Beyond Skills: Firms, Automation and Wage Inequality

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This paper studies how firm heterogeneity in automation adoption shapes wage inequality. While the existing literature has focused on inequality between skills, I show that automation also creates wage dispersion between otherwise similar workers depending on whether they are employed at automation leaders or laggards. I develop a static general equilibrium model with heterogeneous producers that endogenously choose their automation level in a task-based production technology, compete monopolistically, and set wages in imperfectly competitive labor markets. Automation lowers production costs by replacing workers in certain tasks with capital. In equilibrium, variation in automation levels generates wage dispersion even among workers with identical skills. At more automated firms, workers benefit from a positive productivity effect coming from cost savings, output expansion, and rising labor demand. This effect applies across all skill groups. At the same time, workers with a comparative advantage in tasks closer to those performed by capital face an additional negative displacement effect. Importantly, the model provides an identification strategy that isolates these two effects from unobserved productivity shocks by exploiting joint movements in relative input prices and quantities. Using French manufacturing data that link firm-level investments in industrial robots to administrative employer–employee records, I find that white-collar workers at automating firms experience on average wage gains of 7% relative to their counterparts at non-automating firms, while blue-collar workers gain about 5%, suggesting that firm-level automation benefits also replaceable workers. In this sense, robots do not replace humans, rather humans with robots replace humans without robots.

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1 Introduction

In the last decades, a wealth of new technologies have been deployed to automate the production of goods and services. Industrial robots now handle welding and assembly in manufacturing plants, automated teller machines (ATMs) dispense cash once handed out by bank tellers, and artificial intelligence processes information and makes judgments that previously required human reasoning. This wave of automation has substantially contributed to the growth that developed economies have experienced since World War II (Acemoglu and Restrepo, 2022). However, the benefits of this technological transformation have not accrued equally across workers. A large empirical evidence documents that high-skill workers, those performing cognitive tasks, have ripped most of the gains from automation , while low-skill workers in routine occupations have experienced stagnant or declining wages (Autor et al., 2003; Acemoglu and Autor, 2011). While research has established that differences in skills are crucial to understanding automation's distributional consequences, it has largely overlooked the role played by firms. In fact, automating technologies concentrate among a subset of firms – the largest and most productive ones in each sector (Acemoglu et al., 2020; Koch et al., 2021) – suggesting that workers, even if they have the same skills, are more or less exposed to automation depending on whether they work at a firm that adopts automating technologies or not.

In this paper, I study the role of firms in shaping the impact of automation on wage inequality. More specifically, I develop a theoretical framework linking firm-level automation decisions to wage dispersion and empirically quantify this relationship. The theoretical model has a two-fold purpose. First, it pins down the key economic forces that drive wage differences across workers at automating and non-automating firms. Secondly, based on these insights, it provides a strategy to identify the effect of firm-level automation on wages when unobserved confounders simultaneously drive automation and wages. Guided by this identification strategy, I estimate a set of difference-in-differences regressions comparing the relevant economic outcomes between automating and non-automating firms. To this end, I use exceptionally detailed data on automation investments in French manufacturing spanning 17 years, that I link with wage information from administrative employer-employee records. I find that at automating firms both high- and low-skill workers gain relative to their counterparts at non-automating firms (+7% and +5%, respectively), underscoring that automation's benefits accrue primarily to workers at adopting firms. Finally, I show how to use these estimates to quantify the contribution of firm-level automation to wage inequality and, importantly, compare its contribution to *between-firm* wage dispersion versus *between-skill* wage dispersion.

The model incorporates heterogeneous firms, monopolistic competition, and firm-level wage-setting power into a task-based production framework. First, I firms operate a task-based production technology à la Acemoglu-Restrepo combining capital, low-skill labor, and high-skill labor to perform a continuum of tasks. Crucially, automation involves replacing low-skill workers with capital in the production of a given task, while high-skill workers are not directly displaced. This structure captures the reality of automation in the manufacturing context, which is my empirical setting: industrial robots replace assembly line workers performing routine manual tasks, but do not substitute for engineers who design production processes or managers who coordinate operations. Second, firms differ in their total factor productivity, which creates endogenous variation in automation adoption. More productive firms find it more profitable to automate additional tasks because they can spread the fixed costs of automation over larger production volumes. This generates the empirically-observed pattern where automation technologies concentrate among industry leaders. Third, monopolistic competition in product markets ensures that when firms automate and reduce costs, they gain market share at the expense of competitors. This business-stealing effect is essential for allowing for negative spillovers on workers at non-automating firms, as observed in the data (Aghion et al., 2025a). Fourth, firms possess wage-setting power arising from firm-specific amenities that make workers imperfectly mobile across employers. Without such frictions, perfect labor mobility would equalize wages across firms, eliminating any differential effects of automation.

The model delivers three key main insights. Firstly, larger firms automate more tasks. This is because the benefit of automating an additional task consists, in essence, in paying a fixed cost to reduce the unit cost of production. Therefore larger firms enjoy larger total cost savings as they spread the per-unit cost savings over a larger output. This finding highlights that any unobserved shock that increases firm size, such as positive demand or productivity shocks, also incentivizes firms to automate more tasks, hence confounding the relationship between automation and wages. In the absence of random variation in automation decisions across firms, this challenges the identification of automation's effect on wages, and so on wage inequality. Secondly, wage differences between workers at automating and non-automating firms can be characterized in terms of two effects: a negative displacement effect and a positive scale effect. When a firm increases its automation level, it replaces the low-skill workers carrying-out the marginal task with capital. This is the negative displacement effect of automation and it is faced by low-skill workers only. However, automation also reduces production costs, allowing the firm to lower prices, expand output, and increase labor demand across all skill groups. This is the positive scale effect of automation. Hence, according to the model, high-skill workers at automating firms gain relative to their counterparts at non-automating firms as they experience a positive scale effect. Instead, low-skill workers experience both a positive scale effect and a negative displacement effect, leaving the net effect ambiguous. This result questions the commonly held view that automation necessarily harms replaceable workers at adopting firms: if the scale effect is sufficiently strong, low-skill workers at automating firms may actually benefit despite losing some tasks to machines. Importantly, I show that these two effects are governed by two key elasticities: the elasticity to the firm's automation level of the task-share of low-skill workers and of capital. These elasticities capture the extent to which a marginal increase in the automation level impacts the (productivity-weighted) share of tasks performed by these two inputs, and so measure how much production becomes more intensive in capital and less intensive in low-skill labor. Thirdly, these two elasticities can be identified by comparing relative prices and quantities of capital, low- and high-skill workers across automating and non-automating firms. This identification strategy relies on the insight that automation, by making production more intensive in capital and less intensive in low-skill labor, changes the relative productivities of inputs, while unobserved productivity or demand shocks shift the marginal (revenue) product of all inputs proportionally. As a result, relative prices and quantities capture the automation-induced changes in task-shares, but not these unobserved shocks. The estimates of the task-share elasticities can then be mapped into the between-firm wage differential of automation using the model's characterization and a parsimonious set of parameters (three parameters: the elasticities of substitution across tasks and across goods, and the labor supply elasticity).

Guided by this identification strategy, I investigate empirically the extent to which firm-level automation contributes to wage inequality in the context of the French manufacturing sector between 2003 and 2019, which represents an ideal setting for several reasons. First, France offers exceptional data availability which allows to precisely track firm-level adoption of automating machines and worker outcomes. Indeed, it is one of the few countries making available, at the same time, customs records providing detailed information on firm-level expenditures on automating machines, and administrative linked employer-employee data containing rich information on individual wages and occupations. This combination enables me to classify workers into skill groups and measure their wage, as well as computing firm-level employment by skill group and tracking changes in these outcomes in relation to their firm's automation decisions. Third, the French manufacturing sector has experienced significant automation over the past two decades, being the third-largest robot user in the European Union (IFR, 2020). Lastly, French labor market institutions, including strong employment protection and collective bargaining, create the wage-setting frictions comparable to those in the model.

I estimate a set of difference-in-differences type regressions which compare the relative wages and relative employment of high- to low-skill workers, as well as expenditures in capital per employed worker, across firms adopting automating machines (i.e. increase their automation level) and non-adopting ones (i.e. keep their automation level unchanged). I find that automation, on average, reduces the task-share of low-skill workers by 4% and increases the task-share of capital by 6%. Using the model's characterization and values for the three structural parameters, this implies that high-skill workers at automating firms gain 7% in wages relative to their counterparts at non-automating firms. This finding is consistent with the model's prediction that high-skill workers benefit from the positive scale effect of automation. More surprisingly, I find that low-skill workers at automating firms gain 5% in wages relative to their counterparts at non-automating firms. This suggests that the positive scale effect of automation outweighs the negative displacement effect for low-skill workers, indicating that even replaceable workers can benefit, at least in relative terms, from working at automating firms.

These results are robust across multiple specifications. Specifically, the estimates withstand a variety of controls for market-specific shocks that could potentially be correlated with firm-level automation. In particular, I include local labor market-specific time trends, industry-specific time trends and occupation-specific time trends.

Lastly, I provide a methodology combining the estimated wage effects and the model to quantify the between-firm inequality channel of automation. The exercise consists in decomposing the overall wage dispersion into between-skill and between-firm components, and compute how much of each component is explained by firm-level automation. This decomposition is crucial for two reasons. First, it reveals whether automation's distributional impact operates primarily through widening skill premia – a well-documented channel in the existing literature -— or through the novel channel proposed by this paper which emphasizes wage disparities between automating and non-automating firms. Second, and related, the realized magnitude of between-firm wage gaps depends critically on worker mobility: if workers are highly mobile across firms, wage differentials may be quickly arbitraged away, whereas immobility amplifies them.

Related literature. This paper contributes to two main strands of literature: the theoretical development of task-based models of automation and the empirical literature on automation's effects on individual workers' earnings. While building on significant advances in both areas, this work addresses key limitations in existing empirical approaches and extends the theoretical framework to better capture the effect of automation on wage inequality.

The theoretical foundation for understanding automation's impact on labor markets has been substantially advanced by the task-based approach pioneered by Acemoglu and Autor (2011) and further developed by Acemoglu and Restrepo (2022). This framework models production as requiring the completion of a continuum of tasks, which can be performed by either workers of different skill types or by capital (automation technology). The key insight is that automation operates at the extensive margin—substituting capital for labor in tasks that were previously performed exclusively by workers. As Restrepo (2023) summarizes, the task model captures automation's dual effects: a productivity effect that reduces production costs and potentially increases labor demand, and a displacement effect that directly reduces employment opportunities for workers whose tasks become automated. This framework provides a more nuanced understanding than traditional models that treat automation as merely labor-augmenting technological change. Recent theoretical work has extended the basic task model to incorporate firm heterogeneity and endogenous automation decisions (Hubmer and Restrepo, 2024). This paper contributes to this theoretical literature by: 1) studying endogenous automation decisions in a setup with more than one skill type, allowing for richer interactions between automation and worker heterogeneity, and 2) adding dynamics to analyze how workers adapt to automation shocks through job transitions, skill upgrading, and occupational mobility over their entire careers.

Despite the substantial theoretical advances in understanding automation's effects, there remains relatively scarce worker-level evidence on how automation affects individual workers' earnings and career trajectories. Much of the early empirical work focused on demographic groups (Acemoglu and Restrepo, 2022) or occupation-level analysis Humlum (2021), which, while informative about group-level trends, may mask large significant heterogeneity across individual workers. Yet this heterogeneity is critical for designing targeted labor market policies.

To the best of my knowledge, Bessen et al. (2023) and Acemoglu et al. (2023) are the only two studies to provide estimates of how automation affects individual worker outcomes. Both exploit matched employer-employee administrative datasets and implement difference-in-differences event-study designs. Bessen et al. (2023) use Dutch administrative data to identify "automation events" as lumpy spikes in firm-level expenditures on automation technologies. They compare workers at automating firms to those at firms that will automate later, thereby addressing diverging trends across firm types. They find that incumbent workers at automating firms experience a cumulative earnings loss of 9% of one year's wage over five years, driven by increased non-employment—mainly early retirement—but find no evidence of wage scarring for those who remain employed. Acemoglu et al. (2023), using Dutch data as well, measure robot adoption via firm-level import records. They compare outcomes for workers at automating firms and at non-adopting firms in the same 4-digit industry, instrumenting robot adoption with lagged robot adoption in Korea and Taiwan. They find that robot adoption reduces earnings and employment probabilities for directly-affected workers (those in routine or replaceable occupations), while other workers benefit. Importantly, they also find negative effects on workers at competing non-adopting firms, suggesting substantial industry-level displacement effects.

Crucially, both studies center their analysis on the treated workers within adopting firms, implicitly assuming that the primary effects of automation materialize there. By contrast, this paper shifts the focus to the untreated: workers at non-automating firms. These workers, though not directly exposed to automation within their own firm, are vulnerable to the indirect competitive pressures induced by automation elsewhere. I develop a dynamic general equilibrium model of the labor market in which firms endogenously choose whether to automate tasks and workers can reallocate across firms and sectors. This framework allows me to re-evaluate the earnings losses associated with automation, explicitly accounting for the negative spillovers on workers at non-adopting firms.

In doing so, I uncover that the most severe distributional consequences of automation fall not on the treated, but on those left behind.

Outline. The remainder of the paper is organized as follows. Section 2 develops the model of endogenous automation with heterogeneous firms and workers. Section 3 presents the identification challenge for estimating automation's wage effects and develops a model-based strategy to address it. Section 4 describes the institutional context and data from French manufacturing. Section 6 presents the empirical results. Section 7 discusses the contribution of automation to wage inequality. Section 8 provides a methodology to quantify the contribution of firm-level automation to wage inequality and Section 9 concludes.

2 A model of automation with heterogenous workers and firms

The model developed in this section is designed to quantify how automation affects wages across firms and skill groups while replicating three facts documented in the existing literature that suggest that heterogeneity in firm-level automation rates can generate wage inequality. First, investments in automation technologies concentrate among the most productive firms. Second, firms that adopt these technologies experience significant increases in sales and employment, while their competitors shrink (Acemoglu et al., 2020; Aghion et al., 2025a; Bonfiglioli et al., 2024), suggesting that automation exerts large business-stealing effects on non-automating firms. Third, depending on their skill or tasks in the firm, some workers are more affected than others by automation (Acemoglu and Restrepo, 2022).

To do so, the model incorporates in a task-based production framework (Acemoglu and Restrepo, 2022) four key ingredients: heterogeneous firms, heterogeneous workers, monopolistic competition and wage-setting power at the firm level.

First, firms differ in productivity. Because automation is costly, more productive firms automate more tasks, generating endogenous variation in automation adoption levels. Second, workers are low- or high-skill. The former ones are more productive at tasks that are highly automatable while the latter ones excel at tasks that are little automatable. Third, monopolistic competition in the product market generates demand reallocation: when firms automate and reduce costs, they gain market share at the expense of non-automating competitors, creating negative spillovers on workers at these firms even though they are not directly exposed to automation. Finally, firms have some wage-setting power which arises from firm-specific amenities as modeled in (Card et al., 2018). This is done to allow wages to be differentially affected by automation at automating and non-automating firms, even within skill-group.

2.1 Environment

Workers. A representative household is composed of $N = L + H$ members, of which H are high skilled and L are low skilled. The household allocates workers across firms and uses their labor income to consume a composite final good.

Consumption. The household consumes a set of differentiated goods indexed by $j = 1, \ldots, J$, aggregated into a CES composite:

$$Y = \left(\sum_{j=1}^{J} y_j^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where σ is the elasticity of substitution across varieties. The corresponding price index is

$$P = \left(\sum_{j=1}^{J} p_j^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

which I normalize to 1. Let total household income be E, equal to the sum of labor earnings and distributed firm profits:

$$E = \sum_{j=1}^{J} \left(w_{Lj} L_j + w_{Hj} H_j \right) + \Pi$$

Utility maximization yields the standard CES demand for each variety j:

$$y_j = p_j^{-\sigma} Y, \qquad \text{and} \qquad Y = E \tag{1}$$

Labor supply. Labor supply decision are modeled as in Card et al. (2018). Each worker is endowed with one unit of labor. The household allocates its members across firms so as to to maximize their indirect utility. For workers in skill group $S \in \{L, H\}$, the indirect utility of working at firm j is

$$u_{ij} = \ln w_{Sj} + \ln a_{Sj} + \epsilon_{ij}, \tag{2}$$

where w_{Sj} is the firm-specific wage paid to individual i, $\ln a_{Sj}$ is a firm-specific amenity common to all workers in group S, and ϵ_{ij} captures idiosyncratic preferences for working at firm j (e.g., commuting distance, flexibility). The ϵ_{ij} are independent draws from a type I Extreme Value distribution with dispersion parameter ϕ.

Given posted wages, workers are free to work at any firm. Standard discrete-choice arguments (McFadden, 1977) imply logit choice probabilities:

$$\begin{aligned} P_{ij}^{S}\left(\arg\max_{k \in \{1,\ldots,J\}} \{u_{ik}^{S}\} = j \right) &= \frac{\exp\left(\frac{1}{\phi} \ln w_{Sj} + \ln a_{Sj} \right)}{\sum_{k=1}^{J} \exp\left(\frac{1}{\phi} \ln w_{Sk} + \ln a_{Sk} \right)} \\ &= \Lambda_S \exp\left(\frac{1}{\phi} \ln w_{Sj} + \ln a_{Sj} \right), \end{aligned}$$

where $\Lambda_S = \left[\sum_{k=1}^{J} \exp\left(\frac{1}{\phi} \ln w_{Sk} + \ln a_{Sk}\right)\right]^{-1}$ is the wage index for skill group S which ensures that the aggregate labor markets clear, and so is common to all firms.

The above choice probabilities lead to the following upward sloping labor supply curve:

$$S_j = (w_{Sj})^{\frac{1}{\phi}} \, S \, \Lambda_S \, a_{Sj} \tag{3}$$

Firms. Each variety j is produced by combining a continuum of tasks $x \in [0, 1]$ using a CES aggregator with elasticity of substitution η (Acemoglu and Restrepo, 2022). For example, producing a shirt requires completing a set of tasks: designing the garment, cleaning and carding the fibers, spinning and weaving the fabric, cutting the material, sewing the pieces together, quality inspection, packaging, and logistics. Each of these tasks can potentially be performed by different combinations of capital (automated machinery), low-skill workers (machine operators and assembly workers), or high-skill workers (designers and quality engineers). Firms differ in their total factor productivity z_j. Hence, the technology of firm j is:

$$y_j = z_j \cdot \left(\int_0^1 y(x)^{\frac{\eta-1}{\eta}} dx \right)^{\frac{\eta}{\eta-1}}$$

The technology for each task x is given by:

$$y(x) = \psi_K(x) K(x) + \psi_L(x) L(x) + \psi_H(x) H(x) \tag{4}$$

where $K(x)$, $L(x)$ and $H(x)$ are the amounts of capital, low-skill and high-skill workers used in task x, respectively, and $\psi_K(x)$, $\psi_L(x)$ and $\psi_H(x)$ are the task-specific productivity of capital, low-skill and high-skill workers, respectively. So, inputs are perfect substitutes at the task level. This captures in a stark way that machines can perfectly substitute for workers at narrowly defined tasks. For example, a welding robot is a perfect substitute for workers in the task of welding car parts. A software system is a perfect substitute for humans in the task of receiving and dispatching sales orders.

Following Acemoglu and Restrepo (2022), I assume that each input has a strict comparative advantage in some task. More specifically, I assume that:

$$\frac{\psi_K(x)}{\psi_L(x)} \text{ is decreasing in } x, \quad \text{and} \quad \frac{\psi_L(x)}{\psi_H(x)} \text{ is decreasing in } x. \tag{5}$$

meaning that capital is most productive at lower-indexed tasks, i.e. tasks close to 0, high-skill workers are most productive at higher-indexed tasks, i.e. tasks close to 1, and low-skill workers are most productive in intermediate tasks.

Firms choose the quantity of inputs to employ across tasks. To use capital in a task, the firm has to pay a fixed cost b. Instead, using low- or high-skill workers requires no fixed cost to be paid. An interpretation for this assumption is that using capital requires some installment cost. In order to perform a particular task at a particular plant, it is essential that capital be specially designed for the task and be custom made[1]. Under the assumptions that inputs are perfect substitutes at the task-level (equation (4)), that relative productivities are monotonic over the task interval (equation (5)), and that firms face a strictly positive supply of each skill type at any positive wage (equation (3)), it follows (see Appendix X) that the equilibrium allocation of inputs across tasks is:

$$y(x) = \begin{cases} \psi_K(x)K(x) & \text{if } 0 < x \leq \alpha_1 \\ \psi_L(x)L(x) & \text{if } \alpha_1 < x \leq \alpha_2 \\ \psi_H(x)H(x) & \text{if } \alpha_2 < x \leq 1 \end{cases}$$

where $0 \leq \alpha_1 < \alpha_2 < 1$. This means that, in equilibrium, the firm uses capital in tasks from 0 to α_1, low-skill workers from α_1 to α_2, and high-skill workers from α_2 to 1, where the cutoffs α_1 and α_2 are endogenously determined by the firm. I call α_1 a firm's *automation level*, as it determines the share of tasks performed by capital, and so the extent to which production is automated.

Given such an assignment of inputs to tasks, the technology of firm j can be written as:

$$y_j = z_j \left[\Gamma^K(\alpha_{1j})^{\frac{1}{\eta}} K_j^{\frac{\eta-1}{\eta}} + \Gamma^L(\alpha_{1j}, \alpha_{2j})^{\frac{1}{\eta}} L_j^{\frac{\eta-1}{\eta}} + \Gamma^H(\alpha_{2j})^{\frac{1}{\eta}} H_j^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{6}$$

where $\Gamma^K(\alpha_{1j}) = \int_0^{\alpha_{1j}} \psi_K(x)^{\eta-1}dx$, $\Gamma^L(\alpha_{1j}, \alpha_{2j}) = \int_{\alpha_{1j}}^{\alpha_{2j}} \psi_L(x)^{\eta-1}dx$, and $\Gamma^H(\alpha_{2j}) = \int_{\alpha_{2j}}^{1} \psi_H(x)^{\eta-1}dx$ are inputs' task-shares, i.e. the share of tasks carried out by the input weighted by its task-specific productivity. Technology (8) resembles a CES production function but with endogenous shares Γ^K,Γ^L, Γ^H which determine the intensity with which each factor is used in production. This extends the framework in Hubmer and Restrepo (2024) to multiple skill types, allowing me to study how endogenous automation decisions shape wage differences across workers with varying skill levels.[2].

Firms maximize profits given the production technology, the demand for their variety and the supply of low- and high-skilled workers, the fixed cost of automation b and the rental rate of capital r. They choose the level of output y_j, their price p_j, the demands for capital, low- and high-skilled labor K_j, L_j and H_j, and importantly, the cutoffs α_{1j} and α_{2j} that determine the allocation of

[1] While one can think of examples of capital goods that can be obtained "off the shelf" that may not incorporate much firm-specific design (e.g., a forklift truck), most capital goods—such as assembly lines or dedicated machinery, —require firm-specific design investments and customization for the particular production environment. Indeed, setup costs associated with the use of industrial robots can add up to four times the cost of the actual equipment (see, for example, Leigh and Kraft (2018))

[2] Acemoglu and Restrepo (2022) also features a task-based technology employing workers with multiple skill types. However, their setting does not model automation decisions, and so cannot be readily used for the purpose of this study.

inputs across tasks. Formally, firm j chooses $\mathcal{C} = \{p_j, y_j, L_j, H_j, K_j, \alpha_{1j}, \alpha_{2j}\}$ to solve:

$$\max_{\mathcal{C}} \quad p_j\, y_j - w_{Lj} L_j - w_{Hj} H_j - r K_j - b\alpha_{1j} \tag{7}$$

subject to:

$$y_j = z_j \left[\Gamma^K(\alpha_{1j})^{\frac{1}{\eta}} K_j^{\frac{\eta-1}{\eta}} + \Gamma^L(\alpha_{1j}, \alpha_{2j})^{\frac{1}{\eta}} L_j^{\frac{\eta-1}{\eta}} + \Gamma^H(\alpha_{2j})^{\frac{1}{\eta}} H_j^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{8}$$

$$p_j = \left(\frac{y_j}{Y}\right)^{-\frac{1}{\sigma}} \tag{9}$$

$$w_{Lj} = \left(\frac{L_j}{\bar{L}\Lambda_L a_{Lj}}\right)^{\phi} \tag{10}$$

$$w_{Hj} = \left(\frac{H_j}{\bar{H}\Lambda_H a_{Hj}}\right)^{\phi} \tag{11}$$

taking as given the rental rate of capital r, the total supply of low- and high-skill workers $\bar{L}$ and $\bar{H}$, aggregate output Y, and its own amenity levels a_{Lj} and a_{Hj}.

Equilibrium. The definition of the market equilibrium can be found in Appendix A.1.

Taking stock. The technology resembles a CES production function but with endogenous income shares $\Gamma^K(\alpha_1)$, $\Gamma^L(\alpha_1, \alpha_2)$ and $\Gamma^H(\alpha_2)$ as the firm chooses the share of tasks performed by capital, low- and high-skill workers by setting α_1 and α_2. This feature is crucial to allow for capital productivity improvements to have negative effects on the *wage levels*, as shown by Acemoglu and Restrepo (2022) and in section 2.3 in the context of this model. Indeed, as firms automate more tasks, the firm uses less intensively low-skill labor and so its income share contracts, which, ceteris paribus, leads to decreases in the wage level of low-skill workers. This holds even if the elasticity of substitution between capital and low-skill labor is larger than one. The production technologies posited by alternative, well-known frameworks to analyse the effects of technological change, like those in the literatures on skill-biased technological change (Katz and Murphy, 1992) and capital-skill complementarity (Krusell et al., 2000) also generate increases in *relative wages* across skill groups – the skill-premium – as a result of technological change. However, they cannot generate drops in the *level of wages* for any group, because inputs are *q-complements* and, as such, any form of technological change that increases the productivity of a given factor (the productivity of high-skill labor in the SBTC literature; the productivity of capital in the capital-skill bias literature) increases the price level of any of the factors. This is a big limitation for studying the impact of automation on wage levels between skill groups and firms, as in the last four decades we have observed stagnant or decreasing wages for low-skill workers (Acemoglu and Autor, 2011). For a more in-depth analysis of the differences between these technologies and the task-based framework, see Acemoglu and Restrepo (2022).

In this framework, low-skill and high-skill workers differ fundamentally in their comparative advantage across the task space. Low-skill workers have a comparative advantage in tasks of intermediate complexity—more complex than the simplest tasks but less complex than the most sophisticated ones. Importantly, these intermediate-complexity tasks are more similar to the tasks where capital has comparative advantage than are the high-complexity tasks performed by high-skill workers. Formally, this is captured by the assumption that capital productivity $\psi_K(x)$ is highest for low-indexed (simple) tasks, low-skill labor productivity $\psi_L(x)$ peaks at intermediate-indexed tasks, and high-skill labor productivity $\psi_H(x)$ is highest for high-indexed (complex) tasks. To foster intuition consider the following illustrative example: in automobile manufacturing, industrial robots excel at simple, repetitive tasks such as welding and painting; production line workers have comparative advantage in moderately complex tasks such as assembly and quality inspection that require some judgment and dexterity; while engineers specialize in highly complex tasks such as design and process optimization. When the productivity of industrial robots increases, for instance through improvements in precision and programming, it becomes profitable to substitute capital for low-skill workers in the tasks where their comparative advantages are closest. This comparative advantage structure has a direct implication for elasticities of substitution: the elasticity of substitution between capital and low-skill labor, which I denote η_{KL}, exceeds the elasticity between capital and high-skill labor, η_{KH}. Indeed, the elascity of subsitution, η, is amplified by the displacement of low-skill labor with capital induceed by increased automation following capital productivity improvements:

$$\eta_{KL} = \eta + \frac{\partial \ln \Gamma^K(\alpha_1)/\Gamma^L(\alpha_1, \alpha_2)}{\partial \ln \alpha_1} d \ln \alpha_{1j} \geq \eta$$

Instead, the elasticity of substitution of high-skill labor and capital is not affected by capital productivity and so it is equal to η:

$$\eta_{KH} = \eta$$

Consequently, automation technologies that increase capital productivity increase the skill-premium.

2.2 Optimal automation decisions

The economic decision of firms that is key to understand the impact of automation on wages is the choice of the threshold α_1 the fraction of tasks performed by capital. To spell-out more clearly the trade-off the firm faces, I will work with the minimization problem which is dual to the profit maximization problem given by equations (7) to (11).

The firm chooses the automation level α_1 that minimizes total costs given optimal input choices of capital, low- and high-skill labor.

$$\min_{\alpha_{1j}} \quad b\alpha_{1j} + \frac{c(\alpha_{1j}, \alpha_{2j})}{z_j} y_j$$

$$\text{s.t.} \quad c(\alpha_{1j}, \alpha_{2j}) =$$

$$\left[r^{1-\eta}\Gamma^K(\alpha_{1j}) + (w_{Lj}(1+\phi))^{1-\eta}\Gamma^L(\alpha_{1j}, \alpha_{2j}) + (w_{Hj}(1+\phi))^{1-\eta}\Gamma^H(\alpha_{2j})\right]^{\frac{1}{1-\eta}} \tag{12}$$

where $c(\alpha_{1j}, \alpha_{2j})$ is the unit cost of a firm with productivity $z_j = 1$ given optimal input choices (see Appendix A.5). This resembles a CES cost function, but with endogenous shares $\Gamma^K(\alpha_{1j})$, $\Gamma^L(\alpha_{1j}, \alpha_{2j})$ and $\Gamma^H(\alpha_{2j})$. More specifically, by Shepard's lemma, the income share of capital, i.e. the elasticity of output to capital, and the income shares of low- and high-skill labor, i.e. the elasticity of output to low- and high-skill labor, are respectively:

$$\varepsilon_j^K = \left(\frac{r}{c(\alpha_{1j}, \alpha_{2j})}\right)^{1-\eta} \Gamma^K(\alpha_{1j}), \qquad \varepsilon_j^L = \left(\frac{(w_{Lj}(1+\phi))}{c(\alpha_{1j}, \alpha_{2j})}\right)^{1-\eta} \Gamma^L(\alpha_{1j}, \alpha_{2j})$$

$$\varepsilon_j^H = \left(\frac{(w_{Hj}(1+\phi))}{c(\alpha_{1j}, \alpha_{2j})}\right)^{1-\eta} \Gamma^H(\alpha_{2j})$$

This shows that by investing in the automation level α_{1j}, firm j is in control of the capital-intensity of production as well as that of low-skill labor.

The optimal automation level α_{1j}^* equates the marginal cost and the marginal benefit of automation, where the benefits are given by the cost savings. The firm's first-order condition is:

$$-\frac{\partial c(\alpha_{1j}, \alpha_{2j})/z_j}{\partial \alpha_{1j}} \cdot y_j = b \tag{13}$$

where

$$-\frac{\partial c(\alpha_{1j}, \alpha_{2j})}{\partial \alpha_{1j}} = \Big[\underbrace{\left(\frac{w_{Lj}(1+\phi)}{\psi_L(\alpha_{1j})}\right)^{1-\eta}}_{\substack{\text{marginal cost of low-skill} \\ \text{labor at marginal task}}} - \underbrace{\left(\frac{r}{\psi_K(\alpha_{1j})}\right)^{1-\eta}}_{\substack{\text{marginal cost of capital} \\ \text{at marginal task}}} \Big] \cdot \; c(\alpha_{1j}, \alpha_{2j})^{\eta} \cdot \; \underbrace{\frac{1}{1-\eta}}_{\substack{\text{substitutability} \\ \text{between tasks}}} \tag{14}$$

The left-hand side of equation (13) is the marginal cost of automation and right-hand side is the marginal benefit, which consist in the reduction in *total costs* induced by a marginal increase in α_1. Indeed, as firms automate they replace more expensive low-skill labor with cheaper capital, which reduces the unit cost of production, as captured by the term in square brackets, which measures the difference between the cost of producing the marginal task with low-skill labor and with capital.

Equation (13) makes clear that firms face a trade-off between the cost savings from automation, which consists in replacing low-skill workers with capital, and the cost of automation. If automation was for free, then the firms would choose the automation level that minimizes the unit cost of production $\frac{c(\alpha_{1j}, \alpha_{2j})}{z_j}$. They would then automate until the task where the cost of capital and the cost of low-skill labor are equal, i.e. α_{1j} would be such that $\frac{w_{Lj}(1+\phi)}{\psi_L(\alpha_{1j})} = \frac{r}{\psi_K(\alpha_{1j})}$. However, since automation is costly, the firm will choose a lower level of α_1.

From equation (13), importantly, we see that, when automation is costly, the marginal benefit of automation scales with the size of the firm and so with firm productivity z_j. That is because at larger firms the unit cost reduction of automation is spread over a larger amount of units produced and so leads to larger cost-savings.

Proposition 2.1. *The optimal automation level α^*_{1j} is increasing in firm productivity z_j.*

The proof can be found in Appendix A.5.

The intuition is as follows. A firm that automates an additional task, in essence, is paying a fixed cost to reduce its unit costs. This is more beneficial for firms producing at a larger scale as the *unit* cost savings are spread over a larger amount of units, hence generating larger *total* cost savings. Since more productive firms have larger scale of production, they automate more tasks. In addition, note that, in my setting firms can choose the wages they pay. Since more productive firms have a higher marginal product of labor, they pay higher wages to low-skill workers, ceteris paribus. This makes it even more profitable for them to substitute low-skill labor with capital, as the cost difference between the two inputs at the margin is larger.

This result implies that identifying the effect of automation on wages is challenging as unobservable shocks to firm-level productivity confound the effect of automation. This point is outlined more in depth in section 3.1, and in section 3.2 I propose a solution.

For completeness, I characterize the optimal allocation of high-skill labor across tasks. Contrary to the allocation of capital, there is no cost of allocating labor across tasks, and so the optimal level of α_{2j} minimizes unit costs $\frac{c(\alpha_{1j},\alpha_{2j})}{z_j}$. It is then such that:

$$\frac{w_{Lj}}{\psi_L(\alpha_{2j})} = \frac{w_{Hj}}{\psi_H(\alpha_{2j})} \tag{15}$$

2.3 Heterogenous wage effects of automation across skill groups and firms

In this section I show what are the key economic forces that drive wage differentials at firms automating further their production process – i.e. increasing their automation level α_1 – relative to firms keeping constant.

Such a wage differential can be characterized as the semi-elasticity of wages with respect to the automation level α_{1j}, which measure the percentage change in wages following a marginal increase in the automation level. Indeed, this semi-elasticity captures all the information needed to quantify the wage differential as workers at a non-adopting firm are not affected by an increase in the automation level at its rival other than through changes in the aggregate price level P which are common to both adopting and non-adopting firms and so are netted out.

Proposition 2.2. *Assuming that* $\frac{\psi'_H(\alpha_{2\ell})}{\psi_H(\alpha_{2\ell})} - \frac{\psi'_L(\alpha_{2\ell})}{\psi_L(\alpha_{2\ell})} \to \infty$ *for any firm* ℓ*, the wage differential, in equilibrium, between a firm* j *with a positive change in the automation level (*$d\alpha_{1j} > 0$*) and* j' *with constant automation level (*$d\alpha_{1j} = 0$*) is given, for low-skill workers, by:*

$$d\ln w_{Lj} - d\ln w_{Lj'} = \left[\frac{\phi\eta}{\phi\eta+1}\cdot \underbrace{\frac{\partial \ln \Gamma_{Lj}(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}}}_{\substack{<0 \\ \textit{Displacement Effect}}} + \frac{\phi(\sigma-\eta)}{\phi\eta+1}\cdot \underbrace{\left(-\frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}}\right)}_{\substack{>0 \\ \textit{Scale Effect}}}\right] d\alpha_{1j} \tag{16}$$

and for high-skill workers is:

$$d\ln w_{Hj} - d\ln w_{Hj'} = \left[\frac{\phi(\sigma-\eta)}{\phi\eta+1}\cdot \underbrace{\left(-\frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}}\right)}_{\substack{>0 \\ \textit{Scale Effect}}}\right] d\alpha_{1j} \tag{17}$$

where:

$$\frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}} = \frac{1}{1-\eta}\cdot\left(s_j^L \cdot \underbrace{\frac{\partial \ln \Gamma^L(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}}}_{\substack{<0 \\ \textit{Reduction} \\ \textit{in the Task-Share} \\ \textit{of Low-skill Labor}}} + s_j^K \cdot \underbrace{\frac{\partial \ln \Gamma^K(\alpha_{1j})}{\partial \alpha_{1j}}}_{\substack{>0 \\ \textit{Increase} \\ \textit{in the Task-Share} \\ \textit{of Capital}}}\right) < 0 \tag{18}$$

with $s_{Lj} = \frac{w_{Lj}L_j}{y_j c(\alpha_{1j},\alpha_{2j})/z_j}$ *and* $s_{Kj} = \frac{rK_j}{y_j c(\alpha_{1j},\alpha_{2j})/z_j}$ *are, respectively, the share of labor in total costs (net of automation costs) and the share of capital in total costs (net of automation costs) at firm* j*.*

The proof can be found in Appendix A.3.

Equation (16) shows that, relative to their peers at non-adopting firms, the wages of low-skill workers at adopting firms experience two opposing effects: a negative displacement effect and a positive scale effect. The displacement effect captures the reduction in the marginal product of low-skill workers as some of the tasks they were performing are now assigned to capital, and so the overall production relies less on them. The strength of this effect is given by the reduction in the task-share of low-skill workers caused by a marginal increase in the automation level. In addition, this negative effect is amplified by the elasticitiy of subsitution η. Indeed, for a given reduction in the task share of low-skill workers, the easier is for the firm to substitute across inputs, the more it replaces low-skill workers with capital. Similarly, the more elastic is labor supply, i.e. the higher is ϕ, the larger the drop in the wages of low-skill workers following the reduction in their demand caused by an increase in the automation level.

The scale effect, instead, captures the increase in the marginal product of low-skill workers coming from the increase in output that follows the extra automation. Indeed, firms replacing low-skill workers with capital save on production costs, set lower prices and so experience increases in demand for their good, which raises the marginal product of workers across all skill groups. Equation (18) shows that the percentage change in the per unit-cost savings generated by a marginal increase in the automation level are given by the weighted sum of the elasticities of the task-share all inputs, where the weights are given by their respective shares in total costs. Since the task-share of high-skill workers is unaffected by increases in the automation level, the cost-savings are proportional to the productivity gain of performing the marginal task with capital rather than with low-skill workers, which is given by the increase in the marginal product of capital net of the reduction in the the marginal product of low-skill workers, accounting for the relative importance of these inputs in production as captured by their cost-shares.[3] The more substitutable capital and low-skill labor are—that is, the higher the elasticity of substitution η—the greater the cost savings from automation, since the firm can more readily exploit the rise in the relative productivity of capital by substituting it for low-skill labor. As for the displacement effect, we see from equation (16) that the scale effect is amplified as labor supply is more elastic. In addition, the more subsitutable are goods —the higher is σ— the larger is the wage effect of automation. This is because the reduction in the unit cost, and so in the price of the automating firms relative to its competitors, translates into a larger increase in demand and so in the marginal product of all inputs.

For high-skill workers, instead, equation (17) shows that only the scale effect is at play. Indeed, since high-skill workers do not perform any of the tasks that are automated, their marginal product is not directly affected by increases in the automation level. However, as for low-skill workers, high-skill workers at automating firms benefit from the increase in output that follows automation, which raises their marginal product.

From (16) and (17) note that as ϕ tends to 0 automation at one firm leads to no wage differential between the workers at that firm and those at a non-automating one. This is because, in such an instance, workers are indifferent across firms and so perfectly mobile. As a result, labor reallocates across producers until marginal products, and thus wages, are equalized everywhere. Therefore, some departure from perfect competition is necessary for automation to create wage differences across firms. In this model, such frictions are introduced via firm-specific amenities, which generate monopsonistic power as in Card et al. (2018).

Lastly, and most importantly, equations (16) and (17) show that, for given parameters governing the elasticity of labor supply ϕ, the elasticity of substitution across goods σ, and across tasks η as well as firm-level cost-shares (s_{Lj}, s_{Kj}), all is needed to quantify the wage effects of automation at automating relative to non-automating firms are two semi-elasticities: the semi-elasticity of the

[3] Cost savings arise from the productivity gain of performing the marginal task with capital rather than with low-skill labor. Yet this local change propagates to infra-marginal tasks: by shifting the cutoff between L- and K-tasks, automation changes the overall productivity of capital and low-skill labor in the aggregate production function. The resulting reduction in unit costs therefore depends not only on the size of the marginal productivity gain, but also on how much the firm relies on each input—captured by their respective cost shares. A 1% productivity improvement in capital generates much larger cost savings when capital represents 50% of total costs than when it represents only 5%.

task-share of low-skill workers and of capital to the automation level. In the following section I show how to identify these semi-elasticities from observational data, without requiring random variation in automation levels, and so overcome the identication challenge posed by unobserved confounders.

3 Identifying the wage effects of automation

In this section I first outline the main identification challenge that arises when estimating the wage effects of automation at automating relative to non-automating firms and then I propose a solution to overcome it.

3.1 The identification challenge: unobserved firm-level shocks

I start by laying out the identification challenge that arises when estimating the semi-elasticity of wages to α_{1j}, which captures the partial equilibrium effects of automation.

Identifying the (partial equilibrium) effect of automation on wages empirically is challenging because both wages and the level of automation depend on the unobservable firm productivity, z_j. Standard comparisons across firms or over time conflate two effects: the direct impact of automation on wages and selection into automation by more productive firms. More productive firms both automate more and pay higher wages for reasons unrelated to automation itself. A naive regression would thus overstate the causal effect by attributing productivity-driven wage premia to automation. Put differently, comparing wages of low-skilled workers employed at firms with different automation levels (between-firm variation), or tracking wage changes for low-skilled workers at a given firm as its automation intensity changes (within-firm variation), would attribute wage differences to automation when they actually reflect underlying productivity differences.

The simultaneity problem has a formal manifestation in the framework of the model. For the sake of exposition, suppose one had firm-level data on wages of low- and high-skill workers at firm j in year t, and that she also observes the automation level (or a proxy, like the share of automating machines in total costs) of firm j in year t. The empirical counterpart for the semi-elasticity of wages at automation is given by the following equation:

$$\Delta \ln w_{isjt} = \beta \Delta \alpha_{1jt} + \Delta \epsilon_{isjt} \tag{19}$$

where $\ln w_{isjt}$ are the wages of a worker i that is low-skilled ($s = L$) or high-skilled ($s = H$) in firm j in year t, α_{1jt} is the automation level of firm j in year t, and ϵ_{isjt} is the error term. If the automation level were exogenous, the coefficient β would capture the semi-elasticity of wages to automation. The corresponding model counterpart to Equation (19) is:

$$\ln w_{sjt} = C + \ln g_s(\alpha_{1jt}) + \epsilon_{sjt} \tag{20}$$

where $C = \frac{\phi\eta}{\phi\eta+1} \ln\left(\frac{1}{1+\phi}\frac{\sigma-1}{\sigma}\right)$ is a constant, $g_H(\alpha_{1jt}) = \frac{\phi\eta}{\phi\eta+1}\frac{\sigma-\eta}{\sigma\eta}\ln y_j^*(\alpha_{1jt};\cdot)$ is the effect of autormation on wages of high-skill workers, $g_L(\alpha_{1jt}) = \frac{\phi\eta}{\phi\eta+1}\left(\frac{\sigma-\eta}{\sigma\eta}\ln y_{jt}^*(\alpha_{1jt};\cdot) + \ln\Gamma^L(\alpha_{1jt},\alpha_{2jt})\right)$ is the effect of automation on wages of low-skill workers, and:

$$\epsilon_{sjt} = \frac{\phi\eta}{\phi\eta+1}\ln\left(z_{jt}^{\frac{\eta-1}{\eta}}\, Y_t^{\frac{1}{\sigma}} P_t\, \left(\bar{s}_t\Lambda_{st}a_{sjt}\right)^{-\frac{1}{\eta}}\right) \tag{21}$$

The model makes clear that such a regression is subject to an endogeneity bias because the error term ϵ_{isjt} is correlated with α_{1jt} and wages w_{isjt} through unobserved firm productivity z_j.

More specifically, the coefficient β estimated from (19) is biased upwards because firm-level productivity z_{jt} positively covaries with α_{1jt} and with wages w_{isjt}. To understand why, consider what happens when a firm becomes more productive. On one hand, the marginal product of all inputs goes up and so wages go up. On the other hand, as the firm expands, it becomes more profitable to increase its automation level, which impacts wages through the scale and displacement effects described in section 2.3. In a nutshell, the productivity increase inflates the positive scale effect of automation on wages.

To foster intuition, consider the case of a steel manufacturing plant that discovers a breakthrough in its smelting process—a new arrangement of furnace temperatures and oxygen injection timing that significantly improves the yield of high-quality steel from raw iron ore. This process innovation enables the firm to produce more and better steel from the same inputs, which corresponds to a positive shock to firm-level productivity z_{jt} in the model. Two simultaneous responses follow. On one hand, flush with profits and facing surging demand, the management decides to invest heavily in robotic assembly lines to scale up manufacturing capacity. In the data, we observe α_{1jt} increasing sharply. On the other hand, the firm expands its workforce to meet the higher production targets enabled by the superior smelting process. Competition for workers intensifies, and wages rise across the board. In the data, we observe w_{isjt} increasing for both low-skill and high-skill workers. Now, an econometrician observing this steel mill sees a positive correlation: automation increased, and so did wages. Running regression (19) would suggest that automation raises wages. However, the wage increase primarily reflects the scale effect from the process innovation that made the plant more productive, not the causal impact of the robotic assembly lines themselves.

3.2 The identification strategy: exploiting changes in relative prices and quantities

In the previous section I have shown that comparing wages across firms with different automation levels in a regression like (19) gives an upward-biased estimate of the impact of automation on wage differentials across firms because of unobserved confounders. In this section I present a strategy to identify the causal impact of automation on wage differentials across firms.

The key insight that this strategy exploits is that, while being correlated, unobserved firm-level shocks z_j and choices on automation levels α_{1j} have different implications for the *relative* prices and quantities of inputs[4]. Indeed, shocks to productivity affect equally the marginal product of all factors while, ceteris paribus, additional automation makes capital more productive, low-skill labor less productive, and does not affect the productivity of high-skill labor. This differential impact occurs because automation consists in replacing low-skill labor with capital at specific tasks, and so fundamentally it is making the production technology more capital-intensive and less intensive in low-skill labor. As a result, shocks to productivity z_j do not affect relative prices and quantities while increases in the automation level α_{1j} do so, instead. As a result, changes in relative prices and quantities isolate the impact of automation on the (relative) productivity of inputs. This can be seen more formally in the expressions below, which characterize the changes in the relative price of low- and high-skill labor – *the skill-premium* – and in their relative quantities – *the skill-ratio* – for a given firm j across $t-1$ and t:

$$\underbrace{\Delta \ln \frac{w_{Hjt}}{w_{Ljt}}}_{\substack{\text{Change in}\\ \text{skill premium}}} = \frac{\eta\phi}{1+\eta\phi} \underbrace{\Delta \ln \frac{\Gamma^H(\alpha_{2jt})}{\Gamma^L(\alpha_{1jt}, \alpha_{2jt})}}_{\substack{\text{Change in}\\ \text{relative task-shares}}} - \frac{\phi}{1+\eta\phi} \underbrace{\Delta \ln \frac{H_t \Lambda_{Ht}}{L_t \Lambda_{Lt}}}_{\substack{\text{Change in}\\ \text{relative}\\ \text{labor supply}}} - \frac{\phi}{1+\eta\phi} \underbrace{\Delta \ln \frac{a_{Hjt}}{a_{Ljt}}}_{\substack{\text{Change in}\\ \text{relative}\\ \text{amenities}}} \tag{22}$$

$$\underbrace{\Delta \ln \frac{H_{jt}}{L_{jt}}}_{\substack{\text{Change in}\\ \text{skill ratio}}} = \frac{\eta}{1+\eta\phi} \underbrace{\Delta \ln \frac{\Gamma^H(\alpha_{2jt})}{\Gamma^L(\alpha_{1jt}, \alpha_{2jt})}}_{\substack{\text{Change in}\\ \text{relative task-shares}}} + \frac{\eta\phi}{1+\eta\phi} \underbrace{\Delta \ln \frac{H_t \Lambda_{Ht}}{L_t \Lambda_{Lt}}}_{\substack{\text{Change in}\\ \text{relative}\\ \text{labor supply}}} + \frac{\eta\phi}{1+\eta\phi} \underbrace{\Delta \ln \frac{a_{Hjt}}{a_{Ljt}}}_{\substack{\text{Change in}\\ \text{relative}\\ \text{amenities}}} \tag{23}$$

I refer the reader to appendix A.4 for the derivation of these equations.

Equations (22) and (23) show that changes in the skill-premium and in the skill-ratio can be decomposed into three terms: changes in the relative task-share, changes in aggregate-level relative labor supply, and changes in firm-level relative amenities. If high-skill workers are used more intensely in production relative to low-skill workers – i.e. the relative task-share increases – then firms demand relatively more high-skill workers, pushing up the skill-premium and the skill-ratio. If the relative supply of high-skill to low-skill workers increases, the skill-premium decreases to absorb the rise in the relative supply while the skill-ratio goes up. Similarly, if the firm becomes relatively more attractive to high-skill workers because relative amenities of high-skill to low-skill workers increase, then again the skill-premium decreases while the skill-ratio increases. Hence, as previously stated, it can be seen that changes in relative prices and quantities isolate the impact of automation on the (relative) productivity of inputs from that of unobserved firm-level productivity shocks.

Assuming that high-skill workers are infinitely more productive than low-skill workers at the marginal task relative, firms do not adjust the allocaiton of their current task allocation across

[4] This identification strategy is similar in spirit to the one employed by Lindner et al. (2022)

low- and high-skill workers. In such an instance, changes in the skill-premium and in the skill-ratio at adopting relative to non-adopting firms are informative about the impact of adoption on the task-share of low-skill labor, $\Gamma^L(\alpha_{1jt}, \alpha_{2jt})$.

The model delivers two identifying restrictions that address two related challenges. First, the model implies that TFP shocks shift all tasks proportionally and therefore do not affect relative prices or relative quantities, whereas automation alters the composition of tasks and therefore do move relative P and Q. This separates automation shocks from TFP shocks. However, this identification strategy rests rests on changes in *relative* prices and quantities, while the objects of interest are changes in the *level* of task shares $s_L, ; s_H, ; s_K$. In the absence of some extra restriction, the mapping from these observables to the task shares is undetermined: movements in relative wages, employment, and capital intensity are consistent with an infinity of of level changes in the task shares. The model resolves this by showing that automation substitutes low–skill labor for capital but does not directly affect high–skill workers. By fixing the high–skill task share ($\Delta s_H = 0$), the model removes one free structural parameter and ensures that the two empirical patterns – low– versus high–skill wage and employment movements, and capital intensity by skill group – are sufficient to recover the level changes in Δs_L and Δs_K. In intuitive terms, the identification restriction says that changes in the relative wages and employment of low–skill workers pin down the level change in the low–skill task share, precisely because the task share of high–skill labor is unchanged.

Although comparing relative prices and quantities across firms with different automation levels helps isolate the impact of adoption on the productivity of inputs from that of unobserved firm-level productivity shocks (and from changes in aggregate-level relative labor supply), equations (22) and (23) show that these comparisons capture the effect of changes in firm-level relative amenities, too. For example, a firm that adopts autonomous mobile robots to transport materials around its factory improves workplace safety conditions, making logistic positions more attractive to low-skill workers relative to comparable jobs at non-adopting firms. As a result, we would not be able to tell whether the increase in the skill-premium was driven by the adoption of these type of robots or by an increase in the relative amenities for the low-skill workers. To isolate the effect of adoption on the task-shares from that of changes in relative amenities, it is instructive to note that these changes are different in nature. Indeed, increases in automation levels act as a shifter to the *relative demand* of factors, pushing relative prices and quantities in the same direction, while changes in relative amenities shift the *relative supply* of factors, hence pushing them in opposite directions. Exploiting this insight, we can isolate the effect of the adoption on the task-share of low-skill workers by summing up the extra skill premium paid at adopting firms to the additional skill ratio there.

Define the following operator: $\Delta^{\text{A-N}} y_t \equiv \overline{\Delta y_{jt}}^{\text{Auto}} - \overline{\Delta y_{jt}}^{\text{Non}}$, which measures the difference in the average change of variable y between automating and non-automating firms. Specifically,

$\overline{\Delta y_{jt}}^{g} = \frac{1}{N^g}\sum_{j\in g}\big(y_{jt} - y_{j,t-1}\big),\ g \in \{\text{Auto},\ \text{Non}\}$ denotes the average change in y between periods $t-1$ and t for firms in group g. Using this operator, I can now state the identification result of the paper.

Proposition 3.1. *Assuming that* $\frac{\psi_H'(\alpha_{2\ell t})}{\psi_H(\alpha_{2\ell t})} - \frac{\psi_L'(\alpha_{2\ell t})}{\psi_L(\alpha_{2\ell t})} \to \infty$ *for any* ℓ*, the percentage change in the task-share of low skill workers can be identified as:*

$$\underbrace{\frac{\partial \ln \Gamma^L(\alpha_{1jt},\alpha_{2jt})}{\partial \alpha_{1jt}} \cdot \overline{\Delta\alpha_{1jt}}}_{\substack{\textit{Effect of Automation on}\\ \textit{Task-Share of Low-Skill Labor}}} = -\underbrace{\Delta^{A\text{-}N}\ln\frac{w_{Hjt}}{w_{Ljt}}}_{\substack{\textit{Change in}\\ \textit{Skill Premium at}\\ \textit{Auto vs. Non-Auto}}} - \underbrace{\frac{1}{\eta}\cdot\Delta^{A\text{-}N}\ln\frac{H_{jt}}{L_{jt}}}_{\substack{\textit{Change in}\\ \textit{Skill Ratio}\\ \textit{Auto vs. Non-Auto}}} \tag{24}$$

The percentage change in the task-share of capital can be identified as:

$$\underbrace{\frac{\partial \ln \Gamma^K(\alpha_{1jt})}{\partial \alpha_{1jt}} \cdot \overline{\Delta\alpha_{1jt}}}_{\substack{\textit{Effect of Automation on}\\ \textit{Task-Share of Capital}}} = \underbrace{\frac{1}{\eta}\cdot\Delta^{A\text{-}N}\ln\frac{K_{jt}}{H_{jt}}}_{\substack{\textit{Change in Stock of K}\\ \textit{per H-Skill Worker}\\ \textit{at Auto vs. Non-Auto}}} + \phi\eta\cdot\Big[\underbrace{\Delta^{A\text{-}N}\ln H_{jt}}_{\substack{\textit{Change in}\\ \textit{H-Skill Employment}\\ \textit{at Auto vs. Non-Auto}}} - \frac{1}{\phi}\cdot\underbrace{\Delta^{A\text{-}N}\ln w_{Hjt}}_{\substack{\textit{Change in}\\ \textit{H-Skill Wage at}\\ \textit{Auto vs. Non-Auto}}}\Big] \tag{25}$$

The intuition behind equation (24) is as follows. The higher the skill premium increase at adopting firms relative to non-adopting firms, the more automation has reduced the task-share of low-skill workers. This occurs because automation displaces low-skill workers from their tasks, reducing their relative productivity and thus their relative wage. Similarly, the higher the skill ratio increase at adopting firms relative to non-adopting firms, the more the task-share of low-skill workers has decreased, as firms substitute away from low-skill labor toward high-skill labor in response to automation. The factor $\frac{1}{\eta}$ in front of the skill ratio change reflects the elasticity of substitution between tasks in production—when tasks are more substitutable (higher η), a given change in relative quantities corresponds to a smaller change in relative task productivity, requiring this adjustment factor to correctly measure the underlying task-share change.

By the same logic, equation (25) recovers the change in capital's task-share: a higher high-skill wage at adopters (relative to non-adopters) together with an increase in the high-skill-to-capital ratio implies that Γ^K rises. There is no firm-specific capital price term because the rental rate of capital is common across firms at a point in time; what varies at the firm level are wages (due, inter alia, to amenities). I refer the reader to appendix A.4 for the derivation of equation (25).

4 Data and Institutional Context of French Manufacturing

I study the distributional consequences of automation in the empirical landscape of the French manufacturing sector over the period 2003-2019. In this section I first describe the institutional context of France that makes it an ideal setting for this analysis and then I present the data sources used in the empirical analysis along with summary statistics.

4.1 Institutional Context

France provides an ideal empirical setting to study the distributional consequences of automation across firms and skill groups for several reasons. First, France offers exceptional data availability that enables precise measurement of both automation adoption and its effects on workers. The combination of detailed customs records tracking firm-level imports of automating technologies and comprehensive matched employer-employee data allows me to trace how automation investments affect individual workers across different skill groups and firms. For this reason, France has become one of the preferred settings for recent studies on automation's labor market effects (Aghion et al., 2025b, 2023; Acemoglu et al., 2020).

Second, France's manufacturing sector represents a substantive case study of automation diffusion in a major advanced economy. Indeed, its manufacturing sector has experienced significant automation over the past two decades, making it the third-largest robot user in the European Union after Germany and Italy (IFR, 2020). Moreover, robot adoption in France has accelerated rapidly, with annual installations growing at an average rate of 18 percent between 2014 and 2019 (IFR, 2020). This combination of substantial adoption levels and rapid growth provides sufficient variation to identify automation's effects while remaining representative of automation patterns in other large European manufacturing economies.

4.2 Data and Summary Statistics

The identification strategy described in Section 3.2 compares outcomes across automating and non-automating firms. To implement it empirically, I combine three data sources that, once linked, provide a comprehensive view of automation investments and worker- and firm-level outcomes in French manufacturing between 2003 and 2019. These data sources are: customs data, linked employer-employee payroll data, and firm-level balance sheet data. In the following I describe each data source in turn.

Firm-level expenditures in industrial robots

The French customs administration collects data for domestic firms involved in international transactions. This data collection comes from a compulsory form that firms have to fill out when they import goods. The customs administrations make available to researchers a dataset proving expenditures at the firm-month-year level by 6-digit product code. The coverage is quasi-exhaustive in that all transactions by firms that in a given year trade goods (imports and exports), across all product codes, for more than €420,000 are included. From this dataset I can identify firm-level expenditures in industrial robots (HS-code *847950*), which are – by definition – machines that automate the production of manufacturing goods[5]. Some examples of the tasks performed by industrial robots include welding and painting cars, assembling electronics, packaging and palletizing goods in food and logistics industries, and inspecting or testing products in pharmaceuticals and aerospace.

Because this product category includes items that are, unambiguously, automating machines, it has been widely exploited by the literature to measure firm-level adoption of automating technologies (Acemoglu et al. (2020), Aghion et al. (2023), Aghion et al. (2025a), Koch et al. (2021) among others). Hence, I use imports of industrial robots as my measure of for firm-level expenditures in automating technologies[6].

Linked Employer-Employee Data

The French Ministry of Labor provides data containing payroll information at yearly frequency for the universe of workers employed in France. Because of its rich detail, this dataset has been extensively used in labor economics research and beyond. In this paper, I draw on it to obtain precise information on workers' pay, occupations, firm and industry affiliations, and demographic characteristics. Unfortunately, this information is available, for each worker identifier, only for the current and the past year, preventing the construction of long worker-level panel. However, with information across two consecutive years, I can identify whether the worker is a new entrant, i.e. she was hired during the year, or not, which is an important information I exploit to control for changes in the composition of workers that might be contemporanous to automation investments. Importantly, a firm identifier is provided for each observation so that this dataset can be linked to the customs records.

Firm-level Balance Sheet Data

Administrative records from the French tax authority provide detailed balance sheet information for the universe of French firms. I rely on it to obtain three key pieces of information for the empirical analysis. Firstly, it provides a breakdown of the capital stock by asset type, which allows to distinguish the stock of industrial equipment from other types of capital stock (e.g., land, buildings, etc.). Having precise information on the stock of industrial equipment is key to capture the extent to which automation increases the task share of capital relative to labor, as discussed in section

[5] "Industrial robots classified under HS Code 847950 are automated programmable mechanical devices designed to perform complex tasks with high precision in manufacturing and processing environments." (WCO, 2022)

[6] Resorting to import data to measure automation expenditures carries out some measurement error due to the fact that that I treat firms without imports as non-automating firms while they could purchase automating technologies from domestic producers or domestic retailers. However, almost all industrial robots - the automating technology I consider in the empirical analysis - used in France are not actually produced in the country. I verify that results are robust to this measurement error in a set of robustness checks in Section 6.

(3.2). Secondly, I obtain from balance sheet data firm-level control variables, such as value added, which are relevant to control for trends underlying automation and outcome variables. Thirdly, it contains information on firms' cost structure, which I use to compute firm-level shares of low-skill workers and capital in total costs, which are key to pin down the cost-saving gains of automation as shown in equation (18).

Summary Statistics

In the empirical analysis I focus on the manufacturing sector, and restrict the sample to firms with at least 10 full-time employees in each year over the period of analysis (2003-2019) to ensure that firm-level outcomes are measured with sufficient precision. The sample includes 18,234 unique manufacturing firms observed over the period 2003-2019, for a total of 11,759,761 worker-year observations. Table 4.2 provides summary statistics, separately for automating and non-automating firms. I define automating firms as those with at least one year with positive expenditures in industrial robots. Overall, 37% of firms in the sample are automating firms. On average, automating firms are larger and more productive than non-automating ones. In particular, automating firms have on average 268 employees versus 108 employees at non-automating firms, and value added per worker is €66,800 at automating firms versus €54,600 at non-automating ones. Examining automation expenditures among firms that invest in robots, we observe substantial variation in investment magnitudes. Firms in the manufacturing sample spend on average €344,100 on industrial robots when they make positive investments, with considerable heterogeneity as reflected by the large standard deviation. When scaled by employment, the average investment amounts to €1,400 per worker, while as a share of existing capital stock, robot expenditures represent approximately 4.2% of the previous year's capital stock. This magnitude suggests that robot investments constitute meaningful capital expenditures. Crucially, this substantial heterogeneity in automation expenditures – whether measured in absolute levels, per worker, or relative to existing capital stock – implies that workers across the manufacturing sector face vastly different exposures to automation, creating the variation necessary to study how heterogeneous automation levels affect wage inequality within and across firms.

	All firms	Automating	Non-automating
Firm Characteristics			
Employment	172	268	108
	(195.2)	(284.7)	(132.4)
Value added per worker (thousands €)	60.1	66.8	54.6
	(28.5)	(31.2)	(24.8)
Automation (thousands €)			
Expenditures	-	344.1	-
		(3,035.17)	
Expenditures per worker	-	1.4	-
		(6.09)	
Expenditures over $t-1$'s Capital Stock	-	0.042	-
		(1.966)	
Unique firms	18,234	6,746	11,488
Worker-year obs	11,759,761	1,807,928	9,951,833

Notes: This table shows the characteristics of automating and non-automating firms. I measure firm-level automation from purchases of industrial robots as recorded in French customs. Automating firms are firms with at least one year with positive expenditures in industrial robots. I report average values of outcomes over the sample period 2003-2019. The table shows the mean of firm-level employment, the mean of firm-level value added per worker, the mean of firm-level expenditures in industrial robots, the mean of firm-level expenditures in industrial robots per worker, and the mean of firm-level expenditures in industrial robots as a fraction of one-year-lagged capital stock. I report the standard deviation of these variables in parentheses below.

5 Empirical approach

In this section, I present the regressions that estimate the effect of adoption of automating machines on the task share of low-skill labor and on the task share of capital and which implement the identification strategy characterized by equations (24) and (25).

5.1 Estimating the Change in Skill Premium

To estimate the impact of automation on the skill-premium, I start from a Mincer-type wage regression. In particular, our benchmark empirical model is the following:

(26)

$$\ln \text{wage}_{ijt} = \delta^b \text{high-skill}_{ijt} + \delta^u \text{automation}_{ijt} + \delta^s \text{automation}_{jt} \times \text{high-skill}_{ijt} + \gamma X_{ijt} + \varphi_j + \varsigma_{kt} + \varepsilon_{ijt}$$

where wage_{ijt} is individual i 's wage at firm j at time t, high-skill_{ijt} is a dummy variable for whether worker i is in high-skilled occupation, and automation_{jt} is an indicator variable taking the value one if the firm automates in the current or any of the previous two years. The vector X_{ijt} contains Mincer-type control variables, including gender, age, a dummy variable for whether the worker is a new entrant to the firm to control for selection effects of automation. In the benchmark specification I introduce firm fixed effects (φ_j), and group-specific time effects denoted by ς_{kt} in the equation above. In the benchmark specification ς_{kt} includes (1-digit) industry-time fixed effects and (4-digit) occupation group-time effects. By including the interacted occupation group-year effects I effectively control for occupation-specific wage trends, as well as policy changes that might affect occupation groups differently, such as changes in the minimum wage. In a more saturated model, I also include industry-location-year fixed effects, occupation-location-year fixed effects or industry-occupation-location-year fixed effects.

In the regression above, δ^s, the coefficient on the interaction between high-skill_{ijt} and automation_{jt}, captures the change in skill premium following technological change.

5.2 Estimating the Change in Skill Ratio

To estimate how technological change is related to subsequent changes in the skill ratio of a firm, I start out with equation (23). Guided by this equation, I use a difference-in-differences estimation, where I compare firms that automated at the beginning of the period with non-automating firms in the same industry with similar initial characteristics. In particular, I follow Caroli and Van Reenen (2001) and estimate long-difference regressions of the form:

$$\Delta y_{jt} = \delta^{HL}\text{automation}_{jt} + \gamma \Delta X_{jt} + \gamma^y y_{jt-1} + \varsigma_{kt} + \epsilon_{jt} \tag{27}$$

The left-hand side captures changes in outcome y_{jt} (such as share of high-skill workers, high-skill to low-skill ratio) between year t and $t+6$ at firm j. The variable automation_{jt} is the same key variable included in the worker regression equation (26), i.e. a dummy variable for whether a firm automates in the current or previous two years. Following Caroli and Van Reenen (2001), I control for changes in firm capital and value added, denoted by ΔX_{jt}. However, our results are robust to excluding these potentially endogenous conditioning variables. The specification differences out time invariant firm and labor market characteristics, and I include industry-year fixed effects (ς_{kt}) to control for industry-level labor supply shocks $\left(\Delta \ln \frac{H_t \Lambda_{Ht}}{L_t \Lambda_{Lt}}\right)$. Finally, I control for a lagged value of the outcome variable (y_{jt-1}), to capture initial firm heterogeneity and investigate robustness to excluding the lagged dependent variable in the regression. Standard errors are clustered at the firm level. As argued by Caroli and Van Reenen (2001), such a long difference specification is likely to capture the long-run effects of automation, as opposed to short-run fluctuations in outcomes.

5.3 Estimating the Change in Stock of Capital per High-Skill Worker

To estimate the impact of automation on capital intensity, I follow a specification analogous to (27), where the outcome variable y_{jt} now measures the expenditures in capital (industrial equipment) per high-skilled employee. This ratio captures how much firms rely on high-skill labor relative to their capital stock, providing a direct measure of whether automation leads to capital deepening or substitution between high-skill workers and machines.

The empirical model takes the form:

$$\Delta y_{jt} = \delta^{HK} \text{automation}_{jt} + \gamma \Delta X_{jt} + \gamma^{y} y_{jt-1} + \varsigma_{kt} + \epsilon_{jt} \tag{28}$$

As before, the specification differences out time-invariant firm characteristics and includes industry-year fixed effects to control for sector-specific investment trends and capital price fluctuations. The coefficient δ^{HK} identifies the change in the capital-to-high-skill ratio following automation events, capturing the extent to which automating firms increase their capital stock relative to their high-skill employment. According to equation (25), this coefficient—scaled by $\frac{1}{\eta}$—directly identifies the increase in capital's task-share induced by automation, since the rental rate of capital is common across firms and thus absorbed by the industry-year fixed effects.

6 Empirical Results

6.1 Skill Premium

I start the analysis by studying the relationship between automation and the skill premium. Across specifications (columns 1–4), the estimated coefficients for the interaction term Automation $\times$ High-Skill remain remarkably stable in magnitude and significance once standard worker and firm-level controls are introduced. The point estimates range between 0.03 and 0.07 log-points, closely mirroring the moderate college-premium effects documented in comparable studies of technological change. This robustness suggests that automation systematically raises the relative wages of high-skill workers within adopting firms, independent of model saturation or inclusion of fixed effects.

Table 1: Automation effect on the skill-premium

	(1)	(2)	(3)	(4)
Automation	0.011	0.011	0.004	-0.012
	(0.032)	(0.032)	(0.015)	(0.014)
Automation × High-Skill	0.056*	0.038*	0.060**	0.060**
	(0.030)	(0.022)	(0.024)	(0.026)
Individual controls	No	Yes	Yes	Yes
Firm FEs	No	No	Yes	Yes
Group × Year FEs	No	No	No	Yes
Observations	11,759,761	11,759,761	11,759,761	11,759,761
Firms N.	18,234	18,234	18,234	18,234
R^2	0.51	0.76	0.91	0.92

Note: This table investigates the change in workers' (log) wages following firm-level automation. I measure firm-level automation from purchases of industrial robots recorded in French customs. I report the estimated coefficients on the automation dummy, δ^u, and the automation dummy interacted with whether the individual is in a high-skill occupation, δ^s, from equation (26) described in Section 6.1. The "Automation" dummy indicates whether an industrial robot was imported by the firm in the current year or any previous year. The coefficient of interest is that of the "Automation x High-Skill" interaction, which shows the extent to which the high-skill premium changes following automation at the firm. Column (1) shows the estimates when including only occupation fixed effects and the high-skill dummy as controls. Columns (2)-(4) also include individual-level controls (gender, age, age squared, a dummy for new entrant). Columns (3)-(4) add firm fixed effects. Column (4) adds group (occupation and industry) × year fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. Significance levels are: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

At the same time, the coefficient on Automation alone turns slightly negative as additional controls and fixed effects are added, consistent with a mild decline in low-skill wage growth once composition and firm heterogeneity are accounted for. Taken together, these patterns indicate that automation is associated with an internally consistent widening of within-firm wage differentials—an effect comparable in direction and magnitude to those found for process innovations in Lindner et al. (2022).

In the light of the identification strategy outlined in Section A.4, such a widening of the wage premium measures the reduction in the productivity of low-skill labor as more tasks get assigned to capital, up to changes in the relative supplies of high- and low-skill workers at the firm which may also be causing such an widening. To control for this confounding supply-side factors, I analyse how the skill-ratio at automating firms compares to that of non-automaitng firms.

6.2 Skill Ratio

The regression results presented in Table 5 show that automation events are systematically followed by a decline in the relative employment of low-skilled workers. Across specifications, the estimated coefficients on the automation dummy are positive and statistically significant. The result remains robust when controlling for firm-level changes in value added and capital intensity, confirming that the change in relative employment is not a mechanical consequence of output expansion or investment growth. Rather, it reflects a genuine shift in firms' labor demand away from low-skill tasks as production processes become more automated.

Table 2: Automation effect on the skill-ratio

	(1)	(2)	(3)
Automation	0.023***	0.020*	0.013
	(0.009)	(0.012)	(0.012)
Δ Log VA		-0.023***	-0.0235***
		(0.006)	(0.006)
Industry × Year FEs	Yes	Yes	Yes
Dependent variable $t-1$	No	No	Yes
Firms N.	3612	3612	3612
Observations	50,478	28,445	28,441
R^2	0.05162	0.07376	0.09428

Note: This table shows the relationship between firm-level automation and the subsequent 6-year change in the firm-level high-skill employment share. I measure firm-level automation from purchases of industrial robots recorded in French customs. In the table I report the δ^y coefficient from regression equation (27). The "Automation" dummy indicates whether an industrial robot was imported by the firm in the current year or any previous year. The other explanatory variables in columns (2)–(3) are long differences of log value added. In each regression I include industry-year fixed effects, and in column (3) the lagged dependent variable is also included. Standard errors are clustered at the firm level and are reported in parentheses. Significance levels are: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

These patterns are consistent with international evidence on skill-biased technological change. In particular, Lindner et al. (2022) find that innovation activities in Norway and Hungary led to a two- to three-percentage-point rise in the college-to-non-college employment ratio over a similar period. The similarity in magnitudes suggests that automation and innovation trigger comparable reductions in the relative use of low-skill labor, even across economies at different stages of technological development.

Conceptually, these results fit closely with the predictions of the model developed in Section 2 that automation displaces low-skill workers, and with the increase in the high-skill wage premium documented in the preceding subsection.

6.3 Stock of Capital per High-Skill Worker

The estimates in Table 6 indicate that automation is associated with a large rise in capital stock per high-skilled employee, pointing to a strong reallocation of tasks toward capital. The estimates remain statistically significant across all specifications, indicating that the result is not driven by contemporaneous improvements in firm-level productivity as proxied by changes in value added. This robustness reinforces the interpretation that the rise in capital intensity is a direct consequence of automation itself, rather than a by-product of higher output or temporary investment cycles.

Table 3: Automation effect on the Stock of Capital per High-Skill Worker

	(1)	(2)	(3)
Automation	0.441***	0.451***	0.168**
	(0.089)	(0.090)	(0.074)
Δ Log VA		-0.115***	-0.092***
		(0.039)	(0.033)
Industry $\times$ Year FEs	Yes	Yes	Yes
Dependent variable $t-1$	No	No	Yes
Firms N.	3612	3612	3612
Observations	19,041	18,915	18,909
R^2	0.08317	0.08407	0.26561

Note: This table shows the relationship between firm-level automation and subsequent 6-year change in firm-level stock of capital per high-skill worker. I measure firm-level automation from purchases of industrial robots recorded in French customs. In the table I report the δ^y coefficient from regression equation (27). The "Automation" dummy indicates whether an industrial robot was imported by the firm in the current year or any previous year. The other explanatory variables in columns (2)–(3) are long differences of log value added. In each regression I include industry-year fixed effects, and in column (3) the lagged dependent variable is also included. Standard errors are clustered at the firm level and are reported in parentheses. Significance levels are: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

To evaluate the overall cost implications of this capital deepening, it is necessary to compare the magnitude of the increase in capital stock per worker to the corresponding reduction in the task share of low-skill labor, which will be analyzed in the next section. Only by contrasting these two adjustments can we assess whether automation ultimately yields net cost savings or whether the observed rise in capital intensity primarily reflects a reallocation of production tasks away from low-skill workers toward machines.

7 The Wage Effects of Automation at Adopters Relative to Non-Adopters

In the previous section, I have shown that as firms buy automating machines they pay a higher skill premium and employ relatively more high-skill workers. At the same time, they also increase the amount of capital per high-skill worker. According to the identification strategy outlined in Section 3.2, these changes in relative prices and quantities can be used to back out the two key elasticities that govern the wage effects of automation across firms: the impact of automation on the task share of low-skill labor and capital. Indeed, according to equations (24) and (25), the elasticity of the task share of low-skill workers can be estimated as:

$$\overline{\Delta \ln \Gamma^{L}(\alpha_{1jt}, \alpha_{2jt})} = -\hat{\delta^{s}} - \frac{1}{\eta} \cdot \hat{\delta}^{HL} \tag{29}$$

and the elasticity of the task share of capital can be estimated as:

$$\overline{\Delta \ln \Gamma^{K}(\alpha_{1jt})} = \frac{1}{\eta} \cdot \hat{\delta}^{HK} + \phi\eta(\overline{\Delta \ln H_{jt}} - \overline{\Delta \ln H_{j't}}) - \eta \left(\hat{\delta}^{u} + \hat{\delta}^{s}\right) \tag{30}$$

where $\hat{\delta^{s}}$, $\hat{\delta}^{HL}$, and $\hat{\delta}^{HK}$ are the estimated coefficients from regressions (26), (27), and (28), respectively.

With values for parameters (ϕ, σ, η) governing, respectively, the elasticity of labor supply, the elasticity of substitution across goods, and the elasticity of substitution across tasks, and with firm-level cost-shares (s_{Lj}, s_{Kj}) of low-skill labor and capital, I can then obtain the wage effects of automation at adopting and non-adopting firms using equations (16), (17) and (18).

Before going into the results, it is worth discussing the underlying assumptions for this exercise. As discussed before, this exercise does not require random variation in the adoption of automating machines. Even if there are various aggregate and firm-level shocks (like productivity or amenity shocks coinciding with automation investments) that bias the estimate of automation's impact on the skill premium and the skill ratio, they operate in opposite directions and so can be cancelled out. As a result, the sum of the skill premium and $\frac{1}{\eta}$ times the skill-ratio isolates the impact of automation on the relative productivity of low-skill workers, $\frac{\Gamma_H(\alpha_{2jt})}{\Gamma_L(\alpha_{1jt},\alpha_{2jt})}$. Under the assumption that firms do not re-assign tasks between low- and high-skill workers, changes in the *relative* task-share are driven by changes in the *level* of low-skill workers' task-share, and so identify it. Similarly, the change in the capital stock per high-skill employee, scaled by $\frac{1}{\eta}$, identifies the change in the task-share of capital $\Gamma_K(\alpha_{1jt})$. These estimates, which measure changes in the task-shares of low-skill workers and capital *at automating firms*, can also be linked to wage differentials between workers *at automating versus non-automating firms*. Indeed, relative to their counterparts at non-adopting firms, low-skill workers experience a negative displacement effect, measured by the reduction in their task-share, but also a positive scale effect, which is given by the cost savings gains of a less labor-intensive production process – measured, again, by the reduction in the task-share of low-skill workers (scaled by their share in total costs) – net of the increase in costs associated with a more capital-intensive production process – measured, again, by the increase in task-share of capital (scaled by its share in total costs).

These results follow from the economic environment imposed in Section 2 – CES production function, optimizing firm behavior and a specific wage setting protocol – and the assumption that $\frac{\psi'_H(\alpha_{2\ell t})}{\psi_H(\alpha_{2\ell t})} - \frac{\psi'_L(\alpha_{2\ell t})}{\psi_L(\alpha_{2\ell t})} \to \infty$ for any ℓ. Importantly though, the validity of the exercise relies also on applying the correct parameters (ϕ, σ, η). To this end, I set $\phi = 0.5$, $\sigma = 4.0$ and $\eta = 0.5$. I choose these values as the preferred ones for the following reasons: $\phi = 0.5$ implies firm-specific labor supply elasticity equal to two, which is consistent with recent quasi-experimental estimates from the literature (Caldwell and Oehlsen, 2018; Cho, 2018; Kroft et al., 2025; Bassier et al., 2022); $\sigma = 4.0$ gives a markup of approximately 31% which is the midpoint across of the measurements in De Ridder et al. (2022) which uses French data over the same time period as this paper; lastly, $\eta = 0.5$ is the easlticity estimated by Humlum (2021), which is - to the best of my knowledge- the only paper estimating the task-level elasticity of substitution in a task-based production technology. Regarding the estimates of δ^s, δ^{HL}, and δ^{HK}, I use the coefficients from the most stringent specifications from each regression (column 4 in Tables 4, 5, and 6). Lastly, average firm-level cost-shares $(\overline{s_{Lj}}, \overline{s_{Kj}})$ of low-skill labor and capital at firms making an automation investment are resprectively 0.4 and 0.10. More information about the computation of these cost-shares is provided in Appendix Section **??**.

With these numbers at hand, I can now compute the average change in the task-share of low-skill workers and capital induced by automation at automating firms, as well as the wage effects of automation at adopting versus non-adopting firms. The average change in task-share of low-skill workers induced by automation is $-0.06 - \frac{1}{0.5} \times 0.036 = -0.132$ percent. Similarly, the average change in task-share of capital induced by automation is $\frac{1}{0.5} \times 0.168 - 0.5 \times (0.06) = 0.306$.[7] The finding that at automating firms the task-share of low-skill workers decreases while the task-share of capital increases is reassuring as it aligns with the prediction of the model that automation re-allocates tasks from low-skill workers to capital.

[7] The average change in task-share of low-skill workers and of capital induced by automation are based on equation (29) and (30), respectively. The terms $\overline{\Delta \ln H_{jt}} - \overline{\Delta \ln H_{j't}}$ and $\hat{\delta^u}$ have been set to 0 as they are not statiscally significant (see Tables C.2 and 6.1).

The reduction in the task-share of low-skill workers implies that on average automating firms experience a reduction of $\frac{1}{1-0.5} \times [0.4 \times 0.132] = 0.106$ in unit costs as a result of lower labor costs. In turn, the increase in the task-share of capital implies that on average unit costs go up by around $\frac{1}{1-0.5} \times [0.1 \times 0.306] = 0.0612$ as the firm uses capital more intensely. Hence, on average, investing in automating machines generates cost-savings of around 4.5%.

Finally, I can compute the wage effects of automation at adopting versus non-adopting firms. For low-skill workers, the average difference in wages between adopters and non-adopters is given by $\frac{0.25}{1.25} \times (-0.132) + \frac{0.5 \times 4}{1.25} \times 0.045 = 0.0456$. In turn, for high-skill workers the average difference in wages between adopters and non-adopters is given by $\frac{0.5 \times 4}{1.25} \times 0.045 = 0.072$. These results imply that low-skill workers at automating firms experience a wage increase of around 5% relative to their counterparts at non-automating firms, while high-skill workers at automating firms enjoy a wage increase of around 7% relative to their counterparts at non-automating firms.

8 The Contribution of Automation to Wage Inequality

While the previous section established that automation generates wage disparities both within and between skill groups, the economic significance of within-skill gaps depends critically on worker mobility. If automating firms successfully recruit high-skill workers from competitors, or if displaced low-skill workers transition out of manufacturing to avoid being displaced, the realized wage gaps may be considerably smaller than the direct firm-level effects suggest. I therefore develop a variance decomposition that quantifies automation's contribution to overall wage inequality while explicitly accounting for worker reallocation across firms.

In the presence of imperfect competition in the labor market, we have the following structure of wages:

$$\ln w_{it} = \alpha_t + \psi_i + \ln w_{Sj(i,t)} + \varepsilon_{it},$$

where i denotes workers, j denotes firms, and ε_{it} is a mean zero error term. The ψ_i captures workers' skills that are portable across firms, and therefore not affected by firm-level technological change (at least in the short term). The term $\ln w_{Sj(i,t)}$ represents the skill-group (S) specific firm-level wage premium of firm j. As discussed above, heterogeneous firm-level premiums can emerge as a result of worker's idiosyncratic preferences to work at a particular firm, union bargaining or labor market power.

Applying the law of total variance, the overall dispersion of wages (net of time and worker fixed effects) can be decomposed into the contribution of skill heterogeneity and firm heterogeneity:

$$\text{Var}(\ln w_{it} - \alpha_t - \psi_i) = \underbrace{\text{Var}\big(\mathbb{E}[\ln w_{Sj(i,t)} \mid S]\big)}_{\text{between-skill}} + \underbrace{\mathbb{E}\big[\text{Var}(\ln w_{Sj(i,t)} \mid S)\big]}_{\text{between-firm within skill}} + \underbrace{\text{Var}(\varepsilon_{it})}_{\text{idiosyncratic}} . \tag{31}$$

Moreover, the firm-level component can be further decomposed according to firms' automation status $A_{jt} \in \{0,1\}$:

$$\text{(32)}\quad \mathbb{E}\big[\mathrm{Var}(\ln w_{Sj(i,t)} \mid S)\big] = \underbrace{\mathbb{E}\big[\mathrm{Var}\big(\mathbb{E}[\ln w_{Sj(i,t)} \mid S, A] \mid S\big)\big]}_{\text{between automation statuses within skill}} + \underbrace{\mathbb{E}\big[\mathbb{E}(\mathrm{Var}(\ln w_{Sj(i,t)} \mid S, A) \mid S)\big]}_{\text{between firms within (skill, automation)}}.$$

Together, equations (31) and (32) provide a transparent decomposition of wage dispersion into (i) differences between skill groups, (ii) differences between automating and non-automating firms within each skill group, (iii) residual firm-level heterogeneity, and (iv) idiosyncratic variation.

To implement the variance decomposition empirically, one could proceed by linking each estimated object directly to the terms in equations (31)–(32). The change in the average wage of high- relative to low-skill workers identified in Section 7 corresponds to the between-skill component of equation (31). It captures how automation alters wage differences across skill groups through the scale and displacement effects in equations (12)–(13). Within each skill group, the estimated wage differential between automating and non-automating firms corresponds to the between-firm within-skill component of equation (32). This term measures how automation generates dispersion across firms employing similar workers. Finally, any residual variation in wages among firms with the same automation status represents the within-status firm heterogeneity term in (32), while the individual-level residuals in the worker-level regression account for the idiosyncratic component of equation (31). Together, these mappings allow the model-based estimates of automation's wage effects to be expressed as contributions to each source of overall wage inequality.

9 Conclusion

This paper examines how firm-level automation shapes wage inequality by developing a task-based model where heterogeneous firms endogenously choose to replace low-skill workers with capital and testing its predictions using French manufacturing data from 2003 to 2019. The key methodological contribution is an identification strategy that exploits changes in relative prices and quantities of capital and labor across firms to isolate automation's causal impact from confounding productivity shocks. By comparing relative wages and employment across automating and non-automating firms using difference-in-differences regressions, I estimate that automation reduces the task-share of low-skill workers by 4% and increases the task-share of capital by 6%. These estimates imply that both high- and low-skill workers at automating firms gain 7% and 5% in wages respectively relative to their counterparts at non-automating firms, indicating that the productivity-enhancing scale effect dominates the labor-displacing effect even for replaceable workers.

These findings reveal substantial between-firm wage differentials arising from automation. Workers performing identical tasks experience substantially different wage trajectories depending on whether their employer automates, with the magnitude of these gaps amplified by limited worker mobility across firms. Finally I provide a framework combining the theoretical model, the identification strategy, and the empirical estimates to decompose overall wage dispersion into between-firm and between-skill components and quantify how much of each is explained by firm-level automation. From a policy perspective, these results suggest that interventions targeting the diffusion of automation technologies across firms may be as important as traditional worker-focused policies such as retraining programs in addressing automation-induced inequality.

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A Theoretical appendix

A.1 Equilibrium Definition

Definition A.1 (Small Open Economy Equilibrium)**.** *Given firm characteristics* (z_j, a_{Hj}, a_{Lj})*, labor and capital supplies* $(\bar{L}, \bar{H})$*, factor and task-specific productivities* $(\psi_L(x), \psi_H(x), \psi_K(x))$*, a world interest rate* r *and preference parameter* ϕ*, an equilibrium consists of:*

- *prices* $(\{p_j, w_{Lj}, w_{Hj}\}_j, \Lambda_L, \Lambda_H,)$ *and quantities* $(\{y_j, L_j, H_j, K_j\}_j, Y)$ *for goods, low- and high-skilled labor, capital, and aggregate output*
- *thresholds* $\{\alpha_{Lj}, \alpha_{Hj}\}_j$

such that:

1. *Each worker supplies one unit of labor to the firm* j *that maximizes her indirect utility given by equation* (2)

2. *The household demands the utility-maximizing quantity of goods* j *given by equation* (1)

3. *Each firm* j *chooses its output, price, input demands, and thresholds* α_1 *and* α_2 *to maximize profits subject to the production technology (equation* (8)*), the demand for its variety (equation* (9)*), and the supply of low- and high-skilled workers (equations* (10) *and* (11)*)*

4. *Labor markets clear:*
$$\sum_j L_j = \bar{L}, \quad \sum_j H_j = \bar{H}$$

5. *The ideal-price index condition holds:* $1 = \sum_j p_j^{1-\sigma}$

A.2 Firm problem for given cutoffs

The firm solves:

$$
\begin{aligned}
\max_{L_{jt},H_{jt},K_{jt},p_{jt},y_{jt}} \quad & p_{jt}y_{jt} - w_{Ljt}L_{jt} - w_{Hjt}H_{jt} - r_K K_{jt} \\
y_{jt} &= z_{jt}\left[\Gamma^K(\alpha_{1jt})(A_{Kt}K_{jt})^{\frac{\eta-1}{\eta}} + \Gamma^L(\alpha_{1jt},\alpha_{2jt})(A_{Lt}L_{jt})^{\frac{\eta-1}{\eta}} + \Gamma^H(\alpha_{2jt})(A_{Ht}H_{jt})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \\
p_{jt} &= \left(\frac{y_{jt}}{Y_t}\right)^{-\frac{1}{\sigma}} \\
w_{Ljt} &= \left(\frac{L_{jt}}{\bar{L}_t\Lambda_{Lt}a_{Ljt}}\right)^{\phi} \\
w_{Hjt} &= \left(\frac{H_{jt}}{\bar{H}_t\Lambda_{Ht}a_{Hjt}}\right)^{\phi}
\end{aligned}
$$

In the following I remove the t subscript to ease notation. The f.o.c for L_j is:

$$\frac{\partial y_j}{\partial L_j}p_j + y_j\frac{\partial p_j}{\partial L_j} = w_{Lj} + \frac{\partial w_{Lj}}{\partial L_j}L_j$$

which using the demand and wage equations to compute $\frac{\partial p_j}{\partial L_j}$ and $\frac{\partial w_{Lj}}{\partial L_j}$ becomes:

$$\frac{\partial y_j}{\partial L_j}p_j + y_j\cdot\left(-\frac{1}{\sigma}\frac{p_j}{y_j}\frac{\partial y_j}{\partial L_j}\right) = w_{Lj}(1+\phi)$$

Grouping terms it becomes:

$$\frac{\partial y_j}{\partial L_j}\cdot\frac{\sigma-1}{\sigma}p_j = w_{Lj}(1+\phi)$$

Expliciting out the marginal product of labor we get:

$$z_j^{\frac{\eta-1}{\eta}}\, y_j^{\frac{1}{\eta}}\Gamma^L(\alpha_{1j},\alpha_{2j})L_j^{-\frac{1}{\eta}}\cdot\frac{\sigma-1}{\sigma}p_j = w_{Lj}(1+\phi) \tag{33}$$

Lastly, we replace L_j using the labor supply equation to obtain:

$$w_{Lj} = \left(\frac{1}{1+\phi}\right)^{\frac{\phi\eta}{\phi\eta+1}}\left(z_j^{\frac{\eta-1}{\eta}}\, y_j^{\frac{1}{\eta}}\,\Gamma^L(\alpha_{1j},\alpha_{2j})\,(\bar{L}\Lambda_L a_{Lj})^{-\frac{1}{\eta}}\,\frac{\sigma-1}{\sigma}\,p_j\right)^{\frac{\phi\eta}{\phi\eta+1}} \tag{34}$$

Similarly, the f.o.c. for H_j is:

$$w_{Hj} = \left(\frac{1}{1+\phi}\right)^{\frac{\phi\eta}{\phi\eta+1}}\left(z_j^{\frac{\eta-1}{\eta}}\, y_j^{\frac{1}{\eta}}\,\Gamma^H(\alpha_{2j})\,(\bar{H}\Lambda_H a_{Hj})^{-\frac{1}{\eta}}\,\frac{\sigma-1}{\sigma}\,p_j\right)^{\frac{\phi\eta}{\phi\eta+1}} \tag{35}$$

Lastly, the f.o.c. for K_j is:

$$r = z_j^{\frac{\eta-1}{\eta}}\, y_j^{\frac{1}{\eta}}\Gamma^K(\alpha_{1j})K_j^{-\frac{1}{\eta}}\cdot\frac{\sigma-1}{\sigma}p_j \tag{36}$$

A.3 Proof of Proposition 2.2

Consider equation (34). In equilibrium prices are given by $p_j = \left(\frac{y_j}{Y}\right)^{-\frac{1}{\sigma}} P$ (equation (9)) and firm-level output by $y_j = \left(\frac{\mu \cdot c(\alpha_{1j},\alpha_{2j})}{P}\right)^{-\sigma} Y$. Replacing p_j and y_j with these expressions in (34), one gets that the wages of low-skill workers at firm j can be expressed as:

$$w_{Lj} = \left[B z_j^{\frac{\sigma-1}{\eta}} Y^{\frac{1}{\eta}} \mu^{\frac{\eta-\sigma}{\eta}} c(\alpha_{1j},\alpha_{2j})^{\frac{\eta-\sigma}{\eta}} \Gamma^L(\alpha_{1j},\alpha_{2j}) A_L^{\frac{\eta-1}{\eta}} (\bar{L}\Lambda_L a_{Lj})^{-\frac{1}{\eta}} \right]^{\frac{\phi\eta}{\phi\eta+1}}$$

where $B = \frac{\sigma-1}{\sigma(1+\phi)}$.

Taking logs and totally differentiating one gets:

$$d\ln w_{Lj} = \frac{\phi\eta}{\phi\eta+1} \left[\frac{\sigma-1}{\eta} d\ln z_j + \frac{1}{\eta} d\ln Y + \frac{\eta-\sigma}{\eta} d\ln c(\alpha_{1j},\alpha_{2j}) + d\ln \Gamma^L(\alpha_{1j},\alpha_{2j}) + \right.$$
$$\left. \frac{\eta-1}{\eta} d\ln z_j - \frac{1}{\eta} d\ln(\bar{L}\Lambda_L) - \frac{1}{\eta} d\ln a_{Lj} \right]$$

where[8], under the assumption that $\frac{\psi'_H(\alpha_{2\ell t})}{\psi_H(\alpha_{2\ell t})} - \frac{\psi'_L(\alpha_{2\ell t})}{\psi_L(\alpha_{2\ell t})}$, we have that:

$$d\ln c(\alpha_{1j},\alpha_{2j}) = \frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}} d\alpha_{1j}$$

and:

$$d\ln \Gamma^L(\alpha_{1j},\alpha_{2j}) = \frac{\partial \ln \Gamma^L(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}} d\alpha_{1j}$$

The equilibirum wage change for low-skill workers at a firm j with $d\alpha_{1j} > 0$ relative to a firm j' with $d\alpha_{1j'} = 0$ is then:

$$d\ln w_{Lj} - d\ln w_{Lj'} = \frac{\phi\eta}{\phi\eta+1} \left[\frac{\sigma-1}{\eta}(d\ln z_j - d\ln z_{j'}) + \right.$$
$$\frac{\eta-\sigma}{\eta} \frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}} d\alpha_{1j} + \frac{\partial \ln \Gamma^L(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}} d\alpha_{1j} -$$
$$\left. \frac{1}{\eta}(d\ln a_{Lj} - d\ln a_{Lj'}) \right]$$

As it can be seen from the above expression, the wage effect of automation at firm j relative to firm j' can be decomposed into three components: the effect of changes in relative productivities, represented by the first term in the bracket, the effect of automation at firm j, represented by the second in the bracket, and lastly the effect of changes in relative amenities. The first and third

[8] In equilibrium, w_{Lj} and w_{Hj} change, affecting the unit cost $c(\alpha_{1j},\alpha_{2j})$. However, this effect is second-order since wages are set by firms exactly to minimize unit costs,and so the first-order impact of wage changes on unit costs is zero by an application oif the envelope theorem. This is I consider only the effect of changes in α_{1j} and α_{2j} when totally differentiating $c(\alpha_{1j},\alpha_{2j})$.

effects are changes to model primitives and so are not driven by $d\alpha_{1j}$. Hence, the wage effect of automation at firm j relative to firm j' is given by:

$$d\ln w_{Lj} - d\ln w_{Lj'} = \frac{\phi\eta}{\phi\eta+1}\left[\frac{\eta-\sigma}{\eta}\frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}}d\alpha_{1j} + \frac{\partial \ln \Gamma^L(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}}d\alpha_{1j}\right]$$

Rearranging terms, one obtains the expression in Proposition 2.2.

For high-skill workers, the proof is analogous starting from equation (35).

Lastly I show how to obtain equation (18) which measures the per-unit cost savings from automation. Firstly, note that the share of low-skilled labor in total costs (net of automation costs) at firm j can be obtained as:

$$s_j^L = \frac{w_{Lj}L_j}{y_j c(\alpha_{1j},\alpha_{2j})/z_j} = \frac{w_{Lj}}{y_j c(\alpha_{1j},\alpha_{2j})/z_j}\cdot\frac{\partial y_j\cdot c(\alpha_{1j},\alpha_{2j})/z_j}{\partial w_{Lj}}$$

where the second equality comes from Shepard's lemma. Hence:

$$s_j^L = (w_{Lj}(1+\phi))^{1-\eta}\Gamma^L(\alpha_{1j},\alpha_{2j})/c(\alpha_{1j},\alpha_{2j})^{1-\eta}$$

Similarly, the share of labor in total costs (net of automation costs) at firm j is:

$$s_j^K = r^{1-\eta}\Gamma^K(\alpha_{1j})/c(\alpha_{1j},\alpha_{2j})^{1-\eta}$$

Now, note that the per-unit cost savings can be obtained using (12) as:

$$\frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}} = \frac{1}{1-\eta}\cdot\frac{r^{1-\eta}\Gamma^K(\alpha_{1j})\frac{\partial \ln\Gamma^K(\alpha_{1j})}{\partial\alpha_{1j}} + (w_{Lj}(1+\phi))^{1-\eta}\Gamma^L(\alpha_{1j},\alpha_{2j})\frac{\partial\ln\Gamma^L(\alpha_{1j},\alpha_{2j})}{\partial\alpha_{1j}}}{c(\alpha_{1j},\alpha_{2j})^{1-\eta}}$$

which, given the expressions for the labor and capital costs shares just obtained, becomes:

$$\frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial \alpha_{1j}} = \frac{1}{1-\eta}\cdot\left(s_j^K\cdot\frac{\partial\ln\Gamma^K(\alpha_{1j})}{\partial\alpha_{1j}} + s_j^L\cdot\frac{\partial\ln\Gamma^L(\alpha_{1j},\alpha_{2j})}{\partial\alpha_{1j}}\right)$$

Note that in equilibrium it has to be that $\frac{\partial \ln c(\alpha_{1j},\alpha_{2j})}{\partial\alpha_{1j}} < 0$, meaning that automation reduced unit costs, otherwise firms would not increase their automation level α_{1j}. □

A.4 Proof of Proposition 3.1

Hence the skill-premium is:

(37)
$$\frac{w_{Hj}}{w_{Lj}} = \left(\frac{\Gamma^H(\alpha_{2j},1)}{\Gamma^L(\alpha_{1j},\alpha_{2j})}\right)^{\frac{\eta\phi}{1+\eta\phi}}\left(\frac{\bar{H}\Lambda_H a_{Hj}}{\bar{L}\Lambda_L a_{Lj}}\right)^{-\frac{\phi}{1+\eta\phi}}$$

We can express the skill-ratio, using equation (33) and its counterpart for high-skilled workers, as:

(38)
$$\left(\frac{H_j}{L_j}\right)^{-\frac{1}{\eta}}\frac{\Gamma^H(\alpha_{2j},1)}{\Gamma^L(\alpha_{1j},\alpha_{2j})} = \frac{w_{Hj}}{w_{Lj}}$$

and replacing the right-hand side with (37) we get:

$$\frac{H_j}{L_j} = \left(\frac{\Gamma^H(\alpha_{2j},1)}{\Gamma^L(\alpha_{1j},\alpha_{2j})}\right)^{\frac{\eta}{1+\eta\phi}} \left(\frac{\bar{H}\,\Lambda_H\,a_{Hj}}{\bar{L}\,\Lambda_L\,a_{Lj}}\right)^{\frac{\eta\phi}{1+\eta\phi}} \tag{39}$$

Lastly, rearranging (38) one can obtain:

$$\frac{\Gamma^H(\alpha_{2j})}{\Gamma^L(\alpha_{1j},\alpha_{2j})} = \frac{w_{Hj}}{w_{Lj}}\left(\frac{H_j}{L_j}\right)^{\frac{1}{\eta}}$$

Notice that for two firms j and j' with identical changes in α_{2jt} across two periods ($\Delta\alpha_{2jt} = \Delta\alpha_{2j't}$), but only j automates additional tasks (i.e. $\Delta\alpha_{1jt} > 0$ and $\Delta\alpha_{1j't} = 0$), the log-change in the skill premium and in the skill ratio behave as:

$$\Delta\ln\frac{w_{Hjt}}{w_{Ljt}} - \Delta\ln\frac{w_{Hj't}}{w_{Lj't}} = -\frac{\eta\phi}{1+\eta\phi}\Delta\ln\Gamma^L(\alpha_{1jt},\alpha_{2jt}) - \frac{\phi}{1+\eta\phi}\left(\Delta\ln\frac{a_{Hjt}}{a_{Ljt}} - \Delta\ln\frac{a_{Hj't}}{a_{Lj't}}\right)$$

$$\Delta\ln\frac{H_{jt}}{L_{jt}} - \Delta\ln\frac{H_{j't}}{L_{j't}} = -\frac{\eta}{1+\eta\phi}\Delta\ln\Gamma^L(\alpha_{1jt},\alpha_{2jt}) + \frac{\eta\phi}{1+\eta\phi}\left(\Delta\ln\frac{a_{Hjt}}{a_{Ljt}} - \Delta\ln\frac{a_{Hj't}}{a_{Lj't}}\right)$$

where $\Delta\ln\Gamma^L(\alpha_{1jt},\alpha_{2jt}) = \frac{\partial\ln\Gamma^L(\alpha_{1jt},\alpha_{2jt})}{\partial\alpha_{1jt}}\Delta\alpha_{1jt}$.

Hence, combining the two above equations one obtains the semi-elasticity of the task-share of low-skill labor as:

$$-\Delta\ln\Gamma^L(\alpha_{1jt},\alpha_{2jt}) = \left(\Delta\ln\frac{w_{Hjt}}{w_{Ljt}} - \Delta\ln\frac{w_{Hj't}}{w_{Lj't}}\right) + \frac{1}{\eta}\left(\Delta\ln\frac{H_{jt}}{L_{jt}} - \Delta\ln\frac{H_{j't}}{L_{j't}}\right)$$

To obtain the semi-elasticity of the task-share of capital, divide capital demand from the firm's f.o.c.:

$$K_{jt} = z_{jt}^{\eta-1}y_{jt}\Gamma^K(\alpha_{1jt})^\eta\left(\frac{\sigma-1}{\sigma}\right)^\eta(p_{jt})^\eta r_t^{-\eta}$$

by the demand for high-skill workers:

$$H_{jt} = z_{jt}^{\eta-1}y_{jt}\Gamma^H(\alpha_{2jt})^\eta\left(\frac{\sigma-1}{\sigma}\right)^\eta(p_{jt})^\eta(w_{Hjt}(1+\phi))^{-\eta}$$

which gives:

$$\frac{K_{jt}}{H_{jt}} = \left(\frac{\Gamma^K(\alpha_{1jt})}{\Gamma^H(\alpha_{2jt})}\right)^\eta\left(\frac{r_t}{w_{Hjt}(1+\phi)}\right)^{-\eta}$$

Replacing high-skill wages with (11):

$$\frac{K_{jt}}{H_{jt}^{1+\phi\eta}} = \left(\frac{\Gamma^K(\alpha_{1jt})}{\Gamma^H(\alpha_{2jt})}\right)^\eta\left(\frac{r_t}{1+\phi}\right)^{-\eta}\left(\frac{1}{\bar{H}_t\Lambda_{Ht}a_{Hjt}}\right)^{\phi\eta}$$

Comparing first-differences of $\ln\frac{K_{jt}}{H_{jt}^{1+\phi\eta}}$ across two firms j and j' with j automating additional tasks while j' keeping a constant automation level, one obtains:

$$\begin{aligned}\Delta\ln\frac{K_{jt}}{H_{jt}^{1+\phi\eta}} - \Delta\ln\frac{K_{j't}}{H_{j't}^{1+\phi\eta}} =& \eta\left(\Delta\ln\frac{\Gamma^K(\alpha_{1jt})}{\Gamma^H(\alpha_{2jt})} - \Delta\ln\frac{\Gamma^K(\alpha_{1j't})}{\Gamma^H(\alpha_{2j't})}\right)\\ &-\phi\eta\left(\Delta\ln a_{Hjt} - \Delta\ln a_{Hj't}\right)\end{aligned}$$

which, under the assumption that $\frac{\psi'_H(\alpha_{2\ell t})}{\psi_H(\alpha_{2\ell t})} - \frac{\psi'_L(\alpha_{2\ell t})}{\psi_L(\alpha_{2\ell t})} \to \infty$, becomes:

$$\Delta \ln \frac{K_{jt}}{H_{jt}^{1+\phi\eta}} - \Delta \ln \frac{K_{j't}}{H_{j't}^{1+\phi\eta}} = \eta \Delta \ln \Gamma^K(\alpha_{1jt}) - \phi\eta \left(\Delta \ln a_{Hjt} - \Delta \ln a_{Hj't} \right)$$

Notice that $\ln \frac{K_{jt}}{H_{jt}}$ can be rewritten as:

$$\ln \frac{K_{jt}}{H_{jt}^{1+\phi\eta}} = \ln \frac{K_{jt}}{H_{jt}} \; - \; \phi\eta \, \ln \tilde{H}_t + \varepsilon_{jt}$$

where $\tilde{H}_t = \exp\left\{ \frac{1}{J_t} \sum_{j=1}^{J_t} \ln H_{jt} \right\}$, and $\varepsilon_{jt} = -\phi\eta \left[\ln H_{jt} - \frac{1}{J_t} \sum_{i=1}^{J_t} \ln H_{it} \right]$. Hence, the above expression can be written as:

$$\Delta \ln \frac{K_{jt}}{H_{jt}} - \Delta \ln \frac{K_{j't}}{H_{j't}} = \eta \, \Delta \ln \Gamma^K(\alpha_{1jt}) - \phi\eta \big(\Delta \ln a_{Hjt} - \Delta \ln a_{Hj't} \big) + \big(\Delta\varepsilon_{j't} - \Delta\varepsilon_{jt} \big)$$

Taking averages across j and j':

$$\overline{\Delta \ln \frac{K_{jt}}{H_{jt}}} - \overline{\Delta \ln \frac{K_{j't}}{H_{j't}}} = \eta \, \overline{\Delta \ln \Gamma^K(\alpha_{1jt})} - \phi\eta (\overline{\Delta \ln a_{Hjt}} - \overline{\Delta \ln a_{Hj't}})$$

because the cross-sectional mean of the approximation error ϵ_{jt} is exactly zero, by construction. Hence, the change in the task-share of capital induced by automation can be identified as:

$$\overline{\Delta \ln \Gamma^K(\alpha_{1jt})} = \frac{1}{\eta} \left(\overline{\Delta \ln \frac{K_{jt}}{H_{jt}}} - \overline{\Delta \ln \frac{K_{j't}}{H_{j't}}} \right) + \phi\eta (\overline{\Delta \ln a_{Hjt}} - \overline{\Delta \ln a_{Hj't}})$$

Lastly, to isolate the effect of automation from changes in amenities, notice that by exploiting the labor supply equation for high-skill workers (equation (11)) one can recover changes in supply-side factors as:

$$\Delta \ln H_{jt} - \tfrac{1}{\phi} \Delta \ln w_{Hjt} \;\; = \;\; \Delta \ln \bar{H}_t + \Delta \ln \Lambda_{H,t} + \Delta \ln a_{Hjt}.$$

and so one can measure the automation effect on the task-share of capital net of shocks to firm-specific amenities computing:

$$\overline{\Delta \ln \Gamma^K(\alpha_{1jt})} = \frac{1}{\eta} \left(\overline{\Delta \ln \frac{K_{jt}}{H_{jt}}} - \overline{\Delta \ln \frac{K_{j't}}{H_{j't}}} \right) + \phi\eta \left[\overline{\Delta \ln H_{jt}} - \overline{\Delta \ln H_{j't}} - \tfrac{1}{\phi} \left(\overline{\Delta \ln w_{Hjt}} - \overline{\Delta \ln w_{Hj't}} \right) \right]$$

A.5 Proof of Proposition 2.1

Re-arrange the first-order condition for the automation level (equation (13)) as:

$$\left[(w_{Lj}(1+\phi))^{1-\eta} - r^{1-\eta} \right] \cdot c(\alpha_{1j}, \alpha_{2j})^{\eta} \cdot \frac{y_j}{z_j} = b \cdot \frac{1-\eta}{\eta}$$

The variables that potentially depend on z_j in this expression are only those indexed by j, which are w_{Lj}, α_{2j}, y_j, and z_j itself.

Note that, although it is true that we should consider w_{Hj} as well as it enters $c(\alpha_{1j}, \alpha_{2j})$, an application of the envelope theorem shows that any change in w_{Hj} has no first-order effect as in my setting firms choose the wages they pay. By the same argument, I can ignore the effect of z_j through α_{2j} on $c(\alpha_{1j}, \alpha_{2j})$ as well. Then, I first show that $\frac{y_j}{z_j}$ is increasing in z_j, and later that the per unit cost-savings from automation are also increasing in z_j. Together, these two results imply that the left-hand side of the first-order condition for α_{1j} is increasing in z_j, which implies that the optimal automation level α^*_{1j} is increasing in z_j.

Firstly, in any CES demand system where $\sigma > 1$ – as it is the case in my setting – the term $\frac{y_j}{z_j}$ is increasing in z_j. Indeed:

$$\frac{y_j}{z_j} = Y \cdot (\mu \cdot c(\alpha_{1j}, \alpha_{2j}))^{-\sigma} \cdot z_j^{\sigma-1}$$

Secondly, the wages of low-skill workers w_{Lj} are increasing in z_j. This can be seen from the equilibrium expression for the wage of low-skill workers:

$$w_{Lj} = \left(\frac{\sigma-1}{\sigma(1+\phi)}\right)^{\frac{\phi\eta}{\phi\eta+1}} \left(z_j^{\frac{\sigma-1}{\sigma}} \left(\frac{y_j}{z_j}\right)^{\frac{\sigma-\eta}{\sigma\eta}} \Gamma^L(\alpha_{1j}, \alpha_{2j}) \left(\bar{L}\Lambda_L a_{Lj}\right)^{-\frac{1}{\eta}} Y^{\frac{1}{\sigma}}\right)^{\frac{\phi\eta}{\phi\eta+1}}$$

The only two terms that depend directly on z_j are $z_j^{\frac{\sigma-1}{\sigma}}$ – which is increasing in z_j – and $\left(\frac{y_j}{z_j}\right)^{\frac{\sigma-\eta}{\sigma\eta}}$ – which is also increasing in z_j – since $\sigma > \eta$. This is intuitive: the marginal product of low-skill workers increases as the total-factor productivity of the firm, z_j, goes up.

Optimal automation decision

From standard optimization arguments we know that the Lagrange multiplier of the production technology in the cost minimization problem gives the marginal cost. In addition, when the technology is constant-returns-to-scale, this is identical to the unit cost. Hence, to obtain the unit cost of production for given $(\alpha_{1j}, \alpha_{2j})$ I solve for λ in the following Lagrangean:

$$\begin{aligned}
\mathcal{L}(K_j, L_j, H_j) = & w_{Lj}L_j + w_{Hj}H_j + rK_j + \\
& \lambda\Big\{y_j - z_j\left[\Gamma^K(\alpha_{1j})^{\frac{1}{\eta}} K_j^{\frac{\eta-1}{\eta}} + \Gamma^L(\alpha_{1j}, \alpha_{2j})^{\frac{1}{\eta}} L_j^{\frac{\eta-1}{\eta}} + \Gamma^H(\alpha_{2j})^{\frac{1}{\eta}} H_j^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}\Big\} + \\
& \psi\Big\{w_{Lj} - \left(\frac{L_j}{\bar{L}\Lambda_L a_{Lj}}\right)^{\phi}\Big\} + \\
& \mu\Big\{w_{Hj} - \left(\frac{H_j}{\bar{H}\Lambda_H a_{Hj}}\right)^{\phi}\Big\}
\end{aligned}$$

The f.o.c. are:

$$
\begin{aligned}
&K: && r = \lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^K(\alpha_{1j})^{\frac{1}{\eta}} K_j^{-\frac{1}{\eta}} \\
&L: && w_{Lj} = \lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^L(\alpha_{1j},\alpha_{2j})^{\frac{1}{\eta}} L_j^{-\frac{1}{\eta}} + \psi \cdot \phi \left(\frac{L_j}{\bar{L}\Lambda_L a_{Lj}}\right)^{\phi-1} \frac{1}{\bar{L}\Lambda_L a_{Lj}} \\
&H: && w_{Hj} = \lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^H(\alpha_{2j})^{\frac{1}{\eta}} H_j^{-\frac{1}{\eta}} + \mu \cdot \phi \left(\frac{H_j}{\bar{H}\Lambda_H a_{Hj}}\right)^{\phi-1} \frac{1}{\bar{H}\Lambda_H a_{Hj}}
\end{aligned}
$$

Deriving the Lagrangean with respect to w_{Lj} and w_{Hj} we obtain the multipliers ψ and μ as:

$$
\begin{aligned}
&w_L: && \psi = -L_j \\
&w_H: && \mu = -H_j
\end{aligned}
$$

Using these expressions for ψ and μ in the f.o.c. for L and H we get:

$$
\begin{aligned}
&L: && w_{Lj} = \lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^L(\alpha_{1j},\alpha_{2j})^{\frac{1}{\eta}} L_j^{-\frac{1}{\eta}} - \phi w_{Lj} \\
&H: && w_{Hj} = \lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^H(\alpha_{2j})^{\frac{1}{\eta}} H_j^{-\frac{1}{\eta}} - \phi w_{Hj}
\end{aligned}
$$

which becomes:

$$
\begin{aligned}
&L: && w_{Lj}(1+\phi) = \lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^L(\alpha_{1j},\alpha_{2j})^{\frac{1}{\eta}} L_j^{-\frac{1}{\eta}} \\
&H: && w_{Hj}(1+\phi) = \lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^H(\alpha_{2j})^{\frac{1}{\eta}} H_j^{-\frac{1}{\eta}}
\end{aligned}
$$

I rewrite the f.o.c. to isolate K_j, L_j and H_j :

$$
\begin{aligned}
&K: && K_j = \left(\frac{r}{\lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^K(\alpha_{1j})^{\frac{1}{\eta}}}\right)^{-\eta} \\
&L: && L_j = \left(\frac{w_{Lj}(1+\phi)}{\lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^L(\alpha_{1j},\alpha_{2j})^{\frac{1}{\eta}}}\right)^{-\eta} \\
&H: && H_j = \left(\frac{w_{Hj}(1+\phi)}{\lambda z_j^{\frac{\eta-1}{\eta}} y_j^{\frac{1}{\eta}} \Gamma^H(\alpha_{2j})^{\frac{1}{\eta}}}\right)^{-\eta}
\end{aligned}
$$

Replace these equations into the production technology:

$$
\begin{aligned}
y_j =& z_j\, \lambda^\eta\, z_j^{\eta-1}\, y_j \cdot \\
& \left[r^{1-\eta}\Gamma^K(\alpha_{1j}) + (w_{Lj}(1+\phi))^{1-\eta}\Gamma^L(\alpha_{1j},\alpha_{2j}) + (w_{Hj}(1+\phi))^{1-\eta}\Gamma^H(\alpha_{2j})\right]^{\frac{\eta}{\eta-1}}
\end{aligned}
$$

which gives λ as:

$$
\lambda = \frac{1}{z_j}\, \left[r^{1-\eta}\Gamma^K(\alpha_{1j}) + (w_{Lj}(1+\phi))^{1-\eta}\Gamma^L(\alpha_{1j},\alpha_{2j}) + (w_{Hj}(1+\phi))^{1-\eta}\Gamma^H(\alpha_{2j})\right]^{\frac{1}{1-\eta}}
$$

Denote the term in curly brackets as $c(\alpha_{1j})$. This is the unit cost of a firm with productivity $z_j = 1$. Hence the unit cost of a firm with productivity z_j for given $(\alpha_{1j}, \alpha_{2j})$ is:

$$c(\alpha_{1j}, \alpha_{2j}, z) = \frac{c(\alpha_{1j}, \alpha_{2j})}{z_j}$$

where

$$c(\alpha_{1j}, \alpha_{2j}) = \left[r^{1-\eta}\Gamma^K(\alpha_{1j}) + (w_{Lj}(1+\phi))^{1-\eta}\Gamma^L(\alpha_{1j}, \alpha_{2j}) + (w_{Hj}(1+\phi))^{1-\eta}\Gamma^H(\alpha_{2j})\right]^{\frac{1}{1-\eta}}$$

A.6 Proof of Proposition 3.1

I first introduce a useful lemma and then proceed with the proof of Proposition 3.1.

Lemma A.1. *Let $\alpha^\star_{2\ell t} \in (0,1)$ be the solution to (**??**) for firm ℓ at time t, i.e. it satisfies (in logs):*

$$\ln \psi_H(\alpha^\star_{2\ell t}) - \ln \psi_L(\alpha^\star_{2\ell t}) \;=\; \ln \frac{w_{H\ell t}}{w_{L\ell t}} - \ln \frac{A_{Ht}}{A_{Lt}}$$

Suppose that across two dates $t-1$ and t we have a bounded change in the right-hand side, and assume that the steepness of the productivity of high-skill labor relative to low-skill labor, at the solution, satisfies

$$\frac{\psi'_H(\alpha_{2\ell t})}{\psi_H(\alpha_{2\ell t})} \;-\; \frac{\psi'_L(\alpha_{2\ell t})}{\psi_L(\alpha_{2\ell t})}\bigg|_{\alpha_{2\ell t}=\alpha^\star_{2\ell t}} \;\longrightarrow\; +\infty.$$

Then

$$\Delta\alpha_{2\ell t} \;\equiv\; \alpha_{2\ell t} - \alpha_{2\ell, t-1} \;\longrightarrow\; 0$$

Proof. Define $g(\alpha_2) = \ln \psi_H(\alpha_2) - \ln \psi_L(\alpha_2)$, and $m \equiv \ln \frac{w_H}{w_L} - \ln \frac{A_H}{A_L}$. Also define $F(\alpha_2, m) = g(\alpha_2) - m$. By the Implicit Function Theorem, for interior solutions with $g'(\alpha_2) \neq 0$ there exists a (local) function $\alpha_2 = \alpha_2(m)$ with

$$\frac{\partial \alpha_2}{\partial m} \;=\; \frac{1}{g'(\alpha_2)}.$$

Take a change from $t-1$ to t and apply the mean value theorem to the composite map $m \mapsto \alpha_2(m)$:

$$\Delta\alpha_{2\ell t} = \alpha_2(m_t) - \alpha_2(m_{t-1}) = \frac{\partial \alpha_2}{\partial m}\bigg|_{m=\tilde{m}} \Delta m_t = \frac{1}{g'(\tilde{\alpha}_{2\ell t})} \Delta m_t$$

for some $\tilde{m}$ between m_{t-1} and m_t, and $\tilde{\alpha}_{2\ell t}$ on the segment between $\alpha_{2\ell,t-1}$ and $\alpha_{2\ell t}$. By hypothesis, Δm_t is bounded and $g'(\tilde{\alpha}_{2\ell t}) \to +\infty$ (since g' is continuous and $g'(\alpha_{2\ell t}) \to +\infty$). Hence:

$$\Delta\alpha_{2\ell t} \;=\; \frac{\Delta m_t}{g'(\tilde{\alpha}_{2\ell t})} \;\longrightarrow\; 0.$$

□

Proof of Proposition 3.1. From equation (22), the change in the skill-ratio at a firm j' with constant automation level is:

$$\Delta \ln \frac{w_{Hjt}}{w_{Ljt}} = \frac{\eta\phi}{1+\eta\phi}\Delta \ln \Gamma^H(\alpha_{2jt}) - \frac{\phi}{1+\eta\phi}\Delta \ln \frac{H_t \Lambda_{Ht}}{L_t \Lambda_{Lt}} - \frac{\phi}{1+\eta\phi}\Delta \ln \frac{a_{Hjt}}{a_{Ljt}}$$

Then, subtracting this expression from the analogous one for a firm j that increases its automation level by $d\alpha_{1jt}$ gives:

$$\begin{aligned}\Delta \ln \frac{w_{Hjt}}{w_{Ljt}} - \Delta \ln \frac{w_{Hj't}}{w_{Lj't}} =& \frac{\eta\phi}{1+\eta\phi}\left(\Delta \ln \Gamma^L(\alpha_{1jt},\alpha_{2jt}) - \Delta \ln \Gamma^L(\alpha_{1j't},\alpha_{2j't})\right) + \\ & \frac{\eta\phi}{1+\eta\phi}\left(\Delta \ln \Gamma^H(\alpha_{2jt}) - \Delta \ln \Gamma^H(\alpha_{2j't})\right) + \\ & \frac{\phi}{1+\eta\phi}\left(\Delta \ln \frac{a_{Hjt}}{a_{Ljt}} - \Delta \ln \frac{a_{Hj't}}{a_{Lj't}}\right)\end{aligned}$$

which can be expanded into:

$$\begin{aligned}\Delta \ln \frac{w_{Hjt}}{w_{Ljt}} - \Delta \ln \frac{w_{Hj't}}{w_{Lj't}} =& \frac{\eta\phi}{1+\eta\phi}\Bigg(\frac{\partial \ln \Gamma^L(\alpha_{1jt},\alpha_{2jt})}{\partial \alpha_{1jt}}\Delta\alpha_{1jt} + \\ & \frac{\partial \ln \Gamma^L(\alpha_{1jt},\alpha_{2jt})}{\partial \alpha_{2jt}}\Delta\alpha_{2jt} - \frac{\partial \ln \Gamma^L(\alpha_{1j't},\alpha_{2j't})}{\partial \alpha_{2j't}}\Delta\alpha_{2j't}\Bigg) + \\ & \frac{\eta\phi}{1+\eta\phi}\left(\Delta \ln \Gamma^H(\alpha_{2jt}) - \Delta \ln \Gamma^H(\alpha_{2j't})\right) + \\ & \frac{\phi}{1+\eta\phi}\left(\Delta \ln \frac{a_{Hjt}}{a_{Ljt}} - \Delta \ln \frac{a_{Hj't}}{a_{Lj't}}\right)\end{aligned}$$

Because of the assumption that $\frac{\psi_L'(\alpha_{2\ell t})}{\psi_L(\alpha_{2\ell t})} - \frac{\psi_H'(\alpha_{2\ell t})}{\psi_H(\alpha_{2\ell t})} \to -\infty$ for any ℓ, $\Delta\alpha_{2\ell t} \to 0$, as shown by Lemma A.1. Hence we have that:

$$\begin{aligned}\Delta \ln \frac{w_{Hjt}}{w_{Ljt}} - \Delta \ln \frac{w_{Hj't}}{w_{Lj't}} =& \frac{\eta\phi}{1+\eta\phi}\frac{\partial \ln \Gamma^L(\alpha_{1jt},\alpha_{2jt})}{\partial \alpha_{1jt}}\Delta\alpha_{1jt} + \\ & \frac{\phi}{1+\eta\phi}\left(\Delta \ln \frac{a_{Hjt}}{a_{Ljt}} - \Delta \ln \frac{a_{Hj't}}{a_{Lj't}}\right)\end{aligned}$$

Applying the same steps to equation (23) gives:

$$\begin{aligned}\Delta \ln \frac{H_{jt}}{L_{jt}} - \Delta \ln \frac{H_{j't}}{L_{j't}} =& \frac{\eta}{1+\eta\phi}\frac{\partial \ln \Gamma^L(\alpha_{1jt},\alpha_{2jt})}{\partial \alpha_{1jt}}\Delta\alpha_{1jt} + \\ & \frac{\eta\phi}{1+\eta\phi}\left(\Delta \ln \frac{a_{Hjt}}{a_{Ljt}} - \Delta \ln \frac{a_{Hj't}}{a_{Lj't}}\right)\end{aligned}$$

Finally, computing:

$$\Delta \ln \frac{w_{Hjt}}{w_{Ljt}} - \Delta \ln \frac{w_{Hj't}}{w_{Lj't}} + \frac{1}{\eta}\left(\Delta \ln \frac{H_{jt}}{L_{jt}} - \Delta \ln \frac{H_{j't}}{L_{j't}}\right)$$

gives equation (24).

Following an analogous procedure as the one above, one gets equation (25).

Wage effects on low- vs high-skill workers

Starting from:

$$w_{Lj} = \left(\frac{1}{1+\phi}\right)^{\frac{\phi\eta}{\phi\eta+1}} \left(z_j^{\frac{\eta-1}{\eta}}\, y_j^{\frac{1}{\eta}}\, \Gamma^L(\alpha_{1j},\alpha_{2j})\, A_L^{\frac{\eta-1}{\eta}}\, (\bar{L}_t\Lambda_{Lt}a_{Ljt})^{-\frac{1}{\eta}}\, \frac{\sigma-1}{\sigma}\, p_j\right)^{\frac{\phi\eta}{\phi\eta+1}}.$$

and compute the log-change of w_{Lj} induced by a marginal increase in α_{1j}, for fixed aggregate variables $P, Y, \Lambda_L, \Lambda_H$. This gives the effect of automation, if all other firms did not change their automation level, and so the price index is not affected. This is a partial equilibrium effect. The log-change in w_{Lj} is:

$$d \ln w_{Lj} = \frac{\phi\eta}{\phi\eta + 1} \left(\frac{1}{\eta} d \ln y_j + \frac{\partial \ln \Gamma^L(\alpha_{1j}, \alpha_{2j})}{\partial \alpha_{1j}} d\alpha_{1j} + d \ln p_j \right) \tag{40}$$

which using equation (9) becomes:

$$d \ln w_{Lj} = \frac{\phi\eta}{\phi\eta + 1} \left(\underbrace{\frac{\sigma - \eta}{\sigma\eta} d \ln y_j + \frac{1}{\sigma} d \ln Y}_{\text{Scale Effect}} - \underbrace{\frac{\psi_L(\alpha_{1j})^{\eta - 1}}{\Gamma^L(\alpha_{1j}, \alpha_{2j})} d\alpha_{1j}}_{\text{Displacement Effect}} \right)$$

Alternatively, equation (40) can be rewritten using equation (1) as:

$$d \ln w_{Lj} = \frac{\phi\eta}{\phi\eta + 1} \left(\underbrace{- \left(\frac{\sigma}{\eta} - 1 \right) d \ln p_j + \frac{\sigma}{\eta} d \ln P + \frac{1}{\eta} d \ln Y}_{\text{Scale Effect}} - \underbrace{\frac{\psi_L(\alpha_{1j})^{\eta - 1}}{\Gamma^L(\alpha_{1j}, \alpha_{2j})} d\alpha_{1j}}_{\text{Displacement Effect}} \right)$$

which using $p_j = \frac{\sigma - 1}{\sigma} c(\alpha_{1j}, \alpha_{2j}, z_j)$ becomes:

$$d \ln y_j = - \left(\frac{\sigma}{\eta} - 1 \right) d \ln c(\alpha_{1j}, \alpha_{2j}) + \frac{\sigma}{\eta} d \ln P + \frac{1}{\eta} d \ln Y$$

where $d \ln p_j = d \ln c(\alpha_{1j}, \alpha_{2j})$. This equation emphasizes the role of the cost-savings from automation in generating the scale effect.

B Data appendix

B.1 Survey Data Descriptive Statistics

There are 177 firms $\times$ 5 years = 885 observations. I remove 9 firms for which there is no information in FARE [9], 12 firms for which there is missing information in some years (they were born after 2011 or simply information is missing for some years) and 1 firm which has the legal form of "agricultural cooperative".

Table 4: Descriptive statistics

N-by-year	N	N Eligible	N invest at least once	N never invested pre-2011 (eligible)	N never invested pre-2011 (non-eligible)
710	142	95	106	3	2

The resulting dataset contains 155 firms $\times$ 5 years = 775 observations, out of which 13 firms (65 observations) are non-manufacturing firms. The main dataset throughout the paper is the one with manufacturing firms only. Here the main descriptive statistics:

Robot Investment Magnitudes. Table 5 provides descriptive statistics comparing robot purchases to total investment in industrial equipment and tools. Robot investments represent a meaningful but modest share of firms' overall capital stock. Among firms making positive investments, robots account for an average of 191,000 euros compared to 839,000 euros for all industrial equipment and tools. The contribution of robots to the total stock of industrial equipment and tools averages 11 percent, with a median of 2.5 percent, indicating substantial heterogeneity in automation intensity across firms.

Table 5: Descriptive Statistics by Investment Item

	Industrial robots	Industrial equipment and tools
Total (1,000 €)	38,325	573,055
Mean (conditional on positive inv.)	191	839
Median (conditional on positive inv.)	118	195

Firm Characteristics by Policy Eligibility. Tables 6 and 7 compare eligible and non-eligible

[9] After checking on the online Sirene databse, some of these firms do not exist (firms with siren: 378877000, 529496106, 488134059) while others do exist. Among these ones, some are in the public sector (130017627, 130017684) while others in the private one (662750074, 488328261, 344954896). I was not able to understand why they're not in FARE.

firms across various dimensions in 2013, the year before policy implementation. As expected given the SME eligibility criteria, eligible firms are substantially smaller across all measures: they average 57 employees compared to 281 for non-eligible firms, and have sales of 1.1 million euros compared to 67.9 million euros for non-eligible firms. Despite these size differences, eligible firms show comparable productivity levels, with value added per worker of 61,133 euros compared to 70,860 euros for non-eligible firms.

Table 6: Firm Characteristics by Eligibility Status in 2013

	Non-eligible	Eligible
Age	33.7	26.5
Sales	67,864,349	1,130,131
Assets	76,733,863	1,072,635
Employment	281.0	57.4
Materials	26,663,876	488,507
Industrial equipment (stock)	25,552,010	2,903,369
Other inputs	19,519,915	2,823,320
Profits	2,137,103	313,450
Value added	19,191,821	328,710
Value added per worker	70,860	61,133

Financial characteristics and international exposure also differ systematically between eligible and non-eligible firms. Eligible firms have lower absolute levels of debt and equity financing but similar leverage ratios when scaled by firm size. Non-eligible firms show greater integration with international markets, with higher rates of both importing and exporting activities.

Table 7: Financial Characteristics and International Exposure in 2013

Financial characteristics

	Non-eligible	Eligible
Loans (bank)	410,660	357,561
Loans (other)	5,157,983	1,713,005
Cash	4,517,853	602,805
Equity	20,139,506	2,932,812
International market exposure		
Importers (extra UE)	0.872	0.442
Importers (intra UE)	0.915	0.421
Exporters (total)	0.915	0.789

Sectoral Distribution Figure 1 shows the distribution of firms across sectors in the survey data. The sample is concentrated in traditional manufacturing industries, with the largest representation in fabricated metal products and machinery, followed by rubber and plastic products. This sectoral distribution aligns with expectations about which industries are most likely to adopt industrial robots.

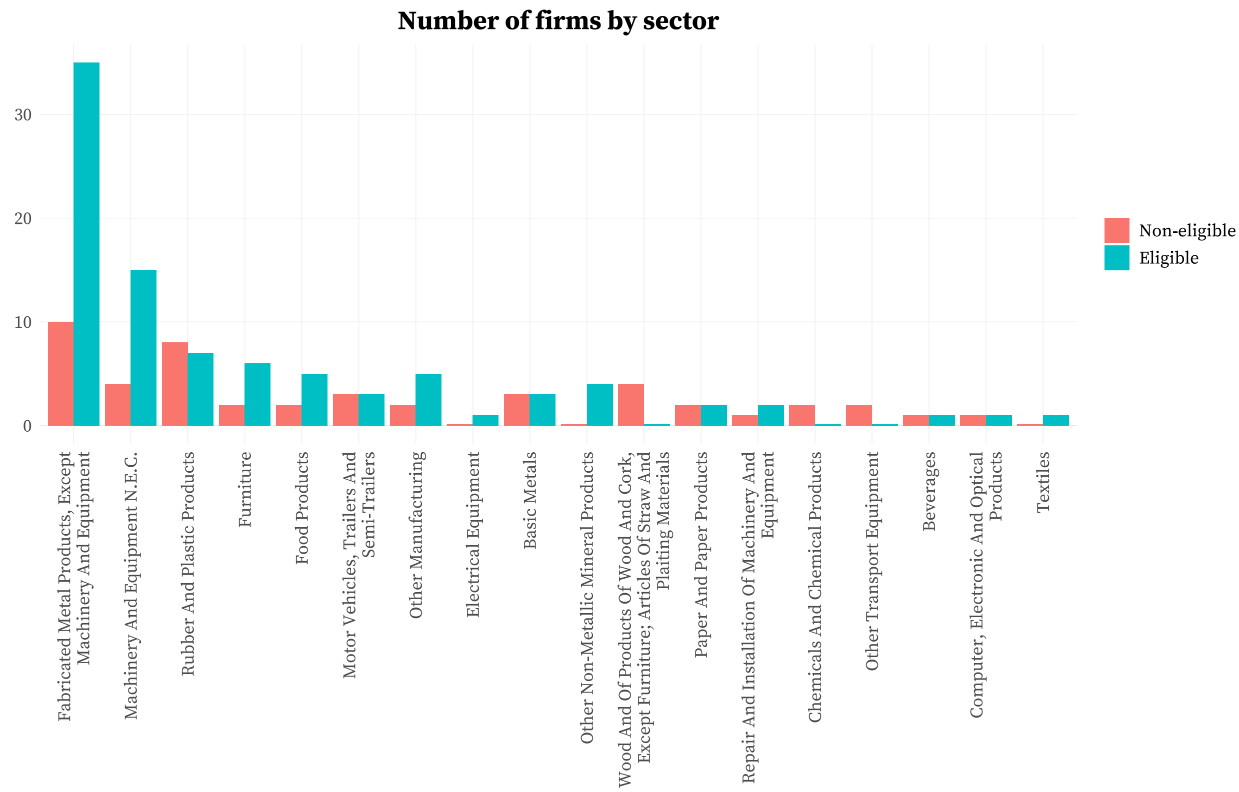

Figure 1: Number of Firms by Sector

B.2 Customs Data Descriptive Statistics

Table 8 presents descriptive statistics for robot purchases identified in the customs data. The firm-level data covers 1,050 unique firms over 2,180 firm-year observations, with robot purchases averaging 235,595 euros. The plant-level data provides a more granular view with 558 plants and 946 plant-year observations. Both datasets show substantial variation in investment magnitudes, ranging from small purchases of around 30 euros to large investments exceeding 6-13 million euros, reflecting the heterogeneous nature of automation adoption across firms and establishments.

Table 8: Descriptive Statistics of Robot Purchases from Customs Data

	N	**N-by-year**	**Mean**	**Min**	**p25**	**p50**	**p75**	**Max**
Firm-level	1,050	2,180	235,595	32	9,200	58,737	220,694	13,554,303
Plant-level	558	946	203,228	33	8,038	50,322	216,044	6,139,027

Note: All monetary values are in euros.

Sectoral Distribution of Robot Imports. Figure 2 displays the cumulative robot imports between 1997 and 2021 by manufacturing industry, based on the customs data. The automotive sector dominates robot adoption, accounting for the largest share of total robot imports, followed by machinery and equipment manufacturing. This pattern reflects the historical development of industrial robotics, which first gained widespread adoption in automotive assembly lines before diffusing to other manufacturing sectors.

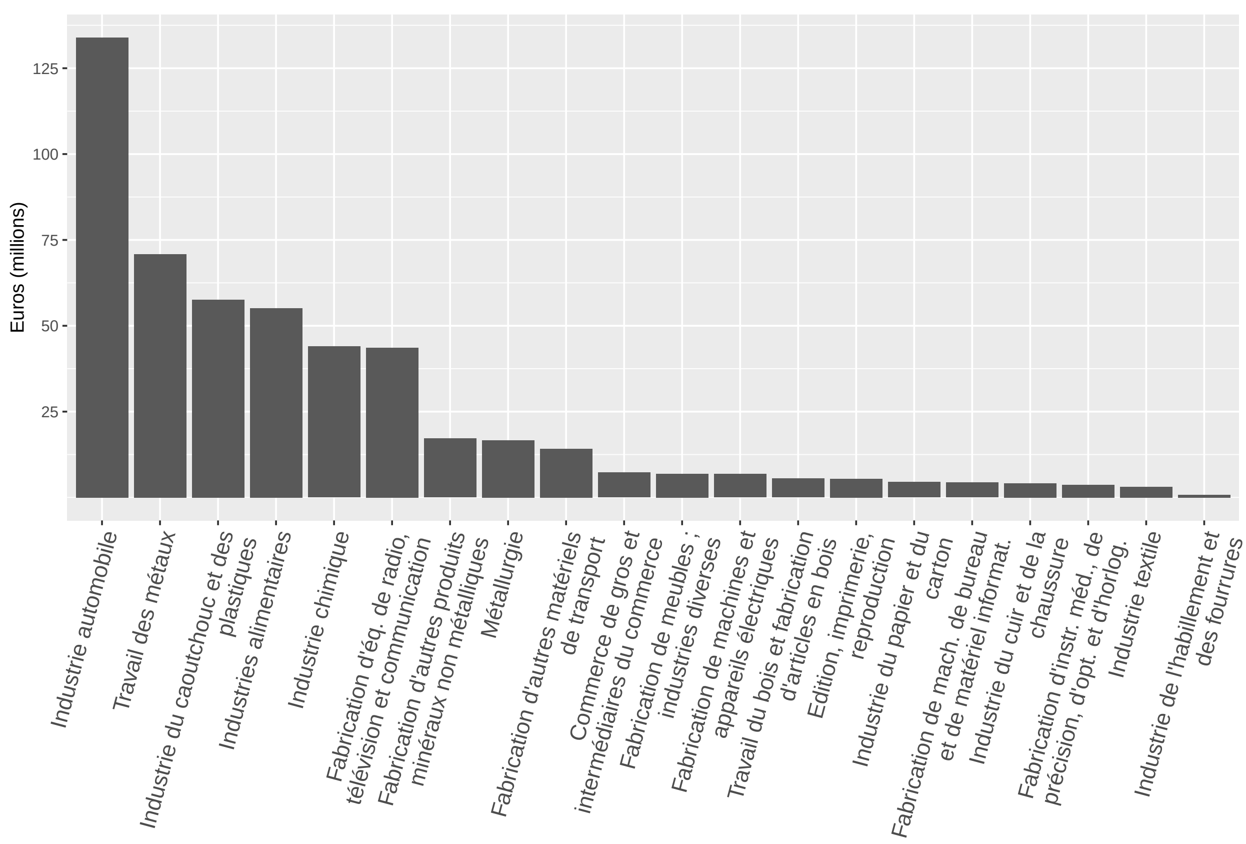

Figure 2: Cumulative Robot Imports between 1997 and 2021 by Manufacturing Industry

C Robustness checks

C.1 Effect of automation on the skill ratio - 6 year difference

Table 9: Automation effect on the skill-ratio

	(1)	(2)	(3)
Automation	0.032**	0.037**	0.022
	(0.014)	(0.021)	(0.021)
vadl_delta6		-0.028***	-0.0285***
		(0.008)	(0.008)
Industry × Year FEs	Yes	Yes	Yes
Dependent variable $t-1$	No	No	Yes
Firms N.	3612	3612	3612
Observations	39,659	17,767	17,763
R^2	0.03468	0.05779	0.09816

Note: Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Standard errors in parentheses.

C.2 Effect of automation on the employment of high-skill workers

Table 10: Automation effect on the employment of high-skill workers

	3-Years Diff.	6-Years Diff.
	(1)	(2)
Automation	0.012	-0.061
	(0.065)	(0.070)
Δ Log VA	0.339***	0.442***
	(0.032)	(0.034)
Industry × Year FEs	Yes	Yes
Dependent variable $t-1$	Yes	Yes
Firms N.	3612	3612
Observations	13,591	7,976
R^2	0.56603	0.58312

Note: Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Standard errors in parentheses.

C.3 Effect of automation on capital stock per high-skill worker - 6 year difference

Table 11: Automation effect on capital stock per high-skill worker

	(1)	(2)	(3)
Automation	0.304***	0.314***	0.265***
	(0.083)	(0.083)	(0.081)
Industry × Year FEs	Yes	Yes	Yes
Dependent variable $t-1$	No	No	Yes
Firms N.	3612	3612	3612
Observations	31,876	31,491	31,272
R^2	0.08635	0.08829	0.15526

Note: Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Standard errors in parentheses.