



Four essays on sustainable finance

Daniel-Wassim Le Lann

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Daniel-Wassim Le Lann. Four essays on sustainable finance. Economics and Finance. Université d'Orléans, 2023. English. NNT : 2023ORLE1012 . tel-04297716

HAL Id: tel-04297716

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UNIVERSITÉ D'ORLÉANS
ÉCOLE DOCTORALE SCIENCE DE LA SOCIÉTÉ
TERRITOIRE, ÉCONOMIE ET DROIT (SSTED)
LABORATOIRE D'ÉCONOMIE D'ORLÉANS
THÈSE

présentée par :

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soutenue le : **07 juillet 2023**

pour obtenir le grade de : **Docteur de l'Université d'Orléans**

Discipline/ Spécialité : **Sciences Économiques**

Four essays on sustainable finance

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Je dédie cette thèse à mon grand-père,
et à Hassan.

Remerciements

Je tiens tout d'abord à exprimer mes sincères remerciements à Sessi Tokpavi et Louis Raffestin pour avoir accepté de superviser cette thèse. Le chemin a été long et plein de revirements, mais j'ai beaucoup appris au cours de ces dernières années. Je tiens aussi à chaleureusement remercier Gunther Capelle-Blancard et Stefan Straetmans de m'avoir fait l'honneur de rapporter cette thèse, ainsi que Christophe Rault et Thierry Roncalli d'avoir accepté de faire partie de mon jury de thèse. Je souhaite également exprimer ma reconnaissance envers mes enseignants de Master, qui m'ont permis de débiter cette thèse dans d'excellentes conditions, et qui m'ont aussi fait confiance lorsqu'il a s'agit de me confier des enseignements. Plus particulièrement, je souhaite remercier Denisa Banulescu, Gilbert Colletaz, Christophe Hurlin, Christophe Rault, Aziz Ndoye pour leur bienveillance et leurs conseils. Je souhaite aussi remercier l'ensemble des membres de l'équipe administrative que j'ai pu côtoyer au long de ces années à l'Université d'Orléans, que ce soit dans le cadre de la vie de laboratoire, de la gestion des enseignements, ou au détour d'une pause-café. J'adresse ainsi de chaleureux remerciements à Emilie Cherry, Patricia Fertier, Samuel Siegwald, Solange Siegwald, Mélie Henault, Mouna Karoud, Karine Naudin, et Pierre-Yves Pochard.

J'ai partagé plusieurs années avec les doctorants du Laboratoire d'Économie d'Orléans. Les rencontres que j'y ai faites, qu'elles soient éphémères ou durables, ont considérablement enrichi mon aventure dans la recherche académique, et bien au-delà. Ces mots sont assez pauvres en comparaison des souvenirs avec lesquels je repars, mais je souhaite tout de même remercier quelques personnes que j'ai pu croiser lors de mon passage ici. L'exercice des remerciements étant périlleux, je prie celles et ceux que j'aurais pu omettre de mentionner de bien vouloir m'excuser. Je souhaite d'abord adresser de sincères remerciements à Olessia, Jérémy, Ophélie, Sullivan et Hajare. Pour les nombreux moments passés ensemble, les fous rires, et plus encore, je souhaite également remercier Dylan, José, Pauline, Inessa, Laura et Hugo. J'adresse aussi de chaleureux remerciements aux héritiers de l'équipe économétrie que j'ai eu le plus grand plaisir à côtoyer : Sébastien et Yannick. J'adresse des remerciements particuliers à Julie, José R., Lucien et Sahar pour toutes les discussions sur la vie que nous avons pu avoir. Je souhaite aussi remercier quelques camarades que j'ai toujours apprécié croiser parmi lesquels : Safa, Cigdem, Mamadou, West, Yakouba, Askandarou, Indigo, Mehdi, Mathilda et Sarah. Enfin, j'adresse des remerciements particuliers à Vanessa

et Rosnel, que j'ai eu l'honneur de rencontrer lors de nos années de Master.

Bien entendu, la réalisation de cette thèse aurait été impossible sans la présence dans ma vie d'un certain nombre de personnes pour lesquelles je porte une grande affection. Je remercie tout d'abord ma mère pour m'avoir toujours soutenu, et mon père pour ses précieux conseils. Je souhaite aussi remercier mon grand frère, Yann, pour avoir toujours trouvé les mots pour me guider lors de mes errances, et pour la joie d'avoir pu collaborer ensemble. Je remercie Amine S. pour nos longues années d'amitié et nos nombreuses aventures depuis la cour de récréation de l'école La Fontaine. Je remercie Amine D. pour sa patience incroyable quand il s'agit d'aider les gens qu'il aime. Je remercie Hakim et Vincent pour ces années d'amitié, et pour m'avoir toujours aéré l'esprit en n'en ayant rien à faire des tenants et aboutissants de ce travail de recherche. Je remercie Noémie, pour son flegme à l'anglaise et ses relectures. Je remercie Hugo H., pour nos discussions et nos idées investissements foyeux. Je remercie Benoît pour sa métamorphose en elfe des bois et ses retours toujours très animés dans le fief orléanais. Je remercie Corentin, pour notre camaraderie depuis le Master, nos discussions passionnées, et notre envie de réinventer le monde. Enfin, je remercie Aynur, pour notre incroyable rencontre, tout le soutien qu'elle m'a apporté, et plus encore.

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¹This chapter is a joint work with BOUCHER Christophe, MATTON Stéphane and TOKPAVI Sessi.

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²This chapter is a joint work with DELOZIERE Gauthier and LE LANN Yann.

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Résumé en français

Cette thèse intitulée « *Four essays on sustainable finance* » porte sur le domaine de l'investissement durable, défini par la Commission Européenne comme le « *processus de prise en compte des considérations environnementales, sociales et de gouvernance (ESG) lors de la prise de décisions d'investissement dans le secteur financier, conduisant à des investissements à plus long terme dans des activités et des projets économiques durables* ». ³ Dans le contexte politique européen, l'investissement durable peut donc être compris comme une forme de financement visant à soutenir une croissance économique alignée avec les objectifs du *Pacte vert pour l'Europe*, tels que l'achèvement de la neutralité carbone et d'une économie circulaire à horizon 2050, et qui intégrerait également des considérations sociales liées aux inégalités, à l'inclusivité, ou encore aux droits humains. Sur le plan international, cette forme d'investissement est aussi fréquemment promue par l'Organisation des Nations Unies dans le cadre de la réalisation des *Objectifs de développement durable*.

La finance durable est donc souvent présentée comme un nouveau paradigme de l'investissement visant à intégrer, dans les prises de décisions des acteurs financiers, non seulement les arbitrages traditionnels entre risque et rendement, mais aussi leurs impacts sur la société et l'environnement (Schoenmaker and Schramade, 2018). Cette vision est motivée par l'importance croissante des questions environnementales et sociales dans le contexte politique actuel, ainsi que par le rôle clé des investisseurs institutionnels dans le financement direct de l'activité économique et dans l'exercice du pouvoir décisionnel au sein des entreprises où ils investissent. De nos jours, l'investissement durable occupe une place significative dans le secteur financier. En 2020, la *Global Sustainable Investment Alliance* recensait plus de 35 000 milliards de dollars d'actifs gérés selon des stratégies d'investissement dites « *durables* » sur les marchés des capitaux des économies développées. ⁴ Cet essor a été rendu possible par la diffusion d'innovations financières telles que les obligations vertes, les obligations sociales ou encore les systèmes de notation ESG, permettant l'intégration des *facteurs ESG* dans les processus décisionnels des investisseurs institutionnels. Les travaux de recherche constituant cette thèse sont donc motivés par l'importance de cette nouvelle approche

³https://finance.ec.europa.eu/sustainable-finance/overview-sustainable-finance_fr

⁴Voir Table 1 et l'introduction de cette thèse pour une définition des stratégies d'investissement « *durables* ».

de l'investissement dans le monde financier, mais aussi par le manque de preuves scientifiques concernant sa contribution à la réalisation des objectifs du développement durable.

Cette thèse se structure de la manière suivante. Dans l'introduction, nous commençons par rappeler et clarifier certains concepts clés de la finance durable. Nous tentons d'abord de définir le rôle du secteur financier dans la réorientation de notre économie vers des activités dites durables, et mettons en avant son rôle de coordination plutôt que de moteur de ces transformations. Cette discussion se justifie par de récentes controverses concernant le rôle du secteur financier dans la transition vers une économie bas carbone, telles que le mouvement anti-ESG américain, ou les déclarations publiques de décideurs politiques mentionnant la responsabilité du secteur financier à enclencher une telle transition.⁵ Nous mettons ensuite en avant des barrières structurelles qui pourraient limiter l'apport de la finance durable à la réalisation des objectifs du développement durable. Premièrement, nous discutons du fait que les considérations environnementales et sociales sont principalement intégrées dans les décisions des investisseurs sous la perspective de la *matérialité financière*, signifiant que les facteurs ESG sont d'abord pris en compte par ces agents en raison de leurs impacts potentiels sur la performance financière de leurs investissements. La considération des impacts environnementaux et sociaux des entreprises nécessitant une prise en compte du long-terme, nous soulignons ensuite l'existence de structures actionnariales pouvant biaiser les décisions des investisseurs institutionnels détenteurs des droits de vote vers le court-terme (Li and Wu, 2020). Enfin, nous rappelons que la réalisation des objectifs de développement durable des Nations-Unies nécessite d'importants investissements dans des biens publics pouvant difficilement déboucher sur des rendements financiers capturables par des investisseurs privés. Le reste de l'introduction est consacré à une discussion plus approfondie sur les difficultés liées à la mesure des impacts socio-environnementaux des entreprises, notamment en raison de l'existence de nombreuses asymétries d'informations.

La thèse propose ensuite quatre contributions originales au domaine de la finance durable, séparées en deux parties. La première partie de la thèse se concentre sur les systèmes de notations ESG et est divisée en deux chapitres (Chapitre 1 et Chapitre 2). Ces chapitres introduisent de nouvelles méthodologies économétriques pour évaluer et construire des notations ESG, visant à répondre à certaines des critiques soulevées par les investisseurs, les régulateurs et autres parties prenantes à ce sujet. La deuxième partie de la thèse adopte une perspective plus large sur le comportement organisationnel et les flux d'investissement dans le contexte du changement climatique. Le Chapitre 3 examine la réponse stratégique des grandes entreprises françaises face à l'activisme climatique des étudiants de grandes écoles, tandis que le Chapitre 4 examine la sensibilité des flux d'investissements fossiles aux politiques d'atténuation du changement climatique ciblant la

⁵Voir par exemple les déclarations du ministre français de l'Economie et des Finances sur la « finance verte » <https://www.vie-publique.fr/discours/278987-bruno-le-maire-10032021-climat>

demande.

Chapitre 1

Le Chapitre 1 développe une procédure de backtesting pour l'évaluation des notations ESG dans une configuration en données de panel. Le backtest est basé sur une approche prédictive et suppose que des notations ESG informatives devraient aider à prévoir une variable cible d'intérêt à un horizon donné. Notre procédure évalue les notations ESG en comparant la capacité prédictive de deux modèles imbriqués : l'un incluant uniquement des variables prédictives liées à la performance financière des firmes, l'autre intégrant les notations ESG en plus de cette information parmi l'ensemble des prédicteurs. Dans ce contexte, notre hypothèse nulle d'absence d'information dans les notations ESG est définie comme l'égalité de performance prédictive entre les deux modèles, impliquant que l'intégration des notations ESG parmi les variables prédictives ne permet pas d'améliorer la prédiction de la variable cible. Techniquement, l'inférence repose sur une extension du test de capacité prédictive conditionnelle de Giacomini et White (2006) à une configuration en données de panel.

Contrairement aux recherches antérieures basées sur une analyse *in-sample*, notre approche tient compte de l'éventuelle mauvaise spécification du modèle économétrique utilisé pour mesurer la relation entre les notations ESG et la variable cible. Nos simulations de Monte-Carlo démontrent les bonnes propriétés de la procédure de test à distance finie, sous divers types de mauvaise spécification du modèle prédictif. De plus, notre évaluation dans un environnement *out-of-sample* intègre par construction la possibilité que la relation estimée entre notations ESG et variable cible ne soit pas généralisable à une période future, tandis que des recherches récentes suggèrent que l'intégration des facteurs ESG dans les prix d'actifs varie au cours du temps (Pástor et al., 2022). Nous appliquons ensuite notre méthodologie à la prévision de la volatilité idiosyncratique des rendements d'actions et évaluons les systèmes de notation ESG de deux agences de premier plan sur trois univers d'investissement (Europe, Amérique du Nord, Asie-Pacifique). Les résultats montrent que l'hypothèse nulle d'absence de contenu informationnel dans les notations ESG est fortement rejetée pour le panel européen, tandis que les résultats sont mitigés dans les autres régions. Nous constatons également que le pouvoir prédictif des notations ESG augmente avec le degré de consensus entre les agences de notation : l'application du test uniquement aux entreprises pour lesquelles il existe un degré élevé de consensus entre agences de notations conduit à un rejet de l'hypothèse nulle pour les trois échantillons.

Chapitre 2

Le Chapitre 2 développe une méthodologie économétrique pour la construction de notations ESG basée sur l'apprentissage supervisé. Tandis que le Chapitre 1 utilise une approche prédictive pour évaluer des notations ESG préexistantes, cette contribution aborde le problème inverse de l'utilisation de l'approche prédictive pour la construction de notations ESG optimales. La méthodologie proposée permet d'agréger un vecteur en grande dimension de mesures extra-financières en une notation globale. Elle permet également d'identifier spécifiquement les informations ESG les plus importantes. Comme elle repose sur l'apprentissage supervisé, notre méthodologie nécessite la spécification d'une variable cible pour produire des notations. Le choix de la variable cible appropriée se doit donc d'être cohérent avec la motivation de l'utilisateur final à utiliser l'information extra-financière. Dans notre cadre, ce choix établit également un critère d'optimalité permettant de discriminer entre différentes règles de construction de notations ESG. Nous montrons alors comment des notations ESG supervisées peuvent être produites en estimant un modèle prédictif de la variable cible incorporant des variables ESG granulaires parmi l'ensemble des prédicteurs. Plus précisément, notre méthodologie consiste à estimer de manière jointe un modèle prédictif et un vecteur de poids permettant d'agréger les variables ESG granulaires en une notation globale. Pour gérer la grande dimension du vecteur d'informations ESG, le modèle prédictif est estimé à l'aide de régressions pénalisées intégrant une pénalité de type L1.

Notre méthodologie nécessitant la spécification d'une variable cible, elle présente l'avantage notable d'éliminer toute confusion sur ce que les notations ESG produites visent à mesurer, contrairement aux méthodes non-supervisées fréquemment utilisées par les agences de notations. Elle a également l'avantage d'être plus flexible et moins coûteuse que des méthodes qui agrégeraient les notations de plusieurs agences, et qui nécessiteraient l'accès à plusieurs bases de données propriétaires. Nous démontrons la pertinence de notre approche en appliquant la méthodologie à un large panel de firmes contenant des données ESG granulaires. Notre analyse se concentre sur deux variables cibles : la volatilité idiosyncratique et les controverses ESG. Nos résultats indiquent que, dans le cas de la prévision de la volatilité idiosyncratique, la méthodologie produit des notations avec un pouvoir de prévision largement supérieur à celui des notations d'une agence de premier plan. Cependant, les informations issues du reporting extra-financier des entreprises ne semblent pas avoir de pouvoir prédictif sur l'implication des entreprises dans des controverses ESG une fois que le modèle prédictif intègre les informations financières, sectorielles, et liées à la localisation des firmes. Alors que de récentes études montrent que les scores ESG des principales agences de notation n'aident pas à prédire les futures controverses ESG (Bams and van der Kroft, 2022; Yang, 2022), ce dernier résultat suggère que le problème pourrait être lié à la nature même de l'information sur laquelle ces notations sont fondées.

Chapitre 3

Le Chapitre 3 examine la réponse stratégique des grandes entreprises face à l'activisme climatique des étudiants de l'enseignement supérieur français. Ce travail de recherche porte sur l'étude du mouvement climat *Réveil écologique* initié en 2018 par des étudiants de grandes écoles menaçant de boycotter les offres d'emploi émises par des employeurs polluants, ou jugés comme tels. L'initiative a connu un fort succès dans l'enseignement supérieur français, en particulier auprès des étudiants enrôlés dans des institutions d'élite, et a également bénéficié d'une couverture médiatique nationale. Cet engouement a suscité des préoccupations quant à la capacité des grandes entreprises les plus polluantes à attirer des travailleurs hautement qualifiés, mais également un espoir quant à l'accélération de leur transition vers des modèles économiques écologiquement soutenables. En 2022, les organisateurs de cette mobilisation reconnaissaient néanmoins l'impact limité du mouvement sur la transformation des grandes entreprises.

Grâce à l'analyse d'une base de données de sondage unique sur les participants à cette mobilisation climat, ce chapitre explore les déterminants individuels du boycott des employeurs jugés polluants, ainsi que la sensibilité d'une telle décision à la communication environnementale des grandes entreprises. En utilisant des mesures répétées des intentions des étudiants de refuser de travailler pour des entreprises polluantes et des modèles de classification, nous calculons une mesure individuelle de la sensibilité des intentions de boycott des employeurs polluants aux promesses environnementales des entreprises. Alors que 86% des répondants ont l'intention de boycotter les offres d'emploi émises par des employeurs polluants, ils sont en moyenne trois fois moins susceptibles de déclarer de telles intentions après avoir été exposés à un engagement environnemental. Cependant, nous observons également une hétérogénéité importante dans les réactions des étudiants aux engagements environnementaux, une part significative des répondants exprimant leur méfiance envers les promesses des entreprises. La sensibilité importante des intentions de boycott à la communication environnementale s'explique par le fait que le refus de travailler pour un employeur polluant et la réaction aux engagements environnementaux des grandes entreprises sont expliqués par des caractéristiques individuelles différentes. Alors que les intentions de refuser de travailler pour un employeur polluant sont principalement motivées par la recherche de sens au travail et les attitudes pro-environnementales, la réaction à la communication environnementale des entreprises est d'abord expliquée par les perspectives de carrière et des facteurs idéologiques liés à la question écologique.

Ce travail de recherche met en évidence l'exposition des grandes entreprises aux risques liés au canal des ressources humaines, mais également un mécanisme incitant à la prise d'engagements environnementaux qui pourrait conduire à des comportements purement opportunistes de la part des firmes dans un cadre institutionnel ne régulant pas leur communication environnementale. En

ce sens, nos résultats viennent tempérer les arguments avancés par certains travaux de recherche mettant en avant l’auto-sélection des travailleurs qualifiés hors des secteurs polluants comme facteur favorisant la transition des entreprises vers des modèles économiques écologiquement soutenables (Brekke and Nyborg, 2008; Brannstrom et al., 2022).

Chapitre 4

Le Chapitre 4 propose une étude empirique portant sur la réponse des investissements pétroliers et gaziers aux politiques d’atténuation du changement climatique ciblant la demande. La gouvernance climatique actuelle se caractérise par deux traits essentiels. Tout d’abord, les gouvernements se concentrent avant tout sur la mise en œuvre de politiques de demande visant à réduire la dépendance des économies aux énergies fossiles plutôt que par des restrictions côté offre. Les partisans du *green paradox* soutiennent que de telles politiques pourraient accélérer l’extraction de ressources fossiles en raison du comportement d’optimisation intertemporelle des propriétaires des ressources (Sinn, 2008). D’autres travaux de recherche soutiennent au contraire que de telles politiques publiques tendraient à diminuer l’investissement dans des infrastructures liées aux énergies fossiles car elles signaleraient une hausse du risque d’actifs échoués associé à des investissements partiellement irréversibles (Fried et al., 2022). Une seconde caractéristique importante de la gouvernance climatique actuelle est sa nature fragmentée. Les efforts d’atténuation du changement climatique varient fortement d’un pays à l’autre en raison de disparités liées à des facteurs économiques et institutionnels tels que le niveau de développement économique, la dépendance des économies nationales aux énergies fossiles, ou la qualité institutionnelle (Lamb and Minx, 2020). Un vaste corpus de recherches, principalement à travers l’utilisation de modèles à équilibre général calculable, met en évidence l’existence de fuites de carbone dans un tel contexte (Carbone and Rivers, 2017) : dans une économie de marché mondialisée, l’extraction de ressources fossiles évitée par l’effort d’un pays pourrait être partiellement compensée par une augmentation de l’extraction induite par le reste du monde.

Notre analyse empirique repose sur l’exploitation d’une base de données de panel couvrant les dépenses en capital d’entreprises d’extraction pétrolières et gazières localisées dans 30 pays, et représentant un quart des réserves mondiales prouvées de pétrole et de gaz. Nous proposons deux nouveaux indicateurs pour évaluer l’effort d’atténuation du changement climatique au niveau national et mondial, basés sur le décompte du nombre de politiques climatiques adoptées durant une certaine période à ces deux échelles. Ces indicateurs sont par la suite intégrés dans un modèle économétrique d’investissement standard. Nos résultats suggèrent que les entreprises pétrolières et gazières réduisent significativement leurs investissements extractifs à la suite d’une

hausse de l'adoption de politiques climatiques dans le pays de localisation de leurs quartiers généraux. L'exploitation de données complémentaires portant sur les questions des investisseurs lors des conférences trimestrielles de résultats financiers nous permet d'attribuer cet effet à une hausse de l'exposition de ces entreprises au risque de transition climatique. Cependant, nos résultats suggèrent également l'existence d'une fuite d'investissement dans les énergies fossiles, car les entreprises localisées dans des pays ne s'efforçant pas d'atténuer le changement climatique, et donc moins exposées au risque d'actifs échoués, augmentent leurs investissements extractifs à la suite d'une hausse de l'effort d'atténuation dans le reste du monde.

Portée des résultats

La portée des résultats de cette thèse est la suivante. Les résultats des deux premiers chapitres soulignent d'abord les difficultés liées à la construction de systèmes de notation de la durabilité des entreprises. Ce point est notamment mis en avant par les résultats du Chapitre 2 soulignant l'intérêt limité de l'information issue du reporting extra-financier pour la prédiction de variables réelles. D'autre part, l'importance de la localisation des quartiers généraux des firmes pour l'intégration des critères ESG dans le prix des actifs, démontrent qu'une simple transparence de l'information n'est pas suffisante pour orienter les décisions des investisseurs vers le financement d'activités durables. Ce point est également soutenu par les résultats empiriques du Chapitre 4 identifiant le rôle clé des décideurs politiques pour l'ancrage des anticipations des agents dans une optique d'alignement des flux financiers avec les objectifs climatiques de l'Accord de Paris. Si la finance durable a pour objectif d'orienter l'allocation du capital vers des activités écologiquement et socialement soutenables, cette thèse souligne donc qu'elle ne peut se soustraire à une action publique qui permettrait d'intégrer les externalités négatives dans la valorisation des actifs financiers. Ce point est réaffirmé par le mode d'intégration des critères ESG dans les décisions d'investissement : sous l'angle de la matérialité financière, une perspective motivée par le devoir fiduciaire des gestionnaires d'actifs envers leurs clients. Une implication directe est qu'une part importante des dommages écologiques causés par l'activité économique n'est sans doute toujours pas intégrée dans le prix des actifs. Ce point est soutenu par la présence d'angles morts dans les bases de données ESG ayant servi à la réalisation de ce travail de recherche et qui ont pu être constatées par l'auteur de la thèse. Quelques exemples notables concernent l'absence de métriques liées aux impacts des entreprises sur les écosystèmes, à l'utilisation des terres, à la pollution des sols ou à la pollution marine. De futurs travaux de recherches devraient donc viser à combler ces angles morts sur une base scientifique, la construction de métriques liées aux impacts environnementaux pouvant être guidée par le cadre de la théorie des limites planétaires, celles liées aux impacts sociaux par les travaux de recherche sur

le bien-être et la santé humaine. Une fois un tel système d'évaluation construit, nous conjecturons qu'une action gouvernementale conditionnant l'octroi de subventions publiques au respect d'un cahier des charges « *ESG* » permettrait de mieux s'approcher des objectifs de l'investissement durable tels que définis par la Commission Européenne.

La deuxième partie de la thèse, constituée des Chapitres 3 et 4, se focalise sur le comportement des organisations et les flux d'investissement à l'aune du changement climatique. Le Chapitre 3 explore l'impact des pressions issues de la société civile sur la transformation du modèle économique des entreprises polluantes. Un résultat clé est de démontrer l'importance de la communication environnementale des grandes entreprises pour atténuer l'impact négatif de mouvements sociaux liés à la question climatique. En conséquence, ce travail de recherche suggère qu'une transition des entreprises polluantes vers des modèles économiques écologiquement soutenables ne saurait advenir par le biais de mécanismes tels que les boycotts. Bien que de tels mécanismes incitatifs soient susceptibles d'affecter le comportement des organisations privées et leurs politiques environnementales, de tels ajustements ne pourraient s'opérer qu'à la marge en raison de l'importance des logiques économiques et de l'ampleur des transformations requises pour limiter l'impact écologique des secteurs les plus polluants. Enfin, les résultats du Chapitre 4 questionnent la capacité de la gouvernance climatique actuelle à réduire l'investissement dans des nouveaux projets d'extraction d'énergies fossiles, alors que de récents travaux de recherche démontrent l'incompatibilité des plans d'investissements du secteur des énergies fossiles avec les objectifs de l'Accord de Paris (Kühne et al., 2022). En ce sens, nos résultats empiriques soutiennent la mise en place de politiques de restriction de l'offre d'énergies fossiles, tel qu'un traité international de non-prolifération des énergies fossiles (Newell and Simms, 2020), pour atténuer efficacement le changement climatique.

General Introduction

General Introduction

“Dr. Seldon, you disturb the peace of the Emperor’s realm. None of the quadrillions living now among all the stars of the Galaxy will be living a century from now. Why, then, should we concern ourselves with events of three centuries distance?”

Foundation, Isaac Asimov

What is sustainable finance? It is with this question that the confusion starts, to the point of causing a major political dispute. In March 2023, U.S Congress voted a bill to prevent pension fund managers from considering environmental, social, and governance (ESG) factors in their investment decisions. From the viewpoint of Republican senators, ESG factors were used by financial institutions to push a woke agenda of climate and social justice over the pursuit of financial returns, therefore violating their fiduciary duties and jeopardizing Americans retirement savings. The event was significant enough for President Joe Biden to trigger the first veto of his mandate. From his perspective, the problem was inverted: the passing of the bill was jeopardizing Americans retirement savings as it was preventing fund managers from considering risk factors material to their investment performance.⁶

A similar confusion might arise when reading public figures’ declarations on sustainable finance. Larry Fink, CEO of the world’s largest asset manager, justifies his considerations of sustainability in investment decision-making as follows:

*“We focus on sustainability not because we’re environmentalists, but because we are capitalists and fiduciaries to our clients.”*⁷ (Larry Fink’s Letter to CEOs, 2022)

Hence, in Fink’s view, the world economy is undergoing massive changes and profit-driven motives requires him to take sustainability issues into account. Throughout his letter, he is careful to distance his company from being seen as the source of these transformations, insisting instead that

⁶<https://www.reuters.com/business/sustainable-business/biden-vetoes-resolution-block-labor-dept-rule-esg-investing-2023-03-20/>

⁷<https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter>

the financial sector merely serves as the catalyst of a transformation impulsed by stakeholders. When expressing his views on finance and climate change, the French Minister of the Economy and Finance adopts a different perspective: the government “*want finance to be fully and wholeheartedly dedicated to the fight against climate change*”. The Minister further expresses his gratitude to all financial institutions that have already committed themselves to this task.⁸⁹

The differences between these views on sustainable finance allows us to get a first intuition on the origin of the dispute. The confusion stems from the role of the financial sector in achieving the transition towards a sustainable economy. The term *sustainable investing* is used to refer both to the act of *investing to change the world* and to the act of *investing in a changing world*. The distinction lies in the force behind the transformation: the ethical will of a benevolent investor or an external force that a rational, profit-driven investor would be wise to acknowledge. More than a matter of semantics, this distinction has significant implications for what can reasonably be expected from sustainable finance in achieving global economic transformation.

The remainder of this introduction is structured as follows. The first section introduces some key concepts of sustainable finance. The second and third sections delve into the construction of measurement systems for corporate sustainability. The final section presents the thesis contribution to the field of sustainable finance.

Key concepts

Sustainable finance is defined by the European Commission (EC) as: *the process of taking environmental, social, and governance (ESG) considerations into account when making investment decisions in the financial sector, leading to more long-term investments in sustainable economic activities and projects*.¹⁰ In contrast, the Global Sustainable Investment Alliance (GSIA), a leading global network promoting sustainable finance, simply defines it as: *an investment approach that considers environmental, social, and governance (ESG) factors in portfolio selection and management* (GSIA, 2021). Both definitions agree that sustainable finance is characterized by the integration of ESG factors, which captures intangible assets related to a company’s management of environmental, social and governance issues, into investment processes. However, the European Commission goes a step further by defining it as a tool for reaching sustainable development. This vision is anchored in the European Union policy-making effort to achieve climate neutrality and a circular economy by 2050 (European Commission, 2021). Hence, from an European policy-maker’s perspective, sustainable finance is to be understood as an attempt to steer capital flows towards

⁸<https://www.vie-publique.fr/discours/278987-bruno-le-maire-10032021-climat>

⁹Bruno Le Maire’s statement refers more specifically to green finance, which is a subfield of sustainable finance that focuses on financing the transition toward a low-carbon economy and addressing other environmental issues. See Roncalli (2022) for a discussion on the subfields of sustainable finance.

¹⁰https://finance.ec.europa.eu/sustainable-finance/overview-sustainable-finance_en

sustainable activities. For a rational investor however, it may be limited to the consideration of ESG criteria in a traditional risk-return analysis.

Table 1: Sustainable investment strategies

Strategy	Definition
ESG integration	The systematic and explicit inclusion by investment managers of environmental, social and governance factors into financial analysis.
Corporate engagement & Shareholder action	Employing shareholder power to influence corporate behaviour, including through direct corporate engagement (i.e., communicating with senior management and/or boards of companies), filing or co-filing shareholder proposals, and proxy voting that is guided by comprehensive ESG guidelines.
Norms-based screening	Screening of investments against minimum standards of business or issuer practice based on international norms such as those issued by the UN, ILO, OECD and NGOs (e.g. Transparency International).
Negative/exclusionary screening	The exclusion from a fund or portfolio of certain sectors, companies, countries or other issuers based on activities considered not investable. Exclusion criteria (based on norms and values) can refer, for example, to product categories (e.g., weapons, tobacco), company practices (e.g., animal testing, violation of human rights, corruption) or controversies.
Best-in-class/positive screening	Investment in sectors, companies or projects selected for positive ESG performance relative to industry peers, and that achieve a rating above a defined threshold.
Sustainability themed /thematic investing	Investing in themes or assets specifically contributing to sustainable solutions - environmental and social - (e.g., sustainable agriculture, green buildings, lower carbon tilted portfolio, gender equity, diversity).
Impact investing	Investing to achieve positive, social and environmental impacts - requires measuring and reporting against these impacts, demonstrating the intentionality of investor and underlying asset/investee, and demonstrating the investor contribution.
Community investing	Where capital is specifically directed to traditionally underserved individuals or communities, as well as financing that is provided to businesses with a clear social or environmental purpose. Some community investing is impact investing, but community investing is broader and considers other forms of investing and targeted lending activities.

Source: GSIA classification of sustainable investment strategies.

The duality between profit and purpose can be found among the variety of sustainable investment strategies presented in Table 1. These investment approaches differ in the way ESG criteria are integrated into investment processes, and sometimes in the motives for using ESG criteria. ESG integration, for example, involves using ESG factors as determinants of long-term investment risks and opportunities. Negative screening integrates ESG criteria to exclude certain financial assets from the universe of investable assets. This exclusion may aim to satisfy ethical standards or financial motives by reducing a portfolio's exposure to poorly managed ESG issues. In contrast, impact investing seeks to generate measurable positive environmental and social outcomes alongside financial returns. Table 2 displays the assets under management (AUM) by sustainable investment strategy and region in 2020, showing significant differences in their popularity. ESG integration, negative screening, and shareholder engagement tend to be the most popular approaches, while impact investing plays a minor role.

These figures emphasize that non-pecuniary motives may not be the primary driver behind the rise of sustainable finance. Although finance professionals can be driven by ethical considerations, they remain legally bound by their fiduciary duty to their clients. Amel-Zadeh and Serafeim (2018) find that investors primarily consider ESG information because they believe it can impact their

investment performance. Corporate managers seeking to improve the socio-environmental impact of their company face a similar challenge: they have legal obligations towards their shareholders. The stakeholder theory of corporate governance, which posits that private organizations should not focus exclusively on their shareholders interests to be successful, has certainly helped bring environmental and social issues to the business agenda. However, contributing to the common good does not necessarily translate into private profits. Conflicting interests between shareholders and stakeholders are therefore a significant obstacle in the establishment of stakeholder capitalism (Li and Wu, 2020). The existence of these barriers does not imply that the financial sector cannot accelerate the transition towards a sustainable economy. Instead, it clarifies its role, and the role of policymakers, in achieving global economic transformation.

Table 2: AUM by sustainable investment strategy and region

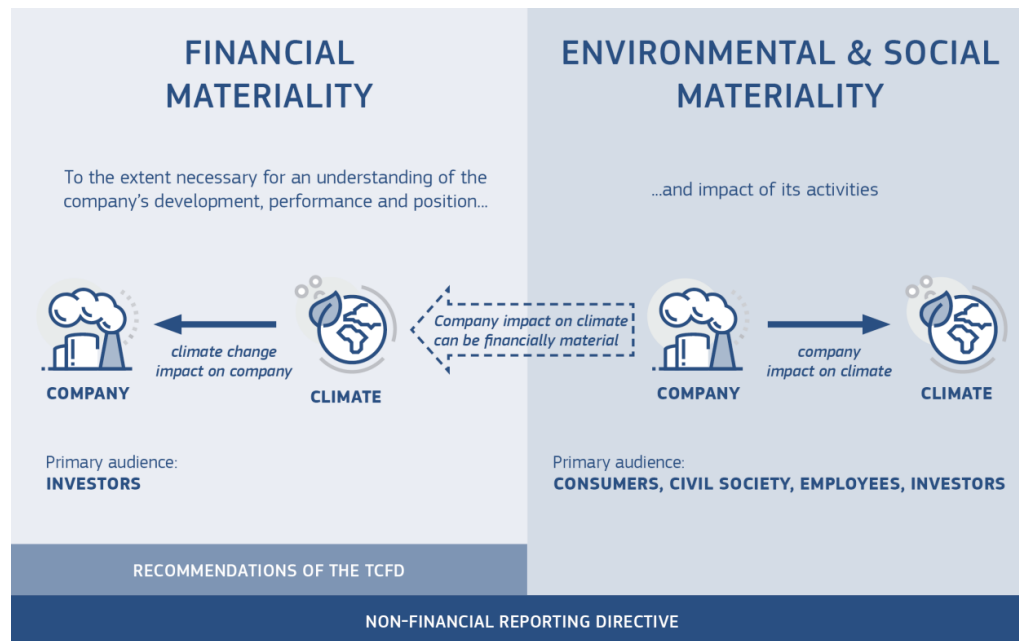
2020 (Billions)	Europe (EUR)	United States (USD)	Canada (CAD)	Australia/New Zealand (AUD)	Japan (JPY)	Global (USD)
Impact/community investing	95 €	212 \$	20 \$	25 \$	140 ¥	352 \$
Positive/best-in-class screening	511 €	658 \$	21 \$	4 \$	14643 ¥	1384 \$
Sustainability-themed investing	130 €	1688 \$	48 \$	5 \$	7989 ¥	1948 \$
Norms-based screening	2745 €	—	1050 \$	—	28308 ¥	4140 \$
Corporate engagement & shareholder action	4236 €	1980 \$	2673 \$	—	187170 ¥	10504 \$
Negative/exclusionary screening	8253 €	3404 \$	1361 \$	127 \$	135263 ¥	15030 \$
ESG integration	3697 €	16059 \$	3008 \$	1135 \$	204958 ¥	25195 \$
Total sustainable investing*	10730 €	17081 \$	3166 \$	1295 \$	310039 ¥	35301 \$

Source: GSIA 2020 report on sustainable investment. *Net values after adjustments to remove double-counting, since managers may apply more than one strategy to a given portfolio of assets.

These perspectives on impact and profitability have practical implications in the assessment of ESG criteria, and are formalized through the concept of materiality. *Financial materiality* is an accounting and financial reporting convention used by companies to determine if an item, event, or piece of information should be disclosed in their financial statements. According to this principle, an element of information is considered to be material if omitting it, or misstating it, might alter the decisions of a reasonable user of a company’s financial statements. In the context of sustainable finance, financial materiality refers to the significance of ESG factors on a company’s financial performance. Currently, ESG standards are primarily assessed from a financial materiality perspective (GRI, 2022).

On the other hand, the concept of *double materiality* encompasses both financial materiality and the socio-environmental impact of a company’s activities. This second component is sometimes referred to as *impact materiality* or *inside-out materiality*, and focuses on corporate externalities affecting the environment, society, and stakeholders. The concept of double materiality was formally proposed in 2019 by the European Commission (European Commission, 2019). Figure 1

Figure 1: Double materiality perspective of the NFRD in the context of reporting climate-related information



* Financial materiality is used here in the broad sense of affecting the value of the company, not just in the sense of affecting financial measures recognised in the financial statements.

Source: Guidelines on Non-financial Reporting – Supplement on Reporting Climate-related Information, published in June 2019 by the European Commission.

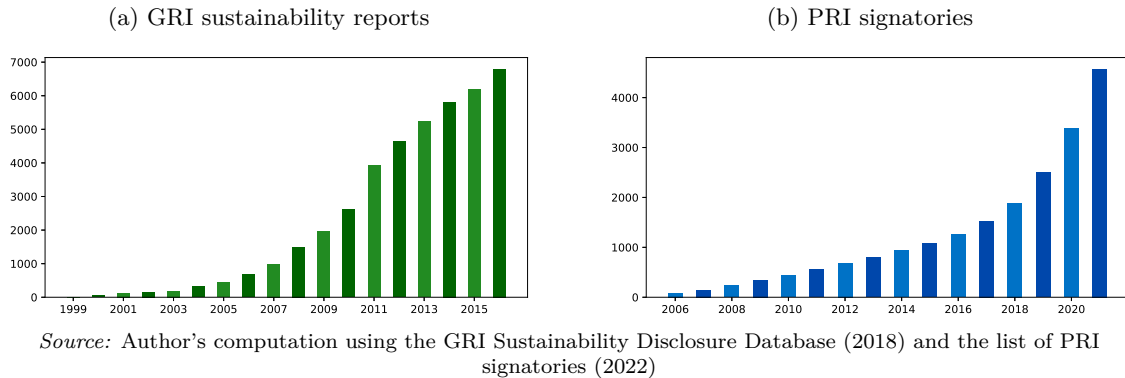
displays the Non-Financial Reporting Directive (NFRD) perspective on double materiality in the context of climate-related reporting. The adoption of a double materiality approach to assess companies' sustainability is still in its early stages and faces numerous challenges, beginning with the establishment of appropriate norms and standards to measure impact (Adams et al., 2021).

The differences between these concepts are subtle enough to warrant an example. Let us consider two firms, A and B, that are identical with the exception that firm A has established a credible decarbonization plan, unlike firm B. From a financial materiality perspective, firm A demonstrates better management of ESG risks: by planning, it is better equipped to handle a sudden increase in carbon prices. However, from an impact materiality perspective, firms A and B are equivalent. One could argue that the decarbonization plan suggests that firm A will improve its environmental impact in the future, but that may not be the case. If a freeze in climate policy-making anchors expectations in low carbon prices for the coming years, a cost-benefit analysis might discourage firm A from implementing its plan. At this point, the ethical standards of firm A's managers and shareholders might play a role: they could still decide to initiate the decarbonization plan. The move could lead to reputational benefits, thus turning into an investment in intangible assets. It might also reduce firm A's competitiveness and drive it out of business.¹¹ A second significant implication of the evaluation of ESG criteria through the financial materiality lens is

¹¹Sustainable investors are not mentioned in this example. Their role would be to encourage companies to adopt credible decarbonization plans, either through shareholder engagement or by increasing firm B's cost of capital.

that corporate negative externalities, not anticipated to be priced in the near future —such as economic impacts on ecosystems and biodiversity— have no rationale for being accounted for and integrated into investment decisions.

Figure 2: Diffusion of ESG standards



The development of sustainable finance has necessitated access to new sources of data. A few years ago, most publicly traded companies disclosed only financial information. The GHG Protocol (1998) and the Carbon Disclosure Project (2000) represent early attempts to establish a standardized accounting framework for quantifying and managing greenhouse gas emissions. Today, sustainability reporting is a standard accounting practice. This evolution has been guided by a growing demand from stakeholders for corporate accountability and investors' interest in ESG factors as drivers of investment performance (Herzig and Schaltegger, 2011). It has also led to the establishment of multiple sustainability accounting standards. These frameworks primarily differ in the perspective of materiality they adopt and whether they cover general sustainability reporting or focus solely on climate-related disclosure. For example, the SASB and the GRI are both leading accounting standards for global sustainability reporting. However, the SASB adopts a financial materiality perspective, while the GRI tends to integrate a double materiality approach. In contrast, the TCFD and CDSB standards focus solely on climate-related disclosure.

The widespread adoption of sustainability reporting has been facilitated by the diffusion of non-binding sustainability agreements promoted by the United Nations throughout the corporate and financial world, such as the UN Global Compact Initiative and the Principles for Responsible Investment (PRI). Figure 2 illustrates the exponential growth in the number of GRI sustainability reports, as well as the number of PRI signatories, a framework that encourages investors to integrate ESG issues into their investment processes. A milestone has been the adoption of mandatory sustainability reporting regulations in many capital markets worldwide, such as the European NFRD. These mandatory disclosure standards have played a critical role both in increasing disclosure and enhancing the credibility and comparability of sustainability reports (Ioannou and Serafeim,

2017). Corporate sustainability reports' have become a valuable source of information for financial analysts, as they serve as the foundation of measurement systems of corporate sustainability.

ESG Ratings

The vast amount of data made accessible by increased sustainability disclosure has led to the emergence of ESG rating agencies. The core function of these institutions is to evaluate companies' ESG performance through the attribution of ESG ratings, which enables the implementation of sustainable investment strategies.¹² ESG rating agencies appeared in the 1980s, with the foundation of pioneers such as Eiris, ISS, and KLD, to provide extra-financial analysis to socially responsible investors. They are now major players in the sustainable finance ecosystem. Before delving into the rating production process, it is necessary to first discuss what ESG rating agencies aim to measure. Table 3 introduces the ESG ratings of some leading rating providers. It shows that ESG ratings primarily aim to capture companies' exposure to long-term risks. This implies that ESG ratings are designed with a financial materiality perspective, a state of affairs acknowledged by the GRI (GRI, 2022). In a world where traditional business models are jeopardized, ESG ratings hence seek to capture companies' ability to manage long-term risks and opportunities related to the future transformations of our economic system.

Table 3: ESG ratings providers

ESG ratings provider	Rating definition	Data sources
ISS	Assess companies' sustainability performance based on ESG criteria with a rules-based methodology.	Public information.
MSCI	Measure a company's resilience to long-term, industry material ESG risks.	Public disclosure, news media, NGO documents.
Refinitiv	Designed to measure a company's relative ESG performance, commitment and effectiveness, based on company-reported data.	Public disclosure, news media, NGO documents.
S&P Global	Assessment of the entity sustainability, based on active management of ESG-related risks and opportunities, governance, and entity's ability to adapt to change and take advantage of long-term trends and disruptive opportunities.	Public disclosure, news media, stakeholder analysis, web-based questionnaire.
Sustainalytics	Measure a company's exposure to industry-specific material ESG risks and how well a company is managing those risks.	Public disclosure, news media, NGO documents.

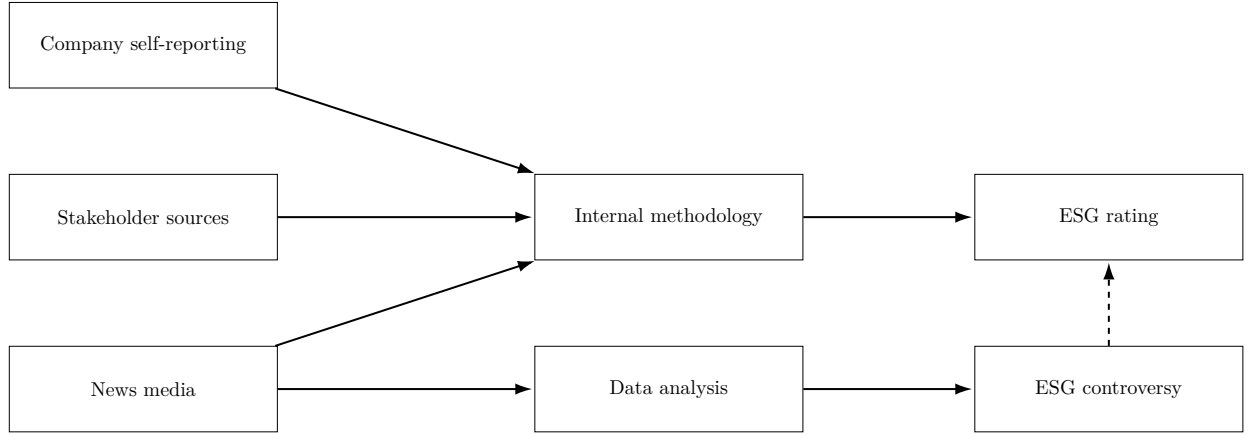
Source: Information gathered by the author from the websites and brochures of rating providers.

The production process of ESG ratings described in Figure 3 is composed of two steps: data collection and data aggregation. ESG rating agencies gather data from various sources, including companies disclosures (e.g., sustainability reports, financial statements, and websites), third-party databases, government and regulatory filings, news articles. They may also engage with companies directly to collect additional information or seek clarifications. The data are then treated and aggregated into overall ESG ratings using a methodology proper to the rating agency. News media sources can also be screened to identify ESG controversies, which capture the involvement of a

¹²Other financial innovations enabling investors to assess ESG factors in investment processes include dedicated financial instruments such as social bonds and green bonds, which are not studied in this thesis.

company in an adverse ESG event. Some well-known examples of ESG controversies include the Dieselgate, the Cambridge Analytica scandal, or the recent Orpea scandal. Depending on the rating methodology, ESG controversies may or may not be used to compute ESG ratings. They also provide valuable information as ESG scandals can have an important impact on firm value (Derrien et al., 2021; Glossner, 2021).

Figure 3: ESG rating production process



Note: The dashed arrow indicates that some ESG ratings may integrate information on ESG controversies.

ESG ratings have not only served financial analysts, they have also been widely used by researchers. Numerous empirical studies have relied on them to investigate topics such as the link between ESG performance and cost of capital (El Ghouli et al., 2011; Goss and Roberts, 2011; Chava, 2014), between ESG performance and firm risk (Albuquerque et al., 2019), or the effect of ownership structure on ESG performance (Dyck et al., 2019; Chen et al., 2020). However, ESG rating agencies use non-standardized, heterogeneous, and opaque methodologies to produce ESG ratings and do not necessarily agree on how to assess a company's ESG performance. Consequently, there can be substantial disagreement between rating agencies' evaluations of the same company. This issue is a well-known stylized fact that has been extensively documented by prior research (Chatterji et al., 2016; Berg, Koelbel and Rigobon, 2022). For instance, Berg, Koelbel and Rigobon (2022) finds that the correlations between the ratings from six leading ESG providers average to 54%, whereas the credit ratings from the main credit rating agencies exhibit an average correlation of 99%. ESG rating disagreement is a significant limitation that has raised concerns among regulators and investors regarding the informativeness of ESG ratings. Furthermore, both theoretical and empirical evidence show that rating disagreement has important implications for asset pricing (Gibson Brandon et al., 2021; Avramov et al., 2022).

Sustainability under information asymmetry

Corporate sustainability assessments largely depend on companies self-reported information. Reliability is thus a key issue, especially considering firms' incentives to provide a positive image of their environmental and social responsibility. The benefits associated with such an image can be substantial, including preempting regulatory action (Maxwell et al., 2000), increasing political access (Werner, 2015), facing more lenient regulatory enforcement (Hong et al., 2019), dampening the adverse consequences of environmental controversies (Barrage et al., 2020), and attracting a more productive workforce (Hedblom et al., 2019). However, due to information asymmetries, companies may be more inclined to appear sustainable rather than actually being sustainable. A vast body of literature has explored the circumstances under which such a discrepancy can occur, as well as the various forms it can take, primarily in the context of environmental impact (Lyon and Montgomery, 2015).

A first issue is the partial disclosure of a company's impact. Partial disclosure occurs when the information disclosed by a company does not adequately depict its real social and environmental impact because the company refrains from sharing potentially negative information. This situation is likely to arise in institutional settings characterized by voluntary and non-standardized regimes of non-financial reporting, a lack of regulation, and weak third-party oversight (Lyon and Maxwell, 2011; Marquis et al., 2016). It is particularly salient in assessing corporate sustainability because it can materialize as missing or unreliable impact metrics (Kim and Lyon, 2011). However, experiences from emissions trading systems demonstrate that a high level of information quality can be achieved under mandatory disclosure rules, third-party monitoring, and significant regulatory penalties for noncompliance (Schmalensee and Stavins, 2017; Zhang et al., 2019).

A more profound problem is that of symbolic compliance, which occurs when a company implements sustainability policies, programs, or objectives without actually implementing meaningful changes or addressing the underlying issues (Bowen, 2014). For example, companies can signal the implementation of a broad range of sustainability policies but not provide adequate resources or support to ensure their effectiveness. In this setting, sustainability symbols are merely used as window dressing for business-as-usual practices. This issue can materialize as a failure to achieve corporate commitments or as large policy implementation gaps (Ramus and Montiel, 2005; Boiral, 2007). The superficial adoption of sustainability practices can be caused by a misalignment of managerial incentives with ESG issues (Eccles et al., 2014), by the high costs supported to meaningfully address ESG issues (Durand et al., 2019), or by conflicting interests between shareholders and stakeholders (Li and Wu, 2020).

In building measurement systems of corporate sustainability, this situation is particularly challenging as it implies that multiple companies reporting identical sustainability practices may cor-

respond to entirely different realities on the ground. It has direct implications for ESG scoring because a large share of the information used in the computation of ESG ratings measures whether a company adopts specific sustainability policies, programs, or targets. As a consequence, Bams and van der Kroft (2022) argues that companies have incentives to inflate their ratings by signaling the adoption of sustainability practices that do not translate into a future improvement of their impact. This issue might explain why some recent studies find that ESG ratings have poor predictive power for future ESG controversies (Bams and van der Kroft, 2022; Yang, 2022). Symbolic compliance could be a difficult obstacle to overcome because it may require access to costly additional data to monitor corporate behavior.

While the questions surrounding organizations' true commitment to sustainability had primarily targeted non-financial companies, the promises of sustainable finance has expanded the scrutiny to the behavior of financial actors. Although the largest financial institutions and asset managers around the world have committed to the Principles for Responsible Investment, several events have arisen regarding their commitment towards ESG standards. These controversies encompass the sustained role of the banking industry in fossil fuel financing (Kirsch et al., 2021) and the recent investigation for greenwashing of DWS, one of the world's leading asset managers.¹³ Consequently, regulatory oversight is now expanding to the ESG promises of institutional investors, while a burgeoning literature investigates the conditions of their commitment to ESG practices (Gibson Brandon et al., 2022; Kim and Yoon, 2023).

Thesis contribution

This thesis proposes four original contributions to the growing field of sustainable finance. It is split into two parts. The first part of the thesis focuses on ESG ratings and is divided into two chapters (Chapter 1 and Chapter 2). These chapters introduce new tools to evaluate and construct ESG ratings, aiming to address some of the criticisms raised by investors, regulators, and stakeholders regarding ESG ratings. The second part of the thesis takes a broader focus on organizational behavior and investment flows in the context of increasing efforts to fight climate change. Chapter 3 investigates organizations' strategic responses to the threat of climate activist movements, while Chapter 4 examines the dynamics of fossil investment flows under the climate policy-making effort to mitigate climate change.

Chapter 1 develops a backtesting procedure for the evaluation of ESG ratings in a panel data setting. The backtest is based on a predictive approach, as it assumes that informative ESG ratings should help to forecast a target variable of interest. Our procedure evaluates ESG ratings by comparing the forecasting abilities of two nested models that differ solely in the inclusion or

¹³<https://www.reuters.com/business/finance/deutsche-banks-dws-allegations-greenwashing-2022-06-09/>

exclusion of ESG ratings within the set of predictor variables. In this setting, our null hypothesis of a lack of informational content in ESG ratings is defined as the equality in forecast accuracy between the two nested models, implying that integrating ESG ratings among predictor variables does not help to forecast the specified target variable. Technically, the inference is based on an extension of the conditional predictive ability test of Giacomini and White (2006) to a panel data setting. Contrary to previous research based on an in-sample analysis, our approach accounts for possible misspecification of the econometric model used to measure the relationship between ESG ratings and the outcome variable. Monte Carlo simulations demonstrate the good small-sample properties of the backtest under various types of model misspecification. We apply our methodology to the forecasting of stock returns' idiosyncratic volatility and evaluate the ESG rating systems of two leading agencies across three investment universes (Europe, North America, Asia-Pacific). The results show that the null hypothesis of an absence of informational content in ESG ratings is strongly rejected in Europe, whereas results appear mixed in the other regions. Importantly, we find that the forecasting power of ESG ratings increases with the degree of consensus between rating agencies. As a consequence, applying the test only to firms over which there is a high degree of consensus leads to higher predictive accuracy gains for all three universes.

Chapter 2 develops a methodology for ESG ratings production based on supervised learning. This contribution therefore tackles the reverse problem of using supervised learning to construct ESG ratings in an optimal fashion. The proposed methodology enables the aggregation of a high-dimensional vector of extra-financial metrics into an overall rating. As it relies on supervised learning, the approach requires the specification of a target variable to produce ratings. The choice of the appropriate target variable should be consistent with the end-user's motivation for using extra-financial information. Within our framework, this choice also establishes an optimality criterion that allows for discrimination between competing ESG rating construction rules. We then show how supervised ESG ratings can be produced by estimating a predictive model of the target variable that incorporates granular ESG metrics as predictors. Our methodology proceeds by jointly estimating the predictive model and a weighting scheme that allows for the aggregation of granular ESG metrics into an overall rating. To manage the large dimension of the granular ESG information vector, the predictive model is estimated using penalized regressions.

As the methodology inherently requires the specification of a target variable, it has the notable advantage of alleviating any confusion about what ESG ratings aim to measure, unlike methodologies founded on unsupervised learning. It also has the advantage of being more flexible and less costly compared to approaches that aggregate the ratings from several rating agencies, which require access to multiple proprietary datasets. We demonstrate the effectiveness of our approach by applying the methodology to a large panel dataset containing granular ESG data. Our analysis

focuses on two target variables: firm idiosyncratic risk and ESG controversies. Our results indicate that, in the case of forecasting firm idiosyncratic risk, the methodology produces ratings with considerably greater forecasting power than the ratings from a leading rating agency. However, information from extra-financial reporting has limited explanatory power in forecasting companies' involvement in ESG controversies once financial, country, and sector-specific information is taken into account. While recent studies show that ESG ratings from leading rating agencies do not help to predict future ESG controversies (Bams and van der Kroft, 2022; Yang, 2022), this last result goes a step further as it suggests that the issue might be caused by the nature of the information on which ratings are founded.

Chapter 3 investigates organizations' strategic responses under the threat of climate activists through a case study on a French climate movement led by elite *Grandes Écoles* students who threatened to boycott job offers from polluting employers. Owing to its extensive success and media coverage, the initiative raised concerns about the ability of numerous large French companies to attract highly-skilled human capital. Through the analysis of a unique survey database on climate movement participants, this chapter explores how corporate environmental pledges could help mitigate such negative impacts on organizational attractiveness. Using repeated measurements of students' intentions to refuse to work for polluting companies and machine learning classifiers, we compute an individual-level measure of the extent to which corporate environmental pledges can deter these intentions. While 86% of respondents intend to boycott job offers from polluting companies, they are, on average, three times less likely to have these intentions after being exposed to an environmental pledge. However, we also observe substantial heterogeneity in students' reactions to environmental pledges, as a significant share of respondents express their distrust towards corporate promises. We find that this result can be explained by the fact that intentions to refuse to work for polluting companies and reactions to environmental pledges are driven by different factors. While intentions to refuse to work for polluting employers are primarily driven by one's search for meaning through work and pro-environmental attitudes, reactions to environmental pledges are rather driven by career perspectives, beliefs about the ecological crisis, and support for radical action in the name of ecology.

This chapter highlights the growing stakeholder demand on polluting companies to take climate action, as well as their exposure to risks related to attracting human capital. Consequently, unsustainable business models may not only be jeopardized by incoming regulation but also by various types of costly stakeholder action. In this vein, some scholars have argued that the self-selection of talented workers away from polluting companies could be a powerful lever to foster businesses' sustainability transition (Brekke and Nyborg, 2008; Brannstrom et al., 2022). However, our findings suggest that polluting companies could at least temporarily address this challenge by pledging to

improve their environmental impact. While pledges can be made in good faith, they can also be made free of charge. A failure of our institutional settings to hold companies responsible for their commitments makes it difficult to distinguish genuine efforts from empty promises, thereby raising concerns about pledges credibility. Furthermore, our results might also explain why companies exposed to boycott movements initially respond by increasing their prosocial claims (McDonnell and King, 2013).

Chapter 4 focuses on the alignment of financial flows with the Paris Agreement through an empirical investigation on the drivers of investment in fossil energy infrastructures. The current climate governance is characterized by two key features. First, the approach taken to mitigate climate change is dominated by the implementation of demand-side policies designed to reduce economies' reliance on fossil energy rather than by supply restrictions. Proponents of the Green Paradox argue that such a policy setting could accelerate climate change through the supply-side response of fossil resource owners (Sinn, 2008). Other scholars argue that it would instead slow down investments in fossil energy infrastructures due to the exposure of irreversible investments to climate transition risk (Fried et al., 2022). A second feature of climate governance is that climate policy stringency displays strong cross-country heterogeneity, with a small coalition of countries leading the effort. An extensive body of research, mostly via computable general equilibrium models, highlights that carbon leakages are likely to occur in this setting (Carbone and Rivers, 2017).

Our empirical analysis is based on a panel dataset covering the capital expenditures of oil and gas extractive companies located in 30 countries, representing a quarter of the world's proven oil and gas reserves. We propose two new proxies for the policy-making effort to fight climate change at the national and global levels. These proxies are based on counting the number of climate policies passed over a certain period, and integrated into standard investment regressions. Our findings suggest that oil and gas companies significantly reduce their investments following an increase in their headquarters' country's climate policy effort, a result that we find to be explained by a rise in the climate transition risk exposure of these firms. However, our findings also suggest the existence of a "fossil investment leakage", as investments by firms located in countries with weak or no climate policy efforts, and therefore less exposed to stranded asset risks, increase following periods of high global climate policy efforts.

Chapter 1

Chapter 1

Are ESG Ratings informative to forecast idiosyncratic risk?¹

1.1 Introduction

According to the Global Reporting Initiative (GRI), most of the ESG rating systems currently in use are designed to assess how effectively a company manages sustainability issues that have financial implications for its business. In other words, these systems evaluate a company's potential exposure to financial risks resulting from inadequate management of sustainability issues.² However, ESG ratings are derived using heterogeneous methodologies and can be quite divergent across rating agencies (Berg, Koelbel and Rigobon, 2022; Dimson et al., 2020), which raises concerns about their accuracy as a risk measure. Is there any informational content in the various existing ESG rating systems? Is this informational content related to what it is supposed to measure, which is the exposure of a company to sustainability-related risks ? There is clearly great interest in this issue as ESG is currently one of the most well-known acronyms in the financial world and beyond. Today, ESG ratings increasingly shape the investment decisions of investors. According to Bloomberg, ESG assets are on track to exceed \$53 trillion by 2025, representing more than a third of projected total assets under management in North America, Europe, and Asia-Pacific capital markets.³ This article aims to provide a statistical methodology to answer these questions by developing a backtesting procedure to assess the informational content of ESG ratings in forecasting a company's risk-related outcome. Our test evaluates the effectiveness of extra-financial metrics in predicting a company's risk exposure beyond the information conveyed by traditional financial variables.

¹This chapter is a joint work with BOUCHER Christophe, MATTON Stéphane and TOKPAVI Sessi.

²<https://www.globalreporting.org/media/vyelrdub/gri-perspective-abc-of-esg-ratings-08.pdf>

³<https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/>

The global craze for responsible investment has by now led to an abundant and rich literature that has tried, with mixed results, to evaluate how sustainable investment impacts market variables, and asset prices in particular. Some studies have found that ESG has a positive impact on asset prices (Mozaffar et al., 2016; Amel-Zadeh and Serafeim, 2018; Dyck et al., 2019; Hartzmark and Sussman, 2019), and Mozaffar et al. (2016) for instance present evidence that firms doing well on ESG issues outperform firms doing poorly on these issues. Amel-Zadeh and Serafeim (2018) reaffirm that ESG ratings have a material impact on asset prices and more specifically on the cost of capital, as investors expect higher return on equity for companies with strong ESG performance. Other contributions highlight that socially responsible investors can substantially reduce the cost of capital of responsible companies by tilting their portfolio allocation towards these firms (Gollier and Pouget, 2022; Zerbib, 2022). Dyck et al. (2019) also demonstrate that engagement by investors has a positive impact on ESG performance and ultimately on financial returns, especially in countries where ESG issues are important. A study of US mutual funds flows confirms that investors find value in sustainability as a positive predictor of future returns (Hartzmark and Sussman, 2019).

Arguing the other side though are some works (Riedl and Smeets, 2017; Pástor et al., 2021; Pedersen et al., 2020) based on the impact of investor preferences on the dynamics of asset prices (Fama and French, 2007), which report that ESG practices have either a negative or a positive impact on asset prices. Considering investor preferences for ESG, Riedl and Smeets (2017) notice that investors are willing to accept lower expected returns and higher management fees for holding companies with strong ESG performance. Pástor et al. (2021) model investor preferences for ESG in a mean-variance framework and show that in equilibrium, assets considered green generally have lower expected returns but provide greater utility and offer the ability to hedge against climate risk. They also introduce an ESG-factor that reacts to unexpected change in ESG, then conclude that green assets outperform when a positive shock hits this factor. Pedersen et al. (2020) extend the mean-variance-ESG framework by adding a third type of investor who is unaware of the ESG performance of firms. How the ESG ratings affect expected returns then depends on the wealth of this third investor.

Although this literature provides useful information on the link between extra-financial performance and asset price dynamics, it does not provide a formal methodology to assess whether the available rating systems are effective in measuring a company's exposure to financially material sustainability risks. This gap in the literature is all the more worrying as the correlations between the ratings of the various available providers are weak. Indeed, the divergence of ESG ratings has been widely documented (Chatterji et al., 2009; Semenova and Hassel, 2015; Chatterji et al., 2016; Berg, Koelbel and Rigobon, 2022; Dimson et al., 2020), and Berg, Koelbel and Rigobon (2022) find, for instance, that correlations between the ESG ratings of providers are on average 54% for

a set of six different ESG providers, whereas the credit ratings from the main agencies exhibit, on average, a correlation of 99%. They further explore the source of this divergence by splitting it into three components and looking at scope, or the selection of ESG categories to be measured; measurement, or how the ESG categories are assessed; and weight, or the importance given to each category. They observed that measurement explains more than 50% of the total divergence.⁴ The divergence of ESG rating systems has important implications for sustainable investing. ESG ratings disagreement can lead to completely opposite opinions on one and the same company, dispersing ESG preferences of investors (Billio et al., 2019). It also makes it difficult to empirically assess the impact of ESG performance on stock returns (Berg, Koelbel, Pavlova and Rigobon, 2022) and can result in risk premiums for companies with high rating disagreement (Gibson Brandon et al., 2021).

Against this background, our paper introduces a statistical inferential procedure that allows to test the informational content of a given ESG rating system in forecasting a company's risk-related outcomes. The test is based on the idea that ESG ratings should have significant power in predicting the materialization of sustainability-related financial risks, as they are supposed to be informative about a company's exposure to such risks. Previous literature on the relationship between ESG ratings and firm-level risk outcomes has focused on two types of outcomes: ESG incidents and measures of financial risk. Several studies have found a link between ESG risks and idiosyncratic volatility (Jo and Na, 2012; Mishra and Modi, 2013; Bouslah et al., 2013; Sodjahnin et al., 2017; Hoepner et al., 2018; Albuquerque et al., 2019; Ilhan et al., 2019). For example, Mishra and Modi (2013) note that companies with lower leverage and high ESG ratings are better at capturing the benefits of ESG performance to reduce idiosyncratic risk.

Other studies, such as Champagne et al. (2022) and Serafeim and Yoon (2022a), have examined the link between extra-financial performance or ESG ratings and the likelihood of adverse ESG events. Their analysis is based on the hypothesis that firms with strong extra-financial performance, such as good environmental externalities, employee relationships, and governance, are less likely to face ESG events such as environmental problems, employee claims, social conflicts, or boycotts and negative media campaigns. Champagne et al. (2022) use logistic regression to test whether a firm's extra-financial performance in a given year significantly helps anticipate ESG events in the following year. They find that an increase of one unit in a firm's rating reduces its probability of facing adverse events during the following year by 8%, controlling for financial performance. Similarly, Serafeim and Yoon (2022a) investigate whether ESG ratings predict future ESG news and associated market reactions. Using a firm-day panel dataset, they find that the latest consensus ESG rating is associated with future ESG news, but the link weakens for firms over which there is

⁴Unlike credit ratings, ESG ratings are most often created mainly from non-standardised information and are not regulated. Methodologies can be opaque and proprietary, leading to substantial rating divergence.

large disagreement among raters.

Our contribution is related to these works, but differs in several aspects. First, these works do not provide a formal test to check the informational content of ESG ratings in forecasting firm-related risks, which is the purpose of this article. We test the informational content of ESG ratings using a dynamic forward-looking approach in an out-of-sample environment, which is consistent with the practice of institutions revising their ratings over time to incorporate new information on environmental, social, and governance practices. Second, our approach accounts for possible misspecification of the econometric model used to measure the relationship between ESG ratings and the outcome variable. This differs from the previous literature, where the correctness of the econometric model is critical to establishing the existence of this link. Third, while previous studies identify significant correlations between ESG ratings and firm risks, they fail to quantify the improvement in model fit resulting from incorporating extra-financial information. Our method compares the predictive ability of nested models containing financial and extra-financial information, allowing for such quantification. Technically, our inferential procedure extends the conditional predictive ability test of Giacomini and White (2006) to a panel setting. We derive the Gaussian asymptotic distribution of the test statistic under weak assumptions. Monte Carlo simulations, performed under different types of model misspecification, demonstrate that our test has good small sample properties, with good size and increasing power as the number of firms and sample length increase.

On the empirical side, we apply our procedure to the forecasting of a company's market risk measured by the idiosyncratic volatility of its stock price. While in practice our test procedure can be applied to any target variable, we opt for a measure of market risk rather than an outcome measuring the materialization of ESG incidents for multiple reasons. First, measures of ESG incidents often rely on proprietary tools that can be divergent across providers. The rank correlations between ESG incidents from Sustainalytics and Asset4 for instance are weak at 43% for Europe, 43% for North-America and 34% for the Asia-Pacific region.⁵ Second, as acknowledged by the GRI, most of existing ESG rating systems seek to capture a company's financial exposure to poorly managed sustainability issues rather than its impact. This definition is in line with most of asset managers needs as the vast majority of them use ESG information for its materiality on investment performance (Amel-Zadeh and Serafeim, 2018). On the other side, while ESG incidents captured by negative news media coverage can have a substantial impact on stock prices, they are not always financially relevant for investors (Serafeim and Yoon, 2022*b*). As a consequence, and consistent with what most of ESG rating agencies seek to capture, we opt for a direct measure of financial risk captured by the market risk of a company's stock price.

⁵These figures are computed over the period from January 2010 to October 2018.

We conduct empirical applications to illustrate our methodology, using two leading ESG rating systems, Sustainalytics and Asset4, for Europe, North America and the Asia-Pacific region. Our results show that the null hypothesis of no informational content in ESG ratings is strongly rejected in Europe, whereas results appear mixed, and predictive accuracy gains are low in the other regions. Furthermore, we find that predictive accuracy gains are higher when assessing the environmental rating compared to other dimensions of ESG rating. Lastly, and importantly, we find that the predictive accuracy gains derived from ESG ratings increase with the level of consensus between rating agencies for all three universes. This final finding can be linked to that highlighted by Serafeim and Yoon (2022a), who find that the market reaction to ESG news is moderated by the consensus rating. From a practical standpoint, our results provide crucial information for portfolio managers who integrates ESG rating to assess companies' risk profile, as we show that it is necessary to cross-check the information gathered from multiple ESG rating providers before integrating ESG into the management process.

The rest of the article is organised as follows. Section 2 describes our backtesting procedure for ESG ratings, focusing on the formulation of the null hypothesis, the construction of the test statistic and the analysis of its asymptotic distribution. Section 3 simulates the small sample properties of the test statistic under various settings, and empirical applications are considered in Section 4. The last section concludes the paper.

1.2 The backtesting procedure

This section gives a description of the backtesting procedure for evaluating statistically the informational content in ESG ratings. In the first part, we fix the notations and clearly define the null hypothesis of interest, while in the second part we provide the test statistic and its asymptotic distribution for inference.

1.2.1 Notations and the null hypothesis

To formulate the null hypothesis of our test, we consider an investment universe with n traded firms, and let $y_{i,t}$ denote the value at month t of a target variable that is intended to measure firm-specific risks. For instance, a socially motivated investor seeking to manage the environmental and social impact of their asset portfolio can use a variable $y_{i,t}$ that measures ESG incidents, such as the ones provided by well-known providers (Sustainalytics, Asset4, TrueValue Labs, etc.), to test whether ESG ratings help predict future corporate misconduct. On the other hand, investors who are interested in the materiality of ESG information on investment performance can use a target variable that measures a firm's specific exposure to financial risks, such as idiosyncratic volatility.

Therefore, our framework is general, as it enables users to choose a target variable relevant to their investment objectives.

Let $x_{i,t}$ be a vector of length p in which the elements are innovations on p financial variables that measure the financial strength of firm i for the month t . Examples of such variables are dividend yield, sales over assets, debt over assets, or the quick ratio. They measure different facets of a firm's solvency including its size, returns, risk, liquidity, debt and leverage. Innovations can be obtained through autoregressive filtering on raw financial variables, or simply as deviations from the long-term average. Finally, the value of an ESG rating is available for each firm i at month t and we denote it as $\omega_{i,t} \in \mathbb{R}$. This can be a global ESG rating measuring environmental, social and governance issues, or only one of these three components.

Now let $m_{i,t+\tau}^{(0)} = \mathbb{E}(y_{i,t+\tau} | x_{i,t})$ be the unknown expected value of $y_{i,t}$ for firm i at time $t + \tau$, conditional on its financial strength as measured by innovations $x_{i,t}$ in financial variables, with τ as a given forecast horizon. We can use a given predictive model, whether parametric, semi-parametric or non-parametric, to forecast $m_{i,t+\tau}^{(0)}$. The forecast we denote $\hat{m}_{i,t+\tau}^{(0)}(\hat{\beta}_{t,b_t}^{(0)})$ is based on the information set available at time t for all firms, so $\mathcal{F}_t^{(0)} = \{x_{i,s}, s = t - b_t + 1, \dots, t, i = 1, \dots, n\}$, where b_t refers to the size of the estimation sample and $\hat{\beta}_{t,b_t}^{(0)}$ collects all the estimated parameters. In a parametric model like a linear regression, $\hat{\beta}_{t,b_t}^{(0)}$ is the vector of the estimates of the unknown parameters. Otherwise, it corresponds to whatever semi-parametric or non-parametric estimators are used to forecast $m_{i,t+\tau}^{(0)}$.

Let $m_{i,t+\tau}^{(1)} = \mathbb{E}(y_{i,t+\tau} | x_{i,t}, \omega_{i,t})$ be defined as $m_{i,t+\tau}^{(0)}$, but with the conditional set extended to $\omega_{i,t}$, so $\mathcal{F}_t^{(1)} = \{x_{i,s}, \omega_{i,s}, s = t - b_t + 1, \dots, t, i = 1, \dots, n\}$. In other words, $m_{i,t+\tau}^{(1)}$ is the expected value of $y_{i,t}$ for firm i at time $t + \tau$, conditional on its financial states as given by $x_{i,t}$ and also on its ESG rating as given by $\omega_{i,t}$. We denote $\hat{m}_{i,t+\tau}^{(1)}(\hat{\beta}_{t,b_t}^{(1)})$ as the forecast value at time $t + \tau$.

Suppose that we produce T_0 out-of-sample forecasts of both the expected values $m_{i,t+\tau}^{(0)}$ and $m_{i,t+\tau}^{(1)}$ for each firm, so $\hat{m}_{i,t+\tau}^{(0)}(\hat{\beta}_{t,b_t}^{(0)})$ and $\hat{m}_{i,t+\tau}^{(1)}(\hat{\beta}_{t,b_t}^{(1)})$, $i = 1, \dots, n$, $t + \tau = 1, \dots, T_0$. With a loss function at hand that we denote $\mathcal{L}(\cdot)$, we can evaluate the predictive performance of each model, generating two panels of losses as $\mathcal{L}_{i,t+\tau}^{(0)} \equiv \mathcal{L}_{i,t+\tau}^{(0)}(y_{i,t+\tau}, \hat{m}_{i,t+\tau}^{(0)}(\hat{\beta}_{t,b_t}^{(0)}))$ and $\mathcal{L}_{i,t+\tau}^{(1)} \equiv \mathcal{L}_{i,t+\tau}^{(1)}(y_{i,t+\tau}, \hat{m}_{i,t+\tau}^{(1)}(\hat{\beta}_{t,b_t}^{(1)}))$, where again $y_{i,t+\tau}$ is the value of $y_{i,t}$ for firm i at time $t + \tau$. From these panels, let $\Delta\mathcal{L}_{i,t+\tau} = \mathcal{L}_{i,t+\tau}^{(1)} - \mathcal{L}_{i,t+\tau}^{(0)}$ be the panel of loss differentials, $i = 1, \dots, n$, $t = 1, \dots, T_0$, and $\mu_i(\hat{\beta}_{t,b_t}^{(0)}, \hat{\beta}_{t,b_t}^{(1)})$ the expected value of the loss differentials for firm i .

Hence, our null hypothesis of overall equal predictive ability of the two forecasting models can be stated as :

$$\mathbb{H}_0 : \bar{\mu}(\hat{\beta}_{t,b_t}^{(0)}, \hat{\beta}_{t,b_t}^{(1)}) = 0, \quad (1.1)$$

with the alternative hypothesis being :

$$\mathbb{H}_1 : \bar{\mu}(\hat{\beta}_{t,b_t}^{(0)}, \hat{\beta}_{t,b_t}^{(1)}) < 0, \quad (1.2)$$

where $\bar{\mu}(\hat{\beta}_{t,b_t}^{(0)}, \hat{\beta}_{t,b_t}^{(1)})$ is defined as :

$$\bar{\mu}(\hat{\beta}_{t,b_t}^{(0)}, \hat{\beta}_{t,b_t}^{(1)}) = \frac{1}{n} \sum_{i=1}^n \mu_i(\hat{\beta}_{t,b_t}^{(0)}, \hat{\beta}_{t,b_t}^{(1)}). \quad (1.3)$$

This null hypothesis calls for several remarks. First, when it holds, it means that overall (for all i and t) including the ESG rating $\omega_{i,t}$ in the information set does not help for forecasting $y_{i,t}$. In consequence, we should conclude that the ESG rating system investigated is void of information about $y_{i,t}$. Under the alternative hypothesis, considering the ESG rating in forecasting $y_{i,t}$, overall, gives real benefit across all firms and times.

Second, in contrast to the traditional framework for comparing predictive ability in Diebold and Mariano (1995) and West (1996), we can observe that the null hypothesis involves $\mu_i(\hat{\beta}_{t,b_t}^{(0)}, \hat{\beta}_{t,b_t}^{(1)})$, which depends on $\hat{\beta}_{t,b_t}^{(0)}$ and $\hat{\beta}_{t,b_t}^{(1)}$, which are the estimated values of the parameters instead of their population values. As discussed by Giacomini and White (2006) in a pure time series context, this helps preserve the finite sample behaviour of the estimators in the evaluation procedure, hence reflecting the effect of estimation uncertainty on the relative performance of the forecasts. This estimation uncertainty allows the comparison of nested forecasting models contrary to previous tests of predictive ability. However, they underline that adopting such a framework means remembering that the null hypothesis does not check the equal predictive ability of the competing models, but rather of the forecasting methods, where these methods include the models as well as the estimation procedures and the possible choices of estimation window.

This last remark means that some care is required in applying our test procedure to check for the validity of the null hypothesis in (1.1). First, the size of the estimation window should be kept fixed in the rolling window procedure ($b_t = b$) to ensure that parameter uncertainty does not vanish asymptotically. This naturally rules out an expanding window forecasting scheme, but allows for iterated or fixed schemes. Second, we should retain the same forecasting model and scheme and the same estimation window length to generate the forecasts $\hat{m}_{i,t+\tau}^{(0)}(\hat{\beta}_{t,b}^{(0)})$ and $\hat{m}_{i,t+\tau}^{(1)}(\hat{\beta}_{t,b}^{(1)})$. This is an important requirement, as it guarantees that the two forecasts diverge only by the set of information used, $\mathcal{F}_t^{(0)}$ or $\mathcal{F}_t^{(1)}$, the first of which excludes data on the ESG ratings for all firms.

1.2.2 Test statistic and asymptotic distribution

In this section, we provide the test statistic to check for the null hypothesis of a lack of informational content in an ESG rating system as expressed in (1.1). To do this we use the literature on comparing

predictive ability in panel data settings (Davies and Lahiri, 1995; Timmermann and Zhu, 2019; Akgun et al., 2020). This literature considers extending the traditional predictive accuracy test for time series to a panel framework and it provides a test for overall equal predictive ability, meaning for all cross-sectional and time units as specified in (1.1), and also tests for joint equal predictive ability across cross-sectional units or time clusters.

Specifically, we draw on the framework of Akgun et al. (2020) who extend the test of Diebold and Mariano (1995) to a panel data setting, considering the following test statistic based on the sample mean of loss differentials over time and units, so

$$\bar{\mu}_{n,T_0} = (nT_0)^{-1} \sum_{i=1}^n \sum_{t+\tau=1}^{T_0} \Delta \mathcal{L}_{i,t+\tau}, \quad (1.4)$$

and is given by

$$\mathcal{T}_{n,T_0} = \frac{\bar{\mu}_{n,T_0}}{\bar{\sigma}_{n,T_0}/\sqrt{nT_0}}, \quad (1.5)$$

where

$$\bar{\sigma}_{n,T_0}^2 = n^{-1} \sum_{i=1}^n \sigma_{i,T_0}^2, \quad (1.6)$$

and $\sigma_{i,T_0}^2 = \text{var}(\sqrt{T_0}\bar{\mu}_i(\hat{\beta}_{t,b}^{(0)}, \hat{\beta}_{t,b}^{(1)}))$ is the long run variance of the i th time series of loss differentials.

As our null hypothesis is an extension to a panel setting of the unconditional predictive ability test of Giacomini and White (2006), rather than the one of Diebold and Mariano (1995), we need here assumptions that differ from those of Akgun et al. (2020), to establish the asymptotic distribution of the test statistic in (1.5).

Assumption 1 *For a given forecast horizon $\tau \geq 1$ and estimation window size $b < \infty$, suppose that (i) $\{(y_{i,t}, x'_{i,t}, \omega_{i,t})', t = 1, \dots, T_0\}$ for a given i is mixing with ϕ of size $-r/(2r-2)$, $r \geq 2$, or α of size $-r/(r-2)$, $r > 2$; (ii) $\mathbb{E}|\Delta \mathcal{L}_{i,t+\tau}|^{2r} < \infty$ for all t and a given i ; (iii) $\sigma_{i,T_0}^2 = \text{var}(\sqrt{T_0}\bar{\mu}_i(\hat{\beta}_{t,b}^{(0)}, \hat{\beta}_{t,b}^{(1)})) > 0$ for all T_0 sufficiently large and a given i .*

Assumption 2 $\bar{\mu}_{i,T_0} = T_0^{-1} \sum_{t+\tau=1}^{T_0} \Delta \mathcal{L}_{i,t+\tau}$, $i = 1, \dots, N$ are independent, and

$$\mathbb{E}(|\bar{\mu}_{i,T_0}|)^{2+\delta} < C < \infty, \quad (1.7)$$

for some $\delta > 0$ for all i . $\bar{\sigma}_{n,T_0}^2 = n^{-1} \sum_{i=1}^n \sigma_{i,T_0}^2 > \delta' > 0$ for all n sufficiently large.

Assumption 1 includes regularity conditions for the validity of Theorem 4 in Giacomini and White (2006). These conditions ensure that the test statistic for the unconditional predictive ability applied to a fixed cross-sectional unit converges to a standard Gaussian distribution, with

$$\mathcal{T}_i = \frac{\bar{\mu}_{i,T_0}}{\sigma_{i,T_0}/\sqrt{T_0}} \xrightarrow[T_0 \rightarrow \infty]{\mathcal{D}} N(0, 1). \quad (1.8)$$

Assumption 2 assumes the independence between the n random variables $\bar{\mu}_{i,T_0}, i, \dots, n$, meaning the average values over time of the loss differentials for each firm. This assumption allows the Central Limit Theory (CLT) applied to independent and heterogeneous random variables (White, 2001, Theorem 5.10) to hold. Note that this assumption is not a strong one within our framework, as opposed to macroeconomic forecasting. Indeed, our focus is on target variables that are related to firm-specific risk, which is by its nature a specific measure for each firm and hence primarily driven by firm characteristics rather than common factors. The following proposition provides the asymptotic distribution of the test statistic in (1.5).

Proposition 1 *Under the null hypothesis of a lack of informational content in ESG ratings as stated in (1.1), and if Assumptions 1-2 hold, we have that*

$$\mathcal{T}_{n,T_0} = \frac{\bar{\mu}_{n,T_0}}{\bar{\sigma}_{n,T_0}/\sqrt{nT_0}} \xrightarrow[T_0, n \rightarrow \infty]{\mathcal{D}} N(0, 1). \quad (1.9)$$

Thus we reject the null hypothesis when $\mathcal{T}_{n,T_0} < z_\eta$ with z_η the quantile of order η of the standard Gaussian distribution, and η the nominal significance level. The proof of Proposition 1 is straightforward following Akgun et al. (2020), as we may note that under \mathbb{H}_0 ,

$$\sqrt{nT_0}\bar{\mu}_{n,T_0} = \frac{1}{\sqrt{n}} \sum_{i=1}^n \sqrt{T_0}\bar{\mu}_{i,T_0}, \quad (1.10)$$

with $\bar{\mu}_{i,T_0}$ as defined in Assumption 2. For a fixed i , if Assumption 1 holds, $\sqrt{T_0}\bar{\mu}_{i,T_0} \xrightarrow[T_0 \rightarrow \infty]{\mathcal{D}} \psi_i$, with $\psi_i \sim N(0, \sigma_{i,T_0}^2)$, and $\sigma_{i,T_0}^2 = \text{var}(\sqrt{T_0}\mu_i(\hat{\beta}_{t,b}^{(0)}, \hat{\beta}_{t,b}^{(1)}))$. See Theorem 4 in Giacomini and White (2006). Hence the rest of the proof proceeds by noting that under Assumption 2, the CLT for heterogeneous but independent variables (White, 2001, Theorem 5.10) holds and $(1/\sqrt{n}) \sum_{i=1}^n \psi_i \xrightarrow[T_0, n \rightarrow \infty]{\mathcal{D}} N(0, \bar{\sigma}_{n,T_0}^2)$, where again $\bar{\sigma}_{n,T_0}^2 = n^{-1} \sum_{i=1}^n \sigma_{i,T_0}^2$.

Note that to compute our test statistic \mathcal{T}_{n,T_0} , we need a consistent estimate $\hat{\sigma}_{n,T_0}^2$ of $\bar{\sigma}_{n,T_0}^2$. Under the assumption of cross-sectional independence of loss differentials, it follows that $\hat{\sigma}_{n,T_0}^2 = n^{-1} \sum_{i=1}^n \hat{\sigma}_{i,T_0}^2$, where $\hat{\sigma}_{i,T_0}^2$ is a suitable HAC estimator of the long-run variance σ_{i,T_0}^2 of the i th time series of loss differentials, with

$$\hat{\sigma}_{i,T_0}^2 = T_0^{-1} \sum_{t+\tau=1}^{T_0} \Delta \mathcal{L}_{i,t+\tau}^2 + 2[T_0^{-1} \sum_{j=1}^{pT_0} w_{T_0,j} \times \sum_{t+\tau=1+j}^{T_0} \Delta \mathcal{L}_{i,t+\tau} \Delta \mathcal{L}_{i,t+\tau-j}], \quad (1.11)$$

and $\{pT_0\}$ is a sequence of integers such that $pT_0 \rightarrow \infty$ as $T_0 \rightarrow \infty$, $pT_0 = o(T_0)$, and $\{w_{T_0,j} : T_0 = 1, 2, \dots; j = 1, \dots, pT_0\}$ is a triangular array such that $|w_{T_0,j}| < \infty$, $T_0 = 1, 2, \dots; j = 1, \dots, pT_0$, $w_{T_0,j} \rightarrow 1$ as $T_0 \rightarrow \infty$ for each $j = 1, \dots, pT_0$ (Andrews, 1991).

1.3 Small sample properties

In this section we use a realistic simulation framework to analyse the small sample properties of the test. We begin by describing the simulation setup and then provide results for the sizes and the powers of the test under different forms of misspecification for the forecasting method retained.

1.3.1 Simulation setup

Our simulation setup proceeds by first simulating a vector $x_{i,t}$ of length $p = 10$ of innovations in financial variables that measure the financial strength of firm i at time t , with $t = 1, \dots, T$ and $T \in \{120, 180, 240\}$ as the sample size corresponding to 12, 15 and 20 years of monthly data. To have a realistic setup, these p variables are generated from a multivariate Gaussian distribution with mean vector \bar{x} and covariance matrix Ω calibrated using real data (see Appendix 1.6 for details about the calibration). With the vector $x_{i,t}$ of length p ready at hand, we generate the logarithmic value of the target variable $y_{i,t}$ for firm i , as⁶ :

$$\log(y_{i,t+1}) = c_i^* + x'_{i,t}\beta_i^* + \gamma\omega_{i,t} + u_{i,t+1}, \quad (1.12)$$

with $u_{i,t+1}$ following a standard Gaussian distribution, c_i^* as the constant term and β_i^* as a vector of parameters of length p . Note that we allow for heterogeneity across firms with specific values for the parameters for each firm. The values of c_i^* are generated as follows :

$$c_i^* = c^* + U(-|\frac{c^*}{10}|; |\frac{c^*}{10}|), \quad (1.13)$$

with $U(a; b)$ as a uniform random variable over the set $[a, b]$. The same perturbation principle is used to generate each component of the vector β_i^* , with :

$$\beta_{i,j}^* = \beta_j^* + U(-|\frac{\beta_j^*}{10}|; |\frac{\beta_j^*}{10}|), \quad (1.14)$$

$j = 1, \dots, p = 10$. The reference values c^* and β^* of the parameters are calibrated using real data (see Appendix 1.6 for details).

In equation (1.12), $\omega_{i,t}$ is the ESG rating, which for firm i and at each date t is generated from a uniform distribution over the set $[0, 1]$, and $\gamma \in \mathbb{R}_-$ is a parameter.⁷ Note that our null hypothesis holds for $\gamma = 0$, since the ESG rating does not have any predictive content for $y_{i,t}$. With γ diverging from zero, the null hypothesis does not hold, because high lagged values of the

⁶We use the logarithm, as most of possible candidate variables for $y_{i,t}$ are positive, including ESG incident variables.

⁷Note that we also considered a setup in which the ESG ratings $\omega_{i,t}$ are generated using a persistent AR(1) process to match the stylized fact of infrequent changes in ESG ratings. Simulations results available from the authors upon request show similar small sample properties of our inferential procedure.

ESG rating decrease the values of $y_{i,t}$.

Based on our design and for each Monte Carlo replication, with n and T fixed, the above simulation design is run for the n firms, with $n \in \{100, 250, 500\}$. This leads to a pure heterogeneous panel for $y_{i,t}$, the $p = 10$ innovations in financial variables $x_{i,t}$, and the ESG rating $\omega_{i,t}$, with $i = 1, \dots, n$ and $t = 1, \dots, T$.

1.3.2 Sizes and powers under a medium level of misspecification

For each Monte Carlo replication, we use the generated variables $y_{i,t}$, $x_{i,t}$ and $\omega_{i,t}$, $i = 1, \dots, n$, $t = 1, \dots, T$ and a fixed forecasting method to generate the forecast of $m_{i,t+1}^{(0)} = \mathbb{E}(y_{i,t+1} | x_{i,t})$ and $m_{i,t+1}^{(1)} = \mathbb{E}(y_{i,t+1} | x_{i,t}, \omega_{i,t})$, so $\hat{m}_{i,t+1}^{(0)}(\hat{\beta}_{t,b}^{(0)})$ and $\hat{m}_{i,t+1}^{(1)}(\hat{\beta}_{t,b}^{(1)})$ with b the estimation sample that we set to $b = [0.75T]$, and $[a]$ the integer part of a . This means that we use the first 75% of the T observations for each firm as the estimation sample, and generate T_0 forecasts corresponding to the last 25% of the observations, meaning $T_0 = [0.25T]$ and $T = T_0 + b$.

The forecasts for both models are obtained using pooled OLS regression models. This means that both forecasting models are misspecified, because the true panel structure of the data is heterogeneous across units. Besides, there is another form of misspecification that arises because the true data generating process uses a linear form for the *logarithm* of $y_{i,t}$ (see Eq. 1.12), while the pooled OLS regression models are fitted for the *raw* values of the same variable. Our goal is to evaluate how robust our inferential procedure is to these two levels of misspecification, which we call medium in comparison to another more severe form of misspecification that we will consider next. It may be recalled that the asymptotic behaviour of our test statistic under the null hypothesis suggests that with $\gamma \in \mathbb{R}_-$ in (1.12) diverging from zero, the null hypothesis is more likely to be rejected for $T_0, n \rightarrow \infty$, or equivalently, $T, n \rightarrow \infty$.

Figure 1.1 displays the rejection frequencies of the null hypothesis with respect to the parameter γ for a given couple (n, T) , with the nominal significance level set to 5%. The rejection frequencies are computed over 1,000 simulations. Overall the test exhibits very good small sample properties, and we observe that the rejection frequencies for all couples (n, T) are close to 5% for $\gamma = 0$ and increase monotonically as γ diverges from 0.

We also observe that for a fixed n and $\gamma < 0$ the powers increase with T . Indeed, for $n = 100$ and $\gamma = -0.25$, the rejection frequencies for T of 120, 180 and 240 are 39.10%, 53.30% and 61.00% respectively. The same behaviour is observed for a fixed T and $\gamma < 0$ with the powers increasing with n . For instance with $T = 120$ and $\gamma = -0.25$, the rejection frequencies for $n = 100, 250$ and 500 are respectively 39.10%, 71.50% and 91.30%. Hence our inferential procedure exhibits very good small sample properties. Figure 1.7.1 in Appendix 1.7 displays the rejection frequencies for the same simulation setup using the absolute error loss function. We can observe similar small

sample properties, offering proof that our test is robust to the loss function.

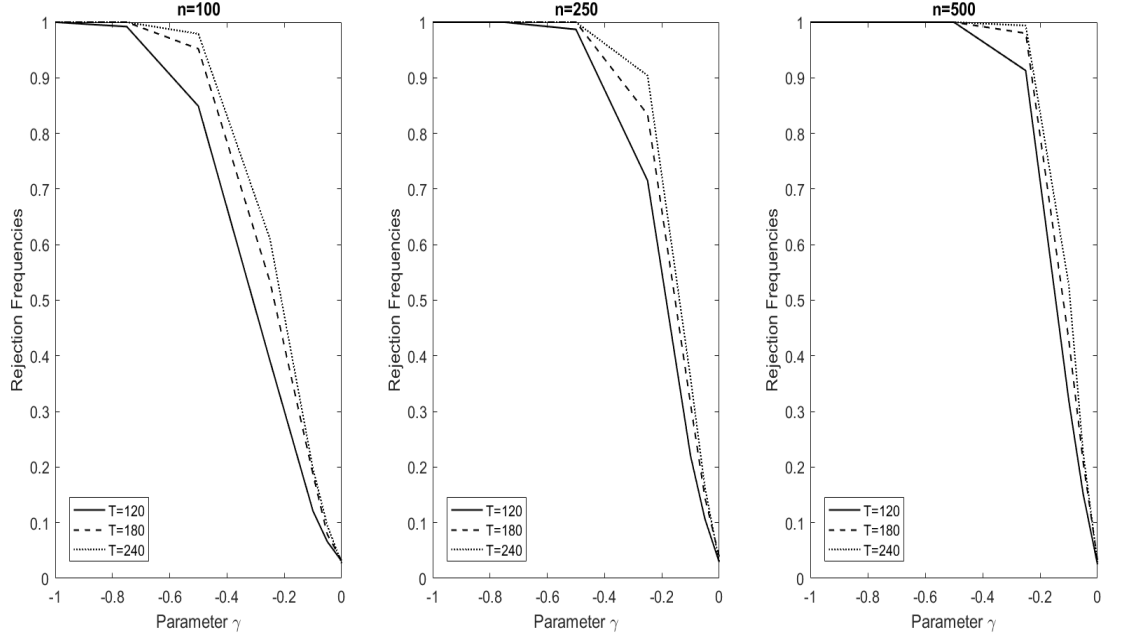


Figure 1.1: Rejection frequencies under a medium level of misspecification with the squared error loss function

1.3.3 Sizes and powers under a high level of misspecification

We now consider a configuration that will help us evaluate the properties of the test with respect to the choice of financial variables. In the last subsection we assumed that the user of the test includes in the forecast models all the $p = 10$ innovations in the financial variables that enter the specification of the true model, but we make here the assumption that only some of these variables are retained. In each Monte Carlo replication, the following two pooled OLS models are estimated to compute out-of-sample forecasts $\hat{m}_{i,t+1}^{(0)}(\hat{\beta}_{t,b}^{(0)})$ and $\hat{m}_{i,t+1}^{(1)}(\hat{\beta}_{t,b}^{(1)})$ of $m_{i,t+1}^{(0)} = \mathbb{E}(y_{i,t+1} | x_{i,t})$ and $m_{i,t+1}^{(1)} = \mathbb{E}(y_{i,t+1} | x_{i,t}, \omega_{i,t})$:

$$y_{i,t+1} = c + \tilde{x}_{i,t}'\beta + v_{i,t+1}^{(0)}, \quad (1.15)$$

$$y_{i,t+1} = c + \tilde{x}_{i,t}'\beta + \omega_{i,t}\gamma + v_{i,t+1}^{(1)}, \quad (1.16)$$

with $v_{i,t+1}^{(0)}$ and $v_{i,t+1}^{(1)}$ as the error terms and $\tilde{x}_{i,t}$ as a vector with $p/2$ randomly chosen financial variables from the $p = 10$ relevant ones as its elements, and $\hat{\beta}_{t,b}^{(0)} = (\hat{c}, \hat{\beta}')'$, $\hat{\beta}_{t,b}^{(1)} = (\hat{c}, \hat{\beta}', \hat{\gamma})'$. Assessing the small sample properties of the test with this additional form of misspecification is of great interest because such misspecification could probably arise in empirical applications where users are very likely to be wrong in their choice of the financial variables that matter.

Figure 1.2 displays the rejection frequencies over 1,000 simulations. We observe that the

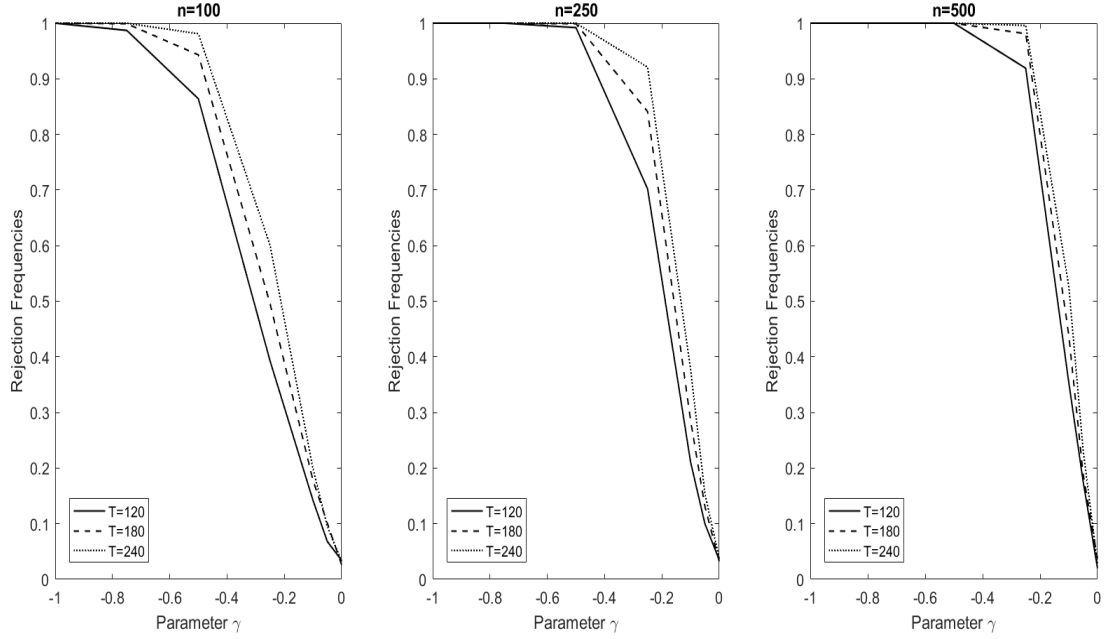


Figure 1.2: Rejection Frequencies under a high level of misspecification with the squared error loss function

proposed test is robust to this form of misspecification. Indeed, the rejection frequencies are similar to those displayed in Figure 1.1, suggesting that making a mistake in the choice of financial variables is not harmful. Results available from the authors upon request show that the robustness holds even when the misspecification is more pronounced as only a quarter of the financial variables of interest are chosen. The robustness to the choice of the loss function can be seen in Figure 1.7.2 in Appendix 1.7.

1.4 Empirical applications

This section illustrates our backtesting procedure using real datasets. We apply our methodology to two popular providers of ESG ratings, Sustainalytics and Asset4, over three universes from North America, Europe and the Asia-Pacific region. We first describe our datasets and the related variables, and then conduct inferences to evaluate the informational content of each of the rating systems.

1.4.1 Description of the datasets and variables

The dataset for each of the three universes contains information for n firms at a monthly frequency over a period ranging from January 2010 to October 2018, giving a total of $T = 106$ months. Note that we restrict our investigations to this period, as Sustainalytics has made a major change

in the methodology for constructing its ratings in December 2018, with an inconsistency in the chaining of the ratings before and after this date. Precisely, before (after) this date, the ratings are performance (risk) measures, with higher (lower) ratings corresponding to best practices for environmental, social and governance issues. Obviously, one solution would be to transform the risk-ratings into performance-ratings, but such a transformation would be arbitrary, and would not guarantee consistency in the scales of values. The North America, Europe and Asia-Pacific datasets gather information on respectively $n = 326$, $n = 238$ and $n = 217$ firms. This deep panel structure ensures a high power for our backtesting methodology (see Monte Carlo simulations), with a total of 34,556, 25,228 and 23,002 pooled observations for the North America, Europe and Asia-Pacific universes.

Information on ESG data

Table 1.1 displays pooled descriptive statistics of the ESG ratings for the two providers over the three universes. We may note that for both providers, higher values of the ESG ratings indicate higher ESG performance.

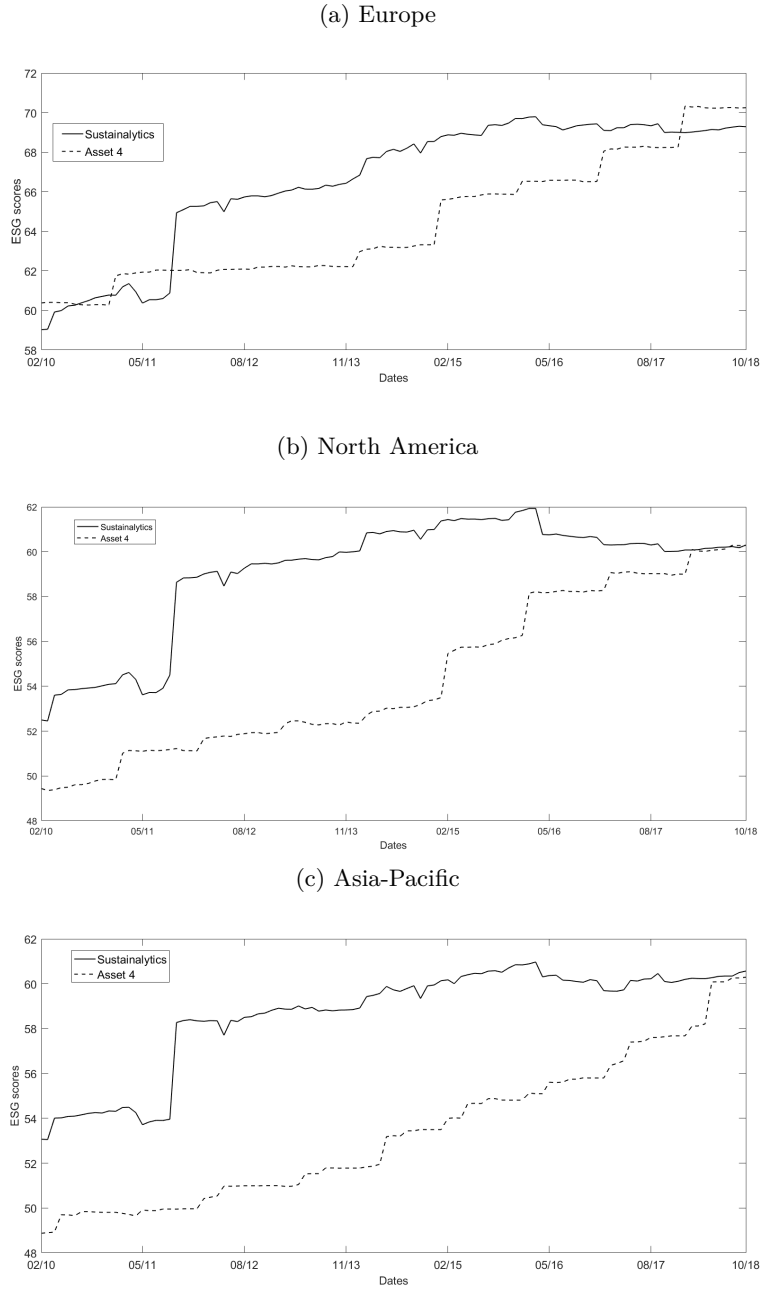
Table 1.1: Pooled descriptive statistics of the ESG ratings

	Min.	Max.	Mean	Median	Std.
Europe					
Sustainalytics	36.0000	89.6900	66.5310	67.3000	9.6449
Asset4	5.4700	94.1500	64.4389	66.1300	15.7645
North America					
Sustainalytics	33.0000	88.0000	59.0831	59.0000	8.6864
Asset4	2.4700	94.7700	54.4304	56.5200	18.8691
Asia-Pacific					
Sustainalytics	32.0000	90.0900	58.5848	59.0000	8.3848
Asset4	2.3500	90.2700	53.3590	56.1900	18.2707

Notes: The table displays pooled descriptive statistics of the ESG ratings for the two providers (Sustainalytics and Asset4) over the three universes. The datasets contain monthly observations over the period from January 2010 to October 2018, giving a total of 106 months. The North America, Europe and Asia-Pacific datasets contain information on respectively $n = 326$, $n = 238$ and $n = 217$ firms. Min. refers to minimum, Max. to maximum, and std. to standard deviations.

The average values of the ESG ratings for the Europe universe are 66.53 for Sustainalytics and 64.43 for Asset4. This means the central statistics are similar for both providers, as is confirmed by the values of the median of 67.30 for Sustainalytics and 66.13 for Asset4 for the Europe universe. This stylised fact holds for the other two universes. However, the Asset4 ESG ratings have more variability across time and firms as given by the values of the standard deviations and ranges. The standard deviations of the Asset4 ESG ratings for instance are approximately twice as high as those for Sustainalytics.

Figure 1.3: Dynamics of the cross-sectional means of the ESG ratings

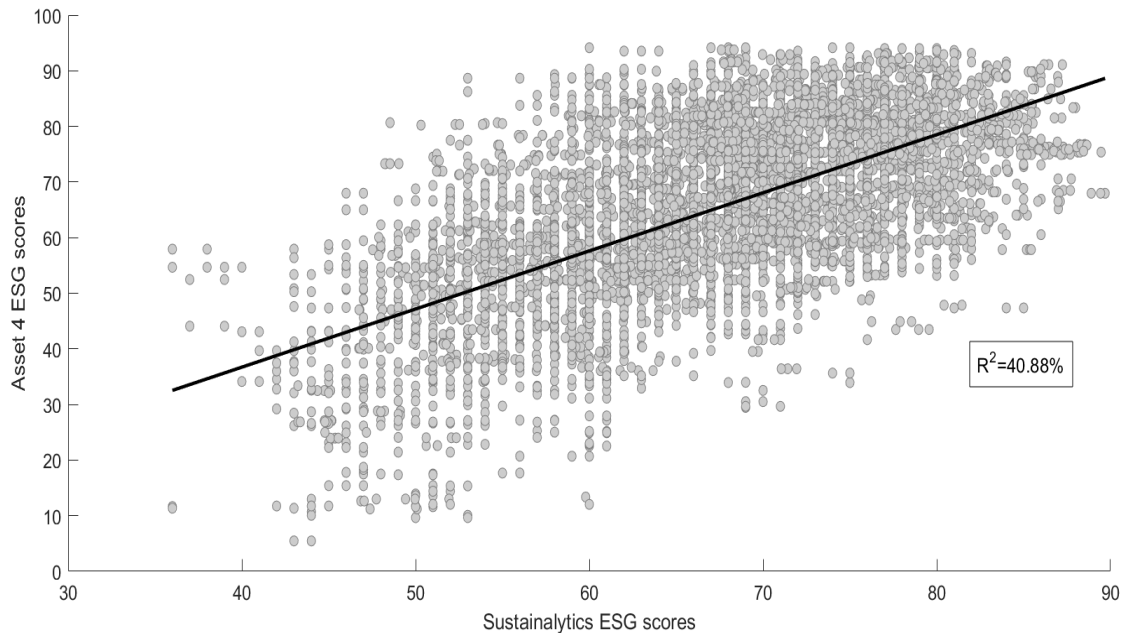


Source: The figure displays the evolution over time of the cross-sectional means of the ESG ratings for the two providers considered (Sustainalytics and Asset4). The dataset contains monthly observations for $n = 238$ firms from January 2010 to October 2018, giving a total of 106 months.

Figure 1.3 displays the evolution over time of the cross-sectional averages of the ESG ratings for the two providers in the three universes. We observe growth over time in the cross-sectional averages, which suggests a tendency towards upward revisions of the ESG ratings for firms. Assuming that ESG ratings accurately reflect ESG performance, this shows an overall improvement trend over time in the corporate behavior of firms across the three universes regarding environmental, social, and governance best practices.

To evaluate the link between the two rating systems, Figure 1.4 displays the scatter plot of the pooled ESG ratings from the two providers for the Europe universe. The figure also displays the fitted least square regression line, along with the adjusted R-squared, which is equal to 40.88%. Hence the link across firms and time between the two ESG ratings is weak, though it is positive. As already underlined, this has been highlighted many times in the literature and constitutes the main motivation of our paper, which proposes, in a context of limited convergence, a formal backtesting procedure for evaluating the informational content of ESG rating systems. The phenomenon is not only European and is also highlighted for the other two universes as shown by Figures 1.7.3 and 1.7.4 in Appendix 1.7. The trend is of the same order for the North America universe with an R-squared of 46.46%, but we observe a more pronounced divergence in the Asia-Pacific universe with an R-squared of only 32.65%.

Figure 1.4: Relation between the Sustainalytics and Asset4 ESG ratings: Europe



Source: The figure displays the scatter plot that shows the graphical relation between the ESG ratings for the two providers considered (Sustainalytics and Asset4). The dataset contains monthly observations for $n = 238$ firms from January 2010 to October 2018, giving a total of 106 months.

Information on the target variable

In this sub-section, we provide information on the target variable. We consider the idiosyncratic volatility of stock returns as our dependent variable of interest. This variable measures market risk at the firm level that is not captured by traditional risk factors. ESG ratings could significantly help predict this target variable as stock markets can react to the arrival of firm-specific ESG events (Serafeim and Yoon, 2022a) or global news corresponding to innovations in an ESG factor (Pástor et al., 2021; Ardia et al., 2022).

Another choice could be a variable or score measuring ESG incidents from leading providers. However, they seem divergent across providers, as the rank correlations between ESG incidents from Sustainalytics and Asset4 for instance are weak at 43% for Europe, 43% for North America and 34% for the Asia-Pacific region. Moreover, in this paper, we adopt the perspective of an investor using ESG information for its materiality on investment performance because this is the primary reason why investors use ESG information and many rating agencies adopt this perspective (Amel-Zadeh and Serafeim, 2018). Since ESG news is not always financially relevant for investors (Serafeim and Yoon, 2022b), using a direct measure of financial risks, such as idiosyncratic volatility, seems more appropriate in our context.

To compute idiosyncratic volatility for each firm i , we collect daily stock returns $r_{i,s}$ over our period of investigation from January 2010 to October 2018, with a total of 2,304 observations. For each universe, we also collect the daily returns $r_{m,s}$ of the MSCI stock index over the same period, using MSCI Europe, MSCI USA and MSCI Pacific for the Europe, North America and Asia-Pacific universes. Residual returns are thus extracted assuming that the Capital Asset Pricing Model (CAPM) holds, with:

$$r_{i,s} = \alpha_i + \beta_i r_{m,s} + \epsilon_{i,s}, \quad (1.17)$$

where α_i is the alpha of the stock, β_i is the beta or exposure of the stock to the market, and $\epsilon_{i,s}$ is the innovation or residual return for stock i at day s . With the daily residual returns, we compute monthly idiosyncratic realized volatility as follows:

$$IRV_{i,t} = \sum_{s_k=1}^{v_t} \hat{\epsilon}_{i,s_k}^2, \quad (1.18)$$

with t the index of the month, v_t the number of daily observations in month t , and $\hat{\epsilon}_{i,s_k}^{th}$ the s_k^{th} fitted residual returns within month t . For each firm i in a given universe, we obtain a time series of monthly idiosyncratic realized volatility of length 106, which thus matches the monthly frequency and the length of the ESG data analysed in the previous sub-section. The backtesting procedure is then applied using the logarithmic transform of the idiosyncratic realized volatility as the target variable.

Remark 1 *The CAPM model in (1.17) is likely to be misspecified. In this case, our target variable $y_{i,t} \equiv \log(IRV_{i,t})$ would be correlated across firms. However, recall that Proposition 1 does not require cross-sectional independence between $y_{i,t}$, but rather between loss differentials averaged over time. Besides, we further use a multi-factorial model to check the sensitivity of our results to the choice of the factor model.*

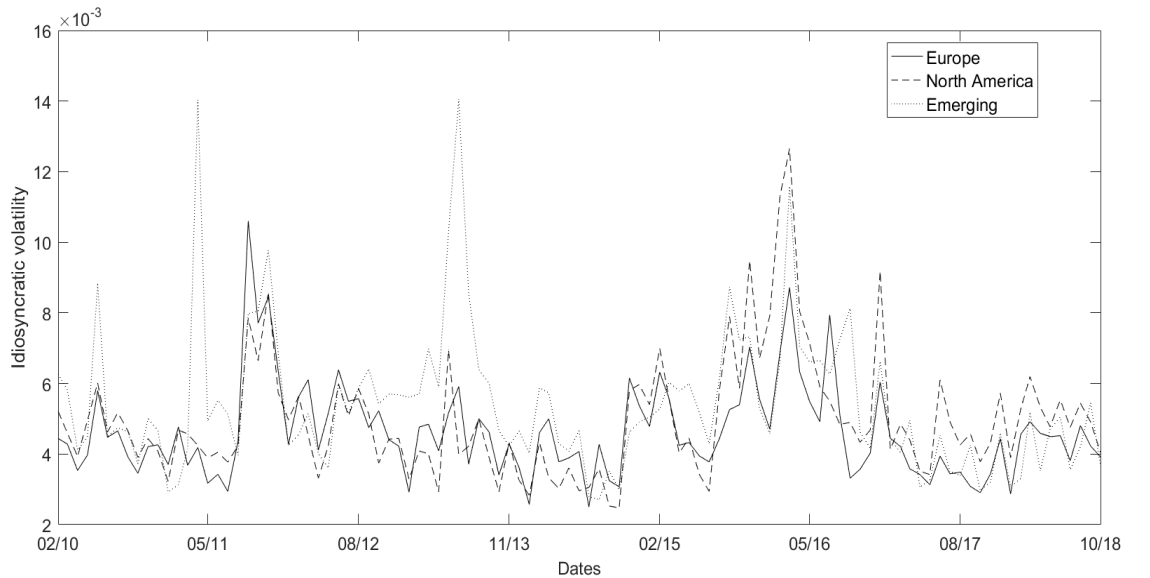
Table 1.2: Pooled descriptive statistics of idiosyncratic realised volatility

	Min (%)	Max (%)	Mean (%)	Median (%)	Std (%)
Europe	0.0133	24.6450	0.4634	0.2927	0.7064
North America	0.0099	50.6339	0.4970	0.2632	0.9217
Asia-Pacific	0.0236	33.3244	0.5416	0.3697	0.7303

Notes: The table displays pooled descriptive statistics of monthly idiosyncratic realised volatilities for the three universes. Idiosyncratic realised volatilities are computed from residual asset returns from the CAPM. The datasets contain monthly observations from January 2010 to October 2018, giving a total of 106 months. The North America, Europe and Asia-Pacific datasets contain information on respectively $n = 326$, $n = 238$ and $n = 217$ firms. Min. refers to minimum, Max. to maximum, and std. to standard deviations.

Table 1.2 displays the pooled descriptive statistics of monthly idiosyncratic volatilities for the three universes. The Asia-Pacific universe appears as the one where firms have on average the highest levels of idiosyncratic volatility. In terms of dispersion, the North America universe has more variability in the measure of the volatility of residual returns, as given by the values for the standard deviation and the range.

Figure 1.5: Dynamics of the cross-sectional means of idiosyncratic realised volatility

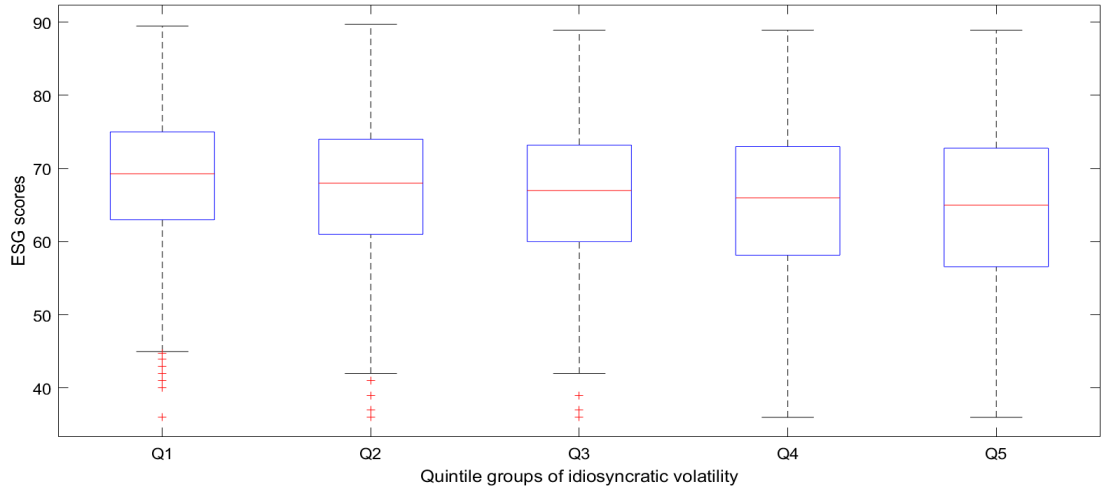


Source: The figure displays the evolution over time of the cross-sectional means of monthly idiosyncratic realised volatilities. Idiosyncratic realised volatilities are computed from residual stock returns from the CAPM. The datasets contain monthly observations from January 2010 to October 2018, giving a total of 106 months. The North America, Europe and Asia-Pacific datasets contain information on respectively $n = 326$, $n = 238$ and $n = 217$ firms.

To get an overhead view of the monthly series of idiosyncratic realised volatilities, Figure 1.5 displays the evolution over time of the cross-sectional means of monthly idiosyncratic realised volatilities. We observe the typical dynamics, with volatility clusters that nevertheless seem less pronounced because we are dealing with idiosyncratic volatility, and not total volatility which includes the systematic part.

It may be recalled that our backtesting procedure is designed to test the informational content of the ESG ratings by checking whether they have predictive power for future market risk, as measured here by increased idiosyncratic volatility of stock returns. Hence, the relationship that the test aims to validate is that high ESG ratings lead to low idiosyncratic volatilities and low ratings lead to high volatilities.

Figure 1.6: ESG ratings by idiosyncratic volatility quintiles: Sustainalytics (Europe)

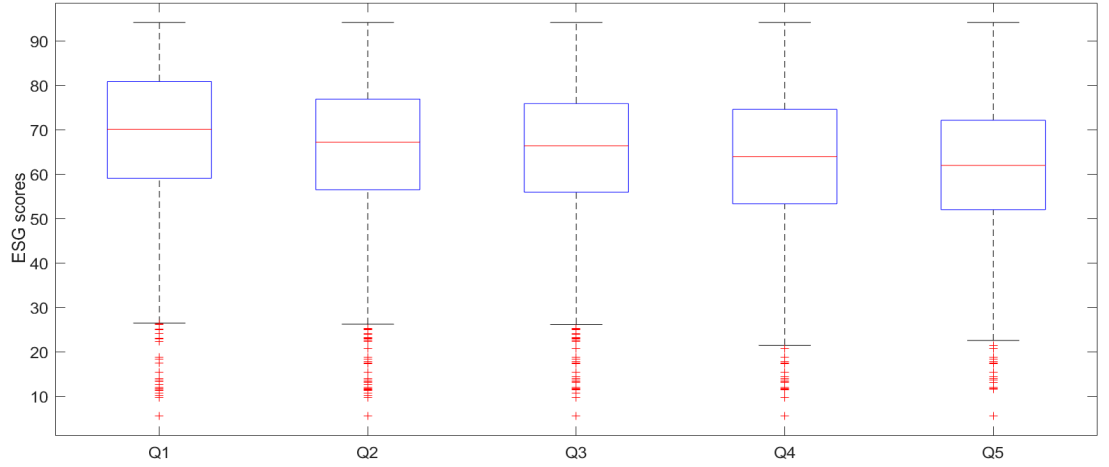


Source: For the Europe universe, the figure displays the means of the Sustainalytics ESG ratings within the five groups defined by the quintiles of idiosyncratic volatility computed with residual asset returns from the CAPM. The dataset contains monthly observations for $n = 238$ firms from January 2010 to October 2018, giving a total of 106 months.

So before we apply the backtesting procedure formally, Figures 1.6 and 1.7 try to illustrate whether there is such a relationship in the Europe universe. These figures report the distribution of the lagged values of the ESG ratings (Figure 1.6 for Sustainalytics and Figure 1.7 for Asset4) by idiosyncratic volatility quintiles. Overall we observe that a negative relation arises, with high values of lagged ESG ratings associated with low idiosyncratic volatilities, while the median values of the lagged ESG ratings decrease with the order of the quintiles. Robustness across the universes is confirmed in Appendix 1.7, with Figures 1.7.5 and 1.7.6 for the North America universe, and 1.7.7 and 1.7.8 for the Asia-Pacific universe.

To control for potential confounding factors of the link between ESG ratings and idiosyncratic volatility, retain $p = 10$ financial variables for which the monthly observations are available for

Figure 1.7: ESG ratings by idiosyncratic volatility quintiles: Asset4 (Europe)



Source: For the Europe universe, the figure displays the means of Asset4 ESG ratings within the five groups defined by the quintiles of idiosyncratic volatility computed with residual asset returns from the CAPM. The dataset contains monthly observations for $n = 238$ firms from January 2010 to October 2018, giving a total of 106 months.

all firms over the three universes and the timespan considered. These variables are tax burden, interest burden, operating margin, asset turnover, leverage, current ratio, net debt to earnings before interest, taxes, depreciation, and amortisation (EBITDA), capital expenditure (Capex) to depreciation, current assets, and current liabilities (see table 1.3 for a complete description of these variables). Innovations are extracted for each of these financial variables and for each firm by centering the raw values on the time average.

Table 1.3: Description of financial variables

Variables	Ratios	Description
Tax Burden	Net Income/Pretax Income	Profits retained after taxes
Interest Burden	Pretax Income/EBIT	Profits retained after interest paid
Operating Margin	EBIT/Revenue	Return on sales
Asset Turnover	Revenue/Total Assets	Revenue generated by own resources
Leverage	Total Assets/Total Equity	Measure of financial leverage
Current Ratio	Current Assets/Current Liab.	Measure of short-term resources
Net Debt to EBITDA	Net Debt/EBITDA	Capacity to finance debt
Capex to Dep.	Capex/Depreciation	Rate at which assets are renewed
Current Assets	Current Assets/Total Assets	Measure of short-term resources
Current Liab.	Current Liab./Total Liab.	Measure of short-term liabilities

Notes: The table gives the description of the financial variables retained. Innovations in these variables are used to control for the impact of financial factors when assessing the predictive contents of ESG ratings on the idiosyncratic volatility of a firm's assets.

1.4.2 Backtest results

Using the three categories of variables defined above as ESG ratings, idiosyncratic volatility and innovations in financial variables, we compute our test statistics and make inference for the predictive

content of the two ESG rating systems considered. To predict the target idiosyncratic volatility variable, we consider a pooled OLS regression for the two models needed to run our backtesting procedure, which are the model that contains only innovations in the $p = 10$ financial variables, and the model that extends this set to include the lagged values of the ESG ratings. Recall that our procedure compare the predictive performance of the two models:

$$\log (IRV_{i,t+1}) = \alpha_0 + \beta_0 X_{i,t} + \varepsilon_{i,t+1}^{(0)} \quad (1.19)$$

$$\log (IRV_{i,t+1}) = \alpha_1 + \beta_1 X_{i,t} + \gamma ESG_{i,t} + \varepsilon_{i,t+1}^{(1)}, \quad (1.20)$$

where $X_{i,t}$ denotes the vector of innovations in financial variables.

In line with our out-of-sample testing environment, we consider two different forecasting schemes: (i) a fixed forecasting scheme where the first 75% of the total $T = 106$ months for each firm are used to estimate both models, and the forecasts are computed over the last 25% of observations, which are considered as the test sample; (ii) a rolling-window forecasting scheme with the forecasts computed by moving the estimation sample forward by including one more month and excluding the first, giving different estimation samples with the same fixed size of $b = [0.75T]$.

Table 1.4 displays the outcome of the test for each provider across the three panel datasets. The test statistics are computed using the squared error loss. To gain more insights on the predictive power of the ratings, we perform inference on the aggregate ESG ratings of each providers and also on the specific dimensions of the ratings (environmental, social and governance). The values displayed represent the MSE variation in percentage when the ESG rating (in column) is added to the information set containing only innovations in financial variables. This presentation allows us to test our null hypothesis and to measure the magnitude of the predictive accuracy gain. Negative values are associated to MSE reductions with respect to the model excluding information about the ESG rating (or rating component), and hence to gains in predictive ability. We also report the sign of the regression coefficient associated with the ratings in parentheses. For the rolling window forecasting scheme, the coefficient is averaged across the estimation windows.

For the Europe (EU) universe, the inclusion of ESG information significantly improves the model's predictive accuracy in all configurations except one. Among Sustainalytics ratings, the environmental rating is the strongest predictor of idiosyncratic volatility, with an MSE reduction of 3.8% and 4.7% for the rolling and fixed forecasting schemes, respectively. Among Asset4 ratings, the social rating provides more information, resulting in a 3.5% (4.5%) reduction in MSE using a rolling (fixed) forecasting scheme. Overall, the governance rating appears to be less informative in predicting stock return idiosyncratic volatility, as it is associated with the lowest predictive

Table 1.4: Backtest of ESG ratings: results for squared error loss and idiosyncratic returns from CAPM

Sustainalytics					
		ESG	E	S	G
Rolling Window	EU	-3.0%*** (-0.01)	-3.8%*** (-0.009)	-1.9%*** (-0.008)	-0.54%*** (-0.005)
	NA	0.12% (-0.01)	-0.53%*** (-0.008)	0.51% (-0.006)	0.21% (-0.006)
	AP	-0.21%** (-0.004)	-0.56%*** (-0.004)	-0.030% (-0.001)	0.019% (0.0001)
Fixed Window	EU	-4.0%*** (-0.01)	-4.7%*** (-0.009)	-2.6%*** (-0.008)	-1.1%*** (-0.007)
	NA	0.81% (-0.01)	-0.42% (-0.01)	1.3% (-0.008)	0.54% (-0.01)
	AP	-0.55%* (-0.005)	-0.66%** (-0.004)	-0.17% (-0.003)	-0.30%* (-0.003)
Asset 4					
		ESG	E	S	G
Rolling Window	EU	-3.1%*** (-0.008)	-3.1%*** (-0.006)	-3.5%*** (-0.007)	-0.063% (-0.002)
	NA	-0.0069% (-0.006)	-0.30%* (-0.003)	-0.10% (-0.005)	0.39% (-0.002)
	AP	-0.028%** (3e-05)	-0.12%*** (-0.0003)	-0.36%*** (-0.0008)	-0.061% (0.0006)
Fixed Window	EU	-4.2%*** (-0.008)	-3.3%*** (-0.005)	-4.5%*** (-0.006)	-0.55%* (-0.003)
	NA	-0.67% (-0.008)	-0.52% (-0.004)	-0.71% (-0.007)	0.51% (-0.003)
	AP	-0.17%*** (-0.0005)	-0.30%*** (-0.0006)	-0.50%*** (-0.0009)	0.081% (-0.0003)

Notes: This table displays the variation in mean squared error (MSE) when ESG information is included in the model. Idiosyncratic volatilities are computed using the residual asset returns from CAPM. The datasets contain monthly observations from January 2010 to October 2018, giving a total of 106 months. The North America, Europe and Asia-Pacific datasets include information on respectively $n = 326$, $n = 238$ and $n = 217$ firms. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

accuracy gains in all configurations. The results are mixed for the North America (NA) and Asia-Pacific (AP) universes. For the NA universe, and for both ESG rating systems, only the inclusion of the environmental rating in the rolling window forecasting scheme leads to significant predictive accuracy gains. The predictive accuracy gains are also lower than those for the EU universe. For the AP universe, we reject our null hypothesis in several configurations, but predictive accuracy gains remain modest compared to those for the EU universe. Furthermore, for most rejections of our null hypothesis, we find a negative association between ESG ratings and idiosyncratic volatility, indicating that higher ESG ratings are, on average, associated with lower stock return idiosyncratic volatility.

1.4.3 Robustness to factor models

Here we evaluate the sensitivity of our results to the choice of factor model used to compute the target idiosyncratic realized volatility variable. We thus extend the CAPM model and consider a multifactorial model. This extension is anchored to the findings of academic research into the existence of common risk factors beyond the market index. This strand of the literature, which can be dated back to the seminal work of Fama and French (1992), has discovered many market variables or factors that may be able to explain the cross-sectional variations of stock returns. These include the size and value factors in Fama and French (1992) and the momentum factor in Jegadeesh and Titman (1993).

To consider the multifactorial model, we extend the CAPM model in (1.17) by adding investable factors identified in the literature to drive the cross-sectional variations of the stock's returns. For the Europe and the North America universes these are the MSCI Small/Large Capitalisation factor, which approximates the size anomaly, the MSCI Value/Growth factor associated with the value premium, the MSCI Momentum factor, the MSCI quality factor, and the MSCI Minimum Volatility factor. The lack of data for the Asia-Pacific universe means we consider three factors beyond the market, these being the MSCI Small/Large Capitalisation factor, the MSCI Value/Growth factor, and the MSCI Minimum Volatility factor. Table 1.5 displays the tests results for the idiosyncratic volatility computed using a multifactorial model and the squared error loss function. Overall, we reach qualitatively similar conclusions, suggesting that our results are robust to the choice of the factor model.

Table 1.5, which displays the backtest results using the squared loss error, shows similar results as Table 1.4. For the absolute error loss, results are displayed in appendix B (see Table 1.7.2) and are to be compared to the ones in Table 1.7.1. Taken together, these results suggest that our previous conclusions are robust to the choice of the factor model. For the rest of the paper, we restrict our analysis to the dependent variable constructed using the multifactorial model and to

Table 1.5: Backtest of ESG ratings: results for squared error loss and idiosyncratic returns from multifactorial model

Sustainalytics					
		ESG	E	S	G
Rolling Window	EU	-3.3%*** (-0.01)	-4.2%*** (-0.01)	-2.1%*** (-0.009)	-0.67%*** (-0.006)
	NA	-0.076% (-0.01)	-0.63%*** (-0.009)	0.39% (-0.009)	0.088% (-0.009)
	AP	-0.14%* (-0.003)	-0.59%*** (-0.005)	-0.030%* (0.0002)	0.028% (0.002)
Fixed Window	EU	-4.4%*** (-0.01)	-5.0%*** (-0.01)	-2.9%*** (-0.009)	-1.3%*** (-0.008)
	NA	0.56% (-0.02)	-0.43% (-0.01)	1.2% (-0.01)	0.27% (-0.01)
	AP	-0.42%* (-0.005)	-0.65%** (-0.005)	-0.084% (-0.001)	-0.13% (-0.002)
Asset 4					
		ESG	E	S	G
Rolling Window	EU	-3.4%*** (-0.009)	-3.4%*** (-0.006)	-3.6%*** (-0.007)	-0.054% (-0.003)
	NA	-0.33% (-0.008)	-0.53%** (-0.004)	-0.26% (-0.007)	0.42% (-0.003)
	AP	0.15% (0.0008)	-0.043%*** (-9e-05)	-0.089%*** (-0.0001)	-0.23%*** (0.001)
Fixed Window	EU	-4.5%*** (-0.009)	-3.6%*** (-0.006)	-4.6%*** (-0.007)	-0.64%** (-0.003)
	NA	-1.2%* (-0.01)	-0.86%* (-0.005)	-0.88% (-0.008)	0.38% (-0.005)
	AP	0.15% (0.0004)	-0.17%*** (-0.0003)	-0.042%*** (-8e-05)	-0.11%** (0.0004)

Notes: This table displays the variation in mean squared error (MSE) when ESG information is included in the model. Idiosyncratic volatilities are computed using the residual asset returns from a multifactorial model. The datasets contain monthly observations from January 2010 to October 2018, giving a total of 106 months. The North America, Europe and Asia-Pacific datasets include information on respectively $n = 326$, $n = 238$ and $n = 217$ firms. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

the squared error loss function.

To evaluate the sensitivity of the test to the choice of the loss function, Table 1.7.1 and Table 1.7.2 displays the results using the absolute error loss function for the idiosyncratic volatility from the CAPM and multifactorial model respectively. In comparison with the squared error loss function, the absolute error loss function is more robust to outliers. We find that results are highly similar for the two loss functions, suggesting that our results are robust to the choice of the loss function.

So far, our results show that the predictive power of ESG ratings varies depending on the universe considered. We find strong evidence that higher ESG ratings are associated with lower future stock return idiosyncratic volatility for the European universe, and to a lesser extent for

the North America and Asia-Pacific universes. This finding can be explained by the fact that European regulation on ESG issues is more stringent, with the establishment of a high-level expert group on sustainable finance (HLEG) in 2016 and the subsequent introduction of the EU taxonomy for sustainable activities.⁸ As a result, European investors are more likely to consider ESG information valuable for their investment decisions compared to US investors (Amel-Zadeh and Serafeim, 2018). Regarding the rating dimensions, the environmental rating appears to carry the most information, followed by the social rating, while predictive accuracy gains are consistently lower for the governance rating. This is consistent with the findings of Berg, Koelbel and Rigobon (2022), who reported that the noise in ratings is higher for the governance component, followed by the social component, with the environmental component being the least noisy. In the next subsection, we conduct additional empirical investigations to check the robustness of our results.

1.4.4 Disagreement between raters and the informational content of the ESG ratings

Our results suggest that both rating systems are informative for forecasting idiosyncratic volatility in Europe, where regulation on ESG is more stringent, and to a lesser extent in other regions. Another factor that could affect the link between ESG ratings and return volatility is ESG ratings disagreement. Serafeim and Yoon (2022a) analyzed the link between ESG ratings and ESG risks as measured by ESG-related events and showed that the consensus rating predicts future news, but its predictive ability diminishes for firms where there is a large disagreement between raters. They also found that the consensus rating moderates the stock market reaction to ESG risks. Therefore, the forecasting power of ESG ratings could be moderated by ESG rating disagreement as it affects both the likelihood of ESG events and the stock market reaction to ESG risk materialization. In our sample, we find that ESG ratings are quite divergent across the three universes. The R-squared for the linear regression between the two rating agencies is equal to 40.88% for the EU universe, 46.46% for the NA universe, and 32.65% for the AP universe (see Figures 1.4, 1.7.3, and 1.7.4).

To check for this stylised fact, we replicate the results of Table 1.5 but partition each panel into consensus and disagreement groups, based on the firm level correlation between the ratings of the two providers. For each universe, the consensus group contains firms belonging to the top 25% of highest correlations, while the disagreement group contains firms belonging to the top 25% lowest correlations. Among the consensus group, the average correlation between ESG ratings of the two providers are equal to 75%, 72% and 70% for the EU, NA and AP universes, respectively. Among the disagreement group, these figures are equal to -35%, -46% and -44%, meaning that there is considerable divergence between ratings. Table 1.6 shows the sector distribution in the consensus

⁸https://finance.ec.europa.eu/publications/high-level-expert-group-sustainable-finance-hleg_en

Table 1.6: Distribution of sectors in consensus and disagreement samples

Sector	Consensus	Disagreement
Consumer Discretionary	20.3%	19.5%
Industrials	20.3%	21.1%
Information Technology	14.7%	13.5%
Energy	10.2%	8.4%
Materials	9.1%	12.0%
Consumer Staples	8.1%	8.0%
Healthcare	6.1%	6.0%
Communication Services	5.6%	5.2%
Utilities	4.6%	5.6%
Financials	1.0%	0.8%

Notes: The table displays distribution of sectors in the consensus and disagreement samples.

and disagreement samples. Since the consensus rating is driven by the different methodologies used by rating agencies rather than by firm characteristics (Berg, Koelbel and Rigobon, 2022), we observe a similar distribution of sectors across the two groups.

Table 1.7 displays the backtest results for the consensus and disagreement groups using a rolling window forecasting scheme. The results using a fixed window are displayed in Appendix B (Table 1.7.3). We observe significant differences in terms of the rejection of the null hypothesis between the two groups. Among the consensus group, we observe 17 rejections out of 24 tests at the 1% nominal risk level, while this figure drops to 5 rejections for the disagreement group. Moreover, the forecasting power of ESG ratings is consistently greater for consensus firms across the three universes. For example, considering the EU universe, the MSE reduction due to the inclusion of Sustainalytics environmental rating is equal to 7.7% in the consensus sample, but only 2.3% in the disagreement sample. For the NA universe, these figures are 2.6% for the consensus sample and 0.14% for the disagreement sample. Similar conclusions hold for most configurations and universes.

To assess the sensitivity of the previous results to the threshold used to define the consensus firms, we repeated the analysis for alternative levels of ESG consensus. We started with the full sample and excluded the top $x\%$ of firms with the highest level of disagreement before applying our inferential procedure. Figure 1.8 displays the results for values of x ranging between 0% and 75% using a rolling window forecasting scheme. Results obtained using a fixed window forecasting scheme are displayed in the appendix (Figure 1.7.9). We find that the forecasting power of ESG ratings increases with the level of ESG consensus. This result is consistent for both rating agencies and across the three universes. Overall, predictive accuracy gains due to the inclusion of ESG information increase with the level of ESG consensus.

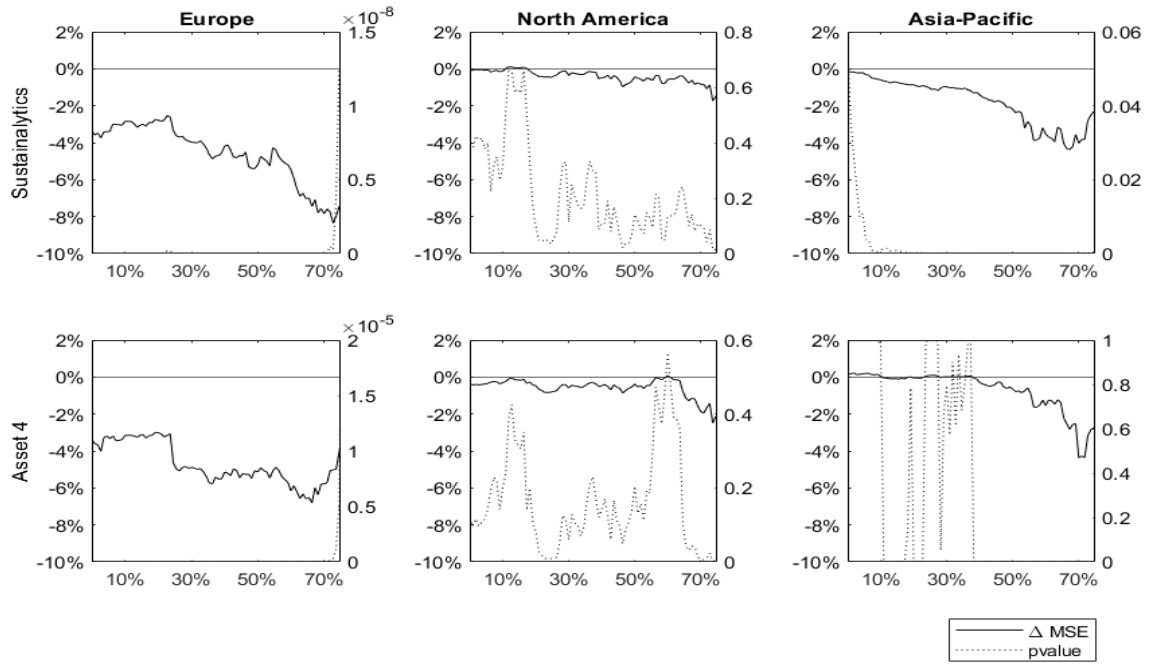
We next test if the predictive ability of ESG ratings is the same for consensus firms with high and low ratings. To do so, we apply our test separately to consensus firms with a high ESG

Table 1.7: Consensus vs disagreement between providers using a rolling window forecasting scheme (MSE)

Sustainalytics					
		ESG	E	S	G
Consensus	EU	-7.7%*** (-0.02)	-7.1%*** (-0.01)	-5.0%*** (-0.01)	-3.7%*** (-0.01)
	NA	-1.6%** (-0.02)	-2.6%*** (-0.01)	-1.0%* (-0.01)	0.97% (-0.009)
	AP	-2.4%*** (-0.01)	-3.5%*** (-0.01)	-0.64%*** (-0.003)	-1.1%** (-0.008)
Disagreement	EU	-2.9%*** (-0.01)	-2.3%*** (-0.007)	-2.8%*** (-0.01)	-0.032% (-0.003)
	NA	-0.091% (-0.01)	-0.14% (-0.01)	0.035% (-0.009)	0.027% (0.0003)
	AP	-1.3%*** (0.006)	0.29% (-0.001)	-1.1%* (0.009)	-1.4%** (0.008)
Asset 4					
		ESG	E	S	G
Consensus	EU	-4.0%*** (-0.008)	-4.8%*** (-0.007)	-4.7%*** (-0.007)	-0.056%* (-0.0002)
	NA	-2.3%*** (-0.009)	-5.1%*** (-0.008)	-2.1%*** (-0.006)	0.46% (-0.002)
	AP	-2.5%*** (-0.006)	-3.2%*** (-0.005)	-0.78%** (-0.003)	-0.33%*** (-0.001)
Disagreement	EU	-1.2%* (-0.008)	-3.4%*** (-0.005)	-1.4%* (-0.008)	0.74% (-0.001)
	NA	0.64% (-0.008)	0.21% (-0.003)	0.55% (-0.005)	0.48% (-0.005)
	AP	-0.30% (0.002)	-0.92%** (0.002)	0.28% (0.001)	-0.24%* (0.0007)

Notes: This table displays the variation in mean squared error (MSE) when ESG information is included in the model. Idiosyncratic volatilities are computed using the residual asset returns from a multifactorial model. Results are computed using a rolling window forecasting scheme. For a given universe, the consensus group contains firms with the 25% highest correlations between the ratings of the two providers. The disagreement group contains firms with the 25% lowest correlations. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

Figure 1.8: Decrease in forecast error in function of ESG consensus (rolling window)



Source: This table displays the variation in MSE when ESG information is included in the model as a function of the level of consensus between ESG providers. The x-axis represents the level of consensus between rating agencies. For a level of consensus x , only the firms with the $1 - x$ highest correlations between the ratings of the two providers were included in the sample.

rating (above the median) and a low ESG rating (below the median). Results using a rolling (fixed) window forecasting scheme are displayed in Table 1.8 (Table 1.7.4). We find that for both rating agencies, the predictive ability is greater for consensus firms with a low rating in the NA universe, but that the predictive accuracy gains depend on the rating agency considered for the other universes.

From a practical point of view, our results provide crucial information for portfolio managers who integrate ESG information into their investment decisions. We show that it is necessary to cross-check the information gathered from multiple ESG rating providers before integrating ESG into the management process. The focal point of our results is that consensus about the ESG ratings is informative about idiosyncratic risk, while ESG ratings with disagreement are less valuable from this viewpoint.

Table 1.8: Consensus firms: high vs low ESG rating (rolling window)

Sustainalytics					
		ESG	E	S	G
High ESG	EU	-2.9%*** (-0.01)	-5.8%*** (-0.01)	-0.16% (-0.005)	0.19% (0.002)
	NA	4.0% (0.01)	0.67% (0.002)	6.8% (0.009)	-0.37% (-0.003)
	AP	-0.68%** (-0.005)	-0.47% (-0.005)	-0.75%** (-0.003)	0.037% (6e-05)
Low ESG	EU	-4.8%*** (-0.01)	-4.3%*** (-0.009)	-2.1%*** (-0.008)	-3.7%*** (-0.01)
	NA	-1.7%** (-0.02)	-2.6%*** (-0.01)	-0.60% (-0.01)	0.12% (-0.008)
	AP	-1.9%*** (-0.005)	-0.63%** (-0.0007)	-1.4%*** (-0.005)	-2.1%*** (-0.008)
Asset 4					
		ESG	E	S	G
High ESG	EU	-8.5%*** (-0.02)	-2.5%*** (-0.005)	-6.6%*** (-0.01)	-1.2%*** (-0.003)
	NA	0.23% (0.003)	-0.75% (-0.004)	0.66% (0.008)	0.88% (-0.002)
	AP	-3.6%*** (-0.009)	-0.97%** (-0.004)	-0.86%** (-0.003)	-0.54%** (-0.0009)
Low ESG	EU	0.25% (0.0007)	-2.8%*** (-0.004)	-0.71%*** (-0.001)	-1.7%*** (0.005)
	NA	-4.6%*** (-0.01)	-7.0%*** (-0.009)	-4.3%*** (-0.008)	-0.20%* (-0.0003)
	AP	-0.14% (-0.0006)	-0.074% (-0.0003)	-0.11% (0.0008)	0.47% (-0.001)

Notes: This table displays the variation in mean squared error (MSE) when ESG information is included in the model for consensus firms. Idiosyncratic volatilities are computed using the residual asset returns from a multifactorial model. Results are computed using a rolling window forecasting scheme. High (low) ESG sample represents firms above (below) the median ESG rating. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

1.5 Conclusion

The contribution of this article is to propose a formal statistical procedure for assessing the informational content in ESG ratings. The test proceeds by evaluating how well these extra-financial metrics help in predicting a given target variable intended to measure firm-specific risks. Our framework allows users to choose a target variable related to their investment objectives. Technically, our inferential procedure for checking the informational content in ESG ratings is based on extending the conditional predictive ability test of Giacomini and White (2006) to a panel setting. Under weak assumptions, including cross-sectional dependencies among loss functions for firms, we derive the Gaussian asymptotic distribution of the test statistic. Monte Carlo simulations conducted under different types of model misspecification show that the test has good small sample properties.

Empirical applications are conducted using the idiosyncratic volatility of stock returns, a measure of firm-specific risk, as our target variable. We apply our procedure to evaluate two leading ESG rating systems (Sustainalytics and Asset4) in three investment universes (Europe, North America, and the Asia-Pacific region). The results show that the null hypothesis of a lack of informational content in ESG ratings is strongly rejected for Europe, while the results are mixed and predictive accuracy gains are lower for the other regions. Furthermore, we find that the predictive accuracy gains are higher for the environmental dimension of the ESG ratings. Importantly, we find that the predictive accuracy gains derived from ESG ratings increase with the level of consensus between rating agencies in all three universes, while they are low for firms over which there is a high level of disagreement.

The results have important implications for investors and researchers. For investors, our back-test procedure provides a useful and practical framework for considering ESG rating providers before integrating the ratings into the investment process. Our results suggest prudence about the information content of ESG ratings when they diverge. For researchers in asset pricing, it is crucial to check properly the quality of ESG ratings before using them, especially when the ratings are divergent. Moreover, the link between ESG ratings and idiosyncratic volatility when the ratings are convergent suggests that ESG investing is not just an issue of the preferences of investors, but that ESG ratings can also provide information about future fundamentals and risks. A future application for investors could be to compare the ratings of competing ESG rating agencies, since our inferential procedure can be easily adapted to compare the informational content in the ESG ratings. This would help investors in selecting one agency among several competing ones in non-nested comparisons, or in considering additional competing agencies to combine with their already existing ratings in nested comparisons.

1.6 Appendix A: Details on the Monte Carlo simulations

In this Appendix we provide details about the simulations of innovations in the financial variables for generating the small sample properties of the test (see Section 1.3). These variables are generated via a multivariate Gaussian distribution with mean vector \bar{x} and covariance matrix Ω calibrated using real data. The dataset we use contains historical monthly values of $p = 10$ innovations in the financial variables for 238 European firms from January 2010 to October 2018, giving a total of 106 months.

Innovations are computed as deviations from the overall means. The financial variables are, in order: tax burden ratio, interest burden ratio, operating margin ratio, asset turnover ratio, leverage as measured by the ratio of total assets to total equity, current ratio as measured by the ratio of current assets to current liabilities, debt ratio, capex as measured by the ratio of capital expenditures to depreciation, current assets as measured by the ratio of current assets to total assets, current liabilities as measured by the ratio of current liabilities to total liabilities.

The mean vector is thus equal to

$$\bar{x} = [0.8137; 0.8333; 0.1391; 0.8265; 3.8713; 1.4031; 1.7466; 1.2779; 0.3634; 0.2880],$$

and the covariance matrix Ω equal to

$$\Omega = \begin{pmatrix} 4.098 & -0.061 & -0.007 & -0.003 & -0.003 & 0.008 & 0.209 & -0.023 & -0.001 & -0.001 \\ -0.061 & 17.732 & -0.008 & 0.037 & 5.704 & 0.057 & -0.136 & -0.021 & 0.017 & 0.007 \\ -0.007 & -0.008 & 0.012 & -0.025 & -0.369 & 0.010 & -0.018 & 0.025 & -0.005 & -0.006 \\ -0.003 & 0.037 & -0.025 & 0.284 & -0.559 & -0.025 & -0.358 & -0.067 & 0.042 & 0.037 \\ -0.003 & 5.704 & -0.369 & -0.559 & 5012.291 & -0.521 & 30.792 & 4.391 & -0.160 & -0.092 \\ 0.008 & 0.057 & 0.010 & -0.025 & -0.521 & 0.642 & -0.420 & 0.042 & 0.053 & -0.040 \\ 0.209 & -0.136 & -0.018 & -0.358 & 30.792 & -0.420 & 32.172 & 0.550 & -0.154 & -0.058 \\ -0.023 & -0.021 & 0.025 & -0.067 & 4.391 & 0.042 & 0.550 & 1.841 & -0.023 & -0.022 \\ -0.001 & 0.017 & -0.005 & 0.042 & -0.160 & 0.053 & -0.154 & -0.023 & 0.029 & 0.014 \\ -0.001 & 0.007 & -0.006 & 0.037 & -0.092 & -0.040 & -0.058 & -0.022 & 0.014 & 0.018 \end{pmatrix}.$$

For the simulation of the target variable of idiosyncratic volatility, we run a pooled OLS regression with the dependent variable being the logarithm of the monthly time series of idiosyncratic realised volatility over the same period (January 2010 to October 2018) for the 238 European firms. The explanatory variables are the innovations in the 10 financial variables as described above.

c^*	β_1^*	β_2^*	β_3^*	β_4^*	β_5^*	β_6^*	β_7^*	β_8^*	β_9^*	β_{10}^*
-5.9165	0.0070	-0.0015	-0.8739	-0.0679	0.0048×10^{-2}	0.0941	0.0044	0.0605	0.1869	0.0824

For the $p = 10$ financial variables, the estimated coefficients are displayed above. These estimates are used to generate data for simulating the logarithm of idiosyncratic realised volatility, and applying the exponential function leads to the target variable.

1.7 Appendix B: Additional Tables and Figures

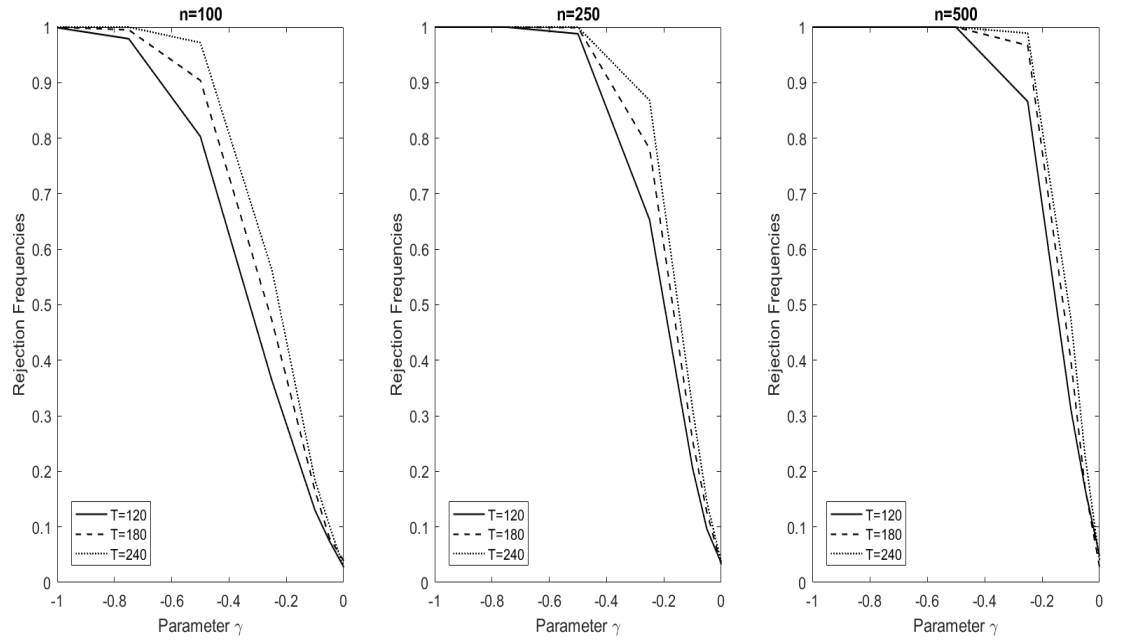


Figure 1.7.1: Rejection Frequencies under a medium level of misspecification with the absolute error loss function

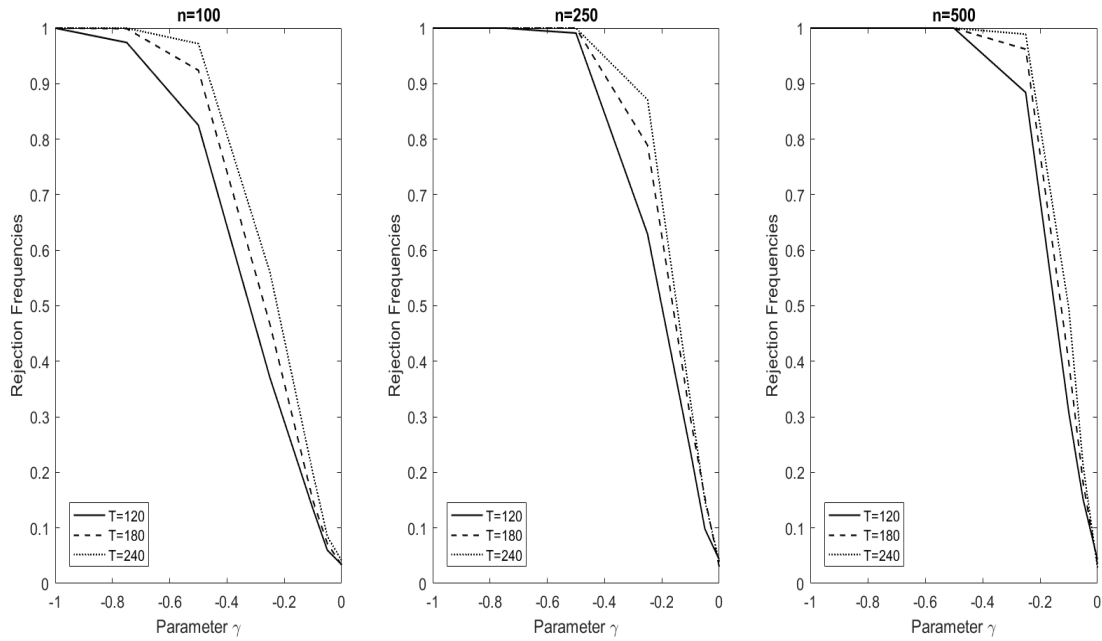
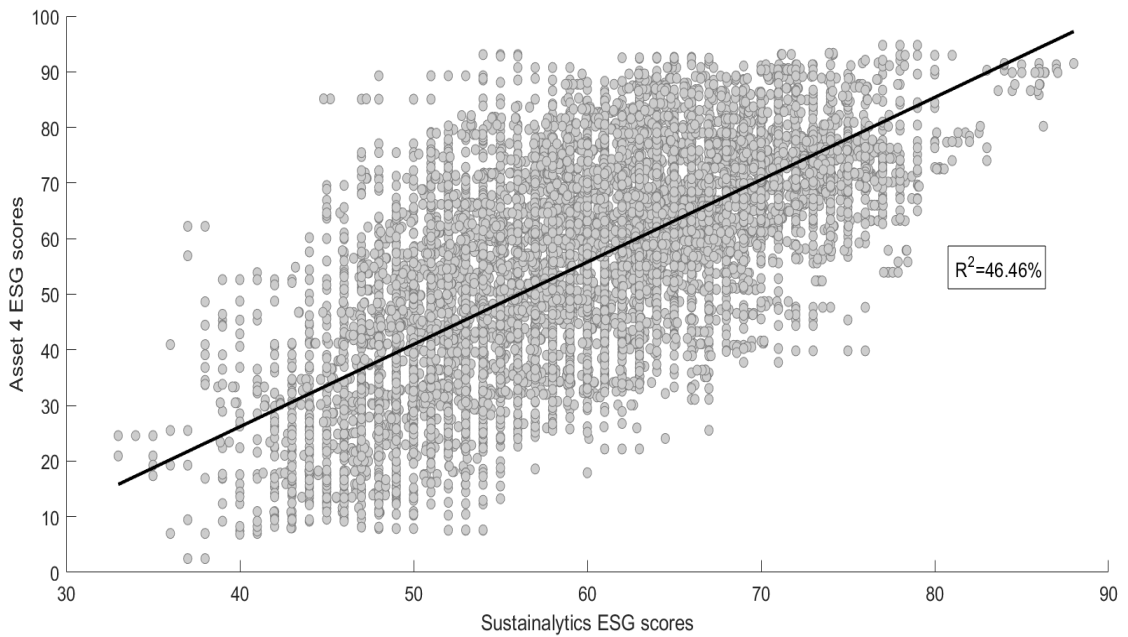


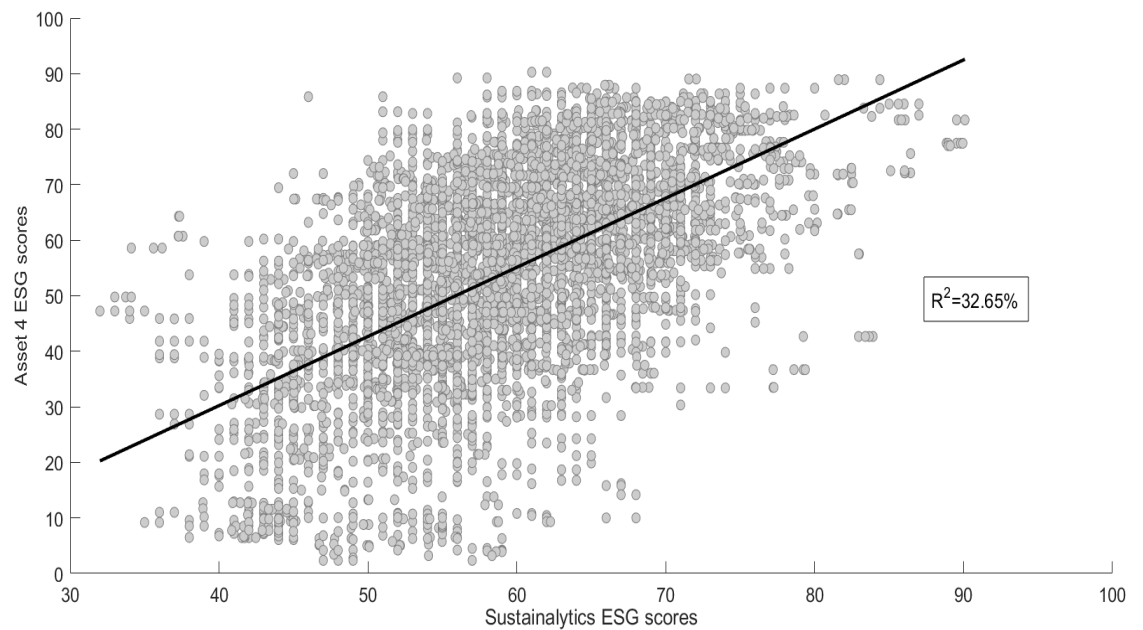
Figure 1.7.2: Rejection Frequencies under a high level of misspecification with the absolute error loss function

Figure 1.7.3: Relation between the Sustainalytics and Asset4 ESG ratings: North America



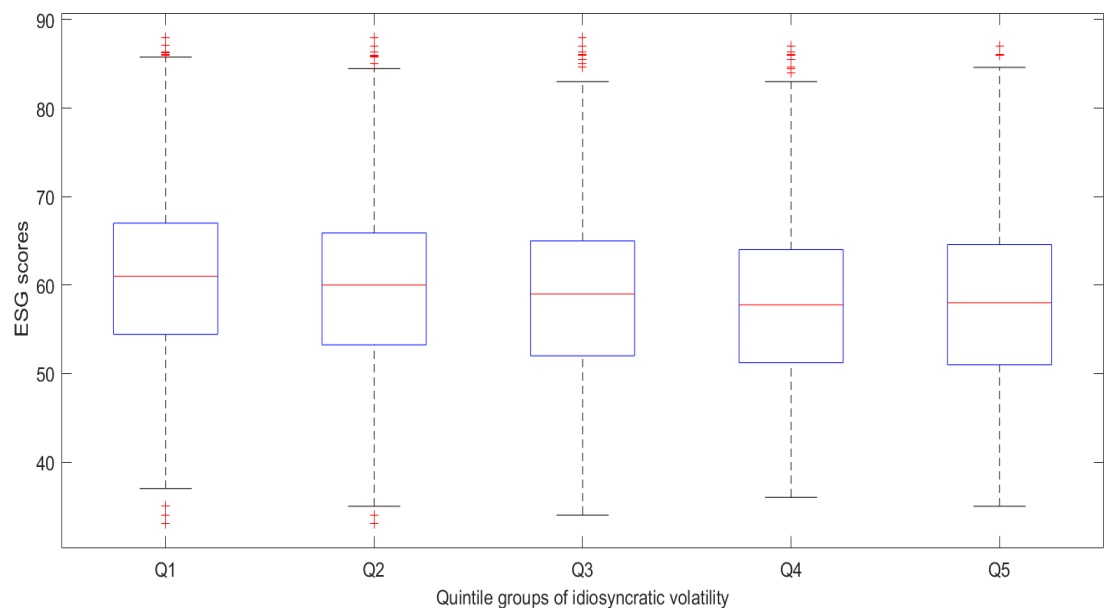
Source: The figure displays the scatter plot that shows the graphical relation between the ESG ratings for the two providers considered (Sustainalytics and Asset4). The datasets contain monthly observations for $n = 326$ firms from January 2010 to October 2018, giving a total of 106 months.

Figure 1.7.4: Relation between the Sustainalytics and Asset4 ESG ratings: Asia-Pacific



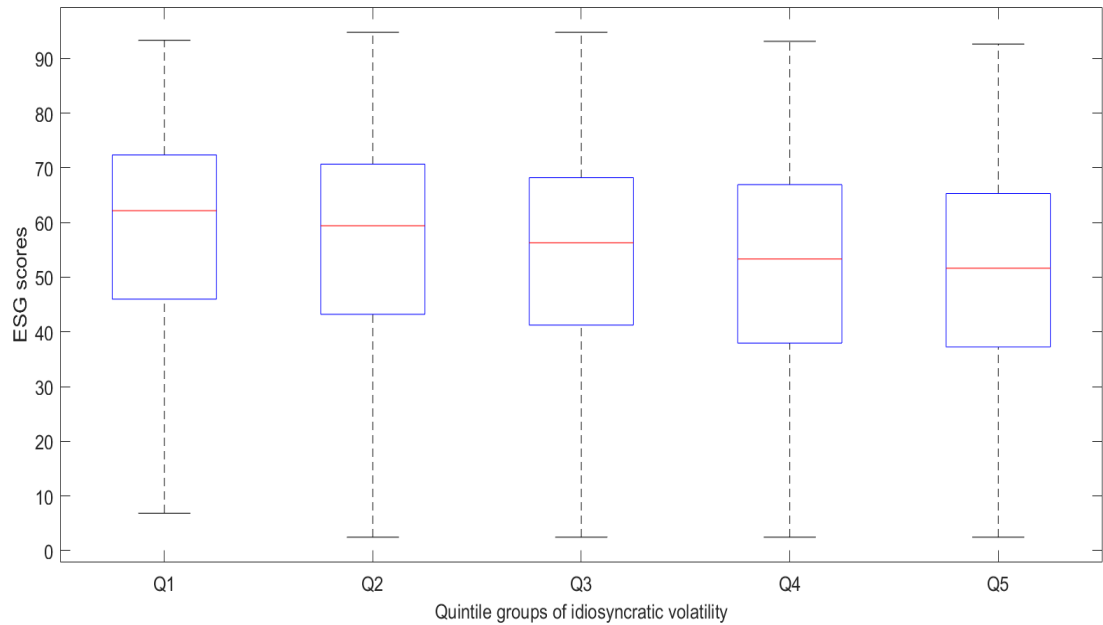
Source: The figure displays the scatter plot that shows the graphical relation between the ESG ratings for the two providers considered (Sustainalytics and Asset4). The datasets contain monthly observations for $n = 217$ firms from January 2010 to October 2018, giving a total of 106 months.

Figure 1.7.5: ESG ratings by idiosyncratic volatility quintiles: Sustainalytics (North America)



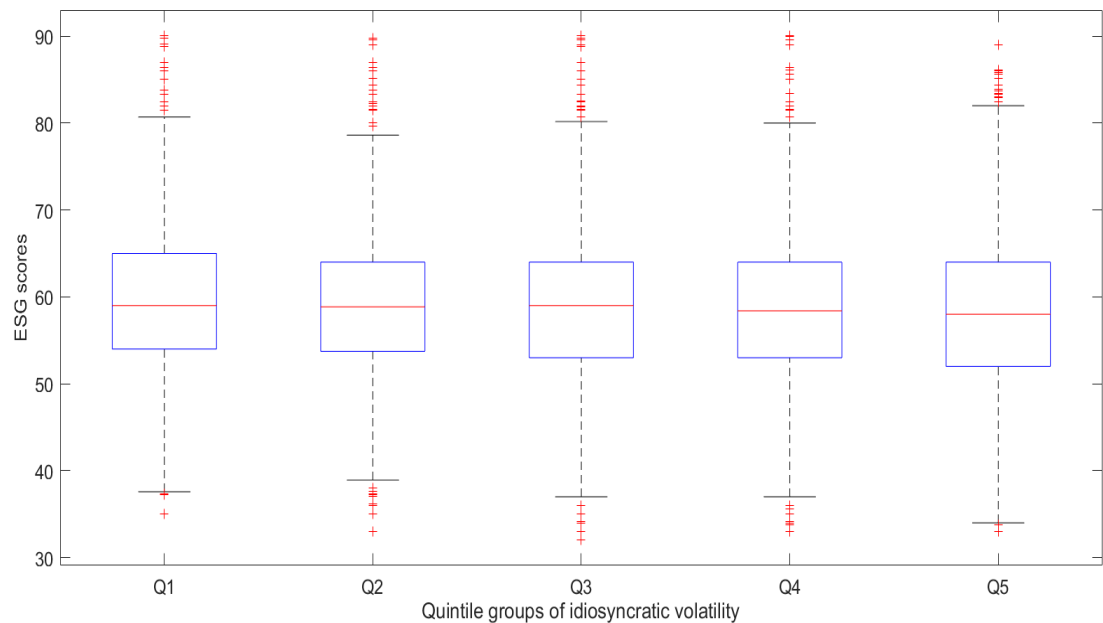
Source: For the North America universe, the figure displays the means of Sustainalytics ESG ratings within the five groups defined by the quintiles of idiosyncratic volatility computed with residual asset returns from the CAPM. The dataset contains monthly observations for $n = 326$ firms from January 2010 to October 2018, giving a total of 106 months.

Figure 1.7.6: ESG ratings by idiosyncratic volatility quintiles: Asset4 (North America)



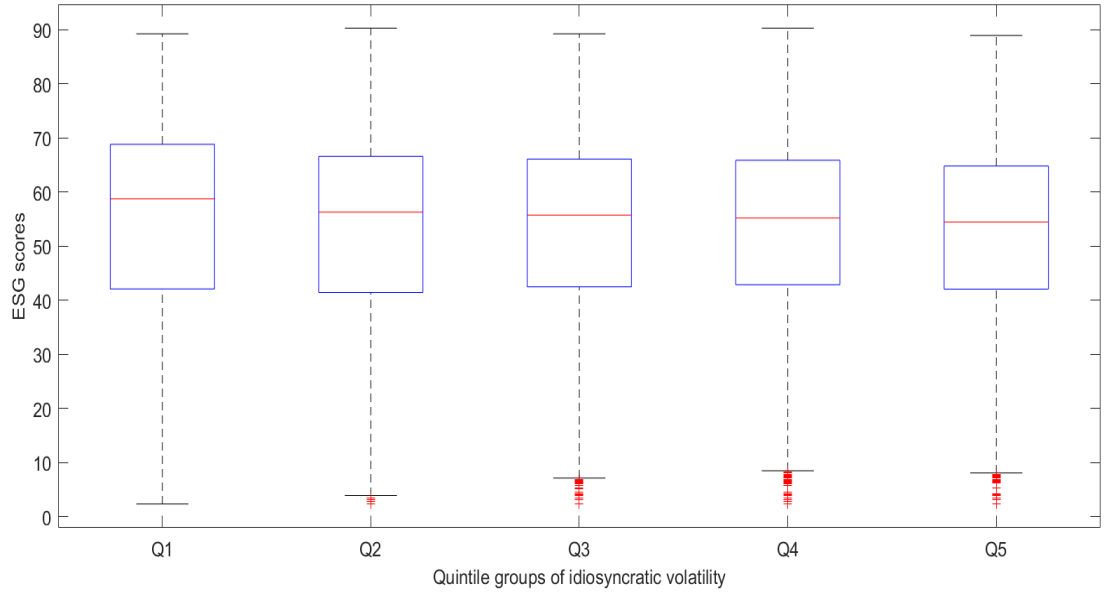
Source: For the North America universe, the figure displays the means of Asset4 ESG ratings within the five groups defined by the quintiles of idiosyncratic volatility computed with residual asset returns from the CAPM. The dataset contains monthly observations for $n = 326$ firms from January 2010 to October 2018, giving a total of 106 months.

Figure 1.7.7: ESG ratings by idiosyncratic volatility quintiles: Sustainalytics (Asia-Pacific)



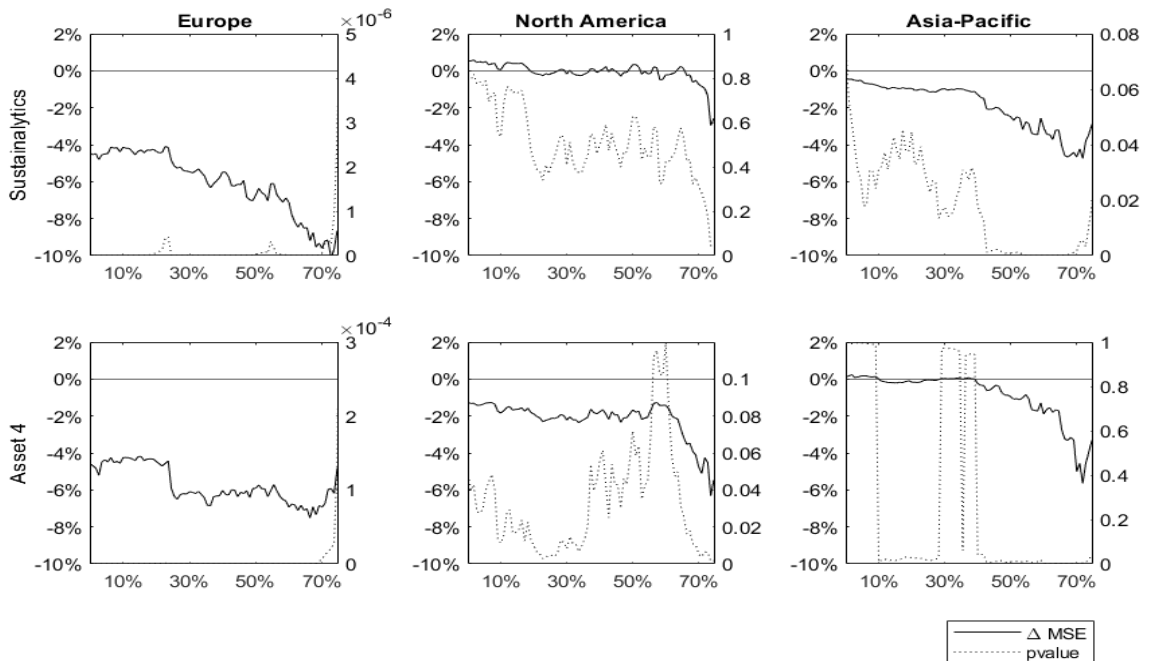
Source: For the Asia-Pacific universe, the figure displays the means of Sustainalytics ESG ratings within the five groups defined by the quintiles of idiosyncratic volatility computed with residual asset returns from the CAPM. The dataset contains monthly observations for $n = 217$ firms from January 2010 to October 2018, giving a total of 106 months.

Figure 1.7.8: ESG ratings by idiosyncratic volatility quintiles: Asset4 (Asia-Pacific)



Source: For the Asia-Pacific universe, the figure displays the means of Asset4 ESG ratings within the five groups defined by the quintiles of idiosyncratic volatility computed with residual asset returns from the CAPM. The dataset contains monthly observations for $n = 217$ firms from January 2010 to October 2018, giving a total of 106 months.

Figure 1.7.9: Decrease in forecast error in function ESG consensus (fixed window)



Source: This table displays the variation in MSE when ESG information is included in the model as a function of the level of consensus between ESG providers. The x-axis represents the level of consensus between rating agencies. For a level of consensus x , only the firms with the $1 - x$ highest correlations between the ratings of the two providers were included in the sample.

Table 1.7.1: Backtest of ESG ratings: results for absolute error loss and idiosyncratic returns from CAPM

Sustainalytics					
		ESG	E	S	G
Rolling Window	EU	-1.6%*** (-0.01)	-2.1%*** (-0.009)	-0.98%*** (-0.008)	-0.38%*** (-0.005)
	NA	-0.075% (-0.01)	-0.43%*** (-0.008)	0.17% (-0.006)	0.060% (-0.006)
	AP	-0.14%** (-0.004)	-0.39%*** (-0.004)	-0.0024% (-0.001)	0.0079% (0.0001)
Fixed Window	EU	-2.3%*** (-0.01)	-2.7%*** (-0.009)	-1.4%*** (-0.008)	-0.74%*** (-0.007)
	NA	0.14% (-0.01)	-0.56%** (-0.01)	0.52% (-0.008)	0.22% (-0.01)
	AP	-0.37%** (-0.005)	-0.44%** (-0.004)	-0.12% (-0.003)	-0.19%** (-0.003)
Asset 4					
		ESG	E	S	G
Rolling Window	EU	-2.0%*** (-0.008)	-1.6%*** (-0.006)	-2.3%*** (-0.007)	-0.19%*** (-0.002)
	NA	-0.23%* (-0.006)	-0.26%** (-0.003)	-0.29%** (-0.005)	0.10% (-0.002)
	AP	$2.9e-05\%$ ($3e-05$)	-0.069%*** (-0.0003)	-0.17%*** (-0.0008)	-0.062%** (0.0006)
Fixed Window	EU	-2.5%*** (-0.008)	-1.8%*** (-0.005)	-2.8%*** (-0.006)	-0.46%*** (-0.003)
	NA	-0.81%** (-0.008)	-0.51%** (-0.004)	-0.76%** (-0.007)	0.12% (-0.003)
	AP	-0.089%*** (-0.0005)	-0.18%*** (-0.0006)	-0.25%*** (-0.0009)	0.055% (-0.0003)

Notes: This table displays the variation in mean absolute error (MAE) when ESG information is included in the model. Idiosyncratic volatilities are computed using the residual asset returns from CAPM. The datasets contain monthly observations from January 2010 to October 2018, giving a total of 106 months. The North America, Europe and Asia-Pacific datasets include information on respectively $n = 326$, $n = 238$ and $n = 217$ firms. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

Table 1.7.2: Backtest of ESG ratings: results for absolute error loss and idiosyncratic returns from multifactorial model

Sustainalytics					
		ESG	E	S	G
Rolling Window	EU	-1.8%*** (-0.01)	-2.3%*** (-0.01)	-1.0%*** (-0.009)	-0.44%*** (-0.006)
	NA	-0.16% (-0.01)	-0.52%*** (-0.009)	0.16% (-0.009)	0.037% (-0.009)
	AP	-0.11%** (-0.003)	-0.45%*** (-0.005)	0.0095% (0.0002)	0.033% (0.002)
Fixed Window	EU	-2.3%*** (-0.01)	-2.7%*** (-0.01)	-1.4%*** (-0.009)	-0.81%*** (-0.008)
	NA	0.034% (-0.02)	-0.56%** (-0.01)	0.49% (-0.01)	0.028% (-0.01)
	AP	-0.34%** (-0.005)	-0.49%** (-0.005)	-0.066% (-0.001)	-0.090%* (-0.002)
Asset 4					
		ESG	E	S	G
Rolling Window	EU	-2.0%*** (-0.009)	-1.7%*** (-0.006)	-2.2%*** (-0.007)	-0.20%** (-0.003)
	NA	-0.31%* (-0.008)	-0.34%** (-0.004)	-0.29%* (-0.007)	0.17% (-0.003)
	AP	0.097% (0.0008)	-0.022%** (-9e-05)	-0.026%** (-0.0001)	-0.14%*** (0.001)
Fixed Window	EU	-2.5%*** (-0.009)	-1.8%*** (-0.006)	-2.7%*** (-0.007)	-0.52%*** (-0.003)
	NA	-0.86%** (-0.01)	-0.57%** (-0.005)	-0.68%* (-0.008)	0.064% (-0.005)
	AP	0.084% (0.0004)	-0.11%*** (-0.0003)	-0.024%*** (-8e-05)	-0.065%** (0.0004)

Notes: This table displays the variation in mean absolute error (MAE) when ESG information is included in the model. Idiosyncratic volatilities are computed using the residual asset returns from a multifactorial model. The datasets contain monthly observations from January 2010 to October 2018, giving a total of 106 months. The North America, Europe and Asia-Pacific datasets include information on respectively $n = 326$, $n = 238$ and $n = 217$ firms. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

Table 1.7.3: Consensus vs disagreement between providers using a fixed window forecasting scheme (MSE)

Sustainalytics					
		ESG	E	S	G
Consensus	EU	-8.9%*** (-0.02)	-6.8%*** (-0.009)	-6.3%*** (-0.01)	-5.9%*** (-0.01)
	NA	-3.0%** (-0.02)	-4.8%*** (-0.01)	-0.93% (-0.01)	0.70% (-0.01)
	AP	-3.0%** (-0.01)	-2.8%** (-0.008)	-0.49% (-0.002)	-4.4%*** (-0.01)
Disagreement	EU	-1.8%** (-0.007)	-1.8%** (-0.005)	-1.4%** (-0.005)	-0.28% (-0.004)
	NA	-4.2% (-0.02)	-4.7% (-0.01)	-2.5% (-0.01)	-0.97% (-0.004)
	AP	-0.63%* (0.004)	0.47% (-0.002)	-0.43% (0.006)	-0.76%* (0.003)
Asset 4					
Consensus	EU	-4.8%*** (-0.007)	-5.1%*** (-0.006)	-5.8%*** (-0.006)	-0.052% (-0.0007)
	NA	-6.2%*** (-0.01)	-8.3%*** (-0.009)	-4.7%*** (-0.007)	-0.24% (-0.004)
	AP	-3.1%* (-0.007)	-3.9%*** (-0.005)	-1.2% (-0.004)	-0.51% (-0.002)
Disagreement	EU	-1.8%* (-0.005)	-1.8%** (-0.002)	-2.5%* (-0.006)	0.84% (-0.003)
	NA	-5.0% (-0.01)	-3.0% (-0.004)	-3.6% (-0.008)	-3.3% (-0.007)
	AP	0.24% (0.002)	-0.38% (0.002)	0.58% (0.001)	-0.059%* (0.0001)

Notes: This table displays the variation in mean squared error (MSE) when ESG information is included in the model. Idiosyncratic volatilities are computed using the residual asset returns from a multifactorial model. Results are computed using a fixed window forecasting scheme. For a given universe, the consensus group contains firms with the 25% highest correlations between the ratings of the two providers. The disagreement group contains firms with the 25% lowest correlations. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

Table 1.7.4: Consensus firms: high vs low ESG rating (fixed window)

		Sustainalytics			
		ESG	E	S	G
High ESG	EU	−3.2% (−0.01)	−7.1%*** (−0.009)	−1.7% (−0.01)	3.4% (−0.007)
	NA	2.7% (−0.003)	0.66% (−0.0008)	3.8% (−0.003)	0.91% (−0.003)
	AP	−1.2%** (−0.005)	−2.6%** (−0.009)	1.2% (0.006)	−2.4%* (−0.01)
Low ESG	EU	−3.6%*** (−0.008)	−1.6%*** (−0.002)	−1.7%** (−0.005)	−4.9%*** (−0.01)
	NA	−3.1%** (−0.02)	−5.7%*** (−0.01)	−0.59% (−0.02)	0.70% (−0.01)
	AP	−1.8% (−0.01)	−1.4% (−0.006)	0.71% (−0.007)	−5.2%*** (−0.01)
		Asset 4			
		ESG	E	S	G
High ESG	EU	−3.3% (−0.01)	−1.4%* (−0.004)	−8.6%*** (−0.01)	0.044% (−0.0002)
	NA	15.% (−0.009)	18.% (−0.01)	−1.5%* (0.002)	13.% (−0.004)
	AP	−9.4%*** (−0.01)	−6.6%*** (−0.01)	−2.3%*** (−0.003)	0.14% (0.0002)
Low ESG	EU	1.0% (0.002)	−1.6%*** (−0.003)	0.29% (0.0003)	−1.4% (0.004)
	NA	−7.6%*** (−0.01)	−9.7%*** (−0.009)	−6.3%*** (−0.008)	−0.75% (−0.002)
	AP	0.50% (−0.004)	−1.2% (−0.002)	0.45% (−0.001)	1.0% (−0.002)

Notes: This table displays the variation in mean squared error (MSE) when ESG information is included in the model for consensus firms. Idiosyncratic volatilities are computed using the residual asset returns from a multifactorial model. Results are computed using a fixed window forecasting scheme. High (low) ESG sample represents firms above (below) the median ESG rating. *, ** and *** indicate rejection of the null hypothesis of lack of informational content in ESG ratings at the 10%, 5% and 1% nominal risk levels respectively. Regression coefficients associated to the ESG rating are reported in parentheses.

Chapter 2

Chapter 2

Supervised ESG Ratings

2.1 Introduction

The paradigm of sustainable investment promotes the idea that investors can simultaneously secure long-term financial returns and contribute to making the world a better place by allocating their capital towards socially and environmentally responsible companies. In practice, this investment strategy relies on the incorporation of extra-financial information, or environmental, social, and governance (ESG) metrics, into investment processes to assess companies' sustainability performance. Sustainable investing has already had a profound impact on the asset management industry as sustainable investments reached \$35 trillion in assets under management in 2020 in North America, Europe and Asia-Pacific capital markets, representing 35% of total assets under management in these regions according to the Global Sustainable Investment Alliance (GSIA, 2021).

To integrate extra-financial information into their investment processes, investors commonly rely on ESG ratings provided by rating agencies, which are scores designed to capture companies' ESG performance. To produce ESG ratings, rating agencies collect information on companies' extra-financial performance, primarily from public sources, and use internal models to aggregate this information into an overall ESG rating delivered to the end-user. The steps to compute ratings are opaque, and the end-user obtains a score aggregating hundreds of extra-financial metrics without knowledge of the decisions made to produce it. These features of the ESG ratings production process have led to several confusions. First, because rating producers do not necessarily agree on their definition of ESG performance and how to measure it, ESG ratings can differ significantly across rating agencies. The issue of ESG rating disagreement has been well-documented by prior research (Chatterji et al., 2016; Berg, Koelbel and Rigobon, 2022) and can have a substantial impact on asset prices (Avramov et al., 2022; Boucher et al., 2023).

Second, the lack of transparency in the ESG ratings production process does not only result in significant confusion regarding *how* ESG performance is measured, but also regarding *what* it actually measures. This limitation is exacerbated by the fact that ESG ratings are often produced using an unsupervised approach (Roncalli, 2022). Intuitively, one would expect good ESG ratings to be associated with companies leading the efforts to reduce their environmental and societal impact. However, according to the Global Reporting Initiative (GRI), most rating agencies instead produce ESG ratings that measure companies’ exposure to financial risks due to a poor management of sustainability issues:

“It is with this question that the confusion starts: what do ESG ratings actually stand for? Do they measure a company’s sustainability risk or its impact? [...] with very few exceptions, ESG ratings measure a company’s exposure to (industry-specific) sustainability risks and how well it manages them. What this means is that users need to understand that ESG ratings do not necessarily measure whether a highly rated company is a leader in reducing its socio-economic and environmental impact, and thereby contributing to a more sustainable world.” (The ABC of ESG ratings, GRI 2022)

This definition of an ESG rating is in line with the needs of most asset managers, as the majority of them use ESG information because it is material to investment performance (Amel-Zadeh and Serafeim, 2018). However, a significant portion of investment professionals also use ESG information for ethical reasons and to respond to a growing stakeholder demand. ESG information can thus serve two purposes: to provide a better assessment of a company’s exposure to financial risks and opportunities related to sustainability, or to control the environmental and socio-economic impacts of investments. Do these two objectives imply a similar use of ESG information? It is not obvious that two ESG ratings based on these distinct goals should be equal. In a recent study, Bams and van der Kroft (2022) showed that sustainable investment strategies using ESG ratings from leading rating agencies can result in the construction of asset portfolios up to three times more exposed to the risk of corporate irresponsible behavior than the market portfolio.

Due to these shortcomings, there is an urgent need for greater transparency regarding how ESG ratings are produced and what they actually measure. This paper introduces a methodology based on supervised learning to transparently aggregate granular extra-financial information into overall ESG ratings, providing full knowledge to the end-user regarding how the final rating is computed and what it measures. The supervised ESG rating system (SL-ESG) methodology is founded on a predictive approach, assuming that ESG ratings should convey information to forecast a target variable of interest. A similar idea can be found in Boucher et al. (2023), who propose a methodology to backtest ESG ratings by testing if they carry information to forecast a variable of interest. SL-ESG therefore resolves the issue of “what ESG ratings measures” by inherently

requiring the specification of an objective, or target variable, to produce ratings. The choice of the target variable is thus an essential part of the SL-ESG methodology and should be consistent with the end-user’s motivation for using extra-financial information. Within SL-ESG, this choice also establishes an optimality criterion that allows to discriminate between competing ratings based on the maximization of the ESG ratings’ forecasting power.

SL-ESG produces ESG ratings by estimating a predictive model of the target variable that incorporates granular ESG data as predictors. Our methodology proceeds by jointly estimating the predictive model and a weighting scheme to aggregate the granular ESG vector into an overall rating. To manage the large dimension of the granular ESG information vector, we use penalized regression to estimate the predictive model. This procedure enables the production of ratings that maximize the information content for forecasting the target variable. Furthermore, the approach is flexible as different weighting schemes of the granular ESG vectors can be proposed. In the paper, we introduce an aggregation rule that accounts for the materiality of ESG information.

We demonstrate the effectiveness of our approach by applying SL-ESG to a panel containing granular ESG data on 4,484 non-financial companies from 2003 to 2021. Our analysis focuses on two target variables of interest: firm idiosyncratic risk and ESG incidents. To evaluate our methodology, we compare the forecast accuracy of multiple forecasting models, which differ in the way they incorporate ESG information, using a formal forecasting performance comparison procedure. In the case of forecasting firm idiosyncratic risk, the results indicate that SL-ESG can produce ESG ratings with considerably greater forecasting power than the ratings from a leading rating agency. Our results also highlight that the weighting scheme used to aggregate granular ESG data should account for materiality to yield informative ratings. However, our results suggest that information from extra-financial reporting is not relevant for forecasting companies’ involvement in ESG incidents once financial, country, and sector-specific information is taken into account.

This paper contributes to the literature on sustainable investment and ESG performance measurement in several ways. First, to the best of our knowledge, this study is the first to formalize a methodology for aggregating granular ESG data into ESG ratings based on supervised learning. While Boucher et al. (2023) proposes a supervised approach to backtest existing ESG ratings, our paper tackles the reverse problem of using a supervised approach to construct ESG ratings. Two related studies are Bams and van der Kroft (2022) and Berg, Koelbel, Pavlova and Rigobon (2022). Bams and van der Kroft (2022) construct scores of realized ESG performance by applying a rank-ordering algorithm to granular ESG data, but their methodology relies on an unsupervised approach. On the other hand, Berg, Koelbel, Pavlova and Rigobon (2022) propose a methodology that uses ESG ratings from multiple rating agencies to instrument ESG performance, but they do not propose a formal ESG rating system. Furthermore, although aggregating ESG ratings from

multiple rating agencies could produce more informative ratings, such a procedure would be extremely costly, as it would require access to multiple proprietary tools. In contrast, our procedure greatly reduces this cost, as it only requires access to a single dataset containing granular ESG information, while being more transparent.

Second, our paper contributes to the literature on the forecast of ESG incidents, which has received little attention thus far. Champagne et al. (2022) find that ESG ratings are significantly related to the occurrence of ESG incidents. However, their study uses news coverage from a unique journal to measure ESG incidents and is limited to S&P500 companies. Furthermore, they focus exclusively on an in-sample environment, while their results reveal that the model fit gains associated with the inclusion of ESG ratings to forecast ESG incidents are extremely small. On the other hand, (Yang, 2022) finds that ESG ratings do not help to predict future ESG incidents, a result that he attributes to ESG ratings inflation. Svanberg et al. (2022) use machine learning models to predict ESG incidents using information from extra-financial reporting but their analysis suffers from several methodological flaws. They focus solely on the prediction of environmental controversies and their results never reveal the extent of predictive accuracy gains yielded by the incorporation of extra-financial information, nor their statistical significance. More importantly, they use a synthetic cross-sectional dataset obtained by a longitudinal averaging of the variables. In contrast, our analysis is founded on a real panel dataset and integrates a formal forecast evaluation procedure, highlighting that information from extra-financial reporting yields little to no forecasting power on future ESG incidents once financial, sector, and country information are taken into account.

The remainder of the article is organized as follows: Section 2 describes the data used in the analysis; Section 3 presents the methodology for computing ESG ratings with a supervised approach; Section 4 conducts our empirical applications; the final section concludes the paper.

2.2 Data

The data is extracted from the Refinitiv ESG universe (formerly known as Asset4 ESG), which comprises over 400 granular ESG variables for thousands of public companies worldwide. To obtain a working sample, a series of filters are applied to the Refinitiv ESG universe. First, although the database starts in 2003, many companies were added to the Refinitiv ESG universe at later dates. Therefore, a company’s inclusion date in the Refinitiv ESG universe is identified as the first year with a non-missing value for its ESG Refinitiv score, and any observations prior to this date are excluded from the final sample. Second, since the study aims to predict ESG incidents reported by media coverage on corporate misconduct, companies based in countries with a press freedom level

deemed below “satisfactory” by *Reporters Without Borders* are excluded from the analysis. This filtering step helps to prevent country bias in the reporting of ESG controversies. The final sample is a panel consisting of 4,484 listed non-financial companies located in 22 developed economies from 2003 to 2021, totaling 32,476 firm-year observations. Tables 2.6.1 and 2.6.2 in Appendix 2.6 provide a description of the sample in terms of companies headquarters’ location and sector of activity.

In the Refinitiv ESG universe, numerous granular ESG variables convey similar information. To account for this, a list of 131 non-controversy ESG variables is retained from the original dataset following Bams and van der Kroft (2022) (see Table 2.6.3 in Appendix 2.6 for a list of the ESG variables). After excluding business and accounting controversies, controversies with fewer than 100 events in the sample, and merging similar controversies, a list of eight variables measuring the materialization of ESG incidents is retained. Before using the ESG Refinitiv data for empirical applications, several treatments for missing value imputation are required. Following Bams and van der Kroft (2022), for boolean variables measuring policies, targets, or corporate activities, it is assumed that: (i) Refinitiv sources accurately assess the sustainable practices implemented by companies, and (ii) companies have incentives to report their sustainable practices. Consequently, missing information is interpreted as a lack of policy, target, or activity by the company. The correction of incomplete ESG controversy variables is conducted similarly, assuming that missing information corresponds to the absence of controversy in Refinitiv news media sources. After these treatments, new variables are computed to measure the number of years since the first implementation of a given policy, activity, or target, to take into account firms’ ESG performance history.

For continuous ESG metrics, such as resource consumption or waste emissions, missing values are assumed to represent information not disclosed by companies. In this case, missing values are replaced with zero, and an indicator variable was created, taking the value of one if the information was not disclosed and zero otherwise. ESG variables, such as resource use, energy use, or waste emissions, are rescaled by total assets. Continuous metrics are winsorized at the lower and upper 0.5% percentiles and standardized to obtain regression coefficients that are comparable across ESG variables. After completing the ESG data processing, a list of 256 ESG variables is obtained.

In addition to granular ESG variables, firms’ accounting and financial information are collected from Refinitiv. Before the analysis, financial variables were winsorized at the lower and upper 0.5% percentiles to mitigate the impact of outliers. The industry classification system used in this analysis is the Sustainability Industry Classification System (SICS), developed by the Sustainability Accounting Standards Board (SASB). The SICS offers the advantage of grouping companies based on their sustainability-related risks and opportunities, allowing for the consideration of ESG

information materiality in our supervised approach.

2.3 Methodology

This section introduces notations, key definitions and the procedure for computing optimal ESG ratings using a supervised approach, assuming a panel data structure. We first define the concept of linear aggregation rule to compute a company's ESG rating from ESG granular data.

Definition 1 Let $\mathbf{ESG}_{i,t} = \left(ESG_{i,t}^{(1)}, \dots, ESG_{i,t}^{(P)} \right)^\top$ be a vector of P granular ESG variables for firm i at time t and γ a column vector of weights of length P . The linear aggregation rule of elements $(\gamma, \mathbf{ESG}_{i,t})$ to compute $ESG_{i,t}$, the ESG rating of firm i at time t , is given by: $ESG_{i,t} = \gamma^\top \mathbf{ESG}_{i,t}$.

A linear aggregation rule requires both a vector of ESG information, $\mathbf{ESG}_{i,t}$, and a vector of weights, γ , as inputs to calculate a company's overall ESG rating. Our definition assumes linearity in the weights and allows elements of the ESG information vector to be non-linear transformations of the original data. As demonstrated by Berg, Koelbel and Rigobon (2022), ESG ratings from leading rating agencies can be accurately reconstructed using linear aggregation rules. However, these ratings stem from opaque methodologies, which means that both the ESG information and weights used to determine a company's ESG rating remain unknown to the end user. The following definition introduces the concept of an optimal aggregation rule using a predictive approach.

Definition 2 Suppose there is a set of M competing linear aggregation rules to compute a company's ESG rating, and let $(\gamma^{(m)}, \mathbf{ESG}_{i,t}^{(m)})$ denote the elements of the m -th linear aggregation rule. Let $y_{i,t}$ denote the target variable for firm i at time t . Denote by $\hat{y}_{i,t+1}^{(m)}$ the forecast of $y_{i,t+1}$ at horizon one, computed using information at time t on a set of control variables and $ESG_{i,t}^{(m)}$, the ESG rating derived from the m -th linear aggregation rule. Assuming that there is a sequence of out-of-sample forecasts for a set of n firms, the optimal aggregation rule, based on the objective $y_{i,t+1}$ and the loss function $\mathcal{L}(\cdot)$, is given by:

$$\left(\gamma^*, \mathbf{ESG}_{i,t}^{(*)} \right) = \arg \min_{\gamma^{(m)}, \mathbf{ESG}_{i,t}^{(m)}} \frac{1}{n} \sum_{i=1}^n \mathcal{L}(y_{i,t+1}, \hat{y}_{i,t+1}^{(m)}).$$

The optimality criterion introduced by this second definition states that the ESG rating derived from the optimal linear aggregation rule should minimize the error in forecasting a target variable of interest. It therefore assumes that ESG ratings should convey information to forecast a quantity of interest and relies on an objective, the target variable, and a loss function to evaluate forecast accuracy and compare the performance of competing aggregation rules. In the case of regression

models, typical loss functions are the squared loss or the absolute loss.¹ This notion of optimality is typically used by the banking industry for creditworthiness assessment (Dumitrescu et al., 2022). Here the target variable should be defined in accordance with the investor motivation to use ESG information. For example, an investor using ESG information to better assess firm exposure to financial risks should specify a target variable capturing those risks. An ethical investor aiming to control the environmental and social impact of his asset portfolio might instead specify a target variable that captures corporate socially irresponsible behavior, such as the occurrence of ESG incidents. According to this definition, an optimal aggregation rule inherently requires the specification of a target variable, which guarantees complete transparency concerning what a company's final ESG rating computed using this methodology is measuring.

The following presents a methodology for estimating linear aggregation rules using high-dimensional granular ESG information. It is assumed that the target variable $y_{i,t}$ for firm i at time t is continuous and has been defined in accordance with the motivation for using ESG information. Consider a company belonging to an industry sector k , and assume a large set of P granular ESG indicators, denoted by $ESG_{i,t}^{(1)}, \dots, ESG_{i,t}^{(P)}$, is available. To construct optimal ESG ratings, the following predictive linear regression is considered:

$$y_{i,t+1} = \alpha + \beta X_{i,t} + ESG_{i,t}^* + \varepsilon_{i,t+1}, \quad (2.1)$$

where $X_{i,t}$ is a vector of control variables, $\varepsilon_{i,t+1}$ is an error term, and $ESG_{i,t}^*$ is the ESG rating obtained from the linear aggregation rule using granular ESG information on firm i at time t . In the empirical applications, the two following aggregation rules are considered:

$$ESG_{i,t}^* = \sum_{j=1}^P \gamma_j ESG_{i,t}^{(j)}, \quad (2.2)$$

$$ESG_{i,t}^* = \sum_{k=1}^K \sum_{j=1}^P \gamma_{kj} \mathbb{1}_{ik} ESG_{i,t}^{(j)}, \quad (2.3)$$

where $\mathbb{1}_{ik}$ is an indicator variable taking the value one if firm i belongs to sector k , and K denotes the number of sectors. The two aggregation rules differ in how they aggregate ESG granular variables to generate forecasts. Equation (2.2) represents a simple linear aggregation of ESG granular variables, while Equation (2.3) includes interaction terms with the company's sector of activity to account for the materiality of specific ESG information in that sector. Consequently, the two aggregation rules also differ in the number of weights needed to compute the overall ESG rating: P for aggregation rule (2.2), and KP for aggregation rule (2.3). Throughout the remainder

¹Definition 2 is formulated in terms of minimizing a cross-sectional average of the loss function for convenience. It can be generalized to other metrics of predictive ability, such as maximizing an out-of-sample R^2 or an AUC score. Additionally, it could be expressed with the assumption of a panel structure for the forecasts.

of the paper, we refer to ESG ratings derived from aggregation rules (2.2) and (2.3) as *Optimal ESG* and *Optimal Material ESG*, respectively.

Several remarks must be made regarding the model specification provided by Equation (2.1). First, it is important to note that this model specification assumes a joint estimation of the predictive model and the aggregation rule. As a result, the coefficient associated with $ESG_{i,t}^*$ in regression (2.1) is normalized to one because the ESG parameters to estimate correspond to the vector γ , which consists of the weights in the aggregation rule. If the predictive model and the aggregation rule were not jointly estimated, as would be the case if $ESG_{i,t}^*$ corresponds to an ESG rating computed by a rating agency, specification (2.1) should include an additional parameter associated with $ESG_{i,t}^*$.

Second, it is crucial to ensure that the specification of the predictive model captures potential confounding factors of a company’s extra-financial performance, such as its financial strength, by properly specifying the vector of control variables $X_{i,t}$. Additionally, control variables should be consistent across competing forecasting models to ensure that differences in forecast accuracy can be solely attributed to the way models integrate extra-financial information. In the empirical applications, several sets of control variables are tested, which include financial variables, country of headquarter, and sector of activity. Third, in our empirical applications, there are $K = 10$ sectors and a vector of ESG granular variables of length $P = 256$, corresponding to 256 and 2560 ESG parameters to estimate in order to compute the *Optimal ESG* and *Optimal Material ESG* ratings, respectively. Therefore, it is necessary to use penalized regression to estimate the model, particularly with a ℓ_1 type penalty (Lasso), as it enables to perform variable selection.

Finally, using the linear regression (2.1) assumes that the target variable is continuous. If the target variable of interest does not satisfy this assumption, generalized linear models can be used for proper modeling of the target variable while maintaining a linear aggregation rule. For instance, if the target variable corresponds to a binary outcome such as the occurrence of an ESG incident, a logistic regression specification can be used. In this case, the model specification is as follows:

$$Pr(y_{i,t+1} = 1 | X_{i,t}, \mathbf{ESG}_{i,t}) = (1 + \exp(-\alpha - \beta X_{i,t} - ESG_{i,t}^*))^{-1} \quad (2.4)$$

2.4 Empirical applications

In this section, we implement our supervised approach to produce overall ESG ratings from a large granular ESG vector for two key target variables: a company’s financial risk exposure and its involvement in ESG incidents.

2.4.1 Forecasting idiosyncratic risk

As a proxy for firm-specific financial risk exposure, we calculate a company’s idiosyncratic risk using the residual returns from the Capital Asset Pricing Model (CAPM):

$$r_{i,s} = \alpha_i + \beta_i r_{m,s} + \epsilon_{i,s}, \quad (2.5)$$

where $r_{i,s}$ represents the daily excess US dollar return of stock i , and $r_{m,s}$ denotes the daily US dollar excess stock market return. In our empirical applications, excess returns are calculated using the US one-month T-bill rate as the risk-free rate, and $r_{m,s}$ is determined using the daily returns on the MSCI index of the company’s country of headquarters. For each firm in our sample, we estimate model (2.5) and extract the residual returns to compute the annual idiosyncratic realized volatility of residual returns as follows:

$$IRV_{i,t} = \sum_{s_k=1}^{v_t} \hat{\epsilon}_{i,s_k}^2, \quad (2.6)$$

with t as the index of the year, and v_t representing the number of daily observations in year t . The procedure outlined in the previous section is then applied using the logarithmic transformation of the idiosyncratic volatility (IVOL) as the target variable. This proxy has been employed in numerous studies to examine the relationship between ESG ratings and firm idiosyncratic risk (Jo and Na, 2012; Mishra and Modi, 2013; Boucher et al., 2023). Table 2.1 presents summary statistics for IVOL and the other financial variables used in the analysis.

Table 2.1: Summary statistics for financial variables

Variable	Count	Mean	STD	Min	Q25	Median	Q75	Max
IVOL	32476	-2.45	0.96	-5.24	-3.15	-2.56	-1.87	2.67
Cash Flow	32476	0.09	0.1	-0.47	0.05	0.09	0.13	0.41
Leverage	32476	0.26	0.19	0.0	0.13	0.25	0.38	0.97
Market to Book Ratio	32476	3.05	5.31	-19.33	1.22	2.08	3.58	44.82
ROA	32476	0.03	0.11	-0.69	0.01	0.04	0.08	0.35
Sales Growth	32476	0.09	0.37	-0.87	-0.04	0.05	0.15	3.62
Size	32476	22.02	1.66	14.15	20.99	22.04	23.09	27.41

Note: This table displays summary statistics for the financial variables utilized in the analysis.

To demonstrate the usefulness of our methodology, we conduct the forecasting exercise described in the following. We first define three alternative specifications of the linear model given by Equation (2.1), distinguished by the set of control variables included in the regression model. We consider a model incorporating only financial variables as controls, a model including financial variables and country indicators, and a model encompassing these variables and sector indicators. By comparing multiple sets of control variables, this approach enables us to assess the robustness of our results to the specification of model (2.1).

We examine four alternative methods for incorporating ESG information into specification

(2.1): no ESG, the Asset 4 ESG rating, the optimal ESG, and the optimal material ESG. The “no ESG” setting corresponds to the case where all weights in the aggregation rules are restricted to zero, implying that granular ESG information is irrelevant for forecasting the target variable. The “Asset 4 ESG rating” case serves as a benchmark, enabling us to assess whether our methodology produces aggregation rules that outperform the one established by the ESG data provider. The optimal ESG and optimal material ESG refer to the aggregation rules defined in the previous section and represented by Equation (2.2) and (2.3), respectively. Note that the “no ESG” case is nested within the other cases, implying that a failure to increase forecast accuracy relative to the “no ESG” case would correspond to a situation where ESG information is irrelevant for forecasting the target variable.² Overall, our setting involves a total of 12 competing forecasting models differing by the set of control variables and the way ESG information is integrated into the model. Furthermore, for all these specifications, only ESG information from companies’ extra-financial reporting is incorporated, excluding past history of ESG controversies.

Figure 2.1: Out-of-sample R^2 of IVOL forecasts

Note: This figure displays the out-of-sample R^2 associated with IVOL forecasts. The columns represent different models with varying control variables. Column (1) shows forecasting models that include only financial variables. Column (2) shows models that include financial variables and country indicators. Column (3) shows models that include financial variables, country indicators, and sector indicators.

To evaluate the models’ forecasting abilities, we generate a panel of out-of-sample forecasts associated with each model using an expanding window forecasting scheme. We begin by estimating the models for the period from 2003 to 2010 and generate a sequence of forecasts for the year 2011. We then include the year 2011 in the estimation sample and generate forecasts for the year 2012. We repeat these iterations until the final year of the sample. The forecasting models in the “no ESG” and “Asset 4 ESG rating” cases are estimated using pooled OLS. The models corresponding to the “optimal ESG” and “optimal material ESG” cases require the estimation of large vector of parameters and are thus estimated using penalized linear regression with a lasso penalty. This

²This interpretation is analogous to the methodology developed by Boucher et al. (2023) for evaluating whether ESG ratings contain information for predicting a target variable. This approach involves comparing the forecasting abilities of nested models that differ solely in the inclusion or exclusion of ESG information within the set of predictors.

penalty allows for shrinking irrelevant weights towards zero. To calibrate the penalty parameter, we set it to the value that minimizes the AIC over the estimation sample, for values of the penalty parameter ranging between 1 and 10,000.

Table 2.2: Models performance in forecasting idiosyncratic risk (MSE)

Year	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG
2011	0.393	0.397	0.455	0.369***
2012	0.535	0.534	0.46	0.404***
2013	0.529	0.525	0.439	0.375***
2014	0.496	0.49	0.419	0.366***
2015	0.469	0.468***	0.586	0.525
2016	0.474***	0.475***	0.53	0.488
2017	0.529	0.521	0.5	0.443***
2018	0.445***	0.45	0.481	0.455
2019	0.504	0.506	0.5	0.451***
2020	1.457***	1.482	1.487	1.469
2021	0.406***	0.406	0.454	0.453

Note: This table displays the models performance in forecasting IVOL, as measured by the mean squared error (MSE). All specifications include financial control variables, as well as country and industry indicators. The notation *** indicates that a particular model is included in the set of best models, defined by the model confidence set, at the 1% significance level.

To ensure that the models have good out-of-sample forecasting abilities, we first compute the out-of-sample R^2 associated with the forecasting models for each year separately. Figure 2.1 displays the out-of-sample R^2 of the forecasting models for the period from 2011 to 2021. The three plots correspond to the different sets of control variables specified in the model. All models yield positive out-of-sample R^2 , with the exception of the year 2020, which includes the stock market crash associated with the first COVID-19 lockdown. When including only financial variables as controls, the optimal material ESG model outperforms the others in terms of forecast accuracy during the period 2011-2019, more than doubling the out-of-sample R^2 in some years compared to the model excluding ESG information. However, this gap is attenuated by the inclusion of other control variables. When all control variables are included in the forecasting models, the optimal material ESG model outperforms the other models in some years, especially in the beginning of the period, but yields a comparable performance in others. In contrast, the optimal ESG model yields a systematically lower forecast accuracy, indicating that ESG information should be included in a way that accounts for its materiality.

We assess whether these differences in forecast accuracy are statistically significant by applying a model confidence set (MCS). Among a set of competing forecasting models, the MCS allows for the identification of the subset of models with similar forecasting ability that outperform the remaining approaches (Hansen et al., 2011). Table 2.2 displays the results of the MCS using the squared loss function to evaluate forecasts when all control variables are included in the models.

Figure 2.2: Out-of-sample R^2 of IVOL forecasts by region

Note: This figure displays the out-of-sample R^2 associated with IVOL forecasts by region. The columns represent different models with varying control variables. Column (1) shows forecasting models that include only financial variables. Column (2) shows models that include financial variables and country indicators. Column (3) shows models that include financial variables, country indicators, and sector indicators.

We find that for 6 out of 11 years, the optimal material ESG model, corresponding to aggregation rule (2.3), is included in the MCS at the 1% significance level. Furthermore, when included in the MCS, it is the only model belonging to the MCS, meaning that it has a forecasting ability outperforming all other models. In contrast, the optimal ESG model, corresponding to aggregation rule (2.2), is never included in the MCS. The model excluding ESG information outperforms the others in some cases and is included in the MCS in 4 out of 11 years. To assess the robustness of these results to the choice of the loss function used to evaluate the forecasts, we apply the MCS using the absolute loss. Results are displayed in Table 2.6.4 in Appendix 2.6, and yield qualitatively similar conclusions, with the optimal material ESG model being included in the MCS 7 out of 11 years.

Prior research demonstrates that the link between ESG ratings and firm idiosyncratic risk is heavily influenced by the location of firms' headquarters. To account for this, we conduct our forecasting exercise again with the sample divided into three regions: Asia-Pacific, Europe, and North America. The out-of-sample R^2 values for the forecasting models are displayed in Figure 2.2, indicating that they yield positive out-of-sample R^2 in most instances. Table 2.3 presents the results of the MCS using the squared loss function. The optimal material ESG model significantly outperforms the other methods for the Asia-Pacific and Europe regions. In these regions, it is the only model included in the MCS in 8 and 7 configurations, respectively. The results for the

North America region are more nuanced, with the optimal material ESG model being the sole model included in the MCS in only 5 years, primarily at the beginning of the period. Table 2.6.5 in Appendix 2.6 shows that our conclusions remain robust regardless of the loss function chosen to assess the forecasts. In summary, our findings suggest that by employing a supervised approach combined with an aggregation rule that accounts for materiality, as described in Equation (2.3), we can efficiently aggregate granular ESG information to produce ESG ratings that offer valuable insights for assessing firm-specific risk.

2.4.2 Forecasting ESG incidents

We now turn our attention to producing ESG ratings that optimally forecast companies' involvement in ESG incidents. To implement our supervised approach, we consider a binary dependent variable computed as:

$$y_{i,t}^{(k)} = \begin{cases} 1 & \text{if firm } i \text{ is involved in an ESG controversy of type } k \text{ in year } t, \\ 0 & \text{otherwise.} \end{cases} \quad (2.7)$$

In our empirical applications, we use Refinitiv ESG controversy variables to evaluate whether a company has been involved in an ESG incident during a specific year. We differentiate between various types of environmental and social controversies, resulting in a total of eight target variables measuring the occurrence of different kinds of ESG incidents. Table 2.4 gives a description of the controversy variables used in the analysis.

We conduct the previous forecasting exercise again, with the key difference being the use of a logistic regression model to account for the binary nature of the target variables. The forecasting models in the “no ESG” and “Asset 4 ESG rating” cases are thus estimated using pooled logistic regression. The models corresponding to the “optimal ESG” and “optimal material ESG” cases are estimated using penalized logistic regression with a lasso penalty. The optimal penalty parameter value is determined through four-fold cross-validation and set to the value that maximizes the AUC score over the validation samples. Figure 2.3 displays the out-of-sample AUC score associated with the forecasting models for each year. Overall, the models exhibit an excellent ability to distinguish between the two classes, as evidenced by the average AUC scores ranging from 0.80 to 0.88 for the eight target variables. However, based on the graphical representation, models incorporating ESG information do not appear to offer a superior ability to differentiate between the two classes. In fact, the inclusion of irrelevant granular ESG information can sometimes result in a decrease in model performance.

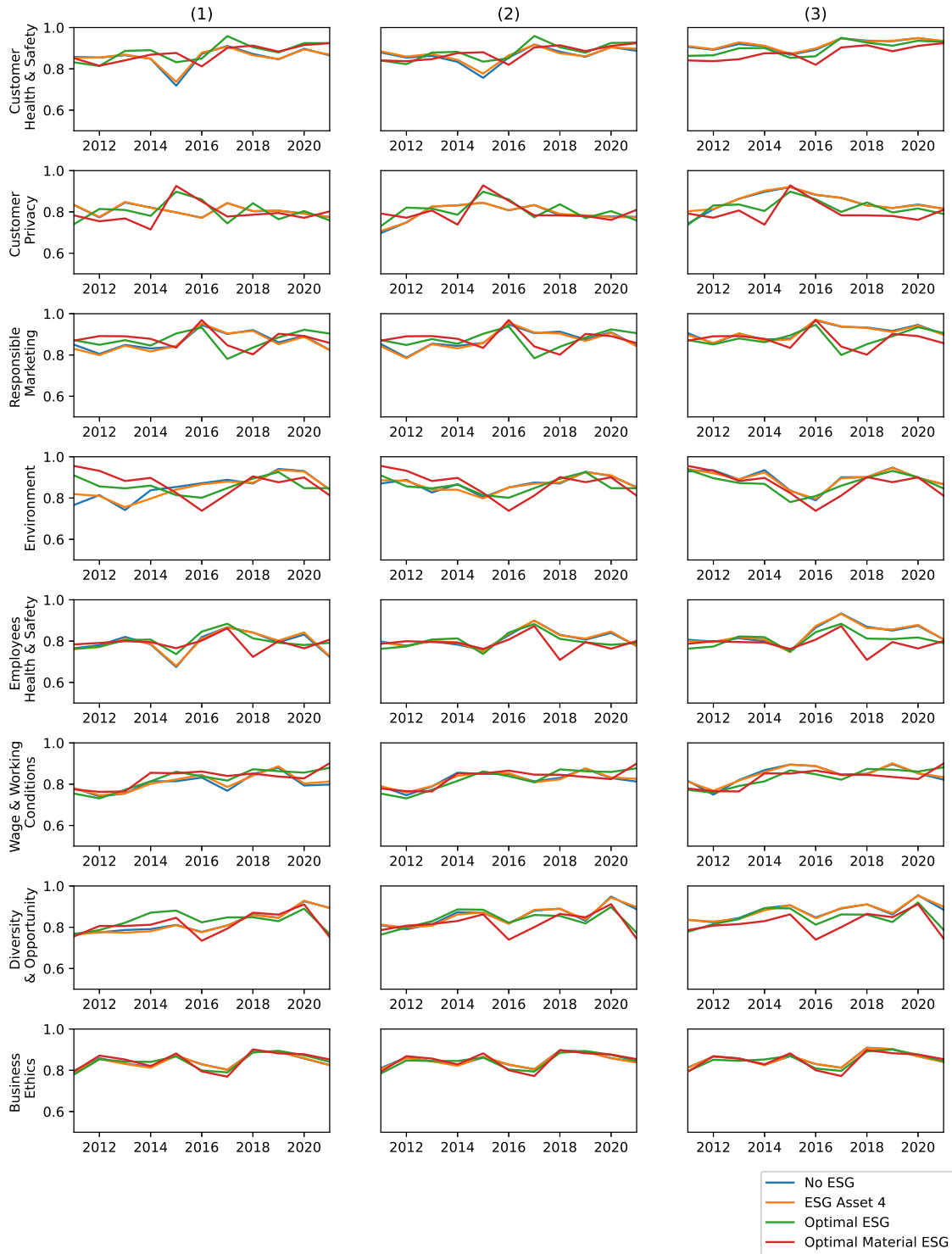
To evaluate the statistical difference between the models' ability to forecast ESG incidents, we

Table 2.3: Model performance in forecasting idiosyncratic risk by region (MSE)

Year	Panel A: Asia-Pacific				Panel B: Europe				Panel C: North America			
	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG
2011	0.432	0.431	0.366	0.357***	0.3	0.303	0.342	0.281***	0.455***	0.402	0.449***	0.505
2012	0.434	0.435	0.391	0.387***	0.48	0.479	0.434	0.363***	0.622	0.624	0.498	0.457***
2013	0.443***	0.443***	0.535	0.43***	0.451	0.444	0.355	0.259***	0.635	0.63	0.468	0.421***
2014	0.436	0.435	0.404	0.323***	0.496	0.485	0.402	0.311***	0.542	0.536	0.448	0.371***
2015	0.461	0.463	0.497	0.422***	0.354	0.351***	0.464	0.39	0.536	0.534***	0.676	0.605
2016	0.416	0.416	0.398	0.361***	0.378***	0.378***	0.441	0.379***	0.551***	0.553	0.653	0.606
2017	0.508	0.507***	0.554	0.527	0.575	0.556	0.441	0.383***	0.511	0.503	0.508	0.45***
2018	0.443	0.444	0.431	0.376***	0.421***	0.429	0.482	0.418***	0.448***	0.451	0.476	0.483
2019	0.392	0.392	0.374	0.331***	0.381	0.387	0.381	0.313***	0.539	0.54	0.535	0.477***
2020	0.793***	0.798	0.85	0.876	0.975***	1.014	1.108	1.105	1.798***	1.827	1.78***	1.779***
2021	0.416	0.414	0.399	0.358***	0.317***	0.317	0.436	0.451	0.443***	0.443***	0.469	0.488

Note: This table displays the models performance in forecasting IVOL by region, as measured by the mean squared error (MSE). All specifications include financial control variables, as well as country and industry indicators. The notation *** indicates that a particular model is included in the set of best models, defined by the model confidence set, at the 1% significance level.

Figure 2.3: Out-of-sample AUC score of ESG incidents forecasts



Note: This figure displays the out-of-sample AUC score for forecasting ESG controversies.

Table 2.4: Summary of controversy variables

Controversy	% of observations	N
Customer Health & Safety	2.4%	787
Customer Privacy	1.8%	573
Responsible Marketing	2.0%	635
Environmental	1.3%	434
Employees Health & Safety	2.5%	821
Wages & Working Condition	3.2%	1032
Diversity & Opportunity	1.6%	523
Business Ethics	4.9%	1588

Note: This table presents summary statistics for the controversy variables used in the analysis.

apply a MCS using the Brier score loss. Results are displayed in Table 2.5 for the eight controversy variables for the period from 2016 to 2021. In most configurations, the MCS encompasses all forecasting models, indicating that they yield statistically similar forecasting abilities. Table 2.6.6 in Appendix 2.6 presents the MCS results using the negative log loss to evaluate forecasts, showing that this finding is robust to the choice of the loss function used to evaluate forecasts. Moreover, given that the “no ESG” model is nested within the other cases, its inclusion in every instance of the MCS can be understood as evidence that incorporating information from extra-financial reporting into the forecasting models do not significantly improve their ability to predict ESG incidents. This finding suggest that the information contained in extra-financial reporting is irrelevant for forecasting companies’ involvement in ESG incidents once financial, country, and sector-specific information is taken into account.

Table 2.5: Model performance in forecasting ESG controversies (Brier score)

Controversy	Year	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG
Business Ethics	2016	0.051***	0.052***	0.054***	0.051***
	2017	0.049***	0.049***	0.051***	0.05
	2018	0.024***	0.024***	0.029***	0.025***
	2019	0.025***	0.025***	0.025***	0.023***
	2020	0.018***	0.018***	0.017***	0.017***
	2021	0.017***	0.017***	0.016***	0.016***
Customer Health & Safety	2016	0.033***	0.032***	0.036***	0.036***
	2017	0.017***	0.017***	0.017***	0.018
	2018	0.013***	0.014***	0.013***	0.014***
	2019	0.014***	0.014***	0.015***	0.015***
	2020	0.009***	0.009***	0.009***	0.01***
	2021	0.008***	0.008***	0.009***	0.009***
Customer Privacy	2016	0.021***	0.021***	0.02***	0.021***
	2017	0.02***	0.02***	0.021***	0.022
	2018	0.019***	0.019***	0.019***	0.021***
	2019	0.02***	0.02***	0.019***	0.02***
	2020	0.018***	0.018***	0.019***	0.02***
	2021	0.013***	0.013***	0.014***	0.014***
Responsible Marketing	2016	0.009***	0.009***	0.013***	0.015***
	2017	0.009***	0.009***	0.012***	0.012
	2018	0.01***	0.01***	0.012***	0.012***
	2019	0.011***	0.011***	0.012***	0.012***
	2020	0.008***	0.008***	0.009***	0.008***
	2021	0.007***	0.007***	0.008***	0.007***
Diversity and Opportunity	2016	0.011***	0.011***	0.012***	0.011***
	2017	0.012***	0.012***	0.012***	0.012
	2018	0.009***	0.009***	0.01***	0.009***
	2019	0.008***	0.008***	0.008***	0.008***
	2020	0.004***	0.004***	0.004***	0.004***
	2021	0.006***	0.006***	0.007***	0.007***
Employees Health & Safety	2016	0.014***	0.015***	0.018***	0.022***
	2017	0.006***	0.007***	0.006***	0.008
	2018	0.01***	0.011***	0.009***	0.009***
	2019	0.009***	0.01***	0.009***	0.008***
	2020	0.009***	0.009***	0.009***	0.009***
	2021	0.009***	0.009***	0.008***	0.008***
Environmental	2016	0.031***	0.031***	0.032***	0.033***
	2017	0.013***	0.013***	0.019***	0.017
	2018	0.012***	0.012***	0.011***	0.012***
	2019	0.01***	0.009***	0.011***	0.01***
	2020	0.011***	0.011***	0.011***	0.012***
	2021	0.012***	0.012***	0.012***	0.013***
Wages & Working Conditions	2016	0.025***	0.025***	0.026***	0.027***
	2017	0.019***	0.02***	0.018***	0.02
	2018	0.016***	0.017***	0.016***	0.017***
	2019	0.021***	0.021***	0.021***	0.02***
	2020	0.015***	0.015***	0.015***	0.017***
	2021	0.013***	0.013***	0.012***	0.013***

Note: This table displays the models performance in forecasting ESG controversies, as measured by the mean Brier score. All specifications include financial control variables, as well as country and industry indicators. The notation *** indicates that a particular model is included in the set of superior models, defined by the model confidence set, at the 1% significance level.

2.5 Conclusion

The contribution of this article is to propose a formal procedure for computing ESG ratings using supervised learning (SL-ESG). The procedure requires specifying a target variable consistent with the user’s motivation for using ESG information, as well as having access to a vector of granular ESG information. Technically, SL-ESG is based on the estimation of penalized predictive regressions to determine a weighting scheme allowing to aggregate granular ESG information into overall ratings. The procedure yields ESG ratings that maximize the information content relevant for forecasting the variable of interest. Additionally, it provides full transparency on how ratings are computed and what they measure. Contrary to approaches that aggregate multiple proprietary ESG ratings, this procedure also has the advantage of only requiring access to a single dataset of granular ESG information.

We demonstrate the effectiveness of our approach by applying SL-ESG to a large panel of granular ESG data, considering two target variables of interest: firm idiosyncratic risk and ESG incidents. To evaluate our methodology, we compare the forecast accuracy of multiple forecasting models, which differ in the way they incorporate ESG information, using a formal forecasting performance comparison procedure. In the case of forecasting firm idiosyncratic risk, the results indicate that SL-ESG can produce ESG ratings with considerably greater forecasting power than the ratings from a leading rating agency. Our results also highlight that the weighting scheme used to aggregate granular ESG data should account for materiality to yield informative ratings. However, our results suggest that information from extra-financial reporting is not relevant for forecasting companies’ involvement in ESG incidents once financial, country, and sector-specific information is taken into account.

2.6 Appendix: Additional Tables and Figures

Table 2.6.1: Companies headquarters' location

Headquarters' location	Number of firms	% of observations
United States	2199	43.8%
United Kingdom	344	9.8%
Canada	280	7.4%
Australia	273	7.0%
Germany	174	3.7%
Sweden	147	2.3%
France	145	4.0%
Taiwan	138	3.5%
South Korea	123	2.9%
Switzerland	109	2.3%
South Africa	98	2.5%
Italy	64	1.2%
Spain	63	1.7%
New Zealand	53	1.0%
Norway	53	1.0%
Netherlands	47	1.3%
Belgium	42	1.0%
Denmark	39	1.1%
Finland	38	1.1%
Austria	25	0.6%
Ireland	18	0.4%
Portugal	12	0.3%

Note: This table presents the representation of the sample by the geographic location of the companies' headquarters.

Table 2.6.2: Sectors

Sector	Number of firms	% of observations
Technology & Communications	738	15.3%
Infrastructure	668	16.0%
Resource Transformation	612	14.1%
Health Care	560	9.3%
Extractives & Minerals Processing	485	13.2%
Consumer Goods	429	9.8%
Services	375	8.1%
Food & Beverage	289	7.0%
Transportation	264	6.2%
Renewable Resources & Alternative Energy	64	1.0%

Note: This table presents the representation of the sample by companies' sector of activity.

Table 2.6.3: List of granular ESG variables

Name	Category	Subcategory
Biodiversity Impact Reduction	Environment	Emissions
CO2 Equivalent Emissions Direct, Scope 1	Environment	Emissions
CO2 Equivalent Emissions Indirect, Scope 2	Environment	Emissions
CO2 Equivalent Emissions Indirect, Scope 3	Environment	Emissions
Emission Reduction Target Percentage	Environment	Emissions
Emissions Trading	Environment	Emissions
Environmental Expenditures	Environment	Emissions
Environmental Expenditures Investments	Environment	Emissions
Environmental Investments Initiatives	Environment	Emissions
Environmental Partnerships	Environment	Emissions
Environmental Provisions	Environment	Emissions
Environmental Restoration Initiatives	Environment	Emissions
Hazardous Waste	Environment	Emissions
NOx Emissions	Environment	Emissions
NOx and SOx Emissions Reduction	Environment	Emissions
Ozone-Depleting Substances	Environment	Emissions
Policy Emissions	Environment	Emissions
SOx Emissions	Environment	Emissions
Self-Reported Environmental Fines	Environment	Emissions

Staff Transportation Impact Reduction	Environment	Emissions
Targets Emissions	Environment	Emissions
VOC Emissions	Environment	Emissions
VOC or Particulate Matter Emissions Reduction	Environment	Emissions
Waste Recycled To Total Waste	Environment	Emissions
Waste Reduction Initiatives	Environment	Emissions
Waste Total	Environment	Emissions
Water Pollutant Emissions	Environment	Emissions
e-Waste Reduction	Environment	Emissions
Animal Testing	Environment	Innovation
Eco-Design Products	Environment	Innovation
Environmental Products	Environment	Innovation
Environmental Project Financing	Environment	Innovation
Organic Products Initiatives	Environment	Innovation
Product Environmental Responsible Use	Environment	Innovation
Product Impact Minimization	Environment	Innovation
Real Estate Sustainability Certifications	Environment	Innovation
Renewable/Clean Energy Products	Environment	Innovation
Sustainable Building Products	Environment	Innovation
Take-back and Recycling Initiatives	Environment	Innovation
Water Technologies	Environment	Innovation
Energy Use Total	Environment	Resource Use
Environment Management Team	Environment	Resource Use
Environment Management Training	Environment	Resource Use
Environmental Materials Sourcing	Environment	Resource Use
Environmental Supply Chain Management	Environment	Resource Use
Green Buildings	Environment	Resource Use
Land Environmental Impact Reduction	Environment	Resource Use
Policy Energy Efficiency	Environment	Resource Use
Policy Environmental Supply Chain	Environment	Resource Use
Policy Sustainable Packaging	Environment	Resource Use
Policy Water Efficiency	Environment	Resource Use
Renewable Energy Use Ratio	Environment	Resource Use
Resource Reduction Policy	Environment	Resource Use
Resource Reduction Targets	Environment	Resource Use
Targets Energy Efficiency	Environment	Resource Use
Targets Water Efficiency	Environment	Resource Use
Toxic Chemicals Reduction	Environment	Resource Use
Water Recycled	Environment	Resource Use
Water Withdrawal Total	Environment	Resource Use
CSR Sustainability Committee	Governance	CSR Strategy
CSR Sustainability External Audit	Governance	CSR Strategy
CSR Sustainability Report Global Activities	Governance	CSR Strategy
ESG Reporting Scope	Governance	CSR Strategy
GRI Report Guidelines	Governance	CSR Strategy
Global Compact Signatory	Governance	CSR Strategy
Integrated Strategy in MD&A	Governance	CSR Strategy
Stakeholder Engagement	Governance	CSR Strategy
Board Member LT Compensation Incentives	Governance	Management
Executive Compensation LT Objectives	Governance	Management
Policy Board Diversity	Governance	Management
Policy Executive Compensation ESG Performance	Governance	Management
Sustainability Compensation Incentives	Governance	Management
Corporate Responsibility Awards	Social	Community
Crisis Management Systems	Social	Community
Employee Engagement Voluntary Work	Social	Community
OECD Guidelines for Multinational Enterprises	Social	Community
Policy Bribery and Corruption	Social	Community
Policy Business Ethics	Social	Community
Policy Community Involvement	Social	Community
Policy Fair Competition	Social	Community
Product Sales at Discount to Emerging Markets	Social	Community
Total Donations To Revenues in million	Social	Community
Whistleblower Protection	Social	Community
Ethical Trading Initiative ETI	Social	Human Rights
Fundamental Human Rights ILO UN	Social	Human Rights
Human Rights Breaches Contractor	Social	Human Rights
Human Rights Contractor	Social	Human Rights
Human Rights Policy	Social	Human Rights
Policy Child Labor	Social	Human Rights

Policy Forced Labor	Social	Human Rights
Customer Satisfaction	Social	Product Responsibility
Healthy Food or Products	Social	Product Responsibility
Policy Customer Health & Safety	Social	Product Responsibility
Policy Data Privacy	Social	Product Responsibility
Policy Fair Trade	Social	Product Responsibility
Policy Responsible Marketing	Social	Product Responsibility
Product Access Low Price	Social	Product Responsibility
Product Recall	Social	Product Responsibility
Product Responsibility Monitoring	Social	Product Responsibility
Quality Mgt Systems	Social	Product Responsibility
Retailing Responsibility	Social	Product Responsibility
Six Sigma and Quality Mgt Systems	Social	Product Responsibility
HSMS Certified Percent	Social	Social
Accidents Total	Social	Workforce
Average Training Hours	Social	Workforce
Day Care Services	Social	Workforce
Employee Fatalities	Social	Workforce
Employee Satisfaction	Social	Workforce
Employees Health & Safety Team	Social	Workforce
Employees With Disabilities	Social	Workforce
Flexible Working Hours	Social	Workforce
Gender Pay Gap Percentage	Social	Workforce
HRC Corporate Equality Index	Social	Workforce
Health & Safety Policy	Social	Workforce
Health & Safety Training	Social	Workforce
Internal Promotion	Social	Workforce
Lost Time Injury Rate Contractors	Social	Workforce
Net Employment Creation	Social	Workforce
Occupational Diseases	Social	Workforce
Policy Diversity and Opportunity	Social	Workforce
Policy Supply Chain Health & Safety	Social	Workforce
Salaries and Wages from CSR reporting	Social	Workforce
Salary Gap	Social	Workforce
Supplier ESG training	Social	Workforce
Targets Diversity and Opportunity	Social	Workforce
Total Injury Rate Employees	Social	Workforce
Trade Union Representation	Social	Workforce
Training and Development Policy	Social	Workforce
Turnover of Employees	Social	Workforce
Women Employees	Social	Workforce
Women Managers	Social	Workforce

Table 2.6.4: Model performance in forecasting idiosyncratic risk (MAE)

Year	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG
2011	0.509	0.512	0.537	0.485***
2012	0.601	0.6	0.537	0.506***
2013	0.6	0.597	0.522	0.48***
2014	0.574	0.569	0.503	0.471***
2015	0.527	0.525***	0.594	0.567
2016	0.524***	0.524***	0.554	0.528***
2017	0.589	0.582	0.56	0.526***
2018	0.503***	0.505	0.523	0.51
2019	0.547	0.546	0.54	0.505***
2020	0.986***	0.999	0.999	1.003
2021	0.494***	0.494	0.538	0.539

Note: This table displays the models performance in forecasting IVOL, as measured by the mean absolute error (MAE). All specifications include financial control variables, as well as country and industry indicators. The notation *** indicates that a particular model is included in the set of best models, defined by the model confidence set, at the 1% significance level.

Table 2.6.5: Model performance in forecasting idiosyncratic risk by region (MAE)

Year	Panel A: Asia-Pacific				Panel B: Europe				Panel C: North America			
	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG
2011	0.545	0.545	0.485***	0.505	0.439	0.442	0.457	0.424***	0.554	0.559	0.537***	0.581
2012	0.526	0.528	0.476***	0.475***	0.58	0.579	0.515	0.481***	0.653	0.654	0.571	0.544***
2013	0.507	0.506		0.544	0.564	0.559	0.46	0.396***	0.673	0.669	0.55	0.517***
2014	0.521	0.521	0.504	0.451***	0.58	0.572	0.472	0.422***	0.602	0.597	0.529	0.484***
2015	0.537	0.54	0.561	0.503***	0.442	0.438***	0.523	0.496	0.577	0.574***	0.648	0.609
2016	0.503	0.503	0.484	0.463***	0.48***	0.479***	0.507	0.496	0.56***	0.561	0.618	0.601
2017	0.575	0.574***	0.592	0.58	0.623	0.607	0.524	0.486***	0.574	0.568	0.56	0.529***
2018	0.523	0.524	0.514	0.477***	0.475***	0.475***	0.52	0.483	0.506***	0.509	0.521	0.531
2019	0.498	0.498	0.489	0.446***	0.47	0.47	0.468	0.422***	0.567	0.566	0.559	0.524***
2020	0.706***	0.709	0.734	0.745	0.795***	0.818	0.852	0.865	1.129	1.142	1.124***	1.138
2021	0.498	0.497	0.5	0.464***	0.438***	0.439	0.53	0.537	0.516***	0.516	0.548	0.555

Note: This table displays the models performance in forecasting IVOL by region, as measured by the mean absolute error (MAE). All specifications include financial control variables, as well as country and industry indicators. The notation *** indicates that a particular model is included in the set of best models, defined by the model confidence set, at the 1% significance level.

Table 2.6.6: Model performance in forecasting ESG controversies (negative log loss)

Controversy	Year	No ESG	ESG Asset 4	Optimal ESG	Optimal Material ESG
Business Ethics	2016	0.188***	0.188***	0.208***	0.211***
	2017	0.189***	0.189***	0.196***	0.208
	2018	0.096***	0.098***	0.113***	0.103***
	2019	0.097***	0.099***	0.098***	0.097***
	2020	0.078***	0.079***	0.075***	0.075***
	2021	0.075***	0.076***	0.07***	0.071***
Customer Health & Safety	2016	0.125***	0.121***	0.141***	0.15***
	2017	0.063***	0.064***	0.066***	0.072
	2018	0.054***	0.056***	0.053***	0.058***
	2019	0.055***	0.055***	0.061***	0.063***
	2020	0.039***	0.039***	0.04***	0.045***
	2021	0.036***	0.037***	0.038***	0.04***
Customer Privacy	2016	0.093***	0.092***	0.091***	0.094***
	2017	0.091***	0.091***	0.105***	0.105
	2018	0.094***	0.093***	0.086***	0.1***
	2019	0.098***	0.097***	0.091***	0.093***
	2020	0.083***	0.083***	0.087***	0.097***
	2021	0.062***	0.062***	0.068***	0.063***
Responsible Marketing	2016	0.042***	0.042***	0.054***	0.056***
	2017	0.04***	0.042***	0.054***	0.056
	2018	0.043***	0.044***	0.054***	0.058***
	2019	0.048***	0.048***	0.052***	0.051***
	2020	0.036***	0.037***	0.037***	0.039***
	2021	0.035***	0.035***	0.033***	0.034***
Diversity and Opportunity	2016	0.053***	0.054***	0.059***	0.06***
	2017	0.053***	0.053***	0.055***	0.06
	2018	0.043***	0.043***	0.046***	0.044***
	2019	0.042***	0.041***	0.041***	0.04***
	2020	0.023***	0.023***	0.021***	0.022***
	2021	0.033***	0.031***	0.037***	0.04***
Employees Health & Safety	2016	0.071***	0.073***	0.079***	0.09***
	2017	0.04***	0.043***	0.035***	0.04
	2018	0.051***	0.053***	0.047***	0.052***
	2019	0.048***	0.049***	0.045***	0.043***
	2020	0.045***	0.046***	0.044***	0.046***
	2021	0.047***	0.048***	0.043***	0.042***
Environment	2016	0.21***	0.179***	0.148***	0.17***
	2017	0.063***	0.062***	0.077***	0.075
	2018	0.053***	0.052***	0.047***	0.051***
	2019	0.04***	0.039***	0.044***	0.046***
	2020	0.051***	0.049***	0.05***	0.053***
	2021	0.062***	0.06***	0.059***	0.066***
Wages & Working Conditions	2016	0.101***	0.102***	0.108***	0.107***
	2017	0.085***	0.087***	0.083***	0.087
	2018	0.074***	0.077***	0.068***	0.075***
	2019	0.085***	0.085***	0.088***	0.092***
	2020	0.068***	0.069***	0.066***	0.075***
	2021	0.061***	0.061***	0.054***	0.054***

Note: This table displays the models performance in forecasting ESG controversies, as measured by the mean negative log loss. All specifications include financial control variables, as well as country and industry indicators. The notation *** indicates that a particular model is included in the set of superior models, defined by the model confidence set, at the 1% significance level.

Chapter 3

Chapter 3

Greenwashing the Talents: Attracting human capital through environmental pledges¹

3.1 Introduction

In times of global ecological crisis, the transformation of organizations into sustainable businesses is crucial. In this process, large corporations are increasingly pointed out for their responsibility in environmental degradation. As a result of this growing pressure, there has been a surge in private organizations' pledges to take environmental action in recent years. More than one-third of the world's largest publicly traded companies now have net-zero targets, 20% of the plastic packaging market is under pledges to achieve a circular economy for plastic, and 55% of the companies most involved in deforestation have pledged to eliminate it by 2025. While some have applauded the integration of nature into business decision-making, many have criticized the gap between voluntary commitments and credible action. This issue has been recently recognized by the United Nations, through the establishment of the High-Level Expert Group on Net-Zero Emissions Commitments, which acknowledges that the current growth in pledges "misleads consumers, investors, and regulators with false narratives, and feeds a culture of climate misinformation and confusion".²

These criticisms are founded, as the effectiveness of environmental pledges is far from straightforward. The current boom in corporate voluntary commitments is accompanied by a proliferation of criteria, scope, and benchmarks, some of which are irrelevant for achieving environmental goals

¹This chapter is a joint work with DELOZIERE Gauthier and LE LANN Yann.

²Figures on net-zero targets, plastic pollution, and deforestation are retrieved from the Net Zero Tracker, the Ellen MacArthur Foundation, and Forest 500, respectively. For the United Nations' position on climate pledges, see <https://www.un.org/en/climatechange/high-level-expert-group> and the High-Level Group report.

(Garrett et al., 2019; LeBaron and Lister, 2021). Furthermore, their implementation is also questionable, as stakeholders often rely on self-reported information to assess companies' environmental impact, with a lack of regulation to punish false claims and hold companies accountable for their commitments. An extensive body of literature demonstrates that these information asymmetries rise corporations incentives to disconnect their environmental communication from their true environmental impact (Lyon and Maxwell, 2011; Delmas and Burbano, 2011), which can lead to a failure to implement environmental commitments (Ramus and Montiel, 2005; Kim and Lyon, 2011).

On the other hand, corporations have strong incentives to make environmental pledges to preserve their reputation. Some of the main benefits include preempting political action (Maxwell et al., 2000), increasing political access (Werner, 2015), facing more lenient regulatory enforcement (Hong et al., 2019), or dampening the adverse consequences of environmental controversies (Barrage et al., 2020). Notably, being perceived as more environmentally responsible can significantly enhance an organization's ability to attract human capital. Early studies on the determinants of employer attractiveness highlight that pro-environmental messaging in recruitment brochures can significantly improve job pursuit intentions (Bauer and Aiman-Smith, 1996; Greening and Turban, 2000). Job seekers with high pro-environmental preferences and seeking meaning through their work are particularly responsive to pro-environmental messaging during the recruitment process (Gully et al., 2013; Jones et al., 2014). On the broader topic of corporate social responsibility (CSR), of which environmental responsibility is a dimension, the recent field experiment of Hedblom et al. (2019) shows that the selection effect resulting from job seekers' perception of a company's CSR has a substantial impact on firm productivity. Other empirical studies show that this increased organizational attractiveness also translates into lower reservation wages for firms perceived as more environmentally and socially responsible (Nyborg and Zhang, 2013; Burbano, 2016; Non et al., 2022; Krueger et al., 2021). Environmental responsibility can, therefore, be used as leverage to attract productive and skilled employees and is already used as a strategic human resources management tool by large corporations (Bhattacharya et al., 2008).

In this paper, we demonstrate that companies exposed to a negative organizational attractiveness shock caused by a poor environmental responsibility have incentives to make environmental pledges to remain attractive to high-skilled human capital. Using a case study on a French climate movement initiated by *Grandes Écoles* elite students threatening to boycott job offers from polluting employers, we show how environmental pledges can significantly dampen this threat and identify key individual characteristics moderating the students' response to corporate environmental pledges. This event provides a unique opportunity to study talent attraction strategies in times of increasing societal pressure for climate action. Indeed, *Grandes Écoles* are elite institutions of

higher education parallel to the public university system that admit students through a highly competitive selection process. They play a key role in the social reproduction of French elites (Bourdieu, 1998) and their graduates occupy a significant portion of key decision-making positions in public administration and the private sector (Dudouet and Joly, 2010; Reberioux and Roudaut, 2018).

Furthermore, the climate movement under consideration, which took place in 2018, had significant success in the French higher education system, gathering more than 30,000 participants across 400 institutions and gaining national media coverage. Notably, it was strongly supported by future engineers, with 51% of the participants being enrolled in engineering schools, in a context of high risk of skill shortage in the engineering profession in France and Europe.³ A large portion of the graduate students involved in this movement also belong to the class of workers that seeks meaning through their job (75% of our survey respondents seek a job “useful for society”, 78% a job “compatible with their values”), while recent findings on non-monetary incentives at work suggest that meaning-driven agents can enhance organizational performance (Cassar and Meier, 2018). Lastly, although the manifesto spread to the whole French higher education system, it met considerable success among the most selective and prestigious institutions that traditionally produce future corporate elites. This climate movement, therefore, constitutes a negative shock on polluting companies’ ability to attract high-skilled and productive human capital, thus giving them incentives to address this issue.

Supporting this idea, we find evidence of negative abnormal stock returns among the largest French greenhouse gas (GHG) emitters around a public meeting which gathered organizers of the climate movement, ministers of the French government, and top executives of publicly listed French companies. Furthermore, the climate movement took place during a period of increasing climate pledges made by French multinationals. The French Business Climate Pledge, an initiative supported by the main employer federation launched in 2015, now gathers pledges to take climate action from 102 of the largest publicly listed French companies. Moreover, private organizations have become more engaged with the climate movement, and several multinational companies agreed to meet its organizers to publicly answer questions on their environmental policies.⁴ Given the proximity between the *Grandes Écoles* and corporate elites, participants in the climate movement are therefore highly exposed to environmental pledges, raising questions about how such pledges would impact their intentions to refuse to work for polluting companies.

³In 2016, the engineering profession was ranked in the top five occupations with the highest risk of skill shortage in Europe (CEDEFOP, 2016). According to the French Employment Office data, engineer was ranked six among the ten professions with the most recruitment projects in 2021 excluding seasonal workers, yet 65.6% of these recruitment projects were judged as difficult to fill by companies. French engineers also benefit from an enhanced work mobility with an unemployment rate more than two times lower than the national average according to surveys from the Society of Engineers and Scientists of France (<https://www.iesf.fr/>). In comparison to the social movement figures, 42800 young engineers graduated in 2019 (<http://www.cdefi.fr/fr/la-cdefi/chiffres-cles>).

⁴See Section 2 for a more detailed discussion.

Exploiting a unique anonymized survey database of 2,307 climate movement participants and 127 predictor variables measuring individuals' education, socio-demographic characteristics, work values, career perspectives, environmental attitudes, and beliefs on the ecological crisis, we investigate the reaction of students intending to boycott polluting employers to environmental pledges. We use a survey experiment with repeated measurement of respondents' intentions to refuse to work for polluting companies to study their reaction to environmental pledges. Although less conservative than a between-subject experiment, this design has the advantage of increasing the number of independent observations and therefore the power of the statistical procedures (Charness et al., 2012). Furthermore, a recent study by Clifford et al. (2021) indicates that repeated measurement designs tend to yield the same results as more conservative designs, but with a substantial increase in the precision of treatment effect estimation.

Our survey experiment consists of measuring respondents' intentions to refuse to work for a polluting employer, and their intentions to refuse to work for a polluting employer making a pledge to improve its environmental impact in the future. While 86% of survey respondents have intentions to refuse to work for polluting employers, this proportion falls to 28% for polluting employers making environmental pledges. We find evidence that the primary mechanism explaining why some respondents are not affected by environmental pledges is skepticism towards the pledge's honesty. To explain this finding and identify drivers of the students' response to corporate environmental promises, we take advantage of our repeated measurement design to compute a measure of the reaction to environmental pledges at the individual level. This quantity, which we refer to as the *reaction*, measures how much less likely an individual is to intend to refuse to work for a polluting employer after being exposed to an environmental pledge. We then estimate this quantity for each individual in our sample using machine learning classifiers. We find that, on average, respondents are more than three times less likely to have intentions to refuse to work for a polluting employer after being exposed to an environmental pledge, with students enrolled in engineering schools being particularly responsive to pledges. We then apply the SHAP interpretability method of Lundberg and Lee (2017) to identify the most important moderators of the reaction and use the reaction measure as a dependent variable in linear regressions to draw inference.

Consistent with previous personnel psychology findings, we find that intentions to refuse to work for polluting companies are primarily driven by one's search for meaning through work and environmental attitudes (Gully et al., 2013; Jones et al., 2014). However, these factors only play a minor role in explaining the reaction to environmental pledges. We find that the most important drivers of the reaction to environmental pledges are whether one integrates large companies into their career perspectives, beliefs on the ecological crisis, and support for radical action in the name of ecology. Quantitatively, these sole factors explain 73% of the variation in the reaction

to environmental pledges. The strong effect of pledges can therefore be explained by the fact that the desire to work for an environmentally responsible employer and the reaction to corporate environmental promises are driven by different individual characteristics.

Our analysis indicates that students incorporating large companies into their career perspectives are 31% more sensitive to environmental pledges. One possible reason for that is that students who are interested in working for large companies may assume that their future employer could have a significant impact on the environment. Therefore, a polluting employer that pledges to improve its environmental impact would be more likely to align with their personal preferences, making it more attractive compared to a polluting employer that does not make such a pledge. As a consequence, the least reactive individuals are the ones switching from traditional career paths. In addition, individuals having a strong disbelief in the ability of the current economic system and technological development to solve the ecological crisis react less to environmental pledges: a one-point increase in our index measuring this disbelief is associated with a -5% decrease in the reaction. Support for radical political action in the name of ecology is also associated with a strong decrease in the reaction: believing that society should be changed by revolution is associated with a -17% decrease, and a one-point increase in the support of material damage in the name of ecology is associated with a -9% decrease.

Our results have several implications. First, while some scholars have argued that the self-selection of talented workers outside of polluting companies could foster businesses' sustainability transition (Brekke and Nyborg, 2008; Brannstrom et al., 2022), their analysis did not take into account the effect of potentially misleading corporate environmental communication. Our results thus highlight that opportunistic environmental pledges could render this channel less effective. Second, past empirical results show that companies increase their prosocial claims to preserve their reputation when threatened by boycott movements (McDonnell and King, 2013). Our results shed new light on this organizational behavior by taking a person-centric approach, and contribute to explaining the surge of corporate environmental pledges that is currently observed. Our findings also contribute to identifying new individual factors moderating the reaction of job seekers to CSR communication. Finally, a number of studies have highlighted the heterogeneity of beliefs on the ecological crisis in the French climate movement (Gaborit, 2020; Le Lann et al., 2021; Alexandre et al., 2021). Our findings show that this heterogeneity has practical consequences regarding individual responses to environmental communication.

The rest of the article is organized as follows. Section 2 reviews the climate movement history and firms' reactions, Section 3 describes the econometric methodology, Section 4 describes the data, Section 5 explains the computation of our dependent variables and the decision-making process, Section 6 presents our empirical results. The last section concludes the paper.

3.2 Climate movement history and firms’ reactions

In this section, we review the history of the climate movement and examine how large French companies responded to it.

In March 2018, a group of students from French *Grandes Écoles*⁵ launched the “Student Manifesto for an Ecological Awakening”. The petition gathered over 30,000 signatures across 400 institutions and received national media coverage. The call was primarily directed towards political and economic decision-makers who were blamed for not taking action in response to the climate emergency. The largest companies, which are traditionally the main employers of these students upon graduation, were specifically targeted. The climate movement aimed to use the unique position of elite students to accelerate the pace of change among political and economic actors. To exert pressure, one suggested course of action was to integrate environmental criteria into their future career path decisions:

“As we approach our first job, we realize that the system of which we are part of directs us towards positions often incompatible with our reflections and locks us into daily contradictions. We are determined, but cannot act alone: we can overcome these contradictions only with the active involvement of economic and political decision-makers, whose sole objective must be to serve the general interest in the long term. We, future workers, are ready to question our comfort zone so that society changes profoundly. We want to take advantage of the leeway we enjoy as students by turning to employers whom we deem in accordance with our demands expressed in this manifesto.” (Student Manifesto for an Ecological Awakening, 2018 pledge)

Highlighting the unique position of *Grandes Écoles* students in the French education system, a general meeting held on March 7, 2019 brought together 180 initiators of the manifesto, top executives from four CAC40 listed companies (Engie, Sanofi, Kering, Schneider Electric), the Secretary of State for Ecological and Inclusive Transition, the Minister of Ecological and Solidary Transition and the Minister of Higher Education, Research and Innovation.⁶ Since then, the ecological commitment of *Grandes Écoles* graduates has remained a recurring topic in national media coverage. However, the initiators of the manifesto acknowledge the limited impact the movement had in promoting the transformation of large companies into sustainable businesses, pointing out the lack of concrete action that followed environmental pledges:

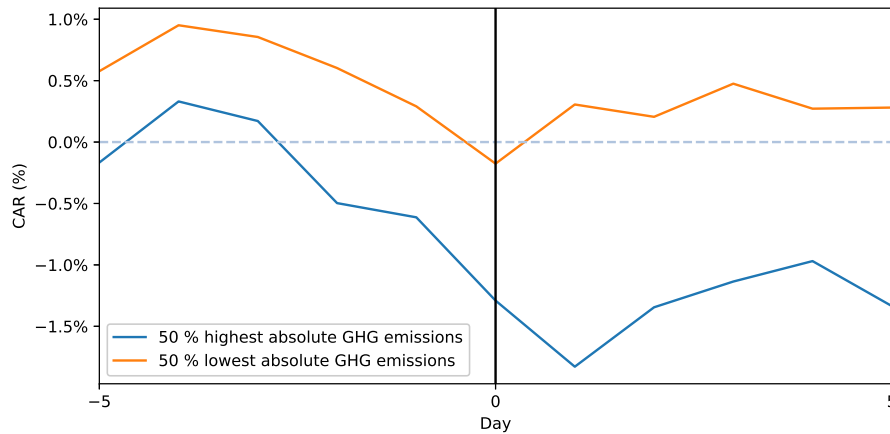
“For more than two years, we have been trying to mobilize companies [...]. We denounce those who limit their efforts to publicity effects, and salute those who, unfortunately

⁵The initiators of the climate movement were from École Polytechnique, HEC Paris, AgroParisTech, ENS Ulm, and CentraleSupélec.

⁶<https://escp.eu/news/le-manifeste-etudiant-pour-un-reveil-ecologique-organise-son-grand-debat>

much less numerous, have carried out a truly ambitious process of reducing their impact. But we are faced with a largely insufficient result.” (Student Manifesto for an Ecological Awakening, 2022 pledge)

Figure 3.1: CAR of the SBF120 companies around the 7th March 2019 meeting



Note: CAR are calculated using the CAPM and return on the MSCI France index. Day 0 is when the meeting took place. Carbon intensity is computed as Scope 1 plus Scope 2 carbon emissions divided by total assets. We adopt a 255-trading day estimation window ending 46 trading days prior to the event. For each firm, we require a minimum of 40 observations in the estimation window. Data are retrieved from Refinitiv.

On the firm side, the climate movement took place during a period of increasing environmental pledges made by the largest French companies. The MEDEF, the main French employers' federation, launched the French Business Climate Pledge in 2015, an initiative which encourages firms to make voluntary commitments to take climate action. The first edition gathered 39 companies, while 109 participated in the 2020 edition, and by the end of 2022, 322 companies had signed the pledge. Despite this success, signatories face heterogeneous incentives to take concrete action, as they belong to different industry sectors and are not held accountable for their commitments. As a result, the scope and specificity of commitments vary from abstract statements to quantified targets. In this context of strong environmental communication and due to the proximity between *Grandes Écoles* and corporate elites, corporations have become more involved with the climate movement. The initiators of the manifesto were invited to the 2019 summer meeting of the MEDEF to express their views, and several multinational companies, including 26 companies currently listed on the CAC40 index, agreed to meet with the initiators of the manifesto to publicly answer questions on their environmental policy.⁷

Previous research indicates that climate activism can have a negative impact on the valuation of carbon-intensive companies (Ramelli et al., 2021). To demonstrate that polluting companies have incentives to respond to this negative organizational attractiveness shock, we examine the stock price movements of SBF120 companies around the March 7, 2019 meeting. SBF120 companies

⁷<https://pour-un-reveil-ecologique.org/en/les-entreprises-nous-repondent/>

Table 3.1: SBF120 companies' reaction to 7th March 2019 meeting, by level of carbon dioxide equivalent emissions

Absolute emissions	Window	N	Mean CAR	Neg : Pos	Adjusted BMP	Adjusted Patell
<u>Panel A: Highest emitters</u>						
Top 50 %	[0, 1]	49	−2.57%	41 : 8	−4.8***	−4.823***
	[0, 2]	49	−1.46%	37 : 11	−3.257***	−3.272***
	[0, 3]	49	−1.19%	32 : 16	−2.711***	−2.724***
	[0, 4]	49	−0.41%	30 : 19	−0.587	−0.589
	[0, 5]	49	0.08%	22 : 27	1.003	1.008
Top 25 %	[0, 1]	25	−2.34%	20 : 5	−3.199***	−3.241***
	[0, 2]	25	−1.24%	20 : 5	−1.752**	−1.775**
	[0, 3]	25	−1.04%	17 : 8	−1.411*	−1.429*
	[0, 4]	25	−0.62%	16 : 9	−0.191	−0.193
	[0, 5]	25	−0.25%	12 : 13	0.74	0.75
<u>Panel B: Lowest emitters</u>						
Bottom 50 %	[0, 1]	49	−0.99%	32 : 16	−1.516*	−1.539*
	[0, 2]	49	−0.58%	30 : 18	−0.74	−0.751
	[0, 3]	49	−0.24%	25 : 23	−0.022	−0.022
	[0, 4]	49	0.06%	25 : 24	0.605	0.614
	[0, 5]	49	0.77%	18 : 30	1.823	1.849
Bottom 25 %	[0, 1]	25	−1.05%	16 : 9	−1.086	−1.112
	[0, 2]	25	−0.51%	14 : 10	−0.268	−0.275
	[0, 3]	25	−0.19%	12 : 12	0.226	0.232
	[0, 4]	25	0.29%	13 : 12	0.828	0.848
	[0, 5]	25	0.66%	10 : 14	1.272	1.302

Note: Cumulative abnormal returns (CARs) are calculated using the CAPM and the return on the MSCI France index. The event day is labeled as Day 0. The estimation window for the CAR calculation is set at 255 trading days, ending 46 days before the event. A minimum of 40 observations is required for each firm in the estimation window. The sample is divided by absolute total CO2 emissions (Scope 1 + Scope 2 emissions). The “Neg:Pos” column shows the ratio of firms with negative versus positive CARs over the event window. The BMP and Patell tests are used to test the nullity of the mean CAR against the alternative that the mean CAR is negative. Test statistics are corrected for cross-sectional correlation using Kolari and Pynnönen (2010) adjustment. The notations *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

are likely to be exposed to this shock as *Grandes Écoles* are the primary recruitment pool of their executives (Reberioux and Roudaut, 2018). We calculate the cumulative abnormal returns (CARs) of the SBF120 companies using the CAPM and returns on the MSCI France index. Following standard practices in the event study literature, we adopt a 255-trading day estimation window ending 46 days prior to the meeting and require a minimum of 40 observations in the estimation window for a firm to be included in the sample. We then partition the sample by level of absolute carbon dioxide equivalent emissions, taking into account Scope 1 and Scope 2 emissions, before computing average CARs. Figure 3.1 shows the average CARs of the 50% highest and lowest GHG emitters in a 5-day window surrounding the March 7, 2019 meeting. In Table 3.1, we observe negative and significant average CARs for up to three days following the meeting for the highest GHG emitters, a pattern that is not present among the lowest emitters. Similar results are displayed in Table 3.10.1 and Table 3.10.2 in Appendix 3.10 when the sample is partitioned by absolute Scope 1 and Scope 2 emissions, respectively. These simple tests suggest that a negative organizational attractiveness shock caused by a poor environmental responsibility could adversely affect the valuation of the most polluting companies, thereby increasing their incentives to adre

this issue.

3.3 Econometric Methodology

In this section, we present our methodology for identifying agents' reactions to corporate environmental pledges and their drivers, assuming a repeated measurement design.

Let Y_i denote a random variable that takes the value of one if an agent intends to refuse to work for a polluting company and zero otherwise. In the survey, this outcome is captured by measuring respondents' intentions to refuse to work for a fictitious company that they have been informed has a negative environmental impact. Here, the notion of a polluting company can also be taken to mean that the agent has a prior belief that the firm emitting the job offer has a negative impact on the environment. We assume a repeated measurement design in which this outcome variable is observed twice for every agent: once without the polluting company making a pledge to improve its environmental impact and once with the company making such a pledge. We denote the outcome in each state by $Y_i^{(0)}$ and $Y_i^{(1)}$, respectively. We are interested in modeling the conditional probability that an agent intends to refuse to work for a polluting employer in both states. Let X_i be the random vector of the agent's individual characteristics, and D_i be an indicator variable that takes the value of one if the agent has been exposed to the environmental pledge and zero otherwise. The probabilities of having intentions to refuse to work for a polluting company given the agent's characteristics in both states are given by:

$$\mathbb{P}\left(Y_i^{(0)} = 1 | X_i\right) = \mathbb{P}(Y_i = 1 | X_i, D_i = 0), \quad (3.1)$$

$$\mathbb{P}\left(Y_i^{(1)} = 1 | X_i\right) = \mathbb{P}(Y_i = 1 | X_i, D_i = 1). \quad (3.2)$$

Equation (3.1) represents the conditional probability that an agent intends to refuse to work for a company when they only have knowledge of its negative environmental impact. On the other hand, Equation (3.2) represents this conditional probability when the agent has both knowledge of the company's negative environmental impact and has been exposed to a pledge by the company to improve its impact in the future. Note that in our repeated measurement setting, the treatment is exogenous and received by each agent, implying that both observed and unobserved characteristics do not vary across the two states. Consequently, any difference in the probabilities of having intentions to refuse to work for a polluting company given by Equation (3.1) and Equation (3.2) is purely resulting from the exposure of the agent to the environmental pledge. Comparing the value of the two probabilities therefore allows to measure the effect of the environmental pledge on the agents' intentions. We take advantage of our repeated measurement design to compute a measure

of the reaction to the environmental pledge at the individual level:

$$\tau_i = \frac{\mathbb{P}(Y_i = 1 | X_i, D_i = 0)}{\mathbb{P}(Y_i = 1 | X_i, D_i = 1)}. \quad (3.3)$$

This quantity measures how much less likely an agent is to refuse to work for a polluting company after being exposed to an environmental pledge. In the rest of the paper, we refer to this quantity as *reaction to the environmental pledge* or simply *reaction*. It should be noted that in our setting, this quantity can be estimated for each individual in our database. A reaction greater than one corresponds to the agent being less likely to refuse to work for a polluting company after being exposed to an environmental pledge. A value lower than one corresponds to a backfire of the pledge, with the agent being more likely to refuse to work for the employer. A value equal to one would correspond to the absence of an effect of the environmental pledge. In this study, we find evidence that participants to the climate movement threatening to boycott polluting employers have heterogeneous responses to the environmental pledge. We are therefore interested in identifying individual drivers of this reaction in order to assess why some individuals react while other do not.

To highlight the importance of agents' reactions to environmental pledges, consider a company subject to a negative shock on its organizational attractiveness due to its poor environmental impact. To mitigate this selection effect, an honest firm can take costly actions to improve its environmental impact and signal its good practices to job seekers. However, an opportunistic firm, knowing the pro-environmental preferences of its recruitment pool, can make an environmental pledge to maintain its organizational attractiveness without taking significant action to improve its impact. In this case, the environmental pledge corresponds to purely opportunistic behavior to shift job seekers' perceptions of the firm. Extensive literature indicates that both honest and dishonest firms can make environmental commitments (Lyon and Montgomery, 2015), implying that such commitments carry little information regarding a company's future environmental impact. While honest firms could provide greater evidence of their efforts, if simple pledges are enough to shift job seekers' selection intentions, it would raise companies' incentives to engage in purely opportunistic behavior. Therefore, the impact of a selection effect caused by a company's poor environmental performance depends not only on job seekers' intentions to avoid companies with a negative environmental impact but also on how they react to corporate environmental promises.

The reaction to the environmental pledge given by Equation (3.3) is estimated by using plug-in estimators of the conditional probabilities (3.1) and (3.2). In empirical applications, these conditional probabilities are estimated jointly by building a classification model of Y_i , using the vector (X_i, D_i) as a set of explanatory variables. As previously emphasized, we find evidence that the reaction to environmental commitments is moderated by individual characteristics, as some

respondents shift their intentions to refuse to work for a polluting company after being exposed to the commitment whereas others do not react. To account for this, we use semi-parametric estimation of the link function mapping (X_i, D_i) to Y_i based on machine learning classifiers that allow interactions between the treatment and individual characteristics. Specifically, we use random forest classifiers (Breiman, 2001) to estimate the conditional probabilities required to compute the reaction. Random forests are an ensemble learning method that generates predictions by averaging the results of many randomized decision trees constructed during a training phase. This procedure has several advantages. First, it has established theoretical properties, including consistency results (Biau and Scornet, 2016). Second, it has shown superior empirical performance over a wide range of classification tasks and data types (Fernández-Delgado et al., 2014). Third, it performs simultaneously model selection and estimation while being robust to the presence of irrelevant features (Chi et al., 2022), which is of primary interest here as we use a large set of explanatory variables, while only a small subset may be driving agents’ reactions to corporate commitments.

After estimating the reaction to the environmental pledge using a machine learning classifier, we use Shapley value (SV) decomposition to identify its most important drivers. Methods based on Shapley value decomposition have become standard for explaining the output of black-box models (Lundberg and Lee, 2017), because they enable the computation of the marginal contributions of predictors to model outputs, including non-linear combinations of outputs such as the reaction measure. Therefore, we apply this methodology to identify individual characteristics that drive the reaction to the environmental pledge. Details on how to compute the marginal contributions based on SV decomposition in our framework are provided in Appendix 3.8. In addition, we complement this approach with classic inference by using the reaction measure as a dependent variables in linear regressions.

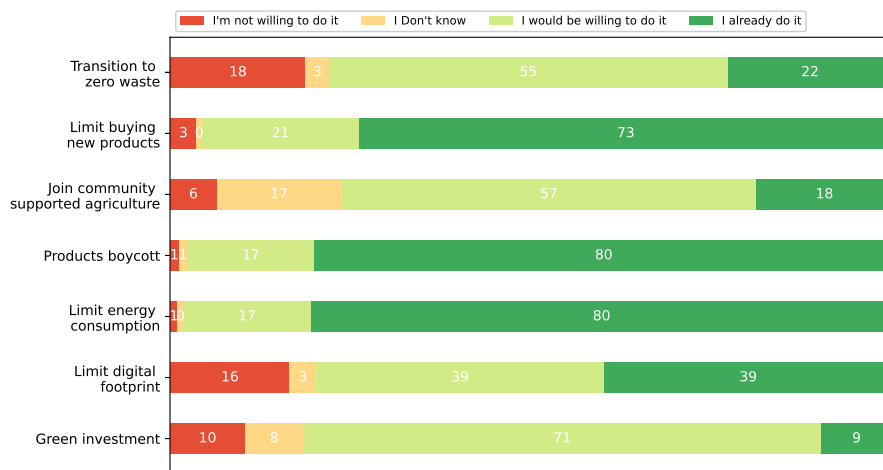
3.4 Data

The self-administered questionnaire was distributed via the newsletter of the organizers of the “Student manifesto for an ecological awakening” petition. Data collection took place from July to October 2019, and we collected 3607 responses, from which we obtained a complete dataset representing 2,307 manifesto signatories.⁸ The questionnaire consists of 54 questions structured into five parts: studies and professional perspectives, ecological commitments and practices, political values and positioning, relation to the manifesto, and socio-demographic characteristics. An English translation of the questionnaire is available in Appendix 3.9. To capture respondents’ representations of a good job, we used the questions from the 2008 wave of the European Values

⁸Table 3.10.3 in Appendix 3.10 compares our sample relative to the population of signatories.

Survey, allowing respondents to select up to five items from the 17 proposed. Socio-demographic characteristics were measured using questions from the European Social Survey. These include variables such as age, gender, religion, mother and father’s socioeconomic status, perceptions of familial financial resources, monthly financial resources, employment status, number of working hours per week, and living situation. To capture respondents’ environmental attitudes and beliefs, we used previous questions from surveys conducted on the French climate movement (Gaborit, 2020; Le Lann et al., 2021; Alexandre et al., 2021). We measured attitudes towards pro-environmental behavior, support for political action and collective mobilization for the ecological cause, and beliefs regarding the causes and solutions to the ecological crisis. Table 3.10.4 in Appendix 3.10 displays the questions that were used to measure these factors.

Figure 3.2: Attitudes towards pro-environmental behavior



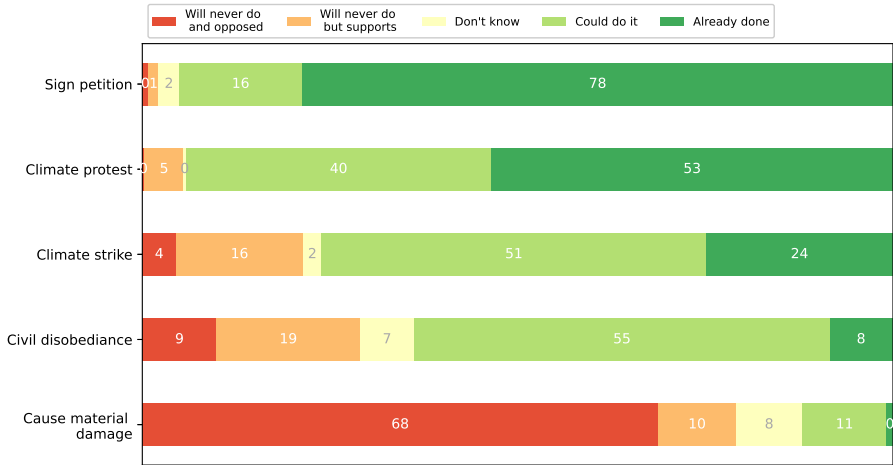
Note: This figure displays the distribution of attitudes towards environmentally responsible behavior, as measured on a four-level scale.

We give a description of the average respondent in the following. Women represent 51% of our sample and the average age is of 22.1 years old. Most of the respondents are close to their graduation, as 63% of them are at least in fourth year of higher education studies.⁹ 53% of them had a job at the time of the study: 14% had a day job and 39% a job related to their educational background (internship or apprenticeship). With regard to parental socioeconomic status, 69% of respondents have at least one parent occupying an executive position or intellectual profession, and 86% perceive their family’s financial resources to be fine or comfortable. *Grandes Écoles* students represent 68% of the sample, with 10% of respondents enrolled in business schools and 58% in engineering schools. Consequently, most respondents are confident regarding their position in the job market: 86% of them believe they will easily find a job in their field of study, with only 4% of them considering unemployment risk in their career perspectives. Respondents are also highly interested in finding meaning through their work: 75% of respondents want a job that is

⁹In France, the junior executive job market usually takes place after five years of post-secondary education.

useful for society, and 79% want a job that is compatible with their own values. They have a high level of overall satisfaction with their training, with 83% of them satisfied or very satisfied with the studies they are following. However, a majority of students are dissatisfied with their training on environmental issues, as only 31% of respondents believe that they are well prepared to tackle ecological problems.

Figure 3.3: Attitudes towards political actions in name of ecology

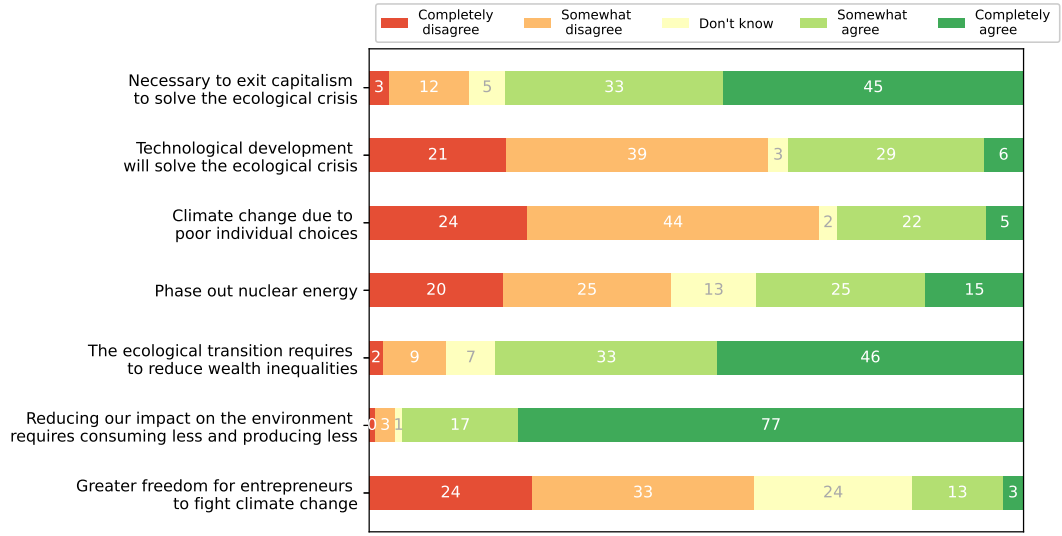


Note: This figure displays the distribution of attitudes towards political action in the name of the ecological cause, as measured on a five-level scale.

Figure 3.2 displays respondents attitudes towards pro-environmental behavior. Overall, they have highly favorable attitudes towards environmentally responsible behavior and several eco-friendly behavior, such as limiting the purchase of new products or limiting their energy consumption, are already adopted by a majority of the sample. Respondents are also strongly supportive of taking punitive economic action against environmentally irresponsible products, with 80% of them already boycotting such products and 97% being willing to do so. More involving eco-gestures, such as implementing zero waste or reducing their digital footprint, are less commonly practiced, but a significant portion of respondents perform them, and the large majority has positive attitudes towards them.

Figure 3.3 shows respondents’ attitudes towards collective mobilization and political actions in the name of ecology. A significant portion of the sample has prior experience in climate activism, with half of the respondents having already participated in a climate protest and one-quarter in a climate strike. Overall, there is strong support for political actions in the name of ecology. However, this support diminishes for riskier and more divisive actions, and it is reversed when considering radical actions such as causing material damage. Figure 3.4 shows the distribution of beliefs regarding the causes and solutions to the ecological crisis. A large majority of respondents believe that it is necessary to exit capitalism to solve the ecological crisis, that the ecological transition requires reducing wealth inequalities, and that limiting our impact on the environment

Figure 3.4: Beliefs on the causes and solutions to the ecological crisis



Note: This figure displays the distribution of beliefs regarding causes and solutions to the ecological crisis, as measured on a five-level scale.

requires consuming and producing less. However, there is greater heterogeneity among respondents' beliefs regarding the role of technological development in addressing the ecological crisis, the role of individual responsibility in climate change, and whether we should phase out nuclear energy.

Table 3.2: Indexes computation

Index	Predictors (weight in index)	Predictors values	Measurement	Interpretation
<i>Environmental Attitude Index</i>	Reduce new purchases (1) Limit energy consumption (1) Green investment (1) Limit digital footprint (1) Products boycott (1) Join CSA (1) Zero waste (1)	Four-level scale: Already do (2) Willing to do (1) Don't know (0) Not willing to do (-1)	Overall attitudes towards pro-environmental behavior.	Higher (lower) values correspond to more (less) favorable attitudes towards environmentally responsible behavior.
<i>Political Action Index</i>	Civil disobedience (1) Climate protest (1) Climate strike (1) Sign petition (1) Material damages (1)	Five-level scale: Already done (2) Could do (1) Don't know (0) Will never do it but supports (-1) Will never do it and opposed (-2)	Overall attitudes towards political and collective for ecology.	Higher (lower) values correspond to stronger (weaker) support for political action and collective mobilization for ecology.
<i>Out of System Index</i>	Exit capitalism (1) Exit nuclear (1) Reduce inequalities (1) Reduce production and consumption (1) Technological solution (-1) Individual responsibility (-1) Entrepreneurs freedom (-1)	Five-level scale: Completely agree (2) Somewhat agree (1) Don't know (0) Somewhat disagree (-1) Completely disagree (-2)	Level of skepticism or belief in the ability of a market economy and technological development to solve the ecological crisis.	Higher (lower) values correspond to greater (lesser) skepticism in the ability of a market economy and technological development to solve the ecological crisis.
<i>Work Values CSR Index</i>	People treated equally (1) Compatible values (1) Useful for society (1)	Binary: Yes (1) No (0)	Overall attraction towards organization CSR or seek of meaning through work.	Higher (or null) values correspond to a greater (or no) attraction towards the search for meaning through work.

Note: This table displays the main indexes constructed by aggregating survey questions measuring similar attributes.

To capture respondents' overall attitudes and beliefs, we compute indexes by aggregating the answers to multiple questions measuring a similar attribute. By incorporating both indexes and singular attributes in our classification model and utilizing machine learning classifiers for the automatic selection of relevant information, we capture both global and singular information. We construct four principal indexes: the *Environmental Attitude Index*, the *Out of System Index*, the *Political Action Index*, and the *Work Values CSR Index*. These indexes respectively measure one's overall attitudes towards pro-environmental behavior, belief in the current economic and

political system’s responsibility and ability to solve the ecological crisis, attitude towards collective mobilization in the name of ecology, and attraction towards CSR or search for meaning through work (see Table 3.2 for details on their computation and interpretation).

3.5 Dependent variables and decision-making process

3.5.1 Dependent variables construction

To evaluate the effect of environmental pledges on respondents’ intentions to boycott job offers from polluting employers, we conducted a survey experiment with repeated measurements of the dependent variable. Although less conservative than a between-subject experiment, this design has the advantage of increasing the number of independent observations and therefore the statistical power of the procedures (Charness et al., 2012). Furthermore, a recent study by Clifford et al. (2021) indicates that repeated measurement designs tend to yield the same results as more conservative designs, but with a substantial increase in the precision of treatment effect estimation. We thus take advantage of this design to gain further insights into the heterogeneity of responses to environmental pledges.

We built our first measure of intentions to refuse to work for a polluting company using responses to the question: “*Would you be willing to give up a job offer in a company that has a negative impact on the environment?*”. This question refers to a fictitious firm for which respondents are only informed about its negative environmental impact. In the survey, this question was asked in the final part of the section relative to work values and professional perspectives. Answers were collected using a five-item scale ranging from *completely willing* to *not at all willing*. Our dependent variable $Y_i^{(0)}$ measures a respondent intentions to refuse to work for a polluting company and is computed by applying the following binary transformation to the responses:

$$Y_i^{(0)} = \begin{cases} 1 & \text{if respondent } i \text{ survey answer is } \textit{totally willing} \text{ or } \textit{willing}, \\ 0 & \text{otherwise.} \end{cases} \quad (3.4)$$

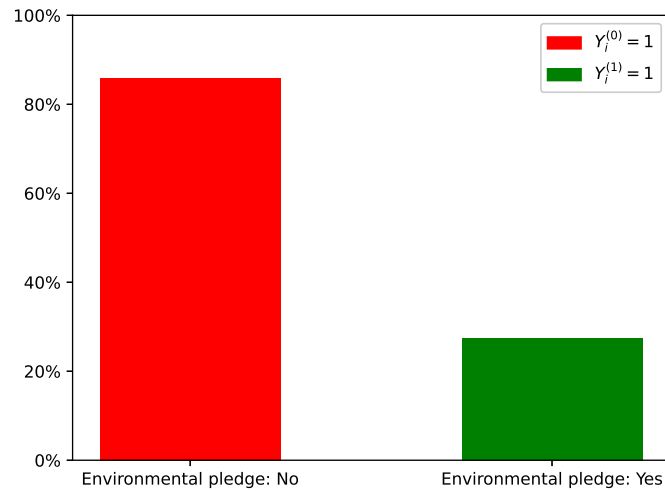
Second, we measured respondents’ intentions to refuse to work for a polluting company that makes a pledge to improve its environmental impact in the future. To do this, we asked a similar question, but referred to the company as “*a company that has a negative impact on the environment but declares to be committed to an ecological transition*”. Answers were also collected using a five-item scale ranging from *completely willing* to *not at all willing*. In contrast to the first question, this second question introduces information regarding the company’s negative environmental impact but also its pledge to improve this impact in the future. As we used a repeated measurement

setting, both questions were asked to every respondent. To limit potential carry-over effects, a temporal distance was introduced between the two measures, taking the form of a block of eight questions separating them. Similarly to the first question, a binary transformation was applied to the responses, with the two items associated with the highest level of intentions to refuse to work for polluting employers encoded as a one, and the others as a zero. We denote by $Y_i^{(1)}$ the resulting dependent variable which measures a respondent intentions to refuse to work for a polluting company making an environmental pledge.

The situation captured by our measures can be illustrated by a graduate student with pro-environmental preferences close to his entry on the job market. While having a negative prior on a potential employer’s environmental impact, the student can be exposed to a corporate commitment at some point of the information acquisition step, leading to a revision of his job pursuit intentions. As our setting allows to control for individual invariant characteristics, it also allows to estimate the causal effect of such corporate commitments on the graduates self-selection intentions.

3.5.2 Decision-making process

Figure 3.5: Frequency of intentions to refuse to work for polluting employers



Note: This figure displays the proportion of respondents having intentions to refuse to work for polluting companies with and without being exposed to an environmental pledge.

An important question to consider is whether exposure to the environmental pledge changed the frequency of intentions to refuse to work for polluting employers, and if so, in which direction. Figure 3.5 displays the proportion of individuals who intend to refuse to work for polluting employers, with and without exposure to an environmental pledge. While 86% of respondents have such intentions, this proportion falls to 28% after exposure to the environmental pledge. Given that we are studying a population with a high level of engagement in climate activism, this result suggests that environmental pledges could be a powerful tool for companies seeking to mitigate

negative organizational attractiveness shocks due to their poor environmental responsibility.

It may be argued that this major switch in the frequency of intentions to refuse to work for polluting companies could be caused by a lack of true environmental concern. From this perspective, some respondents may not care about working for an environmentally responsible firm due to their personal ethical standards, but rather due to social desirability. In this case, environmental pledges may be merely a way to appear morally cautious. To rule out this possibility, we verified whether respondents who were willing to refuse a job in a polluting company actually cared about their employer’s environmental impact. We measured how respondents evaluated a potential employer’s environmental impact and the importance they gave to this type of information when making their employment decision. First, we found that respondents who had intentions to refuse to work for a polluting company also paid high attention to an employer’s environmental impact: 99% of them deemed at least one information to be “important” or “very important”, and 81% deemed at least four different elements of information to be important.

Table 3.3: Information on employer’s environmental impact deemed important by respondents.

Information	Weak intentions	Strong intentions
CSR report	39.0%	39.6%
Carbon footprint	67.0%***	74.0%***
Biodiversity impact study	71.5%***	78.7%***
Reason for existence of the company	76.2%***	82.6%***
Reduction strategy for GHG emissions	74.9%	72.1%
Possibilities for action within the company	72.4%	68.1%
Feeling on the company’s environmental policy	84.6%	87.4%

Note: This table displays the frequency of responses indicating that information about an employer’s environmental impact is “very important” or “important”. The weak intentions group refers to individuals for whom $Y_i^{(0)} = 1$ and $Y_i^{(1)} = 0$ ($n = 1387$). The strong intentions group refers to individuals for whom $Y_i^{(0)} = 1$ and $Y_i^{(1)} = 1$ ($n = 596$). A two-sided test of equality of proportions was used. ***, **, and * indicate rejection of the null hypothesis of equality of proportions at the 1%, 5%, and 10% nominal level, respectively.

We compared the importance given to information on an employer’s environmental impact between respondents who had intentions to refuse to work for polluting companies but did react to the environmental pledge ($Y_i^{(0)} = 1$, $Y_i^{(1)} = 0$), which we refer to as the *weak intentions* group, and those who did not react ($Y_i^{(0)} = 1$, $Y_i^{(1)} = 1$), which we refer to as the *strong intentions* group. Table 3.3 displays the frequency of the answers *very important* and *important* for seven elements of information about an employer’s environmental impact in the two groups and the results from a two-sided test of equality of proportions. We find that members of the strong intentions group accorded significantly more importance to three measures of environmental impact: carbon footprint, biodiversity impact study, and evaluation of the company purpose. However, the gaps are small between the two groups compared to the magnitude observed in Figure 3.5: 67% against 74%, 71.5% against 78.7%, 76.2% against 82.6%, respectively. For the other elements of information, we failed to reject the null hypothesis at the 10% nominal level. Overall, this suggests that the

magnitude of the treatment effect is unlikely to be explained by a difference in environmental concern between the two groups.

Another important point to note is that respondents assign more importance to their subjective evaluation of a firm’s environmental impact compared to more objective measures such as the company’s level of carbon emissions or its strategy to reduce its emissions. In fact, both groups consider the evaluation of the company’s reason for existence and their subjective feelings towards its environmental policy as the two most important pieces of information. This trend becomes even more apparent when considering the entire sample and the frequency of the answer “very important”: the two most crucial pieces of information are the respondents’ subjective evaluation of the company’s reason for existence (45%) followed by their feelings about its environmental policy (41%). On the other hand, the reduction strategy of GHG emissions is ranked fifth (28%), while the footprint is ranked second to last (23%).

To further understand why some individuals did not change their intentions to refuse to work for polluting companies even after exposure to the environmental pledges, we asked them the reasons for their choice in an open question. We found that 70% of them did not trust the pledges’ honesty,¹⁰ with 23% of the responses explicitly using the term “greenwashing”. Therefore, the absence of a treatment effect on a part of the sample is first explained by a distrust in the honesty of environmental pledges made by corporations rather than by immediate preferences to work for an environmentally responsible employer.

3.6 Results

This section presents the results of our study on the drivers of reactions to environmental pledges, as defined by Equation (3.3). To estimate the reaction for each individual in our sample, we jointly estimated the probabilities given by Equations (3.1) and (3.2) using a random forest classifier. We used a vector of 128 predictor variables, denoted as X_i , and the exposure variable D_i as inputs to the model. The optimal random forest classifier was selected by minimizing the out-of-bag log-loss through a random grid search with 10,000 iterations. Appendix 3.10 presents the list of hyperparameters used in this step and their optimal values. Our analysis reveals that the optimal random forest classifier can effectively distinguish between the two classes. To assess its performance, we randomly divided the original data into ten train-test splits, with each test sample representing 25% of the observations. For each split, we computed the associated AUC score. The average AUC score across the ten splits was 0.87, indicating that the model has a strong ability to differentiate

¹⁰Answers were classified as skeptical if they expressed doubts about the honesty of the pledge, contained the term *greenwashing*, or asked for action rather than words. Examples of such answers include: “I’m afraid of lies as bait”, “I do not want to engage in a firm based on a promise, I want to see facts”, “What are the guarantees that this company is really engaging in an ecological transition?”.

between the two classes. After estimation of the optimal random forest, we use the probabilities predicted by the classifier to calculate the reaction for each individual in the sample.

In our empirical analysis, we use the reaction as the dependent variable in our regressions, and we also directly identify its most important predictors using Shapley value decomposition. We used the KernelShap methodology, which is implemented in the SHAP package Lundberg and Lee (2017), to compute the Shapley values. Appendix 3.8 provides details on the computation of the Shapley values in our setting. After computing a Shapley value for each individual and each predictor in our dataset, we aggregate the Shapley values to identify the most important predictors of the reaction. We first average absolute Shapley values across groups of variables that measure similar attributes to compute factor importance. We gather the predictors into nine factors: beliefs on the ecological crisis, career perspectives, education, political action for ecology, political positioning, pro-environmental attitude, sociodemographics, work values, and a final factor that includes variables that could not be grouped under the previous factors, such as associative engagement. We also compute predictor importance as measured by the sum of absolute Shapley values associated with a given predictor across all individuals.

3.6.1 Drivers of intentions to boycott polluting employers

Before applying our methodology to identify drivers of the reaction to the environmental pledge, we first identify the drivers of individuals' intentions to refuse to work for polluting companies. Previous personnel psychology research on the determinants of recruitment found that job seekers are more attracted to organizations that better fit their own values (Judge and Bretz, 1992; Chapman et al., 2005). In the specific case of environmental communication to attract job seekers, previous work has found that job seekers with higher pro-environmental attitudes and a desire to have an impact through their work are more attracted to environmentally responsible companies (Gully et al., 2013; Jones et al., 2014).

To check for these findings in our sample, we estimate Equation (3.1) using a logistic regression. We use socio-demographic characteristics as control variables and include the *Environmental Attitude Index*, the *Political Action Index*, and the *Work values CSR Index* as explanatory variables in our model to proxy for environmental preferences and the search for meaning through work. Results are displayed in Table 3.4. Consistent with previous research, we find that respondents with higher pro-environmental attitudes, more supportive of political action for ecology, and seeking meaning through their work are significantly more likely to have intentions to refuse to work for polluting companies.

To check that the effect of environmental preferences and search of meaning through work are properly captured by the random forest classifier, we also apply the Shapley value decomposition

Table 3.4: Drivers of intentions to refuse to work for polluting companies

	(1)	(2)	(3)	(4)	(5)
Constant	1.582*** (0.60)	0.207 (0.66)	0.950 (0.65)	1.324** (0.60)	-0.0323 (0.70)
Age	-0.00524 (0.028)	-0.00603 (0.031)	-0.0368 (0.031)	-0.0104 (0.027)	-0.0284 (0.033)
Gender - Man	0.235* (0.12)	0.324** (0.13)	0.455*** (0.13)	0.279** (0.12)	0.478*** (0.13)
Employed	0.170 (0.12)	0.227* (0.13)	0.159 (0.13)	0.192 (0.13)	0.222* (0.13)
Monthly financial resources	0.000110 (0.00011)	0.0000733 (0.00011)	0.0000388 (0.00012)	0.0000737 (0.00011)	0.00000892 (0.00012)
Family financial situation	0.0572 (0.056)	0.0347 (0.059)	0.0349 (0.058)	0.0523 (0.058)	0.0281 (0.060)
Work values CSR Index		0.892*** (0.086)			0.642*** (0.095)
Environmental Attitude Index			0.188*** (0.016)		0.131*** (0.018)
Political Action Index				0.170*** (0.018)	0.0849*** (0.021)
Observations	2307	2307	2307	2307	2307
Pseudo R^2	0.005	0.070	0.078	0.053	0.124

Note: This table presents the results of estimating Equation (3.1) using logistic regression. Standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

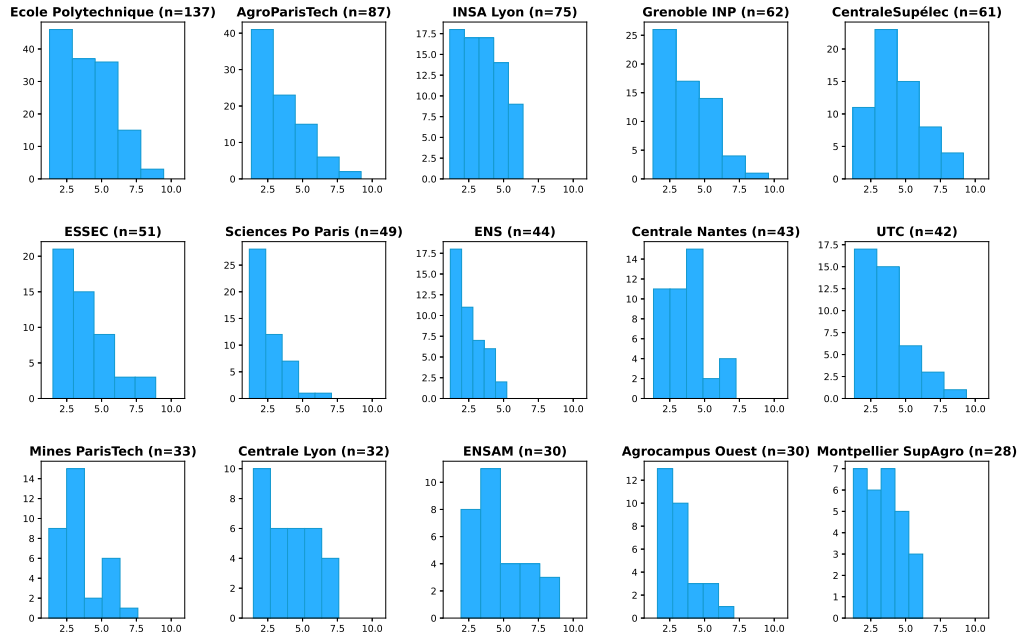
to the predicted intentions to refuse to work for polluting companies. Factors and predictors' importance to explain the random forest classifiers' prediction of intentions to refuse to work for polluting companies, as measured by average absolute Shapley values, are displayed in Figure 3.10.1 and Figure 3.10.2 in Appendix 3.10. Supporting our previous finding, we find that predictors associated with pro-environmental attitudes, support for political action for ecology, and the search for meaning through work are ranked as the most important predictors of these intentions.

3.6.2 Drivers of the reaction to environmental pledges

In this section, we aim to identify the factors that influence the reaction to environmental pledges. As a reminder, the reaction, represented by Equation (3.3), measures of how much less likely an individual is to intend to refuse to work for a polluting employer after being exposed to an environmental pledge. For the rest of our analysis, we consider only those individuals who initially had intentions to refuse to work for polluting employers ($Y_i^{(0)} = 1$), resulting in a sample size of $n = 1983$. In our sample, the average reaction is equal to 3.6, indicating that respondents are on average more than three times less likely to intend to refuse to work for a polluting employer after being exposed to an environmental pledge.

Figure 3.6 displays the distribution of the estimated reaction for the fifteen most represented institutions in our sample. We observe a significant heterogeneity in respondents' reactions depending on their institution of study. Respondents enrolled in Sciences Po Paris and École Normale

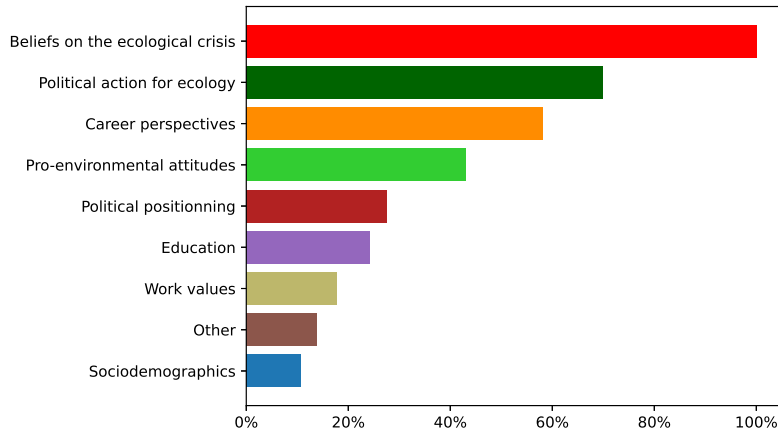
Figure 3.6: Distribution of the reaction by institution



Note: This figure shows the distribution of the reaction to the environmental pledge among individuals who initially had intentions to refuse to work for polluting companies ($n = 1983$) in the fifteen most represented institutions in our sample. The reaction is computed using the output of a random forest classifier.

Supérieure, which are institutions focused on social and political sciences and scientific research, respectively, are less reactive than average. On the other hand, students from top engineering schools, such as CentraleSupélec and ENSAM, are highly responsive to the environmental pledge, with a mean reaction of 4.4 and 4.6, respectively.

Figure 3.7: Ranking of factors to predict the reaction to the environmental pledge

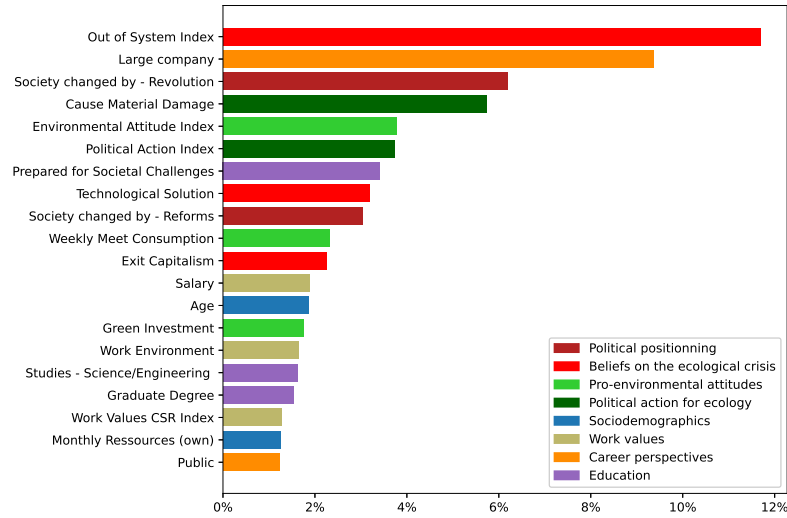


Note: This figure displays the importance of factors in predicting the reaction to the environmental pledge, as measured by the mean absolute Shapley value. The reaction, given by Equation (3.3), is estimated using the output of a random forest classifier. Results are expressed as a percentage of the most important factor.

Figure 3.7 displays the factor ranking in terms of their ability to explain the reaction to the environmental pledge, as measured by the average absolute Shapley value. The results are ex-

pressed as a percentage of the most important factor. We find that the three most critical factors in explaining this reaction are one’s beliefs about the ecological crisis, support for political action in the name of ecology, and one’s career perspectives. In contrast to the drivers of intentions to refuse to work for a polluting company, pro-environmental attitudes and work values appear to be less important in explaining the reaction to the environmental pledge.

Figure 3.8: Top 20 predictors of the reaction to the environmental pledge



Note: This figure displays the twenty most important predictors of the reaction to the environmental pledge, as measured by the sum of absolute Shapley values. The reaction, given by Equation (3.3), is estimated using the output of a random forest classifier. Results are expressed as a percentage of the total sum of absolute Shapley values.

Figure 3.8 presents the ranking of the top twenty most important predictors in explaining the reaction to the environmental pledge. We observe that the most influential predictors of the reaction are beliefs regarding the causes and solutions to the ecological crisis, as measured by the *Out of System Index*, whether one seeks to work for a large company, and markers of political radicalism, such as believing that society should be changed through revolution or being supportive of causing material damage in the name of ecology. Collectively, these four predictors account for one-third of the total predictor importance.

To draw inference on the drivers of the reaction to environmental pledge, we next estimate the following regression model:

$$\log(\hat{\tau}_i) = \alpha + \beta X_i + \varepsilon_i, \quad (3.5)$$

where the vector of explanatory variables X_i includes socio-demographic characteristics, as well as some of the most important predictors that have been identified.

The results are presented in Table 3.5. We find that the full model has good explanatory power for the reaction, as it accounts for 74% of its variance. Our analysis indicates that incorporating

Table 3.5: Drivers of the reaction to the environmental pledge

	(1)	(2)	(3)	(4)	(5)
Constant	1.834*** (0.11)	1.790*** (0.091)	1.850*** (0.091)	2.157*** (0.074)	1.832*** (0.065)
Age	-0.0300*** (0.0049)	-0.0248*** (0.0040)	-0.0238*** (0.0041)	-0.0196*** (0.0034)	-0.0168*** (0.0028)
Gender - Man	0.0255 (0.021)	-0.0325* (0.017)	0.0486*** (0.016)	-0.0460*** (0.013)	-0.0327*** (0.011)
Employed	0.0156 (0.021)	-0.0000363 (0.018)	-0.00825 (0.016)	-0.0167 (0.014)	-0.0216* (0.011)
Monthly financial resources	-0.0000616*** (0.000018)	-0.0000641*** (0.000015)	-0.0000396*** (0.000014)	-0.0000233** (0.000012)	-0.0000269*** (0.0000095)
Family financial situation	0.0145 (0.0098)	0.0113 (0.0083)	0.0159** (0.0077)	0.00131 (0.0063)	0.00368 (0.0052)
Work values CSR Index		-0.0982*** (0.012)			0.00677 (0.0086)
Career perspectives - Large company		0.490*** (0.019)			0.270*** (0.013)
Environmental Attitude Index			-0.0252*** (0.0026)		-0.0137*** (0.0018)
Political Action Index			-0.0450*** (0.0036)		-0.00345 (0.0028)
Cause Material Damage			-0.137*** (0.0093)		-0.0998*** (0.0063)
Out of System Index				-0.0699*** (0.0019)	-0.0476*** (0.0018)
Society changed by - Revolution				-0.270*** (0.014)	-0.193*** (0.011)
Observations	1983	1983	1983	1983	1983
R ²	0.031	0.313	0.455	0.609	0.740

Note: This table displays the results of regression (3.5). The reaction, given by Equation (3.3), is estimated using the output of a random forest classifier. Standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

large companies into one's career perspectives is significantly associated with a 31% increase in the reaction to environmental pledges. One possible explanation for this result is that students who are interested in working for large companies may assume that their future employer could have a significant impact on the environment. Therefore, a polluting employer that commits to improving its environmental impact would be more likely to align with their personal preferences, compared to a polluting employer that does not make such a commitment.

We also find that variables measuring political radicalism have an important effect on the reaction, with individuals who are more supportive of radicalism being less reactive to the environmental pledge. Believing that society should be changed by revolution is associated with a -17% decrease in the reaction, while a one-point increase in support for causing material damage in the name of ecology is associated with a -9% decrease. Additionally, being more skeptical towards the ability of a market economy and technological development to solve the ecological crisis, as measured by the *Out of System Index*, is associated with a decrease in the reaction: a one-point increase in the *Out of System Index* is associated with a -5% decrease in the reaction. In comparison, pro-environmental attitudes have a lower effect: while the *Environmental Attitude Index* is significant at the 1% level, a one-point increase in the index is only associated with a -1% decrease in the reaction. Finally, while seeking meaning through work was one of the most important drivers of intentions to refuse to work for polluting companies, it does not appear to have a significant effect on the reaction to environmental pledges.

As a robustness check for our results, we applied the same methodology using an XGBoost classifier. We found a strong correlation of 83% between the measures of predictor importance, as measured by the average absolute Shapley value, obtained for the XGBoost and random forest classifiers. As a result, the predictor ranking associated with both classifiers is very similar. Appendix 3.10 shows Figure 3.10.3 and Figure 3.10.4, respectively displaying the factor and predictor ranking to explain the reaction computed using the output of the XGBoost classifier. We find that seventeen out of twenty predictors belong to both rankings, although in a different order. We then replicate the findings of Table 3.5 using the reaction computed from the output of the XGBoost classifier. The results are displayed in Table 3.10.6 and yield qualitatively similar conclusions.

In conclusion, our findings suggest that environmental pledges can have a substantial impact in counteracting selection effects caused by a poor environmental responsibility. Although the environmental pledge did not change the intentions of a significant portion of survey respondents, a large majority of them switched their intentions. This finding can be explained by the fact that the drivers of intentions to refuse to work for polluting companies are different from the drivers of the reaction to environmental commitments. While intentions to refuse to work for environmentally irresponsible employers are primarily driven by one's search for meaning through work and high pro-environmental preferences, these factors play a minor role in explaining the reaction. Individuals who react the least to environmental pledges tend to self-select outside of large companies, are skeptical about the capacity of a market economy and technological development to solve the ecological crisis, and are supportive of radical action in the name of ecology. On the contrary, the most reactive individuals include large companies in their career path, have faith in a market economy or technological development to solve the ecological crisis, and are not supportive of political radicalism.

3.7 Conclusion

In this paper, we examine a climate movement initiated by elite French students which had a significant impact on the French higher education system. To hasten the sustainable transition of businesses, participants in the climate movement threatened to boycott job offers from polluting employers. To investigate the credibility of this incentive scheme, we assess the effect of corporate environmental pledges on students' intentions to refuse to work for polluting employers using a survey experiment with repeated measurements. We employ machine learning classifiers to calculate a measure of the extent to which an individual's intentions to refuse to work for a polluting employer change after being exposed to an environmental pledge. To identify the most important factors moderating students' reactions to environmental pledges, we apply the SHAP

interpretability method to this measure and use it in traditional linear regressions to draw inference.

While intentions to refuse to work for polluting companies are primarily explained by one's environmental attitudes and pursuit of meaning through work, these factors play only a minor role in explaining reactions to environmental pledges. As a result, environmental pledges have a strong effect on intentions to refuse to work for polluting employers: respondents initially intending to refuse a job offer from a polluting company are, on average, more than three times less likely to maintain these intentions after exposure to an environmental pledge. However, there is significant heterogeneity in reactions to the environmental pledge, with one-third of respondents maintaining their intentions to refuse a job offer from a polluting employer despite the pledge. We find that the most important drivers of reactions to environmental pledges are career perspectives, beliefs about the ecological crisis, and support for radical action in the name of ecology. Individuals who are not responsive to environmental pledges exclude large companies from their career perspectives, do not believe in the ability of a market economy and technological development to solve the ecological crisis, and support radical action in the name of ecology. In contrast, those who react the most to the pledges include large companies in their career perspectives, are less skeptical about the ability of a market economy and technological development to address the ecological crisis, and do not support radical action.

This contribution highlights the growing stakeholder demand on polluting companies to take climate action, as well as their exposure to risks related to attracting human capital. Consequently, unsustainable business models may not only be jeopardized by incoming regulation but also by various types of costly stakeholder action. In this vein, some scholars have argued that the self-selection of talented workers away from polluting companies could be a powerful lever to foster businesses' sustainability transition (Brekke and Nyborg, 2008; Brannstrom et al., 2022). However, our findings suggest that polluting companies could at least temporarily address this challenge by pledging to improve their environmental impact. While pledges can be made in good faith, they can also be made free of charge. A failure of our institutional settings to hold companies responsible for their commitments makes it difficult to distinguish genuine efforts from empty promises, thereby raising concerns about pledges credibility. Furthermore, our results might also explain why companies exposed to boycott movements initially respond by increasing their prosocial claims (McDonnell and King, 2013).

3.8 Appendix A: Shapley value for machine learning interpretability

3.8.1 Computation

Consider a random vector $X_i \equiv (X_{i1}, X_{i2}, \dots, X_{ip})$ that represents the individual characteristics of an agent. The vector is composed of p predictor variables, and $x_i \equiv (x_{i1}, x_{i2}, \dots, x_{ip})$ represents the corresponding vector of realizations. Let D_i be an indicator variable that takes the value one if the agent has been exposed to an environmental pledge and zero otherwise. The probability of intending to refuse to work for a polluting company, conditional on the agent's characteristics and exposure to the environmental pledge, is:

$$\mathbb{P}(Y_i = 1 | X_i, D_i). \quad (3.6)$$

Let $\hat{p}_i \equiv \hat{g}(D_i, X_i)$ denote an estimator of (3.6) from a given classifier, which corresponds to a predictive model of (3.6). In our setting, we do not treat D_i as a random variable, as we use a repeated measurement design in which the outcome variable is measured before and after receiving treatment for every individual. Consequently, we denote by $\hat{p}_{0,i} \equiv \hat{g}(0, X_i)$ and $\hat{p}_{1,i} \equiv \hat{g}(1, X_i)$ the predicted conditional probability of having intentions to refuse to work for polluting companies in the two states, respectively. Usually, the model prediction for individual i is obtained by setting the random vector X_i to its realized value x_i in \hat{p}_i . However, the Shapley value (SV) computation proceeds by generating predictions when some predictors are set to their realized values, and others are randomly selected. We introduce the following notations to formalize this computation. Let $P \equiv \{1, \dots, p\}$ denote the complete set of predictor variable indexes, and $S \subseteq P$ be a subset of indexes. We define a vector X_i^S , where the k -th element of X_i^S is set to x_{ik} if $k \in S$, and X_{ik} otherwise. This vector corresponds to X_i when a subset of predictors, indexed by S , have been set to their realized value. We denote by $\hat{p}_{0,i}^S \equiv \hat{g}(0, X_i^S)$ and $\hat{p}_{1,i}^S \equiv \hat{g}(1, X_i^S)$ the associated predicted conditional probabilities. Here, in contrast to the point prediction associated with individual i , which sets every component of X_i to its realized value, the information on predictors not included in S is treated as unknown.

The SV can be defined using the previous notations. First, consider the intentions to refuse to work for a polluting company without being exposed to an environmental pledge. The SV of predictor j for individual i , or the marginal contribution of predictor j to $\hat{p}_{0,i}$, is given by:

$$\phi_{ij} = \sum_{S \subseteq P \setminus \{j\}} \frac{|S|(p - |S| - 1)!}{p!} \left[\mathbb{E} \left(\hat{p}_{0,i}^{S \cup \{j\}} \right) - \mathbb{E} \left(\hat{p}_{0,i}^S \right) \right], \quad (3.7)$$

where the expectations are taken with respect to the joint distribution of the predictors excluded

from the indexes subsets.

The SV computation works by averaging the difference between the model predicted probabilities when information on predictor j is known versus when this information is masked, across all existing subsets of predictors. The term *known* refers to the situation in which the value of predictor j is set to its observed value for individual i , while *masked* refers to the situation in which this value is randomly drawn. In other words, for each information subset that excludes predictor j , formula (3.7) calculates the change in the predicted probability resulting from adding predictor j to the information set. These differences are then averaged across all existing information subsets. In practice, the expectations needed for the SV computation are estimated by randomly sampling from the empirical joint distribution of masked predictors. However, this procedure becomes computationally infeasible when the number of predictors exceeds a dozen. As a result, the SV computation typically relies on heuristics such as KernelShap or TreeShap (Lundberg and Lee, 2017; Lundberg et al., 2020).

The previous formula can be adapted to explain a non-linear combination of model outputs. Specifically, our main interest lies in identifying factors that drive the reaction to environmental pledges as described by equation (3.3). Let $\hat{\tau}_i = \frac{\hat{p}_{0,i}}{\hat{p}_{1,i}}$ represent the plug-in estimator of (3.3). To calculate the marginal contribution of the j -th predictor to $\hat{\tau}_i$, we modify equation (3.7) as follows:

$$\phi_{ij}^* = \sum_{S \subseteq P \setminus \{j\}} \frac{|S|(p - |S| - 1)!}{p!} \left[\mathbb{E} \left(\hat{\tau}_i^{S \cup \{j\}} \right) - \mathbb{E} \left(\hat{\tau}_i^S \right) \right]. \quad (3.8)$$

3.8.2 Interpretation

Let $\hat{p}_{k,i}(x_i) = \hat{g}(k, x_i)$ denote the predicted probability associated with individual i , where the subscript k denotes that D_i is set to k . The efficiency property of the Shapley Value (SV) facilitates its interpretation in terms of deviation from the average (Lundberg and Lee, 2017). Considering the SV given by equation (3.7), it yields:

$$\sum_{j=1}^p \phi_{ij} = \hat{p}_{0,i}(x_i) - \mathbb{E}(\hat{p}_{0,i}). \quad (3.9)$$

This property states that the sum of predictors' marginal contributions to $\hat{p}_{0,i}(x_i)$ is equal to the difference between $\hat{p}_{0,i}(x_i)$ and the average prediction. Therefore, ϕ_{ij} can be interpreted as the contribution of the j -th predictor's value to the deviation of the prediction associated with individual i from the average. A positive (negative) value of ϕ_{ij} corresponds to a predictor associated with an increased (decreased) predicted probability of having intentions to refuse to work for a polluting company with respect to the average. A greater absolute value of ϕ_{ij} corresponds to a greater marginal contribution. Conversely, $\phi_{ij} = 0$ would correspond to a predictor having no

effect on the model output across all information subsets.

Considering now the SV given by equation (3.8), let $\hat{\tau}_i(x_i) = \frac{\hat{p}_{0,i}}{\hat{p}_{1,i}}$ denote the estimated reaction for individual i . The efficiency property yields:

$$\sum_{j=1}^p \phi_{ij}^* = \hat{\tau}_i(x_i) - \mathbb{E}(\hat{\tau}_i). \quad (3.10)$$

Interpretations remain similar in this case.

3.9 Appendix B: Questionnaire

Studies and professional perspectives

1. What year of study are you in?

First year; Second year; Third year; Fourth year; Fifth year; Sixth year; Seventh year; Eighth year; More than eighth year

2. What is the last degree you obtained?

CAP, BEP; General Baccalaureate (economics and social sciences); General Baccalaureate (science); General Baccalaureate (literature); Technological Baccalaureate; Professional Baccalaureate; BTS, DUT; Bachelor's degree; Master's degree; Doctorate; Other

3. What type of program are you following?

BTS; Preparatory classes for Economics and Business; Preparatory classes for Literature; Preparatory classes for Science; Post-baccalaureate engineering school; Post-preparatory engineering school; School of Public Administration; Post-baccalaureate Business and Management School; Post-preparatory Business and Management School; Agricultural or Halieutic Training School; Artistic Training School; Health and Social Training School; Journalism School; Nursery School; Midwifery School; Veterinary School; École Normale Supérieure (ENS); Higher School of Architecture; Institute of Political Studies (IEP); Institute of Medical Electroradiology Manipulators Training; Institute of Occupational Therapy Training; Institute of Podiatry Training; Nursing School; University Institute of Technology; PACES; University (Faculty of Dentistry); University (Faculty of Economics and Management); University (Faculty of Education); University (Faculty of Computer Science); University (Faculty of Chemistry); University (Faculty of Law and Political Science); University (Faculty of Humanities); University (Faculty of Mathematics); University (Faculty of Medicine); University (Faculty of Music and Musicology); University (Faculty of Pharmacy); University (Faculty of Physics); University (Faculty of Psychology); University (Faculty of Life and Earth Sciences); University

(Faculty of Social and Human Sciences); Other

4. What is the name of your institution?

5. What is the name of the study program or specialty you are following this year?

6. What is your overall satisfaction with the studies you are following?

Very satisfied; Satisfied; Dissatisfied; Very dissatisfied; PNA (Don't know, don't say)

7. Do you have any comments about this?

8. Do you feel properly prepared by your education to address societal challenges?

Very well prepared; Well prepared; Poorly prepared; Very poorly prepared; PNA (Don't know, don't say)

9. Do you feel properly prepared by your education to address ecological problems?

Very well prepared; Well prepared; Poorly prepared; Very poorly prepared; PNA (Don't know, don't say)

10. In your opinion, what elements of your curriculum should be modified to better prepare you to actively participate in the ecological transition?

11. At the end of your studies, do you think you can find a job in your field of specialization...

Very easily; Quite easily; Quite difficultly; Very difficultly; PNA (Don't know, don't say)

12. What type of organization would you like to work for?

(a) in a large company

(b) in an intermediate-sized, small or medium-sized company

(c) in a startup

(d) for the State or local authorities

(e) for an international organization (UN, IMF...)

(f) for an NGO

(g) for an association, a cooperative, or a mutual

(h) other:

13. What job do you want to have after your studies?

14. Here are some traits that can be considered important for a job or professional activity. For you personally, which ones do you consider the most important? Please pick a maximum of five answers...

- | | |
|---|--|
| (a) it pays well | (l) what you do is interesting |
| (b) the working atmosphere is good | (m) it's a job where you can use your abilities |
| (c) you're not rushed | (n) you learn new skills |
| (d) you're not at risk of unemployment | (o) it's a job that is compatible with family life |
| (e) the working hours are satisfactory | (p) you can be heard during important decisions |
| (f) you have initiative | (q) it's a job where everyone is treated equally |
| (g) it's a job that is useful for society | (r) it's a job that is in line with my values |
| (h) there are good vacation days | |
| (i) it allows you to meet people | |
| (j) it's a job that gives the impression of achieving something | |
| (k) you have responsibilities | |

15. Would you be willing to give up a job offer in a company that has a negative impact on the environment?

Completely willing; Willing; Not willing; Not at all willing; PNA (Don't know, don't say)

16. (If completely willing/willing for 15.) How important are the following elements in making this decision?

- (a) the CSR report
- (b) the carbon footprint
- (c) a biodiversity impact study
- (d) the company's reason for existence
- (e) the company's strategy for reducing greenhouse gas emissions
- (f) the possibility of taking action within the company (given voice to young graduates, to employees...)
- (g) your feelings about the company's environmental policy

Very important; Important; Rather important; Not very important; Not at all important; Don't know or not familiar with this information; PNA (Don't know, don't say)

17. (If completely willing/willing to 15.) Free comment, or other important elements for you in making the decision.

18. Furthermore, would you be willing to accept a job offer in a company that has a negative impact on the environment but declares to be committed to an ecological transition?

Completely willing; Willing; Not willing; Not at all willing; PNA (Don't know, don't say)

19. (If not willing/not at all willing to 18.) For what reason(s) ?

20. Do you have any comment to make on this subject ?

Ecological commitments and practices

21. Please check the box or boxes of the following organization categories that you belong to, if any:

- | | |
|--|--|
| (a) association in the fields of education,
music, or culture | (f) professional or student association |
| (b) religious organization | (g) humanitarian or charitable association |
| (c) trade union | (h) consumer association |
| (d) movement or political party | (i) other groups |
| (e) association for the environment, ecology,
animal rights | (j) I am not involved in an organization |
| | (k) no answer |

22. What is the name of this/these organization(s)?

23. Among the following ecological practices, please tell us which ones you already do, which ones you would be willing to do, and which ones you are not willing to do:

- (a) transition to zero waste
- (b) limit buying new products
- (c) join a community-supported agriculture
- (d) boycott certain brands or products
- (e) limit energy consumption (heating, air conditioning, electrical appliances...)
- (f) limit digital footprint (email storage, video viewing...)
- (g) invest money in ecological funds, green projects, etc.

I already do it; I would be willing to do it; I'm not willing to do it; PNA (Don't know, don't say)

24. Regarding meat, how often do you consume it?

Never (vegan); Never (vegetarian); Once a week or less; Between 2 and 4 times a week; More than 4 times a week; Every day

25. How many times do you take a plane for leisure per year?

Zero; 1 round trip; 2 round trips; 3 round trips; 4 round trips; More than 4 round trips

Relation to the manifesto

26. How did you hear about the Student Manifesto for an Ecological Awakening?

Facebook; Facebook group of my school; Email; Media; Word of mouth; Linkedin; Other

27. For you, the Student Manifesto for an Ecological Awakening is...

28. Would you be willing to share your commitments with the Student Manifesto for an Ecological Awakening through a post on social (Facebook, Twitter) or professional (LinkedIn) networks?

Yes; Maybe, if I see that people around me are doing the same; No

Political values and positioning

29. Do you think that the division between the right and the left still makes sense today?

Yes; No; No answer

30. Where would you place yourself...

Far-left; Left; Center; Right; Far-right; Neither left nor right; PNA (Don't know, don't say)

31. Which list did you vote for in the 2019 European elections?

Front National; La République en Marche; Les Républicains; La France Insoumise; Europe Ecologie les Verts; Place Publique - Parti socialiste - Nouvelle Donne - Parti radical de gauche; Debout la France; Parti communiste français; Generation.s - DiEM25; Union des démocrates et indépendants; Parti animaliste; Urgence écologique; Other; Abstention; Blank vote; Did not have the right to vote; PNA (Don't know, don't say)

32. Some people think that society should be radically changed, others that it should be improved through reforms, others still that it should be protected against change. What is your opinion?

Society should be radically changed through revolutionary action; Society should be gradually improved through reforms; Society should be protected against change; PNA (Don't know, don't say)

33. For the following statements, please indicate whether you completely agree, somewhat agree, somewhat disagree or completely disagree:

(a) it is necessary to exit the capitalist system to solve the ecological crisis

(b) the development of current and future technologies will allow us to solve the ecological crisis

- (c) climate change is primarily the consequence of poor individual choices
- (d) it is necessary to phase out nuclear energy
- (e) the ecological transition requires reducing wealth inequalities
- (f) reducing our impact on the environment involves consuming less, and therefore producing less
- (g) the fight against climate change involves giving more freedom to entrepreneurs

Completely agree; Somewhat agree; Somewhat disagree; Completely disagree; PNA (Don't know, don't say)

34. In the name of the ecological cause, which of the following actions have you already done, would be willing to do, or would be willing to support those who do them?

- (a) Sign a petition, such as l’Affaire du Siècle
- (b) sign the Student Manifesto for an Ecological Awakening
- (c) protest in a climate march
- (d) take part in a student strike for the climate
- (e) take part in an act of civil disobedience
- (f) cause material damage

Already done; Could do it; Will never do it but supports the action; Will never do it and does not support the action; PNA (Don't know, don't say)

Socio-demographics

35. What is the situation of your father?

Employed; Job seeking; Retired; Invalid; On paternity leave; Other inactive (stay-at-home dad...); Not applicable (unknown father)

36. What is/was your father's profession? (If job seeking or retired, please consider the last occupation held.)

Farmer; Self-employed artisan, self-employed merchant, entrepreneur; Executive or intellectual profession (e.g. sales executive, engineer, teacher, lawyer...); Intermediate profession (e.g. nurse, educator, nursery nurse, supervisor, teacher...); Employee (e.g. police officer, secretary, caregiver, salesperson, cashier, security guard...); Industrial or construction worker (e.g. mechanic, agricultural worker, driver, salaried artisan...); Not applicable (unknown father); Inactive (stay-at-home dad, invalid...)

37. Name of the profession

38. What is the situation of your mother?

Employed; Job seeking; Retired; Invalid; On maternity leave; Other inactive (stay-at-home mom...); Not applicable (unknown mother)

39. What is/was your mother's profession? (If job seeking or retired, please consider the last occupation held.)

Farmer; Self-employed artisan, self-employed merchant, entrepreneur; Executive or intellectual profession (e.g. sales executive, engineer, teacher, lawyer...); Intermediate profession (e.g. nurse, educator, nursery nurse, supervisor, teacher...); Employee (e.g. police officer, secretary, caregiver, salesperson, cashier, security guard...); Industrial or construction worker (e.g. mechanic, agricultural worker, driver, salaried artisan...); Not applicable (unknown mother); Inactive (stay-at-home mom, invalid...)

40. Name of the profession

41. Do you have one or more parents of foreign nationality?

Yes; No

42. (If Yes to 41.) Is it...

Your father; Your mother; One of your grandparents

43. What is the nationality of this person?

44. Regarding your family's financial resources, which of the following best describes their situation?

You are comfortable; It's fine; It's tight, you have to be careful; You are struggling; No response

45. You are living...

Alone in an individual housing; As a couple in an individual housing; In a flatshare; In student accommodation; With your parents or other family members

46. Do you have a religion?

Yes; No; No response

47. (If Yes to 46.) Which one?

Catholic; Protestant; Muslim; Jewish; Other religion

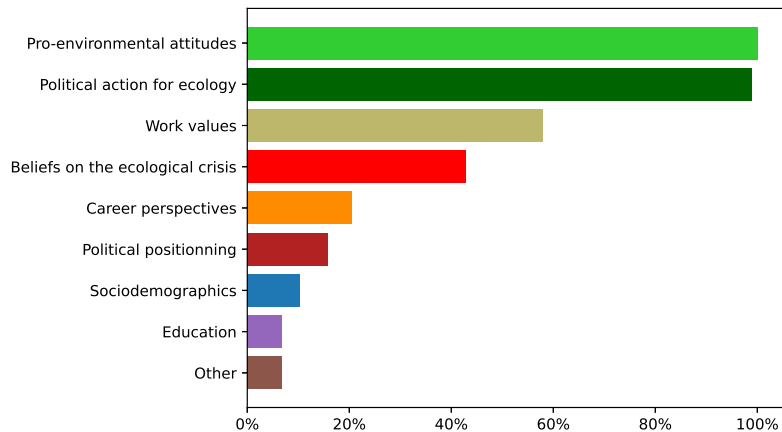
48. (If Yes to 46.) Usually, how often do you go to a place of worship...

Several times a week; Once a week; Once or twice a month; A few times a year; Less than once a year; Never

49. What are your monthly resources? Estimation of financial support from relatives (rental payment, possible registration fees, food expenses assistance, etc...) and own resources (allowances, salary, scholarship...):
- (a) financial support from relatives
 - (b) own resources
50. Do you have a job alongside your studies?
Yes, a part-time job; Yes, I am on an apprenticeship; Yes, I am doing an internship; No
51. If yes, how many hours per week?
52. What is your gender?
Female; Male; Other
53. What is your nationality?
54. What is your age?

3.10 Appendix C: Additional Tables and Figures

Figure 3.10.1: Ranking of factors to predict intentions to refuse to work for polluting companies



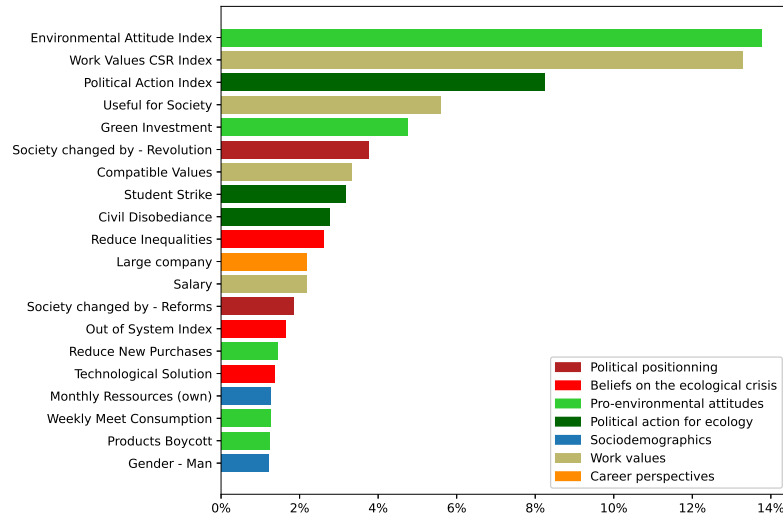
Note: This figure displays the importance of factors in predicting intentions to refuse to work for polluting companies, as measured by the mean absolute Shapley value. Intentions to refuse to work for a polluting company, given by Equation (3.1), are estimated using a random forest classifier. Results are expressed as a percentage of the most important factor.

Table 3.10.1: SBF120 companies' reaction to 7th March 2019 meeting, by level of carbon dioxide equivalent emissions (Scope 1 emissions)

Absolute emissions	Window	N	Mean CAR	Neg : Pos	Adjusted BMP	Adjusted Patell
Panel A: Highest emitters						
Top 50 %	[0, 1]	42	-2.58%	35 : 7	-4.752***	-4.777***
	[0, 2]	42	-1.49%	32 : 10	-3.165***	-3.181***
	[0, 3]	42	-0.95%	27 : 15	-1.788**	-1.797**
	[0, 4]	42	-0.13%	24 : 18	0.145	0.145
	[0, 5]	42	0.4%	18 : 24	1.378	1.386
Top 25 %	[0, 1]	21	-2.37%	17 : 4	-3.704***	-3.743***
	[0, 2]	21	-1.24%	17 : 4	-2.354***	-2.378***
	[0, 3]	21	-0.95%	14 : 7	-1.345*	-1.359*
	[0, 4]	21	-0.52%	13 : 8	-0.074	-0.075
	[0, 5]	21	-0.28%	10 : 11	0.565	0.571
Panel B: Lowest emitters						
Bottom 50 %	[0, 1]	42	-1.25%	28 : 13	-1.725**	-1.749**
	[0, 2]	42	-0.73%	27 : 14	-1.151	-1.167
	[0, 3]	42	-0.6%	23 : 17	-0.882	-0.894
	[0, 4]	42	-0.17%	24 : 18	-0.052	-0.052
	[0, 5]	42	0.5%	17 : 25	1.274	1.292
Bottom 25 %	[0, 1]	21	-0.99%	13 : 8	-0.768	-0.791
	[0, 2]	21	-0.25%	11 : 9	0.133	0.137
	[0, 3]	21	-0.04%	8 : 11	0.443	0.456
	[0, 4]	21	0.53%	10 : 11	1.043	1.074
	[0, 5]	21	0.94%	7 : 14	1.451	1.494

Note: Cumulative abnormal returns (CARs) are calculated using the CAPM and the return on the MSCI France index. The event day is labeled as Day 0. The estimation window for the CAR calculation is set at 255 trading days, ending 46 days before the event. A minimum of 40 observations is required for each firm in the estimation window. The sample is divided by absolute Scope 1 CO₂ emissions. The “Neg:Pos” column shows the ratio of firms with negative versus positive CARs over the event window. The BMP and Patell tests are used to test the nullity of the mean CAR against the alternative that the mean CAR is negative. Test statistics are corrected for cross-sectional correlation using Kolari and Pynnönen (2010) adjustment. The notations *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Figure 3.10.2: Top 20 predictors of intentions to refuse to work for polluting companies



Note: This figure displays the twenty most important predictors of intentions to refuse to work for polluting companies, as measured by the sum of absolute Shapley values. Intentions to refuse to work for a polluting company, given by Equation (3.1), are estimated using a random forest classifier. Results are expressed as a percentage of the total sum of absolute Shapley values.

Table 3.10.2: SBF120 companies' reaction to 7th March 2019 meeting, by level of carbon dioxide equivalent emissions (Scope 2 emissions)

Absolute emissions	Window	N	Mean CAR	Neg : Pos	Adjusted BMP	Adjusted Patell
Panel A: Highest emitters						
Top 50 %	[0, 1]	42	-2.77%	35 : 7	-5.09***	-5.104***
	[0, 2]	42	-1.62%	35 : 7	-3.829***	-3.84***
	[0, 3]	42	-1.3%	29 : 12	-3.065***	-3.074***
	[0, 4]	42	-0.71%	29 : 13	-1.27	-1.273
	[0, 5]	42	-0.16%	21 : 21	0.595	0.596
Top 25 %	[0, 1]	21	-2.53%	17 : 4	-3.046***	-3.086***
	[0, 2]	21	-1.4%	17 : 4	-2.001**	-2.027**
	[0, 3]	21	-1.2%	15 : 6	-1.652**	-1.674**
	[0, 4]	21	-0.85%	14 : 7	-0.796	-0.806
	[0, 5]	21	-0.23%	10 : 11	0.346	0.351
Panel B: Lowest emitters						
Bottom 50 %	[0, 1]	42	-0.98%	28 : 13	-1.186	-1.208
	[0, 2]	42	-0.58%	24 : 17	-0.542	-0.552
	[0, 3]	42	-0.23%	21 : 20	0.081	0.082
	[0, 4]	42	0.4%	19 : 23	0.986	1.004
	[0, 5]	42	1.09%	14 : 28	1.967	2.002
Bottom 25 %	[0, 1]	21	-0.92%	12 : 9	-0.615	-0.634
	[0, 2]	21	-0.47%	11 : 9	-0.078	-0.08
	[0, 3]	21	0.15%	9 : 11	0.551	0.568
	[0, 4]	21	0.81%	10 : 11	1.118	1.153
	[0, 5]	21	1.45%	7 : 14	1.653	1.705

Note: Cumulative abnormal returns (CARs) are calculated using the CAPM and the return on the MSCI France index. The event day is labeled as Day 0. The estimation window for the CAR calculation is set at 255 trading days, ending 46 days before the event. A minimum of 40 observations is required for each firm in the estimation window. The sample is divided by absolute Scope 2 CO₂ emissions. The “Neg:Pos” column shows the ratio of firms with negative versus positive CARs over the event window. The BMP and Patell tests are used to test the nullity of the mean CAR against the alternative that the mean CAR is negative. Test statistics are corrected for cross-sectional correlation using Kolari and Pynnönen (2010) adjustment. The notations *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.

Table 3.10.3: Sample characteristics compared to the signatories population

	Sample	Population
Gender		
Man	0.482	0.485
Woman	0.506	0.515
Other	0.012	
Institution Type		
Business schools	0.105	0.185
Engineering schools	0.583	0.507
IEP, ENS, ENA	0.075	0.090
University	0.139	0.188
Other	0.098	0.030

Note: Population statistics were computed using first names and school names from the signatories list obtained from the organizers ($n = 24365$).

Table 3.10.4: Environmental attitudes, support for political action, and beliefs on the ecological crisis

Factor	Questions	Answers
<i>Environmental attitudes</i>	<p>Among the following ecological practices, please tell us which ones you already do, which ones you would be willing to do, and which ones you would not be willing to do.</p> <ul style="list-style-type: none"> • Transitioning to zero waste. • Limiting the purchase of new products. • Joining a local community supported agriculture. • Boycotting certain brands or certain products.. • Limiting energy consumption (heating, air conditioning, household appliances...). • Limiting your digital footprint (storage of emails, viewing of videos...). • Investing your money in ecological investment funds, in green projects, etc.. 	<p>Four-level scale:</p> <p>Already do</p> <p>Willing to do</p> <p>Don't know</p> <p>Not willing to do</p>
<i>Political actions for ecology</i>	<p>In the name of the ecological cause, which of the following actions have you already done, would be willing to do, or would be willing to support those who do them?</p> <ul style="list-style-type: none"> • Signing a petition, such as the 'Affaire du Siècle' for example. • Participating in a climate march demonstration. • Taking part in a student strike for the climate. • Taking part in an act of civil disobedience. • Causing material damage. 	<p>Five-level scale:</p> <p>Already done</p> <p>Would do it</p> <p>Don't know</p> <p>Will never do it, but supports the action</p> <p>Will never do it and does not support the action</p>
<i>Beliefs on the ecological crisis</i>	<p>For the following statements, please indicate whether you completely agree, somewhat agree, somewhat disagree or completely disagree:</p> <ul style="list-style-type: none"> • It is necessary to exit the capitalist system to solve the ecological crisis. • The development of current and future technologies will allow us to solve the ecological crisis. • Climate change is primarily the consequence of poor individual choices. • It is necessary to phase out nuclear energy. • The ecological transition requires reducing wealth inequalities. • Reducing our impact on the environment involves consuming less, and therefore producing less. • The fight against climate change involves giving more freedom to entrepreneurs. 	<p>Five-level scale:</p> <p>Completely Agree</p> <p>Somewhat Agree</p> <p>Don't know</p> <p>Somewhat Disagree</p> <p>Completely Disagree</p>

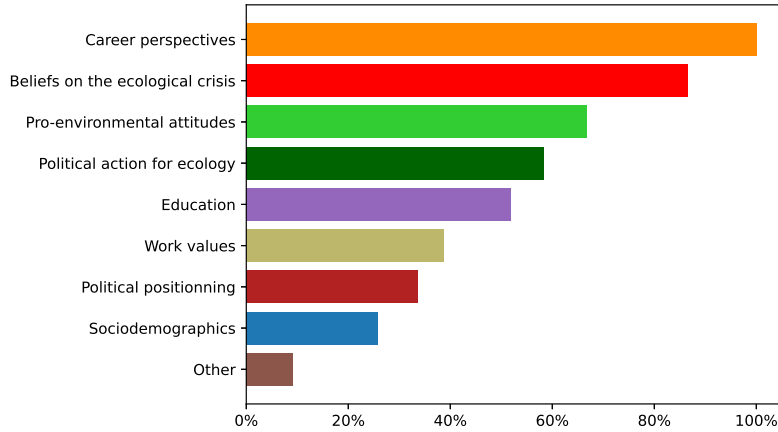
Note: This table displays questions and possible answers used to measure respondents' environmental attitudes, support for political action in the name of ecology, and beliefs on the ecological crisis.

Table 3.10.5: Hyperparameters selection

Hyperparameter set	Random Forest	XGBoost
Learning rate		0.01-0.1 (0.05)
Columns subsample ratio		0.025-0.25 (0.225)
Max tree depth	2-30 (16)	1-15 (4)
Number of estimators	50-1000 (350)	50-1000 (200)
Subsample rate	0.5-1 (1)	0.5-1 (1)
Minimum leaf size	1-20 (15)	
Features used for each split	2-40 (40)	

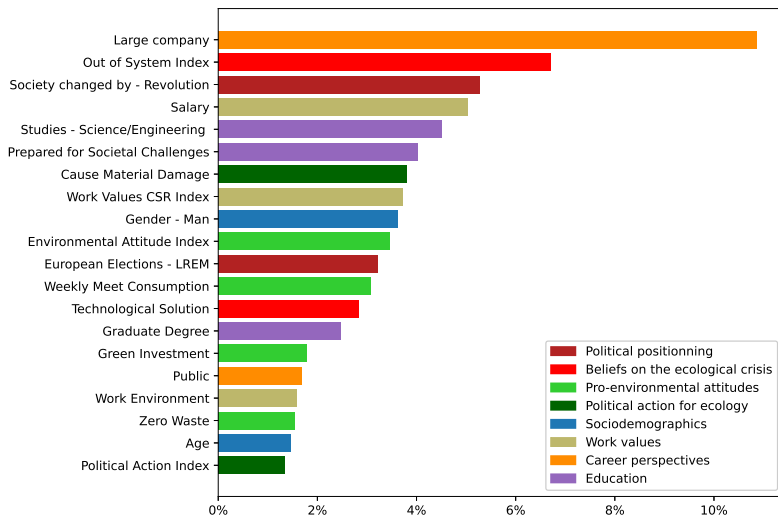
Note: This table displays the hyperparameters tuned to calibrate the random forest and XGBoost classifiers. The optimal hyperparameter values are reported in parentheses.

Figure 3.10.3: Ranking of factors to predict the reaction to the environmental pledge (XGBoost)



Note: This figure displays the importance of factors in predicting the reaction to the environmental pledge, as measured by the mean absolute Shapley value. The reaction, given by Equation (3.3), is estimated using the output of an XGBoost classifier. Results are expressed as a percentage of the most important factor.

Figure 3.10.4: Top 20 predictors of the reaction to the environmental pledge (XGBoost)



Note: This figure displays the twenty most important predictors of the reaction to the environmental pledge, as measured by the sum of absolute Shapley values. The reaction, given by Equation (3.3), is estimated using the output of an XGBoost classifier. Results are expressed as a percentage of the total sum of absolute Shapley values.

Table 3.10.6: Drivers of the reaction to the environmental pledge (XGBoost)

	(1)	(2)	(3)	(4)	(5)
Constant	2.193*** (0.14)	2.246*** (0.11)	2.338*** (0.12)	2.565*** (0.11)	2.354*** (0.088)
Age	-0.0419*** (0.0065)	-0.0346*** (0.0049)	-0.0341*** (0.0056)	-0.0300*** (0.0050)	-0.0258*** (0.0039)
Gender - Man	0.00311 (0.025)	-0.0794*** (0.020)	0.0125 (0.020)	-0.0787*** (0.018)	-0.0875*** (0.014)
Employed	0.0213 (0.026)	-0.00267 (0.020)	-0.00492 (0.020)	-0.0152 (0.018)	-0.0213 (0.014)
Monthly financial resources	-0.0000562** (0.000023)	-0.0000587*** (0.000018)	-0.0000290 (0.000019)	-0.0000120 (0.000017)	-0.0000182 (0.000013)
Family financial situation	0.0148 (0.013)	0.0116 (0.010)	0.0166 (0.010)	-0.000506 (0.0092)	0.00384 (0.0075)
Work values CSR Index		-0.195*** (0.014)			-0.0806*** (0.011)
Career perspectives - Large company		0.650*** (0.022)			0.417*** (0.018)
Environmental Attitude Index			-0.0388*** (0.0033)		-0.0226*** (0.0024)
Political Action Index			-0.0570*** (0.0047)		-0.00545 (0.0037)
Cause Material Damage			-0.128*** (0.012)		-0.0895*** (0.0082)
Out of System Index				-0.0799*** (0.0025)	-0.0465*** (0.0023)
Society changed by - Revolution				-0.318*** (0.019)	-0.226*** (0.015)
Observations	1983	1983	1983	1983	1983
R^2	0.033	0.411	0.419	0.542	0.723

Note: This table displays the results of regression (3.5). The reaction, given by Equation (3.3), is estimated using the output of an XGBoost classifier. Standard errors robust to heteroskedasticity are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Chapter 4

Chapter 4

Fossil investment under climate policy: Empirical evidence

4.1 Introduction

Climate mitigation pathways compatible with a well-below 2 degrees scenario require stopping investments in new fossil resource extraction projects and ceasing the use of many fossil energy infrastructures before the end of their economic lifetime (Bouckaert et al., 2021; Shukla et al., 2022). However, the current investment plans of the fossil energy industry remain incompatible with the climate targets set by the Paris Agreement, and economically viable fossil fuel reserves far exceed the remaining carbon budget consistent with these mitigation pathways (McGlade and Ekins, 2015; Welsby et al., 2021). Kühne et al. (2022) estimate that the 425 largest fossil fuel exploitation projects exceed the global 1.5 degrees carbon budget by a factor of two, with 40% of these projects not having started extraction yet.

So far, the dominant approach taken to mitigate climate change has been the implementation of demand-side policies designed to reduce economies' reliance on fossil energy. These policy interventions can take various forms, such as subsidizing low-carbon technologies, establishing carbon taxes, or investing in energy efficiency. Currently, there is no international agreement to restrict fossil resource extraction, and only a handful of policies or court decisions have been established to impose limitations on new fossil resource extraction projects. Although renewable energy investments have increased worldwide in recent years, this does not necessarily imply a reduction in fossil energy use, as energy sources tend to be added rather than substituted (York and Bell, 2019). Moreover, the ability of climate policies focused exclusively on demand to limit climate change has been the subject of significant academic debates in recent years. Scholars of the Green Paradox argue that the passing of demand-side policies heralding a gradual tightening of

climate policy could accelerate global warming (Sinn, 2008; Van der Ploeg and Withagen, 2012). The theoretical argument is based on an application of Hotelling’s rule: to maximize the net present value of their rent, rational resource owners should shift their extraction pathway towards the present in response to future revenue loss due to upcoming climate policies. As a result, the supply-side response to demand-side climate policies may lead to an acceleration of fossil resource extraction.

On the other hand, alternative theoretical approaches argue that such policy settings would instead slow down investments in fossil energy infrastructure due to the exposure of irreversible investments to climate transition risk (Bauer et al., 2018; Baldwin et al., 2020; Fried et al., 2022). This conclusion is rooted in the finding that policy uncertainty has a strong negative impact on the investment of firms with a high degree of asset irreversibility (Julio and Yook, 2012; Gulen and Ion, 2016). Only a few empirical studies investigated the green paradox. Di Maria et al. (2014) and Lemoine (2017) find indirect evidence of the Green Paradox through the reaction of commodity prices to environmental policy shocks; however, results are inconclusive when considering production data (Di Maria et al., 2014). Supporting the assumption of an irreversible investment channel, Kellogg (2014) and Ilyas et al. (2021) find that oil and gas investments are negatively impacted by economic policy uncertainty. Focusing on climate policy uncertainty, Berestycki et al. (2022) finds that climate policy uncertainty measures computed using news media are negatively correlated with investments in capital-intensive and carbon-intensive industries.

Theoretical models investigating the relationship between climate policy and fossil resource extraction frequently assume uniform policy stringency around the world. However, despite the Paris Agreement, current climate governance exhibits considerable heterogeneity in countries’ efforts to address climate change. In a world with free capital flows and sustained demand for fossil fuels, the benefits of climate policies enacted by a small coalition of countries may be partially offset by increased carbon emissions in the rest of the world—a situation referred to as carbon leakage. Numerous studies based on computable general equilibrium (CGE) models have found positive leakage rates, typically ranging from 10 to 30 percent (Carbone and Rivers, 2017). Burniaux and Oliveira Martins (2012) however argues that leakage rates are likely to be small for realistic values of the supply elasticity of carbon-intensive fuels. Among the few empirical investigations focusing on climate policy-induced leakage, Naegle and Zaklan (2019) and Dechezleprêtre et al. (2022) find no evidence that European multinational companies displaced their carbon emissions towards the rest of the world following the implementation of the European Union Emissions Trading System. However, these studies focus exclusively on carbon emissions displacement rather than fossil resource extraction. Due to these limitations, it is crucial to gain a deeper understanding of the effectiveness of climate governance characterized by demand-side and sub-global policies in slowing

down fossil resource extraction.

In this study, we investigate the reaction of oil and gas investment flows to climate policies enacted at both national and global levels. To achieve this, we use a quarterly panel of 207 oil and gas companies active in the upstream sector, located in 30 countries, over the period 2009-2021. Our sample includes the largest publicly traded oil and gas companies, representing one quarter of the world's oil and gas proved reserves. To disentangle the effect of climate policies passed in a firm's country of headquarters and climate policies passed in the rest of the world, we construct two measures of national and global climate policy effort using the Climate Laws of the World database. This publicly available database records climate change laws and policies worldwide, covering the full range of interventions available to policymakers for achieving the transition towards a low-carbon economy. It has been previously used to study the dynamics of climate law-making (Fankhauser et al., 2016), climate governance (Averchenkova et al., 2017), and the drivers of national greenhouse gas emissions (Eskander and Fankhauser, 2020). In our set-up, the number of climate policies passed over a certain period at both the national and global levels serve as proxies for the policy-making effort to fight climate change. Furthermore, these measures have the advantage of being available at a high frequency and for every country in the world.

We integrate our national climate policy and global climate policy effort measures into standard investment regressions. Our findings indicate that oil and gas firms significantly decrease their investments following an increase in the climate policy effort of their country of headquarters. In terms of economic relevance, the decrease in investment rates reaches -3.5% compared to the sample average following the addition of one climate policy at the national level in the previous four quarters. This effect is more pronounced for climate mitigation and energy-sector targeted climate policies, for larger firms, and for Exploration and Production companies, which are more reliant on their upstream segment. This result holds up to a variety of robustness tests, including the use of various measures of corporate investment.

A potential channel explaining this finding could be the increased exposure of these companies to unfavorable governmental or court decisions when operating under a pro-climate government. A well-known example is the Keystone XL pipeline project, which was hindered by multiple adverse governmental decisions before being definitively abandoned in 2021 after President Joe Biden's executive order revoked the project permit. Furthermore, multinational companies' operations outside their headquarters' country may still fall under their home country's jurisdiction, as some laws, such as the French Duty of Care Act, could hold them accountable for the environmental impact of their activities worldwide (Aczel, 2021). Hence, we postulate that this finding is explained by an increase in the climate transition risk exposure of companies located in countries with a high climate policy effort. Companies more exposed to climate transition risk would consequently

reduce their investment because of the increased risk of stranded assets associated with irreversible investments. Supporting this mechanism, we find that investors' concerns about a company's climate change exposure, as measured by the frequency of climate change-related keywords in investors' questions during earnings call conferences, significantly increase following a rise in the climate policy effort of the company's country of headquarters.

While oil and gas firms located in countries with high climate policy effort reduce their fossil investments, those in countries with weak or no climate policy effort, and therefore less exposed to stranded asset risks, have incentives to increase their investments in fossil energy due to the sustained global demand for fossil fuels. Consequently, we find evidence that firms in countries with weak or no climate policy effort increase their fossil investments following periods of high global climate policy effort. In terms of magnitude, the increase in investment rates reaches 0.8% relative to the sample average following the addition of one worldwide mitigation policy beyond the global trend. In contrast, we do not find evidence of such an effect from the global climate policy-making effort for companies located in countries showing a sustained effort to address climate change. Our results therefore suggest that the passing of climate policies at a sub-global level may lead to fossil investment leakages.

Our research adds to the existing body of literature on the relationship between climate policies and fossil resource depletion. While numerous theoretical studies have explored this link, they have emphasized different mechanisms having opposite effects. Some studies suggest that supply-side responses to demand-side climate policies could accelerate fossil resource depletion (Sinn, 2008; Barnett, 2019; Van der Ploeg, 2020), while others conclude that these policies could reduce fossil investments due to the existence of sunk costs (Bauer et al., 2018; Baldwin et al., 2020; Fried et al., 2022). Empirical evidence addressing these conflicting results is scarce. Previous studies have primarily focused on the United States, examining the commodity price reactions to environmental policy shocks (Di Maria et al., 2014; Lemoine, 2017). In contrast to these studies, we investigate the relationship between climate policies and fossil resource depletion using an international panel on oil and gas investment flows. Furthermore, we propose an empirical strategy that allows us to disentangle the effects of climate policies enacted at both the national and global levels. Our findings have significant policy implications, as they underscore the necessity of coordinated global efforts to effectively mitigate climate change.

The remainder of this paper is organized as follows. Section 2 and Section 3 introduce the data and the econometric methodology, respectively. Section 4 presents the results, and Section 5 concludes.

4.2 Data

The sample used in our analysis is composed of 207 publicly traded oil and gas firms located in 30 countries over the period 2009Q1-2021Q4, corresponding to a total of 7,721 firm-quarter observations (see Table 4.1 for a description of the sample). To be included in the analysis, firms must satisfy the following conditions: (i) have oil and gas as their core business and be active in the extractive sector, (ii) have non-missing observations for all the financial variables for at least two consecutive years, (iii) have assets greater than 100,000 USD. Condition (i) restricts the sample to firms with an upstream segment and ensures that investment is related to fossil fuel extraction, while sample restrictions (ii) and (iii) are standard in the investment literature. Subsidiaries are also excluded when their ultimate parent belongs to the sample to avoid duplicates.

Table 4.1: Description of the sample

Country	Number of companies	Largest companies	Headquarters country	Total proven reserves
Canada	80	Saudi Arabian Oil Co	Saudi Arabia	257.8
United States	76	Gazprom PAO	Russia	119.7
Israel	5	NK Rosneft ¹ PAO	Russia	40.8
Russia	5	Exxon Mobil Corp	United States	21.9
Norway	5	BP PLC	United Kingdom	17.8
China	4	NK Lukoil PAO	Russia	16.6
Indonesia	3	Shell PLC	Netherlands	12.2
Sweden	3	Novatek PAO	Russia	11.8
Brazil	3	Chevron Corp	United States	11.3
Netherlands	2	TotalEnergies SE	France	11.0
United Kingdom	2	Petroleo Brasileiro SA Petrobras	Brazil	10.9
Austria	1	Conocophillips	United States	7.1
Spain	1	Tatneft ¹ PAO	Russia	6.7
Ireland	1	Eni SpA	Italy	6.6
Romania	1	Canadian Natural Resources Ltd	Canada	6.3
Argentina	1	Equinor ASA	Norway	5.1
Portugal	1	Suncor Energy Inc	Canada	3.9
Bulgaria	1	Occidental Petroleum Corp	United States	3.1
Colombia	1	Cenovus Energy Inc	Canada	2.7
Poland	1	Antero Resources Corp	United States	2.6
Japan	1	EOG Resources Inc	United States	2.5
Italy	1	Inpex Corp	Japan	2.5
Hungary	1	Devon Energy Corp	United States	2.2
Chile	1	EQT Corp	United States	2.2
Turkey	1	Repsol SA	Spain	1.9
Croatia	1	Range Resources Corp	United States	1.9
France	1	APA Corp (US)	United States	1.9
Mexico	1	Ovintiv Inc	United States	1.8
Saudi Arabia	1	Ecopetrol SA	Colombia	1.7
New Zealand	1	Marathon Oil Corp	United States	1.6

Note: This table outlines the sample used in the analysis and showcases the largest oil and gas companies with complete information on proven reserves. The total proven reserves are averaged across the sample and expressed in billions of barrels of oil equivalent, following the convention that 6,000 cubic meters of natural gas equal one barrel of oil equivalent.

One limitation of our study is that it does not include some of the largest state-owned oil and gas firms, such as the National Iranian Oil Company, due to their lack of financial disclosure. Despite this limitation, the sample remains pertinent for examining the dynamics of oil and gas investment in the context of climate change. Indeed, the sample includes all Big Oil companies and numerous major oil and gas producers, such as Gazprom PAO, Lukoil, PetroChina, Saudi Aramco, and Sinopec. At the beginning of 2020, liquid and gas proven reserves for firms in the sample totaled 404 billion barrels of oil equivalent and 42 trillion cubic meters, respectively, representing one quarter of the world's total proven oil and gas reserves.¹

¹These figures are based on the estimations from BP's 2021 Statistical Review of World Energy

Financial and accounting variables are collected from Refinitiv. Following Ilyas et al. (2021), financial variables are winsorized at the bottom and top 5% to alleviate the possible effects of outliers.² Data on GDP growth are collected from the OECD website. The GEPU index of Davis (2016) is used to measure global economic policy uncertainty. Climate policy data are retrieved using the *Climate Laws of the World* database. This publicly available dataset, compiled by the Grantham Research Institute, records climate change laws and policies worldwide. It has been previously used to study the dynamics of climate law-making (Fankhauser et al., 2016), climate governance (Averchenkova et al., 2017), and the drivers of national greenhouse gas emissions (Eskander and Fankhauser, 2020). The database adopts a broad definition of climate legislation and policy, including parliamentary acts, executive orders, and dedicated policies. It covers the full range of interventions relevant to achieving the transition towards a low-carbon economy, from framework laws and dedicated climate measures to sector-targeted policies. For simplicity, we refer to these measures as climate policies in the following.

4.3 Econometric specification

To investigate the effect of climate policies passed at the domestic level on fossil investment, we use a standard investment model (e.g., Julio and Yook, 2012; Gulen and Ion, 2016; Ilyas et al., 2021) controlling for firm characteristics and macroeconomic conditions, augmented by a measure of national climate policy effort:

$$\begin{aligned} INV_{i,j,t} = & \alpha_i + \gamma_t + \beta_1 NCE_{j,t-1} + \beta_2 Q_{i,t-1} + \beta_3 CF_{i,t-1} + \beta_4 SG_{i,t-1} + \beta_5 Size_{i,t-1} \\ & + \beta_6 Lev_{i,t-1} + \beta_7 \% \Delta GDP_{j,t-1} + \varepsilon_{i,t}, \end{aligned} \quad (4.1)$$

where i indexes firms, j indexes countries and t indexes quarters. The α_i are firm fixed effects that control for time-invariant firm characteristics, and the γ_t are time effects that allow us to control for macroeconomic conditions affecting the whole cross-section of firms simultaneously, such as the level of oil prices or oil price uncertainty. Using quarterly data ensures a sufficient number of clusters in the individual and time dimensions for the asymptotic theory of Cameron et al. (2011) to apply. Standard errors are therefore always clustered at the firm and quarter level to account for both serial and cross-sectional correlation in the error term (Petersen, 2009).

The dependent variable is corporate investment (INV) measured as capital expenditure scaled by lagged total assets. The model includes standard control variables: Tobin's Q (Q), computed as market value of equity plus book value of liabilities divided by the book value of assets, cash

²Our main results are robust to the choice of a more conservative winsorization threshold of 1%.

flow (CF), measured as operating cash flows scaled by lagged total assets, and sales growth (SG), calculated as year-on-year growth in quarterly sales. These variables are meant to control for investment opportunities (Julio and Yook, 2012; Gulen and Ion, 2016). Leverage (Lev), calculated as total debt divided by total assets, and firm size (Size), calculated as the natural logarithm of total assets, are included among the control variables following Ilyas et al. (2021). Quarterly growth in real GDP ($\% \Delta GDP$) is included to control for demand conditions. A definition of all variables used is given in the appendix (Table 4.6.1).

The explanatory variable of interest is the national climate policy effort (NCE), which is computed as the number of climate policies passed in the firm’s country of headquarters during the previous four quarters.³ This computation builds on Eskander and Fankhauser (2020), who found a strong negative association between a country’s carbon intensity and rolling windows of lagged climate policies. Counting the number of climate policies passed to measure the intensity of a country’s efforts in fighting climate change has several advantages. First, it provides a time-varying measure of a country’s climate policy effort available at a high frequency and for every country in the world, which also displays significant cross-sectional heterogeneity. Second, it encompasses the full range of interventions available to policymakers to achieve a transition towards a low-carbon economy. This feature is particularly appealing because, while many different tools are available to policymakers to achieve this transition, their effects, scope, and mechanisms are difficult to compare. Rather than focusing on a specific climate policy, this measure captures the overall policymaking effort of a nation to transition away from fossil fuels. Lastly, the classification of the *Climate Change Laws of the World* dataset allows for a focus on more specific policies such as mitigation policies or energy sector-targeted policies.

The model specification given by (4.1) can be used to examine the effect of climate policy effort at the national level on oil and gas investment. To investigate the effect of climate policy effort at the global level, we consider the following model specification:

$$INV_{i,j,t} = \alpha_i + \gamma M_{t-1} + \beta_1 GCE_{t-1} + \beta_2 NCE_{j,t-1} + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t-1} + \beta_5 SG_{i,t-1} \\ + \beta_6 Size_{i,t-1} + \beta_7 Lev_{i,t-1} + \beta_8 \% \Delta GDP_{j,t-1} + \varepsilon_{i,t}, \quad (4.2)$$

where the global climate policy effort (GCE) is computed as the number of climate policies passed worldwide in the previous four quarters, detrended assuming a linear time trend. Unlike model (4.1), this specification does not include time effects because it would result in perfect collinearity with GCE, as this variable does not display cross-sectional variation. In the absence of time

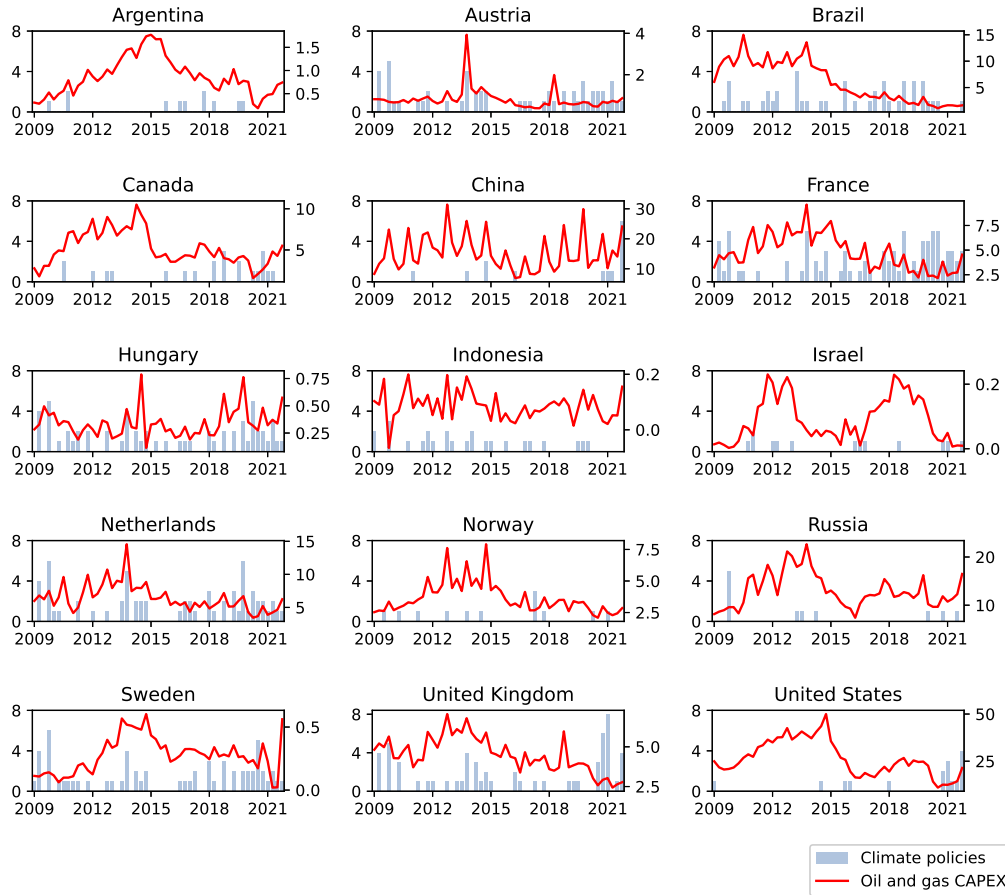
³For European Union member states, an important part of climate policies is passed at the EU level and is legally binding for its member states. Therefore, for these countries, laws and policies passed by the EU are also added to the national counting.

effects, GCE is detrended to avoid spurious discoveries caused by common or reverse trends in the dependent variable. Furthermore, a set of control variables denoted by M_{t-1} is introduced to control for confounding macroeconomic factors. The additional control variables include the logarithm of the GEPU index of Davis (2016) and oil price uncertainty, which is computed as the logarithm of the quarterly realized volatility of daily oil returns.

4.4 Results

4.4.1 Descriptive statistics

Figure 4.1: Climate policies and oil and gas investment expenses



Note: This figure displays the quarterly number of climate policies passed and oil and gas investment expenses for the fifteen most represented countries in the sample. The data covers the period from January 2009 to December 2021. Capital expenditures (in billions of dollars) are aggregated across firms at the country level and are represented on the right-hand axis.

Table 4.6.2 and 4.6.3 in Appendix respectively reports sample summary statistics and the results of baseline investment regressions. Consistent with empirical and theoretical results on the determinants of investment, we find that growth opportunities, as measured by Tobin's q , cash flow, and sales growth, are associated with an increase in investment rates. On the contrary, an increase in the debt burden, as measured by leverage, is associated with a decrease in investment

rates. Firm size is also negatively associated with investment rates, which is consistent with the stylized fact that larger oil and gas companies have lower investment expenses relative to their total assets.

Figure 4.1 displays the quarterly oil and gas capital expenditures for the fifteen most represented countries in the sample between January 2009 and December 2021. Capital expenditures are summed across firms at the country level and expressed in billions of dollars. Oil and gas investment expenses are affected by common factors related to oil price variations: a decrease in capital expenditures can be observed across all countries during the 2014-2016 oil price decline and the COVID-19 recession. The figure also displays the number of climate policies passed in each country over the period, highlighting that climate policy effort is heterogeneous across countries. Graphically, a decreasing trend in oil and gas investment expenses can be observed for some countries with strong climate policy efforts, such as Brazil and the United Kingdom. This pattern is not necessarily observed for countries with weak climate policy efforts, such as China or Russia. This finding is supported by the negative and statistically significant correlations between the three national climate effort indices and corporate investment rates: -14.6% , -12.6% , and -13.2% for the indices calculated using all climate policies, mitigation policies only, and energy sector targeted policies, respectively.

4.4.2 Effect of national climate efforts

Table 4.2 presents the estimation results of model (4.1) using three alternative methods to measure national climate policy effort. The first column displays the results using national climate policy effort, as measured by the number of all climate policies enacted in the firm's country of headquarters during the previous four quarters. The second and third columns limit this measure to climate mitigation policies only and to energy-sector targeted policies, respectively. We find that oil and gas firms reduce their investment following high climate policy effort in their country of headquarters, as the coefficient estimates associated with NCE are negative and statistically significant at the 5% level for all three specifications. Decreases in conditional investment rates following the addition of one climate policy in the previous four quarters range from -0.000522 to -0.00111 . The effect is stronger when considering only climate mitigation policies and energy-sector targeted policies to measure NCE. In terms of economic magnitude, the associated estimates correspond to economically relevant decreases in investment rates, ranging from -1.6% to -3.5% relative to the sample average.

We next conduct a heterogeneity analysis of the results. The sample is first divided by firm size, using the threshold of 10 billion in average total assets to define large and small firms. Indeed, Green Paradox effects depend on the remaining time before full exhaustion of hydrocarbon reserves,

Table 4.2: Effect of national climate policy effort on oil and gas investment rate

Dependent Variable:	CAPEX/lagged Total Assets		
	All climate policies	Mitigation policies	Energy sector policies
Tobin's q	0.0114*** (0.0016)	0.0114*** (0.0016)	0.0113*** (0.0016)
Cash flow	0.0413** (0.018)	0.0413** (0.018)	0.0407** (0.018)
Sales growth	0.00296*** (0.00083)	0.00299*** (0.00082)	0.00297*** (0.00082)
GDP growth	0.0112 (0.028)	0.00859 (0.028)	0.00797 (0.028)
Firm size	-0.00299** (0.0014)	-0.00301** (0.0014)	-0.00301** (0.0014)
Leverage	-0.0315*** (0.0047)	-0.0313*** (0.0046)	-0.0312*** (0.0046)
National climate effort	-0.000522** (0.00025)	-0.000769** (0.00030)	-0.00111*** (0.00035)
Observations	7721	7721	7721
R^2	0.438	0.438	0.439
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Clustered by firm	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes

Note: This table presents the estimation results of model specification (4.1). The dependent variable is the investment rate, measured by CAPEX/lagged Total Assets. The data are quarterly and cover the period from January 2009 to December 2021. All independent variables are lagged by one period with respect to the dependent variable (see 4.6.1 for variable definitions). Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

with larger reserves being associated with longer exhaustion times (Grafton et al., 2012). However, information on proved reserves is missing for a large portion of the sample. Since oil and gas firms' proved reserves are strongly correlated with their total assets⁴, this partitioning allows us to investigate heterogeneity in the effect of NCE due to firms' level of hydrocarbon reserves. The results are reported in Table 4.3 Panel A and are qualitatively similar to those obtained for the full sample. In five out of six configurations, NCE is negatively associated with investment rates, with coefficients reaching the 5% significance level. As investment rates decrease with firm size, the relative impact of NCE is more pronounced for larger firms, with decreases in conditional investment rates reaching -4.2% (-3.3%) for large (small) firms compared to the average.

The sample is next divided by firm type. Two types of firms are represented in the dataset: Exploration and Production (E&P) and Integrated companies. These firms differ in their business segmentation. E&P companies operate exclusively in the upstream (extraction) and midstream (transportation) segments. While their core business remains upstream and midstream activity, Integrated companies are more diversified as they also operate in the downstream segment and sometimes include an alternative energy segment. As Integrated companies are more diversified

⁴Across firms with non-missing reserve information, the sample correlation between total proved reserves and total assets is equal to 63.5%.

compared to E&P companies, they could be less exposed to national climate policy efforts. Consistent with this notion, we observe that the negative impact of NCE on investment rates is higher in magnitude for E&P companies. For these companies, NCE is negatively associated with investment rates at the 5% significance level in every configuration, with decreases in conditional investment rates ranging from -2.3% to -3.4% compared to the average. For Integrated companies, we find evidence of a negative effect of NCE on conditional investment rates only when considering energy-sector targeted climate policies; the association being negative but not significant for the other measures.

The previous findings hold up to a battery of robustness checks. We begin by assessing the sensitivity of the results to changes in the initial sample. First, we ensure that NCE is not simply picking up the effect of common factors related to the COVID-19 recession that are not captured by time effects. We proceed by estimating model (4.1), excluding all observations following the COVID-19 outbreak. We next address the concern that results may be driven by countries with disproportionate representation by alternately excluding firms located in United States and Canada, the two most represented country in the sample. The results of these estimations are displayed in Table 4.6.4 in the Appendix. We next assess the sensitivity of the results to the use of alternative measures of corporate investment. Following prior research, we use CAPEX scaled by lagged PPE and the forward net PPE growth as dependent variables (Julio and Yook, 2012; Ilyas et al., 2021). Results are reported in Table 4.6.7 in the Appendix. For all of these robustness tests, we reach qualitatively similar results, finding a negative and statistically significant association between NCE and oil and gas investment rates.

Through which channel could NCE negatively affect oil and gas investment? As numerous theoretical studies demonstrate that climate transition risk has a negative effect on fossil capital investment (e.g, Fried et al., 2022), we postulate that NCE negatively impacts oil and gas investment due to an increase in companies' exposure to climate transition risk. Companies more exposed to climate transition risk would therefore reduce their investment because they face an increase in the risk of stranded assets associated with irreversible investments.

To test for this mechanism, we compute a firm-level measure of a company's climate transition risk exposure by applying Sautner et al. (2020)'s climate change dictionary to investors' questions in quarterly earnings call conferences. Earnings conference calls provide an opportunity for investors to assess a company's risk profile by directly addressing questions to its top executives. Sautner et al. (2020) demonstrate that climate change exposure measures based on earnings conference call conversations capture economic factors identified as important correlates of climate change exposure. Our measure is thus a proxy for investors' concerns about climate change, as measured by the number of climate change-related keywords appearing in investors' questions during a given

Table 4.3: Heterogeneity in the effect of national climate policy effort on oil and gas investment rate

	Panel A: Firm size									Panel B: Firm type								
	Assets ≤ \$10 billions						Assets > \$10 billions						E&P			Integrated		
	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies
Tobin's q	0.0112*** (0.0017)	0.0112*** (0.0017)	0.0112*** (0.0017)	0.00840* (0.0043)	0.00830* (0.0043)	0.00827* (0.0042)	0.0114*** (0.0016)	0.0114*** (0.0017)	0.0114*** (0.0017)	0.000637 (0.0031)	0.000520 (0.0031)	0.000535 (0.0031)	0.000637 (0.0031)	0.000520 (0.0031)	0.000535 (0.0031)	0.000637 (0.0031)	0.000520 (0.0031)	0.000535 (0.0031)
Cash flow	0.0390** (0.019)	0.0392** (0.019)	0.0389** (0.019)	0.0628* (0.035)	0.0630* (0.035)	0.0616* (0.035)	0.0447** (0.019)	0.0447** (0.019)	0.0445** (0.019)	-0.0198 (0.031)	-0.0200 (0.031)	-0.0209 (0.031)	-0.0198 (0.031)	-0.0200 (0.031)	-0.0209 (0.031)	-0.0198 (0.031)	-0.0200 (0.031)	-0.0209 (0.031)
Sales growth	0.00272*** (0.00086)	0.00275*** (0.00085)	0.00273*** (0.00085)	0.00396*** (0.0013)	0.00399*** (0.0012)	0.00401*** (0.0012)	0.00281*** (0.00083)	0.00284*** (0.00082)	0.00282*** (0.00083)	0.000910 (0.0012)	0.000947 (0.0012)	0.000949 (0.0012)	0.000910 (0.0012)	0.000947 (0.0012)	0.000949 (0.0012)	0.000910 (0.0012)	0.000947 (0.0012)	0.000949 (0.0012)
GDP growth	0.0134 (0.045)	0.00891 (0.046)	0.00717 (0.046)	0.00628 (0.014)	0.00535 (0.012)	0.00570 (0.011)	0.0203 (0.046)	0.0155 (0.047)	0.0138 (0.046)	0.0152 (0.012)	0.0151 (0.012)	0.0151 (0.011)	0.0152 (0.012)	0.0151 (0.012)	0.0151 (0.011)	0.0152 (0.012)	0.0151 (0.012)	0.0151 (0.011)
Firm size	-0.00251* (0.0014)	-0.00252* (0.0014)	-0.00251* (0.0014)	-0.00903*** (0.0017)	-0.00905*** (0.0017)	-0.00904*** (0.0017)	-0.00297** (0.0014)	-0.00298** (0.0014)	-0.00297** (0.0014)	-0.00970* (0.0047)	-0.00982** (0.0047)	-0.00987** (0.0047)	-0.00970* (0.0047)	-0.00982** (0.0047)	-0.00987** (0.0047)	-0.00970* (0.0047)	-0.00982** (0.0047)	-0.00987** (0.0047)
Leverage	-0.0321*** (0.0051)	-0.0320*** (0.0051)	-0.0321*** (0.0051)	-0.0290** (0.011)	-0.0281** (0.011)	-0.0272** (0.011)	-0.0308*** (0.0048)	-0.0307*** (0.0048)	-0.0308*** (0.0048)	-0.0449*** (0.010)	-0.0443*** (0.0099)	-0.0441*** (0.010)	-0.0449*** (0.010)	-0.0443*** (0.0099)	-0.0441*** (0.010)	-0.0449*** (0.010)	-0.0443*** (0.0099)	-0.0441*** (0.010)
National climate effort	-0.000825** (0.00035)	-0.000991** (0.00040)	-0.00112** (0.00046)	-0.000200 (0.00019)	-0.000536** (0.00026)	-0.00116*** (0.00033)	-0.000774** (0.00035)	-0.000990** (0.00039)	-0.00116** (0.00044)	-0.000108 (0.00014)	-0.000230 (0.00018)	-0.000502*** (0.00017)	-0.000108 (0.00014)	-0.000230 (0.00018)	-0.000502*** (0.00017)	-0.000108 (0.00014)	-0.000230 (0.00018)	-0.000502*** (0.00017)
Observations	5779	5779	5779	1942	1942	1942	6479	6479	6479	1242	1242	1242	6479	6479	6479	1242	1242	1242
R ²	0.419	0.419	0.419	0.645	0.646	0.649	0.431	0.431	0.431	0.524	0.524	0.525	0.431	0.431	0.431	0.524	0.524	0.525
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the estimation results of model specification (4.1) using two sample splits: (A) by firm size, and (B) by firm type. The dependent variable is the investment rate, measured by CAPEX/lagged Total Assets. The data are quarterly and cover the period from January 2009 to December 2021. All independent variables are lagged by one period with respect to the dependent variable (see 4.6.1 for variable definitions). Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4.4: Effect of national climate policy effort on investors' climate change concerns

		All climate policies	Mitigation policies	Energy sector policies
Log questions length	1.426*** (0.22)	1.384*** (0.20)	1.406*** (0.20)	1.390*** (0.20)
Tobin's q	0.0981 (0.44)	0.0163 (0.44)	0.0612 (0.44)	0.0970 (0.43)
Cash flow	-8.958*** (2.45)	-8.951*** (2.39)	-8.989*** (2.51)	-8.483*** (2.50)
Sales growth	-0.252** (0.13)	-0.241* (0.13)	-0.268** (0.12)	-0.251** (0.12)
GDP growth	3.815 (4.89)	3.274 (5.21)	3.421 (5.23)	3.126 (5.22)
Leverage	0.156 (1.27)	0.165 (1.21)	0.132 (1.21)	0.102 (1.21)
Firm size	0.164 (0.27)	0.127 (0.26)	0.151 (0.26)	0.193 (0.26)
National climate effort		0.0580** (0.027)	0.0694** (0.032)	0.137*** (0.046)
Observations	2142	2142	2142	2142
Pseudo R^2	0.387	0.389	0.389	0.391
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Clustered by firm	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes

Note: This table presents the results of PPML regressions using the number of climate change bigrams in investors' questions from quarterly earnings call transcripts as the dependent variable. The data are quarterly and cover the period from January 2009 to December 2021. Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

earnings conference call. We regress this proxy on financial variables and NCE using PPML regressions because a majority of earnings conference calls do not mention a single climate change-related bigram. We also control for total question length in our regressions. Results are reported in Table 4.4. Consistent with the intuition that NCE increases companies' exposure to climate transition risk, we find that investors' concerns about a firm's climate change exposure significantly increase following an increase in NCE. Consequently, the negative effect of NCE on oil and gas investment can be explained by an increase in the risk of stranded assets associated with irreversible investments.

4.4.3 Effect of global climate efforts

We next investigate the effect of global climate policy effort (GCE) on oil and gas investment. GCE is computed as the excess number of climate policies passed worldwide in the previous four quarters. As with NCE, we use three alternative methods to compute GCE using all climate policies, climate mitigation policies only, and energy-sector targeted climate policies only, respectively. Table 4.5 reports the estimation results of model (4.2). Contrary to the case of NCE, we find a positive and statistically significant relationship between the GCE measure computed using mitigation policies only and oil and gas investment rates. However, the effect is lower in magnitude compared to NCE.

Table 4.5: Effect of global climate policy effort on oil and gas investment rate

Dependent Variable:	CAPEX/lagged Total Assets		
	All climate policies	Mitigation policies	Energy sector policies
Oil price uncertainty	−0.00328*** (0.00077)	−0.00337*** (0.00075)	−0.00339*** (0.00077)
GEPU	−0.00425* (0.0023)	−0.00420* (0.0023)	−0.00405* (0.0023)
Tobin's q	0.0132*** (0.0016)	0.0130*** (0.0016)	0.0132*** (0.0016)
Cash flow	0.0616*** (0.018)	0.0584*** (0.018)	0.0596*** (0.018)
Sales growth	0.00311*** (0.00095)	0.00307*** (0.00095)	0.00305*** (0.00096)
GDP growth	−0.0750*** (0.019)	−0.0813*** (0.024)	−0.0781*** (0.020)
Firm size	−0.00292** (0.0013)	−0.00291** (0.0013)	−0.00291** (0.0013)
Leverage	−0.0385*** (0.0052)	−0.0380*** (0.0050)	−0.0382*** (0.0051)
National climate effort	−0.000723** (0.00030)	−0.00103** (0.00038)	−0.00131*** (0.00047)
Global climate effort	0.0000484 (0.000031)	0.0000901** (0.000036)	0.0000583 (0.000049)
Observations	7721	7721	7721
R^2	0.413	0.415	0.413
Firm FE	Yes	Yes	Yes
Time FE	No	No	No
Clustered by firm	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes

Note: This table presents the estimation results of model specification (4.2). The dependent variable is the investment rate, measured by CAPEX/lagged Total Assets. The data are quarterly and cover the period from January 2009 to December 2021. All independent variables are lagged by one period with respect to the dependent variable (see 4.6.1 for variable definitions). Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

In terms of economic magnitude, the passing of one additional climate mitigation policy in excess of the global trend is associated with a 0.3% increase in conditional investment rates relative to the sample average.

To assess the sensitivity of this result, we also conduct a heterogeneity analysis and perform a battery of robustness tests. Table 4.6.5 in Appendix 4.6 reports the results of the heterogeneity analysis. For all sample partitioning considered, we find a positive relationship between GCE and investment rates: significant at the 5% level for small, large, and E&P companies, and at the 10% level for Integrated companies. Table 4.6.6 and Table 4.6.8 in the Appendix respectively display the results of the robustness tests related to changes in the original sample and to the use of alternative measures of corporate investment, yielding qualitatively similar results.

Our results suggest that oil and gas companies increase their investment in response to high

climate policy activity outside their country of headquarters. We propose the following mechanism to explain this finding: while firms located in countries with high climate policy effort reduce their fossil fuel investments, those in countries with weak or no climate policy effort, and therefore less exposed to stranded asset risks, have incentives to increase their investments in fossil energy due to the sustained global demand for fossil fuels. To test this mechanism, we consider the following specification:

$$\begin{aligned}
 INV_{i,j,t} = & \alpha_i + \gamma M_{t-1} + \beta_1^+ GCE_{t-1} \times \mathbb{1}_{j,t}^+ + \beta_1^- GCE_{t-1} \times \mathbb{1}_{j,t}^- + \beta_2 NCE_{j,t-1} + \beta_3 Q_{i,t-1} \\
 & + \beta_4 CF_{i,t-1} + \beta_5 SG_{i,t-1} + \beta_6 Size_{i,t-1} + \beta_7 Lev_{i,t-1} + \beta_8 \% \Delta GDP_{j,t-1} + \varepsilon_{i,t},
 \end{aligned} \tag{4.3}$$

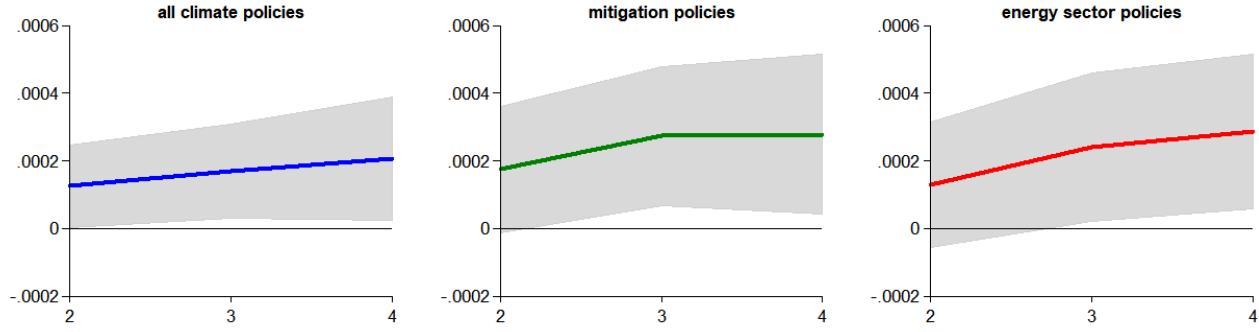
where the indicator variable $\mathbb{1}_{j,t}^-$ ($\mathbb{1}_{j,t}^+$) takes the value one if the firm's country of headquarters has weak (high) climate effort and zero otherwise. Unlike Equation (4.2), this specification allows the effect of GCE to interact with the level of climate policy effort in the firm's country of headquarters. According to the postulated mechanism, the coefficient β_1^- should be positive and higher in magnitude relative to the coefficient β_1^+ . To construct the indicator variables, we apply the following rule: in a given quarter, a country is classified as having weak climate policy effort if it did not pass a single climate policy in the previous h years. Conversely, countries that have passed at least one climate policy in the previous h years are classified as having high climate policy effort.

This figure displays the estimates associated with specification (4.3). Figure (a) shows the estimates of coefficient β^- , which measures the effect of global climate policy effort on the fossil fuel investments of firms located in countries with weak climate policy efforts. Figure (b) shows the estimates of coefficient β^+ , which measures this effect for firms located in countries with high climate policy efforts. The x-axis represents the minimum number of consecutive years without passing a climate policy for a country to be classified as having weak climate efforts. The shaded area corresponds to the bands of a 95% point-wise confidence interval.

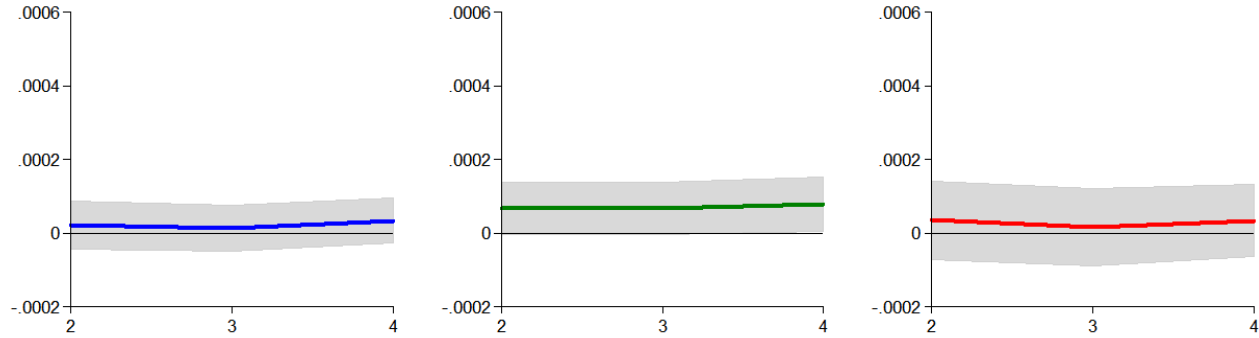
Figure 4.2 displays the estimates of coefficients β_1^- and β_1^+ using values of h ranging from two to four years. In line with the proposed mechanism, we find that the positive effect of GCE is more pronounced for firms headquartered in countries with low climate policy effort. This effect is statistically significant in most cases and increases with the number of years without passing a single climate policy. When considering the case $h = 3$, the increase in conditional investment rates ranges from 0.5% to 0.8% for an additional climate policy in excess of the global trend. In contrast, we find little evidence of a positive effect of GCE on oil and gas investment rates for firms located in countries with high climate policy effort, as the estimate is statistically non-significant in most instances.

Figure 4.2: Effect of global climate policy effort on oil and gas investment rate

(a) Weak national climate policy effort



(b) High national climate policy effort



Note: This figure displays the estimates associated with specification (4.3). Figure (a) shows the estimates of coefficient β^- , which measures the effect of global climate policy effort on the fossil fuel investments of firms located in countries with weak climate policy efforts. Figure (b) shows the estimates of coefficient β^+ , which measures the effect of global climate policy effort on the fossil fuel investments of firms located in countries with high climate policy efforts. The x-axis represents the minimum number of consecutive years without passing a climate policy for a country to be classified as having weak climate efforts. The shaded area corresponds to the bands of a 95% point-wise confidence interval.

4.5 Conclusion

The current climate governance is characterized by the implementation of demand-side climate policies aimed at reducing economies' reliance on fossil energy, with climate policy efforts varying across nations. This paper examines the impact of climate policies on fossil investments using an international panel of 207 oil and gas companies operating in the extractive sector, located in 30 countries, over the period 2009-2021. Our results indicate that oil and gas companies decrease their fossil capital investments following an increase in the climate policy effort of their country of headquarters, due to a heightened risk of stranded assets. The effect is economically significant and more pronounced for larger firms, and is robust to the use of alternative measures of corporate investment. However, we find evidence that following periods of high global climate policy effort, oil and gas companies located in countries with weak or nonexistent climate policy efforts, and thus less exposed to the risks of stranded assets, increase their fossil investments.

In terms of policy implications, this study highlights the need for sustained national efforts to achieve a transition towards a low-carbon economy in order to slow down fossil resource extraction. However, coordinated efforts across nations are necessary to effectively mitigate climate change. More broadly, interactions between unsynchronized national and international policies could delay the alignment of financial flows with environmental objectives. Our research also indicates that investors' evaluation of stranded asset risk is strongly influenced by the policy-making effort to mitigate climate change. Further research could assess whether the reduction in fossil energy investment observed in countries with a strong climate policy effort has been offset by sufficient investments in alternative sources of energy. Additionally, further research could explore the effects on future fossil investments by the recent invasion of Ukraine and the associated oil price shock, which may have delayed the climate policy effort.

4.6 Appendix: Additional Tables and Figures

Table 4.6.1: Variables definitions

Variable	Definition
Investment rate	Capital expenditures scaled by lagged total assets.
Tobin's q	Market value of equity plus book value of liabilities divided by book value of assets.
Cash flow	Operating cash flows scaled by lagged total assets.
Sales growth	Year-on-year growth in quarterly sales.
GDP growth	Quarterly real GDP growth of the firm's headquarters country..
Firm size	Natural logarithm of total assets.
Leverage	Total debt divided by total assets.
Oil price uncertainty	Natural logarithm of the quarterly realized volatility of crude oil daily log-returns.
GEPU	Natural logarithm of the global economic policy uncertainty index from Davis (2016).
National climate effort	The number of climate policies passed in the firm's headquarters country during the previous four quarters. Three versions of this indicator are calculated using: all climate policies, only mitigation policies, and exclusively energy sector policies.
Global climate effort	Global climate effort refer to the number of climate policies passed worldwide during the previous four quarters, detrended assuming a linear time trend. Three versions of this indicator are calculated using: all climate policies, only mitigation policies, and solely energy sector policies.

Note: This table presents the definitions of the variables used in the analysis.

Table 4.6.2: Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Median	Maximum
Investment rate	0.032	0.029	0.001	0.024	0.109
Tobin's q	1.271	0.572	0.541	1.113	2.722
Cash flow	0.025	0.028	-0.032	0.025	0.077
Sales growth	0.192	0.674	-0.653	0.044	2.080
Leverage	0.216	0.165	0.000	0.207	0.559
Firm size	20.694	3.079	11.699	20.843	27.080
GDP Growth	0.005	0.021	-0.194	0.006	0.184
Oil price uncertainty	-3.894	1.157	-5.834	-4.064	1.662
GEPU	5.116	0.363	4.547	5.059	5.947
National climate effort	1.683	2.176	0.000	1.000	18.000
Global climate effort	0.225	17.662	-50.253	5.212	32.365

Note: This table presents summary statistics for the main variables used in our analysis. The data are quarterly and extend from January 2009 to December 2021.

Table 4.6.3: Classic investment regressions

Dependent Variable:	CAPEX/lagged Total Assets				
	(1)	(2)	(3)	(4)	(5)
Tobin's q	0.0125*** (0.0014)		0.0123*** (0.0014)	0.0121*** (0.0014)	0.0114*** (0.0016)
Cash flow		0.0630*** (0.021)	0.0487** (0.019)	0.0377** (0.019)	0.0420** (0.018)
Sales growth				0.00262*** (0.00086)	0.00298*** (0.00083)
GDP growth				0.0164 (0.034)	0.00946 (0.030)
Firm size					−0.00298** (0.0013)
Leverage					−0.0320*** (0.0048)
Observations	7761	7761	7761	7721	7721
R^2	0.419	0.395	0.420	0.424	0.438
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Clustered by firm	Yes	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of the standard investment regressions. The data are quarterly and cover the period from January 2009 to December 2021. All independent variables are lagged by one period with respect to the dependent variable. Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4.6.4: Effect of national climate policy effort on oil and gas investment rate (sample robustness)

Dependent Variable:	CAPEX/lagged Total Assets								
	Panel A: excluding COVID-19			Panel B: excluding COVID-19 × excluding US			Panel C: excluding COVID-19 × excluding Canada		
	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies
Tobin's q	0.0111*** (0.0018)	0.0111*** (0.0018)	0.0111*** (0.0018)	0.0108*** (0.0021)	0.0108*** (0.0021)	0.0108*** (0.0021)	0.0115*** (0.0024)	0.0114*** (0.0024)	0.0115*** (0.0024)
Cash flow	0.0468** (0.021)	0.0467** (0.021)	0.0468** (0.021)	0.0298 (0.029)	0.0297 (0.029)	0.0296 (0.029)	0.0415 (0.025)	0.0414 (0.025)	0.0404 (0.025)
Sales growth	0.00270*** (0.00087)	0.00272*** (0.00087)	0.00273*** (0.00087)	0.00249** (0.0011)	0.00252** (0.0011)	0.00253** (0.0011)	0.00219* (0.0011)	0.00223** (0.0011)	0.00220* (0.0011)
GDP growth	0.0522 (0.054)	0.0447 (0.054)	0.0429 (0.053)	0.0928* (0.051)	0.0853 (0.051)	0.0850 (0.051)	0.0252 (0.064)	0.0197 (0.064)	0.0179 (0.063)
Firm size	-0.00310** (0.0015)	-0.00311** (0.0015)	-0.00313** (0.0015)	-0.00379** (0.0017)	-0.00383** (0.0017)	-0.00382** (0.0017)	-0.00257 (0.0024)	-0.00258 (0.0024)	-0.00257 (0.0024)
Leverage	-0.0324*** (0.0063)	-0.0323*** (0.0062)	-0.0324*** (0.0062)	-0.0285*** (0.0081)	-0.0284*** (0.0080)	-0.0286*** (0.0080)	-0.0349*** (0.0079)	-0.0348*** (0.0078)	-0.0350*** (0.0078)
National climate effort	-0.000797*** (0.00026)	-0.00111*** (0.00040)	-0.00103** (0.00040)	-0.000674** (0.00030)	-0.000898* (0.00049)	-0.000922 (0.00058)	-0.000792** (0.00033)	-0.00162*** (0.00058)	-0.00184*** (0.00063)
Observations	6404	6404	6404	4043	4043	4043	3973	3973	3973
R ²	0.449	0.449	0.448	0.428	0.428	0.428	0.504	0.505	0.505
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table replicates the findings of Table 4.2 when: (A) the COVID-19 period (years 2020-2021) is excluded from the sample, (B) both the COVID-19 period and firms located in the US are excluded, and (C) both the COVID-19 period and firms located in Canada are excluded. Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4.6.5: Heterogeneity in the effect of global climate efforts on oil and gas investment

	Panel A: Firm size						Panel B: Firm type					
	Assets ≤ \$10 billions			Assets > \$10 billions			E&P			Integrated		
	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies
Oil price uncertainty	-0.00403*** (0.00090)	-0.00414*** (0.00091)	-0.00414*** (0.00091)	-0.00195*** (0.00070)	-0.00193*** (0.00064)	-0.00192*** (0.00067)	-0.00430*** (0.00082)	-0.00441*** (0.00083)	-0.00442*** (0.00083)	-0.000296 (0.00049)	-0.000322 (0.00048)	-0.000357 (0.00053)
GEPU	-0.00359 (0.0028)	-0.00367 (0.0028)	-0.00347 (0.0028)	-0.00493** (0.0022)	-0.00493** (0.0022)	-0.00511** (0.0022)	-0.00344 (0.0026)	-0.00345 (0.0026)	-0.00328 (0.0026)	-0.00587** (0.0025)	-0.00583** (0.0025)	-0.00583** (0.0025)
Tobin's q	0.0133*** (0.0017)	0.0131*** (0.0017)	0.0133*** (0.0017)	0.00942** (0.0043)	0.00955** (0.0043)	0.00912** (0.0042)	0.0134*** (0.0017)	0.0132*** (0.0016)	0.0134*** (0.0017)	0.00331 (0.0037)	0.00295 (0.0036)	0.00318 (0.0037)
Cash flow	0.0559*** (0.019)	0.0530*** (0.019)	0.0537*** (0.019)	0.0988** (0.042)	0.0921** (0.039)	0.0969** (0.040)	0.0651*** (0.019)	0.0614*** (0.019)	0.0627*** (0.019)	0.00427 (0.036)	0.00269 (0.036)	0.00304 (0.036)
Sales growth	0.00327*** (0.00096)	0.00321*** (0.00096)	0.00318*** (0.00097)	0.000834 (0.0014)	0.000947 (0.0014)	0.00114 (0.0014)	0.00314*** (0.00095)	0.00310*** (0.00095)	0.00305*** (0.00097)	-0.000898 (0.0011)	-0.00106 (0.0012)	-0.000787 (0.0011)
GDP growth	-0.0932*** (0.027)	-0.100*** (0.033)	-0.0967*** (0.027)	-0.0478*** (0.017)	-0.0504*** (0.015)	-0.0462*** (0.015)	-0.109*** (0.025)	-0.116*** (0.029)	-0.113*** (0.025)	0.0123 (0.0093)	0.00848 (0.0100)	0.0106 (0.0097)
Firm size	-0.00251* (0.0014)	-0.00248* (0.0014)	-0.00247* (0.0014)	-0.00871*** (0.0019)	-0.00876*** (0.0019)	-0.00887*** (0.0018)	-0.00288** (0.0014)	-0.00285** (0.0013)	-0.00285** (0.0013)	-0.00988** (0.0038)	-0.0106** (0.0039)	-0.0103** (0.0038)
Leverage	-0.0388*** (0.0055)	-0.0386*** (0.0054)	-0.0388*** (0.0055)	-0.0410*** (0.012)	-0.0385*** (0.011)	-0.0388*** (0.012)	-0.0383*** (0.0053)	-0.0380*** (0.0051)	-0.0382*** (0.0052)	-0.0497*** (0.013)	-0.0495*** (0.012)	-0.0499*** (0.013)
National climate effort	-0.000841** (0.00039)	-0.00103** (0.00047)	-0.00127** (0.00057)	-0.000506** (0.00022)	-0.00106*** (0.00031)	-0.00156*** (0.00037)	-0.000924** (0.00040)	-0.00117** (0.00046)	-0.00143** (0.00056)	-0.000145 (0.00017)	-0.000360* (0.00021)	-0.000422* (0.00024)
Global climate effort	0.0000503 (0.000034)	0.0000923** (0.000041)	0.0000558 (0.000056)	0.0000463 (0.000037)	0.0000908** (0.000038)	0.0000713 (0.000048)	0.0000525 (0.000032)	0.0000955** (0.000039)	0.0000585 (0.000053)	0.0000180 (0.000045)	0.0000775* (0.000041)	0.0000597 (0.000054)
Observations	5779	5779	5779	1942	1942	1942	6479	6479	6479	1242	1242	1242
R ²	0.393	0.394	0.393	0.587	0.595	0.594	0.405	0.407	0.405	0.411	0.419	0.413
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No	No	No	No	No
Clustered by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the estimation results of model specification (4.2) using two sample splits: (A) by firm size, and (B) by firm type. The dependent variable is the investment rate, measured by CAPEX/lagged Total Assets. The data are quarterly and cover the period from January 2009 to December 2021. All independent variables are lagged by one period with respect to the dependent variable (see 4.6.1 for variable definitions). Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4.6.6: Effect of global climate policy effort on oil and gas investment rate (sample robustness)

Dependent Variable:	CAPEX/lagged Total Assets								
	Panel A: excluding COVID-19			Panel B: excluding COVID-19 × excluding US			Panel C: excluding COVID-19 × excluding Canada		
	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies
Oil price uncertainty	-0.00381*** (0.00086)	-0.00247*** (0.00091)	-0.00383*** (0.00085)	-0.00292*** (0.00098)	-0.00182* (0.0011)	-0.00289*** (0.00097)	-0.00366*** (0.00082)	-0.00200** (0.00080)	-0.00345*** (0.00083)
GEPU	-0.00273 (0.0030)	0.00212 (0.0031)	-0.00195 (0.0030)	-0.00410 (0.0033)	0.000226 (0.0037)	-0.00378 (0.0035)	-0.00273 (0.0031)	0.00287 (0.0030)	-0.00170 (0.0030)
Tobin's q	0.0132*** (0.0018)	0.0122*** (0.0017)	0.0132*** (0.0018)	0.0131*** (0.0020)	0.0121*** (0.0020)	0.0131*** (0.0021)	0.0128*** (0.0025)	0.0120*** (0.0024)	0.0127*** (0.0025)
Cash flow	0.0709*** (0.021)	0.0680*** (0.021)	0.0703*** (0.021)	0.0466 (0.029)	0.0482* (0.029)	0.0464 (0.029)	0.0682** (0.027)	0.0622** (0.027)	0.0663** (0.027)
Sales growth	0.00321*** (0.00100)	0.00305*** (0.00096)	0.00323*** (0.0010)	0.00307** (0.0011)	0.00287** (0.0011)	0.00310** (0.0012)	0.00246** (0.0012)	0.00230** (0.0011)	0.00243** (0.0012)
GDP growth	-0.0601 (0.067)	-0.0659 (0.063)	-0.0764 (0.065)	0.0216 (0.072)	0.0558 (0.068)	0.0103 (0.073)	-0.114 (0.075)	-0.114 (0.069)	-0.142* (0.074)
Firm size	-0.00309** (0.0015)	-0.00316** (0.0014)	-0.00307** (0.0014)	-0.00404** (0.0017)	-0.00415** (0.0016)	-0.00400** (0.0017)	-0.00246 (0.0024)	-0.00246 (0.0024)	-0.00251 (0.0024)
Leverage	-0.0408*** (0.0067)	-0.0381*** (0.0064)	-0.0407*** (0.0067)	-0.0374*** (0.0087)	-0.0345*** (0.0082)	-0.0374*** (0.0087)	-0.0423*** (0.0081)	-0.0405*** (0.0080)	-0.0424*** (0.0080)
National climate effort	-0.000837*** (0.00031)	-0.000829* (0.00044)	-0.000926* (0.00049)	-0.000553* (0.00030)	-0.000601 (0.00048)	-0.00048 (0.00054)	-0.000926*** (0.00030)	-0.00118** (0.00047)	-0.00157*** (0.00058)
Global climate effort	0.0000484 (0.000045)	0.000266*** (0.000069)	0.000108 (0.000066)	0.0000367 (0.000055)	0.000227** (0.000088)	0.0000795 (0.000081)	0.0000415 (0.000047)	0.000284*** (0.000063)	0.000121* (0.000064)
Observations	6404	6404	6404	4043	4043	4043	3973	3973	3973
R ²	0.425	0.432	0.425	0.398	0.403	0.398	0.479	0.487	0.480
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No	No
Clustered by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table replicates the findings of Table 4.5 when: (A) the COVID-19 period (years 2020-2021) is excluded from the sample, (B) both the COVID-19 period and firms located in the US are excluded, and (C) both the COVID-19 period and firms located in Canada are excluded. Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4.6.7: Effect of national climate policy effort on oil and gas investment rate (alternative measures of investment)

Dependent Variable:	Panel A: CAPEX/lagged PPE			Panel B: PPE Growth		
	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies
Tobin's q	0.0125*** (0.0018)	0.0125*** (0.0018)	0.0125*** (0.0018)	0.0241*** (0.0044)	0.0240*** (0.0044)	0.0240*** (0.0044)
Cash flow	0.0673*** (0.024)	0.0671*** (0.024)	0.0674*** (0.024)	0.137** (0.064)	0.136** (0.064)	0.135** (0.064)
Sales growth	0.00246** (0.0011)	0.00248** (0.0011)	0.00250** (0.0011)	0.00691** (0.0027)	0.00697** (0.0027)	0.00694** (0.0027)
GDP growth	0.0603 (0.066)	0.0527 (0.067)	0.0499 (0.065)	0.160 (0.31)	0.133 (0.30)	0.132 (0.30)
Firm size	−0.00329* (0.0017)	−0.00330* (0.0017)	−0.00331* (0.0017)	−0.0109*** (0.0034)	−0.0109*** (0.0034)	−0.0110*** (0.0034)
Leverage	−0.0424*** (0.0078)	−0.0422*** (0.0077)	−0.0424*** (0.0078)	−0.0535** (0.020)	−0.0529** (0.020)	−0.0526** (0.020)
National climate effort	−0.000814** (0.00035)	−0.00116** (0.00053)	−0.000895 (0.00053)	−0.00305* (0.0016)	−0.00449** (0.0022)	−0.00529** (0.0025)
Observations	6395	6395	6395	6354	6354	6354
R^2	0.432	0.432	0.432	0.239	0.239	0.239
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by firm	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table replicates the results of Table 4.2, excluding the COVID-19 period and using two alternative measures of corporate investment: A) CAPEX/lagged PPE and B) Forward PPE growth. Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4.6.8: Effect of global climate policy effort on oil and gas investment (alternative measures of investment)

Dependent Variable:	Panel A: CAPEX/lagged PPE			Panel B: PPE Growth		
	All climate policies	Mitigation policies	Energy sector policies	All climate policies	Mitigation policies	Energy sector policies
Oil price uncertainty	−0.00426*** (0.0011)	−0.00237* (0.0012)	−0.00426*** (0.0011)	−0.00120 (0.0056)	0.00228 (0.0057)	−0.000258 (0.0054)
GEPU	−0.00415 (0.0037)	0.00243 (0.0038)	−0.00316 (0.0038)	0.00519 (0.018)	0.0169 (0.021)	0.0109 (0.018)
Tobin's q	0.0156*** (0.0019)	0.0143*** (0.0018)	0.0156*** (0.0019)	0.0293*** (0.0052)	0.0271*** (0.0049)	0.0290*** (0.0052)
Cash flow	0.0987*** (0.026)	0.0955*** (0.025)	0.0985*** (0.025)	0.184** (0.071)	0.184** (0.073)	0.191** (0.074)
Sales growth	0.00341*** (0.0012)	0.00320*** (0.0011)	0.00345*** (0.0012)	0.0128*** (0.0037)	0.0127*** (0.0036)	0.0130*** (0.0037)
GDP growth	−0.0692 (0.083)	−0.0780 (0.078)	−0.0920 (0.082)	−0.361 (0.37)	−0.431 (0.41)	−0.479 (0.40)
Firm size	−0.00331* (0.0017)	−0.00341** (0.0016)	−0.00328* (0.0017)	−0.0173*** (0.0046)	−0.0176*** (0.0044)	−0.0175*** (0.0045)
Leverage	−0.0546*** (0.0084)	−0.0510*** (0.0080)	−0.0546*** (0.0083)	−0.0810*** (0.019)	−0.0766*** (0.018)	−0.0816*** (0.019)
National climate effort	−0.000869** (0.00039)	−0.000777 (0.00055)	−0.000741 (0.00059)	−0.00363* (0.0020)	−0.00216 (0.0031)	−0.00464 (0.0039)
Global climate effort	0.0000537 (0.000054)	0.000359*** (0.000088)	0.000145* (0.000081)	0.0000257 (0.00019)	0.000605* (0.00032)	0.000342 (0.00031)
Observations	6395	6395	6395	6354	6354	6354
R^2	0.402	0.412	0.403	0.141	0.143	0.142
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No
Clustered by firm	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by time	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table replicates the results of Table 4.5, excluding the COVID-19 period and using two alternative measures of corporate investment: A) CAPEX/lagged PPE and B) Forward PPE growth. Robust standard errors, clustered by firm and time, are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

General Conclusion

General Conclusion

This thesis proposes four original contributions to the burgeoning academic literature on sustainable finance. The first part of the thesis focuses on ESG ratings, which aim to capture a company's exposure to long-term risks and opportunities related to environmental, social, and governance factors. ESG ratings have faced significant criticisms due their high level of disagreement and the confusion regarding what they truly measure (Berg, Koelbel and Rigobon, 2022; Pucker and King, 2022). Chapters 1 and 2 propose methodologies that aim at overcoming some of these limitations. The second part of the thesis adopts a broader perspective on organizational behavior and investment flows in the context of increasing efforts to address climate change. Chapter 3 explores organizations' strategic responses to the threat posed by climate activist movements, while Chapter 4 proposes an empirical investigation on the ability of the current climate governance to slow down fossil resource extraction.

Chapter 1 develops a backtesting procedure that allows for the evaluation of ESG ratings in a panel data setting. The backtest is based on a predictive approach, as it assumes that informative ESG ratings should help in forecasting a target variable of interest. Our procedure evaluates ESG ratings by comparing the forecasting abilities of two nested models that differ solely in the inclusion or exclusion of ESG ratings within the set of predictor variables. In this setting, our null hypothesis of a lack of informational content in ESG ratings is defined as the equality in forecast accuracy between the two nested models, implying that integrating ESG ratings among predictor variables does not improve forecasts of the target variable. We apply our methodology to the forecasting of companies' idiosyncratic risk and evaluate the ESG rating systems of two leading agencies across three investment universes (Europe, North America, Asia-Pacific). Our results indicate that the informativeness of ESG ratings strongly depend on the location of companies' headquarters and on the rating component. ESG ratings are more informative of companies' idiosyncratic risk for firms located in Europe and when considering their environmental component. Importantly, we find that the forecasting power of ESG ratings increases with the degree of consensus between rating agencies.

Chapter 2 tackles the reverse problem of using supervised learning to construct ESG ratings in

an optimal fashion. The proposed methodology enables the aggregation of granular ESG metrics into an overall rating. As it relies on supervised learning, the approach requires the specification of a target variable to produce ratings. The choice of the appropriate target variable should be consistent with the end-user’s motivation for using extra-financial information. We show how supervised ESG ratings can be produced by jointly estimating a predictive model of the target variable and a weighting scheme that allows for the aggregation of granular ESG metrics into an overall rating. As the proposed methodology inherently requires the specification of a target variable, it has the notable advantage of alleviating any confusion about what ESG ratings aim to measure, contrary to methodologies founded on unsupervised learning. We demonstrate the effectiveness of our approach by applying the methodology to a large panel dataset containing granular ESG data. We focus on two target variables: firm idiosyncratic risk and ESG controversies. Our results indicate that the methodology can produce ratings with significantly greater explanatory power for forecasting firms’ idiosyncratic risk than the ratings from a leading rating agency. However, they also suggest that information from extra-financial reporting has limited usefulness in forecasting companies’ involvement in ESG controversies.

Chapter 3 investigates organizations’ strategic responses to the threat of climate activists through a case study on a French climate movement led by elite *Grandes Écoles* students who threatened to boycott job offers from polluting employers. Owing to its widespread success and media coverage, the initiative raised concerns about the ability of numerous large French companies to attract highly-skilled human capital. Through the analysis of a unique survey database on climate movement participants, this chapter explores how corporate environmental pledges could help mitigate such negative impacts on organizational attractiveness. Taking advantage of a survey with repeated measurements of students’ intentions to refuse to work for polluting companies, we use machine learning classifiers to compute an individual-level measure of the extent to which corporate environmental pledges can deter these intentions. While most respondents intend to boycott job offers from polluting companies, they are, on average, three times less likely to have these intentions after being exposed to an environmental pledge. However, we observe substantial heterogeneity in students’ reactions to environmental pledges primarily explained by career perspectives and beliefs about the ecological crisis. This chapter demonstrates the growing stakeholder demand on polluting companies to take climate action, as well as their exposure to risks related to attracting human capital. Our findings highlight that polluting companies could at least temporarily address this issue by pledging to improve their environmental impact. Hence, normative pressures on polluting companies to take climate action, combined with an institutional setting that fails to ensure accountability for their commitments, makes it difficult to distinguish genuine efforts from empty promises.

Chapter 4 examines the capacity of current climate governance, characterized by the implementation of demand-side and sub-global climate policies, to slow down fossil resource extraction. The limitations of such climate governance have been explored by an important theoretical literature. This literature emphasizes the contrasting influences of different mechanisms, such as green paradox effects (Sinn, 2008), stranded assets risk (Fried et al., 2022), and carbon leakage (Carbone and Rivers, 2017). However, there are few empirical studies on this topic. Chapter 4 proposes an empirical investigation of investment flows into fossil energy infrastructures under climate policy. Our analysis is based on a panel dataset covering capital expenditures on oil and gas extractive companies located in 30 countries, representing a quarter of the world's proven oil and gas reserves. The econometric methodology relies on investment regressions incorporating two new proxies for national and global policy-making efforts to combat climate change. Our results suggest that oil and gas companies significantly reduce their investments following an increase in their headquarters' country's climate policy effort, a result that we find to be explained by a rise in the climate transition risk exposure of these firms. However, our findings also suggest the existence of a "fossil investment leakage", as investments by firms located in countries with weak or no climate policy efforts, and therefore less exposed to stranded asset risks, increase following periods of high global climate policy efforts. This chapter emphasizes the importance of the climate policy-making effort, but also the limitations of fragmented climate governance, in order to effectively mitigate climate change.

The scope of the results of this thesis is as follows. The findings from the first two chapters first highlight the challenges associated with constructing corporate sustainability rating systems. This point is notably emphasized by the results of Chapter 2, underscoring the limited relevance of information derived from non-financial reporting for predicting real variables. On the other hand, the significance of companies' headquarters' location in integrating ESG factors into asset prices demonstrates that mere information transparency is insufficient to steer investment flows toward financing sustainable activities. This point is further supported by the empirical results of Chapter 4, identifying the key role of policymakers in anchoring agents' expectations towards aligning financial flows with the climate objectives of the Paris Agreement. If sustainable finance aims to redirect capital allocation towards environmentally and socially sustainable activities, this thesis thus underscores that it cannot escape from public action that would allow integrating negative externalities into the valuation of financial assets. This is reaffirmed by the current way ESG factors are integrated into investment decisions, from the perspective of financial materiality, a situation motivated by the fiduciary duty of asset managers to their clients. A direct implication is that a significant portion of ecological damages caused by economic activity is probably not yet integrated into asset prices. This is supported by blind spots in ESG databases used in this

research, as observed by the author. Notable examples include the absence of metrics related to companies' impacts on ecosystems, land use, soil pollution, or marine pollution. Future research should aim to fill these blind spots on a scientific basis, with the construction of metrics related to environmental impacts guided by the framework of planetary boundaries and those related to social impacts by research on well-being and human health. Once such an evaluation system is constructed, we posit that governmental action conditioning the allocation of public subsidies on compliance with « *ESG* » requirements would allow to better approach the goals of sustainable investment as defined by the European Commission.

The second part of the thesis, comprising Chapters 3 and 4, focuses on the behavior of organizations and investment flows in the face of climate change. Chapter 3 explores the impact of societal pressures on transforming the business model of polluting companies. A key result is demonstrating the importance of environmental communication by large companies to mitigate the negative impact of social movements related to climate change. Consequently, this research suggests that the transition of polluting companies to environmentally sustainable business models cannot occur through mechanisms such as boycotts. Although such incentive mechanisms may influence the behavior of private organizations and their environmental policies, these adjustments would only occur marginally due to the importance of economic imperatives and the scale of transformations required to limit the ecological impact of the most polluting sectors. Finally, the results of Chapter 4 question the current climate governance's ability to reduce investment in new fossil energy extraction projects, while recent research highlights the incompatibility of fossil energy sector investment plans with the goals of the Paris Agreement (Kühne et al., 2022). In this sense, our empirical results support the implementation of policies restricting the supply of fossil energy, such as an international treaty on fossil energy non-proliferation (Newell and Simms, 2020), to effectively mitigate climate change.

At the conclusion of this thesis, several points could become the subject of future developments. First, as discussed, future research could investigate how to incorporate new sources of information to more accurately assess companies' environmental and social impacts. Potential research avenues could include the use of geospatial data combined with ownership information (Caldecott et al., 2022), the use of input-output tables (Trucost et al., 2013), the integration of recent developments on double materiality frameworks (Wassénus et al., 2023), or data on working conditions. Second, in light of the insights from Chapter 3 and the surge in net-zero emissions plans, future research could develop methodologies to identify credible corporate climate pledges. If successful, these methodologies could be used to construct credible net-zero portfolios. Such portfolios would have the dual benefit of serving investors looking to control their exposure to the risk of increase in carbon prices and reducing the cost of capital for companies taking concrete climate action. Finally,

Chapter 4 underscores the significance of climate policies in shaping both investment flows and investor expectations. Thus, we might expect the policy context to be a critical factor influencing ESG investment performance and the engagement of institutional investors in addressing ESG issues. Noteworthy examples include the recent anti-ESG movement in the United States, or the decrease in BlackRock's support for climate-related shareholder proposals following the invasion of Ukraine.⁵ Early evidence on this topic includes the studies of Stroebe and Wurgler (2021) and Pástor et al. (2022). Future empirical and theoretical research could thus explore this question in greater depth.

⁵<https://www.blackrock.com/corporate/literature/publication/commentary-bis-approach-shareholder-proposals.pdf>

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Daniel-Wassim LE LANN

Quatre essais sur la finance durable

Résumé :

Cette thèse contribue au champs de recherche émergeant sur la finance durable. La première partie de la thèse vise à adresser certaines des critiques soulevées par les investisseurs, régulateurs, et autre parties prenantes, sur les notations ESG. Le Chapitre 1 développe ainsi un backtest permettant d'évaluer les notations ESG. Nos applications empiriques indiquent que la qualité de l'information contenue dans ces notations dépend fortement de la localisation des entreprises et du niveau de consensus entre agences de notations. Le Chapitre 2 propose une méthodologie de construction des notations ESG fondée sur l'apprentissage supervisé. La méthodologie a l'avantage important d'éliminer toute confusion sur ce que ces notations mesurent réellement. Nos applications empiriques démontrent son intérêt, mais aussi les limites de l'information contenue dans les rapports RSE pour prédire les controverses ESG. Les résultats de ces deux chapitres soulignent les difficultés considérables liées à l'objectif de bâtir des systèmes de mesure crédibles de la durabilité des organisations. La seconde partie de la thèse adopte une perspective plus large sur le comportement des organisations et les flux d'investissement à l'aune du changement climatique. Le Chapitre 3 examine la réponse stratégique des organisations menacées par l'activisme climatique à travers l'étude d'un mouvement climat initié par des étudiants de grandes écoles menaçant de boycotter les employeurs polluant. Tandis que l'initiative a soulevé des inquiétudes sur la capacité des grandes entreprises à attirer du capital humain hautement qualifié, nous montrons que les entreprises polluantes pourraient, au moins temporairement, atténuer cette difficulté en promettant d'améliorer leur impact environnemental. Le Chapitre 4 examine la capacité de la gouvernance climatique actuelle à ralentir l'extraction de ressources fossiles à travers une étude empirique des flux d'investissement dans le secteur pétrolier. Nos résultats démontrent l'importance des politiques climatiques, mais également les limites d'une gouvernance climatique fragmentée, pour atténuer le changement climatique.

Mots clés : Econométrie; Machine learning; Finance; Finance durable; Notations ESG; Risques ESG; Mouvements climat; Greenwashing; Comportement des organisations; Investissements fossiles; Gouvernance climatique; Politiques climatiques; Actifs échoués; Risque de transition.

Four essays on sustainable finance

Abstract:

This thesis contributes to the burgeoning research field of sustainable finance. The first part of the thesis aims to address some of the criticisms raised by investors, regulators, and stakeholders on ESG ratings. Chapter 1 develops a backtest methodology to evaluate ESG ratings. Our empirical applications indicate that the informativeness of ESG ratings strongly depends on the location of firms' headquarters and the level of consensus among rating agencies. Chapter 2 proposes a new methodology for the production of ESG ratings based on supervised learning. The methodology has the advantage of eliminating any confusion regarding what ESG ratings truly measure. Our empirical applications highlight its usefulness, but also the limitations of using information from sustainability reports to predict corporate irresponsible behavior. The findings of Chapter 1 and Chapter 2 demonstrate the considerable challenges involved in building accurate measurement systems for corporate sustainability. The second part of the thesis takes a broader perspective on organizational behavior and investment flows in the context of climate change. Chapter 3 investigates organizations' strategic responses to the threat of climate activists through a case study of a French elite student climate movement that threatened to boycott polluting employers. While the initiative has raised concerns about the ability of large companies to attract human capital, our findings indicate that polluting firms could, at least temporarily, address this challenge by committing to improve their environmental impact. Chapter 4 examines the capacity of current climate governance to slow down fossil resource extraction through an empirical investigation of investment flows into fossil energy infrastructures. Our results emphasize the importance of climate policy-making, but also the limitations of fragmented climate governance, in effectively mitigating climate change.

Keywords: Econometrics; Machine learning; Finance; Sustainable finance; ESG ratings; ESG risks; Climate activism; Greenwashing; Organizational behavior; Fossil investments; Climate governance; Climate policy; Stranded assets; Climate transition risk.