# How Much Do Workers Care About Corporate Social Responsibility?

## Compensating Differentials and Sorting Implications of Firm Sustainability Ratings

Amedeo Zorzi

*Toulouse School of Economics*

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[PRELIMINARY AND INCOMPLETE]

**Abstract**

Corporate Social Responsibility (CSR) refers to firm-level initiatives that improve environmental performance, social outcomes, or governance and now underpins a global asset market exceeding $30 trillion. I argue that an important, understudied driver of CSR's rise is that sustainability has become a valued job attribute, turning CSR into a strategic tool for attracting and retaining talent. To quantify this mechanism, I develop a labor market model in which workers' utility depends on firms' CSR choices and estimate it using a matched employer–employee dataset covering all French firms combined with detailed CSR metrics for the period between 2002 and 2021. Importantly, my framework accounts for unobserved worker and firm heterogeneity in productivity, mitigating biases in simple wage comparisons. Two-way fixed effect estimates show that a standard deviation increase in a firm's sustainability score is associated with a 3 to 11% reduction in hourly wages in later years of my sample period. The estimated relationship varies significantly over time and across firms, suggesting heterogeneous incentives to engage in CSR. This also implies that policies aimed at stimulating CSR investment can affect wage-setting and workforce composition, and should be designed taking firm labour-related motives into account.

# 1 Introduction

Corporate Social Responsibility (CSR) designates any type of corporate initiative which aims at improving a firm's environmental impact, fostering a safe, inclusive and diverse workplace environment and making internal decision-making processes fair and transparent. Despite the investment that it requires, Corporate Social Responsibility has been gathering considerable momentum over the recent years and businesses all around the world are striving to adopt sustainability initiatives. Rajan, Ramella, and Zingales (2023) show, for example, that the percentage of companies mentioning environmental and diversity related objectives in their shareholder letter has risen from 20% in 1980 to 90% in 2020. At the same time, Environment Social and Governance (ESG) rankings, which are measures of CSR performance produced by third-party rating agencies, have taken increasingly more space in investors' decisions. According to Bloomberg, total ESG assets worldwide reached $30 trillion in 2022 are projected to surpass $40 trillion by 2030, which would represent about 25% of total assets under management. These figures raise an obvious question: why would profit-driven companies engage in CSR activities at all, given that they are costly?

Many possible explanations can justify the adoption of CSR practices by the firm. For instance, the fact that companies might care about CSR because of shareholder or consumer activism is well established (Broccardo, Hart, and Zingales, 2022; Gollier and Pouget, 2022; Oehmke and Opp, 2025; Leonidou, Katsikeas, and Morgan, 2013). Less attention has, however, been given to another important mechanism that could explain the rise of ESG in the corporate world, namely workers' preferences and their impact on employment decisions (Edmans, 2012; Edmans et al., 2024). Indeed, one may not only want to buy green products and invest in ESG assets, but also work for a socially responsible company. Job-seekers might preferentially look for green companies and potentially even accept a lower salary to work in a firm that is deemed more sustainable. Corporate sustainability, as measured by ESG scores, could then be perceived as a workplace amenity. If this is the case, investing to improve a company's social and environmental impact would become a way to attract and retain talent.

In this paper, I aim to quantify the importance of labor cost savings due to firm sustainability and their impact on firm incentives to adopt CSR policies. In particular, I leverage rich matched employer-employee data from France to estimate a model of the labour market where workers' utility is allowed to depend on their company's CSR level, as measured by their firm ESG Score. The framework

allows for unobserved heterogeneity both in firm and worker productivity, so that it can capture differing sensitivities to corporate responsibility across worker types and can therefore accommodate rich patterns of labour market sorting. Also, I show that not accounting for unobserved differences in productivity might lead to biases in standard wage regressions. My empirical strategy proceeds in two steps, progressively adding more structure. I start by implementing the classical two-way fixed effect regression framework of Abowd, Kramarz, and Margolis (1999) with the correction of Kline, Saggio, and Sølvsten (2020) to get an initial estimate of the average compensating differential at different points in time, under specific functional forms and strong assumptions on unobservables. Then, I relax these assumptions, by exploiting the structure of matched employer-employee data, through a group fixed effect approach and additional moment conditions derived from the model that allow to recover the full parameter space (Bonhomme, Lamadon, and Manresa, 2019; Lamadon, Mogstad, and Setzler, 2022).

My results shed light on three aspects. First, I recover workers' preferences directly exploiting my theoretical framework and information on their observed wage and employment choices, I characterize the magnitude of the compensating differential and its trend in time. Evidence from surveys and experimental studies on online job search platforms suggests that workers indeed might accept lower salaries to work in a company that mentions CSR engagement in its job offers (Burbano, 2016; Colonnelli et al., 2024; Climate Vault Solutions, 2023). Only one study, however, directly estimates the compensating differential associated with CSR from observational data, relying on matches between ESG leader and laggard firms by industry, under the assumption that skill is observed and that firms have comparable productivity (Krueger, Metzger, and Wu, 2023). I contribute to this stream of literature by providing the first attempt, to the best of my knowledge, at estimating wage differences from historical data using a model of the labour market that includes CSR amenities. Importantly, I offer an approach that enables the estimation of the wage penalty associated to CSR in the absence of a reliable proxy for worker skill and allowing for unobserved differences in firm productivity. This is particularly crucial because ignoring such heterogeneity when it is there can introduce bias in simple wage regressions.

Unobserved differences across workers and firms also play a key role in shaping how corporate sustainability ratings affect labor market sorting. A main source of difficulty in the estimation of labour market models is that the econometrician usually does not observe how the set of available job offers

varies across worker unobserved skill (Rosen, 1974; Lavetti, 2023). Similarly, just as worker skills may be unobserved, firm differences in productivity are also likely to be unobservable. These two dimensions can interact in complex ways: if they are complementary, high-skill workers will tend to sort into more productive firms (Abowd, Kramarz, and Margolis, 1999; Bonhomme, Lamadon, and Manresa, 2019; Bagger and Lentz, 2019; Lentz, Piyapromdee, and Robin, 2023). But if workers are heterogeneous in their preference for CSR, one also expects more engaged workers to work preferentially for more responsible firms. How do these two aspects interact? In my model, imperfect competition prevents perfect assortative matching and answering this question is non-trivial. Importantly, the intensity and distribution of preferences for CSR across different worker types critically determine the magnitude of aggregate sorting effects and may vary over time. I thus contribute to the labor economics literature by analyzing the interplay between amenity and productivity sorting, and by providing evidence that temporal variation in amenities and attitudes toward them can significantly influence labor market sorting patterns (Lamadon, Mogstad, and Setzler, 2022).

Finally, worker preferences and sorting are both fundamental to determine the relative contribution of labour costs in a firm's decision to engage in CSR initiatives. If workers are willing to accept a lower wage to work for a more responsible firm, then firms that increase their ESG level can simultaneously boost production while reducing their total wage bill. In my model, ESG levels are endogenously determined by the firm, which allows this effect to be estimated using panel data. By measuring it, I contribute to the broader literature on the motivations behind CSR adoption by firms (Bénabou and Tirole, 2010; Friedman, 1970; Hart and Zingales, 2017; Gillan, Koch, and Starks, 2021). Results show the importance of the labour contribution to corporate green transitions and have relevant policy consequences. Indeed, when workers value sustainability in a heterogeneous way, policies that stimulate green and social investments will differentially impact the level of wages and the workforce composition of firms, generating heterogeneous incentives in firm responses. Policymakers should then account for labour market effects when drafting proposals aimed at improving corporate environmental and social performance.

The rest of the paper is organized as follows. Section 2 discusses the structure of the model and its main theoretical implications under simple assumptions. Section 3 illustrates the data and the empirical research design, while the subsequent two sections, 4 and 5, detail the two empirical methods and their results. Section 6 concludes.

# 2 Theoretical Framework

In my model, I revisit a setting of imperfect competition in the labour market, such as in Lamadon, Mogstad, and Setzler (2022) and Colonnelli et al. (2024), but I allow corporate sustainability levels to be costly and endogeneously chosen by the firm. In this section, I show the fundamental assumptions of the model and I characterize its equilibrium, highlighting the features that are relevant to address the questions raised in the introduction and discussing its theoretical implications.

## 2.1 Model

**Setting.** I consider a labour market with $I$ workers, indexed by $i$, and $J$ firms, indexed by $j$. Each worker has a type $s$ from a finite, discrete set of types $\{\varsigma_1, \varsigma_2, ..., \varsigma_S\}$, and corresponding productivity $A(s)$. Firms have productivity $A_j$ that I also consider to take values from a finite, discrete set of firm productivity levels.

Worker $i$ derives the following utility from working at firm $j$:

$$u_{ij}(w_j, E_j, B_j) = \log w_j + \log G(s_i, E_j) + \log B_j(s_i) + \frac{1}{\tau}\varepsilon_{ij} \tag{1}$$

where $w_j$ is the wage offered by firm $j$, $s_i$ is the type of worker $i$, $B_j$ are the non-wage amenities at firm $j$, $\tau$ is a parameter and $\varepsilon_{ij}$ is an idiosyncratic component which is specific to the worker-firm match. The term $G$ encapsulates the "green" amenity, i.e. how much utility a worker of type $s_i$ derives from the social responsibility level of firm $j$, $E_j$. There are many possible justifications for this term. For example, workers that care about environmental or social issues might benefit from the fact of working with like-minded people. The presence of this type of network effects would lead "green" workers to care about the ESG dimension of the firm because it would mean that they are more likely to find other "green" employees at that firm. Also, workers might value adhering to their own moral standards. Suppose for example that a job-seeker cares a lot about recycling. Then working in a company that does differentiate waste and promotes recycling could enable her to keep her habit on the workplace and it might be valuable *per se*.

Notice that both the valuation of the sustainability amenity and other non-wage amenities depend on worker type, because I want to allow for heterogeneous preferences for ESG initiatives. Indeed, it is

hard to believe that all workers would care equally for corporate sustainability. Still, my assumption implies that workers of the same type cannot have different valuations of corporate sustainability. Up to this point, I have been agnostic on the content of the type, but since each type $s$ maps to a specific productivity $A(s)$, this is equivalent to say that equally productive workers have the same valuation of social responsibility. This is true if there exist some link between components of type, such as skill, and preferences. For example, high-skill workers are usually more educated and individuals that are more educated are also more likely to be informed about climate and social issues. That could be one reason why high-skill workers might care relatively more for the environment. This assumption can however be limiting and I plan to relax it in a more general version of my model.

Firms face the following production function:

$$Y_j = A_j \left( \sum_s A(s) L_j(s) \right)^{1-\alpha} \tag{2}$$

where $Y_j$ is output of firm $j$, $A(s)$ is the productivity of workers with skill $s$, $A_j$ is the productivity of the firm, $L_j(s)$ is the number of employed workers of type $s$ and $\alpha$ is a parameter governing returns to scale. I will assume $0 < \alpha < 1$, i.e. diminishing returns to scale. The chosen shape of the production function implies that workers of different skills as substitutes, while firm productivity and worker productivity are complementary.

Firms face monopsonistic competition on the labour market. They have some market power, but they are small relative to the market, so they anticipate the effect of their choices on their own labour supply but they do not internalize the consequences on other firms, i.e. they do not behave strategically with respect to their competitors. Formally, firms choose demand by posting wages for each worker type and corporate social responsibility levels so that profit is maximized subject to the constraint that demand must not exceed supply. The problem of the firm is then:

$$\max_{w_j(s), E_j} A_j \left( \sum_s A(s) L_j(s) \right)^{1-\alpha} - \sum_s w_j(s) L_j(s) - C_j(E_j) \quad \text{s.t.} \quad L_j(s) = S_j(s, w_j, E_j) \tag{3}$$

where $C_j$ is the cost of picking CSR level $E_j$ and is assumed to be non-decreasing in $E_j$, i.e. $C'(E_j) \geq 0$ for all $j$. I will indicate the profit of the firm $\Pi_j$ as a function of labour demand for each type wages

for each type $\{L_j(s)\}_{s=1}^S$, wages for each type $\{w_j(s)\}_{s=1}^S$ and social responsibility level $E_j$.

**Equilibrium.** An equilibrium in this setting is a set of worker choices $j(i)$ for each $i$, offered wages $w_j(s)$ for each firm $j$ and each worker type $s$ and CSR level $E_j$ for each firm $j$ such that workers choose the firm that maximizes their utility and firms choose offered wages $\{w_j(s)\}_{s=1}^S$ and ESG level $E_j$ that maximize their profit.

Under the assumption that $\varepsilon_{ij}$ follows a Type-1 generalized extreme value distribution, if all workers choose optimally, the share of workers of of type $s$ that pick firm $j$ given the set of offered wages $W(s) = \{w_j(s)\}_{j=1}^J$ is

$$\mathbb{P}[j(i) = j | s_i = s, W(s)] = \frac{[w_j(s)G(s, E_j)B_j(s)]^\tau}{\sum_{j'}[w_{j'}(s)G(s, E_{j'})B_{j'}(s)]^\tau} \tag{4}$$

Suppose further that there are $N(s)$ workers of type $s$ so that $\sum_{s'} N(s') = I$. Then supply of workers of type $s$ to firm $j$ is simply:

$$S_j(s, w_j, E_j) = N(s)\mathbb{P}[j(i) = j | s_i = s, W] \tag{5}$$

Labour supply for a firm $j$ is therefore increasing in wages offered by $j$ and in the level of corporate sustainability $E_j$ as long as no worker type dislikes ESG, i.e. $G'(s, E_j) \geq 0$ for all $s$. Notice that if firms are small relative to the size of the market, the elasticity of labour supply for a given worker type $\eta_{js}$ is constant across firms and types and approximately equal to $\eta_{js} \approx \tau$.

For any firm $j$, first order conditions with respect to wages give the following expression for any worker type $s$:

$$w_j(s) = \underbrace{\frac{\tau}{1+\tau}}_{\text{markdown}} \underbrace{A_j(1-\alpha)\left(\sum_{s'} A(s')L_j(s')\right)^{-\alpha} A(s)}_{\text{marginal product of labour}} \tag{6}$$

In words, firms equate wages to marked-down marginal product of labour. Market power indeed allows firms to lower wages below marginal product and still attract workers. The wedge between marginal product of labour and wages defines a markdown that directly depends on the labour supply elasticity and thus on the intensity of worker utility idiosyncratic preference shocks.

As for ESG levels, substituting the constraint directly into the objective allows to find the first

order condition with respect to corporate sustainability $E_j$:

$$\frac{\partial C_j(E_j)}{\partial E_j} = \sum_{s'} \frac{w_j(s')}{\tau} \frac{\partial S_j(s', w_j, E_j)}{\partial E_j} \tag{7}$$

This equation has a straightforward interpretation. Each firm will raise its level of responsibility until the marginal cost of raising it further equates the marginal net benefit of increasing production and reducing total wage bill across worker types. This is supposing that the net benefit is positive. If some workers dislike $E_j$ strongly enough, it might be that the RHS of equation (7) is negative for any $E_j > 0$. In this case, the only solution would be for firms to pick $E_j = 0$. However, if $E_j$ is indeed an amenity and the RHS is positive, than any firm would have an incentive to set $E_j > 0$.

## 2.2 Theoretical Insights

I now turn to how the model can accommodate many features that I expect to arise from the data. Specifically, I derive an expression for the compensating wage differential and show that it is differentiated across types. With a measure of the compensating differential for different types, it is immediate to obtain an expression for the impact of ESG level choice on the total wage bill. This in turn allows to characterize the different incentives faced by firms with different levels of productivity and, finally, to characterize how the sorting implications of corporate sustainability depend on the shape and intensity of worker preferences.

**Compensating differentials.** The optimal choice of wages depends on the level of ESG chosen by the firm. Implicit differentiation of the first order condition in (6) allows to recover an expression for the variation of the wage offered by firm $j$ to a worker of type $s$ when the level of corporate responsibility varies:

$$\frac{\partial w_j^*(s, E_j)}{\partial E_j} = (-\alpha)\Lambda_j^{-1}(E_j) w_j^*(s, E_j) \sum_{s'} \frac{\partial S(s', w_j^*(E_j), E_j)}{\partial E_j} A(s') \tag{8}$$

where $\Lambda_j(E_j) = \sum_s A(s) S(s, w_j^*(s, E_j), E_j)$. The term $\frac{\partial S(s', w_j^*(E_j), E_j)}{\partial E_j}$ represents the total derivative of supply with respect to the ESG level of firm $j$. Since the optimal $w_j^*$ depends on $E_j$, it can be expressed as the sum of a direct effect of corporate sustainability on supply and an indirect effect of

ESG levels on wages, which in turn influence supply. Clearly the sign and magnitude of these effects depend on the preferences of workers for ESG and are thus an empirical question. However, suppose simply that no type of worker dislikes corporate social responsibility and some strictly do. Formally:

**Assumption 1.** *Corporate social responsibility is an amenity, i.e. no worker type dislikes it and at least one type strictly likes it. Mathematically,* $G'(s, E_j) \geq 0, \forall s$ *and for at least one* $s'$*, the inequality holds strictly* $G'(s', E_j) > 0$*.*

It is interesting to see that Assumption 1 is sufficient to obtain that the compensating differential will be negative for all types of workers.

**Proposition 1.** *Under Assumption 1, the compensating differential* $\frac{\partial w_j^*(s,E_j)}{\partial E_j}$ *is negative for any firm* $j$ *and any worker type* $s$*.*

*Proof.* See Appendix A.1. □

However, labour supply increases only for the workers who care about corporate sustainability. Indeed, the increased attractiveness due to greater corporate social responsibility compensates these types of workers from the utility loss due to lower wages. For the workers that are instead insensitive to ESG practices, only the wage effect survives. Thus, labour supply of indifferent workers would decrease. This result crucially hinges on Equation 2, which implicitly assumes that different types of workers are substitutes. For a firm this implies that a raise in its corporate environmental and social performance makes sensitive workers relatively cheaper and as a consequence provides an incentive to substitute towards workers that care about sustainability. Substitution takes place by reducing wages for all workers. While workers that are indifferent decide to quit, those who are most sensitive to corporate sustainability stay and are even drawn to the company.

**Corporate Social Responsibility choice.** Under Assumption 1, all workers are either indifferent or enjoy corporate social responsibility practices. Therefore, if they have not yet invested in environmental and social performance, companies face a marginal benefit of increasing their ESG level, because this would allow them to make at least one type of labor cheaper. Substituting towards that type or those types leads to increased production and lower wage bill. The RHS in the first order conditions of the problem of the firm with respect to $E_j$ (equation 7) is always positive. As a consequence, all firms would set $E_j > 0$.

Firms will however choose different levels of $E_j$ depending on their productivity $A_j$. In order to see that, consider that the optimal wage choice is a function of the productivity parameter $A_j$ and the choice variable $E_j$. Thus, it is possible to rewrite the profit of any firm as a function of $A_j$ and $E_j$ only. Proceeding by monotone comparative statics, it can be shown that high $A_j$ firms will choose high $E_j$ in equilibrium when Assumption 1 holds.

**Proposition 2.** *Under Assumption 1, in equilibrium, high-productivity firms will choose high levels of corporate social responsibility.*

*Proof.* See Appendix A.2. □

Formally, this is due to the fact that the cross derivative of profit with respect to $A_j$ and $E_j$ is positive. The intuition is that, if wages are chosen optimally by the firms, substitution towards workers that are sensitive to corporate social responsibility leads to greater wage cuts and bigger production increases for firms that are more productive, as long as costs do not depend on productivity $A_j$. This in turn is fundamentally due to the fact that worker skill and firm productivity are complements in the way I defined total production in equation (2). Therefore high-productivity firms will have larger incentives to raise $E_j$ to achieve greater wage cuts.

**Sorting.** Notice that if I divide equation (6) and (8) for the same firm and two worker types $s$ and $s'$, I get:

$$\frac{\frac{\partial w_j^*(s',E)}{\partial E}}{\frac{\partial w_j^*(s,E)}{\partial E}} = \frac{w^*(s',E)}{w^*(s,E)} = \frac{A(s')}{A(s)} \tag{9}$$

Therefore, within the same firm, the compensating differential will be greater for workers that are more productive, as the evidence from Krueger, Metzger, and Wu (2023) seems to suggest. Keep in mind, however, that this conclusion is only valid *within firm* and it abstracts from considerations about how the worker's employment decision interacts with firm productivity, which also matters.

Indeed, the skill wage gap *across firms*, which can be characterized comparing the average wage at firm $j$, i.e. $\frac{1}{J}\sum_j w_j(s)$ across types $s$, crucially depends on the proportion of differently productive workers deciding to work at differently productive firms. It is useful here to think in terms of an ideal experiment comparing two scenarios. In scenario A, Assumption 1 does not hold and all workers are indifferent to firms' corporate sustainability ratings. In Scenario B, Assumption 1 holds and some

workers enjoy the green amenity. In A, no firm engages in CSR and all $E_j$ will be null. When switching from A to B, all firms raise $E_j$ and choose a positive level according to first order condition (7). However, higher $A_j$ firms choose higher levels of $E_j$, in accordance with Proposition 2. Hence, the more productive a firm is, the more it raises its production and the more the share of workers that like ESG raises at that firm.

Now, it becomes crucial which type of workers enjoys corporate social responsibility. Suppose for example that workers that are more productive care more about ESG initiatives. Then this type of worker will be more likely to work for a high-productivity firm in B than in A. In other words, assortative matching on CSR preferences increases assortative matching on productivity. Under this assumption, the introduction of ESG ratings leads to higher aggregate output. Nevertheless, the change in across-firms average skill wage gap is ambiguous. On one hand, the more productive workers are willing to give up more of their wage for CSR on the workplace, because their preferences are stronger. On the other hand, the share of high-productivity workers matched to high-productivity firms is higher, so their average wage is higher as well. Depending on which effect prevails, the most skilled workers might earn on average more or less in B than in A. Another way to see this mechanism, is that the introduction of ESG creates correlation between $A_j$ and $E_j$. When high-skill workers like $E_j$, the attractiveness of ESG levels is more likely to compensate the utility impact of idiosyncratic shock realizations $\varepsilon_{ij}$. Thus, corporate social responsibility tends to "correct" the distortion due to horizontal differentiation. This way, endogeneous firm choice of corporate social responsibility would justify the results from the counterfactual of Colonnelli et al. (2024).

It is important to keep in mind that the opposite situation is possible if instead the workers that are less productive care more about CSR practices. In this case, the low-skilled workers would be the ones that are more attracted to high $A_j$ firms when going from scenario A to scenario B. Consequently, assortative matching based on firm sustainability would counter positive assortative matching based on productivity. In other words, the indifference to ESG would lead the most productive workers away from the most productive firms and thus exacerbate the distortion due to differentiation.

In general, the theoretical framework is rich enough to accommodate the features that are likely to arise from the data. I also showed how the structure of the model, namely worker substitutability and skill-productivity complementarity, implies very specific patterns of firm responses to worker preferences for CSR under the very simple Assumption 1. In my empirical analysis, this assumption

will not be imposed, and one outcome of interest will precisely be to verify if there is evidence that it holds.

# 3 Empirical Framework

Even though the theoretical analysis provided many insights on how workers' preferences for CSR could influence labour market outcomes, it is evident that empirical work is needed. Indeed, the magnitude and sign of the effects crucially depend on the shape of the workers' preferences, i.e. the function $G$, as well as on how these vary across different workers types. Another dimension that is critically relevant is heterogeneity in productivity both on the firms and workers' side. My objective is then to characterize the $G$ function, along with the distribution of firm and employee productivity, from observed labour market data. Other than being object of interest on their own, these elements will allow to determine the economic significance of compensating differentials associated to corporate social responsibility in my sample, the impact of the introduction of CSR on corporate profitability and the interplay between sorting based on corporate sustainability and sorting based on productivity.

## 3.1 Empirical Research Design

Given the model described in the previous Section 2, I discuss next my empirical strategy. First, I derive a set of structural equations that will constitute the basis for identification and estimation of my model. Then, I illustrate how I can use two different specifications based on these equations to estimate different parts of the model with varying degrees of structure, starting from a simple two-way fixed effect approach, and then scaling up to a full-fledged structural estimation. Indeed, the equations derived from the model, together with additional assumptions, allow to interpret results from an interactive regression specification *à la* Abowd, Kramarz, and Margolis (1999) as evidence of compensating differentials. With the method proposed by Bonhomme, Lamadon, and Manresa (2019) it is possible instead to relax some of these assumptions, exploiting the full structure of wages and moves across firms to characterize type-specific preferences.

**Structural Equations.** As shown in Appendix B.2, solving the theoretical model leads to the following system of equations:

$$Y_j = A_j^{\frac{1+\tau}{1+\tau\alpha}} H_j^{1-\alpha} \tag{10}$$

$$w_j(s) = \frac{\tau}{(1+\tau)}(1-\alpha) A_j^{\frac{1}{1+\tau\alpha}} H_j^{-\alpha} A(s) \tag{11}$$

$$\mathbb{P}[j|s,W] = \frac{\left[A_j^{\frac{1}{1+\tau\alpha}} H_j^{-\alpha} G_j(s) B_j(s)\right]^{\tau}}{\sum_{j'} \left[A_{j'}^{\frac{1}{1+\tau\alpha}} H_{j'}^{-\alpha} G_{j'}(s) B_{j'}(s)\right]^{\tau}} \tag{12}$$

where $\mathbb{P}[j|s,W]$ is the probability that a worker $i$ chooses firm $j$ conditional on her type being $s$ and the offered wage set being $W$. The term $H_j$ is the solution to a fixed point equation and is defined as:

$$H_j = \left[\sum_s \frac{A(s)N(s)}{\sum_{j'}[w_{j'}(s)G(s,E_{j'})B_{j'}(s)]^{\tau}} \left[\frac{\tau(1-\alpha)}{(1+\tau)} A(s) G(s,E_j) B_j(s)\right]^{\tau}\right]^{\frac{1}{1+\tau\alpha}} \tag{13}$$

It is possible to intuitively think of $H_j$ as the relative importance of individual specific factors (both worker type productivity and preferences) with respect to the market aggregate utility indicator $D(s)$, summed across markets for worker types. Conversely, $H_j$ can also be seen as the relative importance of total workforce productivity with respect to firm-specific productivity.

**Empirical Strategy.** My empirical strategy proceeds in two steps. First, I exploit structural equation (11) to perform a reduced-form regression analysis of a two-way fixed effect specification in the spirit of Abowd, Kramarz, and Margolis (1999), with variances corrected used the method of Kline, Saggio, and Sølvsten (2020). Under specific assumptions, including a functional form for ESG preferences, this approach recovers compensating differentials across firms. In a second step, I leverage the method of (Bonhomme, Lamadon, and Manresa, 2019) to calculate type-specific wage distributions and employment shares, after an initial estimation of the labour supply elasticity $\tau$ and the returns to scale $\alpha$ parameter. Equation (12) can then be used to estimate compensating differentials relaxing some of the assumptions underlying the fixed effect regression.

The first approach will be referred to as AKM specification in the rest of the paper. The motivation for a two-way fixed effect regression in my setting comes from (11). Notice indeed that taking natural

logarithms of this expression leads to:

$$\log w_j(s) = \underbrace{\log \frac{\tau}{(1+\tau)}(1-\alpha)}_{\text{intercept } M} + \underbrace{\frac{1}{1+\tau\alpha}\log A_j - \alpha \log H_j}_{\text{firm effect } \psi_j} + \underbrace{\log A(s)}_{\text{worker effect } \theta_s} \tag{14}$$

The logarithm of wages can then be decomposed in two effects: a firm fixed effect $\psi_j$ and a type fixed effect $\theta_s$. In practice, I can estimate this equation by assuming that wages are observed with a measurement error, and that there are as many types as individuals. Then both sets of fixed effects can be recovered by regressing log-wages on firm and individual dummies, exactly as in the seminal paper by Abowd, Kramarz, and Margolis (1999). The effect of CSR on wages will be incorporated in the $\psi_j$ term directly through $H_j$ and indirectly through technology $A_j$. Indeed, if Assumption 1 holds, Proposition 2 suggests that firms with high productivity will on average invest more on ESG. Therefore, ESG preferences will be fundamentally indistinguishable from the pure effect of technology $A_j$. Still, a regression of $\psi_j$ on ESG scores by firm will be informative about which of the two effects prevails. I can also couple (14) with additional assumptions on the exact shape of $G_j$ and leverage variation in ESG Scores to get tentative estimates of the compensating differential. The validity of results will however crucially hinge on the accuracy of the assumptions in my context of study.

The second approach exploits the methodology introduced by Bonhomme, Lamadon, and Manresa (2019) and will thus be referenced as the BLM specification. Using the full structure of wages and moves across firms, it is indeed possible to perform a three-step procedure to recover worker preferences disentangling from productivity effects. First, the idiosyncratic taste and returns to scale parameters are estimated relying on assumptions on the evolution of unobserved productivity. Second, a k-means clustering of firms into classes based on their empirical distribution of wages allows to use an EM algorithm in order to estimate worker type proportions across firm classes and class-type specific log-earnings distributions. As a result, each firm is assigned a class, and it is possible to calculate the posterior probability that a worker belongs to a type for each worker. Equation (14) can then be estimated with type fixed effects. Finally, computing the posterior probability of joining a class given the type and the wage of a worker allows to back out the preferences terms from equation (12).

More specifically, a measure of $\mathbb{P}[j|s, W]$ in equation (12) can be computed using the estimated wage distributions. Notice that of all offers in $W$ I only observe the accepted one, i.e. the current

wage of each individual $w_{ijt}$. Then using the class-type proportions and the class-type distributions of log-wages, it is possible to calculate $\mathbb{P}[j|s, w_{ijt}]$ for every individual, every type and every period $t$. Taking logarithms of (14) and rearranging I get:

$$\begin{aligned}\log \mathbb{P}[j|s, w_{ijt}] = \tau \log w_{ijt} + \tau \log G_j(s, E_j) + \tau \log B_j(s) \\ - \log \sum_{j'} \left[ \frac{\tau}{1+\tau} (1-\alpha) A_{j'}^{\frac{1}{1+\tau\alpha}} H_{j'}^{-\alpha} G(s, E_{j'}) B_{j'}(s) A(s) \right]^{\tau}\end{aligned} \tag{15}$$

This equation can now be estimated because the last term depends only on type $s$ and can thus be captured by a type fixed effect, the firm fixed effect is exactly the same as in (14) and the $\tau$ parameter has been previously estimated. It is then possible to characterize how the $G$ function varies with unobserved worker type $s$ and ESG Score $E_j$.

## 3.2 Data

**ESG Scores.** Data on ESG Scores comes from the London Stock Exchange (LSEG) Workplace platform (formerly known as Refinitiv). ESG Scores are computed both from corporate communications and third party information, such as statistics made available from NGOs and media companies. The score is yearly and for the current year it is updated weekly. It includes a wealth of variables, which are divided in pillars (Environmental, Social and Governance), categories and subcategories. I am able to observe the combined score, as well as each category and subcategory separately. For an overview of the methodology used to compute the scores, refer to London Stock Exchange Group (2025).

In my sample, I restrict attention to French firms. In France, a total of 378 public and private companies have received ESG Scores at some point in the time period that goes from 2001 to 2024. The set of firms receiving a score varies over time, in part due to exit, mergers and acquisitions and in part due to information availability. On average, a firm is scored for a span of 12 years in my sample. The summary statistics for last year (2024) are shown in Table 1.

A couple of remarks are in place. Evidence suggest that these scores might be suffering both in terms of comparability with other provider's scores (Berg, Koelbel, and Rigobon, 2022) and in terms of historical accuracy (Berg, Fabisik, and Sautner, 2020). While the first might not be a crucial source

Table 1: Summary Statistics for last observation of ESG Scores (2024)

| | ESG Score | ESG Combined | Environmental | Social | Governance |
|---|---|---|---|---|---|
| Average | 58.8 | 55.1 | 60.2 | 64.0 | 50.4 |
| Std. Dev. | 20.5 | 19.1 | 25.8 | 22.4 | 24.4 |
| Min. | 3.1 | 3.1 | 0.0 | 0.7 | 3.4 |
| $q_{25}$ | 44.6 | 41.8 | 42.7 | 50.2 | 30.8 |
| $q_{50}$ | 62.2 | 57.2 | 66.8 | 67.6 | 54.6 |
| $q_{75}$ | 75.7 | 70.7 | 79.1 | 81.7 | 68.7 |
| Max. | 92.9 | 89.5 | 98.0 | 97.2 | 96.6 |
| $N$ | 221 | 221 | 221 | 221 | 221 |

of concern, the second is more worrying. LSEG mentions in their site that it reserves the right to make changes to already published scores up to 5 years prior the most recent observation. Since my analysis will concern the 2001-2022 period, I am at least partially reassured that the data affected by possible revision is limited to the years 2020-2022. A separate potential issue is that the Social pillar of the score contains variables related to the workforce. This is in principle a threat for the separate identification of $G$ ad $B$ function, because it might introduce correlation between the ESG rating and other workplace amenities.

**Matched employer-employee data.** I employ the matched employer-employee data from the "Base Tous Salariés" (BTS, formerly known as DADS) dataset produced by the French "Institut National de la Statistique et des Études Économiques" (INSEE). It covers the universe of firms in the country and all workers born in October for each firm (about 8% of the workforce) in the period from 1976 to 2022. It contains detailed data on firm and worker matches, including wages, hours of work, working location and several demographic variables (year of birth, residence, etc.).

**Sample construction.** Given my empirical strategy, I carefully build a sample that is appropriate for my analysis. In particular, I merge ESG Scores with matched employer-employee data through unique firm identifiers and I filter the merged dataset in order to obtain observations that are comparable. The wealth of variables and variability in type of employment and conditions impose a number of choices, which I detail in Appendix B.1.

It is also important to mention that when performing the AKM analysis I need to focus on a

subset of firms that are connected by at least one move, otherwise the firm fixed effects will not be identified and there might be spurious comparisons. Before every interactive regression, I extract from the subset of all movers the unique identifiers of the firms and select only those that are in the largest connected set.

The next sections presents each of my empirical specifications and show their results. Section 4 focuses on the AKM empirical model, while section 5 presents the full estimation of all parameters in the model.

# 4 Two-way fixed effects: AKM Approach

**AKM Specification.** The key equation for an approach in the spirit of Abowd, Kramarz, and Margolis (1999) is (14), which corresponds to a two-way fixed effect regression of log-wages on firm fixed effects $\psi_j$ and individual fixed effects $\theta_i$, under the assumption that types are as many as the number of individuals. Equation (14) then results in the following specification:

$$\log w_{ijt} = m + \psi_j + \theta_i + \eta_{ijt} \tag{R.1}$$

that can be estimated with OLS under the following assumption:

**Assumption I.** *(Conditional mean independence.) The error term $\eta_{ijt}$ satisfies $[\eta_{ijt}|i,j] = 0$.*

In the rest of the paper, whenever I introduce measurement error I also implicitly assume that log-earnings are observed with an independent and identically distributed error that respects the conditional mean independence assumption (I).

A few remarks are here in order. First, remember that the firm effect $\psi_j$ is a composition of an $A_j$ term, which refers to productivity, and an $H_j$ term which refers to both productivity and preferences. The relationships between these terms and ESG Scores are interesting in their own right. In particular, it is interesting to check whether Proposition 2, which states that high-productivity firms choose higher corporate responsibility levels, holds in my setting. At the same time, the term $H_j$ is directly linked to ESG preferences $G_j$: the stronger worker preferences for ESG are, the greater is $H_j$. Therefore, theory predicts both $A_j$ and $H_j$ to be positively correlated with ESG Scores $E_j$. However, $A_j$ enters $\psi_j$ positively, while $A_j$ enters negatively. Consequently, the global relationship

between $H_j$ and $E_j$ is only informative about which of the two effects prevails but not on each of them separately. Not explicitly accounting for unobserved heterogeneity in either worker or firm productivity can therefore lead to an estimate of the firm fixed effect that would be biased.

Second, notice that all time-invariant differences in wages across individuals and firms are captured by either one of the two fixed effects, but in the original contribution of Abowd, Kramarz, and Margolis (1999) and subsequent work, it is usual to include time-varying characteristics that might be of interest, both at the individual and the firm level. The goal is usually to separate out the contribution of these observed characteristics from unobserved individual and firm-level factors. In my case, however, I am only interested in distinguishing the variation in wages that can be ascribed to firms from the variation that can be ascribed to workers, no matter whether it is related to observed or unobserved factors. It is important therefore to take into account variables that could confound this distinction, even though I have not explicitly modelled them. One such variable for example is tenure. The goal of this analysis is not forcibly to separate tenure from unobserved individual effects $\theta_i$, because in principle I could consider a worker type to include tenure as well. All the discussion so far would still apply. However, I do care about distinguishing the effect of tenure from firm effects $\psi_j$. If all the individuals that move between firm A and firm B have longer experience than those that move from A to firm C I might infer $\psi_B$ to be larger than $\psi_C$ even though firms might be equally productive.

A closely related issue is the time dimension. My analysis in Section 2 is conditional on a time period $t$, without restriction. But the implicit assumption behind regression (R.1) is that firm and worker productivity are fixed in time, as well as preferences and ESG Scores. Variation in log-wages over time will be entirely imputed to the error $\eta_{ijt}$. Two problems then arise: (i) omitting time-varying characteristics can lead to biased estimates of the fixed effects and (ii) this specification does not allow to exploit the time variation in ESG Scores observed in the data. Regarding (i), if time-varying characteristics make log-wages on average higher on some periods, Assumption I clearly does not hold. Rather than focusing on each variable separately, a simple way to address this concern is to add year fixed effects, as in Lachowska et al. (2023). Taking stock of the observations raised in the current and the previous paragraph, one would ideally augment (R.1) to include both time and

experience, so that the following specification would be robust to trends:

$$\log w_{ijt} = m + \beta x_{it} + \psi_j + \theta_i + t + \eta_{ijt} \tag{R.2}$$

where $x_{it}$ is experience and $t$ is a dummy for years. As pointed out in Card et al. (2018), however, including both experience and time fixed effects can be problematic for the correct estimation of individual fixed effects. I will therefore also report results from the regression without controls for worker experience.

As for (ii), estimating (R.2) for the whole period between 2002 and 2021 will still give me a unique firm fixed effect $\psi_j$ per firm $j$. All moves between firms at all years are used to compute the fixed effect. But firms are assigned an ESG Score every year. Therefore, the only meaningful way to compare the firm fixed effect to ESG Scores is to regress it on the mean ESG Score over the 2002-2021 period.

Results from both regression (R.1) and (R.2), performed on the respective largest connected set of firms, are shown in Table 2. Individual fixed effects are significantly increasing in mean (log) ESG Scores, no matter the set of controls. In particular, one standard deviation increase in the log sustainability scores (0.45, about 57% increase) is associated to a 12-16% increase in the individual wage component. This might happen because more productive workers sort into greener firms as predicted by my model. Firm fixed effects instead do not exhibit a significant relationship with (log) ESG Scores. Perhaps the effect of technology and worker preferences for ESG offset each other in the period of study. Alternatively, comparing aggregate fixed effects across time with mean ESG Scores might mask a lot of across-years variations. I will explore this possibility in the next paragraph.

**TV-AKM Specification.** Given the previous paragraph specification and results, one is left wondering whether it is possible to refine the analysis, making use of the yearly nature of the ESG ratings. If I consider the choice of ESG investment to be performed at each time period, then the $H_j$ term varies across time. The appropriate specification becomes:

$$\log w_{ijt} = m + \beta x_{it} + \psi_{jt} + \theta_i + \eta_{ijt} \tag{R.3}$$

where $\psi_{jt}$ is a year-firm fixed effect. Beware that I had to drop the year fixed effects because they would be collinear to year-firm fixed effects. This application of the AKM framework is sometimes called "time-varying" AKM or TV-AKM (Lachowska et al., 2023). Comparing the fixed effect $\psi_{jt}$

Table 2: Results from the AKM Specification.

| | Firm FE | | | | | | | Individual FE | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | OLS | | | | KSS | | | OLS | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Mean ESG Score | -0.03 | 0.03 | 0.05 | 0.09 | -0.11 | -0.03 | -0.02 | 0.33*** | 0.32*** | 0.26*** |
| | (0.13) | (0.11) | (0.11) | (0.18) | (0.08) | (0.07) | (0.07) | (0.01) | (0.00) | (0.00) |
| Mean Size | | | | 0.03 | | | | | | |
| | | | | (0.06) | | | | | | |
| Intercept | 0.82 | 0.30 | 0.21 | | | | | 1.27*** | 1.22*** | 1.03*** |
| | (0.51) | (0.45) | (0.44) | | | | | (0.02) | (0.02) | (0.02) |
| *First stage controls* | | | | | | | | | | |
| Time FE | | Y | Y | Y | | Y | Y | | Y | Y |
| Experience | | | Y | Y | | | Y | | | Y |
| *Second stage controls* | | | | | | | | | | |
| Sector FE | | | | Y | | | | | | |
| Clustered SE | | | | Sector | | | | | | |
| Observations | 125 | 125 | 125 | 122 | 97 | 97 | 97 | 113,009 | 113,009 | 112,976 |
| R-squared | 0.00 | 0.00 | 0.00 | 0.28 | - | - | - | 0.04 | 0.02 | 0.02 |

*Notes*: The dependent variables are estimated fixed effects from the AKM regression. Independent variables are in logarithms. First stage controls refer to observables (in logarithms) and fixed effects included in the AKM regression. A few individual observations (33) are missing in column (10) because experience is null. Standard errors are in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

across firms $j$ and years $t$ still combines productivity and preferences variations. To illustrate, consider any $j \in 1, \ldots, J$ and any $t \in [2001, 2021]$. Then:

$$\begin{aligned} \psi_{jt} &= \underbrace{\frac{1-\alpha(1-\tau)}{1+\tau\alpha}}_{a_1} \log A_j - \underbrace{\frac{\alpha}{1+\tau\alpha}}_{a_2} \log H_{jt} = \\ &= a_1 \log A_j - a_2 \log \sum_s A(s) D_t(s) \left[ \underbrace{\frac{\tau(1-\alpha)}{(1+\tau)}}_{a_3} A(s) G(s, E_{jt}) B_j(s) \right]^{\tau} \end{aligned} \tag{16}$$

where $D_t(s) = \frac{N(s)}{\sum_{j'} [w_{j't}(s) G(s, E_{j't}) B_{j'}(s)]^{\tau}}$ is a market index for an individual of type $s$ at time $t$. So the correlation between $\psi_{jt}$ and $E_{jt}$ will be a compounded effect of the variation of $A_j$, $D_t$, $E_{jt}$ and $B_j$. Firm and time effects control for the presence of the $A_j$, $D_t$ and $B_j$, as long as non-ESG amenities $B_j$ do not vary differentially over time (cf. Appendix B.3), as stated in the following:

**Assumption II.** *During the period of study, non-ESG amenities are separable in firm and time components, i.e.* $B_{jt}(s) = B_j(s) B_t(s)$ *for all* $s$*, all* $t$ *and all* $j$*.*

Furthermore, observe that each element in the second term summation can be seen as $G(s, E_{jt})$ weighted by a coefficient that depends both on $j$, $t$ and $s$. A regression of $\psi_{jt}$ on $E_{jt}$ would thus approximately identify an upper bound on the average rate of change of $G(s, E_{jt})$ across $s$, as shown under an additional assumption in Appendix B.3. in particular, under the specific functional form $G(s, E_{jt}) = E_{jt}^{\gamma_{st}}$, the regression exactly identifies the weighted average of the slope of preferences with respect to $E_{jt}$, across types $s$ for a given period $t$. Let me write formally:

**Assumption III.** *Worker preferences for ESG have the shape* $G(s, E_{jt}) = E_{jt}^{\gamma_{st}}$*.*

Under Assumption (I) to (III) it is then possible to estimate a (weighted) average slope of worker preferences for corporate sustainability across worker types through a regression of the firm-year fixed effect $\psi_{jt}$ on yearly ESG scores $E_{jt}$, controlling for firm and year effects. Alternatively, it is possible to directly estimate an enhanced AKM model of the form $\log w_{ijt} = a + \beta x_{it} + \beta_t \log E_{jt} + t + \psi_j + \theta_i + \nu_{ijt}$.

The above specifications, estimated on the largest connected set of year-firm pairs, produces the results shown in Table 3 for individuals. Interestingly, the relationship between year-firm fixed effects

and (log) ESG Score is positive and significant, but becomes insignificant when adding controls for year and firm. Since OLS is biased when projecting a fixed effect estimates on observables, I also implement the correction of Kline, Saggio, and Sølvsten (2020) and find it to be positive and significant. The effect is not, however, economically important, as the estimate implies that one standard deviation increase (0.490, about 63%) in log ESG score is associated to a 0.6% increase in hourly wages, which is quite modest.

Restricting the coefficient to be unique across time also masks significant across-year heterogeneity. I report coefficients of the regression of the fixed effect on ESG Score by period for the years 2005, 2008, 2013, 2016 and 2021 in Table 4 (full results in Appendix Table 9). Also, in Figure 3 I plot the coefficients by year from the OLS and KSS projections, as well as for the AKM specification including the ESG scores directly in the AKM specification. All specifications suggest the same pattern across time. In particular, it stands out from the results that coefficients for the earlier years, when significant, are mostly positive, indicating that the compensating differential for higher ESG Score at the beginning of the period of study was positive. In later years, the coefficient becomes negative, indicating a negative compensating differential.

However, specifications differ in the magnitude of the estimated effect. Notice that a standard deviation increase in (log) ESG score oscillates between 0.25 and 0.63, that is between a 29% and a 89% increase in the score. The AKM specification with direct inclusion of sustainability as a regressor, suggests that initially, between 2004 and 2008, a one standard deviation increase in log ESG score increases wages by 2-8%. Then, starting from 2012, one standard deviation increase in log score is associated with a 3 to 11% decrease in wages. The AKM specification with subsequent projection of the fixed effect on the ESG score suggests that earlier, around 2005, a standard deviation increase in log ESG score is associated with a 4% increase in wages, while in later years (2014-2017), a similar increase is associated with a 2-4% *decrease* in wages. With the KSS correction, a standard deviation in log ESG score is slightly bigger, between 0.26 and 0.66 (29% to 93%) and the associated variation in wage is about a 2 to 8% increase between 2004 and 2008 versus a 2 to 16% decrease in 2011-2021. Overall, these results are in line with the prediction that at least some worker types in the later years do care about ESG Scores and are willing to accept lower wages in order to work for a firm that has a better sustainability score.

The results from the regression of individual fixed effects on ESG Scores show a significant positive

Table 3: Results from TV-AKM and Enhanced AKM, with KSS correction.

| | Firm FE | | | | Individual FE | |
|---|---|---|---|---|---|---|
| | OLS | | KSS | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mean ESG Score | 0.21** | 0.017 | 0.025 | 0.013*** | 0.32*** | 0.26*** |
| | (0.06) | (0.04) | (0.044) | (0.003) | (0.005) | (0.004) |
| Intercept | -0.47 | | | | 1.52*** | 1.37*** |
| | (0.26) | | | | (0.02) | (0.02) |
| *First stage controls* | | | | | | |
| Experience | | | | | | Y |
| *Second stage controls* | | | | | | |
| Year FE | | Y | | Y | | |
| Firm FE | | Y | | Y | | |
| Clustered SE | Year & Firm | Year & Firm | | | | |
| Observations | 1,175 | 1,175 | 976 | 976 | 104,079 | 104,049 |
| R-squared | 0.04 | 0.85 | - | - | 0.05 | 0.04 |

*Notes*: Dependent variables are estimated fixed effects from the AKM regression that include corresponding controls. Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Results from TV-AKM Specification by year.

| | OLS | KSS | log Wage |
|---|---|---|---|
| | (1) | (2) | (3) |
| ESG Score × 2005 | 0.071** | 0.10*** | 0.08** |
| | (0.028) | (0.006) | (0.04) |
| ESG Score × 2008 | -0.050 | 0.05*** | 0.05* |
| | (0.065) | (0.008) | (0.03) |
| ESG Score × 2013 | -0.017 | -0.19*** | -0.15*** |
| | (0.055) | (0.01) | (0.03) |
| ESG Score × 2016 | -0.089* | -0.16*** | -0.12** |
| | (0.050) | (0.008) | (0.05) |
| ESG Score × 2021 | 0.039 | -0.38*** | -0.26 |
| | (0.093) | (0.01) | (0.14) |
| *Second stage controls* | | | |
| Year FE | Y | Y | Y |
| Firm FE | Y | Y | Y |
| Clustered SE | Year & Firm | | Year & Firm |
| Observations | 1,175 | 976 | 496,151 |
| R-squared | 0.86 | - | 0.91 |

*Notes*: The dependent variables are estimated fixed effects from the AKM regression in columns (1)-(4) and log-wages in columns (5)-(6). Independent variables are in logarithms. First-stage controls refer to observables (in logs) and fixed effects included in the AKM regression. See full results in Table 9. Standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

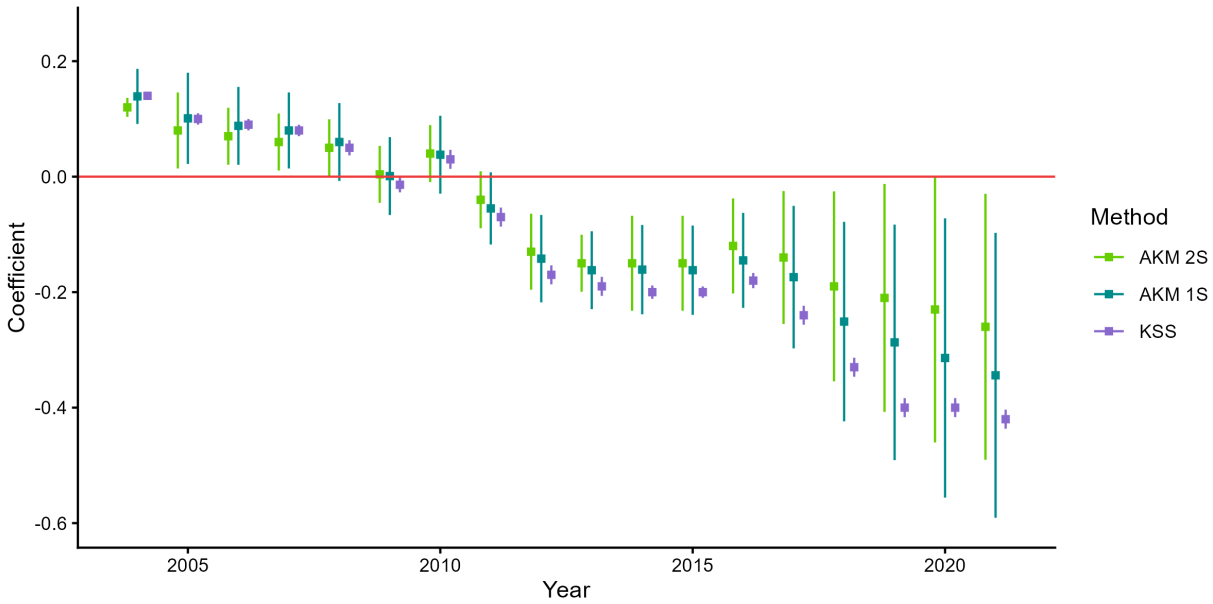



Figure 1: Coefficients from the Enhanced AKM Regression.

relationship, thus confirming results from AKM and suggesting that more productive individuals sort into firms with better ESG scores.

# 5 Grouped Fixed Effects: BLM Approach

I turn next to the estimation procedure proposed by Bonhomme, Lamadon, and Manresa (2019). Remember that the model predicts that wage depends on worker type and the productivity of her current firm's class. Firm productivity likely evolves across time and influences both wages and value added. Under the assumption that productivity follows a unit root process, it is therefore possible to use the evolution in value added to partial out the transitory part of the productivity shock from the wages (Lamadon, Mogstad, and Setzler, 2022; Guiso, Pistaferri, and Schivardi, 2005). Assuming wage measurement error allows to calculate the likelihood of a worker belonging to each type, given the parameters of the distribution and her class. Developing this intuition, Bonhomme, Lamadon, and Manresa (2019) suggests first to classify firms into classes through k-means clustering of the empirical wage distributions. Then, following the logic of an Expectation-Maximization (EM algorithm), they recover type-class proportions and the parameters of the distributions. Finally, the estimated wage distributions allow to compute posterior probabilities that a worker chooses to work for a firm, given her salary and type, which can be used to recover preference estimates.

## 5.1 Estimation of passthrough parameters.

Notice that taking logarithms of the production and wages equation in (10) and (11) leads to:

$$\begin{aligned} w_{ijt} &= m + \frac{1}{1+\tau\alpha} a_{jt} - \alpha h_{jt} + a(s) \\ y_{jt} &= \frac{1+\tau}{1+\tau\alpha} a_{jt} + (1-\alpha) h_{jt} \end{aligned} \tag{17}$$

where all lowercase variables represent the natural logarithm of the corresponding uppercase variables. Then the passthrough of productivity shocks from value added to wages identifies the idiosyncratic taste $\tau$ parameter. Indeed:

$$\frac{\partial w_{ijt}}{\partial a_{jt}} \Big/ \frac{\partial y_{jt}}{\partial a_{jt}} = \frac{1}{1+\tau} = \gamma \tag{18}$$

Since productivity $a_{jt}$ is likely to vary over time, identifying the idiosyncratic taste parameter is key because it allows to partial out the time-varying productivity changes from the wages using value added observations. Notice that value added does not depend directly on $a(s)$, therefore, following

the logic of Lamadon, Mogstad, and Setzler (2022), one can use its variation over time to partial out the accumulation of shocks, provided estimates of the $\tau$ and $\alpha$ parameters are available. For this procedure to be valid, the following assumptions are needed:

**Assumption IV.** *The amenity term $h_{jt}$ is fixed within the estimation period, i.e. $h_{jt} = h_j$ for any $t$.*

**Assumption V.** *The productivity term $a_{jt}$ follows a unit root process, $a_{jt} = p_j + z_{jt}$ where $z_{jt} = z_{jt-1} + u_t$ and $u_t$ is a productivity shock with positive variance.*

Under these assumptions, a shock in value added can be fully attributed to changes in productivity. As the transitory component might be autocorrelated, the shock enters both value added and wages directly in the contemporaneous measure and in lags and leads up to $\bar{e}$ periods after and $\bar{e}+1$ periods after. Therefore, it is a good instrument for the regression of long difference in wages on long differences in productivity, excluding leads up to $\bar{e}$ and lags up to $\bar{e}+1$. The following moment conditions on stayers ($S_i = 1$) therefore enable to estimate the passthrough and the $\tau$ parameter:

$$\mathbb{E}[\Delta\tilde{y}_{jt}(\tilde{w}_{it+e} - \tilde{w}_{it-e'} - \gamma(y_{jt+e} - \tilde{y}_{jt-e'}))|S_i = 1, j(i) = j] = 0 \tag{19}$$

for $e \geq \bar{e}$, $e' \geq \bar{e}+1$, where $\tilde{y}_{jt} = y_{jt} - \bar{y}_t$ and $\tilde{w}_{ijt} = w_{ijt} - \bar{w}_t$ are deviations from yearly means $\bar{y}_t = \mathbb{E}[y_{jt}|S_i = 1, j(i) = j] = 0$ and $\bar{w}_t = \mathbb{E}[w_{ijt}|S_i = 1, j(i) = j] = 0$ and $\Delta\tilde{y}_{jt} = \tilde{y}_{jt} - \tilde{y}_{jt-1}$ is the one-period shock.

**Simulation.** In the simulation, the transitory component is assumed to follow an MA(1) process so the estimation uses $\bar{e} = 2$. I report IV results and the true values in Table 5. The estimate of $\tau$ using IV gives a point estimate of about 0.97 versus a true value of 0.9. The corresponding estimate of $\alpha$ is 0.22 versus a true value of 0.2. The passthrough estimation is therefore able to recover the original parameters quite well.

Table 5: Passthrough Estimation (IV)

| | Estimate | True |
|---|---|---|
| $\tau$ | 0.973 | 0.9 |
| | (0.001) | |
| $\alpha$ | 0.194 | 0.2 |
| | (0.002) | |

With $\tau$ and $\alpha$ it is possible to construct adjusted wages of the form:

$$w_{ijt}^a = w_{jt} - \frac{1}{1+\tau}(y_{jt} - y_{j1}) = c + \frac{1}{1+\tau\alpha}p_j - \alpha h_j + a(s) \tag{20}$$

which only depend on amenities and the permanent component of productivity and thus nicely fit the structure of the grouped fixed effect framework.

## 5.2 Grouped Fixed Effects

Suppose each firm $j$ belongs to a class $k \in [0, ..., K]$. Then my model implies that each individual wage in my dataset will follow (20) with a $k$ subscript instead of $j$, multiplied by an idiosyncratic error. Assume further that this error is such that wages are distributed according to a lognormal distribution.

**Assumption VI.** *For each worker of type $s$ employed by a firm of class $k$, wages are observed with a measurement error so that they follow a log-normal distribution $f_{sk}$ with class-type specific mean and variance $\mu_{sk}$ and $\sigma_{sk}$.*

Then, if I observe a panel, I can write the first period distribution of log-earnings $w$ per firm in the following way:

$$\mathbb{P}[w_{i1} \leq w_1 | j] = \sum_{s=1}^{S} F_{sk}(w_1)\pi_{sk1} \tag{21}$$

where $\pi_{sk1}$ is the prior probability of belonging to type $s$ for a worker in a firm of class $k$ at period one. This distribution does not depend on $j$ other than through the class $j$ belongs to, $k$. I can then use the empirical distribution of wages in the first period to perform k-means clustering of firms into classes.

Given firm classification, the log-likelihood of job movers between two periods can be written as:

$$\sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{k'=1}^{K} \mathbf{1}[k_{i1} = k]\mathbf{1}[k_{i2} = k'] \log\left(\sum_{s=1}^{S} \pi_{skk'} f_{sk}(w_1) f_{sk'}(w_2)\right) \tag{22}$$

where $\pi_{skk'}$ is the prior probability of belonging to type $s$ for an employee that switched job between a firm of class $k$ and class $k'$. The distribution parameters $\mu_{sk}$ and $\sigma_{sk}$, as well as the type distributions

$\pi_{skk'}$ can then be recovered through an EM algorithm, that can be generalized for any number of periods. The intuition behind this procedure is that starting from a value for the distribution parameters and prior probabilities of a worker being of a given type, it is possible to compute posterior probabilities (E-step) and then fixing the posterior probabilities, log-likelihood maximization allows to compute a new value for the distribution parameters and the prior probabilities (M-step). Each iteration guarantees that the likelihood will be higher so convergence leads to the parameters that maximize it.

**Simulation.** The simulation is based on $S = 3$ types of workers and $K = 3$ classes of firms. The EM algorithm implemented on the simulated data adjusted with the estimated passthrough parameters produces point estimates that are very close to the true means and variances. I report here the true and estimated matrix of group-class specific means and variances, as well as the estimated and true type proportions for reference and comparison. The estimated and true type transition matrices for all worker types are shown in full in Appendix E.

Estimated $\mu_{sk}$ for first period.

| | k | | |
|---|---|---|---|
| **s** | **1** | **2** | **3** |
| **1** | 2.74 | 3.03 | 3.46 |
| **2** | 3.17 | 3.46 | 3.89 |
| **3** | 3.67 | 3.97 | 4.40 |
| **4** | 4.24 | 4.54 | 4.96 |

True $\mu_{sk}$.

| | k | | |
|---|---|---|---|
| **s** | **1** | **2** | **3** |
| **1** | 2.75 | 3.04 | 3.47 |
| **2** | 3.17 | 3.47 | 3.90 |
| **3** | 3.68 | 3.98 | 4.41 |
| **4** | 4.25 | 4.55 | 4.97 |

Estimated $\sigma_{sk}$.

| | k | | |
|---|---|---|---|
| **s** | **1** | **2** | **3** |
| **1** | 0.10 | 0.10 | 0.10 |
| **2** | 0.10 | 0.10 | 0.10 |
| **3** | 0.10 | 0.10 | 0.10 |
| **4** | 0.10 | 0.10 | 0.10 |

True $\sigma_{sk}$ for first period.

| | k | | |
|---|---|---|---|
| **s** | **1** | **2** | **3** |
| **1** | 0.10 | 0.10 | 0.10 |
| **2** | 0.10 | 0.10 | 0.10 |
| **3** | 0.10 | 0.10 | 0.10 |
| **4** | 0.10 | 0.10 | 0.10 |

Table 6: True and estimated type proportions.

| | **1** | **2** | **3** | **4** |
|---|---|---|---|---|
| **True** | 0.333 | 0.278 | 0.222 | 0.167 |
| **Estimated** | 0.334 | 0.278 | 0.229 | 0.159 |

### 5.3 Preference Estimation

In a last step, given the estimates of the wage distribution obtained through grouped fixed effects, it is possible to calculate the conditional probability of joining a class given the worker type and the observed wage, $\mathbb{P}[k|s, w_{ijt}]$, for all individuals $i$ and all types $s$, using Bayes rule. Rewriting equation (12) at the class level gives:

$$\mathbb{P}[k|s] = \frac{[\theta_s \psi_k G_k(s) B_k(s)]^\tau}{\sum_{k'} [\theta_s \psi_{k'} G_{k'}(s) B_{k'}(s)]^\tau} \tag{23}$$

where $\psi_k$ is a class effect that can be obtained through a TWFE weighted regression of wages on class and type fixed effects. This equation directly enables to estimate $G_k(s)B_k(s)$ from estimated parameter $\tau$, fixed effects $\theta_s, \psi_k$ and conditional probability $\mathbb{P}[k|s]$.

## 6 Conclusion

In this paper, I propose a framework to analyze the impact of corporate social responsibility on the labour market. In the model, the preference of some types of workers towards CSR leads firms that engage in sustainable practices to substitute towards those types. When CSR is strictly an amenity, since firms that are more productive have an incentive to choose higher levels of ESG investment, the distribution of worker preferences for ESG matters. When the most productive workers are also those that are more concerned with corporate sustainability, then matching on greenness preferences enhances assortative matching based on productivity. This creates un unintended beneficial side effect of CSR adoption, namely improved economic efficiency and would therefore make green incentive policies even more attractive.

However, effects crucially hinge on the shape of the underlying preference distribution and whether CSR is strictly an amenity is an empirical question. To shed light on this aspect, I take my model to the data, developing an empirical research design that comprises two consecutive steps: (i) a

two-way fixed effect approach *à la* Abowd, Kramarz, and Margolis (1999), and (ii) a grouped fixed effects strategy in the spirit of Bonhomme, Lamadon, and Manresa (2019) that allows to identify all parameters and perform counterfactual analysis.

Following (i), I show that, under some assumptions, a regression of year-firm fixed effects from an AKM specification on yearly ESG Scores identifies a weighted average of worker preferences across time. Results from this procedure show that the relationship between the fixed effect and ESG Scores is positive for the earlier years in the period of my study, but the magnitude of the coefficient decreases over time and becomes negative for later years. This is direct evidence of a sign reversal in compensating differentials for ESG Scores, meaning that workers in recent years have on average accepted lower wages to work for a firm with higher corporate sustainability. These results motivate further empirical analysis, which is necessary to disentangle preferences from productivity effects and to fully quantify wage bill savings from increased CSR adoption across different firms.

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# A Proofs and Derivations

## A.1 Proposition 1.

*Proof.* Dropping the $j$ subscript, for any $s$, differentiation of (8) leads to:

$$\frac{\partial w^*(s,E)}{\partial E} = (-\alpha)\Lambda^{-1}(E)w^*(s,E)\sum_{s'}\left[\frac{\partial S(s')}{\partial w^*(s',E)}\frac{\partial w^*(s',E)}{\partial E} + \frac{\partial S(s')}{\partial E_j}\right]A(s') \tag{24}$$

where $\frac{\partial S(s')}{\partial E_j}$ is the derivative of $S(s',w,E)$ with respect to the third argument only – calculated at $w = w^*(s',E)$ – and I make an abuse of notation, by indicating $\frac{\partial S(s')}{\partial w^*(s',E)}$ the derivative of $S(s',w,E)$ with respect to the second argument, calculated at $w^*(s',E)$. Formally, it would be $\frac{\partial S(s')}{\partial w^*(s',E)} = \frac{\partial S(s')}{\partial w}\Big|_{w=w^*(s',E)}$.

Now, I can use the fact that compensating differentials are proportional across type and within the same firm, as a consequence of equation (9):

$$\frac{\partial w^*(s',E)}{\partial E} = \frac{w^*(s',E)}{w^*(s,E)}\frac{\partial w^*(s,E)}{\partial E}$$

Replacing back in (8):

$$\frac{\partial w^*(s,E)}{\partial E} = (-\alpha)\Lambda^{-1}(E)\left[\sum_{s'}\frac{\partial S(s')}{\partial w^*(s',E)}w^*(s',E)\frac{\partial w^*(s,E)}{\partial E}A(s') + w^*(s,E)\sum_{s'}\frac{\partial S(s')}{\partial E_j}A(s')\right] \tag{25}$$

And finally rearranging:

$$\frac{\partial w^*(s,E)}{\partial E}\left[1+\alpha\Lambda^{-1}(E)\sum_{s'}\frac{\partial S(s')}{\partial w^*(s',E)}w^*(s',E)A(s')\right] = (-\alpha)\Lambda^{-1}(E)w^*(s,E)\sum_{s'}\frac{\partial S(s')}{\partial E_j}A(s') \tag{26}$$

Under Assumption 1, the term on the RHS is negative, because labour supply is strictly increasing in $E$ for at least some worker type. The coefficient in the square brackets on the LHS is positive because labour supply is increasing in wages. Therefore, the compensating differential $\frac{\partial w^*(s,E)}{\partial E}$ is negative for any $s$. □

## A.2 Proposition 2.

*Proof.* Let me indicate with $w_j^*(s, A_j, E_j)$ the optimal wage for type $s$ at firm $j$ given $A_j$ and $E_j$. Replacing the constraint, the profit of the firm wit respect to corporate social responsibility can be written as:

$$\begin{aligned}\Pi_j(A_j, E_j) =& A_j \left( \sum_s A(s) S_j(s, w_j^*(s, A_j, E_j), E_j) \right)^{1-\alpha} - \\ &- \sum_s w_j^*(s, A_j, E_j) S_j(s, w_j^*(s, A_j, E_j), E_j) - C_j(E_j)\end{aligned} \tag{27}$$

I proceed by monotone comparative statics. Suppose two firms $p$ and $q$ differ in productivity and $A_p > A_q$. Denote $E_p$ the value of ESG that maximizes $\Pi_e$ and $E_q$ the maximizer of $\Pi_q$. Then, $E_p > E_q$ if for any $j$, $\frac{\partial^2 \Pi_j}{\partial A_j \partial E_j} > 0$. To prove the proposition, it is then sufficient to show that the cross derivative of profit $\Pi_j$ is positive.

Let me denote $\Lambda_j(A_j, E_j) = \sum_s A(s) S_j(s, w_j^*(s, A_j, E_j), E_j)$. Start by computing the derivative of profit $\Pi_j$ with respect to $A_j$. I drop the subscript $j$ for readability:

$$\begin{aligned}\frac{\partial \Pi}{\partial A} &= \Lambda(A,E)^{1-\alpha} + A(1-\alpha)\Lambda(A,E)^{-\alpha}\frac{\partial \Lambda}{\partial A} - \sum_s \left[ \frac{\partial w^*(s)}{\partial A} S(s) + w^*(s) \frac{\partial S(s)}{\partial w^*(s)} \frac{\partial w^*(s)}{\partial A} \right] = \\ &= \Lambda(A,E)^{1-\alpha} + \sum_s \left[ A(1-\alpha)\Lambda(A,E)^{-\alpha} A(s) \frac{\partial S(s)}{\partial w^*(s)} \frac{\partial w^*(s)}{\partial A} - \frac{\partial w^*(s)}{\partial A} S(s) - \right. \\ &\qquad \left. - w^*(s) \frac{\partial S(s)}{\partial w^*(s)} \frac{\partial w^*(s)}{\partial A} \right] = \\ &= \Lambda(A,E)^{1-\alpha} + \sum_s \left[ \frac{1+\tau}{\tau} w^*(s) \frac{\partial S(s)}{\partial w^*(s)} \frac{\partial w^*}{\partial A} - \frac{\partial w^*}{\partial A} S(s) - w^*(s) \frac{\partial S(s)}{\partial w^*(s)} \frac{\partial w^*(s)}{\partial A} \right] = \\ &= \Lambda(A,E)^{1-\alpha} - \sum_s \frac{\partial w^*}{\partial A} S(s) \left[ \frac{1+\tau}{\tau} \frac{w^*}{S(s)} \frac{\partial S(s)}{\partial w^*} - 1 - \frac{w^*}{S(s)} \frac{\partial S(s)}{\partial w^*} \right] = \\ &= \Lambda(A,E)^{1-\alpha}\end{aligned} \tag{28}$$

The last passage is due to the fact that $\tau$ is the elasticity of labour supply. Now the cross derivative is:

$$\frac{\partial \Pi}{\partial A \partial E} = (1-\alpha)\Lambda(A,E)^{-\alpha} \sum_s A(s) \left[ \frac{\partial S(s)}{\partial w^*} \frac{\partial w^*}{\partial E} + \frac{\partial S(s)}{\partial E} \right] \tag{29}$$

Under Assumption 1, the compensating differential is negative so from equation (24) I know that the sum on the RHS is positive. This is equivalent to say that when workers like sustainability then raising sustainability increases the total workforce efficiency. I conclude then that the cross derivative is positive and thus demonstrate the proposition.

□

# B Empirical Analysis Details.

## B.1 Sample Selection

The main variable of interest for my empirical research design is gross salary in constant euros, which I divide by the number of hours worked to obtain a measure of hourly wages. I filter out all observations that have missing values (only 3) or null gross salary (0 observations). Also, I select individuals between 25 and 55 years of age to avoid confounding effects due to the start and end of careers (student jobs, retirement specificities, etc.).

It is important to mention that the variable for number of hours in my dataset indicates the total number of hours paid according to the contract, but it may not reflect the actual number of hours worked. There is significant variability in the relationship between the number of hours and pay duration. For example, people who worked year-round have anywhere between 0 and 6,000 hours worked. Even when selecting only individuals that are reported as full-time employees, there remains considerable dispersion. For this reason, I use both the number of hours and employment duration (in days) together to select only workers who worked at least one week in the entire year and had a total number of hours paid per week between 35 and 44, which are the minimum and maximum limits allowed under French law for a full employment contract. This results in a much more regular relationship between hours worked and employment duration.

In my dataset, observations are already selected to ensure a single entry per year per individual per plant. Yet the sample still contains about 2,600 repeated observations, where the same workers appear in two different firms in the same year. I could simply select the worker-firm-year observation that has the longest duration or the highest pay but a quick check suggests that this could lead to losing many moves across firms in the sample. For example, suppose there is an individual who worked for firm A in 2017, still worked for A in 2018 but switched to B in the same year and finally moved

to firm C in 2019. If I keep only the longest or the best paid job I might pick A for 2018 as well and loose the information about the intermediate connection through B. After a quick check, the number of double observations are 1,148, for a total of 573 potential connections that I might loose. Therefore I filter these observations in order to always keep the intermediate link (firm B in the example). To break all remaining ties, I select jobs with the latest start date in the year or the first firm by unique identifier in case the start date is the same.

## B.2 Definition (13) and derivation of fixed point equation.

Solving the model leads to the following system of equations:

$$Y_j = A_j \left( \sum_s A(s) S_j(s) \right)^{1-\alpha} \tag{30}$$

$$w_j(s) = \frac{\tau}{(1+\tau)} (1-\alpha) A_j \left( \sum_{s'} A(s') S_j(s') \right)^{-\alpha} A(s) \tag{31}$$

$$S_j(s) = N(s) \frac{[w_j(s) G(s, E_j) B_j(s)]^\tau}{\sum_{j'} [w_{j'}(s) G(s, E_{j'}) B_{j'}(s)]^\tau} \tag{32}$$

$$C_j'(E_j) = \sum_s \frac{w_j(s)}{\tau} \frac{\partial S_j(s)}{\partial E_j} \tag{33}$$

Let me show why defining $H_j$ as in (13), i.e. $H_j = \sum_s A(s) D(s) \left[ \frac{\tau(1-\alpha)}{(1+\tau)} A(s) G(s, E_j) B_j(s) \right]^\tau$ is particularly helpful. Define $D(s)$ as in Section 4 (omitting the time subscript for readability), i.e. $D(s) = \frac{N(s)}{\sum_{j'} [w_{j'}(s) G(s, E_{j'}) B_{j'}(s)]^\tau}$. The term $D(s)$ then depends exclusively on $s$ and represents an aggregate indicator of offered utility by all firms $j', \in \{1, \ldots, J\}$ in the market for workers of type $s$.

Then (32) becomes $S_j(s) = D(s)[w_j(s)G(s,E_j)B_j(s)]^\tau$. I can plug the expression into (31) to get:

$$
\begin{aligned}
w_j(s) = \frac{\tau}{(1+\tau)}(1-\alpha)A_j\left(\sum_{s'}A(s')D(s')[w_j(s')G(s',E_j)B_j(s')]^\tau\right)^{-\alpha}A(s) \quad \leftrightarrow \\
\leftrightarrow \quad A(s)D(s)[w_j(s)G(s,E_j)B_j(s)]^\tau = \\
= A(s)D(s)\left[\frac{\tau}{(1+\tau)}(1-\alpha)A_j\left(\sum_{s'}A(s')D(s')[w_j(s')G(s',E_j)B_j(s')]^\tau\right)^{-\alpha}A(s)G(s,E_j)B_j(s)\right]^\tau \\
\rightarrow \quad \sum_s A(s)D(s)[w_j(s)G(s,E_j)B_j(s)]^\tau = \\
= \sum_s A(s)D(s)\left[\frac{\tau}{(1+\tau)}(1-\alpha)A_j\left(\sum_{s'}A(s')D(s')[w_j(s')G(s',E_j)B_j(s')]^\tau\right)^{-\alpha}A(s)G(s,E_j)B_j(s)\right]^\tau \\
\leftrightarrow \quad \left[\sum_s A(s)D(s)[w_j(s)G(s,E_j)B_j(s)]^\tau\right]^{1+\tau\alpha} = \sum_s A(s)D(s)\left[\frac{\tau(1-\alpha)}{(1+\tau)}A_jA(s)G(s,E_j)B_j(s)\right]^\tau \\
\leftrightarrow \quad \left[\sum_s A(s)S_j(s)\right]^{1+\tau\alpha} = A_j^\tau\sum_s A(s)D(s)\left[\frac{\tau(1-\alpha)}{(1+\tau)}A(s)G(s,E_j)B_j(s)\right]^\tau
\end{aligned}
\tag{34}
$$

We then define:

$$
\left[\sum_s A(s)S_j(s)\right] = A_j^{\frac{\tau}{1+\tau\alpha}}\underbrace{\left[\sum_s A(s)D(s)\left[\frac{\tau(1-\alpha)}{(1+\tau)}A(s)G(s,E_j)B_j(s)\right]^\tau\right]^{\frac{1}{1+\tau\alpha}}}_{H_j} \tag{35}
$$

Therefore, $H_j$ depends directly on preferences only through $G(s,E_j)$. Of course, $D(s)$ still contains terms $w_j(s)$ and $G(s,E_j)$, but these will be aggregated at the level of the market for workers of skill $s$. Focusing on the RHS (35) and definition (13), it is possible to intuitively think of $H_j$ as the relative importance of individual specific factors (both worker type productivity and preferences) with respect to the market aggregate utility indicator $D(s)$, summed across markets for worker types. Looking at the LHS of (35), I can also think of $H_j$ as the relative importance of total workforce productivity with respect to firm-specific productivity.

Let me now derive from the system of equations a fixed point correspondence in $H_j$. It is immediate

from the last expression (35) and equation (2) that $H_j$ also satisfies:

$$\left(\frac{Y_j}{A_j}\right)^{\frac{1}{1-\alpha}} = A_j^{\frac{\tau}{1+\tau\alpha}} H_j \tag{36}$$

But, combining the production equation (2) respectively with the wages equation (31) and with the supply equation (32), I obtain:

$$w_j(s) = \frac{\tau}{(1+\tau)}(1-\alpha)A_j \left(\frac{Y_j}{A_j}\right)^{-\frac{\alpha}{1-\alpha}} A(s) \tag{37}$$

$$\left(\frac{Y_j}{A_j}\right)^{\frac{1}{1-\alpha}} = \sum_s A(s)N(s)\frac{[w_j(s)G(s,E_j)B_j(s)]^\tau}{\sum_{j'}[w_{j'}(s)G(s,E_{j'})B_{j'}(s)]^\tau} \tag{38}$$

Putting these two expression together:

$$\begin{aligned}\left(\frac{Y_j}{A_j}\right)^{\frac{1}{1-\alpha}} &= \sum_s A(s)N(s)\frac{\left[\frac{\tau}{(1+\tau)}(1-\alpha)A_j\left(\frac{Y_j}{A_j}\right)^{-\frac{\alpha}{1-\alpha}} A(s)G(s,E_j)B_j(s)\right]^\tau}{\sum_{j'}\left[\frac{\tau}{(1+\tau)}(1-\alpha)A_{j'}\left(\frac{Y_{j'}}{A_{j'}}\right)^{-\frac{\alpha}{1-\alpha}} A(s)G(s,E_{j'})B_{j'}(s)\right]^\tau} \quad \leftrightarrow \\ \leftrightarrow \quad \left(\frac{Y_j}{A_j}\right)^{\frac{1+\tau\alpha}{1-\alpha}} A_j^{-\tau} &= \sum_s A(s)N(s)\frac{[G(s,E_j)B_j(s)]^\tau}{\sum_{j'}\left[A_{j'}\left(\frac{Y_{j'}}{A_{j'}}\right)^{-\frac{\alpha}{1-\alpha}} G(s,E_{j'})B_{j'}(s)\right]^\tau}\end{aligned} \tag{39}$$

This defines a fixed point equation in $Y_j$. To show how I can express it as a function of $H_j$ instead, it is sufficient to use (36) to get:

$$H_j = \sum_s A(s)N(s)\frac{[G(s,E_j)B_j(s)]^\tau}{\sum_{j'} A_{j'}^{\frac{\tau}{1+\tau\alpha}} H_{j'}^{-\tau\alpha}[G(s,E_{j'})B_{j'}(s)]^\tau} \tag{40}$$

Ideally, I want to show that there exists a solution to this equation and that it is unique, using a fixed point theorem. It is also possible to show that the solution will depend only on an average of $A_j$, while depending directly on $G_j, B_j$ for every $s$.

## B.3 Interpretation of TV-AKM Regression

Let me start from equation (16):

$$\psi_{jt} = a_1 \log A_j - a_2 \log \sum_s A(s) D_t(s) \left[a_3 A(s) G(s, E_{jt}) B_j(s)\right]^\tau \tag{16}$$

Define weights $\omega_{jt}(s) = A(s)^{1+\tau} D_t(s) a_3^\tau B_j(s)^\tau$. Then:

$$\begin{aligned}
\psi_{jt} &= a_1 \log A_j - a_2 \log \sum_s \omega_{jt}(s) G(s, E_{jt})^\tau = \\
&= a_1 \log A_j - a_2 \log \sum_s \frac{\omega_{jt}(s) G(s, E_{jt})^\tau}{\sum_s \omega_{jt}(s)} - a_2 \log \sum_s \omega_{jt}(s) \leq \\
&\leq a_1 \log A_j - a_2 \tau \sum_s \frac{\omega_{jt}(s) \log G(s, E_{jt})}{\sum_s \omega_{jt}(s)} - a_2 \log \sum_s \omega_{jt}(s)
\end{aligned} \tag{41}$$

where the last inequality is due to the concavity of the logarithmic function and Jensen's Inequality. Ignoring the effect of $E_{jt}$ on $\omega_{jt}(s)$, the derivative of the RHS with respect to $E_{jt}$ is approximately:

$$-a_2 \tau \sum_s \frac{\omega_{jt}(s)}{\sum_s \omega_{jt}(s)} \frac{G'(s, E_{jt})}{G(s, E_{jt})} \tag{42}$$

Supposing non-ESG amenities $B_j$ are separable in time and firm components, firm and year fixed effects (approximately) control for the last term of the equation. Hence, approximating the relationship between $\psi_{jt}$ and $E_{jt}$ with a linear function will result in the coefficient on $E_{jt}$ being proportional to a weighted average of the relative rate of change of workers' preferences $G(s, E_{jt})$ across worker types $s$, if the rate of change does not depend on $E_{jt}$.

**Assumption VII.** *The rate of change of worker preferences for ESG does not depend on $E_{jt}$, i.e. there exists a function $f(s,t)$ such that $\frac{G'(s,E_{jt})}{G(s,E_{jt})} = f(s,t)$ for all $s$ and all $t$.*

Under Assumptions I, II and VII, a regression of year-firm fixed effects on ESG Scores will be informative about the sign of the compensating differential associated to corporate sustainability. It will also inform about the workers' preferences for ESG $G(s, E_{jt})$, in aggregate. In particular, its sign will be negative if and only if at least for some worker type $s$, $G'(s, E_{jt}) > 0$.

Notice that an example of such preferences is $G(s, E_{jt}) = \exp(\gamma_{st} E_{jt})$. In this case, equation (16) becomes:

$$\psi_{jt} = a_1 \log A_j - a_2 \log \sum_s \omega_{jt}(s) \exp(\gamma_{st} E_{jt})^\tau \tag{43}$$

As a consequence:

$$\frac{\partial \psi_{jt}}{\partial E_{jt}} = -a_2 \frac{\sum_s \omega_{jt}(s) \tau \exp(\gamma_{st} E_{jt})^\tau \gamma_{st}}{\sum_s \omega_{jt}(s) \exp(\gamma_{st} E_{jt})^\tau} \tag{44}$$

which is a again weighted average of $\gamma_{st}$. A linear approximation of the relationship between $\psi_{jt}$ and $E_{jt}$ then gives directly a coefficient which is proportional to a weighted average of $\gamma_{st}$. In particular, this will be negative if and only if at least some $\gamma_{st}$ is positive.

Alternatively, and perhaps more realistically, I can approximate the relationship between $\psi_{jt}$ and $E_{jt}$ with a log-linear relationship, provided the rate of change is proportional to $\frac{1}{E_{jt}}$. This is the case with the functional form specified in Assumption III.

# C Rolling AKM (R-AKM)

An implicit assumption behind AKM specification (R.3) and is that firm productivity and worker types are fixed across time. Although the inclusion of time-varying individual characteristics $x_{it}$ and time trends should be reassuring, one might still worry that systematic unobserved differences across time could confound the variation due to ESG Scores. Also, the firm year fixed effect in $\psi_{jt}$ of (R.3) will be identified by variation in salaries of both workers that move across firms and workers that stay at the same firm for different years. my model is silent about the exact dynamics of job movements, so this is not in principle a problem. Still, I might be concerned that salaries of stayers usually only tend to grow with tenure.

One way to address this concern is to estimate (R.2) on consecutive two-years time windows, so that the firm fixed effect is only identified by movers and worker effects are allowed to vary unrestrictedly across years. This specification is sometimes referred to as "revolving" AKM or R-AKM (Lachowska et al., 2023). Reassuringly, as shown in Table 7 and in Figure 2, individual fixed effects are positively and significantly related to the logarithm of ESG scores and the coefficient does not seem to exhibit a strong time trend. Also, when the regression is performed on year-firm fixed effects instead, coefficients keep the same sign as in the previous TV-AKM specification, but they lack

power. As the relationship between individual fixed effects and ESG scores does not seem to vary a lot across time, it is likely that the lower precision in the R-AKM regression on firm effects is due to the lower number of observations. Remember that each coefficient is identified exclusively by moves between firms in a given year. But the number of connected firms per year varies between 8 and 29, which seems too low to provide the necessary variation for a precise estimate of all firms effects.

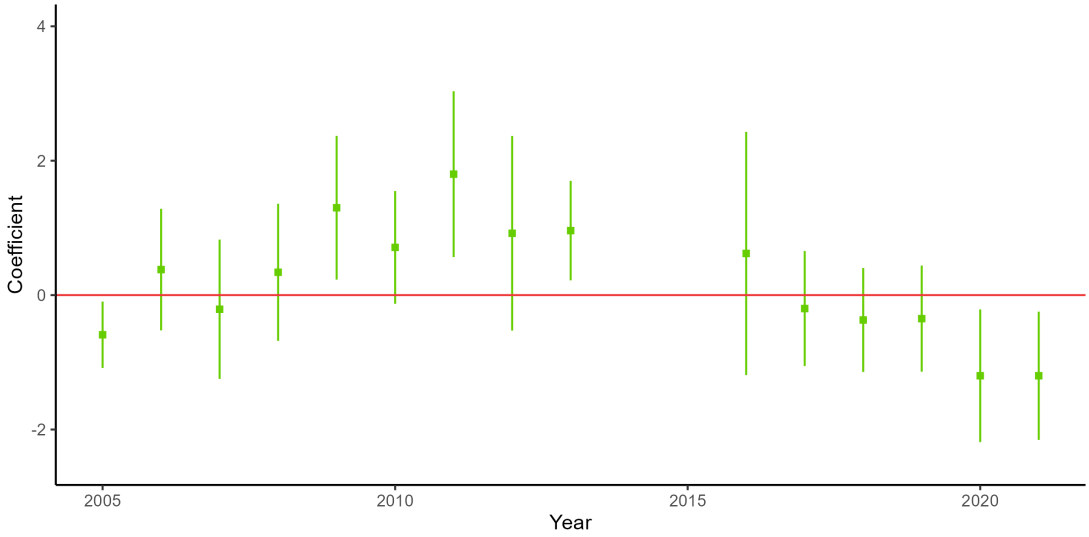



Figure 2: Coefficients from the R-AKM Regression.

Table 7: Results from R-AKM.

| | Year-Firm FE | | | Individual FE | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ESG Score | 0.19 | 0.42 | | 0.37 | |
| | (0.14) | (0.24) | | (0.21) | |
| ESG Score × 2005 | | | -0.59* | | 0.47** |
| | | | (0.30) | | (0.21) |
| ESG Score × 2008 | | | 0.34 | | 0.50** |
| | | | (0.62) | | (0.21) |
| ESG Score × 2013 | | | 0.96** | | 0.46** |
| | | | (0.45) | | (0.20) |
| ESG Score × 2017 | | | -0.20 | | 0.41* |
| | | | (0.52) | | (0.21) |
| ESG Score × 2021 | | | -1.2** | | 0.36* |
| | | | (0.58) | | (0.20) |
| Intercept | -0.70 | | | 1.6* | 1.4 |
| | (0.58) | | | (0.93) | (0.89) |
| *Second stage controls* | | | | | |
| Year FE | | Y | Y | | |
| Firm FE | | Y | Y | | |
| Clustered SE | | | Year & Firm | | Year & Firm |
| Observations | 237 | 237 | 237 | 290,695 | 290,695 |
| R-squared | 0.008 | 0.57 | 0.61 | 0.02 | 0.14 |

*Notes*: The dependent variables are estimated fixed effects from the AKM regression or log wages. Independent variables are in logarithms. See all the coefficients in Table 10. Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

# D Regression Tables

Table 8: Heterogeneity analysis - AKM.

| | Score type | | | Worker subset | | |
|---|---|---|---|---|---|---|
| | Environment | Social | Governance | Men | Women | Age $< 30$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Mean Score | 0.04 | -0.03 | 0.06 | -0.09 | 0.27** | -0.09 |
| | (0.08) | (0.12) | (0.08) | (0.13) | (0.13) | (0.11) |
| Intercept | 0.25 | 0.51 | 0.18 | 0.64 | -0.41 | -0.24 |
| | (0.30) | (0.46) | (0.30) | (0.51) | (0.54) | (0.46) |
| Observations | 121 | 125 | 125 | 111 | 92 | 72 |
| R-squared | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 |

*Notes*: The dependent variable is the firm fixed effect from the regression of wages on firm and individual effects. All specifications include time fixed effects and experience in the first stage. Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9: Full results from TV-AKM and Enhanced AKM, with KSS correction.

| | OLS | KSS | log Wage |
|---|---|---|---|
| | (1) | (2) | (3) |
| ESG Score × 2002 | 0.044 | -0.253*** | -0.26*** |
| | (0.24) | (0.027) | (0.05) |
| ESG Score × 2003 | -0.05 | -0.130*** | -0.06** |
| | (0.06) | (0.032) | (0.03) |
| ESG Score × 2004 | 0.035 | 0.133*** | 0.12*** |
| | (0.028) | (0.004) | (0.01) |
| ESG Score × 2005 | 0.071** | 0.10*** | 0.08** |
| | (0.028) | (0.006) | (0.04) |
| ESG Score × 2006 | -0.008 | 0.08*** | 0.07** |
| | (0.049) | (0.006) | (0.03) |
| ESG Score × 2007 | -0.007 | 0.08*** | 0.06* |
| | (0.054) | (0.006) | (0.03) |
| ESG Score × 2008 | -0.050 | 0.05*** | 0.05* |
| | (0.065) | (0.008) | (0.03) |
| ESG Score × 2009 | -0.014 | -0.007 | 0.004 |
| | (0.058) | (0.007) | (0.03) |
| ESG Score × 2010 | -0.017 | 0.03 | 0.04 |
| | (0.054) | (0.01) | (0.03) |
| ESG Score × 2011 | -0.009 | -0.063*** | -0.04 |
| | (0.044) | (0.01) | (0.03) |
| ESG Score × 2012 | 0.035 | -0.15*** | -0.13*** |
| | (0.052) | (0.01) | (0.04) |
| ESG Score × 2013 | -0.019 | -0.17*** | -0.15*** |
| | (0.055) | (0.01) | (0.03) |
| ESG Score × 2014 | -0.146*** | -0.18*** | -0.15*** |
| | (0.054) | (0.007) | (0.05) |
| ESG Score × 2015 | -0.116** | -0.18*** | -0.15*** |
| | (0.054) | (0.005) | (0.05) |
| ESG Score × 2016 | -0.089* | -0.16*** | -0.12** |
| | (0.050) | (0.008) | (0.05) |
| ESG Score × 2017 | 0.108* | -0.20*** | -0.14** |
| | (0.062) | (0.01) | (0.07) |
| ESG Score × 2018 | 0.063 | -0.28*** | -0.19* |
| | (0.052) | (0.01) | (0.10) |
| ESG Score × 2019 | 0.066 | -0.34*** | -0.21 |
| | (0.059) | (0.01) | (0.12) |
| ESG Score × 2020 | 0.066 | -0.37*** | -0.23 |
| | (0.069) | (0.01) | (0.14) |
| ESG Score × 2021 | 0.039 | -0.38*** | -0.26 |
| | (0.093) | (0.01) | (0.14) |
| Clustered SE | Year & Firm | | Year & Firm |
| Observations | 1,175 | 976 | 496,151 |
| R-squared | 0.86 | - | 0.91 |

*Notes*: See notes in Table 4. All specifications include firm and year fixed effects in the second stage. Standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 10: Full results from R-AKM.

| | Year-Firm FE | | | Individual FE | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ESG Score | 0.19 | 0.42 | | 0.37 | |
| | (0.14) | (0.24) | | (0.21) | |
| ESG Score × 2005 | | | -0.59* | | 0.47** |
| | | | (0.30) | | (0.21) |
| ESG Score × 2006 | | | 0.38 | | 0.43** |
| | | | (0.55) | | (0.20) |
| ESG Score × 2007 | | | -0.21 | | 0.38* |
| | | | (0.63) | | (0.21) |
| ESG Score × 2008 | | | 0.34 | | 0.50** |
| | | | (0.62) | | (0.21) |
| ESG Score × 2009 | | | 1.3* | | 0.34 |
| | | | (0.65) | | (0.21) |
| ESG Score × 2010 | | | 0.71 | | 0.41* |
| | | | (0.51) | | (0.21) |
| ESG Score × 2011 | | | 1.8** | | 0.39* |
| | | | (0.75) | | (0.20) |
| ESG Score × 2012 | | | 0.92 | | 0.46** |
| | | | (0.88) | | (0.20) |
| ESG Score × 2013 | | | 0.96** | | 0.46** |
| | | | (0.45) | | (0.20) |
| ESG Score × 2015 | | | 6.5*** | | 0.72*** |
| | | | (0.39) | | (0.22) |
| ESG Score × 2016 | | | 0.62 | | 0.32 |
| | | | (1.1) | | (0.20) |
| ESG Score × 2017 | | | -0.20 | | 0.41* |
| | | | (0.52) | | (0.21) |
| ESG Score × 2018 | | | -0.37 | | 0.44* |
| | | | (0.47) | | (0.22) |
| ESG Score × 2019 | | | -0.35 | | 0.46** |
| | | | (0.48) | | (0.20) |
| ESG Score × 2020 | | | -1.2* | | 0.37* |
| | | | (0.60) | | (0.20) |
| ESG Score × 2021 | | | -1.2** | | 0.36* |
| | | | (0.58) | | (0.20) |
| Intercept | -0.70 | | | 1.6* | 1.4 |
| | (0.58) | | | (0.93) | (0.89) |
| *Second stage controls* | | | | | |
| Year FE | | Y | Y | | |
| Firm FE | | Y | Y | | |
| Clustered SE | | | Year & Firm | | Year & Firm |
| Observations | 237 | 237 | 237 | 290,695 | 290,695 |
| R-squared | 0.008 | 0.57 | 0.61 | 0.02 | 0.14 |

*Notes*: The dependent variables are estimated fixed effects from the AKM regression or log wages. Independent variables are in logarithms. Year 2014 is missing because no employee movement was observed for the reference firm in 2013-2014. Standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 11: Results from the AKM Specification - Full sample.

| | Firm FE | | Individual FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Mean ESG Score | 0.10 | 0.09 | 0.197*** | 0.221 |
| | (0.08) | (0.07) | (0.004) | (0.180) |
| Intercept | 0.05 | -0.05 | 2.109*** | 2.044*** |
| | (0.29) | (0.27) | (0.016) | (0.774) |
| *First stage controls* | | | | |
| Time FE | | Y | | Y |
| Experience | | | | Y |
| Clustered SE | | | | Year & Firm |
| Observations | 181 | 181 | 480,498 | 480,498 |
| R-squared | 0.00 | 0.00 | 0.02 | 0.03 |

*Notes*: The dependent variables are estimated fixed effects from the AKM regression on the full sample of firms. Independent variables are in logarithms. First stage controls refer to observables (in logarithms) and fixed effects included in the AKM regression. Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 12: Results from TV-AKM - Full sample.

| | (1) | (2) | (3) |
|---|---|---|---|
| ESG Score | 0.07** | -0.05** | |
| | (0.036) | (0.030) | |
| ESG Score × 2002 | | | -0.208*** |
| | | | (0.048) |
| ESG Score × 2003 | | | -0.047* |
| | | | (0.032) |
| ESG Score × 2004 | | | 0.017 |
| | | | (0.026) |
| ESG Score × 2005 | | | 0.000 |
| | | | (0.021) |
| ESG Score × 2006 | | | -0.054** |
| | | | (0.022) |
| ESG Score × 2007 | | | -0.085*** |
| | | | (0.022) |
| ESG Score × 2008 | | | -0.032 |
| | | | (0.046) |
| ESG Score × 2009 | | | -0.059* |
| | | | (0.038) |
| ESG Score × 2010 | | | -0.148*** |
| | | | (0.022) |
| ESG Score × 2011 | | | -0.105*** |
| | | | (0.036) |
| ESG Score × 2012 | | | -0.124*** |
| | | | (0.042) |
| ESG Score × 2013 | | | -0.102** |
| | | | (0.045) |
| ESG Score × 2014 | | | -0.173*** |
| | | | (0.037) |
| ESG Score × 2015 | | | -0.185*** |
| | | | (0.033) |
| ESG Score × 2016 | | | -0.149*** |
| | | | (0.048) |
| ESG Score × 2017 | | | -0.059* |
| | | | (0.034) |
| ESG Score × 2018 | | | 0.018 |
| | | | (0.043) |
| ESG Score × 2019 | | | 0.013 |
| | | | (0.049) |
| ESG Score × 2020 | | | 0.041 |
| | | | (0.062) |
| ESG Score × 2021 | | | 0.070 |
| | | | (0.076) |
| *Second stage controls* | | | |
| Year FE | | Y | Y |
| Firm FE | | Y | Y |
| Observations | 1,075 | 1,075 | 1,075 |
| Adjusted $R^2$ | 0.01 | 0.83 | 0.84 |

*Notes*: Standard errors clustered at the firm and year level in parentheses. Gray text in column (3) indicates statistically insignificant estimates. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

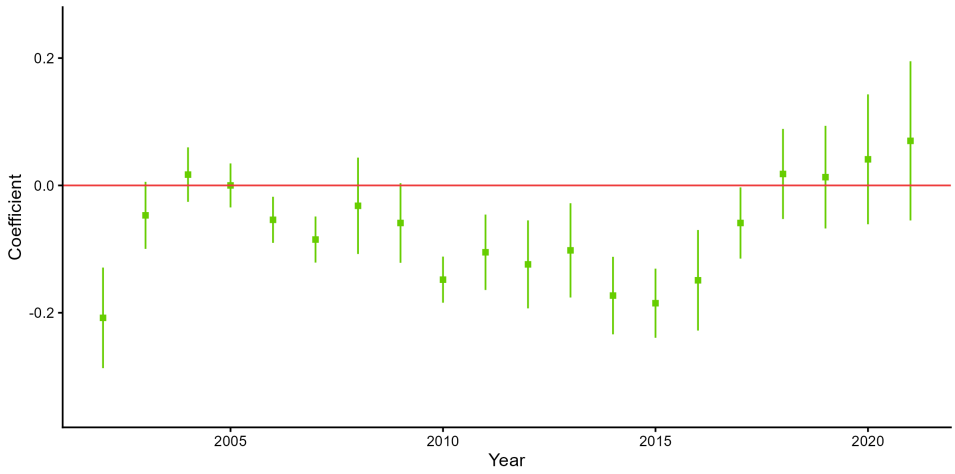



Figure 3: Results from TV AKM - Firms (first stage with full sample).

Table 13: Results from TV-AKM and Enhanced AKM - Movers only.

| | Individual FE | | Firm FE | | | |
|---|---|---|---|---|---|---|
| | | | OLS | | log Wage | |
| | (5) | (6) | (1) | (2) | (3) | (4) |
| ESG Score | 0.39*** | 0.29*** | | | | |
| | (0.01) | (0.00) | | | | |
| Intercept | 1.54*** | 1.44*** | | | | |
| | (0.02) | (0.02) | | | | |
| ESG Score × 2004 | | | 0.21*** | 0.16*** | 0.13*** | 0.08*** |
| | | | (0.05) | (0.04) | (0.02) | (0.02) |
| ESG Score × 2005 | | | 0.15** | 0.12** | 0.08 | 0.04 |
| | | | (0.05) | (0.05) | (0.05) | (0.04) |
| ESG Score × 2006 | | | 0.01 | 0.01 | 0.06 | 0.03 |
| | | | (0.03) | (0.03) | (0.04) | (0.03) |
| ESG Score × 2007 | | | -0.00 | -0.02 | 0.03 | 0.01 |
| | | | (0.04) | (0.04) | (0.03) | (0.03) |
| ESG Score × 2008 | | | -0.06 | -0.05 | 0.04 | 0.03 |
| | | | (0.10) | (0.09) | (0.02) | (0.03) |
| ESG Score × 2009 | | | -0.12* | -0.12* | 0.05 | 0.04 |
| | | | (0.06) | (0.06) | (0.04) | (0.04) |
| ESG Score × 2010 | | | 0.08* | 0.07* | 0.15*** | 0.12*** |
| | | | (0.04) | (0.03) | (0.05) | (0.06) |
| ESG Score × 2011 | | | 0.03 | -0.00 | -0.10** | -0.12** |
| | | | (0.05) | (0.04) | (0.03) | (0.03) |
| ESG Score × 2012 | | | -0.04 | -0.06 | -0.22*** | -0.24*** |
| | | | (0.04) | (0.04) | (0.07) | (0.07) |
| ESG Score × 2013 | | | -0.13*** | -0.14*** | -0.25*** | -0.28*** |
| | | | (0.04) | (0.04) | (0.05) | (0.06) |
| ESG Score × 2014 | | | -0.02 | -0.05 | -0.24*** | -0.30*** |
| | | | (0.06) | (0.06) | (0.09) | (0.10) |
| ESG Score × 2015 | | | -0.10 | -0.11 | -0.19*** | -0.24*** |
| | | | (0.07) | (0.07) | (0.05) | (0.06) |
| ESG Score × 2016 | | | -0.14** | -0.15*** | -0.15** | -0.20** |
| | | | (0.05) | (0.05) | (0.05) | (0.06) |
| ESG Score × 2017 | | | -0.15* | -0.18** | -0.19** | -0.25** |
| | | | (0.08) | (0.08) | (0.08) | (0.08) |
| ESG Score × 2018 | | | -0.11 | -0.14 | -0.26** | -0.30** |
| | | | (0.12) | (0.11) | (0.10) | (0.11) |
| ESG Score × 2019 | | | -0.14 | -0.17 | -0.30** | -0.35** |
| | | | (0.12) | (0.12) | (0.12) | (0.13) |
| ESG Score × 2020 | | | -0.13 | -0.16 | -0.32* | -0.38* |
| | | | (0.16) | (0.16) | (0.13) | (0.15) |
| ESG Score × 2021 | | | -0.18 | -0.23 | -0.34* | -0.41* |
| | | | (0.17) | (0.17) | (0.13) | (0.14) |
| *First stage controls* | | | | | | |
| Experience | | Y | | Y | | Y |
| Clustered SE | | | Year & Firm | Year & Firm | Year & Firm | Year & Firm |
| Observations | 104,079 | 104,049 | 348 | 348 | 438,128 | 438,058 |
| R-squared | 0.05 | 0.04 | 0.96 | 0.94 | 0.91 | 0.91 |

*Notes*: See notes in Table 4. All specifications include firm and year fixed effects in the second stage. Standard errors clustered at the firm and year level are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

# E Additional Simulation Results

Estimated transition matrix for $s = 1$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.885 | 0.031 | 0.032 | 0.080 |
| **2** | 0.048 | 0.896 | 0.042 | 0.168 |
| **3** | 0.063 | 0.068 | 0.921 | 0.251 |
| **-** | 0.005 | 0.006 | 0.005 | 0.502 |

True transition matrix for $s = 1$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.882 | 0.032 | 0.032 | 0.110 |
| **2** | 0.045 | 0.895 | 0.045 | 0.156 |
| **3** | 0.068 | 0.068 | 0.918 | 0.235 |
| **-** | 0.005 | 0.005 | 0.005 | 0.500 |

Estimated transition matrix for $s = 2$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.876 | 0.026 | 0.025 | 0.093 |
| **2** | 0.046 | 0.895 | 0.045 | 0.154 |
| **3** | 0.073 | 0.074 | 0.924 | 0.258 |
| **-** | 0.005 | 0.004 | 0.006 | 0.495 |

True transition matrix for $s = 2$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.876 | 0.026 | 0.026 | 0.088 |
| **2** | 0.042 | 0.892 | 0.042 | 0.146 |
| **3** | 0.077 | 0.077 | 0.927 | 0.266 |
| **-** | 0.005 | 0.005 | 0.005 | 0.500 |

Estimated transition matrix for $s = 3$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.872 | 0.018 | 0.019 | 0.071 |
| **2** | 0.038 | 0.888 | 0.035 | 0.143 |
| **3** | 0.086 | 0.089 | 0.940 | 0.290 |
| **-** | 0.004 | 0.005 | 0.006 | 0.496 |

True transition matrix for $s = 3$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.870 | 0.020 | 0.020 | 0.069 |
| **2** | 0.040 | 0.890 | 0.040 | 0.137 |
| **3** | 0.085 | 0.085 | 0.935 | 0.294 |
| **-** | 0.005 | 0.005 | 0.005 | 0.500 |

Estimated transition matrix for $s = 4$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.855 | 0.017 | 0.014 | 0.040 |
| **2** | 0.041 | 0.884 | 0.038 | 0.174 |
| **3** | 0.101 | 0.092 | 0.943 | 0.312 |
| **-** | 0.003 | 0.007 | 0.006 | 0.475 |

True transition matrix for $s = 4$.

| | **1** | **2** | **3** | **-** |
|---|---|---|---|---|
| **1** | 0.865 | 0.015 | 0.015 | 0.050 |
| **2** | 0.037 | 0.887 | 0.037 | 0.127 |
| **3** | 0.094 | 0.094 | 0.944 | 0.323 |
| **-** | 0.005 | 0.005 | 0.005 | 0.500 |