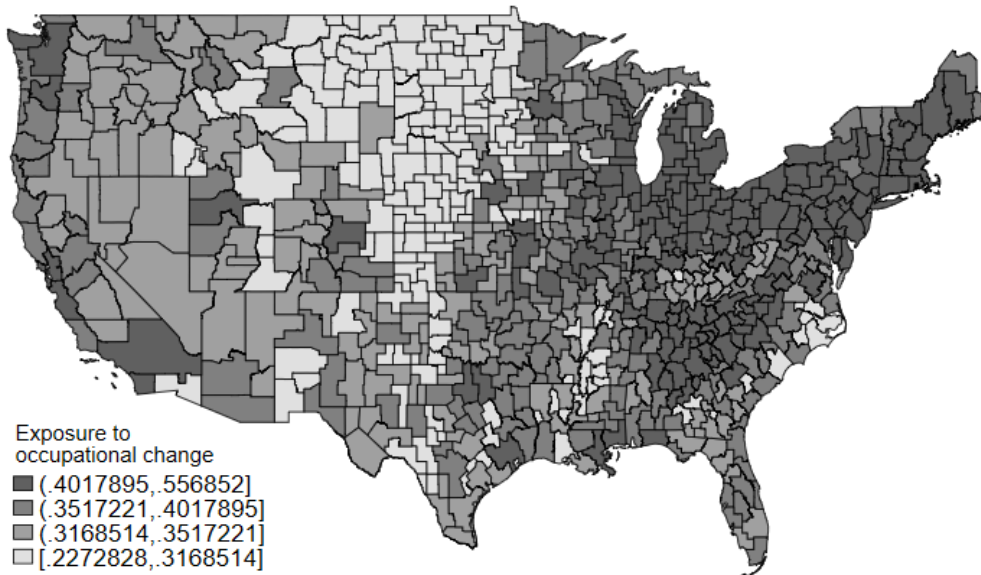
25. Results in the online appendix show robustness to the use of national sector shares of routine jobs in t_0 instead of t_{-1} .

26. Appendix 2.A shows that for the main specification, only 1% (0.107²) of the identification relies on sector shocks of the share of routine jobs. In some specifications presented in the paper, sector shocks never account for more than 16% of the identifying variations.

27. In the online appendix, we also control for the evolution of industry shares using a more detailed classification of 13 industries.

28. For $Exposure_{ct}$ to be a valid instrument, the 10-year lag of period t initial proportion of routine jobs in an industry at the national level, $Routine_{jt_{-1}}$, should also be exogeneous to local development of CZ. However, as stated earlier, most of the identification relies on sector shares rather than sector shocks.

Figure 2.3 – Distribution of the instrument at the CZ level, 1970



Source: Census IPUMS 1% metro sample for 1970. The value of the Bartik shift-share instrument is computed at the commuting zone \times year level using 43 industries.

of routine jobs given their initial industry specialization.

To study the mechanisms at work behind the impact of the routine-biased technological change on wages by education group, we then decompose the wage variations into a between and a within components. The between component corresponds to the composition effect induced by the switch of workers from occupations that disappear to some other occupations which have a different wage rate. The within term, at the heart of the displacement effect of [Acemoglu and Restrepo \(2018\)](#), corresponds to the wage impact within occupations due to higher labor supply in remaining occupations.

More specifically the variation over period t of the average residualized wage in CZ c can be decomposed as follows:

$$\Delta w_{ct} = \sum_j ((\varphi_{cjt_0} + \varphi_{cjt_1})/2)(w_{cjt_1} - w_{cjt_0}) + ((w_{cjt_1} + w_{cjt_0})/2)(\varphi_{cjt_1} - \varphi_{cjt_0}) \quad (2.4)$$

where t_0 correspond to the initial date and t_1 the end of each period t . φ_{cjt_0} and φ_{cjt_1} are the local shares of employment in cell j in t_0 and t_1 . w_{cjt_1} and w_{cjt_0} are the average residualized wages in CZ c and cell j in t_0 and t_1 . Depending on the chosen decomposition, j can index occupations or occupation \times industry cells. The first component is the within term. It corresponds to the variation of average wages within each occupation and CZ, weighted by

the share of this occupation in the CZ (averaged over t_0 and t_1). The second component is the between term and corresponds to changes in the local shares of occupations, weighted by the average residualized wage of each occupation (averaged over t_0 and t_1). It is the composition effect and it captures average wage variations due to occupation (and possibly industry) switches. We first consider a decomposition based on 4 occupation categories (routine, abstract, manual and not-classified) in order to capture the pure occupational downgrading effect described in the literature. We then consider a decomposition based on both 4 occupations and 13 industries.²⁹

In some regressions, we also estimate the impact of the decrease in the share of routine occupations separately for each broad occupational category, to see if the wage impact within occupations is observed in each broad manual or routine occupation, in particular within the manual service sector which is at the heart of the polarization theory of [Autor and Dorn \(2013\)](#). In their analysis, the wage rate increases in the manual service sector, at the bottom of the wage distribution, because of complementarities with abstract jobs. The displacement effect of recent works modeling the task-biased technological change of [Acemoglu and Restrepo \(2018\)](#) goes in the opposite direction.

All the regressions are clustered at the State level and weighted by the share of CZ in the full population in t_0 .

Additionally, we also provide in Appendix 2.C individual-level regressions which are consistent with our CZ-level regressions. We directly estimate a wage equation using individual log wages as dependant variable, which we regress on individual characteristics, CZ time-varying controls and the proportion of routine jobs at the CZ level. Regressions include CZ and year fixed effects. In some of these regressions, we also include occupation or occupation \times industry fixed effects to disentangle the mechanisms at work (composition and within effects). Whereas this strategy using directly individual wage data is slightly different, the identification still relies on spatial differences in variations of the share of routine

29. $4 \times 13 = 52$ bins. We restrict ourselves to few occupation and industry categories in the main specification because, for the decomposition to hold exactly, we need an average residualized wage for each bin in each CZ at each date. With a too detailed classification, we end up with many occupations(\times industry) \times CZ bins with no observation. As robustness we propose an alternative decomposition based on 77 occupations. In order to perform this robustness, we create a new classification of occupations. Similarly to the unification of the industry classification, we unify the occupation classification based on the major categories given by IPUMS. The only exception are occupation ‘258: Sales Engineers’ of the source classification, which has been separated from the ‘Sales Representatives, Commodities’ broad occupation because it is an abstract occupation, while the others are routine occupations. In addition, we combined ‘243: Supervisors and proprietors, sales occupations’ with ‘Sales Representatives, Finance and Business Services’, ‘415: Supervisors of guards’ with ‘Guards’, ‘503: Supervisors, mechanics and repairers’ with ‘Vehicle and Mobile Equipment Mechanics and Repairers’, and ‘558: Supervisors, construction’ with ‘Construction Trades’ for consistency over time. We end up with 77 occupations but we use only 76 of them as we exclude those in the military.

occupations over time and results are qualitatively similar.³⁰ More details are provided in Appendix 2.C.

Several robustness checks are provided in the online appendix (Bosquet et al., 2020a): As mentioned before, our results are robust to calculating the local shares of routine workers over the full working-age population, to the inclusion of part-time, part-year or self-employed workers, to an alternative definition of routine occupations, and to various specifications of the instrument (using the original industry classification with 34 posts instead of 43, using the local sector shares of 1970 instead of 1960, or using the national sector shares of routine jobs in t_0 instead of t_{-1}). The online appendices also show that our results are robust to using different sets of weights (population count instead of population shares or using population fixed in 1970), with controls in levels instead of variations, including state fixed effects, running state-level regressions, and including more controls: the share of individuals born in another state or population density. In online appendix Table O20, we also re-estimate Table 2.1 changing the end date to 2013 instead of 2010 for the last period stacked difference (2000-2013) and also for the long differences estimates (1970-2013). Indeed, in 2010, the economy had not fully recovered from the great recession of 2008 which could have affected the proportion of routine jobs as well as wages of the different education groups. Finally, the last set of robustness checks requires to compute new residuals from equation 2.1: using the sample of workers aged 25-64 years old, using pooled instead of year-specific regressions, trimming top and bottom 2.5% of wages, including the workers for which occupations or industries are missing and using CPS data.

2.4 Results

2.4.1 Baseline results

Table 2.1 presents our baseline results for the three education groups and three specifications: OLS, IV and IV with controls for local variation in broad sector shares.³¹ All the regressions include time fixed effects as well as control variables at the CZ level. (Individual characteristics are controlled for in the first stage.) They all give qualitatively similar results of the impact of a reduction in the proportion of routine jobs on the wage structure in local labor markets. Only the magnitude differs between the OLS and IV estimates.

30. As the Census data does not follow individual over time, we do not estimate the model in first difference as in our main specification using data aggregated at the CZ level.

31. First-stage regressions of the 2SLS estimator are available in the online appendix.

Table 2.1 – First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, OLS and IV, stacked differences

Workers educ.:	OLS			IV					
	low	medium	high	low	medium	high	low	medium	high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sh. of rout. occs ₀	-0.196 ^b (0.075)	-0.112 ^b (0.046)	-0.034 (0.047)	-0.581 ^a (0.114)	-0.437 ^a (0.089)	-0.167 ^b (0.080)	-0.496 ^a (0.149)	-0.372 ^a (0.124)	-0.046 (0.087)
Δ sh. of high skill	0.583 ^a (0.170)	0.657 ^a (0.135)	0.981 ^a (0.092)	0.749 ^a (0.195)	0.797 ^a (0.164)	1.039 ^a (0.111)	0.785 ^a (0.195)	0.835 ^a (0.167)	1.086 ^a (0.114)
Δ sh. of med. skill	-0.353 ^c (0.179)	-0.629 ^a (0.164)	-0.394 ^a (0.132)	-0.235 (0.166)	-0.529 ^a (0.150)	-0.353 ^a (0.127)	-0.180 (0.171)	-0.411 ^b (0.154)	-0.308 ^b (0.136)
Δ sh. of foreign	-0.386 ^a (0.066)	0.077 (0.101)	0.328 ^a (0.059)	-0.394 ^a (0.059)	0.070 (0.109)	0.325 ^a (0.061)	-0.400 ^a (0.059)	0.055 (0.098)	0.322 ^a (0.056)
Δ sh. of manuf.							0.104 (0.298)	-0.133 (0.224)	0.249 (0.153)
Δ sh. of services							-0.149 (0.260)	-0.449 ^b (0.192)	-0.056 (0.144)
R ²	0.05	0.09	0.20					0.08	
Kleibergen-Paap				323	323	323	183	183	183

Notes: Standard errors clustered by state between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. Each regression is weighted by the share of the CZ in the national population. 2888 observations (722 CZ × 4 periods).

The impact of the local initial share of routine occupations is significantly negative for low- and medium-skilled workers in the OLS and IV estimates, meaning that a higher exposure to routine occupations decreases the wages of low- and medium-skilled workers. The estimated coefficients are three times larger in the IV than in the OLS specification, which suggests that the OLS results are downward biased. This could be because the proportion of routine jobs reacts to the wage adjustment or because there is a potential measurement error problem. Reductions in the wage rate of low- and medium-skilled workers could prevent further destruction of routine jobs. The Kleibergen-Paap statistics are well above the threshold values provided by [Stock and Yogo \(2005\)](#), suggesting that exposure to routine occupations is a strong instrument for the local proportion of routine jobs. Columns 7-9 control for variation in the shares of the manufacturing (as in [Autor and Dorn, 2013](#)) and service sectors. These controls only marginally affect the results.³²

The impact seems to be slightly higher for low-skilled than for medium-skilled workers. Given that the differences are neither large nor statistically significant, we conclude that low-

³². In the online appendix, we also control for the evolution of industry shares using a more detailed classification of 13 industries.

and medium-skilled workers are affected in similar proportion by the disappearance of routine jobs. The effects are economically sizeable. According to the IV estimates, a 5.7 percentage point increase in the initial proportion of routine jobs (which corresponds to one standard deviation in the distribution observed at the CZ level for the 1970-2010 period) implies a decrease in average wages of 3.3% for low-skilled and 2.5% for medium-skilled workers over a 10-year period.³³ If we consider the variation in the initial proportion of routine jobs from the first to the top decile of CZs, i.e., 14.6 percentage points, the wages of low- and medium-skilled workers decrease by 8.1% and 6.2% over ten years on average.³⁴

High-skilled workers do not seem affected. The coefficient on the initial share of routine jobs is not significant and close to zero in the OLS regression (column 3) and marginally negative and significant in the IV estimates (column 6), but the effect totally vanishes when we include the industry shares (column 9). This is in line with the literature on task-biased technological change. The occupations in which high-skilled workers are concentrated (abstract) do not disappear. Only a few high-skilled individuals have routine occupations, and medium-skilled workers do not reallocate into abstract occupations and compete for them with high-skilled individuals. As a consequence, high-skilled individuals do not suffer the displacement effect of the disappearance of routine occupations.

Table 2.7 presents the estimates of the baseline IV model dividing each skill group into two subcategories. Two interesting patterns emerge. First, the lower low-skilled category seems to be the most affected (coefficient for routine jobs at -0.620). Then the lower medium-skilled (-0.358), higher medium-skilled (-0.367) and higher low-skilled (-0.368) groups are all affected in the same proportion.

Many alternative specifications to estimate the impact of local shocks can be found in the literature. We provide several additional robustness checks in the appendix. Table 2.8 shows the results with 20-year stacked differences and 40-year long differences (1970-2010) instead of our baseline 10-year stacked differences. Table 2.9 shows the results based on variation in the proportion of routine jobs instead of the initial level. Table 2.10 shows the reduced-form estimates directly using the instrument as a regressor. All these results are qualitatively very similar to those of our main specification. Finally, Appendix 2.C shows the results of the individual-level regressions, which are remarkably consistent with those of the two-stage aggregate specification.

Moreover, Table 2.11 reproduces Table 2.1 but excludes the last decade 2000-2010 from the stacked differences. Interestingly, the impact for medium-skilled workers becomes lower,

33. $\exp(-0.581 \times 0.057) - 1$ and $\exp(-0.437 \times 0.057) - 1$.

34. $\exp(-0.581 \times 0.146) - 1$ and $\exp(-0.437 \times 0.146) - 1$.

decreasing by 39%. The impact for low-skilled workers remains very similar. This suggests that task-biased technological change has become more detrimental to medium-skilled workers in the more recent period. This could be because technological change has increasingly affected complex occupations over time or because within an occupation, low-skilled workers are affected first, and then medium-skilled workers see an effect.

2.4.2 Mechanisms

Within vs. between effects

In this section, we try to understand the channels through which the occupational structure affects the wages of workers with different education levels. A common narrative in the polarization literature is that low-skilled workers are affected due to occupational downgrading, as routine jobs pay higher wages than manual jobs (see, for instance, [Autor, 2019](#)). This reasoning should extend to medium-skilled workers, as they do not seem to reallocate into abstract occupations but into manual ones. As explained earlier, industry switches can also have a wage impact for workers. On the other hand, the existence of the displacement effect highlighted by [Acemoglu and Restrepo \(2018\)](#) suggests that wages for low- and medium-skilled workers could decrease within occupations.

To disentangle the two effects, we perform regressions on the within and between terms of the decomposition presented in equation (2.4). The results are displayed in Table 2.2 for the IV specification. Panel A displays the results for the decomposition based on occupations only, and panel B displays the results for the decomposition based on occupation \times industry bins. Columns 1-3 and 4-6 display the results for low- and medium-skilled workers, respectively. For each skill group, the first column corresponds to the total effect (i.e., the corresponding coefficient from Table 2.1), the second column to the between effect and the third column to the within effect.

Considering occupations alone (panel A), the between term accounts for a very small share of the overall effect for the low- and medium-skilled groups (3.1% and 11.0%, respectively).³⁵ Most of the wage impact of the disappearance of routine occupations for each skill group occurs within occupations. This is at odds with the traditional narrative of the wage impact of polarization on low-skilled individuals. Indeed, the literature often posits that these workers are mainly affected by occupational downgrading, switching from well-paid routine jobs to low-paid manual occupations.

35. $0.018/0.581 = 0.0309$ and $0.048/0.437 = 0.1098$.

Table 2.2 – Decomposition of the IV coefficients from Table 2.1, columns 4 and 5

Workers educ.:	low			medium		
	total	between	within	total	between	within
Effect:	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: based on occupations only						
Sh. of rout. $occs_0$	-0.581 ^a (0.114)	-0.018 ^c (0.010)	-0.563 ^a (0.107)	-0.437 ^a (0.089)	-0.048 ^a (0.011)	-0.390 ^a (0.082)
Δ sh. of high skill	0.749 ^a (0.195)	0.025 (0.016)	0.724 ^a (0.189)	0.797 ^a (0.164)	-0.036 ^b (0.016)	0.833 ^a (0.162)
Δ sh. of med. skill	-0.236 (0.166)	0.089 ^a (0.014)	-0.325 ^c (0.171)	-0.530 ^a (0.150)	0.008 (0.008)	-0.537 ^a (0.148)
Δ sh. of foreign	-0.394 ^a (0.059)	-0.053 ^a (0.008)	-0.341 ^a (0.061)	0.070 (0.109)	-0.002 (0.018)	0.072 (0.093)
Panel B: based on occupations×industries						
Sh. of rout. $occs_0$	-0.581 ^a (0.114)	-0.072 ^a (0.024)	-0.503 ^a (0.098)	-0.437 ^a (0.089)	-0.096 ^a (0.016)	-0.342 ^a (0.077)
Δ sh. of high skill	0.749 ^a (0.195)	0.047 (0.034)	0.705 ^a (0.174)	0.797 ^a (0.164)	-0.009 (0.032)	0.789 ^a (0.149)
Δ sh. of med. skill	-0.236 (0.166)	0.029 (0.021)	-0.278 ^c (0.164)	-0.530 ^a (0.150)	-0.074 ^a (0.018)	-0.472 ^a (0.142)
Δ sh. of foreign	-0.394 ^a (0.059)	-0.056 ^b (0.024)	-0.340 ^a (0.064)	0.070 (0.109)	-0.014 (0.014)	0.073 (0.095)

Notes: See Table 2.1. Occupation classification is composed of 4 posts: manual, routine, abstract and not-classified. Industry classification composed of 13 posts, corresponding to most aggregated industries in the 1990 Census Bureau industrial classification. The Kleibergen-Paap rk Wald F statistic is equal to 323 in all regressions.

Table 2.3 – Individual regressions of residualized wages, OLS

Workers educ.:	low		medium		high	
	(1)	(2)	(3)	(4)	(5)	(6)
Routine	0.122 ^a (0.003)	0.114 ^a (0.004)	0.088 ^a (0.004)	0.081 ^a (0.004)	0.281 ^a (0.007)	0.264 ^a (0.008)
Abstract	0.301 ^a (0.007)	0.293 ^a (0.008)	0.295 ^a (0.006)	0.284 ^a (0.006)	0.531 ^a (0.013)	0.515 ^a (0.014)
CZ FE	no	yes	no	yes	no	yes

Notes: All regressions include year fixed effects. 722 CZ fixed effects are also included in some regressions, as indicated in the bottom of the table. Standard errors clustered by commuting zone between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. All regressions are weighted by individual Census weights multiplied by CZ specific weights. The numbers of observations for each skill are 9,110,818, 4,831,197 and 3,901,517, respectively.

This result is not so surprising when we take a closer look at the data. Table 2.3 shows estimates of the premium from having a routine or an abstract occupation, compared to having a manual occupation, for each education group. The residuals of our individual-level first-stage wage regressions (equation 2.1), which correspond to wages net of individual characteristics, are regressed on dummies for routine and abstract occupations. The coefficients of Table 2.3 thus capture the mean differences in log wages between broad occupational categories.³⁶ All regressions include year fixed effects, and including or not including CZ fixed effects does not make much difference. The routine occupation premium is quite small for both low- and medium-skilled workers (columns 1-4). It is equal to 11.4% and 8.1% according to columns 2 and 4, respectively. This is quite low in comparison to wage dispersion in the US or to the abstract premium, which is close to 30% for low- and medium-skilled workers and greater than 50% for high-skilled workers, as reported in Table 2.3.³⁷ The routine occupation premium is also much lower than the medium (23.7%) and high (61.4%) skill premiums over the 1970-2010 period.³⁸ This finding confirms the important result of [Hunt and Nunn \(2019\)](#), who also contradicts the polarization narrative by showing that occupations are a poor determinant of wage differences, given that wage dispersion within occupations is much larger than the average wage differences across occupations. It is thus not surprising to find that the between effect, related to occupational switching, is quite modest in the overall impact. Most of the wage impact occurs within occupations. This is in line with the displacement effect in [Acemoglu and Restrepo \(2019\)](#)'s model of automation in which destruction of occupations due to technical change displaces labor to other existing occupations, which creates downward pressure on wages. The between effect also exists in their model but depends on the wage differential between the occupations that are destroyed and the occupations into which workers reallocate. This differential is low in our case, which explains the modest role of the between effect. Online appendix Figure O3 shows that the routine premiums tend to decrease over time.

When we take into account industries in the decomposition (occupation \times industry bins), panel B of Table 2.2 shows that the magnitude of the between effect significantly increases to 12.4% of the total impact for the low-skilled group and 22.0% for the medium-skilled group.³⁹ This is consistent with the finding of [Barany and Siegel \(2018\)](#), who suggest that occupational

36. Full individual wage regressions with both individual controls and occupational dummies yield very similar results.

37. The difference between the lowest and highest wage deciles corresponds to 155% during the 1970-2010 period.

38. These premiums are obtained from a simple wage regression with controls for the same individual demographic characteristics.

39. $0.072/0.581 = 0.1239$ and $0.096/0.437 = 0.2196$.

structure changes are related to industrial shocks and structural transformation. The decrease in the proportion of routine occupations goes together with a reallocation of individuals across industries (within occupations). This has a negative wage impact, which means that in the structural change process that makes routine jobs disappear, many individuals do not experience occupational change but rather switch to industries that pay less.

Appendix Table 2.12 reproduces the results of Table 2.2 panel A with 77 occupations.⁴⁰ The between effect accounts for 9.1% of the total effect for low-skilled and 18.5% for medium-skilled workers.⁴¹ The between effect is more important than the within effect in the 4 occupation decomposition. This suggests that some reallocation occurs within the broad occupation categories.⁴²

Appendix Table 2.14 distinguishes the between and within effects directly using micro data. To do so, we introduce occupation, industry and industry×occupation fixed effects in individual wage regressions. This strategy allows us to control for very detailed occupation (77 posts) and industry (43 posts) classifications. The between effect accounts for 13.8% (occupations only) or 24.6% (industry×occupation) of the total wage impact for the low-skilled group and 17.4% (occupations only) or 29.8% (industry×occupation) for the medium-skilled group.⁴³ The results are consistent with those of the aggregate specification: most of the wage impact occurs within occupations.

The results suggest that the most important part of the wage impact from the destruction of routine occupations occurs within occupations and industries. This within effect accounts for more than 70% of the total impact for low- and medium-skilled workers when we look at the detailed classification in the micro regressions and between 80% and 90% when we look at broader occupation categories. This is very consistent with the task-biased technological change and automation model of [Acemoglu and Restrepo \(2018\)](#) and their displacement effect. The traditional occupational downgrading narrative explaining the wage impact of polarization on non-college educated workers and the industry composition effects are still in evidence in the data but are clearly not the main drivers of the wage impact. The fact that occupational downgrading also threatens medium-skilled individuals (and in even higher

40. We prefer to keep the more aggregated classification in the main text for two reasons. First, the literature on polarization distinguishes three broad occupational groups (manual, routine and abstract) and argues that reallocation occurs across those three groups. Second, a more detailed classification makes the decomposition more imprecise since it increases the number of occupation×industry×CZ bins that can be empty. See section 2.3.

41. $0.053/0.581 = 0.0912$ and $0.081/0.437 = 0.1853$.

42. For instance, the share of low-paid occupations could increase within the routine category. The same kind of phenomenon could occur within the manual occupation category.

43. $1 - (1.880/2.182) = 0.1384$, $1 - (1.645/2.182) = 0.2461$, $1 - (1.626/1.970) = 0.1746$, $1 - (1.382/1.970) = 0.2984$.

proportion than low-skilled workers) is consistent with the stylized facts previously discussed: the proportion of medium-skilled workers holding a routine occupation has sharply decreased and has been entirely compensated for by an increase in manual occupations among this population. The proportion of medium-skilled workers who have an abstract job has even slightly decreased, suggesting occupational downgrading for this population rather than upgrading. A quite similar pattern is observed for the low-skilled group, but the wage impact of this occupational shifting is much lower than that for the medium-skilled group.

Wage impact on each occupational category

This section tests whether the large within impact is observed in both manual and routine occupations, consistent with the task-biased technological change literature and the displacement effect. The important within impact could hide some disparities across occupations. An important prediction at the heart of [Autor and Dorn \(2013\)](#) is that wages should increase in manual occupations and, more specifically, manual occupations in services. It is possible that the overall within effect is negative but can remain positive in some specific occupations, notably manual service occupations. We thus perform the previous analysis separately for two manual and three routine broad occupation categories of low- and medium-skilled workers: (1) transport and construction and (2) service occupations (both manual) and (3) production, craft and repair, (4) operative and (5) clerical and administrative support occupations (routine). We do not report results for abstract occupations since only very few low- and medium-skilled individuals work in these occupations.

Panels A and B of Table 2.4 report the results for the low- and medium-skilled workers, respectively. The disappearance of routine occupations has a negative impact on wages within each of the five occupational categories, including manual service occupations. The overall negative impact within occupations does not hide important disparities across occupational categories. Again, this finding seems to be highly consistent with the displacement effect of [Acemoglu and Restrepo \(2018, 2019\)](#). The disappearance of routine jobs makes wages decrease in all the occupations into which workers reallocate. Low- and medium-skilled workers have massively reallocated into manual occupations and not into abstract ones. According to the task-biased technological change models of [Acemoglu and Restrepo \(2018, 2019\)](#) and their exposition of a displacement effect, wages should decrease within each occupation into which workers reallocate. This is precisely what we find. This is at odds with the traditional polarization literature, which suggests stronger wage growth at the bottom of the wage distribution, i.e., for manual occupations.

Table 2.4 – First-difference CZ average residualized wages on the local share of routine jobs, by broad occupation categories, IV, stacked differences

Occupations:	Transport, construction and misc. occ.	Service occ.	Production, craft, repair, occ.	Operative occ.	Clerical and administrative support occ.
	(1)	(2)	(3)	(4)	(5)
Panel A: low-skilled workers					
Sh. of rout. occs ₀	-0.721 ^a (0.128)	-0.516 ^a (0.120)	-0.504 ^a (0.132)	-0.605 ^a (0.109)	-0.337 ^a (0.092)
Δ sh. of high skill	0.768 ^a (0.221)	0.783 ^a (0.231)	0.671 ^a (0.198)	0.636 ^a (0.197)	0.838 ^a (0.180)
Δ sh. of med. skill	-0.264 (0.203)	-0.412 ^b (0.199)	-0.372 ^c (0.199)	-0.378 (0.265)	-0.108 (0.137)
Δ sh. of foreign	-0.517 ^a (0.076)	-0.333 ^a (0.085)	-0.363 ^a (0.078)	-0.669 ^a (0.155)	0.039 (0.082)
N	2888	2888	2886	2882	2888
Kleibergen-Paap	323	323	323	323	323
Panel B: medium-skilled workers					
Sh. of rout. occs ₀	-0.436 ^a (0.098)	-0.399 ^b (0.152)	-0.223 ^b (0.103)	-0.347 ^a (0.115)	-0.311 ^a (0.084)
Δ sh. of high skill	0.697 ^a (0.198)	0.611 ^b (0.231)	0.299 (0.213)	0.871 ^a (0.205)	0.984 ^a (0.166)
Δ sh. of med. skill	-0.547 ^b (0.244)	-0.757 ^a (0.257)	-0.802 ^a (0.214)	-0.732 ^b (0.320)	-0.394 ^a (0.129)
Δ sh. of foreign	-0.119 (0.131)	-0.158 (0.149)	-0.039 (0.122)	-0.298 ^b (0.146)	0.183 ^b (0.082)
N	2888	2887	2888	2883	2888
Kleibergen-Paap	323	325	323	323	323

Notes: See Table 2.1. The Kleibergen-Paap rk Wald F statistic is equal to 323 in all regressions.

In Appendix Table 2.15, we directly use micro data and an interaction term between the proportion of routine jobs in a CZ and dummy variables for routine, manual and abstract occupations. The results are consistent with those of the aggregate-level regressions and show that the wage impact for low- and medium-skilled workers occurs within all (routine and manual) occupation categories in which they remain.

2.4.3 Heterogeneous effects by age

In this section, we look at the heterogeneity in the impact of task-biased technological change on wages by age category.

There are several reasons to think that the impact may be more important for young

individuals who recently entered the labor market. First, wage rigidities could exist, and the wages of existing employees may have been fixed some time ago. Second, the margin of adjustment may be job creation and the vacancy rate of routine jobs rather than an increase in the job destruction rate. A decrease in the vacancy rate should impact new entrants more than insiders. Finally, individuals who entered the labor market when routine employment was flourishing had time to build human capital and experience while working to climb the occupational ladder and perform less routine-intensive tasks. The conditions when workers enter the labor market should matter. [Beaudry et al. \(2016\)](#) argue that the impact of the slowdown in demand for cognitive tasks should mostly affect younger workers who entered the labor market at the time of the slowdown. These authors' empirical analysis accordingly focuses on young workers.

Table 2.5 – First-difference CZ average residualized wages on the local share of routine jobs, by age categories, IV, stacked differences

Workers educ.:	low			medium		
Age categories:	≤ 29	30-49	≥ 50	≤ 29	30-49	≥ 50
	(1)	(2)	(3)	(4)	(5)	(6)
Sh. of rout. occs ₀	-0.729 ^a (0.152)	-0.522 ^a (0.106)	-0.582 ^a (0.105)	-0.649 ^a (0.116)	-0.361 ^a (0.083)	-0.338 ^a (0.082)
Δ sh. of high skill	0.819 ^a (0.268)	0.745 ^a (0.187)	0.670 ^a (0.177)	0.934 ^a (0.219)	0.786 ^a (0.145)	0.600 ^a (0.156)
Δ sh. of med. skill	-0.527 ^b (0.213)	-0.149 (0.165)	0.072 (0.173)	-0.716 ^a (0.241)	-0.362 ^a (0.125)	-0.268 ^c (0.135)
Δ sh. of foreign	-0.460 ^a (0.118)	-0.349 ^a (0.058)	-0.355 ^a (0.062)	-0.129 (0.183)	0.166 ^c (0.090)	0.168 ^a (0.057)

Notes: See Table 2.1. The Kleibergen-Paap rk Wald F statistic is equal to 323 in all regressions.

To test for a differentiated impact by age group, we estimate our IV model for each skill group on three different age classes: workers aged 29 years and below, workers aged between 30 and 49 and workers aged between 50 and 64. The results are displayed in Table 2.5 in columns 1-3 for the low-skilled group and columns 4-6 for the medium-skilled group. Several interesting results emerge. The heterogeneity of the impact is much stronger for medium- than for low-skilled workers. This could be due to the fact that more experienced medium-skilled workers have more stable jobs given their seniority in firms, whereas new entrants are more affected, as they face more adverse labor market conditions. For the low-skilled group, the effect is also heterogeneous but much less so than for the medium-skilled group.

We also split the sample by gender, but there is no significant differences across both subsamples. Men and women appear to be affected in the same proportion in the low- and

medium-skilled groups. The results are reported in Table O3 in the online appendix.

2.5 Conclusion

This paper studies the impact on wages of the massive change in the occupational structure that is occurring in most OECD countries. The most common narrative in the literature is that job polarization should be detrimental to non-college educated workers who hold routine occupations with specific skills (in the middle of the wage distribution) and experience an occupational downgrading to manual occupations that require generic skills. We show that the impact on wages extends beyond non-college educated workers only and that this process also impacts in similar proportion some workers who have been to college and potentially even obtained an intermediate postsecondary degree. Altogether, low- and medium-skilled individuals represent 70% of the US population in 2017. We show that, consistent with the literature on task-biased technological change and the displacement effect highlighted by [Acemoglu and Restrepo \(2018\)](#), more than 70% of this impact occurs within industries and occupations. The rest of the wage loss corresponds to occupational downgrading and some workers (non-college educated workers and workers with intermediate postsecondary education) having to accept work in (manual) occupations and industries that pay less. This composition effect explains less than 30% of the total impact of routine-biased technological change on wages when we use more detailed categories in micro regressions and less than 10% when we look at the broader occupational categories that match the polarization literature narrative.

Our results may contribute to the literature on the wage stagnation affecting an important share of US workers and on wage–productivity decoupling. It is now well documented that the median wage in the US has not evolved for decades (see, for instance, [Pessoa and Van Reenen, 2013](#)). Overall, the labor share of income seems to be decreasing in the US economy ([Autor et al., 2020b](#)): while median wages tracked productivity until 1973, this trend then stopped. Productivity kept growing, but wages remained stagnant. According to [Pessoa and Van Reenen \(2013\)](#), 40% of this wage decoupling is attributable to inflation measurement errors. Still, it seems that wages have not caught up with productivity. This is a prediction of the task-biased technological change model à la [Acemoglu and Restrepo \(2018\)](#) and the displacement effect that occurs when tasks disappear. We empirically show that the change in the occupational structure of the economy at work in OECD countries is likely to explain part of this phenomenon.

Recently, researchers have also suggested that the Phillips curve may have disappeared.

Despite low unemployment in the US, wages do not seem to react accordingly. A potential explanation is the recent modification in the occupational structure, which has accelerated in the decade since the subprime crisis ([Jaimovich and Siu, 2020](#)). The combination of low unemployment and stagnant wages may be due to downward wage pressure induced by the task-biased technological change that occurred simultaneously.

2.A Discussion on the Bartik instrument

In this section we open the black box of the Bartik shift-share instrument we use in the paper. We follow the recommendations of [Goldsmith-Pinkham et al. \(2020\)](#) who provide a methodology to discuss the sources of identification used in such settings. [Goldsmith-Pinkham et al. \(2020\)](#) show that the Bartik estimator can be decomposed into a weighted sum of individual estimators, each using a single industry share and industry shock at a time. From this decomposition, [Goldsmith-Pinkham et al. \(2020\)](#) propose several diagnostic tests in order to discuss if the exclusion restrictions are plausibly satisfied. In particular, the exogeneity of the industries that have the higher (Rotemberg) weights in the estimator, i.e. which drive its identification, needs to be discussed.

Table 2.6 presents various statistics about the Bartik estimator we use in Table 2.1 columns 4-6, for low, medium and high skilled workers. $\hat{\alpha}_j$ is the sum of Rotemberg weights for industry j , g_j is the weighted average national share of routine jobs in industry j over the full period,⁴⁴ $\hat{\gamma}_j$ is the weighted average just-identified instrumental variable estimator that use the share of industry j as an instrument and \widehat{F}_j is the first step F-statistic for the instrument based on the single industry j . Finally, φ_j is the national share of industry j in 1960.

Panel A reports the sum of the negative and positive Rotemberg weights (column 1), their mean value (column 2) and their respective proportion (column 3). 76.1% of the Rotemberg weights are positive. According to [Goldsmith-Pinkham et al. \(2020\)](#), the Rotemberg weights “can be interpreted as sensitivity-to-misspecification elasticities”. In other words, the value of $\hat{\alpha}_j$ represents the potential bias introduced by the instrument of industry j if it is misspecified. If $\hat{\alpha}_j$ is relatively small, then the bias introduced by the the corresponding instrument on the Bartik estimate will be relatively small.

Panel B reports correlations of the various industry statistics. The low correlation coefficient between the Rotemberg weights $\hat{\alpha}_j$ and the average national share of routine jobs in industry j g_j (0,107) indicates that the identification of our Bartik estimator relies mainly on the industry shares rather than the industry shocks.⁴⁵ [Goldsmith-Pinkham et al. \(2020\)](#) argue that it is very unusual in empirical frameworks to be able to rely on both sources of identification. Our framework makes no exception. The reason is quite intuitive: the technology shocks that make routine occupations disappear have affected many industries at the

44. $g_j = \frac{1}{T} \sum_{t=1}^T \hat{\alpha}_{jt} \text{Routine}_{j,t-1}$.

45. This correlation means that the g_j explains about 1.1% (0.107²) of the variance of the Rotemberg weights.

same time. The identification relies on industry shares which distribute this shock across CZ.

Panel C displays the sum of Rotemberg weights for each decade. The first decades have more weights in the total Bartik estimate. This is not surprising: as we use the local industry shares in 1960, Rotemberg weights are higher for the first periods. This is standard when using stacked differences with 10-year variations (see [Goldsmith-Pinkham et al., 2020](#), for examples). The estimates using long run variations over 40 years avoid this problem as we only use one time variation. Results are qualitatively very consistent across the stacked and the long run differences.

Panel D reports the five industries which have the highest Rotemberg weights, their Rotemberg weight $\hat{\alpha}_j$ (column 1), their weighted average national share of routine jobs g_j (column 2), the just-identified IV coefficient $\hat{\gamma}_j$ using the single industry j for the three types of skills (columns 3-5) and the corresponding 1960 national industry shares (φ_j) multiplied by 100. These five industries together account for 52.7% of the Rotemberg weight. This means that 52.7% of the identification comes from those five industries. It is quite standard in the literature using Bartik shift-share instruments that few industries account for an important share of the total weights (see [Goldsmith-Pinkham et al., 2020](#), for examples). It is thus important to ensure that the initial industry shares for those five industries are exogenous to future development in the CZ.

Panel E shows descriptive statistics of $\hat{\gamma}_j$ for positive and negative weights. Column 1 reports the sum of coefficients $\hat{\gamma}_j$ weighted by the Rotemberg weights $\hat{\alpha}_j$ (for the negative and positive Rotemberg weights separately) for the three skill groups. Column 2 reports their share in the Bartik estimate $\hat{\gamma}$ and column 3 presents the mean of $\hat{\gamma}_j$ for the positive and negative Rotemberg weights. The weighted sum of coefficients is very low for the negative weights and much higher and negative for the positive weights. The overall coefficient $\hat{\gamma}$ is thus mostly explained by the industries with positive weights. The unweighted sum of $\hat{\gamma}_j$ is very high for the negative weights. This is due to an industry which is a clear outlier and exhibits a very high $\hat{\gamma}_j$ coefficient (Business and repair services). The weighted sum of coefficients for negative Rotemberg weights is very low because the Rotemberg weight associated with this coefficient is very low (1.93×10^{-5}) and hence, this industry does not matter for the overall Bartik estimate. If this high coefficient is due to a misspecification, this should not invalidate the overall identification strategy.

We now try to convince that the local industry shares in 1960, and more specifically the ones of the five industries that drive the Bartik estimator (i.e. the sum of their Rotemberg weights is greater than 50%), are exogenous to future development that could affect wages in a CZ. As argued in [Goldsmith-Pinkham et al. \(2020\)](#), the local industry shares in 1960

Table 2.6 – Summary of Rotemberg weights for the IV specification reported in columns 4-6 of Table 2.1 for each skill

Panel A: Negative and positive weights						
	Sum	Mean	Share			
Negative	-0.459	-0.027	0.239			
Positive	1.459	0.056	0.761			
Panel B: Correlations						
	$\widehat{\alpha}_j$	g_j	$\widehat{\gamma}_j$	\widehat{F}_j	$Var_j(\varphi_{cj})$	
$\widehat{\alpha}_j$	1					
g_j	0.107	1				
$\widehat{\gamma}_j$	-0.059	-0.997	1			
\widehat{F}_j	-0.049	0.093	-0.123	1		
$Var_j(\varphi_{cj})$	-0.031	-0.373	0.340	0.449	1	
Panel C: Variation across years in $\widehat{\alpha}_j$						
	Sum	Mean				
1980	0.495	0.012				
1990	0.289	0.007				
2000	0.131	0.003				
2010	0.085	0.002				
Panel D: top 5 Rotemberg weight industries						
	$\widehat{\alpha}_j$	g_j	$\widehat{\gamma}_{j,low}$	$\widehat{\gamma}_{j,med}$	$\widehat{\gamma}_{j,hi}$	φ_j
Yarn, thread, and fabric mills	0.189	0.754	0.560	0.258	0.135	1.005
Apparel and accessories, except knit	0.151	0.884	0.337	-0.042	0.027	1.846
Machinery, excl. electrical, n.e.c. and Mach., n.s.	0.141	0.717	-0.747	-0.517	-0.155	1.694
Electrical machinery, equipment, and supplies	0.149	0.673	-0.736	-0.579	-0.377	2.282
Motor vehicles and motor vehicle equipment	0.140	0.679	-1.135	-0.623	-0.145	1.109
Relative weight of top 5 industries:	0.527					
Panel E: Estimates of γ_j for positive and negative weights						
	$\widehat{\alpha}$ weighted sum	Share of overall $\widehat{\gamma}$	Mean			
Low-skill						
Negative	0.076	-0.131	59.858			
Positive	-0.657	1.131	-0.817			
Medium-skill						
Negative	0.112	-0.255	41.574			
Positive	-0.549	1.255	-0.631			
High-skill						
Negative	0.063	-0.378	16.682			
Positive	-0.230	1.378	-0.283			

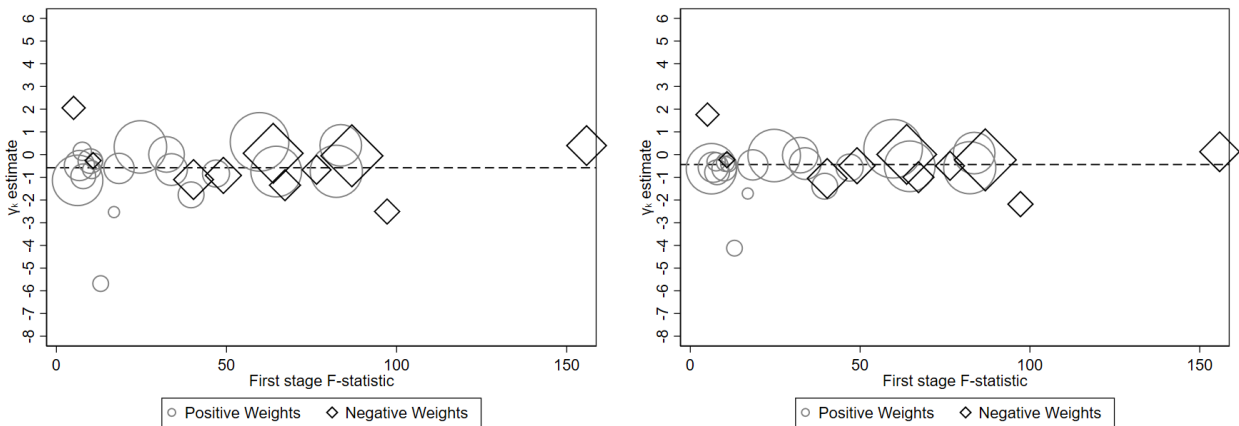
Notes: This table reports statistics about the Rotemberg weights. In all cases, we report statistics about the aggregated weights, where we aggregate a given industry across years. Panel B reports correlations between the weights ($\widehat{\alpha}_j$), the national share of routine jobs (g_j), the just-identified coefficient estimates ($\widehat{\gamma}_j$), the first-stage F-statistic of the industry share (\widehat{F}_j), and the variation in the 1960 industry shares across locations ($Var_j(\varphi_{cj})$). Panel C reports variation in the weights across years. Panel D reports the top five industries according to the Rotemberg weights. φ_j is the national industry share in 1960 (multiplied by 100 for legibility). Panel E reports statistics about how the values of $\widehat{\gamma}_j$ vary with the positive and negative Rotemberg weights.

do not have to be exogenous to wages in levels, but rather to variations of wages since we estimate our model in variation. We first take a 10-year lag relative to the first year of our panel (1970). In Table 2.1, we then control for various factors that can affect the evolution of wages and could be affected by the initial industry shares. First, in all regressions we control for the evolutions of the skills supply and of the share of foreign born workers, which could be related to the initial industry composition. Second, as suggested by [Goldsmith-Pinkham et al. \(2020\)](#), we provide some estimates controlling for the evolution of broad industry shares. The local industry composition in 1960 could lead to major changes in the former industry composition such as variations in the manufacturing sectors which could explain the wage dynamics beyond the decrease in the proportion of routine jobs. On the other hand, as argued by [Barany and Siegel \(2018\)](#), structural change and industry shocks could explain itself the decrease in routine occupations. By controlling for structural change, we could capture part of the polarization phenomenon. [Autor and Dorn \(2013\)](#) control for the share of manufacturing using similar arguments. We can see in columns 7-9 of Table 2.1 that controlling for the variations of broad sector shares only marginally affects the results. Online appendix Table O12 shows regressions controlling for the evolutions of industry shares using a more detailed 13 industry classification. Coefficients are still significant at 1% for the low and medium skilled and insignificant for the high skilled.

Finally, we perform an overidentification test when using the single industry instruments separately. It rejects the null hypothesis of instrument exogeneity. As suggested by [Goldsmith-Pinkham et al. \(2020\)](#), a plausible reason in those kind of settings is that our IV estimate measures a local average treatment effect rather than an average treatment effect. It is very likely that some local labor markets are affected by the instrument very differently than others and that the estimated coefficient $\hat{\gamma}_j$ of a variation in routine may be heterogeneous. Removing one instrument will affect the overall $\hat{\gamma}$ even if the model is well specified. In order to see if this interpretation is correct, we graph on Figure 2.4 the estimated coefficient $\hat{\gamma}_j$ (y-axis) according to their F statistics (x-axis). The figure only includes instruments with first-stage F-statistics above 5. The circles represent positive Rotemberg weights and the squares represent negative weights. The size of the circles and squares corresponds to the value of the Rotemberg weights.

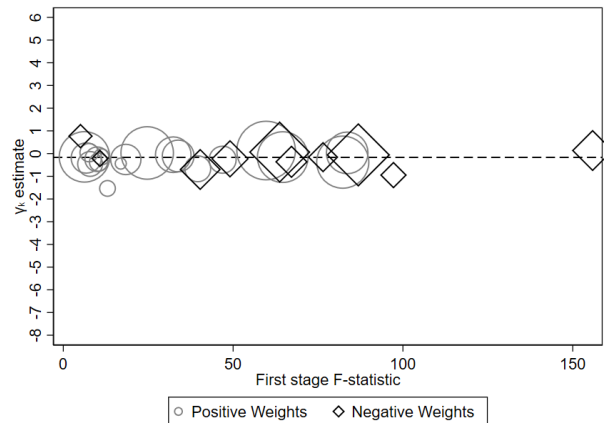
We can see that the dispersion of the estimated coefficients is not very high except for a few outliers which have some very low Rotemberg weights. According to [Goldsmith-Pinkham et al. \(2020\)](#), this gives support for the LATE interpretation of the IV estimate rather than a misspecification. If the model was misspecified, the dispersion of the estimated coefficients would have been higher, and industries with high negative Rotemberg weights would have

Figure 2.4 – Distribution of Rotemberg Weights for each skill



(a) Low-skilled workers

(b) Med. skilled workers



(c) High-skilled workers

Notes: Those figures represent the relationship between each just-identified coefficient $\hat{\gamma}_j$, first stage F-statistics \widehat{F}_j and the Rotemberg weights $\widehat{\alpha}_j$. Each point corresponds to a separate instruments' estimates (industry share). The figure plots the estimated $\hat{\gamma}_j$ for each instrument on the y-axis and the estimated first-stage F-statistic \widehat{F}_j on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\gamma}$ reported in columns 4-6 in Table 2.1 for each skill. The figure excludes instruments with first-stage F-statistics below 5.

been associated with misspecified coefficients, meaning that those coefficients would account for an important part of the overall Bartik estimator. Here, the few outlier coefficients for which we could suspect a misspecification of the model have very low Rotemberg weights.

2.B Additional results

2.B.1 Robustness of Table 2.1

Table 2.7 – First-difference CZ average residualized wages on the local share of routine jobs, by *detailed* skill levels, IV, stacked differences

Workers educ.:	lower low upper low lower med. upper med. lower high upper high					
	(1)	(2)	(3)	(4)	(5)	(6)
Sh. of rout. $occs_0$	-0.620 ^a (0.076)	-0.368 ^a (0.069)	-0.358 ^a (0.062)	-0.367 ^a (0.070)	-0.254 ^a (0.076)	0.006 (0.057)
Δ sh. of up. high skill	1.111 ^a (0.301)	1.599 ^a (0.245)	1.716 ^a (0.242)	1.216 ^a (0.230)	1.311 ^a (0.211)	1.551 ^a (0.215)
Δ sh. of low. high skill	-1.942 ^a (0.440)	-1.392 ^a (0.325)	-1.507 ^a (0.355)	-1.159 ^a (0.367)	-0.176 (0.336)	-0.370 (0.363)
Δ sh. of up. med. skill	-1.111 ^a (0.246)	-0.908 ^a (0.248)	-1.233 ^a (0.253)	-0.998 ^a (0.252)	-0.872 ^a (0.188)	-0.349 ^c (0.202)
Δ sh. of low. med. skill	-0.507 (0.303)	-0.317 (0.255)	-0.668 ^b (0.262)	-0.742 ^a (0.258)	-0.602 ^a (0.195)	-0.214 (0.197)
Δ sh. of up. low skill	-1.473 ^a (0.153)	-0.903 ^a (0.152)	-0.961 ^a (0.172)	-0.833 ^a (0.176)	-0.713 ^a (0.142)	-0.472 ^a (0.140)
Δ sh. of foreign	-0.270 ^b (0.120)	0.157 (0.102)	0.355 ^a (0.121)	0.322 ^a (0.105)	0.590 ^a (0.103)	0.464 ^a (0.092)

Notes: Standard errors clustered by state between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. Each regression is weighted by the share of the CZ in the national population. 2888 observations (722 CZ \times 4 periods).

Table 2.8 – First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, OLS and IV, *long differences and 20-year stacked differences*

Workers educ.:	OLS			IV					
	low	medium	high	low	medium	high	low	medium	high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: long differences									
Sh. of rout. occs ₀	-0.919 ^a (0.222)	-0.737 ^a (0.150)	-0.207 (0.131)	-1.174 ^a (0.275)	-0.849 ^a (0.182)	-0.275 ^c (0.151)	-2.062 ^a (0.408)	-1.199 ^a (0.296)	-0.203 (0.245)
Δ sh. of high skill	0.196 (0.215)	0.199 ^b (0.099)	0.644 ^a (0.122)	0.325 ^c (0.197)	0.256 ^b (0.100)	0.678 ^a (0.119)	0.243 (0.221)	0.222 ^b (0.103)	0.674 ^a (0.124)
Δ sh. of med. skill	0.248 (0.364)	-0.159 (0.203)	-0.212 (0.157)	0.300 (0.361)	-0.136 (0.203)	-0.198 (0.159)	-0.224 (0.341)	-0.349 (0.216)	-0.237 (0.160)
Δ sh. of foreign	-0.313 ^c (0.171)	0.200 ^b (0.093)	0.416 ^a (0.120)	-0.304 ^c (0.168)	0.205 ^b (0.094)	0.418 ^a (0.119)	-0.241 (0.156)	0.230 ^a (0.088)	0.419 ^a (0.118)
Δ sh. of manuf.							-0.190 (0.430)	-0.061 (0.318)	0.179 (0.291)
Δ sh. of services							1.020 ^b (0.423)	0.423 (0.308)	0.175 (0.239)
R ²	0.29	0.29	0.47						
Kleibergen-Paap				512	512	512	89	89	89
Panel B: 20-year stacked differences									
Sh. of rout. occs ₀	-0.320 ^b (0.129)	-0.142 (0.091)	0.029 (0.075)	-0.804 ^a (0.177)	-0.556 ^a (0.119)	-0.125 (0.107)	-1.032 ^a (0.277)	-0.801 ^a (0.226)	-0.076 (0.178)
Δ sh. of high skill	0.238 (0.171)	0.269 ^b (0.114)	0.655 ^a (0.076)	0.463 ^a (0.163)	0.462 ^a (0.128)	0.726 ^a (0.084)	0.405 ^b (0.157)	0.416 ^a (0.110)	0.727 ^a (0.084)
Δ sh. of med. skill	0.495 ^b (0.199)	0.136 (0.132)	0.001 (0.092)	0.626 ^a (0.196)	0.249 ^c (0.142)	0.042 (0.102)	0.522 ^b (0.221)	0.226 (0.173)	0.003 (0.109)
Δ sh. of foreign	-0.186 ^c (0.099)	0.316 ^b (0.150)	0.480 ^a (0.077)	-0.188 ^c (0.103)	0.314 ^c (0.158)	0.479 ^a (0.081)	-0.097 (0.113)	0.369 ^b (0.167)	0.489 ^a (0.085)
Δ sh. of manuf.							0.100 (0.303)	-0.228 (0.285)	0.211 (0.199)
Δ sh. of services							0.657 ^a (0.233)	0.174 (0.209)	0.227 (0.158)
R ²	0.12	0.08	0.29						
Kleibergen-Paap				376	376	376	136	136	136

Notes: See Table 2.7. 722 observations in panel A, 1444 (722 CZ × 2 years) observations in panel B.

Table 2.9 – First-difference CZ average residualized wages on the *variations* of the local share of routine jobs, by skill levels, OLS and IV, stacked differences

Workers educ.:	OLS			IV		
	low	medium	high	low	medium	high
	(1)	(2)	(3)	(4)	(5)	(6)
Δ sh. of rout. occs	0.337 ^c (0.181)	0.136 (0.130)	0.011 (0.140)	1.896 ^a (0.335)	1.428 ^a (0.255)	0.546 ^b (0.255)
Δ sh. of high skill	0.678 ^a (0.193)	0.681 ^a (0.164)	0.972 ^a (0.114)	1.508 ^a (0.265)	1.369 ^a (0.218)	1.257 ^a (0.183)
Δ sh. of med. skill	-0.448 ^b (0.178)	-0.677 ^a (0.161)	-0.405 ^a (0.128)	-0.610 ^a (0.220)	-0.811 ^a (0.194)	-0.461 ^a (0.155)
Δ sh. of foreign	-0.362 ^a (0.079)	0.087 (0.101)	0.329 ^a (0.063)	-0.275 ^a (0.087)	0.159 ^c (0.088)	0.359 ^a (0.062)
R ²	0.05	0.09	0.20			
Kleibergen-Paap				245	245	245

Notes: See Table 2.7.

 Table 2.10 – First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, *reduced form*, stacked differences

Workers educ.:	low	medium	high
	(1)	(2)	(3)
Exposure	-0.336 ^a (0.061)	-0.253 ^a (0.048)	-0.097 ^b (0.045)
Δ sh. of high skill	0.924 ^a (0.210)	0.929 ^a (0.175)	1.089 ^a (0.126)
Δ sh. of med. skill	-0.439 ^b (0.181)	-0.683 ^a (0.165)	-0.412 ^a (0.137)
Δ sh. of foreign	-0.403 ^a (0.061)	0.063 (0.106)	0.322 ^a (0.061)
R ²	0.11	0.13	0.21

Notes: See Table 2.7.

Table 2.11 – First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, OLS and IV, stacked differences, *excluding 2010*

Workers educ.:	OLS			IV		
	low	medium	high	low	medium	high
	(1)	(2)	(3)	(4)	(5)	(6)
Sh. of rout. $occs_0$	-0.159 ^c (0.082)	-0.056 (0.062)	0.027 (0.061)	-0.479 ^a (0.105)	-0.266 ^a (0.094)	-0.071 (0.091)
Δ sh. of high skill	0.810 ^a (0.194)	0.903 ^a (0.165)	1.116 ^a (0.123)	0.969 ^a (0.233)	1.008 ^a (0.203)	1.164 ^a (0.145)
Δ sh. of med. skill	-0.736 ^a (0.250)	-0.998 ^a (0.237)	-0.505 ^a (0.168)	-0.679 ^a (0.248)	-0.961 ^a (0.233)	-0.487 ^a (0.166)
Δ sh. of foreign	-0.523 ^a (0.109)	-0.046 (0.150)	0.318 ^a (0.070)	-0.533 ^a (0.102)	-0.052 (0.156)	0.315 ^a (0.071)
R ²	0.09	0.15	0.26			
Kleibergen-Paap				381	381	381

Notes: See Table 2.7. 2166 (722 CZ \times 3 years) observations.

2.B.2 Robustness of Table 2.2

 Table 2.12 – Decomposition of the IV coefficients from Table 2.1, columns 4 and 5 *on 77 occupation posts*

Workers educ.:	low			medium		
	total	between	within	total	between	within
	(1)	(2)	(3)	(4)	(5)	(6)
Sh. of rout. $occs_0$	-0.581 ^a (0.114)	-0.053 ^b (0.022)	-0.517 ^a (0.095)	-0.437 ^a (0.089)	-0.081 ^a (0.018)	-0.368 ^a (0.077)
Δ sh. of high skill	0.749 ^a (0.195)	0.080 ^a (0.029)	0.667 ^a (0.172)	0.797 ^a (0.164)	-0.043 (0.028)	0.816 ^a (0.153)
Δ sh. of med. skill	-0.236 (0.166)	0.103 ^a (0.019)	-0.351 ^b (0.160)	-0.530 ^a (0.150)	-0.049 ^b (0.021)	-0.503 ^a (0.147)
Δ sh. of foreign	-0.394 ^a (0.059)	-0.071 ^b (0.027)	-0.317 ^a (0.065)	0.070 (0.109)	-0.001 (0.012)	0.061 (0.095)

Notes: See Table 2.7. Occupation classification composed of 77 posts, more details available in Section 2.3. The Kleibergen-Paap rk Wald F statistic is equal to 323 in all regressions.

2.C Individual-level regressions

To estimate the impact of the decrease in the proportion of routine occupations on the individual wages of the three skill groups we have identified, we also apply a local labor market approach on individual data. We regress individual wages on the share of routine occupations in a CZ by skill group:

$$w_{it} = \gamma \text{Routine}_{ct} + X_{it} \beta + Z_{ct} \theta + \alpha_c + \lambda_t + \varepsilon_{it} \quad (2.5)$$

where w_{it} is the log wage of worker i at time t , Routine_{ct} is the share of routine jobs in area (CZ) c at time t , X_{it} is a vector of individual characteristics including gender, age and its square, race and possibly occupation and industry dummies, Z_{ct} is a vector of time-varying area controls and α_c and λ_t are area and time fixed effects, respectively. γ , our main coefficient of interest, is then identified with the time variations of the local shares of routine jobs. As in our baseline specification, we control for the supply of skills and foreign-born individuals in Z_{ct} as it could affect the local equilibrium wages of the different skill groups and the occupational structure of the workforce.

As for our CZ-level regressions, the local share of routine occupations (Routine_{ct}) might be endogeneous. Thus, we also instrument it by the exposure to occupational structure changes. As a reminder:

$$\text{Exposure}_{ct} = \sum_{j=1}^N \varphi_{cj} \text{Routine}_{jt-1} \quad (2.6)$$

In order to study the mechanisms at work behind the impact of the routine-biased technological change on wages by education groups, we introduce additional fixed effects in some specifications. As stated earlier, the effect of a change in the occupational structure on wages could be related to a between industry/occupation effect and/or a within one. In order to disentangle between the two effects, we introduce occupation, industry and occupation \times industry fixed effects in Table 2.14. In Table 2.15 we introduce interactions between the share of routine jobs and individual-level dummies for manual, routine and abstract occupations to test if the effect is heterogenous across the broad occupational categories.

All the regressions are clustered at the commuting zone level and weighted. The weights are equal to the Census weight (i.e. how many persons in the US population are represented

by a given person in an IPUMS sample) multiplied by the CZ specific weight (i.e. the fraction of the county group/PUMA that maps to this given CZ, as mentioned in Section 2.2).

Table 2.13 – Individual (log) wage regressions on the local share of routine jobs, by skill levels

Workers educ.:	OLS			IV		
	low	medium	high	low	medium	high
	(1)	(2)	(3)	(4)	(5)	(6)
Sh. of rout. occs	0.273 ^b (0.129)	0.351 ^a (0.099)	-0.083 (0.115)	2.182 ^a (0.364)	1.970 ^a (0.249)	0.699 ^b (0.280)
Sh. of high skill	0.459 ^b (0.192)	0.464 ^a (0.123)	0.627 ^a (0.123)	1.662 ^a (0.305)	1.403 ^a (0.166)	1.078 ^a (0.201)
Sh. of med. skill	0.100 (0.142)	-0.294 ^a (0.107)	-0.578 ^a (0.145)	-0.011 (0.143)	-0.350 ^a (0.116)	-0.591 ^a (0.150)
Sh. of foreign	-0.173 ^c (0.095)	0.310 ^a (0.074)	0.359 ^a (0.076)	-0.049 (0.108)	0.460 ^a (0.097)	0.444 ^a (0.093)
R ²	0.57	0.55	0.52			
Kleibergen-Paap				216	174	154

Notes: Standard errors clustered by CZ between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. The numbers of observations for each skill are 10,472,235, 5,341,197 and 4,130,037, respectively.

Table 2.14 – Individual (log) wage IV regressions on the local share of routine jobs, by skill levels, with occupation and industry fixed effect

Workers educ.:	low		medium			high			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sh. of rout. occs	1.880 ^a (0.336)	1.656 ^a (0.310)	1.645 ^a (0.307)	1.626 ^a (0.230)	1.419 ^a (0.215)	1.382 ^a (0.211)	0.365 (0.249)	0.173 (0.249)	0.155 (0.242)
Sh. of high skill	1.517 ^a (0.286)	1.460 ^a (0.263)	1.452 ^a (0.260)	1.307 ^a (0.151)	1.238 ^a (0.141)	1.223 ^a (0.138)	0.825 ^a (0.177)	0.711 ^a (0.180)	0.696 ^a (0.175)
Sh. of med. skill	-0.153 (0.130)	-0.142 (0.120)	-0.142 (0.118)	-0.322 ^a (0.104)	-0.300 ^a (0.098)	-0.300 ^a (0.096)	-0.614 ^a (0.126)	-0.615 ^a (0.121)	-0.598 ^a (0.118)
Sh. of foreign	-0.062 (0.101)	-0.082 (0.089)	-0.080 (0.088)	0.387 ^a (0.090)	0.370 ^a (0.088)	0.372 ^a (0.086)	0.359 ^a (0.083)	0.335 ^a (0.082)	0.331 ^a (0.079)
Occ. FE	yes	yes	no	yes	yes	no	yes	yes	no
Ind. FE	no	yes	no	no	yes	no	no	yes	no
Occ. × Ind. FE	no	no	yes	no	no	yes	no	no	yes
Kleibergen-Paap	217	218	218	174	174	174	154	154	154

Notes: See Table 2.13. The numbers of observations are 10,472,235 (10,472,141 in column 3), 5,341,197 (5,341,077 in column 6) and 4,130,037 (4,129,864 in column 9) for low, medium and high-skill workers, respectively.

Table 2.15 – Individual (log) wage IV regressions on the local share of routine jobs, by skill levels, with the routine share interacted with broad occupation dummies

Workers educ.:	low	medium	high
	(1)	(2)	(3)
Sh. of rout. occ. × man.	2.124 ^a (0.337)	1.790 ^a (0.249)	1.133 ^a (0.341)
Sh. of rout. occ. × rout.	1.634 ^a (0.337)	1.709 ^a (0.228)	0.900 ^a (0.298)
Sh. of rout. occ. × abst.	1.609 ^a (0.317)	1.207 ^a (0.217)	0.224 (0.247)
Sh. of high skill	1.504 ^a (0.282)	1.272 ^a (0.145)	0.836 ^a (0.183)
Sh. of med. skill	-0.170 (0.128)	-0.294 ^a (0.102)	-0.612 ^a (0.124)
Sh. of foreign	-0.028 (0.100)	0.423 ^a (0.090)	0.366 ^a (0.081)
Kleibergen-Paap	73	59	53

Notes: See Table 2.13. The numbers of observations for each skill are 9,110,818, 4,831,197 and 3,901,517, respectively.

Chapter 3

The rise and fall of the medium-skill premium

Summary of the chapter

We study the pattern of the medium-skill premium which have exhibited some important fluctuations over the last decades. It has increased until the beginning of the 2000s and then decreased sharply. We show that the decrease is mostly concentrated among the young workers. It is partly related to a composition effect due to wage discrepancies across occupations and industries (25%) while an important part (50%) of the decrease occurs within occupations and industries. We argue using simple descriptive statistics on cohorts and regressions at the commuting zone level that two forces are at work. First, during the recent period, the supply of high-skilled workers increased faster than the quantity of abstract jobs, pushing the medium-skilled out of those high-paying occupations. The simultaneous decrease in routine occupations during the period lead to a massive reallocation of young medium-skilled to manual low-paying occupations, leading to an occupational convergence with the low-skilled. Second, before 2000s the decrease in the quantity of routine occupations (mostly routine manual) seems to affect more the low-skilled individuals which reallocate to manual jobs, leading to an occupational divergence with the medium-skilled. This process stops at the beginning of the 2000s with an acceleration of the destruction of the routine cognitive occupations, disproportionately occupied by the medium-skilled workers, and we observe similar downgrading from routine to manual for the two populations. The resulting decrease in the demand for the medium-skilled from these two forces have exerted a downward pressure on the wages of the medium-skilled relatively to the low-skilled within occupation, consistently with the displacement effect.

Co-authorship

This chapter is taken from "The rise and fall of the medium-skill premium", co-authored with Clement Bosquet and Paul Maarek

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Contents

3.1	Introduction	114
3.2	Data and stylized facts	122
3.3	Mechanisms behind wage dynamics	134
3.4	Identification strategy and regression results	148
3.5	Conclusion	156
3.A	Additional data: IPUMS March Current Population Survey . .	158
3.B	The role of spatial reallocation	158
3.C	Additional results	161
3.D	Robustness of Table 3.3	172
3.E	Robustness of Table 3.4	178

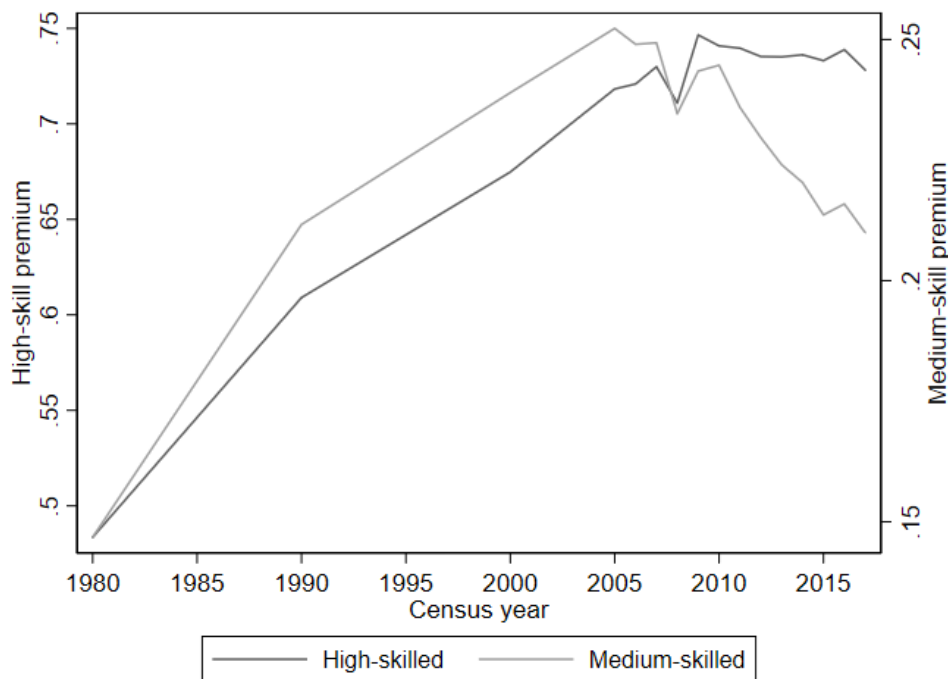
3.1 Introduction

We study the pattern of the medium-skill premium which have exhibited some important fluctuations over the last decades in the US. Figure 3.1 displays the medium- and high-skill premium over the period 1980-2017.¹ As we can see the medium-skill-premium was increasing, similarly to the high-skill premium, until reaching around 25% in 2005. However, in the beginning of the 2000s, both series began to diverge: the medium-skill premium began to decrease, reaching 21% in 2017.

This paper explores the factors behind this specific and relatively unexplored pattern of the medium-skill premium. We argue that it is due to two joint forces. First, the proportion of high-skilled workers increased at a higher rate than the quantity of abstract jobs in the last decade which led to a sharp decrease in the employment opportunities, in abstract high-paying occupations for medium-skilled workers. Second, the share of routine occupations decreased, which was the main occupational categories for medium-skilled worker. Prior to the 2000s, the destruction of routine occupations concerned more the routine manual and affected more low-skilled workers, who reallocate in manual occupations, leading to an occupational divergence between the low- and the medium-skilled and explaining the rise of the medium-skill premium. However, this is not the case anymore after the 2000s. Indeed, the destruction of routine cognitive occupations, which were disproportionately occupied

1. Appendix Figure C1 displays the evolution of the skill premiums on the 25-64 years old population. The pattern remains qualitatively and quantitatively similar.

Figure 3.1 – Evolution of the raw high- and medium-skill premium



Notes: High- and medium-skill premiums respectively calculated as the average log wage of high- and medium-skilled workers minus the average log wage of low-skilled workers. Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. The data used include all working individuals aged 16-64, excluding self-employed, part-time, part-year workers and those employed by the military.

by medium-skilled rather than low-skilled, accelerated during this period. This scarcity of routine occupations, together with the lower employment opportunities in abstract occupations, lead to a massive reallocation of medium-skilled in manual low-paying occupations, especially for young workers, leading to an occupational convergence with the low-skilled after the 2000s. Notably, an important part of the decrease of the medium-skill premium occurs within occupations, which is consistent with the displacement effect highlighted by [Acemoglu and Restrepo \(2018, 2019\)](#). Lower demand for the medium-skilled individuals displaced workers in the remaining occupations, and thus exert a downward wage pressure for the medium-skilled workers relatively to low-skilled workers beyond the wage loss induced by occupation switches from high-paying to low-paying occupations (composition effect).

We define medium-skilled workers as individuals who have been to college but, less than four years (some college). This includes individuals with one or two years of college (lower medium) and individuals with three years (upper medium) which are likely to have completed

a shorter degree than the standard four years college degree. The pattern of the medium-skill premium is quite similar for the two populations. Medium-skilled workers are not studied that much in the literature, there is much more emphasis on low- (no college education) and high-skilled workers (four year degree) and the skill premium usually refers to this population. However, medium-skilled individuals represent a significant share of the population, around 30 percent, which is quite similar to low-skilled individuals. People with at least a four year college degree, represent 40 percent of the working age population. Similarly to the high-skilled, the share of medium-skilled individuals increased dramatically during the 1970's and the 1980's and then increased at a much lower rate. If the premium of medium- and high-skilled workers shared the same dynamics in the 1980's and the 1990's, it then started to diverge. In a context where the costs of higher-education has never been that high, the study of the return to education for this population is an important question.

We use data from the Census and the PSID to understand the factors behind this specific pattern of the medium-skill premium. We start by deriving several interesting stylized facts related to the pattern of the medium-skill premium. We first look at the wage dynamics for each skill category. Surprisingly, we show that the increase in the medium-skill premium occurred in an environment of wage stagnation for the low- and medium-skilled workers whereas the decrease in the medium-skill premium occurs in a context of more robust wage growth for both low- and the medium-skilled individuals. We also show that the decrease in the medium-skill premium is associated with a substantially higher probability to belong to the lowest income decile for medium-skilled workers.

We then focus specifically on the medium-skill premium. We show that lower medium-skilled workers were affected before the upper medium, suggesting a progressive erosion of the premium across the educational ladder. We also show that the medium-skill premium decreased substantially more for younger individual (25-34 year old) than for the rest of the population, suggesting that the deterioration of labor market opportunities affects mostly new entrants relatively to older individuals which have accumulated some experience and eventually climbed the occupational ladder. The medium-skill premium has decreased by around 6 p.p. for the 25-34 against only 1.3 p.p. for the rest of the population.

Finally, we look at the occupations by skill group. The dynamics of the medium-skill premium occur in a context of labor market polarization and a sharp increase of the supply of high-skilled workers. Since the 1970's occupations in the middle of the wage distribution, the so-called routine occupations, are disappearing and are being replaced by either low-paying manual or high-paying abstract ones. The decrease in routine jobs is likely to corresponds to a deterioration of employment opportunities rather than an improvement. 41% of medium-

skilled workers occupied a routine occupation in 1980 against only 33% in 2017. Conversely, 24% of medium-skilled workers occupied a manual occupation in 1980 against 33% in 2017. Finally, the proportion of medium-skilled workers in abstract occupations remained stable or slightly decreased over the period, with 35% in 1980 against 34% in 2017. At first sight, the medium-skilled workers seem to have experienced a deterioration of their labor market opportunities through occupations, especially a reallocation from routine to manual occupations. The relative stability for abstract occupations hides some important heterogeneity. When looking at the younger individuals, medium-skilled workers also experienced a decrease in abstract employment. This occurs at the entry in the labor market, and negates the fact that medium-skilled workers tend to reallocate from routine to abstract occupations during their life cycle, explaining the relative stability observed in the data. Also, we can see an acceleration in the decrease of routine cognitive occupations in the recent period. Those occupations were massively held by medium-skilled workers, contrary to routine manual occupations which were more prevalent amongst the low-skilled and which were destroyed at a faster rate at the beginning of the period.

Second, we perform various decomposition exercises of the medium-skill premium. The pattern of the medium-skill premium could also be related to several changes in the composition of the workforce. At the individual level, characteristics such as gender, race or age of the medium- and low-skilled workers could explain part of the dynamics, as the demographic characteristics of the skill groups may have changed over time. We estimate a Mincer equation and compute the medium-skill premium net of individual characteristics. We show that around 25% of the dynamics are explained by such individual characteristics. We also examine the role of occupation and industry composition in the dynamic of the medium-skill premium. As explained earlier, the share of routine occupations has sharply decreased over the last decades due to task-biased technological change and international trade, which have affected employment opportunity of medium-skilled workers who have partly reallocated to manual jobs. Medium-skilled also faced higher competition with high-skilled individuals in abstract occupations. Manual occupations are considered to be less well paid in average in the polarization literature. The dynamic of the medium-skill premium could thus correspond to a composition effect at the occupation level. The literature has mainly highlighted this phenomenon for the low-skilled individuals but it also exists for the medium-skilled workers as highlighted by [Bosquet et al. \(2020b\)](#). Indeed, we show that changes in the occupational structure notably the polarisation and the associated destruction of routine occupations, has had a negative impact on wages of low- and medium-skilled workers. Here, we complete our previous work by focusing on the relative dynamics between low- and medium-skilled

workers. We try to disentangle which type of worker suffered more from the direct and indirect consequences of the reallocation of workers. In addition, we also consider in this article the occupational structure as a whole, showing that the increased competition for abstract occupations also played a role, instead of only looking at the effect of the disappearance of routine occupations. Similarly, structural change induced by trade (Autor et al. (2013), Barany and Siegel (2018)) or technological change could also lead to industry composition effects on the medium-skill premium. Conversely, it is also possible that the wage dynamics of medium-skilled workers are related to within occupations variation, as a result of the general equilibrium effect induced by the increase of labor supply in the remaining occupations. We include occupation and industry fixed effects in our wage equation and perform a standard decomposition on the variation of the medium-skill premium in order to disentangle the occupation-industry within and between variation of the medium-skill premium. We find that most of the variation (75%) occurs within industry and occupation. The change in composition across industries and occupations accounts for 25% of the decrease in the medium-skill premium. It is very likely that the medium-skilled workers have been affected through the displacement effect induced by the destruction of occupations they massively occupied as in Acemoglu and Restrepo (2018).² Those results hold when focusing on younger individuals which concentrate the bulk of the decrease in the medium-skill premium. Bosquet et al. (2020b) also point the crucial role of within occupations or industries wage variations to explain the wage impact of labor market polarization for each skill category. Here, we focus on the relative wage dynamics of each skill group.

We then focus on the dynamics of the skill-premium and occupational patterns for each cohort of low- and medium-skilled workers over time. The aggregate pattern of the medium-skill premium and occupational composition across skills may hide some very different dynamics across birth-cohorts. The skill- and occupational-premium may decrease over time for each individuals, or new cohorts may start their careers with a lower premium and worse occupations. A preliminary investigation of the medium-skill premium by age suggests that the decrease is substantially more important for the young workers, suggesting that at least part of the explanation is a downgrading for new entrants. Using the PSID, and including individual fixed effects in our Mincer equation, we show that the medium-skill premium in fact slightly increases and do not decreases since 2000. This suggests that the decrease in the medium-skill premium we observe is related to new entrants rather than individuals already on the labour market that experiment a decrease in their premium. The medium-skill

2. We also investigate the role of geography in the pattern of the medium-skill premium. We show that most of the variation of the medium-skill premium is observed within commuting zone.

premium does not decrease within individuals. Looking at the birth-cohorts over time in the Census, we can derive two interesting patterns. First, the medium-skill premium tends to increase over time for each cohort in similar proportions, suggesting a return from experience for the medium- compared to the low-skilled and that this return did not decrease. However, the level of the skill-premium for younger cohorts is substantially lower than for older cohorts at the same stage of their life cycle explaining the overall dynamics of the skill premium. Second, younger medium-skilled cohorts experience a stronger occupational downgrading than the low-skilled over the recent period. Indeed, as for the low-skilled, the decrease in routine occupations induce that the medium-skilled are less likely to start in a routine occupation. Moreover, if the medium-skilled are still able to reallocate to abstract jobs during their life cycle (i.e. climbing the occupational ladder), less medium-skilled start their carriers in abstract occupations. This is especially true for the most recent cohort which starts disproportionately more their carriers in manual low-paying occupation. For those individuals, the opportunity of occupational upgrading is much lower and they get stuck in this type of occupation. Importantly, a striking difference between the low- and medium-skilled workers is that the low-skilled experience occupational downgrading from routine to manual jobs during their life cycle. This is less the case for medium-skilled for which occupational downgrading occurs through new cohorts entering the labor market. As a consequence, everything else equals, wages should decrease within occupations according to the displacement effect.

Finally, we test our preferred hypothesis for the decrease in the medium-skill premium using the Census data at the commuting zone level. We first estimate the impact of the probability of being routine and the probability of being abstract for a medium-skilled compared to a low-skilled on the medium-skill premium, at the commuting zone level using models in stacked-differences and in level. A two-step procedure allows us to control for individual characteristics, and also industry and occupation fixed effects. We show that the model predicts reasonably well the main dynamics of the medium skill premium, i.e. an increase prior to 2000s and then a decrease. Second, we explain the probability of being routine and abstract for the medium-skilled workers by the interplay of two forces: the availability of those jobs and the quantity of skilled workers able to occupy those jobs. The quantity of abstract jobs increased but at a slower rate than the number of high-skilled workers, pushing the medium-skilled out of those positions. The number of routine occupations sharply decreased and the number of medium-skilled sharply increased during the period as compared to the low-skilled, whose proportion decreased sharply.

Our paper is related to several strands of the literature. First, it is obviously linked to the

skill-premium literature. Several authors document that there is a rising premium of being a college-educated worker relatively to being a high-school educated worker (see [Acemoglu and Autor \(2011\)](#) for a literature review).³ The skill-biased technological change literature emerged in order to explain the joint increase of the skill supply and the skill premium. In this literature, the observed increase in the skill-premium is attributed to demand shifts caused by skill-biased technological change.⁴ Traditionally, this literature was more focused on the high-skilled workers. Some papers tried to explore distinct dynamics within the college educated workers by separating them into two groups: the college and post-college graduates. [Lindley and Machin \(2016\)](#) document a significant increase in the premium of the postgraduate workers, relatively to college educated ones.⁵ Another notable exception is [Michaels et al. \(2014\)](#). In this paper, they include three types of workers, similarly to our classification.⁶ They show that industries with faster ICT capital adoption saw a demand shift from medium- to high-skilled workers, approximated by the share in the wage bill. However, they do not look at the relative dynamics of the low- and medium-skilled workers, which is the focus of our paper. Recently, two contributions suggested that the demand for high-skilled workers may slowed down ([Beaudry et al. \(2016\)](#) and [Valletta \(2018\)](#)).⁷ We show that the slowdown for the skill demand is more visible for the medium-skilled. The high-skill premium remains high, even if it does not increase anymore, and high-skilled workers do not experiment occupational downgrading suggesting that the demand for high-skilled did not decrease, but instead do not increase anymore (see [Autor \(2017\)](#)). Another strand of the literature our paper is related to is the polarization literature. Several authors have

3. This trend has not been constant over time. Indeed, [Goldin and Katz \(2008\)](#) show that during the 1940s and the 1970s, this skill-premium was decreasing, mainly for institutional reasons.

4. As noted by [Card and DiNardo \(2002\)](#), two pieces of evidence point in this direction. First, the increase in the skill-premium happened at the same time that the personal computers began to appear in the workplace. Moreover, [Krueger \(1993\)](#) noted that high-skilled workers tend to use more computers and associated technologies, suggesting that technology is complementary with human capital. As a consequence, the rapid increase in the adoption of ICT capital may explain why the high-skill premium increased while the supply of this type of worker increased. [Acemoglu \(1998, 2002\)](#) endogenize technological change which is directed to skilled workers as their supply increases.

5. They show that the demand for the postgraduate workers increased relatively to the others, as they have better skills, more suited for complex tasks in the most paid abstract occupations.

6. Namely, high-school only are the low-skilled workers, some college are the medium-skilled-workers and finally at least college graduates corresponds to the high-skilled ones.

7. [Beaudry et al. \(2016\)](#) develop a theoretical model and show that the demand for skilled workers decreased, due to the fact that the economy reached a steady state in terms of ICT capital, and thus skilled worker are only needed to maintain the level of ICT capital, instead of increasing it as it was the case before. [Valletta \(2018\)](#) shows that the observed slowdown in the high-skill premium observed since the beginning of the 2000s was due to labor market polarization, i.e. the reallocation of workers across occupations until the late 2000s, and that for the decade after, the main driver of this trend was a decrease in the demand for skilled workers, as in the model of [Beaudry et al. \(2016\)](#).

documented a rising polarization of the labor market in term of occupations in the US ([Autor et al. \(2003\)](#), [Autor and Dorn \(2013\)](#)) and in Europe ([Goos and Manning \(2007\)](#), [Goos et al. \(2014\)](#)). This phenomenon, which corresponds to the disappearance of routine occupations usually located in the middle of the wage distribution and which are replaced by manual and abstract occupations located at both extremities of the distribution, is argued to be caused by ICT diffusion. Generally, this process is perceived as detrimental to the low-skilled workers as they reallocate from routine to manual occupations. [Cortes \(2016\)](#) shows that this reallocation is not random: least able workers, proxied by their wages, tend to reallocate into manual occupations. We show that this process also affects the medium-skilled workers as their share working in routine occupation is high and more importantly, that this process seems to have been more detrimental to medium-skilled workers as compared to the low-skilled during the recent period, with the acceleration of destruction of routine cognitive occupations. However, we show that the decrease in routine occupations is only one part of the story. Medium-skilled workers also face an important competition from the increasing share of high-skilled for abstract occupations, which explains their massive reallocation to manual occupations. In addition, a recent contribution from [Dixon et al. \(2019\)](#) show that there has been skill polarization inside firms, due to the adoption of robots, with a decrease in middle-skilled employment among the non-managerial workforce and an increase in low- and high-skilled employment, which is consistent with our findings of a global decrease in the demand for medium-skilled workers.

Also related, our paper contributes to the automation and task-biased technological change literature. [Acemoglu and Restrepo \(2018, 2019\)](#) show that the task-biased technological change and the resulting reallocation of workers across occupations can reduce average wages due to the wage discrepancies across occupations (composition effect) and to the displacement effect which induces an increase in the supply of workers in the remaining occupations, creating a downward wage pressure for the workers within occupations. We show that an important part of the wage dynamics we observe for the different skill groups occurs within occupations. Moreover, our paper is related to the literature on the importance of initial labor markets conditions. [Oreopoulos et al. \(2012\)](#) show that the average worker who graduates in a recession suffers a persistent income penalty. In addition, they show that the impact of recession shocks are more important for young workers that enter the labor market relatively to the ones that already have some experience. Moreover, the impact is heterogeneous depending on the worker's ability: more skilled workers are less affected as their income penalty for graduating in a recession is smaller and less persistent. Another contribution of this study with respect to the literature is to show that the income penalty

is linked to the fact that recessions make young workers apply in less attractive occupations. We show that young workers are struggling to enter in abstract occupations, and that the increase supply in less attractive occupations has a negative impact on wages due to the displacement effect. Finally, our paper contributes to the underemployment literature. Underemployment corresponds to a situation where a worker's educational attainment exceeds the one required for the job he is holding. It is often assumed that there is a positive correlation between the share of college individuals in the population and the share of over-educated workers. This assumption relies on the idea that the massification of higher-education has had a negative effect on the value of college education. [Delaney et al. \(2020\)](#) provide an extensive literature review on this subject and show that the share of over-educated workers tends to decrease in most countries and that over-education rates are negatively correlated with the share of college educated workers, contrary to the popular belief. We show that this is the case for high-skilled workers whose share increase along with the share of abstract jobs. However, this is not the case for medium-skilled workers who clearly experiment an occupational downgrading.

The rest of the paper is organized as follows. Section 3.2 presents the data and some stylized facts regarding the wage dynamics, the evolution of the skill supply and occupational structure over time, with a focus on young workers. Section 3.3 explores different explanations for the dynamics of the medium-skill premium. Identification strategy and results are presented in section 3.4. Section 3.5 concludes.

3.2 Data and stylized facts

In this paper, we will mainly use the Census/American Community Survey, provided by IPUMS and the CPS data for the robustness of our results to alternative data sources. We will also occasionally use the PSID when following individual over the life cycle is needed. This section describes those datasets and the construction of our variables of interest.

3.2.1 Data

Main data sources

Census / American Community Survey

Our analysis will rely on the 1980, 1990, 2000 Census waves, and also on the annual waves from 2005 to 2017. IPUMS provided harmonized variables, which are consistently

coded across years.⁸

We will use three slightly different samples throughout the paper. For all of them, we restrict the dataset to non-military individuals aged between 16 and 64 years old, following [Acemoglu and Autor \(2011\)](#). Most of the variables of our analysis are calculated with this working-age population. We also drop non-working individuals to compute occupational and industrial shares at the national or at the commuting zone level. Finally, we also exclude self-employed, part-time and part-year workers when computing average wages or when estimating skill-premiums.

Our wage variable is the annual labor income of workers during the previous year. Throughout this paper, we will aggregate wage data on various dimensions. Each time, we weight each observation by the Census weight in order to ensure their representativeness with respect to the US population.⁹

PSID

In order to be able to follow individuals over time, we will occasionally use the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal survey of over 18,000 individuals living in 5000 families. Following the same families and their descendants since 1968, the PSID collects data on important economic characteristics, including the educational level of the household head and wife, their occupation and their wage on their main job at the time of the interview. The main advantage of this dataset is that it allows to track an individual over time. Data are available at an annual frequency between 1968 and 1997 and biannually from 1997 onward. As for the Census, we will use data from 1980 to 2015. We mainly follow [Cortes \(2016\)](#) concerning the data management, especially concerning the wage data. We will use wages reported for the current job, as they correspond to the current occupation. In addition, we will restrict the sample to workers aged 16–64 who are part of the core PSID sample (SRC), excluding those in agricultural and military jobs. It is worth noting that all the wage variables available in the PSID allows us to reproduce the skill-premium patterns observed using Census data, even though the decrease occurs a bit earlier.

CPS

8. For some robustness tests, we will also use the 1970 Census wave, for which two slightly different samples are available: the state sample and the metro sample. We use the state sample when working at the national or state level, due to its slightly higher number of observations, and the metro sample when working at the commuting zone (CZ) level, as the smallest identifiable area in the state sample is the state. However, the two datasets are almost identical, and thus using the metro sample for all exercises would not change the results. Both samples are composed of two forms each. We combine both forms for each sample and divide the weights by two for each observation.

9. According to IPUMS, this variable comprises “wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer. Payments-in-kind or reimbursements for business expenses are not included”.

Finally, we also complement Census and PSID data with the IPUMS March Current Population Survey, mainly for descriptive statistics, in order to check the robustness of our main findings to alternative data sources.¹⁰

Measure of routineness

In the literature, we can find two approaches to classify occupations according to their degree of routineness. The first one is to proxy for job tasks by directly using broad occupational categories (see [Acemoglu and Autor \(2011\)](#) or [Verdugo and Allègre \(2020\)](#) among others for example). Another standard method used, for instance, by [Autor and Dorn \(2013\)](#), is to work with data from the Dictionary of Occupational Titles (DOT) or Occupational Information Network (O*NET).¹¹

In this paper, we follow the first method and use the broad occupational groupings defined by [Acemoglu and Autor \(2011\)](#): managerial, professional and technical occupations are specialized in abstract, non-routine cognitive tasks; sales, clerical and administrative support occupations are specialized in routine cognitive tasks; production, craft, repair, and operative occupations are specialized in routine manual tasks; and service occupations are specialized in non-routine manual tasks.¹² As it is standard in the literature, routine manual and routine cognitive occupations are grouped into a single category. We prefer this measure as it does not rely on a rigid task-based classification of occupations made in 1968, as is the case for the DOT. We can easily assume that the task content of occupations was very different at that time from what it is today. In addition, relying on the DOT also requires adopting criteria to weight the different task scores of each occupation.

We will not use the classification of occupations based on the DOT using the criteria of [Autor and Dorn \(2013\)](#). Indeed, this methodology does not allow us to create mutually exclusive categories for the manual, routine and abstract categories, which we need in order to understand the occupational choice of workers.

10. A description of this dataset is presented in Appendix Section 3.A

11. These datasets provide information about the task content of each occupation. Each task of each occupation receives a score between 0 and 5, according to its importance for the occupation. Then, those task scores are aggregated into three categories: manual, routine and abstract. Next, for each occupation, we can compute a routine task intensity measure: $\ln(\text{Routine score}) - \ln(\text{Manual score}) - \ln(\text{Abstract score})$. Finally, occupations that belongs to the top third of the routine task intensity distribution are qualified as routine occupations. [Goos et al. \(2014\)](#) show that the two methodologies are similar, and measures are highly correlated.

12. We directly use the data from [Autor and Dorn \(2013\)](#), which classify each occupation as routine, manual or abstract and are available on the AEA website.

Occupation and industry classification

Throughout this paper, we will rely on three different classification of occupations. When decomposing the wage variation, we will use a classification on 7 categories: “Transport and Construction and service occupations” which corresponds to manual occupations, “Production, craft, repair, occupations” and “Operative occupations which corresponds to routine manual occupations”, “Clerical and administrative support occupations” which corresponds to routine cognitive occupations, “Managerial, professional and technical occupations” which corresponds to abstract occupations, and finally the not-classified ones. We are restricted by the fact that we need to have, for each skill and age group, an average wage for each date in order to correctly decompose the wage variations. In addition, we will use an alternative classification based on 4 posts: manual, routine, abstract and not-classified when decomposing the wage variation on occupation \times industry cells. Finally, we will also use a classification based on 77 posts, as a robustness for our decomposition exercise. This classification will also be used in the Mincer-type wage equations and in our two-step estimation strategy when we control for occupations at the individual level.¹³

Moreover, we will use two industry classification. First, we use a 13 posts industry classification in our decomposition exercise, for the same reasons as in our occupation classification. This industry classification corresponds to the most aggregated classification provided by IPUMS. In addition, we also use a classification based on the major posts, i.e. the level below the most aggregated one, then unify the classification for time-consistency and end up with 34 industries, which will be used in our augmented Mincer equation.

Commuting Zone (CZ)

Following [Autor and Dorn \(2013\)](#)’s methodology, we create local labor markets at the CZ level. Using probabilistic matching, it allows to map sub-state geographic units, such as county group or Public Use Microdata Area (PUMA) in the US Census, to CZs. Each observation in each CZ is then weighted according to the fraction of geographic unit that maps to the given CZ. We end up with 722 CZs in the mainland USA and 741 when Alaska

13. This classification is based on the major categories given by IPUMS. The only exception are occupation ‘258: Sales Engineers’ of the source classification, which has been separated from the ‘Sales Representatives, Commodities’ broad occupation because it is an abstract occupation, while the others are routine occupations. In addition, we combined ‘243: Supervisors and proprietors, sales occupations’ with ‘Sales Representatives, Finance and Business Services’, ‘415: Supervisors of guards’ with ‘Guards’, ‘503: Supervisors, mechanics and repairers’ with ‘Vehicle and Mobile Equipment Mechanics and Repairers’, and ‘558: Supervisors, construction’ with ‘Construction Trades’ for consistency over time. We end up with 77 occupations but we use only 76 of them as we exclude those in the military.

and Hawaii are included.

Skills

Skill levels are coded based on educational attainment information available in the dataset, measured by the highest year of school or degree completed. In this paper, we define the low-skilled as individuals who have completed or dropped out before completing high school, the medium-skilled as individuals who went to college but completed fewer than four years and finally the high-skilled corresponds to individuals who have at least a four-year college degree. In addition, when a more detailed analysis is needed, we also divide the medium-skilled group into two categories: lower medium-skilled workers, who have completed fewer than three years of college and upper medium-skilled workers, who have completed three years of college.¹⁴

3.2.2 Stylized facts

In this section, we present a series of stylized facts.

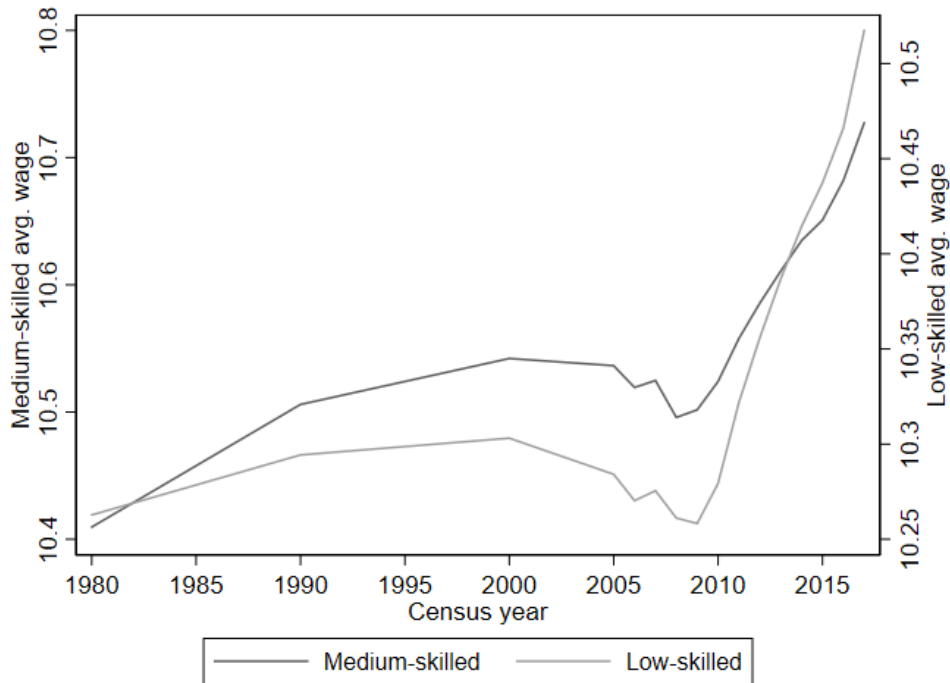
Wage dynamics by skill and the position of the medium-skilled workers in the wage distribution

Figure 3.2 displays the log wages by educational group over time. We can observe that the increase in the medium-skill premium during the period 1980-2005 occurs in an environment of low wage growth for both low- and medium-skilled workers. The average wage of low-skilled workers even decreases during the early 2000s, thus compensating for the absence of wage growth for the medium-skilled. However, the wage growth of low- and medium-skilled workers has been much higher in the recent years. The decrease in the medium-skill premium occurs in a context of robust wage growth that contrasts with the beginning of the period.¹⁵ Not surprisingly, we show that the faster growth of the wage of the low-skilled compared to medium-skilled workers is associated with a higher probability of being at the bottom of the wage distribution for the medium-skilled. Figure 3.3 plots the probability for a medium-skilled worker of belonging to one of the three first income decile, relatively to a low-skilled worker. As we can see, from the beginning of the 1980s to the end of the 2000s,

14. These categories correspond to IPUMS codes 65 to 71 and 80 to 90, respectively.

15. One may argue that the faster wage increases may be due to the switch from Census data to American community Survey data in 2005. However, as we show in appendix Figure C2, the same pattern can be observed in the CPS data.

Figure 3.2 – Evolution of the average log wages for low- and medium-skilled workers



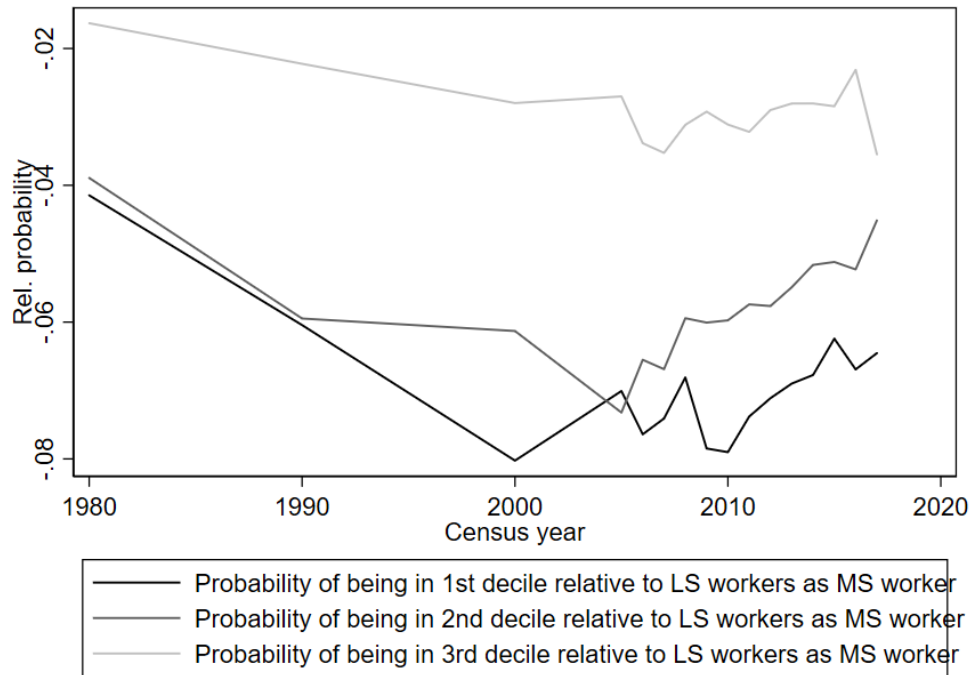
Source: See Figure 3.1

the probability of belonging to the bottom third of the wage distribution was decreasing for a medium-skilled worker, while this tendency began to reverse at the end of the decade, almost returning to its original level in the case of the second income decile. This implies that medium-skilled workers are now more present at the bottom of the wage distribution and the timing coincides roughly with the observed decrease of the medium-skill premium.

The pattern of the lower and upper medium-skill premium

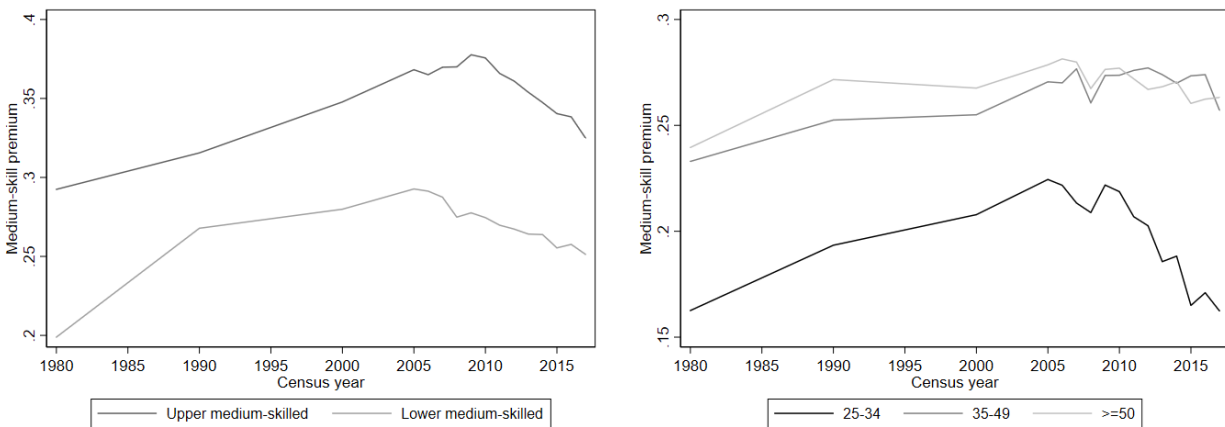
Figure 3.4a displays the pattern of the medium-skill premium by subgroups of skill. We distinguish between the lower medium (less than three years college degree) and the higher medium-skilled (three years college degree). We observe that the lower-medium were affected before the upper-medium, with a peak in 2005 and an overall decrease of 4.59 p.p. between 2005 and 2017. Interestingly, we can also observe that the upper-medium took a bigger hit in the recent years but that the decrease started later, with a 5.36 p.p. decrease between 2009-2017. It seems to indicate a progressive erosion of the medium-skill premium along the skill ladder. Overall, we observe a fast convergence of the upper medium-skill premium and the lower medium-skill premium.

Figure 3.3 – Evolution of the probability of belonging to the first, second and third decile of the income distribution for medium-skilled workers relative to low-skilled workers



Source: See Figure 3.1. Probability calculated from a simple OLS regression on the population of low- and medium-skilled workers, without additional control variables.

Figure 3.4 – Evolution of the raw skill premium: sub-education and age-specific groups



(a) Lower and upper medium-skill premium

(b) Age-specific medium-skill premium

Source: See Figure 3.1. The data in Figure B excludes workers aged 16-24 years old.

The skill premium by age

We now look at the dynamics of the medium-skill premium by age. Young workers that enter the labor market could be disproportionately affected by a lower demand for skills as compared to older cohorts which have accumulated experience. In Figure 3.4b, we display the age specific medium-skill premium, i.e. the average log wage of a medium-skilled worker for an age category minus the average log wage of a low-skilled workers for the same age category. We choose to focus on wage inside age categories because we can compare workers with relatively the same experience, as it is an important determinant of wages. We focus on workers aged 25 years old and more, as in [Valletta \(2018\)](#).¹⁶ Two striking patterns emerge. First, the skill premium is roughly the same between the two oldest group, but it is significantly smaller for the younger group. This suggests that the return to experience is higher for the medium-skilled than for the low-skilled. Second, we can observe that the medium-skill premium for this category decreases much more during the last decades. The premium's variation between 2005 and 2017 is around five times higher for the younger group relatively to the 35-49 years old group (-6.3 and -1.3 p.p. respectively). The fact that the medium-skill premium does not decrease as much for other age categories indicates that there seems to be a positive interaction between being a medium-skill and having experience, which limits the magnitude of the loss in term of premium. We will investigate this in more detail when looking directly at the skill premium for each birth-cohort. Overall, the different dynamics by age categories seem to indicate that the decrease in the medium-skill premium we observe is mostly driven by the drop in the medium-skill-premium for the younger age-category.¹⁷

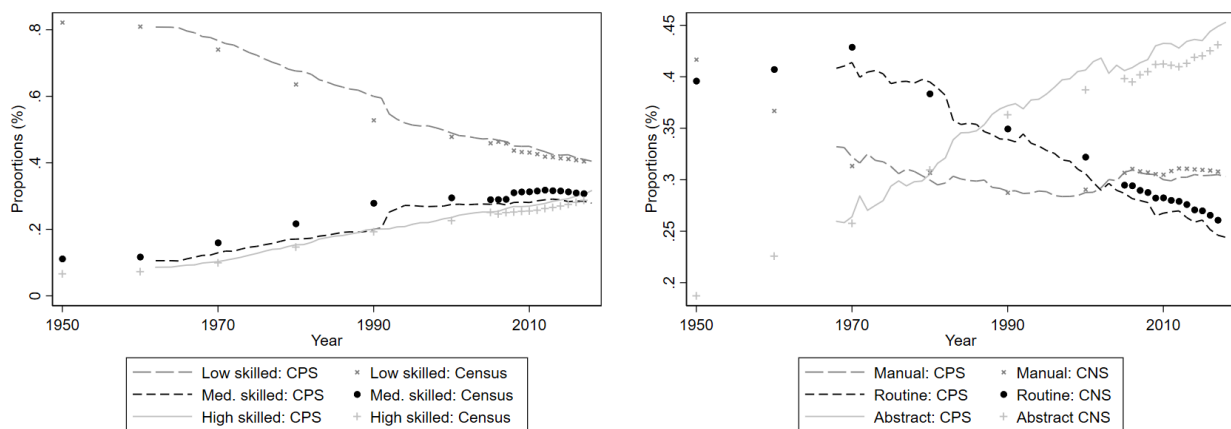
Skill supply and occupational choice by skill

Figure 3.5, which reproduces some stylized facts of [Bosquet et al. \(2020b\)](#), displays the evolution of both educational attainment and occupational distribution of the U.S population since 1950. Focusing first on Figure 3.5a, we can see the share of both medium- and high-skilled workers increased at a steady path since the beginning of the 1970s, while the share of low-skilled workers plummeted. It is worth noting that the share of medium-skilled workers plateaued at the beginning of the 2000s, while the share of high-skilled workers continued

16. Similar patterns can be observed when extending the sample to workers aged 21 years old and above. The corresponding figure can be found in Appendix Figure C3.

17. In addition, we provide in Appendix Figure C4 the evolution of lower and upper medium-skill premium by age category. We find that, similarly to the whole population, lower medium-skilled workers has been impacted before the upper one, but the negative variation over the period 2008-2017 is more important for the latter group. Moreover, we find that the variation are higher for the younger one.

Figure 3.5 – Evolution of workers’ occupations and educational attainment for the overall population



(a) Educational attainment (full pop.)

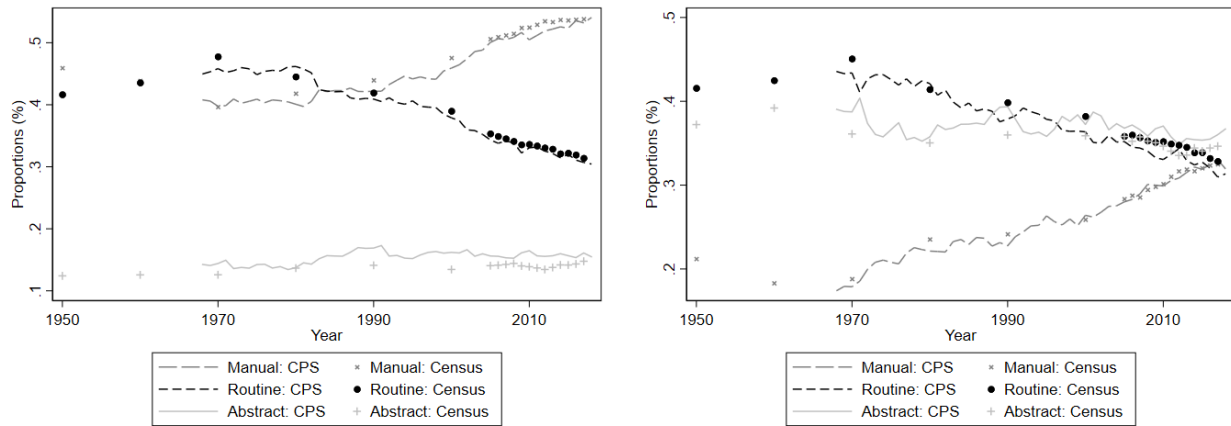
(b) Occupations (workers only)

Sources: March CPS data for years 1963-2017, Census IPUMS 5% samples for 1950, 1960, 1980, 1990 and 2000, Census IPUMS 1% state sample for 1970 and Census American Community Survey for 2005-2017. The data used in figure (b) include all persons aged 16-64, excluding those employed by the military. In figure (a), non-working individuals are also excluded.

to grow. This pattern represents the so-called “massification of higher education”, where an increasing share of individuals gained access to college. In 1980, people who had been to college (i.e. the medium- and high-skilled individuals) represented 36.4% of the working age population, against 59.5% in 2017. More precisely, medium-skilled workers went from 21.7% in 1980 to 30.8% in 2017 and the high-skilled workers represented 14.7% in 1980 and 28.7% in 2017. Moreover, when looking at Figure 3.5b, we can observe the well-known decrease in the share of routine occupations, which went from 38.4% in 1980 to 26.1% in 2017. Those routine occupations have been replaced mainly by abstract occupations, whose share increased from 30.9% in 1980 to 43.1% in 2017. We can see that the number of high-skilled workers increased faster than the quantity of abstract jobs that they disproportionately occupy.

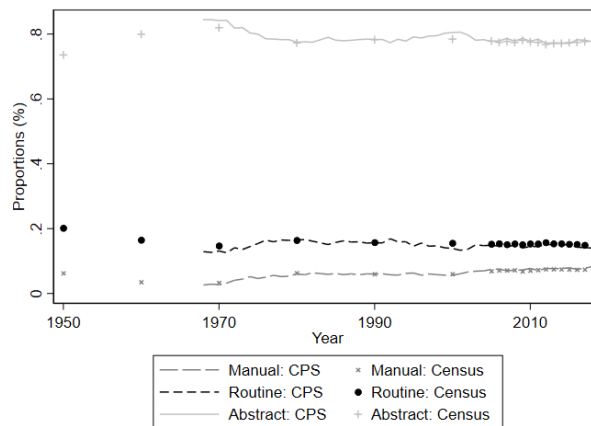
Figure 3.6 plots the evolution of the occupational distribution for each skill category. Low- and medium-skilled workers experienced similar dynamics, even though the levels are different. They both experienced a sharp decrease in the share of workers in routine occupations and an increase in the share of workers in manual occupations. This seems to indicate that both skill groups experienced some occupational downgrading. In addition, we can observe that the distribution of occupations for high-skilled workers remained stable over the period. While around a constant 80% share of the high-skilled workers occupy high-paying abstract jobs, medium-skilled workers saw their employment opportunity decline in middling

Figure 3.6 – Evolution of occupations’ shares for low-, medium- and high-skilled individuals among working population



(a) Low-skilled individuals

(b) Med. skilled individuals



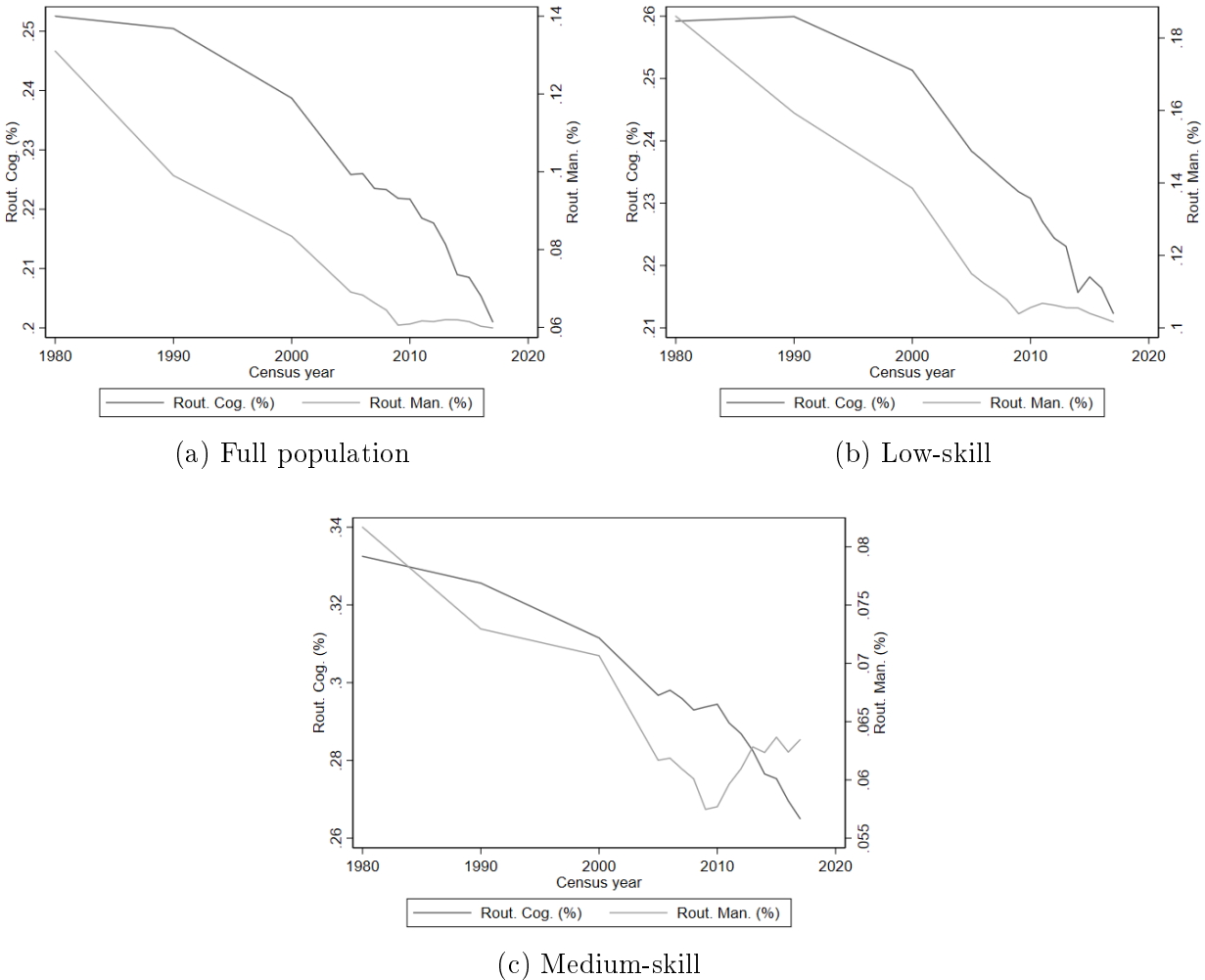
(c) High-skilled individuals

Source: See Figure 3.1

routine occupations, and seem to reallocate towards low-paying manual occupations. Additionally we can see a very modest decrease of the share of medium-skilled workers working in abstract occupations from 2000s. We will see when focusing on birth-cohorts that this apparent stability hide some important heterogeneity: if the medium-skilled continue to climb the occupational ladder during their life cycle, from routine to abstract, the recent cohorts are significantly less likely to start in an abstract occupation. In Appendix Figure C5, we can see that young workers hold less abstracts jobs than the rest of the population. Also, the share of abstract occupations for young workers is clearly decreasing over the recent period. We argue that it is likely that the sharper increase in the supply of high-skilled relatively to the quantity abstract occupations push the medium-skilled out of those occupations, for which

high-skilled have a comparative advantage, especially new entrants in the labor market.

Figure 3.7 – Evolution of the routine manual and cognitive shares for the full population, low and medium-skilled individuals among working population

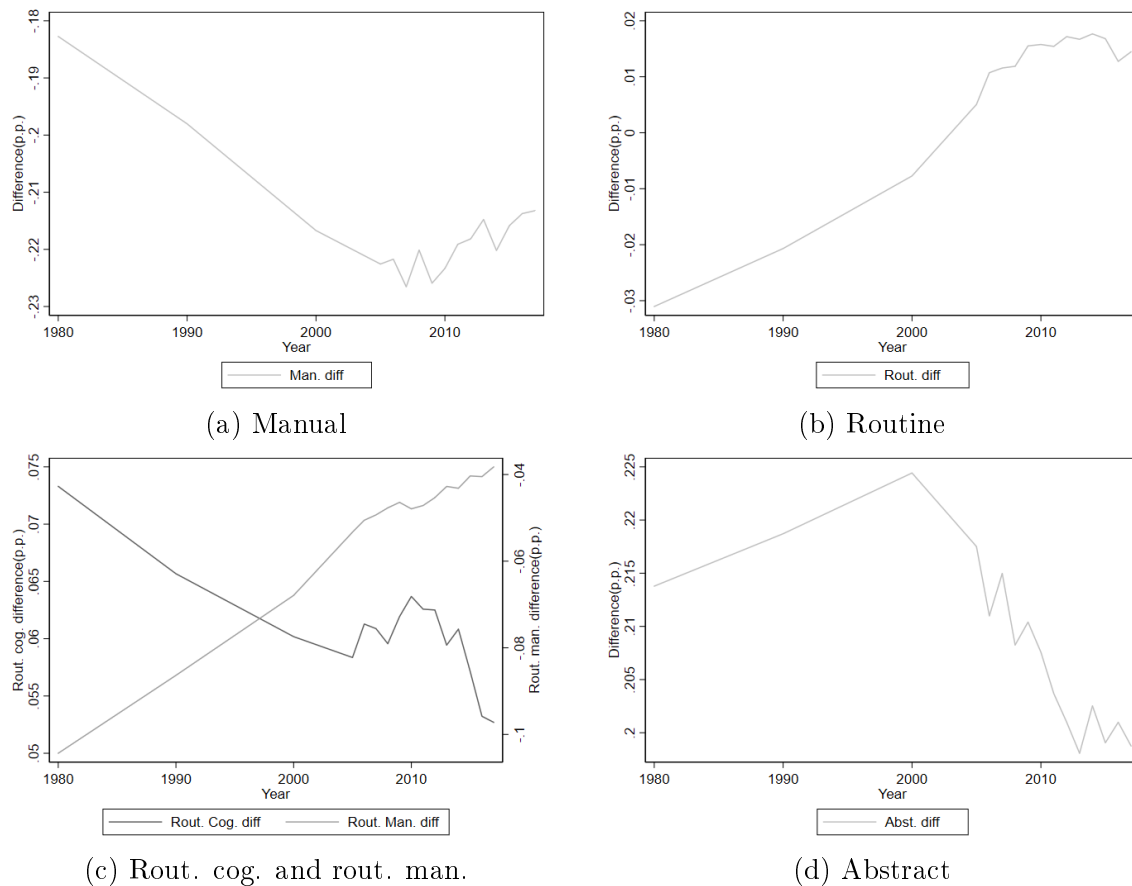


Source: See Figure 3.1. Each panel graphs the difference between the share of an occupation type among medium-skilled workers and the share of this occupation among low-skilled workers.

Figure 3.7 details the evolution of the subgroups constituting the routine category: the routine manual and routine cognitive. Routine manual refers to operators and production workers, while routine cognitive refers to clerical work, such as book-keeping or accounting. First, focusing on the full population in Figure 3.7a, we can observe that the share of routine cognitive occupations decreases faster after 2000 than the share of routine manual occupation while the latter was decreasing much faster than routine cognitive at the beginning of the period. This is in line with the findings of Autor et al. (2015) who show that

the effect of technological progress seems to shift from manufacturing to non-manufacturing activities. Moreover, the distribution is different among low- and medium-skilled workers. Medium-skilled workers hold significantly more routine cognitive jobs than their low-skilled counterparts and as a result we observe a sharper decrease of the routine cognitive for the medium-skilled. This decrease accelerates after the 2000s. In addition, the share of routine manual among medium-skilled workers is slightly increasing since the 2010s.

Figure 3.8 – Evolution of the differences in occupational shares between medium- and low-skilled workers.



Source: See Figure 3.1. Each panel graphs the difference between the share of an occupation type among medium-skilled workers and the share of this same occupation among low-skilled workers.

Finally, we will focus on the relative occupational dynamics between medium- and low-skilled workers. We compute the difference in occupational shares between medium- and low-skilled workers, i.e. the difference between the share of an occupation type among medium-skilled workers and the share of this same occupation among low-skilled workers. Figure 3.8 displays the evolution of those differences for the manual, routine, routine sub-

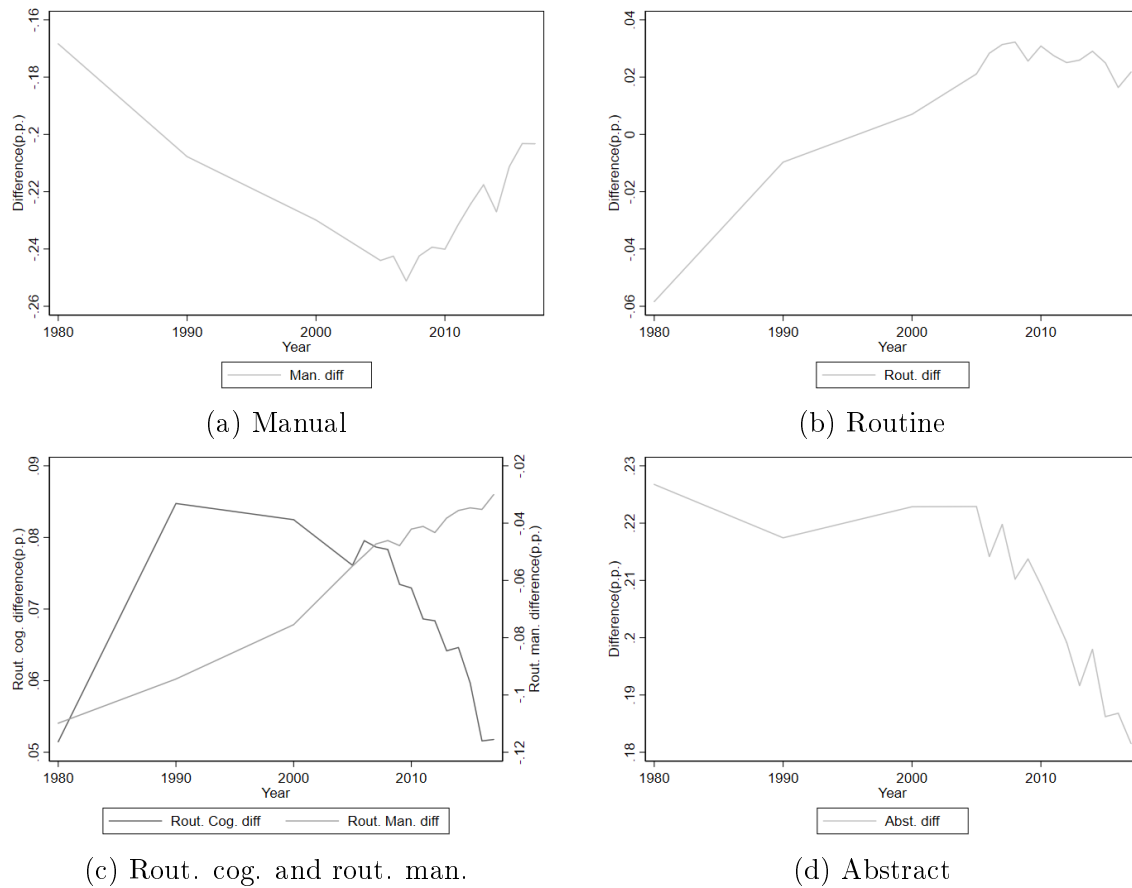
categories and abstract occupations. We can observe that there is roughly two periods. First, before the decade 2000-2010, it seems that there is some occupational divergence, where low- and medium-skilled workers seemed to progressively allocate in different type of occupations: the proportion of medium-skilled workers in manual occupations relatively to the low-skilled decreases sharply, while the share medium skilled in routine (and to a lesser extend in abstract) increases relative to the share of low-skilled workers. For routine, this is mostly due to a bigger decrease of the share of routine in low-skilled workers. However, in the 2000s and 2010s, we can see that the spread begin to decrease over time, especially for the abstract group and a process of occupational convergence starts to appear between the two groups. The proportion of manual, low-paying occupations, in the medium-skilled group relatively to the low-skilled one starts to increase at the end of the 2000s and the proportion of abstract occupations among the medium-skilled relatively to the low-skilled starts to decrease sharply at the beginning of the 2000s (mostly due to the decrease of medium-skilled in abstract jobs). The picture is more nuanced for the routine occupations. The difference in shares starts to flatten during the 2000s. However, this flattening hides an important heterogeneity between routine sub-categories. We can see that the share of routine cognitive among medium-skilled workers sharply decrease relatively to the low-skilled over the period, and the share of routine manual among the medium-skilled relatively to the low-skilled sharply increases, suggesting again an occupational convergence between the two skill categories.

Finally, Figure 3.9 displays the spreads for the young worker groups. For this group of worker, the occupational convergence is stronger over the recent period, notably for the manual and abstract occupations. A medium-skilled worker had 22 p.p more chance of having an abstract job relatively to a low-skilled but only 18p.p in 2017. Conversely a medium skilled had 25 p.p less chance of having a manual occupation than a low-skilled in 2005 but only 20 p.p less chance in 2017. An important difference with the full population concerns the routine cognitive occupations, with an occupational divergence with the low-skilled in the 1980s and a strong convergence that really started in the middle of the 2000s which coincides with the acceleration of the destruction of those occupations.

3.3 Mechanisms behind wage dynamics

In this section, we decompose the variation of the medium-skill premium according to individual characteristics, occupations and industries. Additionnally, we provide in Appendix Section 3.B a decomposition of the medium-skill premium based on commuting zones.

Figure 3.9 – Evolution of the differences in occupational shares between young medium- and low-skilled workers.



Source: See Figure 3.1.

3.3.1 The role of individual characteristics

The recent evolution of the skill premium may be related to changes in the composition of the labour force. Indeed, several individual characteristics play a crucial role in the determination of the wage level, such as the gender, the age or the race. Thus, if the composition changed in a way that less-paid demographic groups are now more represented in the labor force and in some particular skill groups, it may affect the average wage of this skill group and thus explains the variations of the skill premium we observe. It is very likely that the rapid evolution of the share of each skill groups goes together with an important evolution of those groups in terms of individual characteristics. In order to estimate the magnitude of those compositions effects, we will estimate a standard Mincer equation. More precisely, we will estimate:

$$\log(w_{it}) = \beta_{1,t}HS_i + \beta_{2,t}MS_i + X_{it}\Gamma + \delta_t + \epsilon_{it} \quad (3.1)$$

where $\log(w_{it})$ is the log of the wage of an individual i at time t , HS_i is a dummy for being high-skilled, MS_i a dummy for being medium-skilled, X_{it} includes age and its square, gender and race dummies and δ_t is a year fixed effect. Coefficients for each skill group are year-specific and are interpreted relatively to the low-skill group.¹⁸

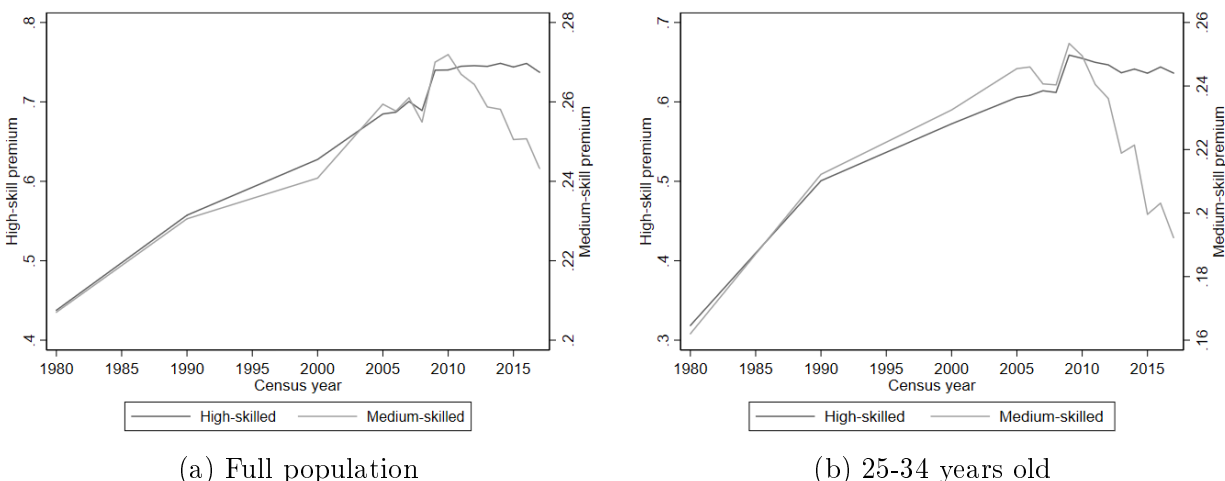
Estimated coefficients for skill-dummies, which represent the skill premiums, are presented in Figure 3.10.¹⁹ As we can see, once we control for individual characteristics, the pattern is slightly different but the overall pattern of the skill premiums remain qualitatively the same: the level of the skill premium is higher and the decrease appears later, around 2010, and is slightly lower too but steeper: without controlling, we observe a 4.2 p.p. decrease over 12 years and a 2.9 p.p. decrease over 7 years when we control for individual characteristics. This means that some individual characteristics play a role in the recent dynamics of the medium-skill premium, but cannot explain fully the dynamics we observe.

Focusing on the young workers group, we can observe that controlling for individual characteristics does not change much the pattern, the variation is only slightly smaller. This is explained by the fact that younger workers drive the overall decrease in the medium-skill premium, and thus, focusing on this group lowers the impact of individual characteristics, and especially the role of the age dimension. In Appendix Table C1, we provide the estimated coefficients for individual characteristics from equation 3.1, and we provide the average value of those individual characteristics for each skill group at different points in time in order to understand which individual characteristics play a significant role in the observed decrease of the medium skill premium. We can observe that the average age grew faster for the low-skilled relatively to the medium-skilled, explaining some of the decrease in the medium-skill premium. Other individual characteristics only play a minor role.

18. By using a pooled specification, we do not allow the return to individual characteristics to vary over time, but the coefficients estimated for the skill dummies are numerically very close even when estimated with a year-specific equation. In addition, note that the skill-premium series calculated using the same wage equation without control for individual characteristics, either in a pooled or year-specific specification, are numerically equivalent to the ratio of average wages. Year-specific estimates are available in Appendix Figure C6.

19. Appendix Figures C7 displays the raw and net premium and their confidence intervals for the medium- and high-skill premium, respectively.

Figure 3.10 – Evolution of the high and medium-skill premium, net of individual characteristics, full population and young workers only



Sources: Census IPUMS 5% samples 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. Coefficient obtained from estimating equation 3.1. The data used include all working individuals aged 16-64, excluding self-employed, part-time, part-year workers and those employed by the military. In figure (b), only workers aged 25-34 years old are included.

3.3.2 The role of occupations and industries

As we saw previously, medium- and low-skilled workers experienced a significant reallocation across occupations, from routine and abstract to manual. Routine and abstract occupations are considered to be better paid in average relatively to manual occupations, as they require more skills or experience. As a consequence, as the share of medium-skilled working in routine and abstract occupations is decreasing over time while it is increasing in manual occupations relatively to low-skilled workers, their relative wage may decrease in average as a result. However, it is also possible that the wage dynamics we observe in the data are related to within occupation dynamics, meaning that there is a stronger wage growth inside occupations for the low- relatively to the medium-skilled, thus explaining the decrease in the medium-skill premium. Wage dynamics within occupations are likely to be related to the reallocation across occupations described earlier, which creates a displacement effect as explained in [Acemoglu and Restrepo \(2018, 2019\)](#). The disappearance of routine occupations and the reallocation across occupations affect wages due to a composition effect given the mean wage across occupations, and within occupations given the downward wage pressure induced by the reallocation of workers in the remaining occupations.

In order to disentangle those two channels, we will estimate an augmented wage equation

with additional occupation and industry fixed-effects:

$$\log(w)_{it} = \beta_{1,t}HS_i + \beta_{2,t}MS_i + X_{it}\Gamma + \delta_t + \epsilon_{it} \quad (3.2)$$

where all variables are the same as before, except that X_{it} now includes an occupation or occupation \times industry fixed effect. By comparing them to the series in Figure 3.10, it will allow us to capture the between effect. Moreover, we will also estimate this equation on the subset of workers aged 25-34, as we saw that the decrease of the medium-skill premium is stronger for younger workers.

In addition, we will provide more direct evidences, by decomposing wage variations into skill-specific between and within components. As the premium corresponds to the difference in log wages of medium- and low-skilled worker, we are able to calculate a global between and within component for the skill premium variation, as the sum of the skill specific components. The between term corresponds to the composition effect induced by the reallocation of workers to other occupations which have different wage rates. The second term is related to the displacement effect and the variation of wage within occupations. Formally, we will decompose the premium variation as:

$$\Delta MSP_t = \Delta \overline{w_{mt}} - \Delta \overline{w_{lt}} \quad (3.3)$$

where MSP corresponds to the medium-skill premium and w_{mt} and w_{lt} are respectively the log of the average wage of a medium- and low-skilled worker. Then, we can decompose each wage variation as:

$$\Delta \overline{w_{gt}} = \sum_k \left(\frac{w_{gkt_0} + w_{gkt_1}}{2} [\alpha_{gkt_1} - \alpha_{gkt_0}] + \frac{\alpha_{gkt_1} + \alpha_{gkt_0}}{2} [w_{gkt_1} - w_{gkt_0}] \right) \quad (3.4)$$

where t_0 corresponds to the initial date and t_1 the end of each period t . We will provide both occupations and occupations \times industry decomposition, thus k refers to both occupation and occupation \times industry cells. α_{gkt_0} and α_{gkt_1} are the shares of employment in cell k for skill g in t_0 and t_1 . w_{gkt_0} and w_{gkt_1} are the average wages in cell k for skill g in t_0 and t_1 . The first component represents the within term. It corresponds to the variation of average wages within each cell, weighted by the share of this occupation within the skill group (averaged over t_0 and t_1). The second component is the between term and corresponds to changes in

the local shares of occupations, weighted by the average wage of each occupation (averaged over $t0$ and $t1$). It is the composition effect and it captures average wage variations due to occupation (and possibly industry) switches. Thus, if we replace the wage variation in equation 3.3 by the decomposition in equation 3.4, we have:

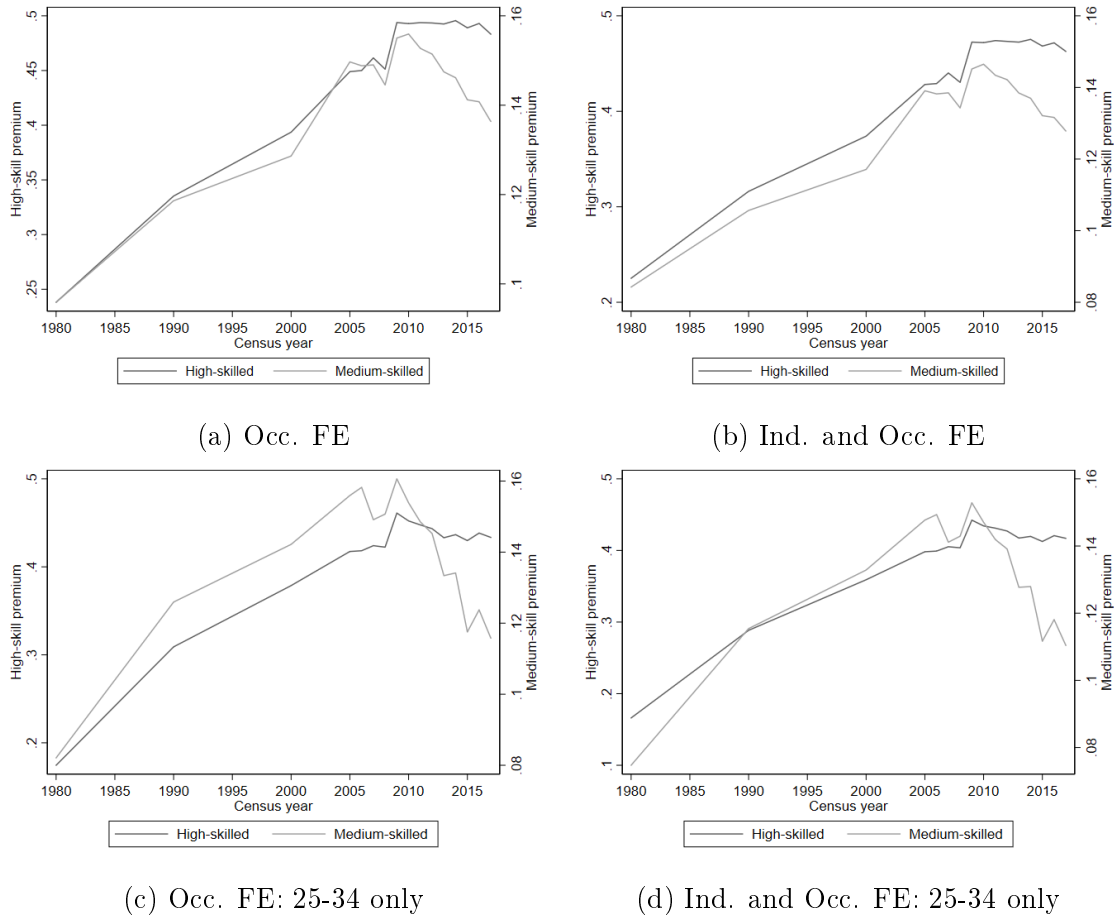
$$\Delta MSP_t = (Within_{mt} - Within_{lt}) + (Between_{mt} - Between_{ls}) \quad (3.5)$$

Here, the first term corresponds to the global within component of the medium-skill premium, the difference between the within variation of the wages of the medium- and low-skilled and the second term corresponds to the global between component of the medium-skill premium, the difference between the between variations in the wages of the medium- and low-skilled workers.

Figure 3.11 displays the estimated coefficients from equation 3.2, for both the full population and the young worker group. When controlling for occupations fixed-effect, we can see that the overall medium-skill premium decreases by 40%, suggesting that even within occupations, there still exists some important wage differences between skill groups. Occupational choice is far from explaining the wage gaps between different skill groups. Also, we can see that most of the observed variation in the medium-skill premium is still unexplained by the occupational structure of each skill groups (a 2.9 p.p variation of the premium net of individual characteristics without controlling and a 2 p.p. variation if we control for occupation fixed-effects). Controlling for both industries and occupations does not change much from only controlling for occupations. Thus, it means that the wage variations within occupations seem to play a more important role in the wage dynamics in order to explain the medium-skill premium than the between occupations component. In addition, when focusing on the young workers group, we can see that the decrease in the medium-skill premium is again much higher than for the whole population. The decrease in the medium-skill premium for the youths is slightly lower when controlling for both industries and occupations (a 4 p.p decrease against 5.5 p.p without industry and occupation controls). An important part of the decrease of the medium-skill premium occurs within occupations as a result.

Table 3.1 shows the results of the wage decomposition. Panel A presents the results for the decomposition based on occupations and Panel B shows the results for the one based on occupations×industries. Looking at the occupations based one, results are similar to the augmented Mincer regressions: we can see that more than 90% of the observed dynamic is due to a within effect. First, between 1980 and 2005 we have a slower increase of average wages of

Figure 3.11 – Evolution of the high and medium-skill premium, net of occupation and industry



Sources: 1980, 1990 and 2000 and Census American Community Survey for 2005–2017. Coefficient obtained from estimating equation 3.2. The data used in figure (a) and (b) include all working individuals aged 16–64, excluding self-employed, part-time, part-year workers and those employed by the military. In figure (c) and (d), only workers aged 25–34 years old are included.

low-skilled workers within occupations, and then, between 2005 and 2017, a faster increase of average wages of low-skilled workers within occupations.²⁰ The results concerning the second decomposition are similar, with a dominant within effect for both period, even though the between effect is stronger in the second period, relatively to the previous decomposition. Around 80% of the variation of the medium-skill premium occurs within occupations and industries. This confirms the pattern highlighted previously using wage equations even if we do not control for the role of individual characteristics in this exercise. Appendix Table C3

20. One may argue that we find a dominant within effect due to the chosen classification of occupations, as it is only composed of 7 posts. We show in Appendix Table C2 that results are similar using a classification in 77 posts. The between effect accounts for 20% of the total decrease in the medium-skill premium.

Table 3.1 – Decomposition of the raw medium-skill premium

	80-05	05-17	80-17
Panel A: based on occupations only			
tot. W. var. LS	.0214	.2333	.2547
tot. W. var. MS	.1269	.1909	.3178
tot. MSP var.	.1055	-.0424	.0631
Within LS	.032	.232	.262
Within MS	.134	.193	.324
Within: tot	.102	-.039	.062
Between LS	-.011	.001	-.007
Between MS	-.007	-.002	-.007
Between: tot	.004	-.003	0
Panel B: based on occupations×industries			
tot. W. var. LS	.0214	.2333	.2547
tot. W. var. MS	.1269	.1909	.3178
tot. MSP var.	.1055	-.0424	.0631
Within LS	.061	.236	.291
Within MS	.165	.202	.365
Within: tot	.104	-.034	.074
Between LS	-.039	-.003	-.036
Between MS	-.038	-.011	-.047
Between: tot	.001	-.008	-.011

Sources: Census IPUMS 5% samples for 1980 and Census American Community Survey for 2005 and 2017. Occupation classification is composed of 7 posts in Panel A and of 4 posts in Panel B. Industry classification composed of 13 posts. More details available in Section 3.2.

reproduces the decomposition exercise for the individuals aged 25-34 and obtains the same results for the share of the within and between variations.

Even though medium-skilled workers now struggle to obtain routine or abstract jobs, and thus experience occupational downgrading relatively to low-skilled workers, the direct effect on wages due to wage differences between routine (or abstract) and manual occupations does not explain the bulk of the medium-skill variation. It is rather likely to be an indirect consequence of this reallocation from routine (and abstract) to manual occupations as suggested by the displacement effect.

We can rationalize those findings by looking at the the occupational premium by skill. Table 3.2 shows estimates of the premium from having a routine or an abstract occupation, compared to having a manual occupation, for low- and medium-skilled workers. As we can see, the occupational premium of having a routine occupation relatively to having a manual

Table 3.2 – Individual (log) wage OLS regressions

Workers educ.	low		med.	
	(1)	(2)	(3)	(4)
Rout.	0.127 ^a (0.005)	0.123 ^a (0.004)	0.100 ^a (0.003)	0.094 ^a (0.003)
Abst.	0.331 ^a (0.007)	0.324 ^a (0.007)	0.325 ^a (0.005)	0.313 ^a (0.004)
CZ FE	no	yes	no	yes

Notes: Sample years are 1980, 1990, 2000, 2010 and 2017. All regressions include 5 Census year fixed effects as well as gender, race and age and its square as individual controls. 741 CZ fixed effects are also included in some regressions, as indicated in the bottom of the table. Standard errors clustered by commuting zone between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. The numbers of observations are 8,535,979 in columns 1 and 2 and 5,373,956 in columns 3 and 4.

occupation is not that high, around 10%. The occupational premium of having an abstract occupation is much higher, at around 30%. Also, as we saw previously, the detailed set of industry and occupations fixed effects only lower the level of the medium-skill premium over the period by 40%. Those occupational premiums are significant, especially for the abstract premium and composition effects due to re-allocations can explain a significant part of the medium-skill premium dynamics (between 20% and 25% of the total raw variation of the medium skill premium according to our estimates). However, the occupational premium component of the skill premium is too low, especially the routine premium, to allow the composition effect to dominate the within effect related to the displacement effect of [Acemoglu and Restrepo \(2019\)](#). Indeed, in their model, the size of the between component depends on the wage differentials between occupation groups.

Overall, the medium-skill premium is more related to a premium within occupations rather than an occupational premium. This in line with [Delaney et al. \(2020\)](#), who show that more skilled workers have much higher wages within occupations relatively to less skilled workers.

Our results are also in line with the findings of [Hunt and Nunn \(2019\)](#), who show that wage inequalities are only weakly related to the occupational structure as wage dispersion within occupation is very high.

In Appendix Section 3.B, we examine the role of the spatial reallocation of workers across the U.S. [Autor \(2020\)](#) shows that since the beginning of the 1980s, the most skilled workers have a tendency to move from rural to urban areas, while it is the opposite for the least skilled ones. Our objective is to estimate the impact of this phenomenon on the observed dynamics of the medium-skill premium as wages, notably for low-skilled, are different across

areas as Autor (2020) shows (urban premium). Using a similar strategy to the one used in this section, we show that most of the decrease in wages occurs within CZ, meaning that the process reallocation across the U.S. territory does not play a significant role in the decrease of the medium-skill premium.

3.3.3 The role of age

In this section, we investigate in details some mechanisms through which younger workers have experienced a stronger decline of the medium-skill premium with respect to the rest of the population. We first use data from the PSID, which allow us to study the pattern of the medium-skill premium at the individual level and understand if the dynamics we observe for the younger individual are due to a lower skill premium of new entrants or a variation of the medium-skill premium over time within individual. More formally, we will estimate:

$$\log(w_{it}) = \beta_{1,t}HS_i + \beta_{2,t}MS_i + X_{it}\Gamma + \delta_t + \rho_i + \epsilon_{it} \quad (3.6)$$

where all the variables are the same as before, with the inclusion of ρ_i an individual fixed-effect, which will allow us to capture unobservable characteristics at the worker level. Figure 3.12 displays the estimated coefficients. As we use a different dataset than before, we also display the estimated coefficients for the standard wage regression without individual fixed effects (which corresponds to the medium-skill premium net of individual characteristics).²¹ When controlling for individual fixed effects, an interesting pattern emerges: we can still observe the same increase of the medium-skill premium we observe at the beginning of the period without individual fixed effects. However, we do not observe the decrease we see for the medium-skill premium starting at the beginning of the 2000s. Instead, the premium seems to be roughly constant or even slightly increasing since the mid 1990s until the end of the period. This seems to suggest that the sharp decrease of the medium-skill premium observed for the young worker group is not due to a decrease of the premium within young individuals, but rather to new entrants who enter the labor market with a lower premium than previous entrants.²²

21. We can note two differences compared to the Census data. First, the series corresponding to the standard wage equation are more noisy, due to the much smaller sample size relatively to the U.S. Census. In addition, the timing of the decrease is slightly different, since it began in the mid 1990s. However, the levels are close and the same pattern can be observed.

22. Appendix Figure C8 plots the evolution of the ratio of the average individual fixed-effect by year and skill-group. We can observe that the ratio was increasing until the mid 1990's, while it is mostly decreasing

Figure 3.12 – Evolution of the medium-skill premium, net of individual fixed effect



Source: PSID data from 1980 onward. Bottom and top 2.5% of the wage distribution trimmed.

We then directly look at the level and evolution of the medium-skill premium for each birth-cohort and the occupational distribution by birth-cohort over time. Due to its small sample size, the PSID data are not suitable for this exercise, so we will again turn to the Census data. We will focus on workers born between 1943 and 1992, and we divide them into five groups: workers born between 1943 and 1952, the ones born between 1953 and 1962, the ones born between 1963 and 1972, the ones born between 1973 and 1982 and finally the ones born between 1983 and 1992. We then compute the medium-skill premium and the occupational shares for each cohort.

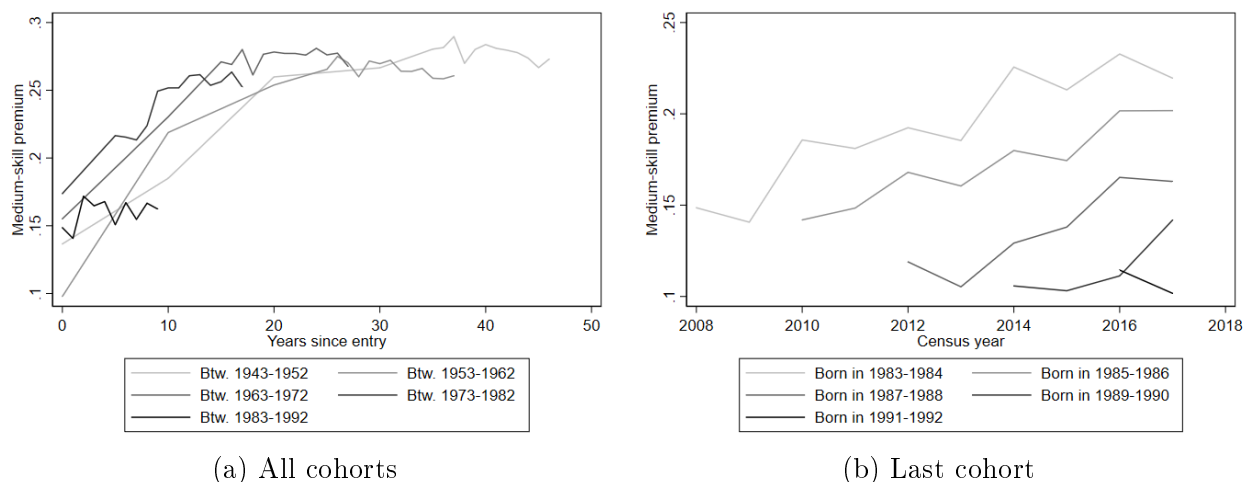
Results are displayed in Figure 3.13 for the cohort specific medium-skill premium and in Figures 3.14 and 3.15 for the low- and medium-skilled workers respectively for cohort specific occupations.²³ For the ease of comparison, we make all series begin at the same point, thus the x-axis represents the evolution over time since the cohort entered the labour market. In other words, we superpose the birth-cohort variables at the same age in order to compare

since, and thus mostly track the variations of the medium-skill premium despite the important volatility in the PSID data.

23. We provide in Appendix Figures C9 and C10 the corresponding figures for high-skilled workers.

the level and trajectories of the cohort at the same point in their life cycle.

Figure 3.13 – Evolution of the raw skill premium by birth-cohort

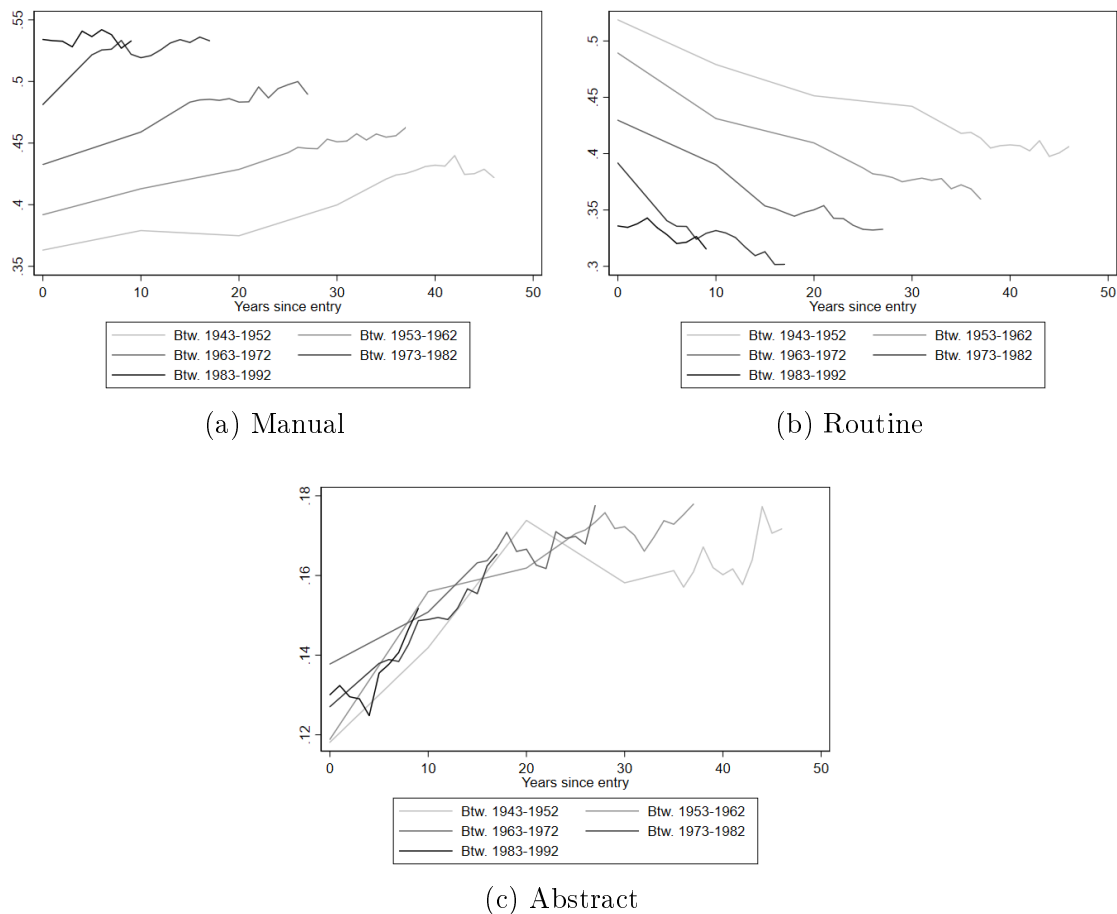


Source: Census IPUMS 1% state sample for 1970, Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. The data used include all working individuals aged 25 and more born after 1943, excluding self-employed, part-time, part-year workers and those employed by the military.

Focusing first on Figure 3.13a, we can observe that the dynamics of the medium-skill premium are similar across birth-cohorts and that the medium-skill premium is increasing over time, except for the most recent one which is characterized by a flat premium over time. It is worth noting that the most recent cohort entered the labor market around the 2008 crisis. This pattern hides some important heterogeneity. Figure 3.13b disaggregates the last cohort into smaller groups. Here, the cohorts are not aligned based on their entry in the labor market. We can see that for the younger cohort each sub-cohort enters the labor market with a relatively lower premium relatively to the previous one but the premium is still increasing over the life cycle suggesting that the flat premium of the younger cohort of panel A is due to an acceleration of the decrease of the premium at entry on the labor market for each sub-cohort. This pattern is consistent with the results obtained using the PSID data. The evolution of the medium-skill premium over the life cycle is quite similar across cohorts and is increasing, however the premium is translated downward for each new cohort among the most recent cohort. This is consistent with the recent decrease of the medium-skill premium in the population and more particularly among the young workers. For the older cohorts, particularly the 1963-1972 cohorts and the 1973-1982 cohorts, the medium skill premium curve translate upward which means that those cohorts have a higher premium than the

previous ones at every point in their life cycle. This start to change 15 years after the entry on the labor market for the 1973-1982 cohort which start to experience a lower premium than the 1963-1972 cohorts at the same stage of their life cycle. This coincides with the period during which the medium-skill premium starts to decrease. Also, we can see that there is a higher return from experience for the medium- relatively to the low-skilled workers since the premium is increasing over the life cycle for every cohorts (even the recent 1983-1992 one when looking at sub-cohorts).

Figure 3.14 – Evolution of low-skilled workers’ occupations by birth-cohort

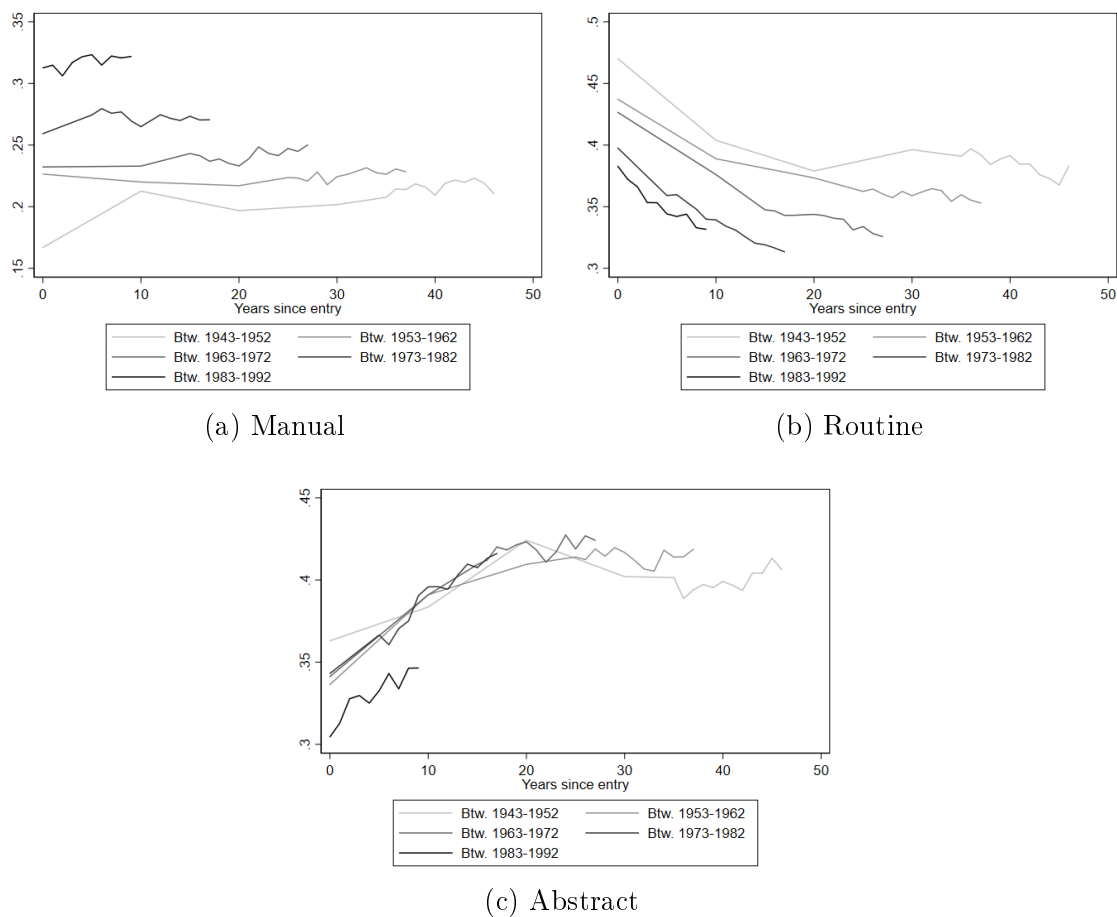


Source: See Figure 3.13.

We then focus on occupations. We can observe that the occupational dynamics by birth cohorts are really different depending on the skill category. Focusing first on low-skilled workers in Figure 3.14, we can observe three important patterns. First, birth-cohorts seem to enter more in manual occupations and less in routine occupations over time. This occupa-

tional downgrading at entry occurs for all birth-cohorts, suggesting a continuous occupational downgrading over generations. Second, the share of manual jobs increases and the share of routine decreases sharply within birth-cohorts, suggesting an occupational downgrading and reallocations over the life cycle. Third, the share of abstract occupations is roughly the same for all birth-cohorts and is quite low. Surprisingly, this share increases within each birth-cohort in some similar proportions suggesting that some of the low-skilled are able to reallocate and climb the occupational ladder over their life cycle and that this upward mobility did not change much over time.

Figure 3.15 – Evolution of medium-skilled workers’ occupations by birth-cohort



Source: See Figure 3.13.

Focusing next on medium-skilled workers in Figure 3.15, some striking patterns emerge. First, similarly to the low-skilled workers, workers from the most recent cohort seem to enter more in manual occupations than their elders. However, contrary to the low-skilled workers,

the series for manual occupations are mostly flat. This indicates that there is not much reallocation from other occupations to manual occupations within the life cycle, contrary to the low-skilled workers. Second, we can observe that the most recent cohort hold less abstract jobs, which corresponds to workers who entered close to or during the 2008 crisis. This is entirely related to a much lower proportion of medium-skilled workers that enter in abstract occupations. The occupational dynamics over the life cycle are then quite similar across all cohorts: we can observe a reallocation within the life cycle from routine to abstract for the medium-skilled and this upward mobility is quite similar for all cohorts over their life cycle. This is interesting when considering one of our stylized fact highlighted before: the fact that the share of abstract occupations for medium-skilled was stable over time hides very different patterns depending on the age group, with younger worker struggling to obtain these jobs. Third, similarly to the low-skilled, the proportion of medium-skilled holding a routine occupation when entering the labor market decreases sharply over birth-cohorts. This is in line with our previous results for the cohort specific medium-skill premium: the variation we observe in the occupational shares for the younger workers are due to an occupational downgrading at the entry of the labor market, impeding their wage rate over the long run. They tend to occupy more manual jobs due to a strong decrease in the proportion of routine and abstract occupations they occupy when they enter the labor market. This pattern is particularly strong over the recent period explaining the occupational convergence with the low-skilled on manual occupations documented previously, and which induced negative wage variations within occupations due to the displacement effect mentioned earlier.

3.4 Identification strategy and regression results

3.4.1 Identification strategy

We saw previously that medium-skilled workers seem to experiment an occupational convergence with low-skilled workers since the 2000s: less medium-skilled are abstract or routine and more have manual occupations, with respect to the low-skilled workers and thus, it triggered a negative wage variation first through the displacement effects, within occupations, and second through a composition effects across occupations. We will estimate the impact of the change in the structure of employment of the medium-skilled with respect to the low-skilled on the medium-skill premium between 1980 and 2010, at the local labor market level, for workers aged between 25 and 34 years old. We focus on the 722 CZs composing the mainland of the U.S., as in [Autor and Dorn \(2013\)](#). We have seen that they are the most affected

group and seem to drive most of the observed variation of the medium-skill premium. In the same spirit as [Bosquet et al. \(2020b\)](#), as the Census data is at the individual level while the change in employment and medium-skill premium is observed at the CZ level, we will use a two-step strategy in order to take into account individual characteristics of the workers. First, we regress individual annual log wages w_i on individual demographic characteristics, for each education group g separately:

$$w_{i \in g} = X_i \beta_g + \delta_t + \epsilon_i \quad (3.7)$$

where X_i includes gender and race dummies, age and its square.²⁴ In addition, we will also estimate the same equation with industry and occupation fixed effects, in order to capture only within occupations and industries wage deviation, as we have seen that an important part of the variation in the skill premium happens within occupations and industries. We want to understand if the change in the relative occupational structure across skill groups can also explain the pattern of the medium-skill premium within each occupations as a result of the displacement effect mentioned earlier and not only through composition effects. Then, we average these residuals over each CZ c and age-group a for each year and education group g $\omega_c = \frac{1}{N_c} \sum_{i \in c} \hat{\epsilon}_i$. The medium-skill premium net of individual characteristics thus corresponds to the average residuals of medium-skilled workers minus the average residuals of low-skilled workers. We then estimate:

$$\Delta MSP_{ct} = \Delta DOS_{ct} \Phi + \Delta Z_{ct} \theta + \delta_t + \epsilon_{ct} \quad (3.8)$$

where MSP_t corresponds to the medium-skill premium inside a CZ for workers aged 25-34 years old, Z_{ct} is a vector of time-varying CZ controls calculated on the whole population, including the shares of the different skills and the share of foreign born worker, and δ_t is a time fixed effect. $DOS_{c,t}$ is our variable of interest: it corresponds to the difference in occupational shares between the medium- and low-skilled workers aged between 25 and 34

24. As a robustness, we also estimated this equation by age-group instead of the full population, results are available in Appendix Table D1. In addition, we alternatively estimated this equation using year-specific regressions in Appendix Table D2. Moreover, we also provide regressions where we directly use the raw medium-skill premium at the local labor market level without controlling for individual characteristics in Appendix Table D3. Also, in Appendix Table D6, we provide a robustness test using the share of the CZ in the national population. Finally, we also provide robustness on the sample, with the inclusion of the year 1970 and the 19 CZs composing Alaska and Hawaii in Appendix Tables D4 and D5, respectively. Results are qualitatively and quantitatively similar in all cases.

years old. Those occupational shares will be the manual, routine and abstract shares. This variable captures the occupational divergence and convergence at the CZ level that we previously documented at the national level. In addition, we also estimate a model where we include both the differences in routine and abstract occupations. Finally, as mentioned before, medium-skilled workers occupy massively routine cognitive occupations and the share of those occupations decreased sharply since the 2000s. We will provide some specifications in which we decompose the difference in routine shares between low- and medium-skilled workers in two terms, the differences in routine cognitive and routine manual shares between low- and medium-skilled workers. This specification will allow us to capture the changing relative occupational distribution between the low- and medium-skilled workers. This model is expressed in variation, but we will also estimate this model in level with additional commuting zone fixed effects as an alternative specification. We control for the supply of medium- and high-skilled workers as we have already seen that it has probably played a role in the dynamics of the skill-premiums over time. Moreover, as it is standard in this literature, we include the variations in the proportion of foreign-born individuals in a CZ as this type of worker may have lower bargaining power in average and often works in the manual service sector (see [Autor and Dorn \(2013\)](#)).

Then, we will try to understand the forces behind the massive reallocation of medium-skilled workers from routine and abstract occupations to manual ones. To do so, we will estimate the effect of the interplay between the relative number of jobs in an abstract or routine occupation relatively to the skill supply, on the probability of having an abstract, routine or manual job. Formally, we will estimate:

$$\Delta OP_{ct} = \beta_1 \Delta RAS_{ct} + \beta_2 \Delta RRS_{ct} + \Delta Z_{ct} \theta + \delta_t + \varepsilon_{ct} \quad (3.9)$$

where OP_{ot} corresponds to the probability of holding an occupation o for young medium-skilled workers, proxied by the share of this occupation among the young medium-skilled workers. Those occupations can be manual, routine or abstract. RAS_{ct} corresponds to the relative abstract supply for young medium-skilled workers, i.e. the number of abstract jobs minus the number of high-skilled workers, divided by the number of medium-skilled workers. Similarly, RRS_{ct} is the relative routine supply for young medium-skilled workers, i.e. the number of routine jobs minus the number of medium-skilled workers, divided by the number of low-skilled workers. These two variables will allow us to capture the changing labour market opportunities in terms of the availability of routine and abstract jobs and the competition

for those jobs. We have in mind a hierarchical model of skill allocation in occupations. The variable RAS_{ct} captures the fact that high-skilled workers are allocated in abstract occupations and the remaining abstract occupations are available for medium-skilled. An increase in the supply of high-skilled workers (or a decrease in abstract occupations), everything else equal decreases medium-skilled workers opportunities of having an abstract occupation. An increase in the supply of medium-skilled decreases the probability that a medium-skilled can obtain an abstract occupation. We have shown that the quantity of abstract occupations increases at a lower rate than the supply of high- and medium-skilled workers. The same logic is at work with RRS_{ct} : a decrease in the number of routine occupations relatively to the medium-skill supply, decreases the probability that a medium-skilled worker has a routine occupation. However, a lower quantity of low-skilled workers can mitigate this effect as low-skilled workers compete with medium-skilled workers for routine occupations. We have shown that the quantity of routine occupations decreased sharply during the last decades along with a strong increase in the supply of medium-skilled workers.²⁵

3.4.2 Regression results

Table 3.3 presents our results for our medium-skill premium specification presented in equation 3.8. Specifications are weighted by the share of the CZ in the national 25-34 years old population. Results for the baseline residuals are displayed in columns 1 to 5 and the results for the residuals net also of occupation and industry fixed-effects are displayed in columns 6 to 10. Year fixed-effects are included in all regressions and CZ fixed-effects are included in the level model. Stacked-differences and level models are respectively in Panel A and B.

Focusing first on Panel A, we can see that the coefficient for the variation in the difference of manual shares between medium- and low-skilled workers is negative and significant. This is in line with the overall pattern of the medium-skill premium. As we saw in Figure 3.9, before the 2000s the difference of manual shares between medium- and low-skilled workers (which is negative as low skilled has more manual jobs than medium skilled) tends to decrease (occupational divergence) which makes the medium-skill premium increases according to our estimates. After 2000s, this difference tends to increase (occupational convergence) which implies a decrease in the medium skill premium according to our estimates. The difference in the shares of routine is not statistically significant in column 2. However, as

²⁵. Similarly to the first set of estimates, we will also provide robustnesses including 1970, Alaska and Hawaii and using the share of the CZ in the national population in Appendix Tables E1, E2 and E3, respectively.

Table 3.3 – First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only

	Baseline resid.					Resid. net of occ. and ind. FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Stacked differences										
Δ Diff. of man. sh.	-0.218 ^a (0.057)					-0.215 ^a (0.057)				
Δ Diff. of rout. sh.	0.096 (0.061)		0.171 ^b (0.064)			0.091 (0.061)		0.166 ^b (0.064)		
Δ Diff. of abst. sh.			0.230 ^a (0.065)	0.290 ^a (0.072)	0.291 ^a (0.072)			0.231 ^a (0.066)	0.289 ^a (0.073)	0.290 ^a (0.073)
Δ Diff of rout. cog. sh.			0.140 ^c (0.070)					0.135 ^c (0.070)		
Δ Diff of rout. man. sh.			0.233 ^b (0.095)					0.230 ^b (0.095)		
Δ sh. of high skill	-0.340 ^b (0.139)	-0.389 ^a (0.145)	-0.291 ^c (0.153)	-0.306 ^b (0.147)	-0.323 ^b (0.151)	-0.317 ^b (0.138)	-0.364 ^b (0.144)	-0.267 ^c (0.150)	-0.282 ^c (0.146)	-0.299 ^c (0.150)
Δ sh. of med. skill	0.184 (0.148)	0.154 (0.150)	0.201 (0.148)	0.200 (0.146)	0.194 (0.146)	0.152 (0.148)	0.123 (0.150)	0.169 (0.149)	0.168 (0.147)	0.163 (0.147)
Δ sh. of foreign	0.480 ^a (0.082)	0.543 ^a (0.085)	0.497 ^a (0.082)	0.467 ^a (0.082)	0.470 ^a (0.082)	0.536 ^a (0.096)	0.599 ^a (0.102)	0.552 ^a (0.095)	0.523 ^a (0.094)	0.526 ^a (0.095)
R ²	0.13	0.10	0.12	0.13	0.13	0.14	0.12	0.14	0.15	0.15
Panel B: Level										
Diff. of man. sh.	-0.225 ^a (0.047)					-0.224 ^a (0.047)				
Diff. of rout. sh.	0.062 (0.047)		0.162 ^a (0.051)			0.059 (0.047)		0.160 ^a (0.050)		
Diff. of abst. sh.			0.254 ^a (0.055)	0.320 ^a (0.061)	0.321 ^a (0.061)			0.256 ^a (0.057)	0.322 ^a (0.063)	0.323 ^a (0.062)
Diff. of rout. cog. sh.			0.182 ^a (0.064)					0.180 ^a (0.062)		
Diff. of rout. man. sh.			0.127 ^b (0.058)					0.123 ^b (0.058)		
Sh. of high skill	0.066 (0.106)	0.035 (0.109)	0.154 (0.103)	0.124 (0.106)	0.129 (0.105)	0.104 (0.110)	0.073 (0.114)	0.193 ^c (0.108)	0.164 (0.110)	0.168 (0.109)
Sh. of med. skill	0.151 (0.127)	0.104 (0.131)	0.119 (0.122)	0.151 (0.124)	0.153 (0.121)	0.106 (0.130)	0.059 (0.134)	0.075 (0.128)	0.106 (0.128)	0.108 (0.125)
Sh. of foreign	0.332 ^a (0.090)	0.377 ^a (0.097)	0.321 ^a (0.091)	0.310 ^a (0.088)	0.307 ^a (0.087)	0.352 ^a (0.110)	0.397 ^a (0.117)	0.340 ^a (0.110)	0.329 ^a (0.107)	0.325 ^a (0.106)
R ²	0.55	0.54	0.55	0.56	0.56	0.58	0.57	0.58	0.58	0.58

Notes: Standard errors clustered by state between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. Each regression is weighted by the share of the CZ in the national 25-34 years old population. 2888 observations (722 CZ × 4 periods) in Panel A, 3610 observations (722 × 5 periods) in Panel B.

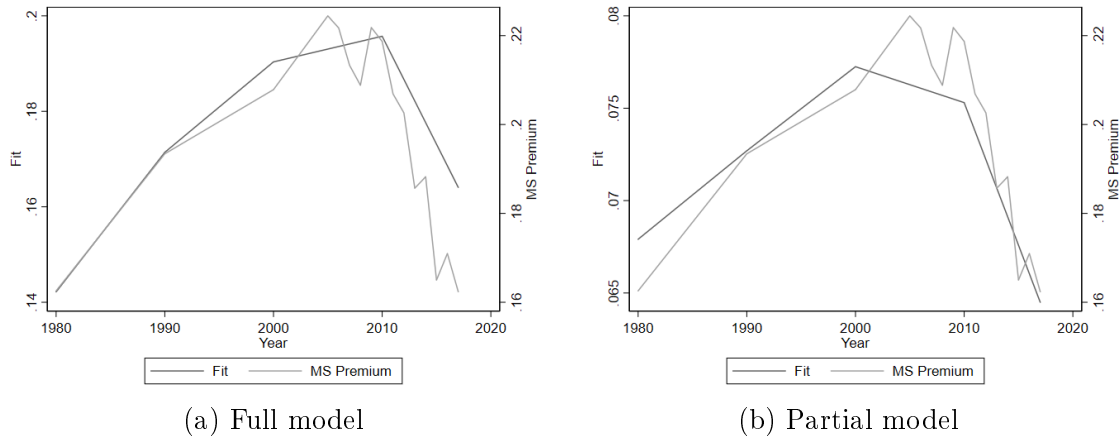
we can see in column 4, when both the differences in routine and abstract occupations are included, both are positive and statistically significant. As we saw in Figure 3.9, the difference of abstract (which is positive since medium skilled has more abstract jobs than low skilled) shares between medium- and low-skilled workers was quite stable until the 2000s

and then decreases sharply (occupational convergence in abstract jobs). This decrease contributes to explain the recent decrease in the medium-skill premium according to our model. For the difference in routine shares between medium- and low-skilled workers, we saw in Figure 3.9 that it increases until the beginning of the 2000s (occupational divergence) and then stabilizes (or slightly decreases) meaning that before the 2000s, the low-skilled experienced more occupational downgrading from routine to manual occupations and that after the 2000s, both skill groups experienced a similar occupational downgrading from routine to manual occupations. Thus, according to our estimate, this pattern contributes to explain the increase in the medium skill premium before the 2000s. After the 2000s, the decrease is more related to a strong occupational downgrading of the medium-skilled from the abstract occupations. Finally, when decomposing the share of routine into a routine cognitive and manual component, we can see that both subcategories have a similar negative effect on the medium-skill premium, even though the effect of the routine cognitive category is greater. This is not surprising as we saw in Figure 3.9 that the relative stability in the difference in the routine shares between the two skill groups hides a strong heterogeneity between routine cognitive and routine manual. Indeed, routine cognitive tends to be disproportionately concentrated among the medium-skilled workers and the difference in the shares between medium- and low-skilled workers in those occupations decreases sharply after the 2000s (occupational convergence) as the destruction of those occupations accelerated after the 2000s. The destruction of those occupations seems to affect more the employment opportunities of the medium-skilled after the 2000s. According to our estimate, it thus contribute to the decrease in the medium-skill premium. When looking at the results for residuals net of industry and occupations, which capture wage deviations inside industries and occupations, we can see that the results are quantitatively and qualitatively similar. This confirms the conclusions of our decomposition exercises done previously, i.e. that an important part of the decrease in the medium-skill premium occurs within industries and occupations. The change in the occupational structure across skill groups can explain within occupations variation in the medium-skill premium, consistently with the displacement effect. Additionally, the level model also gives quantitatively and qualitatively similar results.

Finally, we compare the predictions of our empirical model to the observed dynamics of the medium-skill premium. Results are presented in Figure 3.16.

Figure 3.16a represents the fit of our model using all the estimated coefficients and Figure 3.16b represents the fit using only the occupational shares, our variables of interest. The fit (left axis) is superimposed on the raw medium skill premium (right axis). The fit corresponds to the weighted average predictions at the CZ level calculated from coefficients from Table

Figure 3.16 – Model’s prediction relatively to the medium-skill premium



Source: Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. The fit corresponds to the weighted average predictions at the CZ level calculated from coefficients from Table 3.3 Panel B, column 5.

3.3 Panel B, column 5. Our model seems to qualitatively predict the overall dynamics of the medium-skill premium. Quantitatively, our variables of interest (panel B) predict around 25% of the variation of the medium-skill premium. This is likely to be due to the fact that our identification relies on deviation of the occupational shares at the CZ level with respect to the national variation (year fixed effects) and that the skill premium is a general equilibrium variable which is determined beyond the sole CZ labor market equilibrium.

As a whole, those results provide evidence for the mechanism we have in mind using variations in the occupation shares by skill at the CZ level: the decrease in the medium-skill premium seems to be related to a decrease in the demand for medium-skilled workers in high-paying occupations relatively to low-skilled individuals and the corrolary increase in the share of low-paying manual occupations for this population relatively to the low-skilled. More precisely, the strong decrease in abstract jobs after the 2000s for the medium-skilled individuals relatively to the low-skilled (occupational convergence) seems to be significantly associated with a decrease in the medium-skill premium over this period. On the other hand, before the 2000s, the decrease in the proportion of routine occupations seems to have affected more low-skilled workers (occupational divergence) and contributed to the increase in the medium-skill premium during this period. The decrease seems to also occur within industries and occupations and is not only related to a composition effect, consistent with the model of task-biased technological change and the displacement effect highlighted in those models.

We now look at the results concerning the probability of occupying an occupation for a young medium-skilled worker. Results are displayed in Table 3.4. Similarly to the previous table, stacked-differences and level model are respectively in panel A and B.

Table 3.4 – OLS: Occ. Share, MS only, age-specific: 25 – 34

	Rout. sh.	Abst. sh.	Man. sh.
	(1)	(2)	(3)
Panel A: Stacked differences model			
Δ (Abst. - HS / MS)	-0.108 ^a (0.021)	0.356 ^a (0.023)	-0.248 ^a (0.027)
Δ (Rout. - MS / LS)	0.163 ^a (0.021)	0.006 (0.022)	-0.169 ^a (0.019)
Δ sh. of high skill	-0.300 ^a (0.088)	0.408 ^a (0.083)	-0.108 (0.110)
Δ sh. of med. skill	0.468 ^a (0.098)	-0.115 (0.081)	-0.353 ^a (0.094)
Δ sh. of foreign	-0.100 ^c (0.059)	0.210 ^a (0.064)	-0.111 ^c (0.056)
R ²	0.21	0.32	0.27
Panel B: Level model			
(Abst. - HS / MS)	-0.063 ^a (0.019)	0.314 ^a (0.019)	-0.251 ^a (0.020)
(Rout. - MS / LS)	0.150 ^a (0.017)	0.013 (0.017)	-0.163 ^a (0.013)
Sh. of high skill	-0.272 ^a (0.061)	0.251 ^a (0.060)	0.020 (0.062)
Sh. of med. skill	0.294 ^a (0.096)	-0.052 (0.060)	-0.242 ^a (0.080)
Sh. of foreign	-0.091 (0.061)	0.198 ^a (0.039)	-0.107 ^c (0.054)
R ²	0.71	0.71	0.83

Notes: Standard errors clustered by state between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. Each regression is weighted by the share of the CZ in the national 25-34 years old population. 2888 observations (722 CZ \times 4 periods) in Panel A, 3610 observations (722 \times 5 periods) in Panel B.

Focusing first on the probability of occupying a routine occupation for a medium-skilled worker, we can see that the decrease in the quantity of abstract occupations relatively to the supply of high- and medium-skilled workers has a positive effect on the probability of holding a routine or a manual occupations and a negative effect on the probability of holding an abstract occupation. This suggests that workers reallocate down the wage distribution. Note that the impact is much stronger for the probability of having a manual than the probability of having a routine. This is consistent with the stylized fact presented earlier: as

the quantity of routine jobs decreases sharply, medium-skilled workers reallocate in manual occupations. Overall, this is consistent with the idea that medium-skilled workers struggle to access abstract jobs, as they compete with high-skilled workers whose quantity have increased at a higher rate than the quantity of abstract occupations. The effect of the decrease in the quantity of routine jobs relatively to the supply of medium- and low-skilled workers does not have any effect on the probability of having an abstract job, which is consistent with the fact that workers in routine occupations do not reallocate upward in the distribution. The impact of this decrease is negative on the probability of having a routine occupation and positive on the probability of having a manual occupation which again, suggests a reallocation down the wage distribution for the medium-skilled workers. The results concerning the model in level of Panel B are qualitatively and quantitatively similar. Overall, those results confirm that medium-skilled workers reallocate progressively down the wage distribution, thus creating a downward wage pressure for the medium-skilled individuals on the occupations where they reallocate.

3.5 Conclusion

This paper documents an important evolution of the labor market over the last two decades: a sharp decrease in the medium-skill premium which diverges from the high-skill premium since the 2000s. We show that the decrease is mostly concentrated among young workers and that an important part of the decrease occurs within occupations and industries. This pattern coincides with some important changes in the occupation of the low- and medium-skilled workers. During the is period, if the low-skilled tends to reallocate from the routine to manual occupations (both when entering the labor market and during the life cycle), the medium-skilled experienced a downgrading both from the routine occupations (mostly in cognitive routine occupations in which they were over represented, and which were destroyed at a higher rate during the last two decades) and more recently from abstract occupations due to the increasing competition with high-skilled workers for those occupations. Those two joint forces lead to a bigger increase of manual occupation among the medium-skilled relatively to the low-skilled since the 2000s, which coincides with the observed decrease of the medium-skill premium during this period. Before the 2000s, the medium-skilled were relatively spared. The rate of routine destruction was stronger for manual routine and the low-skilled were more affected as a result. Also, the decrease in the proportion of abstract occupations for medium-skilled workers really started to decrease after the 2000s. The medium-skill premium increased during this period as a result. We then

look at the change in the occupational structure by skills at the CZ level and the basic determinants of the occupational structure. Results seem to confirm our findings at the national level. The pattern of the occupational structure at the CZ level seems to play an important role in the decrease in the demand for skill and on the pattern of the medium-skill premium within occupations and industries.

The evidence presented in this paper is quite descriptive and the paper does not address the question of the fundamental forces behind the drastic change in occupational structure by skill. A study of the technological and institutional forces such as trade openness, behind this massive reallocation of the medium-skilled would help to have a better understanding of this phenomena. We leave this question for future research.

3.A Additional data: IPUMS March Current Population Survey

The March Current Population Survey (CPS) data also comes from the IPUMS website. We use all waves from 1980 to 2018 for the stylised facts presented in Section 3.2 of the paper and in Appendix Figure C2. As for the Census / American Community Survey, we construct three samples for the different exercises. For all of them, we restrict the dataset to non-military individuals aged between 16 and 64 years old, following [Acemoglu and Autor \(2011\)](#). National skill shares depicted in the graphs, for instance, are calculated over this working age population. To calculate occupational shares at the national level, we also drop non-working individuals. Wages are annual income of workers, during the previous year. Concerning top-coded values, we apply the same methodology as in [Acemoglu and Autor \(2011\)](#): all top-coded values are multiplied by 1.5. Another retreatment of top-coded occupations is provided in the IPUMS data, but the choice of the retreatment does not impact the results in any way.

3.B The role of spatial reallocation

We now examine the role of the spatial reallocation of workers across the U.S. [Autor \(2020\)](#) shows that since the beginning of the 1980s, the most skilled workers have a tendency to move from rural to urban areas, while it is the opposite for the least skilled ones.²⁶ If wages for similar workers are different across areas, similarly to the composition effects mentioned concerning individual characteristics, it is possible this reallocation of workers affected the medium-skill premium in a significant way. In other words, the medium-skill premium can change within each area or can change because of a change of the weight of each area across different skill groups. In order to disentangle those two channels, we will provide two types of evidences, similarly to the exercises concerning the role of occupations and industries. First, we will estimate a modified version of equation 3.2 where we replace occupation or industry fixed effects by CZ fixed effects, in order to capture the the impact on wages of the

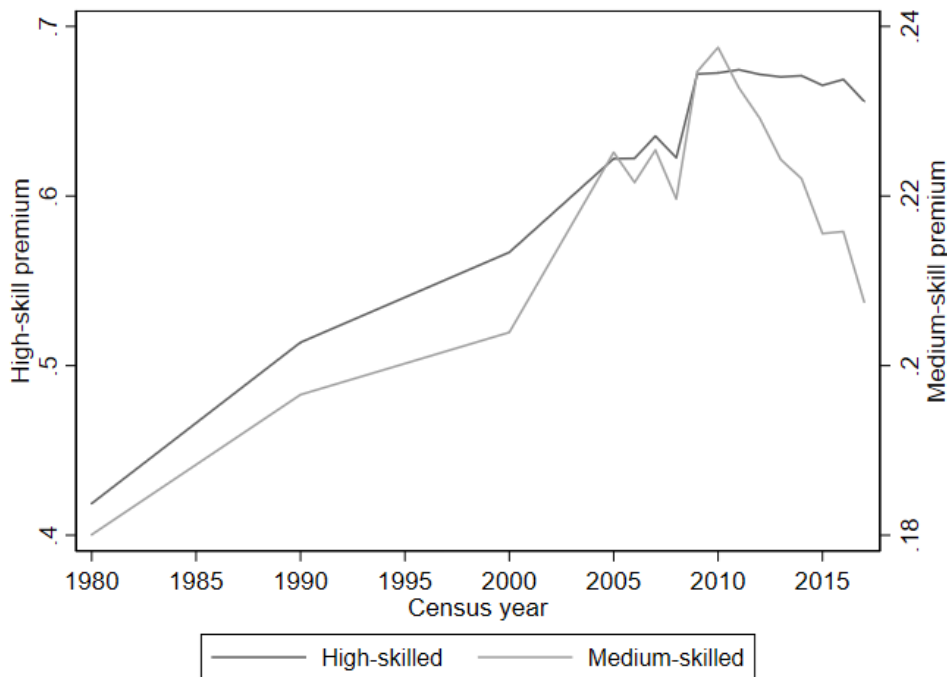
26. His argument is twofold: first, the economic opportunities of low- and medium-skilled workers deteriorated, due to the polarization process, as they progressively reallocate from middling routine occupations to low-paying manual occupations as mentioned previously, and in addition, the premium associated of working in an urban area decreased significantly for those workers.

reallocation of workers across CZ:

$$\log(w_{it}) = \beta_{1,t}HS_i + \beta_{2,t}MS_i + X_{it}\Gamma + \delta_t + \lambda_c + \epsilon_{it} \quad (3.10)$$

where all the variables are the same as before, and λ_c is a CZ fixed effect. In addition, we will decompose the wage variation for each skill groups in two terms, a between and a within component, similarly to the exercise presented in the previous section, except that the decomposition will be based on CZ cells instead of occupation or industry ones. Thus, the first term will capture the reallocation of workers across CZs, while the second term will capture the wage variations happening within each CZs.

Figure B1 – Evolution of the high and medium-skill premium, net of CZ effects



Sources: 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. Coefficient obtained from estimating equation 3.10. The data used include all working individuals aged 25 and more born after 1943, excluding self-employed, part-time, part-year workers and those employed by the military.

Figure B1 displays the estimated coefficients from equation 3.10. We can see the levels are slightly lower, but the variation is almost identical (2.9 p.p. decrease when not controlling, 3 p.p. decrease when controlling for CZ fixed effects), meaning that the reallocation of workers

Table B1 – Decomposition of the raw medium-skill premium, by CZ

	80-05	05-17	80-17
tot. W. var. LS	.0214	.2333	.2547
tot. W. var. MS	.1269	.1909	.3178
tot. MSP var.	.1055	-.0424	.0631
Within LS	.036	.236	.27
Within MS	.144	.194	.338
Within: tot	.108	-.042	.068
Between LS	-.015	-.003	-.016
Between MS	-.017	-.003	-.02
Between: tot	-.002	0	-.004

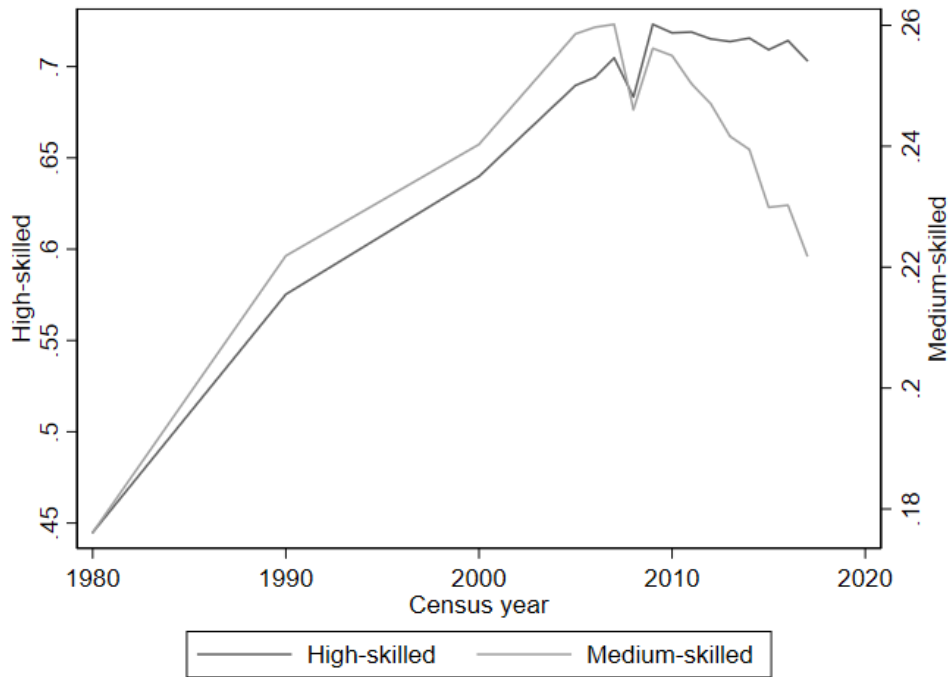
Sources: Census IPUMS 5% samples for 1980 and Census American Community Survey for 2005 and 2017.

across commuting zones does not seem to play a significant role neither in the wage level nor the wage variations over time.

This observation is confirmed by the results of the decomposition displayed in Table B1. The within component is responsible for nearly all the variation observed in both sub-periods, meaning that even though low and- medium-skilled workers seem to leave urban areas in which they are generally better paid, this does not seem to affect the overall pattern of the medium-skill premium whose variation is almost entirely driven by variations of the premium within CZ.

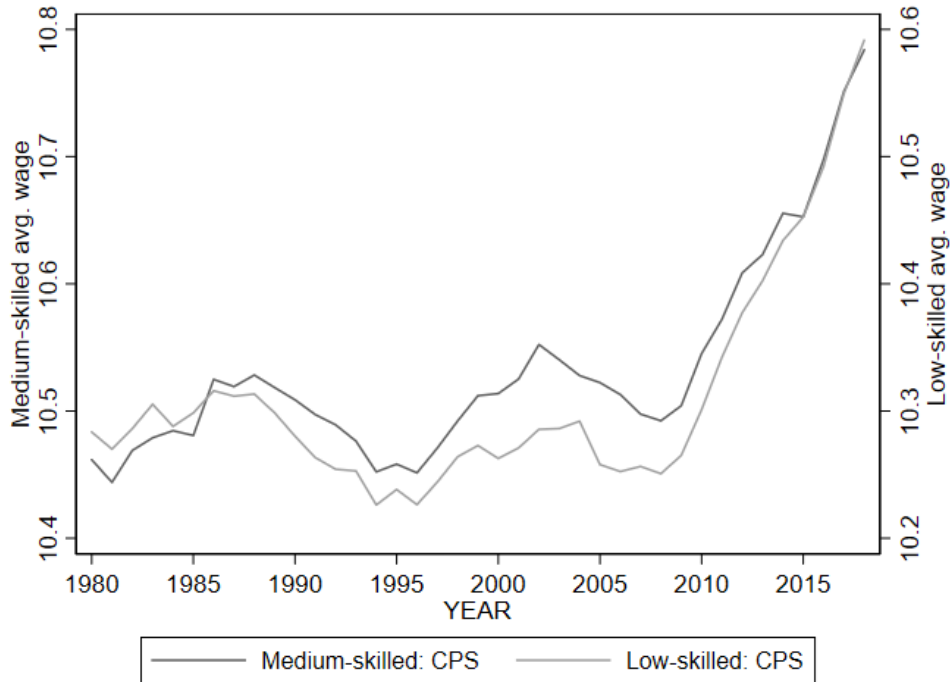
3.C Additional results

Figure C1 – Evolution of the raw high- and medium-skill premium



Notes: High- and medium-skill premiums calculated as the average log wage of high- and medium-skilled workers minus the average log wage of low-skilled workers. Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. The data used include all working individuals aged 25-64, excluding elf-employed, part-time, part-year workers and those employed by the military.

Figure C2 – Evolution of the average wages by educational group: CPS data



Source: March CPS data for years 1963-2017. can Community Survey for 2005-2017. Coefficient obtained from estimating equation 3.10. The data used include all working individuals aged 25 and more born after 1943, excluding self-employed, part-time, part-year workers and those employed by the military.

Table C1 – Coefficients and descriptive statistics.

	Coeff.	Low-skilled			Medium-skilled		
		2005	2010	2017	2005	2010	2017
Male	0.288	0.617	0.610	0.637	0.528	0.509	0.528
Age	0.081	39.965	41.560	41.644	40.344	41.279	41.020
Age ²	-0.001	1736.370	1870.370	1893.883	1758.025	1843.362	1836.048
White	0.100	0.719	0.724	0.697	0.770	0.763	0.734
Black	-0.053	0.128	0.126	0.135	0.130	0.139	0.149

Sources: Census IPUMS 5% samples 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. Coefficients obtained from estimating equation 3.1. The data used include all working individuals aged 16-64, excluding self-employed, part-time, part-year workers and those employed by the military.

Figure C3 – Age-specific medium-skill premium



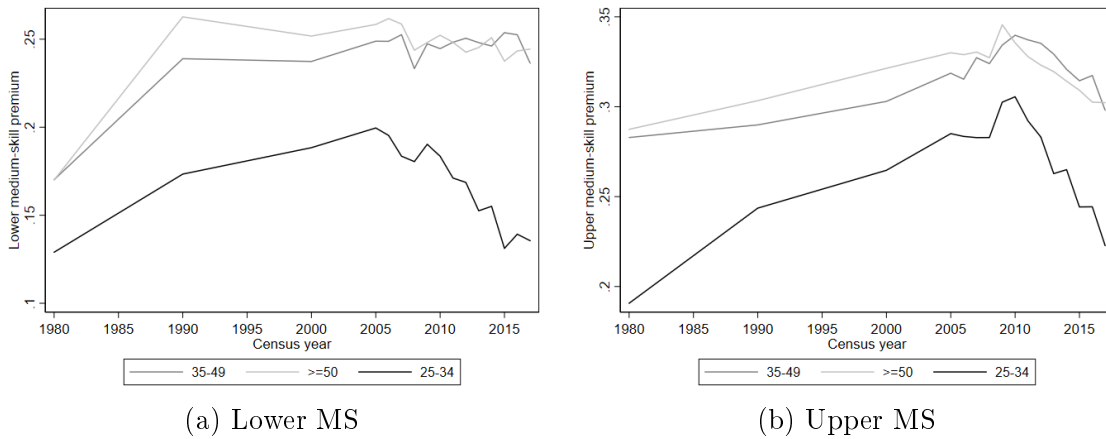
Source: Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. The data used include all working individuals aged 25 and more born after 1943, excluding self-employed, part-time, part-year workers and those employed by the military.

Table C2 – Decomposition of the raw medium-skill premium on 77 occupations

	80-05	05-17	80-17
tot. W. var. LS	.022	.2333	.2552
tot. W. var. MS	.1273	.1909	.3182
tot. MSP var.	.1053	-.0424	.063
Within LS	.051	.244	.296
Within MS	.148	.21	.361
Within: tot	.097	-.034	.065
Between LS	-.029	-.011	-.041
Between MS	-.021	-.019	-.043
Between: tot	.008	-.008	-.002

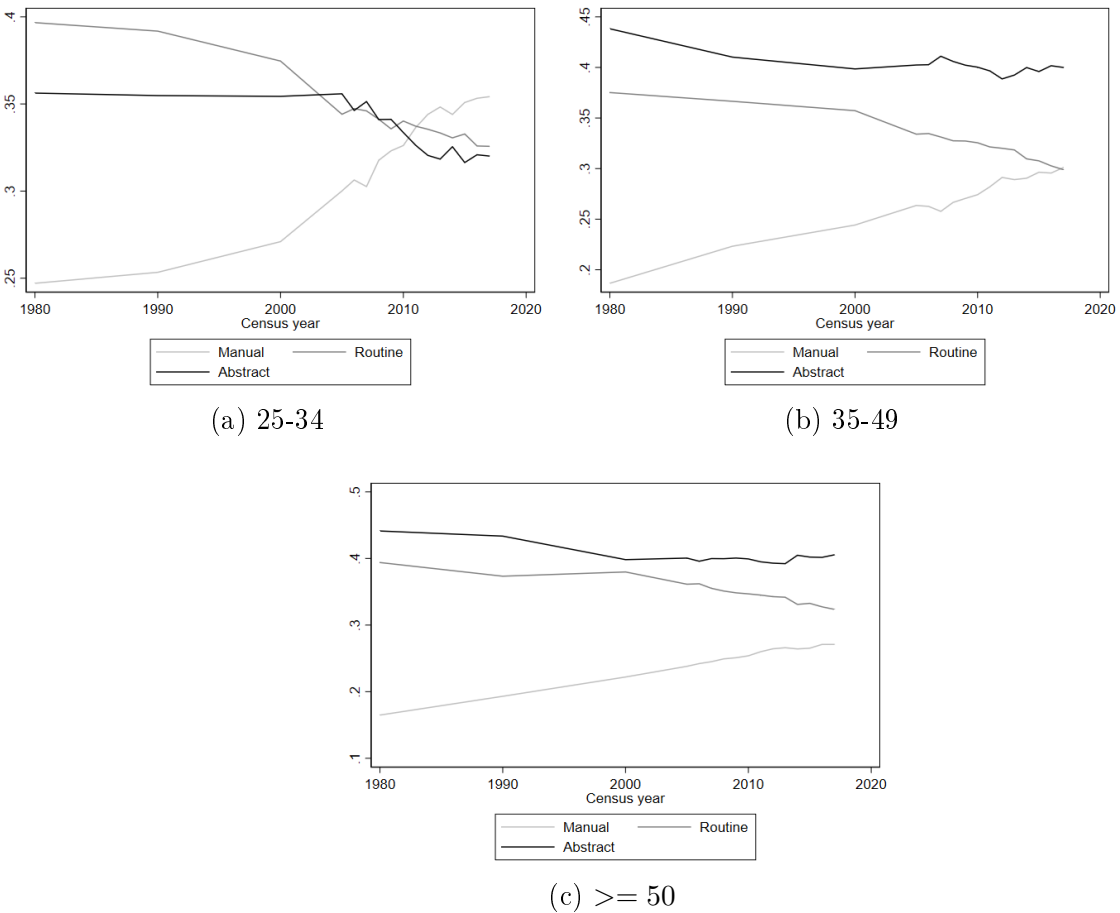
Sources: Census IPUMS 5% samples for 1980 and Census American Community Survey for 2005 and 2017. Occupation classification is composed of 77 posts. More details available in Section 3.2.

Figure C4 – Evolution of the age-specific skill premium by Age Group: Upper and Lower MSP



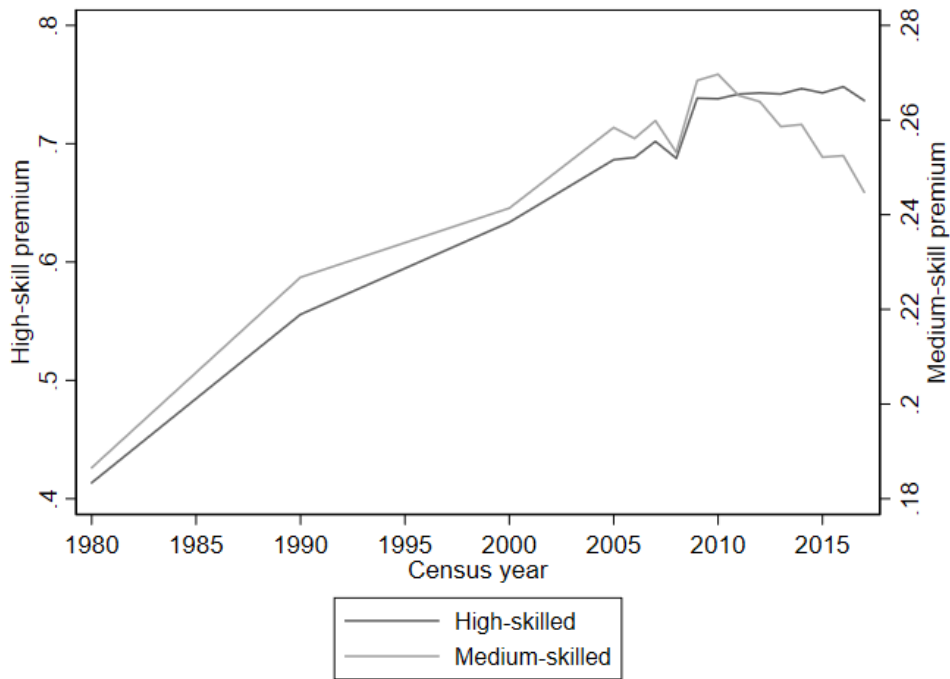
Source: Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. The data used include all working individuals aged 25 and more born after 1943, excluding self-employed, part-time, part-year workers and those employed by the military.

Figure C5 – Evolution of the occupational share: medium-skill, by age category



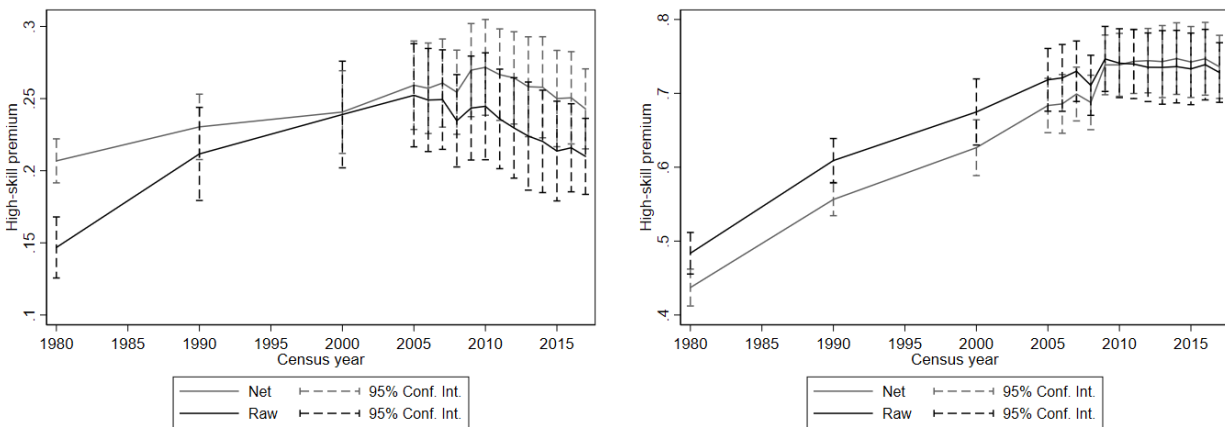
Sources: Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. The data include all working individuals aged 25-64, excluding those employed by the military.

Figure C6 – Evolution of the high and medium-skill premium, net of individual characteristics, year-specific estimation



Source: Census IPUMS 5% samples for 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. Estimated skill premium from a wage equation, controlling for gender, race, age and its square. The data used include all working individuals aged 16 and more born after 1943, excluding self-employed, part-time, part-year workers and those employed by the military.

Figure C7 – Evolution of the medium- and high-skill premium, raw and net of individual characteristics with 95% confidence interval

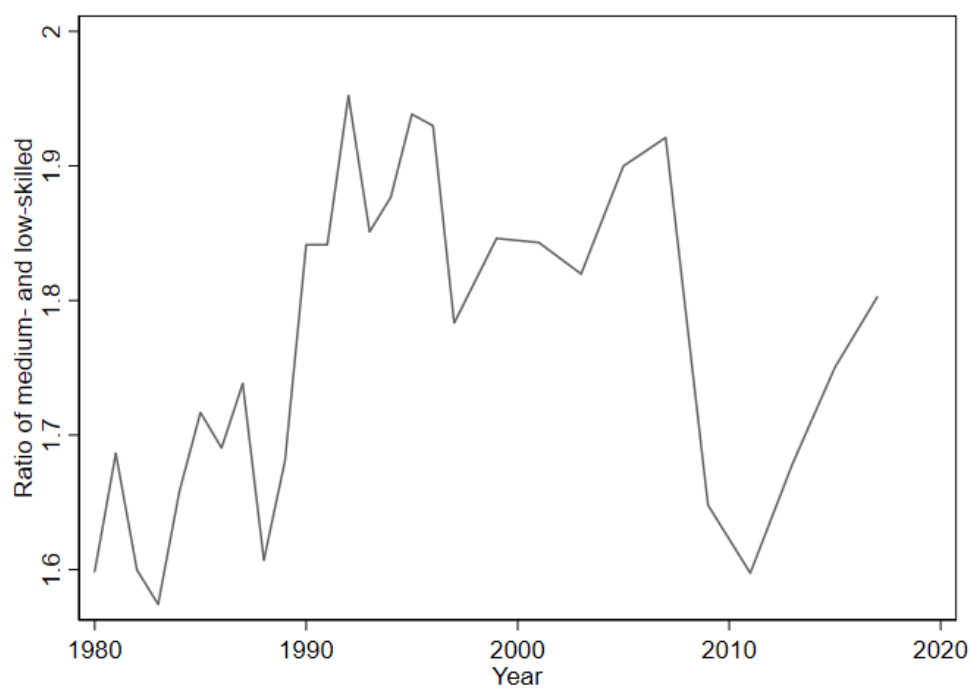


(a) Medium-skill

(b) High-skill

Sources: Census IPUMS 5% samples 1980, 1990 and 2000 and Census American Community Survey for 2005-2017. Coefficients and standard-errors obtained from estimating equation 3.1. The data used include all working individuals aged 16-64, excluding self-employed, part-time, part-year workers and those employed by the military.

Figure C8 – Evolution of the ratio of average individual fixed-effect by skill group



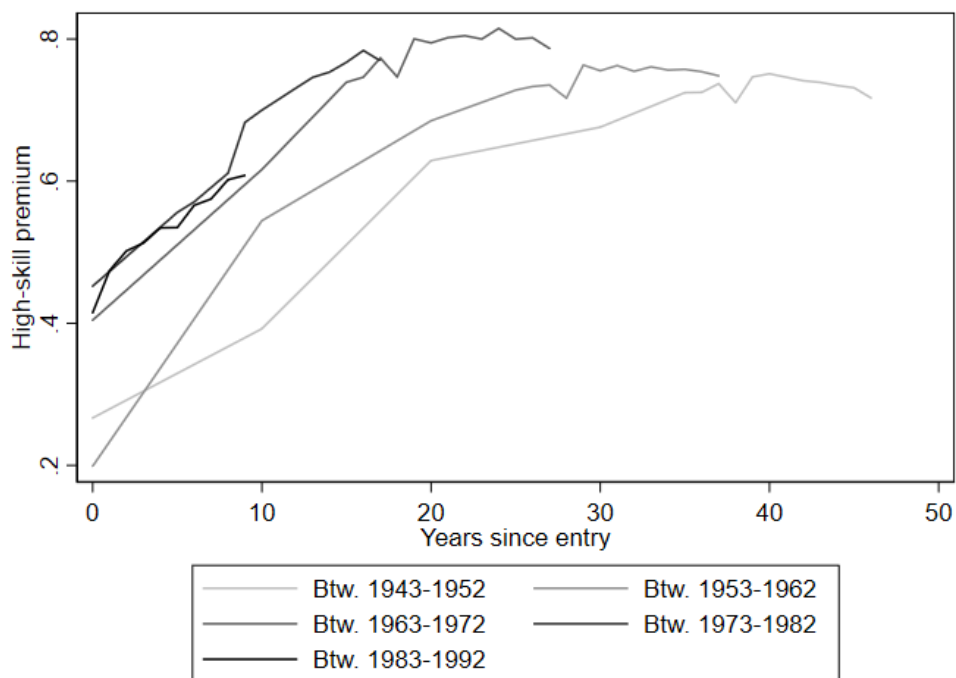
Source: PSID data from 1980 onward. Bottom and top 2.5% of the wage distribution trimmed. The graph represents the ratio of average individual fixed effect by skill group and year, estimated from equation 3.6

Table C3 – Decomposition of the raw medium-skill premium, workers aged 25-34

	80-05	05-17	80-17
Panel A: based on occupations only			
tot. W. var. LS	-.04	.1935	.1535
tot. W. var. MS	.0219	.1314	.1533
tot. MSP var.	.0619	-.0621	-.0002
Within LS	-.028	.198	.171
Within MS	.035	.141	.174
Within: tot	.063	-.057	.003
Between LS	-.012	-.005	-.018
Between MS	-.013	-.009	-.021
Between: tot	-.001	-.004	-.003
Panel B: based on occupations×industries			
tot. W. var. LS	-.04	.1935	.1535
tot. W. var. MS	.0219	.1314	.1533
tot. MSP var.	.0619	-.0621	-.0002
Within LS	-.004	.2	.194
Within MS	.063	.148	.208
Within: tot	.067	-.052	.014
Between LS	-.036	-.006	-.04
Between MS	-.041	-.017	-.055
Between: tot	-.005	-.011	-.015

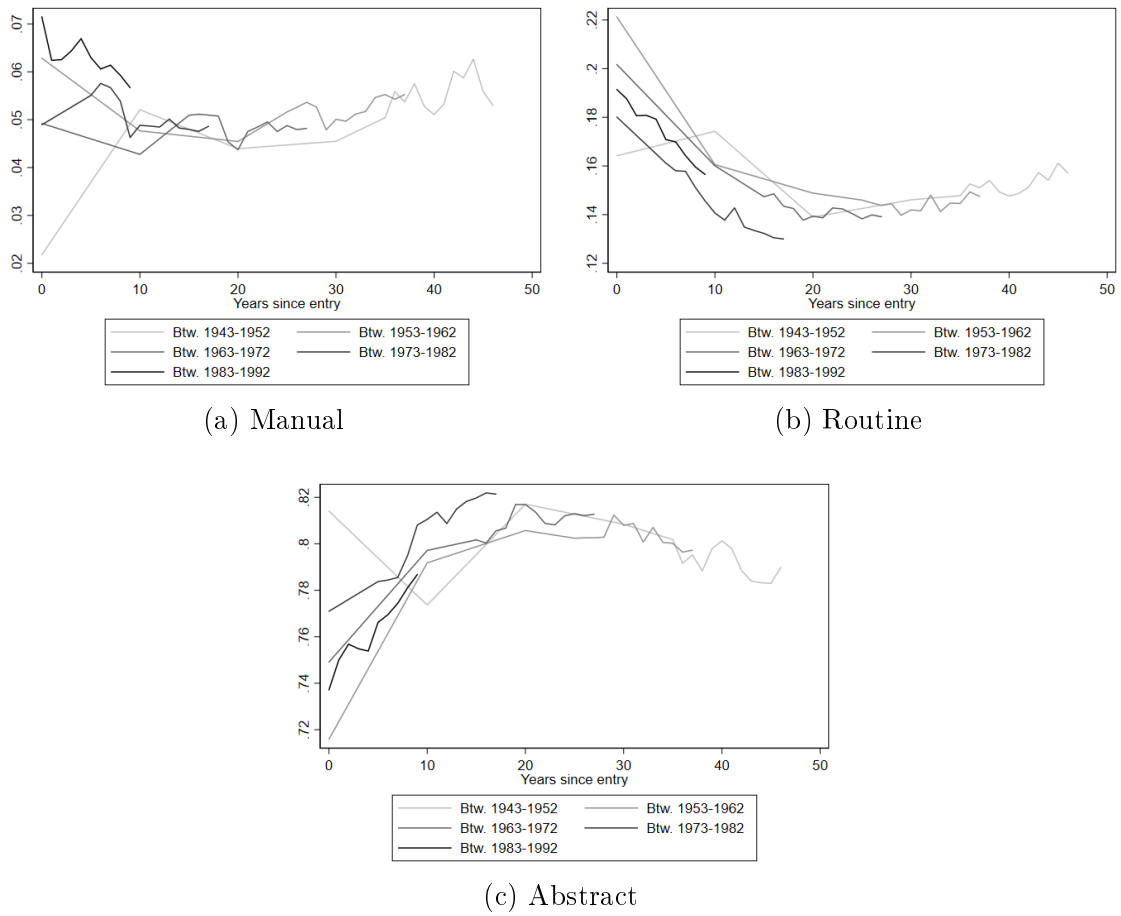
Sources: Census IPUMS 5% samples for 1980 and Census American Community Survey for 2005 and 2017. Include only workers aged 25-34 years old. Occupation classification is composed of 7 posts in Panel A and of 4 posts in Panel B. Industry classification composed of 13 posts. More details available in Section 3.2.

Figure C9 – Evolution of the raw high-skill premium by birth-cohort



Source: See Figure 3.13

Figure C10 – Evolution of high-skilled workers’ occupations by birth-cohort



Source: See Figure 3.13.

3.D Robustness of Table 3.3

Table D1 – First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only. *Residuals calculated on age-specific regressions*

	Baseline resid.					Resid. net of occ. and ind. FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Stacked differences										
Δ Diff. of man. sh.	-0.204 ^a (0.056)					-0.201 ^a (0.056)				
Δ Diff. of rout. sh.		0.083 (0.059)		0.155 ^b (0.063)			0.079 (0.059)		0.151 ^b (0.063)	
Δ Diff. of abst. sh.			0.223 ^a (0.064)	0.277 ^a (0.071)	0.279 ^a (0.072)			0.224 ^a (0.065)	0.277 ^a (0.072)	0.278 ^a (0.072)
Δ Diff of rout. cog. sh.					0.120 ^c (0.069)					0.116 (0.069)
Δ Diff of rout. man. sh.					0.226 ^b (0.094)					0.223 ^b (0.094)
Δ sh. of high skill	-0.324 ^b (0.137)	-0.368 ^b (0.142)	-0.275 ^c (0.149)	-0.289 ^c (0.144)	-0.308 ^b (0.148)	-0.303 ^b (0.137)	-0.347 ^b (0.142)	-0.254 ^c (0.148)	-0.267 ^c (0.144)	-0.288 ^c (0.148)
Δ sh. of med. skill	0.168 (0.147)	0.141 (0.149)	0.186 (0.148)	0.184 (0.146)	0.179 (0.146)	0.145 (0.148)	0.118 (0.150)	0.163 (0.150)	0.162 (0.147)	0.156 (0.147)
Δ sh. of foreign	0.498 ^a (0.085)	0.558 ^a (0.089)	0.512 ^a (0.085)	0.485 ^a (0.085)	0.488 ^a (0.085)	0.540 ^a (0.096)	0.599 ^a (0.102)	0.553 ^a (0.094)	0.527 ^a (0.094)	0.530 ^a (0.094)
R ²	0.06	0.03	0.05	0.06	0.06	0.07	0.05	0.07	0.08	0.08
Panel B: Level										
Diff. of man. sh.	-0.213 ^a (0.047)					-0.212 ^a (0.047)				
Diff. of rout. sh.		0.053 (0.047)		0.150 ^a (0.050)			0.050 (0.046)		0.147 ^a (0.050)	
Diff. of abst. sh.			0.250 ^a (0.055)	0.311 ^a (0.061)	0.312 ^a (0.061)			0.252 ^a (0.056)	0.312 ^a (0.062)	0.313 ^a (0.062)
Diff. of rout. cog. sh.					0.166 ^b (0.063)					0.164 ^b (0.062)
Diff. of rout. man. sh.					0.119 ^b (0.057)					0.117 ^b (0.057)
Sh. of high skill	0.083 (0.107)	0.055 (0.109)	0.170 (0.104)	0.142 (0.106)	0.146 (0.105)	0.115 (0.110)	0.089 (0.113)	0.203 ^c (0.107)	0.176 (0.109)	0.180 (0.109)
Sh. of med. skill	0.123 (0.127)	0.076 (0.131)	0.093 (0.124)	0.122 (0.125)	0.124 (0.123)	0.089 (0.130)	0.043 (0.134)	0.060 (0.129)	0.089 (0.128)	0.091 (0.126)
Sh. of foreign	0.342 ^a (0.095)	0.385 ^a (0.102)	0.330 ^a (0.096)	0.319 ^a (0.093)	0.316 ^a (0.092)	0.358 ^a (0.109)	0.400 ^a (0.117)	0.345 ^a (0.109)	0.335 ^a (0.106)	0.332 ^a (0.106)
R ²	0.54	0.53	0.54	0.54	0.54	0.56	0.55	0.56	0.57	0.57

Notes: See Table 3.3.

Table D2 – First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only. *Residuals calculated on year-specific regressions*

	Baseline resid.				
	(1)	(2)	(3)	(4)	(5)
	Panel A: Stacked differences				
Δ Diff. of man. sh.	-0.144 ^a (0.048)				
Δ Diff. of rout. sh.		0.059 (0.046)		0.119 ^b (0.051)	
Δ Diff. of abst. sh.			0.131 ^b (0.055)	0.183 ^a (0.061)	0.182 ^a (0.060)
Δ Diff of rout. cog. sh.					0.090 (0.056)
Δ Diff of rout. man. sh.					0.174 ^b (0.068)
Δ sh. of high skill	0.067 (0.109)	0.037 (0.116)	0.114 (0.108)	0.092 (0.112)	0.081 (0.113)
Δ sh. of med. skill	-0.009 (0.108)	-0.053 (0.111)	-0.028 (0.105)	-0.002 (0.106)	-0.004 (0.105)
Δ sh. of foreign	0.351 ^a (0.069)	0.374 ^a (0.068)	0.355 ^a (0.073)	0.346 ^a (0.070)	0.349 ^a (0.070)
R ²	0.05	0.04	0.05	0.06	0.06
	Panel B: Level				
Diff. of man. sh.	-0.216 ^a (0.045)				
Diff. of rout. sh.		0.058 (0.045)		0.154 ^a (0.049)	
Diff. of abst. sh.			0.246 ^a (0.054)	0.310 ^a (0.059)	0.310 ^a (0.059)
Diff. of rout. cog. sh.					0.166 ^a (0.061)
Diff. of rout. man. sh.					0.134 ^b (0.057)
Sh. of high skill	0.148 (0.117)	0.118 (0.119)	0.234 ^b (0.110)	0.205 ^c (0.113)	0.208 ^c (0.112)
Sh. of med. skill	0.133 (0.120)	0.087 (0.124)	0.102 (0.115)	0.132 (0.116)	0.133 (0.115)
Sh. of foreign	0.345 ^a (0.073)	0.388 ^a (0.078)	0.334 ^a (0.077)	0.323 ^a (0.073)	0.321 ^a (0.072)
R ²	0.53	0.52	0.53	0.53	0.53

Notes: See Table 3.3.

Table D3 – First-difference CZ *wage* medium-skill premium on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only

	Baseline resid.				
	(1)	(2)	(3)	(4)	(5)
Panel A: Stacked differences					
Δ Diff. of man. sh.	-0.088 ^b (0.036)				
Δ Diff. of rout. sh.		0.016 (0.034)		0.053 (0.037)	
Δ Diff. of abst. sh.			0.122 ^b (0.049)	0.140 ^b (0.053)	0.142 ^b (0.053)
Δ Diff of rout. cog. sh.					0.027 (0.040)
Δ Diff of rout. man. sh.					0.105 ^c (0.054)
Δ sh. of high skill	0.004 (0.107)	-0.011 (0.109)	0.034 (0.111)	0.029 (0.111)	0.015 (0.112)
Δ sh. of med. skill	-0.057 (0.135)	-0.068 (0.138)	-0.045 (0.138)	-0.045 (0.136)	-0.050 (0.136)
Δ sh. of foreign	0.477 ^a (0.096)	0.504 ^a (0.099)	0.476 ^a (0.096)	0.467 ^a (0.095)	0.470 ^a (0.095)
R ²	0.17	0.16	0.17	0.17	0.17
Panel B: Level					
Diff. of man. sh.	-0.181 ^a (0.046)				
Diff. of rout. sh.		0.023 (0.045)		0.112 ^b (0.049)	
Diff. of abst. sh.			0.240 ^a (0.058)	0.286 ^a (0.064)	0.286 ^a (0.064)
Diff. of rout. cog. sh.					0.123 ^b (0.059)
Diff. of rout. man. sh.					0.092 (0.061)
Sh. of high skill	0.197 (0.123)	0.181 (0.126)	0.282 ^b (0.120)	0.261 ^b (0.122)	0.264 ^b (0.121)
Sh. of med. skill	-0.035 (0.141)	-0.078 (0.145)	-0.058 (0.143)	-0.036 (0.141)	-0.035 (0.140)
Sh. of foreign	0.299 ^b (0.135)	0.335 ^b (0.142)	0.283 ^b (0.133)	0.275 ^b (0.131)	0.273 ^b (0.131)
R ²	0.61	0.60	0.61	0.61	0.61

Notes: See Table 3.3.

Table D4 – First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only, *with 1970 included*

	Baseline resid.					Resid. net of occ. and ind. FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Stacked differences										
Δ Diff. of man. sh.	-0.220 ^a (0.053)					-0.217 ^a (0.053)				
Δ Diff. of rout. sh.		0.091 ^c (0.053)		0.176 ^a (0.058)			0.086 (0.052)		0.171 ^a (0.057)	
Δ Diff. of abst. sh.			0.219 ^a (0.058)	0.289 ^a (0.067)	0.290 ^a (0.067)			0.222 ^a (0.059)	0.290 ^a (0.067)	0.291 ^a (0.067)
Δ Diff of rout. cog. sh.					0.159 ^b (0.068)					0.153 ^b (0.067)
Δ Diff of rout. man. sh.					0.210 ^b (0.080)					0.207 ^b (0.080)
Δ sh. of high skill	-0.284 ^b (0.117)	-0.320 ^b (0.121)	-0.248 ^c (0.128)	-0.258 ^b (0.124)	-0.266 ^b (0.124)	-0.264 ^b (0.116)	-0.299 ^b (0.119)	-0.227 ^c (0.125)	-0.238 ^c (0.122)	-0.245 ^b (0.122)
Δ sh. of med. skill	0.247 (0.158)	0.226 (0.163)	0.243 (0.162)	0.252 (0.158)	0.252 (0.159)	0.205 (0.154)	0.185 (0.160)	0.201 (0.158)	0.210 (0.154)	0.210 (0.156)
Δ sh. of foreign	0.612 ^a (0.138)	0.678 ^a (0.150)	0.614 ^a (0.136)	0.592 ^a (0.134)	0.598 ^a (0.134)	0.655 ^a (0.155)	0.721 ^a (0.167)	0.656 ^a (0.152)	0.634 ^a (0.150)	0.640 ^a (0.151)
R ²	0.13	0.11	0.12	0.14	0.14	0.15	0.12	0.14	0.15	0.15
Panel B: Level										
Diff. of man. sh.	-0.257 ^a (0.050)					-0.257 ^a (0.051)				
Diff. of rout. sh.		0.086 ^b (0.041)		0.213 ^a (0.051)			0.081 ^c (0.040)		0.211 ^a (0.051)	
Diff. of abst. sh.			0.221 ^a (0.055)	0.330 ^a (0.065)	0.330 ^a (0.064)			0.227 ^a (0.057)	0.335 ^a (0.067)	0.336 ^a (0.067)
Diff. of rout. cog. sh.					0.255 ^a (0.066)					0.256 ^a (0.065)
Diff. of rout. man. sh.					0.142 ^b (0.053)					0.134 ^b (0.054)
Sh. of high skill	0.117 (0.103)	0.079 (0.103)	0.216 ^b (0.094)	0.169 ^c (0.096)	0.180 ^c (0.095)	0.143 (0.111)	0.107 (0.111)	0.245 ^b (0.102)	0.198 ^c (0.104)	0.210 ^b (0.103)
Sh. of med. skill	0.138 (0.125)	0.080 (0.131)	0.092 (0.128)	0.139 (0.125)	0.150 (0.119)	0.087 (0.131)	0.028 (0.138)	0.042 (0.136)	0.089 (0.131)	0.100 (0.126)
Sh. of foreign	0.420 ^a (0.135)	0.472 ^a (0.146)	0.409 ^a (0.138)	0.398 ^a (0.133)	0.388 ^a (0.128)	0.446 ^a (0.156)	0.498 ^a (0.167)	0.433 ^a (0.159)	0.422 ^a (0.153)	0.411 ^a (0.148)
R ²	0.52	0.50	0.51	0.52	0.52	0.53	0.51	0.52	0.53	0.53

Notes: Standard errors clustered by state between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. Each regression is weighted by the share of the CZ in the national 25-34 years old population. 3610 observations (722 CZ \times 5 periods) in Panel A, 4332 observations (722 \times 6 periods) in Panel B.

Table D5 – First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only, *with Alaska and Hawaii included*

	Baseline resid.					Resid. net of occ. and ind. FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Stacked differences										
Δ Diff. of man. sh.	-0.212 ^a (0.057)					-0.208 ^a (0.057)				
Δ Diff. of rout. sh.		0.089 (0.061)		0.163 ^b (0.064)			0.084 (0.060)		0.158 ^b (0.064)	
Δ Diff. of abst. sh.			0.229 ^a (0.065)	0.286 ^a (0.072)	0.287 ^a (0.072)			0.230 ^a (0.066)	0.285 ^a (0.072)	0.287 ^a (0.073)
Δ Diff of rout. cog. sh.					0.130 ^c (0.070)					0.124 ^c (0.070)
Δ Diff of rout. man. sh.					0.232 ^b (0.095)					0.228 ^b (0.095)
Δ sh. of high skill	-0.374 ^b (0.140)	-0.417 ^a (0.145)	-0.322 ^b (0.153)	-0.339 ^b (0.148)	-0.357 ^b (0.152)	-0.351 ^b (0.139)	-0.393 ^a (0.144)	-0.300 ^c (0.151)	-0.315 ^b (0.146)	-0.334 ^b (0.151)
Δ sh. of med. skill	0.147 (0.149)	0.122 (0.150)	0.166 (0.149)	0.162 (0.147)	0.158 (0.147)	0.114 (0.150)	0.090 (0.151)	0.133 (0.151)	0.130 (0.148)	0.125 (0.148)
Δ sh. of foreign	0.485 ^a (0.082)	0.549 ^a (0.084)	0.500 ^a (0.081)	0.471 ^a (0.082)	0.475 ^a (0.082)	0.540 ^a (0.096)	0.602 ^a (0.101)	0.553 ^a (0.094)	0.525 ^a (0.094)	0.529 ^a (0.094)
R ²	0.12	0.10	0.12	0.13	0.13	0.14	0.12	0.14	0.15	0.15
Panel B: Level										
Diff. of man. sh.	-0.218 ^a (0.047)					-0.216 ^a (0.047)				
Diff. of rout. sh.		0.058 (0.047)		0.155 ^a (0.051)			0.054 (0.046)		0.151 ^a (0.050)	
Diff. of abst. sh.			0.253 ^a (0.055)	0.316 ^a (0.061)	0.317 ^a (0.061)			0.256 ^a (0.056)	0.317 ^a (0.062)	0.318 ^a (0.062)
Diff. of rout. cog. sh.					0.173 ^a (0.064)					0.170 ^a (0.062)
Diff. of rout. man. sh.					0.121 ^b (0.058)					0.117 ^b (0.058)
Sh. of high skill	0.052 (0.107)	0.025 (0.109)	0.142 (0.104)	0.111 (0.107)	0.115 (0.106)	0.088 (0.112)	0.063 (0.114)	0.180 (0.108)	0.150 (0.111)	0.154 (0.110)
Sh. of med. skill	0.132 (0.128)	0.088 (0.131)	0.104 (0.123)	0.132 (0.125)	0.133 (0.123)	0.086 (0.132)	0.043 (0.135)	0.059 (0.129)	0.086 (0.129)	0.088 (0.127)
Sh. of foreign	0.333 ^a (0.091)	0.378 ^a (0.098)	0.322 ^a (0.092)	0.311 ^a (0.089)	0.307 ^a (0.088)	0.351 ^a (0.110)	0.396 ^a (0.118)	0.339 ^a (0.110)	0.328 ^a (0.107)	0.324 ^a (0.107)
R ²	0.56	0.55	0.56	0.57	0.57	0.58	0.57	0.58	0.59	0.59

Notes: Standard errors clustered by state between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. Each regression is weighted by the share of the CZ in the national 25-34 years old population. 2964 observations (741 CZ \times 4 periods) in Panel A, 3705 observations (741 \times 5 periods) in Panel B.

Table D6 – First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only, *weighted by the share of the CZ in the national population*

	Baseline resid.					Resid. net of occ. and ind. FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Stacked differences										
Δ Diff. of man. sh.	-0.218 ^a (0.057)					-0.215 ^a (0.057)				
Δ Diff. of rout. sh.		0.096 (0.061)		0.171 ^b (0.064)			0.091 (0.061)		0.166 ^b (0.064)	
Δ Diff. of abst. sh.			0.230 ^a (0.065)	0.290 ^a (0.072)	0.291 ^a (0.072)			0.231 ^a (0.066)	0.289 ^a (0.073)	0.290 ^a (0.073)
Δ Diff of rout. cog. sh.					0.140 ^c (0.070)					0.135 ^c (0.070)
Δ Diff of rout. man. sh.					0.233 ^b (0.095)					0.230 ^b (0.095)
Δ sh. of high skill	-0.340 ^b (0.139)	-0.389 ^a (0.145)	-0.291 ^c (0.153)	-0.306 ^b (0.147)	-0.323 ^b (0.151)	-0.317 ^b (0.138)	-0.364 ^b (0.144)	-0.267 ^c (0.150)	-0.282 ^c (0.146)	-0.299 ^c (0.150)
Δ sh. of med. skill	0.184 (0.148)	0.154 (0.150)	0.201 (0.148)	0.200 (0.146)	0.194 (0.146)	0.152 (0.148)	0.123 (0.150)	0.169 (0.149)	0.168 (0.147)	0.163 (0.147)
Δ sh. of foreign	0.480 ^a (0.082)	0.543 ^a (0.085)	0.497 ^a (0.082)	0.467 ^a (0.082)	0.470 ^a (0.082)	0.536 ^a (0.096)	0.599 ^a (0.102)	0.552 ^a (0.095)	0.523 ^a (0.094)	0.526 ^a (0.095)
R ²	0.13	0.10	0.12	0.13	0.13	0.14	0.12	0.14	0.15	0.15
Panel B: Level										
Diff. of man. sh.	-0.225 ^a (0.047)					-0.224 ^a (0.047)				
Diff. of rout. sh.		0.062 (0.047)		0.162 ^a (0.051)			0.059 (0.047)		0.160 ^a (0.050)	
Diff. of abst. sh.			0.254 ^a (0.055)	0.320 ^a (0.061)	0.321 ^a (0.061)			0.256 ^a (0.057)	0.322 ^a (0.063)	0.323 ^a (0.062)
Diff. of rout. cog. sh.					0.182 ^a (0.064)					0.180 ^a (0.062)
Diff. of rout. man. sh.					0.127 ^b (0.058)					0.123 ^b (0.058)
Sh. of high skill	0.066 (0.106)	0.035 (0.109)	0.154 (0.103)	0.124 (0.106)	0.129 (0.105)	0.104 (0.110)	0.073 (0.114)	0.193 ^c (0.108)	0.164 (0.110)	0.168 (0.109)
Sh. of med. skill	0.151 (0.127)	0.104 (0.131)	0.119 (0.122)	0.151 (0.124)	0.153 (0.121)	0.106 (0.130)	0.059 (0.134)	0.075 (0.128)	0.106 (0.128)	0.108 (0.125)
Sh. of foreign	0.332 ^a (0.090)	0.377 ^a (0.097)	0.321 ^a (0.091)	0.310 ^a (0.088)	0.307 ^a (0.087)	0.352 ^a (0.110)	0.397 ^a (0.117)	0.340 ^a (0.110)	0.329 ^a (0.107)	0.325 ^a (0.106)
R ²	0.55	0.54	0.55	0.56	0.56	0.58	0.57	0.58	0.58	0.58

Notes: Standard errors clustered by state between brackets. ^a, ^b, ^c indicate significance at the 1%, 5% and 10% level, respectively. Each regression is weighted by the share of the CZ in the national population. 2888 observations (722 CZ × 4 periods) in Panel A, 3610 observations (722 × 5 periods) in Panel B.

3.E Robustness of Table 3.4

Table E1 – First-difference CZ occupational probability on the local relative supply of occupations, OLS, stacked differences and level, 25 – 34 years old only, *with 1970 included*

	Rout. sh.	Abst. sh.	Man. sh.
	(1)	(2)	(3)
Panel A: Stacked differences			
Δ (Abst. - HS / MS)	-0.101 ^a (0.018)	0.298 ^a (0.015)	-0.197 ^a (0.021)
Δ (Rout. - MS / LS)	0.164 ^a (0.018)	0.003 (0.018)	-0.167 ^a (0.017)
Δ sh. of high skill	-0.205 ^a (0.070)	0.316 ^a (0.072)	-0.111 (0.081)
Δ sh. of med. skill	0.465 ^a (0.068)	-0.031 (0.057)	-0.434 ^a (0.071)
Δ sh. of foreign	-0.084 ^c (0.044)	0.221 ^a (0.038)	-0.137 ^a (0.044)
R ²	0.18	0.37	0.31
Panel B: Level			
(Abst. - HS / MS)	-0.044 ^c (0.025)	0.255 ^a (0.019)	-0.212 ^a (0.016)
(Rout. - MS / LS)	0.148 ^a (0.019)	0.012 (0.017)	-0.160 ^a (0.011)
Sh. of high skill	-0.077 (0.068)	0.023 (0.068)	0.054 (0.048)
Sh. of med. skill	0.258 ^a (0.081)	0.020 (0.059)	-0.278 ^a (0.065)
Sh. of foreign	-0.099 ^c (0.053)	0.229 ^a (0.036)	-0.130 ^a (0.046)
R ²	0.68	0.75	0.87

Notes: See Table D4.

Table E2 – First-difference CZ occupational probability on the local relative supply of occupations, OLS, stacked differences and level, 25 – 34 years old only, *with Alaska and Hawaii included*

	Rout. sh.	Abst. sh.	Man. sh.
	(1)	(2)	(3)
Panel A: Stacked differences			
Δ (Abst. - HS / MS)	-0.100 ^a (0.022)	0.353 ^a (0.023)	-0.253 ^a (0.028)
Δ (Rout. - MS / LS)	0.159 ^a (0.020)	0.005 (0.021)	-0.163 ^a (0.019)
Δ sh. of high skill	-0.281 ^a (0.088)	0.410 ^a (0.083)	-0.129 (0.110)
Δ sh. of med. skill	0.468 ^a (0.096)	-0.109 (0.080)	-0.359 ^a (0.092)
Δ sh. of foreign	-0.097 (0.058)	0.212 ^a (0.064)	-0.116 ^b (0.057)
R ²	0.20	0.32	0.27
Panel B: Level			
(Abst. - HS / MS)	-0.059 ^a (0.018)	0.313 ^a (0.019)	-0.254 ^a (0.020)
(Rout. - MS / LS)	0.148 ^a (0.016)	0.013 (0.016)	-0.161 ^a (0.013)
Sh. of high skill	-0.258 ^a (0.062)	0.256 ^a (0.059)	0.002 (0.063)
Sh. of med. skill	0.296 ^a (0.096)	-0.047 (0.059)	-0.249 ^a (0.082)
Sh. of foreign	-0.087 (0.061)	0.201 ^a (0.039)	-0.114 ^b (0.054)
R ²	0.71	0.71	0.83

Notes: See Table D5.

Table E3 – First-difference CZ occupational probability on the local relative supply of occupations, OLS, stacked differences and level, 25 – 34 years old only, *weighted by the share of the CZ in the national population*

	Rout. sh.	Abst. sh.	Man. sh.
	(1)	(2)	(3)
Panel A: Stacked differences			
Δ (Abst. - HS / MS)	-0.108 ^a (0.021)	0.356 ^a (0.023)	-0.248 ^a (0.027)
Δ (Rout. - MS / LS)	0.163 ^a (0.021)	0.006 (0.022)	-0.169 ^a (0.019)
Δ sh. of high skill	-0.300 ^a (0.088)	0.408 ^a (0.083)	-0.108 (0.110)
Δ sh. of med. skill	0.468 ^a (0.098)	-0.115 (0.081)	-0.353 ^a (0.094)
Δ sh. of foreign	-0.100 ^c (0.059)	0.210 ^a (0.064)	-0.111 ^c (0.056)
R ²	0.21	0.32	0.27
Panel B: Level			
(Abst. - HS / MS)	-0.063 ^a (0.019)	0.314 ^a (0.019)	-0.251 ^a (0.020)
(Rout. - MS / LS)	0.150 ^a (0.017)	0.013 (0.017)	-0.163 ^a (0.013)
Sh. of high skill	-0.272 ^a (0.061)	0.251 ^a (0.060)	0.020 (0.062)
Sh. of med. skill	0.294 ^a (0.096)	-0.052 (0.060)	-0.242 ^a (0.080)
Sh. of foreign	-0.091 (0.061)	0.198 ^a (0.039)	-0.107 ^c (0.054)
R ²	0.71	0.71	0.83

Notes: See Table D6.

Conclusion générale

3.6 Conclusion générale

Dans cette section, je vais résumer les principaux résultats montrés dans les différents Chapitres. De plus, je vais présenter les principales limitations des méthodologies employées, ainsi que les possibles solutions pour les résoudre par la suite.

3.6.1 Résultats principaux et contributions

Cette thèse de doctorat apporte de nouveaux résultats sur l'impact de la polarisation du marché du travail en étudiant ses conséquences sur l'emploi en Europe, ainsi que sur les salaires des travailleurs par groupe d'éducatons aux États-Unis.

L'emploi agrégé est impacté par la polarisation du marché du travail dans les pays à haut salaire minimum.

Le Chapitre 1 étudie l'effet du processus de polarisation sur le marché du travail dans les pays Européens disposant d'un salaire minimum national, au travers du taux d'emploi et du taux de participation, en raison de l'absence d'étude empirique dans la littérature. Les estimations produites indiquent que le niveau du salaire minimum joue un rôle crucial dans l'impact de la destruction d'emplois routiniers sur les agrégats du marché du travail. En effet, les pays ayant des salaires minimums élevés ont vus leurs taux d'emploi diminuer au fur et à mesure que ces emplois situés au milieu de la distribution des salaires disparaissaient, tandis qu'aucun effet n'était observable dans les économies caractérisées par un faible salaire minimum. De plus, mes travaux indiquent que le mécanisme principal est que des hauts niveaux de salaire minimum empêchent la création de suffisamment d'emplois manuels, situés en bas de la distribution des salaires, afin de compenser la destruction d'emploi routinier, générant par conséquent une diminution de l'emploi total. Enfin, je montre que ces résultats sont uniquement la conséquence du niveau du salaire minimum et non aux autres institutions

du marché du travail. Ces résultats permettent de mettre en lumière une différence entre l'Europe et les États-Unis. En effet, les résultats des études empiriques sur l'emploi aux États-Unis concluaient que la polarisation n'avait pas d'impact sur le taux d'emploi.

Le processus de polarisation a eu un impact similaire sur les peu- et moyennement qualifiés en termes de salaires.

Dans le Chapitre 2, j'étudie l'impact de la polarisation du marché de l'emploi sur les salaires des travailleurs en fonction de leur niveau d'éducation aux États-Unis, et particulièrement sur les travailleurs moyennement qualifiés. En effet, ce type de travailleur n'a reçu que peu d'attention dans la littérature alors qu'ils représentent environ 30% de la population en âge de travailler. À travers mon analyse, je montre que le processus de polarisation a eu un impact négatif sur les travailleurs peu qualifiés, mais aussi sur les moyennement qualifiés, dans des proportions similaires. Dans un second temps, je montre que cet effet n'est pas dû à la réallocation des travailleurs à travers les occupations et les industries, mais bien à une diminution des salaires moyens au sein des occupations, lié à un accroissement de l'offre de travail dans les occupations où se réallouent les travailleurs ayant perdu leurs emplois. De plus, je montre que cet effet est visible dans toutes les catégories d'occupations, même celles de services. Enfin, nous montrons que cet effet a semblé affecter plus les jeunes travailleurs moyennement qualifiés relativement au reste de la population.

Le premium à être un travailleur moyennement qualifié a diminué de manière importante depuis le début des années 2000.

Enfin, dans le Chapitre 3, j'étudie les dynamiques de salaires relatives entre les travailleurs moyennement et peu qualifiés. Dans ce chapitre principalement exploratoire et descriptif, je montre que le premium à être un travailleur moyennement qualifié a augmenté dans des proportions similaires à celui d'être un travailleur hautement qualifié jusqu'au début des années 2000, puis a fortement diminué jusqu'à nos jours. Cela est dû à une multitude de raisons. Tout d'abord, parmi ces travailleurs, ceux étant le moins qualifiés ont été impacté en premier, mais ceux les plus qualifiés ont été plus durement touché sur la période récente. De plus, je montre que la dynamique du premium des moyennement qualifiés transite principalement par les salaires relatifs au sein des occupations. En effet, durant la première sous-période, le premium augmenta dû à une plus forte croissance du salaire des moyennement qualifiés au sein des occupations, puis dans un second temps, la diminution de ce premium est due à une plus forte croissance du salaire des peu qualifiés au sein des occupations. Enfin, je montre

que cet effet n'est pas homogène dans la population. On peut observer des dynamiques très différentes selon l'âge des travailleurs : les cohortes les plus récentes ont des premiums significativement plus faibles et ont connu des baisses de salaire relatif plus importantes. Je montre que cette observation est en partie liée à des difficultés à entrer sur le marché du travail dans le même type d'occupations que précédemment, ce qui a un impact à long-terme sur leurs salaires, principalement car les travailleurs moyennement qualifiés sont en concurrence avec les travailleurs qualifiés dans un contexte où l'offre de travail très qualifié augmente plus vite que la quantité emplois d'emploi abstraits fortement rémunéré dans l'économie. Ces résultats sont importants car ils permettent d'apporter de nouveaux éléments sur les dynamiques de salaires des jeunes n'ayant pas obtenu un diplôme leur permettant d'être hautement qualifié, dans un contexte où les coûts de l'éducation augmentent rapidement.

3.6.2 Limitations et développements futures

L'impact sur les salaires en Europe

Dans le Chapitre 1, l'hypothèse étudiée est que la polarisation du marché du travail a un effet différent en Europe relativement aux États-Unis dû à la présence d'un salaire minimum empêchant la création de suffisamment d'emplois manuels. Une limite de cette approche est que je ne dispose pas de données de salaires pour l'ensemble des pays de notre échantillon, limitant ma capacité à quantifier la proportion d'emplois manuels payés au salaire minimum. Il est possible que, si le salaire minimum agit comme une contrainte importante sur la détermination des salaires, la part de travailleurs payés au salaires minimums aient connues une forte augmentation dans d'autres pays que la France, ce qui permettrait de compléter l'analyse.

L'impact au sein des industries en Europe

De plus, dans le Chapitre 1, je limite mon analyse aux pays ayant des salaires minimums nationaux. De nombreux pays n'ont pas de salaires minimums définis nationalement, mais ont des salaires minimums par industries, comme l'Allemagne. Une extension possible de l'analyse menée dans le Chapitre 1 serait de faire une analyse au niveau industriel, afin d'observer si les zones étant spécialisées dans des industries à haut salaire minimum ont-elles connues une plus faible croissance des emplois manuels que les zones spécialisées dans des industries à bas salaire minimum. Cela permettrait d'affiner l'analyse tout en augmentant la taille de l'échantillon et le nombre de pays pris en compte.

Facteurs institutionnels et commerce international

Dans le Chapitre 2, je montre que la réduction des salaires a principalement lieu au sein des occupations et des industries. Au-delà de l'effet de déplacement créant une pression à la baisse sur les salaires, il est possible que d'autres facteurs jouent un rôle. Tout d'abord, il existe une importante littérature sur le déclin des syndicats dans les dynamiques au niveau industriel observés aux États-Unis. Il serait donc intéressant d'inclure ce facteur dans mon analyse, afin de déterminer si le recul des syndicats explique une partie de la baisse observée intra occupations et industries. De plus, le commerce international peut lui aussi jouer un rôle. En effet, de nombreux articles ont montré que l'exposition aux importations pouvait avoir un impact significatif sur les salaires et l'emploi. Par conséquent, il serait intéressant d'inclure le rôle du commerce international dans notre analyse, car il est possible qu'il soit l'une des raisons derrière la baisse importante de salaires au sein des occupations.

Le rôle de l'habilité dans les dynamiques salariales des travailleurs moyennement qualifiés

Enfin, dans les Chapitres 2 et 3, je m'intéresse aux salaires des travailleurs par groupe d'éducation. Bien que mon objectif ne soit pas d'expliquer la source des rendements de l'éducation, une limitation de la méthodologie mise en place est que nous ne pouvons pas prendre en compte l'habilité de chaque individu. En effet, bien que j'introduise des effets fixes individuels dans certaines spécifications, ceux-ci capturent une partie des caractéristiques inobservées au niveau des travailleurs, mais pas uniquement son habilité individuelle. Il serait intéressant de pouvoir estimer différentes séries de premium tout en contrôlant pour une variable proxy telle que le quotient intellectuel ou les résultats à un test d'habilité. Cela permettrait de vérifier que la composition des travailleurs moyennement qualifiés n'a pas changé au cours du temps. En effet, si l'habilité moyenne des travailleurs moyennement qualifiés est inférieure pour les cohortes récentes, tandis que celles des travailleurs peu-qualifiés ne change pas, cela pourrait expliquer pourquoi le premium associé aux travailleurs moyennement qualifiés diminue.

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Liste des tableaux

1.1	Summary statistics	30
1.2	Summary statistics: Minimum Wage (new)	35
1.3	OLS regressions: Employment rate	41
1.4	OLS regressions: Participation rate	42
1.5	IV regressions: Employment rate	44
1.6	IV regressions: Participation rate	45
1.7	OLS regressions: Low-paying in numbers (log)	46
1.8	Correlation table: Minimum wage and EPL indexes	50
1.9	OLS regressions: EPL	52
1.10	OLS regressions: Employment rate, <i>with sample stopping in 2010 instead of 2007</i>	56
1.11	OLS regressions: Participation rate, <i>with sample stopping in 2010 instead of 2007</i>	57
1.12	OLS regressions <i>using time-varying minimum wage</i> : Employment rate	58
1.13	OLS regressions <i>using time-varying minimum wage</i> : Participation rate	59
1.14	OLS regressions <i>using mean minimum wage</i> : Employment rate	60
1.15	OLS regressions <i>using mean minimum wage</i> : Participation rate	60
1.16	OLS regressions: Employment rate, <i>controlling for 3 industry shares</i>	61
1.17	OLS regressions: Participation rate, <i>controlling for 3 industry shares</i>	62
1.18	OLS regressions: Employment rate, <i>controlling for 16 industry shares</i>	63
1.19	OLS regressions: Participation rate, <i>controlling for 16 industry shares</i>	64
1.20	OLS regressions: Employment rate, <i>jackknife resampling</i>	65
1.21	OLS regressions: Participation rate, <i>jackknife resampling</i>	66
1.22	First-stage regressions from Table 1.5 and Table 1.6: share of middling occupations	67
1.23	First-stage regressions from Table 1.5 and Table 1.6: share of middling occupations interacted with initial minimum wage.	68

1.24	OLS Regressions: Share of middling occupations, controlling for 16 industry shares	69
1.25	Summary statistics: Average minimum wage and EPL Indexes by country . .	70
1.26	OLS regressions: EPL, without minimum wage	70
2.1	First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, OLS and IV, stacked differences	89
2.2	Decomposition of the IV coefficients from Table 2.1, columns 4 and 5	92
2.3	Individual regressions of residualized wages, OLS	92
2.4	First-difference CZ average residualized wages on the local share of routine jobs, by broad occupation categories, IV, stacked differences	96
2.5	First-difference CZ average residualized wages on the local share of routine jobs, by age categories, IV, stacked differences	97
2.6	Summary of Rotemberg weights for the IV specification reported in columns 4-6 of Table 2.1 for each skill	102
2.7	First-difference CZ average residualized wages on the local share of routine jobs, by <i>detailed</i> skill levels, IV, stacked differences	105
2.8	First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, OLS and IV, <i>long differences and 20-year stacked differences</i>	106
2.9	First-difference CZ average residualized wages on the <i>variations</i> of the local share of routine jobs, by skill levels, OLS and IV, stacked differences	107
2.10	First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, <i>reduced form</i> , stacked differences	107
2.11	First-difference CZ average residualized wages on the local share of routine jobs, by skill levels, OLS and IV, stacked differences, <i>excluding 2010</i>	108
2.12	Decomposition of the IV coefficients from Table 2.1, columns 4 and 5 <i>on 77 occupation posts</i>	108
2.13	Individual (log) wage regressions on the local share of routine jobs, by skill levels	110
2.14	Individual (log) wage IV regressions on the local share of routine jobs, by skill levels, with occupation and industry fixed effect	110
2.15	Individual (log) wage IV regressions on the local share of routine jobs, by skill levels, with the routine share interacted with broad occupation dummies . .	111
3.1	Decomposition of the raw medium-skill premium	141
3.2	Individual (log) wage OLS regressions	142

3.3	First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only	152
3.4	OLS: Occ. Share, MS only, age-specific: 25 – 34	155
B1	Decomposition of the raw medium-skill premium, by CZ	160
C1	Coefficients and descriptive statistics.	162
C2	Decomposition of the raw medium-skill premium on 77 occupations	163
C3	Decomposition of the raw medium-skill premium, workers aged 25-34	169
D1	First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only. <i>Residuals calculated on age-specific regressions</i>	172
D2	First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only. <i>Residuals calculated on year-specific regressions</i>	173
D3	First-difference CZ <i>wage</i> medium-skill premium on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only	174
D4	First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only, <i>with 1970 included</i>	175
D5	First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only, <i>with Alaska and Hawaii included</i>	176
D6	First-difference CZ medium-skill premium net of individual characteristics on the local occupational spread between medium- and low-skilled workers, OLS, stacked differences and level, 25 – 34 years old only, <i>weighted by the share of the CZ in the national population</i>	177
E1	First-difference CZ occupational probability on the local relative supply of occupations, OLS, stacked differences and level, 25 – 34 years old only, <i>with 1970 included</i>	178

E2	First-difference CZ occupational probability on the local relative supply of occupations, OLS, stacked differences and level, 25 – 34 years old only, <i>with Alaska and Hawaii included</i>	179
E3	First-difference CZ occupational probability on the local relative supply of occupations, OLS, stacked differences and level, 25 – 34 years old only, <i>weighted by the share of the CZ in the national population</i>	180

Table des figures

1.1	Evolution of occupations' shares	31
1.2	Evolution of labor market opportunities	33
1.3	Marginal effect of the proportion of routine occupations on labor market outcomes, conditional on the value of the minimum wage.	43
1.4	Evolution of minimum wage workers' shares, low-paying occupations only . .	48
1.5	Evolution of minimum wage workers' shares, middling occupations only . . .	49
1.6	Evolution of the levels of the minimum wage	54
1.7	Evolution of the price indices of ICT Capital per industry in the US	55
2.1	Evolution of workers' occupations and educational attainment for the overall population	81
2.2	Evolution of occupations' shares for low, medium, and high-skilled workers .	82
2.3	Distribution of the instrument at the CZ level, 1970	86
2.4	Distribution of Rotemberg Weights for each skill	104
3.1	Evolution of the raw high- and medium-skill premium	115
3.2	Evolution of the average log wages for low- and medium-skilled workers . . .	127
3.3	Evolution of the probability of belonging to the first, second and third decile of the income distribution for medium-skilled workers relatively to low-skilled workers	128
3.4	Evolution of the raw skill premium: sub-education and age-specific groups .	128
3.5	Evolution of workers' occupations and educational attainment for the overall population	130
3.6	Evolution of occupations' shares for low-, medium- and high-skilled individuals among working population	131
3.7	Evolution of the routine manual and cognitive shares for the full population, low and medium-skilled individuals among working population	132

TABLE DES FIGURES

3.8	Evolution of the differences in occupational shares between medium- and low-skilled workers.	133
3.9	Evolution of the differences in occupational shares between young medium- and low-skilled workers.	135
3.10	Evolution of the high and medium-skill premium, net of individual characteristics, full population and young workers only	137
3.11	Evolution of the high and medium-skill premium, net of occupation and industry	140
3.12	Evolution of the medium-skill premium, net of individual fixed effect	144
3.13	Evolution of the raw skill premium by birth-cohort	145
3.14	Evolution of low-skilled workers' occupations by birth-cohort	146
3.15	Evolution of medium-skilled workers' occupations by birth-cohort	147
3.16	Model's prediction relatively to the medium-skill premium	154
B1	Evolution of the high and medium-skill premium, net of CZ effects	159
C1	Evolution of the raw high- and medium-skill premium	161
C2	Evolution of the average wages by educational group: CPS data	162
C3	Age-specific medium-skill premium	163
C4	Evolution of the age-specific skill premium by Age Group: Upper and Lower MSP	164
C5	Evolution of the occupational share: medium-skill, by age category	165
C6	Evolution of the high and medium-skill premium, net of individual characteristics, year-specific estimation	166
C7	Evolution of the medium- and high-skill premium, raw and net of individual characteristics with 95% confidence interval	167
C8	Evolution of the ratio of average individual fixed-effect by skill group	168
C9	Evolution of the raw high-skill premium by birth-cohort	170
C10	Evolution of high-skilled workers' occupations by birth-cohort	171

Résumé

La structure du marché de l'emploi a connu d'importantes transformations au cours des dernières décennies, notamment à cause du progrès technologique, à travers l'automatisation et la montée en puissance des nouvelles technologies de l'information et de la communication. Cela s'est traduit par une polarisation du marché de l'emploi, c'est-à-dire une recomposition en termes d'occupations, notamment avec une diminution des occupations dites routinières situées au milieu de la distribution des salaires, accompagnée d'une forte croissance des occupations dites manuelles ou abstraites, respectivement situées en bas et en haut de la distribution des salaires. Ces évolutions nous amènent à nous interroger sur les conséquences en termes d'emplois et de salaires pour les travailleurs. Est-ce que la polarisation du travail a-t-elle eu un impact négatif sur l'emploi en Europe en raison de la présence d'institutions du marché du travail plus contraignante et d'un salaire minimum plus élevé qu'aux États-Unis ? Est-ce que la polarisation du marché de l'emploi a eu un impact différencié en fonction du niveau de qualification, ainsi que sur les dynamiques de salaires relatives entre groupes d'éducation ? L'objectif de ma thèse est de répondre de manière empirique à ces questions. Les principales contributions de ce projet de recherche sont les suivantes. En Europe, la polarisation du marché du travail a eu un impact négatif sur le taux d'emploi et de participation dans les pays à haut salaire minimum, en raison de l'incapacité de ceux-ci de créer suffisamment d'emplois manuels en bas de la distribution des salaires afin de compenser la destruction des emplois routiniers. De plus, aux États-Unis, le processus de polarisation et la réallocation des travailleurs entre les occupations a impacté négativement le salaire des peu-qualifiés, mais aussi dans des proportions similaires les travailleurs moyennement qualifiés, principalement dû à une diminution du salaire moyen au sein des occupations plutôt qu'à une différence de salaire moyen entre les occupations. Enfin, les travailleurs moyennement qualifiés ont connu une baisse importante de leur premium en termes de salaires relativement aux peu-qualifiés depuis le début des années 2000, en raison des difficultés des jeunes travailleurs moyennement qualifiés à occuper des emplois abstraits à leur entrée sur le marché du travail ainsi qu'une baisse drastique de leurs opportunités dans les occupations routinières.

Abstract

The structure of the labor market has undergone important transformations in recent decades, especially due technological progress, through automation and the rise of new information and communication technologies. This has resulted in a polarization of the labor market, i.e. a recomposition in terms of occupations, notably with a decrease in so-called routine occupations located in the middle of the wage distribution, accompanied by a strong growth in so-called manual or abstract occupations, respectively located at the bottom and top of the wage distribution. These developments lead us to wonder about the consequences in terms of jobs and wages for workers. Has the polarization of labor had a negative impact on employment in Europe because of the presence of stronger labor market institutions and a higher minimum wage than in the United States ? Has the polarization of the labor market had a heterogeneous impact depending on the level of qualification ? Does the relative wage dynamics between education groups been affected ? The objective of my PhD thesis is to empirically answer these questions. The main contributions of this research project are the following. In Europe, labor market polarization has had a negative impact on employment and participation rates in high minimum wage countries, due to their inability to create enough manual jobs at the bottom of the wage distribution to offset the destruction of routine jobs. Moreover, in the United States, the polarization process and the reallocation of workers across occupations has negatively impacted the wages of low-skilled, but also to a similar extent medium-skilled workers, mainly due to a decrease in the average wage within occupations rather than due to a reallocation of workers to lower-paying occupations. Finally, middle-skilled workers have experienced a significant decline in their wage premium relative to the low-skilled since the early 2000s, due to the difficulties of young middle-skilled workers to hold abstracts when they enter the labor market, along a drastic decrease in their employment opportunities in routine occupations.