AUTOMATION, MARKET POWER AND WELFARE[*]

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Abstract

Using French administrative data, I show that large firms are more likely to adopt automation capital, and that adoption leads to higher productivity and increased labor market power for firms. Given this evidence, I quantify the efficiency costs of automation in a general equilibrium model incorporating oligopsonistic labor markets, automation adoption choice, occupational choice, labor force participation choice, and entry. Calibrating the model to the French manufacturing sector shows that output and welfare gains from automation would be 15.9% and 56.8% higher, respectively, in a world without labor market power.

Keywords. Automation, Production Function Estimation, Misallocation

JEL: J2, 03, D2

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1 Introduction

In recent years, attention has increasingly focused on the distributional implications of automation, especially its role in reallocating workers across occupations and redistributing income between labor and capital. Nevertheless, there remains a gap in our understanding of how automation affects efficiency. This paper aims to bridge this gap.

Using French matched employer-employee data, I provide empirical evidence that large firms are more likely to adopt automation capital, and that adoption leads to increased firm productivity and labor market power. These results suggest that the adoption of automation capital may have significant adverse efficiency effects beyond the negative distributional effects highlighted in the literature.

Understanding the magnitude of these losses is critical for designing optimal policies to address both equity and efficiency concerns with automation. Much of the recent literature has focused on optimal tax policies to mitigate the adverse distributional effects of automation. However, if the efficiency losses are large, then a policy response must also include efficiency-enhancing policies, and steps must be taken to prevent the consolidation of market power in automation-adopting firms. The absence of such measures can increase the inequality between capital and labor.

To rationalize the empirical evidence and to quantify the magnitude of the efficiency implications of automation adoption in imperfectly competitive markets, I construct a general equilibrium model of oligopsonistic labor markets with endogenous automation decisions, occupational choice, labor force participation, and entry.

The model has three main features. First, consistent with empirical evidence, I assume that automation affects a firm's technology in two ways ensuring that it has both distributional and efficiency implications. On the one hand, automation substitutes for workers in routine occupations. This implies that a decline in the relative price of automation capital reduces the demand for routine occupations, which (endogenously) reallocates workers to non-routine occupations or out of the labor force. On the other hand, automation allows firms to scale production, since it also endogenously increases a firm's Hicks-neutral technology.

The second key feature of the model is an oligopsonistic occupational labor market, consistent with recent work by Berger et al. (2022) and Azkarate-Askasua and Zerecero (2020). Consequently, the model implies an endogenous distribution of markdowns in equilibrium. The variance of the distribution of markdowns is the source of allocative inefficiency in this economy.

These two key features, in conjunction, imply that a decline in the price of automation capital, through the adoption of automation and its endogenous effect on firm productivity, will widen the variance of the distribution of markdowns, exacerbating misallocation and reducing allocative efficiency in the economy.

To quantify efficiency losses, I then solve a benevolent social planner's allocation problem and compare it to the decentralized economy. The planner's solution has two key differences from decentralized allocation that generate efficiency losses.

First, the presence of labor market power in the decentralized economy drives a wedge between the marginal product of labor and marginal cost, distorting the optimal size distribution of producers – more productive producers are inefficiently small, while less productive producers are inefficiently large. The social planner corrects this wedge, eliminating the associated allocative inefficiencies and restoring the optimal size distribution.

The second key difference is that automation capital is not misallocated in the planner's allocation. Despite the absence of distortions in the market for automation capital in the decentralized economy, misallocation in the labor market leads to inefficient allocation of automation capital across firms. Comparing the two allocations, for the given set of calibrated parameters, I find that relatively more productive establishments adopt inefficiently low automation capital and less productive establishments adopt inefficiently high automation capital. This is due to capital-labor substitutability in the production function combined with more productive firms hiring inefficiently low amounts of labor in equilibrium.

To study the quantitative implications of the model, I calibrate it to the French manufacturing sector in 2019. The impact of automation on output and welfare is moderated by the parameters that determine the labor supply elasticities of workers, and those that influence the endogenous impact of automation on firm productivity. These parameters are calibrated using values from the literature. In future iterations, I will estimate them directly from microdata using an instrumental variables strategy and exogenous trade shocks as instruments.

Using the calibrated model, I conduct two counterfactuals experiments to quantify the efficiency cost of automation. In the first experiment, which I refer to as the *extensive* margin effect of automation, I compare the decentralized and the planner's allocation with and without automation. In the second experiment, referred to as the *intensive* margin effect of automation, I compare the allocations where the number of automation adopters are held fixed but each adopted facing a lower cost of adoption.

The counterfactual experiments provide four key insights. First, automation increases both output and average welfare at the extensive margin. I find that a decentralized economy with automation has 16.2% higher output and 0.9% higher average welfare than a counterfactual economy without automation. Second, the welfare gains from automation are not evenly distributed. In particular, I find that the gain in average welfare for routine workers is relatively smaller than the gain for non-routine workers. Third, I find that automation exacerbates misallocation, both between and within firms. Importantly, within-firm misallocation accounts for about 50% of the total misallocation. Finally, the gains from automation are lost due to the increase in misallocation and market power. Specifically, in the absence of labor market power, output and average welfare would have increased by 15.9% and 56.8%, respectively.

Related Literature. This paper contributes to several strands of the literature. A key contribution of this paper is that it incorporates recent empirical evidence showing that automation improves firm productivity in a general equilibrium model with oligopsonistic labor markets. A key implication of this model is that automation can endogenously increase misallocation in the economy, reducing both output and welfare. This result is closely related to, but distinct from, recent work on the aggregate effects of automation.

First, recent work by Eden and Gaggl (2018), Vom Lehn (2020), Jaimovich et al. (2021) and Humlum (2022) have all examined the impact of automation on output and welfare. However, they do so in the context of competitive product and labor markets. In contrast, in this paper I develop an endogenous automation framework with heterogeneous labor market power and show that abstracting from imperfect competition can bias our estimates of output and welfare gains.

Second, recent work by Acemoglu and Restrepo (2023) examines the impact of automation on aggregate productivity and welfare with labor market imperfections.[1] They provide an alternative mechanism through which automation can reduce allocative inefficiency. In their framework, automation is directed at high-return jobs, which displaces workers from jobs where their marginal product is highest. This displacement reduces allocative efficiency and thus welfare. In contrast, this paper shows that by affecting the Hicks-neutral productivity of firms, automation can shift the variance of market power in the economy, reducing allocative efficiency and increasing misallocation.

Third, the framework I develop also complements the recent work of Azar et al. (2023). They provide a model that introduces monopsony power in a task-based framework and show that wage-setting power has implications for the level of automation adopted by firms. I extend their work by considering an oligopsonistic labor market, which has two additional implications. First, both the level of automation and market power are endogenous outcomes of the model. Second, the decision to automate now also depends on one's competitors in the market. This is an additional reason for the heterogeneity in the level of automation adoption seen in the data.

Fourth, recent work has linked the increased use of automation to product market concentration in an endogenous markup framework (Firooz et al., 2022). This paper complements this literature by considering the impact of automation in a framework with endogenous occupation-specific markdowns, and emphasizes that future work should include market power on both sides to examine the aggregate impact of market power. See the recent work by Deb et al. (2022), Deb et al. (2023), Gutiérrez (2022) and Trottner (2023), who considers models with both product and labor market power.

Additionally, this paper is also related to the literature that studies both atomistic monopsony (Card et al., 2018, Lamadon et al., 2022) and oligopsonistic labor markets

[1] In their framework, they model imperfections as exogenous wedges between marginal productivity and wages, in the tradition of Hsieh and Klenow (2009) and Baqaee and Farhi (2020).

(Berger et al., 2022). I follow quite closely the recent work of Azkarate-Askasua and Zerecero (2020) and extend their model by allowing for endogenous automation decisions. One implication of this extension is that this paper proposes that the adoption of automation can have implications for the level, and then change, of the distribution of market power in the economy.

This paper also builds on the insights of Beraja and Zorzi (2022) by examining the optimal policy response to automation. While Beraja and Zorzi (2022) focuses on dynamic issues such as the reallocation of workers across occupations and the credit constraints of displaced workers, this paper instead considers the role of oligopsony and efficiency costs of automation.

Finally, this framework has important implications for the literature on optimal robot taxation (see Guerreiro et al., 2022, Costinot and Werning, 2018 and Thuemmel, 2023, Korinek and Stiglitz, 2018). Recent work by Guerreiro et al. (2022) shows that it is optimal to tax robots while routine workers who cannot transition to new occupations remain active, with zero optimal taxes thereafter. This model highlights the importance of considering efficiency-enhancing policies together with optimal tax policies to mitigate both the distributional and efficiency costs of automation.

Outline. The remainder of the paper is structured as follows: In Section 3, I describe the data used in the analysis, Section 3 shows the key facts pertaining to automation's effect on firm productivity and market power, Section 4 presents the model, Section 5 quantifies the model, Section 6 shows the results and the last section concludes.

2 Data

I use four sources of French administrative data: the DADS Postes, FARE, EAP and the French customs data.[2] I focus my analysis on the period between 2009 and 2019. Below is a brief description of these sources.

[2]DADS stands for Déclaration Annuelle des Données Sociales in French.

DADS Postes. DADS Postes is a restricted dataset managed by the French National Statistical Institute (INSEE) and contains worker-level information such as wages, hours worked, the worker's firm identifier, and their occupational title. This information is available for the universe of workers, allowing me to observe the entire workforce of a given firm during the period of my analysis. No individual worker characteristics, such as education level, worker identifier, or labor market experience, are available in the DADS Postes. There is no additional information on the firm beyond the firm identifier and firm-level aggregates on firm size and average wages. Further details on the classification of occupations into abstract, routine, and manual groups can be found in the Appendix C.1. I include all employees between the ages of 18 and 65 in my sample.

FARE. I merge DADS Postes with FARE (using the unique firm identifier "SIREN" in both datasets) which contains balance sheet data of firms. From it, I extract measures of total employment, revenue, value-added, capital, expenditure on intermediate inputs, labor cost and industry affiliation of firms.

French Customs data. Following Aghion et al. (2022) and Acemoglu and Restrepo (2022), I construct a proxy for automation adoption using French customs data on imported intermediate goods from abroad. The imported products used to identify automation investment fall under the following Harmonized System codes: industrial robots, special purpose machines, numerically controlled machines, automatic machine tools, automatic welding machines, weaving and knitting machines, special purpose textile machines, automatic conveyors, and regulating and control instruments. I construct two different definitions of automation. The first definition includes only "industrial robots" (i.e., robot adoption), and the second definition includes all of the variables listed above. For the descriptive analysis presented in section 3, I focus on the first definition.

EAP. To estimate firm-level unobservables such as productivity and labor market power, I need to estimate the firm's production function. Using a revenue-based production function instead of output can potentially lead to identification problems with these unobservables.[3] The EAP (*Enquête Annuelle de Production*) is based on a product-level statistical survey conducted by INSEE, which exhaustively covers manufacturing firms with at least 20 employees or sales of more than 5 million euros, as well as a representative sample of smaller firms. This data allow to observe revenues and quantities separately across 10-digit industries. I follow the same steps as outlined in De Ridder et al. (2022) to construct the data.

3 Facts

In this section, I present three key findings. First, consistent with existing evidence, I show that firms that tend to adopt automation capital are large. Specifically, I analyze the pre-adoption differences between firms that adopt automation and those that don't, focusing on observable characteristics such as sales, capital, and employment.[4] Second, using production function estimation, I document that the adoption of automation leads to an increase in firm productivity.[5] Third, I document a new fact: I find that firms that adopt automation capital reduce the pass-through of productivity to wages and reduce their markdowns, suggesting an increase in their labor market power.

Fact 1: Large firms adopt automation capital

To understand which firms adopt automation capital, I compare firms along observable and unobservable characteristics in the year prior to adoption. In practice, I run the fol-

[3] See the work of Bond et al. (2021) and De Ridder et al. (2022) who point out the potential identification problem in the case of estimating markups with revenue production function.

[4] Humlum (2022) shows that robot adopters are larger in terms of sales, payroll, and employment in Denmark. Acemoglu et al. (2020) shows that 1% of French manufacturing firms adopt robots in 2010-2015, while account for 20% of total employment. Kariel (2021) shows that automating firms in Italy are larger, more productive, and pay higher wages.

[5] Note that Stiebale et al. (2020) uses production function estimation to show that, for 6 European countries, firms that adopted robots increased their productivity, markups, and profits between 2004 and 2013. To complement this finding, I provide new evidence on how these productivity gains are persistent over time.

Table 1: Log difference of firm outcomes in period $t-1$ before adoption

	$\hat{\beta}$	Clustered Standard Errors	R^2	Observations
Log Revenue	1.174***	0.091	0.233	374,203
Log Capital	1.327***	0.116	0.311	369,348
Log Total Employment	0.931***	0.079	0.079	374,214
Log Labor Cost	1.056***	0.085	0.102	374,214
Log Material	1.232***	0.094	0.388	374,189
Log Average Hourly Wage	0.125***	0.015	0.309	374,213
Occupational Employment				
- Abstract	1.345***	0.088	0.282	374,214
- Routine	0.857***	0.083	0.361	374,214
- Manual	0.628***	0.091	0.405	374,214
Occupational Hourly Wages				
- Abstract	0.045***	0.016	0.107	374,209
- Routine	0.081***	0.014	0.209	374,214
- Manual	0.108***	0.019	0.092	374,213

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. I cluster the standard errors by industry $\times$ year. For those firms that adopt automation capital, I only retain them until the first year they adopt automation capital to avoid double counting their effects on the variable of interest. Firm productivity and markdowns are estimated using production function estimation, the details of which are presented in the Appendix B. I use the two-digit occupational codes to classify occupations into Abstract, Routine and Manual occupations based on the classfication adopted by Albertini et al. (2017). Details are provided in Appendix C.1.

lowing regression on the data:

$$\log(Y_{ibt-1}) = c + \beta \times R_{ibt} + \lambda_{bt} + \epsilon_{ibt}$$

where Y_{ibt-1} denotes the dependent variable of interest in the year prior to robot adoption for firm i, industry b, and time period $t-1$, R_{ibt} is a dummy variable that takes the value 1 if a firm adopts automation capital in period t, and λ_{bt} denotes industry $\times$ year fixed effects. The result of this regression is reported in Table 1.

Consistent with existing evidence, I find that the estimated coefficient is positive and

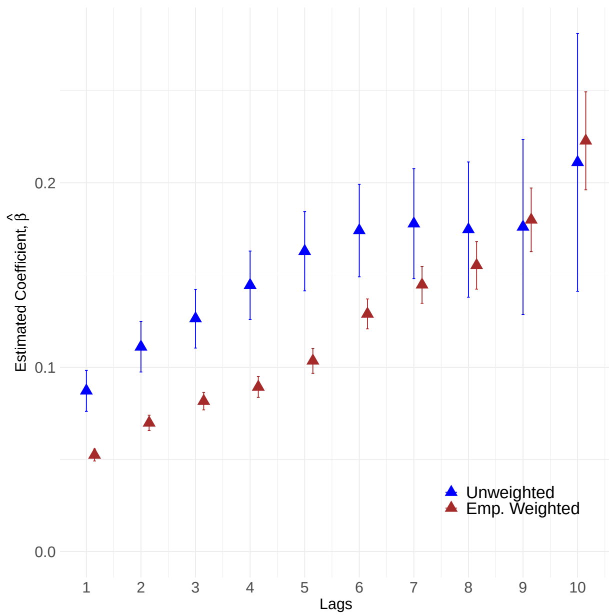
Table 2: Effect of automation adoption on change in future productivity

	(1)	(2)	(3)	(4)	(5)
z_{ibt}	0.961***	0.922***	0.926***	0.341***	0.317***
	(0.006)	(0.009)	(0.008)	(0.024)	(0.040)
R_{ibt}	0.053***	0.053***	0.048***	0.063**	0.069*
	(0.009)	(0.011)	(0.011)	(0.027)	(0.036)
Year FE	✓	×	×	✓	×
Industry FE	×	✓	×	×	×
Industry × Year FE	×	×	✓	×	✓
Firm FE	×	×	×	✓	✓
Observations	763,930	763,930	763,930	763,930	763,930
R^2	0.932	0.931	0.940	0.965	0.969
Adjusted R^2	0.932	0.931	0.939	0.958	0.963

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster standard errors are reported in the parenthesis. I cluster the standard errors by firm. The dependent variable is the estimated Hicks-neutral technology in period $t + 1$. The estimates presented in the table are generated after weighing each firm by its total employment. Note that the difference in the number of observations between Tables 1 and 2 is due to the fact that Table 1 is constructed after merging DADS with FARE, while Table 2 is constructed using FARE only (as no occupational level employment or wages are required).

significantly different from zero. This suggests that firms that adopt automation capital tend to have higher sales, capital, total employment, labor costs, intermediate inputs (materials), average hourly wages, average occupational hourly wages, and occupational employment in the pre-adoption period compared to non-adopters.

Figure 1: Effect of robot adoption on change in firm productivity



Notes: I regress the change in estimated firm productivity between period t and $t-k$, for $k \in \{1, 2, \ldots, 10\}$, on firm productivity in period $t-k$, a dummy indicating automation adoption in $t-k$, and industry $\times$ year fixed effects. The estimated coefficients on the automation adoption dummy are plotted in the graphs, separately for the weighted (red) and unweighted (blue) regressions. The vertical bars indicate the confidence intervals.

Fact 2: Automation increases firm's future productivity

To examine the impact of automation adoption on firm productivity, I estimate the following regression

$$z_{ibt+1} = c + \alpha \times z_{ibt} + \beta \times R_{ibt} + \mathcal{Z}_i + \lambda_{bt} + \epsilon_{ibt} \tag{1}$$

where z_{ibt} denotes the estimated Hicks-neutral productivity at time t.[6] Equation 1 allows me to examine the effect of automation adoption on future firm productivity. In particular, if $\hat{\beta}$ is positive, it implies that adoption has a positive impact on future productivity. The results of this exercise is presented in Table 2.

I estimate β using two different sources of variation. In columns (1)-(3), I estimate the coefficient of interest using *between* variation. Specifically, I compare the future produc-

[6] I use production function estimation to estimate firm-specific Hicks-neutral productivity and $\mathcal{Z}_i$ denotes firm fixed effects. See Appendix B for more details.

tivity of adopters and non-adopters after controlling for their initial productivity, year, industry, and industry $\times$ year fixed effects. The results show that the future productivity of adopters is about 5% higher than that of non-adopters. Since this difference could be driven by unobserved permanent differences across firms, I rely on within-firm variation to estimate β by controlling for firm fixed effects. In this exercise, β is only identified by the change in a firm's adoption status (i.e., R_{jt} going from 0 to 1). The results are shown in columns (4) and (5). In the preferred specification, i.e., column 5, where I control for firm fixed effects along with industry-specific time trends, I find that automation adoption increases firm productivity by about 7% and that the estimated coefficient is significant at 10%.

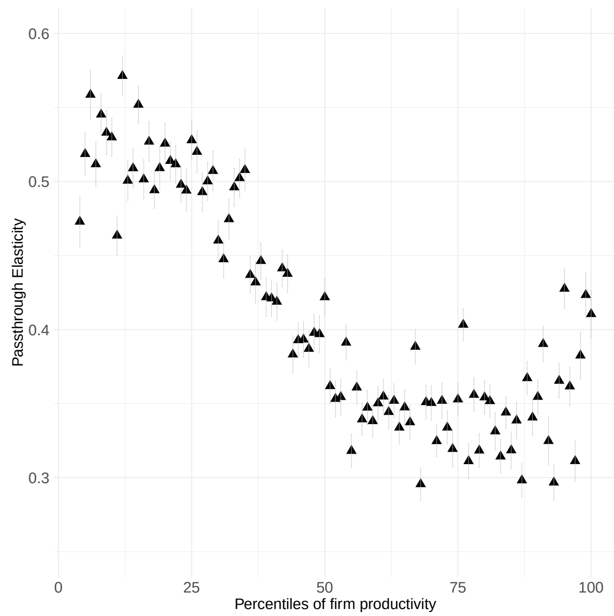
To get a sense of how persistent the productivity advantage of automation adoption is, I regress the change in estimated firm productivity between period t and $t-k$, for $k \in \{1, 2, \ldots, 10\}$, on firm productivity in period $t-k$, a dummy indicating automation adoption in $t-k$, and industry $\times$ year fixed effects. The results of this exercise are shown in figure 1. I find that firms that adopt automation capital not only improve their productivity more than non-adopters, but that this productivity gain they experience persists over time. Moreover, the results are robust to weighting the regression by total employment. This implies that automation adoption provides firms with a substantial and growing productivity advantage that persists over the long run. Next, I examine whether this productivity advantage leads firms to exercise more market power in the labor market.

Fact 3: Automation increases labor market power of firms

To examine the impact of automation on firms' labor market power, I first assess the passthrough of productivity gains to wages. This analysis helps distinguish between competitive and imperfectly competitive market structures, which in turn informs the quantitative analysis in the next section. Specifically, I run the following regression:

$$\Delta \overline{w}_{ibt} = c + \gamma \times \Delta z_{ibt} + \lambda_{bt} + \epsilon_{ibt}$$

Figure 2: Estimated Productivity-Wage Passthrough



Notes: In all of the regressions, I control for industry $\times$ year fixed effects and firm's productivity in period $t-k$. Vertical bars indicate confidence intervals.

where, $\Delta\overline{w}_{ibt} = \overline{w}_{ibt} - \overline{w}_{ibt-1}$ is the change in the average log hourly wage in firm i and $\Delta z_{ibt} = z_{ibt} - z_{ibt-1}$ denotes the estimated change log productivity.[7] As before, I control for industry $\times$ year fixed effects. To understand how passthrough heterogeneity differs by firm size, I run the regression by firm percentile, where firms are assigned a percentile based on their average productivity. The estimate coefficients, $\hat{\gamma}$, are shown in Figure 2.

Next, I examine the effect of automation adoption on the change in passthrough. Specifically, I run the following regression:

$$\Delta\overline{w}_{ibt} = c + \gamma \times \Delta z_{ibt} + \alpha \times R_{ibt} + \beta \times (\Delta z_{ibt} \times R_{ibt}) + \lambda_{bt} + \epsilon_{ibt}$$

The results of this exercise are shown in Table 3. The key variable of interest is the coefficient β, which indicates whether firms reduce the passthrough to wages after adopting automation capital. A reduction in the passthrough is potentially indicative of an increase in firms' market power. As before, I rely on within and between sources of variation to

[7] I use production function estimation to estimate firm-specific Hicks-neutral productivity. See the Appendix B for more details.

Table 3: Effect of robot adoption on change in passthrough

	(1)	(2)	(4)	(5)	(6)
Δz_{ibt}	0.316***	0.315***	0.312***	0.278***	0.281***
	(0.038)	(0.040)	(0.038)	(0.039)	(0.040)
R_{ibt}	0.002	0.003	0.002	0.003	-0.007
	(0.003)	(0.002)	(0.004)	(0.011)	(0.017)
$\Delta z_{ibt} \times R_{ibt}$	-0.118***	-0.122***	-0.090***	-0.078*	-0.055
	(0.043)	(0.041)	(0.035)	(0.044)	(0.038)
Year FE	✓	×	×	✓	×
Industry FE	×	✓	×	×	×
Industry × Year FE	×	×	✓	×	✓
Firm FE	×	×	×	✓	✓
Observations	763,471	763,471	763,471	763,471	763,471
R^2	0.302	0.297	0.408	0.435	0.530
Adjusted R^2	0.301	0.297	0.406	0.318	0.430

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster standard errors are reported in the parenthesis. I cluster the standard errors by industry $\times$ year. The dependent variable is the change in average log wages between t and $t-1$. The estimates presented in the table are generated after weighing each firm by its total employment.

identify the parameter of interest. The results relying on between variation show that firms adopting robots reduce passthrough by 9 percentage points (pp). Using within-firm variation to identify β shows that passthrough is reduced by between 5 and 7 pp, but the preferred specification, which controls for both firm and industry $\times$ year fixed effects, is no longer significant. In unreported results, I also present direct evidence of the adoption of automation on future markdowns. I find that automation adoption reduces future markdowns, and the result is robust to within and between variation in the data.

In sum, the evidence suggests that large firms adopt automation capital, which in turn improves their productivity and market power. In what follows, I construct a general equilibrium consistent with the facts documented in the data to quantify the efficiency costs of automation adoption.

4 Model

The three key elements of the model are that *i)* the adoption of automation responds endogenously to declining prices of automation capital, *ii)* firms that adopt automation also improve their productivity, and *iii)* firms compete in oligopsonistic labor markets. The implications of these features are that declining prices of automation affect the distribution of firms' labor market power, inducing misallocation that reduce aggregate output and welfare relative to the socially efficient outcome. The extension with an endogenous participation decision and entry is described in section 4.4.

Environment. I consider a static economy with four types of agents: L workers, I entrepreneurs, each of whom owns an establishment, a final good producer, and a representative firm supplying automation capital. Workers optimally choose one of three occupations - abstract (a), routine (r), or manual (m) - and their establishment. There are two types of entrepreneurs: those who adopt automation capital and those who do not. This extensive margin is assumed to be exogenous in the baseline model. Both adopters and non-adopters hire workers to produce output. Entrepreneurs consume profits, while workers consume wages as income. I assume that output markets are perfectly competitive and that occupational labor markets are *oligopsonistic*. Specifically, I assume that there are many local labor markets, but only a finite number of firms competing within a market. Occupation-specific markdowns are both endogenously determined in equilibrium and vary across firms. A final good producer aggregates the varieties produced by firms, and a representative firm supplies automation capital at zero profit. In the following, I give an overview of the notation and then describe the problems and solutions for agents in this economy.

Notation. I index establishments by i, workers by n, occupations by o, location by r and industry by b. The economy consists of a set of establishment $\mathcal{I} = \{1, \ldots, I\}$, workers

$\mathcal{N} = \{1, \ldots, L\}$, occupations $\mathcal{O} = \{a, r, m\}$, locations $\mathcal{R} = \{1, \ldots, R\}$, and industries $\mathcal{B} = \{1, \ldots, B\}$. Each establishment i hires workers from all three occupations but is located in a specific location r and belongs to an industry b.[8] I define a local labor market, indexed by j, as a occupation $\times$ location $\times$ industry group cell.[9] I denote the set of local labor market by $\mathcal{J} = \{1, \ldots, J\}$ and the number of establishments within a market by I_j. Finally, I denote the set of local labor markets conditional on occupation o as $\mathcal{J}_o = \{1, \ldots, J_o\}$.[10] In what follows, I use entrepreneurs, firms, plants and establishments interchangeably.[11]

4.1 Workers

The exposition of the worker's problem follows closely the work by Azkarate-Askasua and Zerecero (2020). A worker in the model optimally chooses an occupation and an establishment to work at. Specifically, a worker n chooses the occupation-establishment pair (o, i) that maximizes their utility:

$$u_{nio} = c_n z_{nio} v_{nj}, \tag{2}$$

where c_n denotes consumption of the final good. The term z_{nio} represents an idiosyncratic utility shock specific to worker n's match with establishment i and occupation o. The term v_j captures an idiosyncratic shock specific to the local labor market j where establishment i is located.[12] Following Eaton and Kortum (2002), I assume both idiosyncratic utility shocks are drawn from Fréchet distributions:

1. The occupation-establishment specific shock z_{nio} has the cumulative distribution

[8] In the quantitative exercise, I use commuting zone as location and 4-digit industry classification to define an industry.

[9] Recent work by Nimczik (2020) and Jarosch et al. (2019) defines local labor markets using worker flows and stochastic block models. As a robustness check in future iterations, I will evaluate the sensitivity of the key results to data-driven labor market definitions.

[10] Given a local labor market is defined as an interaction of occupation $\times$ location $\times$ industry, variation in local labor markets within occupation o is either due to change in location or industry or both.

[11] In the empirical counterpart, I define a producer as a firm as I do not have any balance-sheet information at the level of the establishment.

[12] In this model, I only consider the worker's discrete occupational and establishment choice at the extensive margin, not hours supplied at the intensive margin. Implicitly, I assume workers are equally productive and supply labor hours inelastically.

function (cdf) $P(z) = e^{-T_{io}z^{-\epsilon_o}}$ where $T_{io} > 0$ and $\epsilon_o > 1$. T_{io} denotes the average utility derived from the (o, i) pair.

2. The local labor market specific shock v_j has a cdf $P(v) = e^{-v^{-\eta}}$, with $\eta > 1$. The mean of v_j is assumed to be 1 for all labor markets j.

The parameters ϵ_o and η pin down the dispersion of the idiosyncratic shocks, as they are inversely related to the variance of the taste shocks. Intuitively, these parameters govern worker mobility - higher values imply it is easier for workers to switch jobs within and across markets. Consequently, labor supply curve of the worker is more elastic for high values of ϵ_o and η.[13] The parameter ϵ_o is allowed to differ across occupations which implies that workers' ability to switch jobs within a market depends on their occupation. As will be explained later, this gives rise to differences in markdowns across occupations, partially due to differing within market mobility costs. Finally, I assume that $\epsilon_o < \eta < \infty$, which implies that jobs within a market are more substitutable than across markets, for all three occupations.

Optimal labor supply decision. Since wages are the only source of earnings, the indirect utility to worker n from the (o, i) pair is:

$$u_{nio} = w_{io} z_{nio} v_{nj}. \tag{3}$$

The following proposition states the solution to the worker's problem:

Proposition 1. *The probability that worker n selects occupation-establishment pair (o, i) is:*

$$\chi_{io} = \frac{T_{io} w_{io}^{\epsilon_o}}{\Phi_j} \times \frac{\Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}}{\Phi}, \tag{4}$$

[13] Alternatively, following Berger et al. (2022), one could also interpret ϵ_o and η as mobility costs to switch jobs - higher values correspond to lower costs for workers to switch jobs.

where

$$\Phi_j = \sum_{i' \in j} T_{i'o} w_{i'o}^{\epsilon_o}, \quad \Phi = \sum_o \sum_{j \in \mathcal{J}_o} \Phi_{oj}^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}, \quad \Gamma_o = \Gamma\left(\frac{\epsilon_o - 1}{\epsilon_o}\right),$$

and $\Gamma(\cdot)$ *denotes the Gamma function.*

Proof. See Appendix A.1.

Intuitively, the worker makes their optimal choice in two steps. First, they choose the local labor market j based on their draw of the market-specific utility shock v_{nj}. Second, given the chosen market j, they optimally select an establishment i within that market based on the occupation-establishment specific utility z_{nio}. In Proposition 1, the term $\frac{\Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}}{\Phi}$ represents the probability of choosing market j. The term $\frac{T_{io} w_{io}^{\epsilon_o}}{\Phi_j}$ represents the probability of then choosing establishment i within the chosen market j. Given this result, we can characterize the upward-sloping, inverse labor supply function faced by each establishment:

$$l_{io}(w_{io}) = \chi_{io}(w_{io}) \times L. \tag{5}$$

4.2 Producers

There are three types of producers in an economy: First, there are I entrepreneurs in the economy, each of whom produces goods y_i that are perfectly substitutable using either occupational labor or a combination of labor and automation capital.[14] Second, a final good producer who linearly aggregates y_i supplied by entrepreneurs to produce the consumption good Y, and finally automation capital producers who use the final good Y to produce and supply automation capital to entrepreneurs. I will first outline the problem and optimal solutions for the final good and automation capital producers, respectively, followed by that of the entrepreneurs.

[14] I do not include endogenous entry in this framework. For recent work that includes entry with strategic competition, see Edmond et al. (2023) and De Loecker et al. (2018). Recent work by Bao and Eeckhout (2023) has made further progress on this front by incorporating strategic innovation into an entry game to deter competition. In addition, I do not model the endogenous decision of agents to become either workers or entrepreneurs. Recent work by Deb (2023) considers such an endogenous decision with strategic interaction.

Final good producer. The producer of the final good produces the consumption good Y using linear technology and taking the price as given. The final good producer's profit maximization problem is as follows:

$$\Pi = P_Y Y - p\left(\sum_{i=1}^{I_0} y_i^0 + \sum_{i=I_0+1}^{I} y_i^1\right), \quad Y = \left(\sum_{i=1}^{I_0} y_i^0 + \sum_{i=I_0+1}^{I} y_i^1\right) \tag{6}$$

where y_i^1 (y_i^0) denotes the output produced by entrepreneur i who adopts (does not adopt) automation capital and $I - I_0$ denotes the total number of entrepreneurs who adopt automation capital. I normalize the price of the consumption good to be equal to 1. Profit maximization implies that $p = P_Y = 1$.

Automation capital producers. I follow Guerreiro et al. (2022) and assume that automation capital is produced by a representative firm that takes prices as given. It costs ϕ_K units of final good Y to produce one unit of automation capital. One unit of automation capital is sold at price p_X. The representative firm chooses X to maximize profits: $\Pi_X = p_X X - \phi_X X$. It follows that in equilibrium $p_X = \phi_X$ and profits are zero.

Entrepreneurs. Entrepreneurs have CES preferences defined over their consumption c_i:

$$u_i = f(c_i). \tag{7}$$

Their consumption equals their profits from production, which I discuss below. The entrepreneurs are endowed with a technology and are heterogeneous *ex-ante* in terms of their productivity, $\tilde{z}_i$. Entrepreneur i using automation capital has the following nested constant elasticity of substitution (CES) production function:

$$y_i^1 = \underbrace{f(\tilde{z}_i, x_i)}_{= z_i} \times \left[\phi^{\frac{1}{\gamma}} \hat{l}_{iR}^{\frac{\gamma-1}{\gamma}} + (1-\phi)^{\frac{1}{\gamma}} \hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}} \tag{8}$$

$$\hat{l}_{iR} = \left[\phi_R^{\frac{1}{\gamma_R}} l_{iR}^{\frac{\gamma_R-1}{\gamma_R}} + (1-\phi_R)^{\frac{1}{\gamma_R}} x_i^{\frac{\gamma_R-1}{\gamma_R}}\right]^{\frac{\gamma_R}{\gamma_R-1}} \qquad \hat{l}_{iN} = \left[\phi_N^{\frac{1}{\gamma_N}} l_{iA}^{\frac{\gamma_N-1}{\gamma_N}} + (1-\phi_N)^{\frac{1}{\gamma_N}} l_{iM}^{\frac{\gamma_N-1}{\gamma_N}}\right]^{\frac{\gamma_N}{\gamma_N-1}}$$

where x_i denotes the level of automation capital optimally adopted by entrepreneur i; $\hat{l}_{iR}$ denotes the CES aggregate of routine occupation labor and automation capital, where γ_R is the elasticity of substitution between the two inputs; $\hat{l}_{iN}$ denotes the CES aggregate of non-routine abstract and manual occupation labor, where γ_N is the elasticity of substitution between the two occupations; and γ denotes the elasticity of substitution between routine and non-routine CES composites.

The specification of the production function implies that the adoption of automation has implications for the occupational composition of firms and for firm productivity. First, assuming $\gamma_R > 1$, which implies that routine labor and automation capital are gross substitutes, a decline in the price of automation capital will induce firms to substitute away from routine labor toward more automation capital. Second, the adoption of automation has *scale effects* because it endogenously affects productivity at the firm level. While firms differ *ex-ante* in their productivity draws $\tilde{z}_i$, their realized productivity *ex-post* depends on the level of automation capital adopted. [15] Thus, the production function allows automation capital to both substitute for routine occupations and increase firm productivity.

The technology of entrepreneurs that do not adopt automation capital is specified as follows:

$$y_i^0 = \tilde{z}_i \times \left[\phi^{\frac{1}{\gamma}} l_{iR}^{\frac{\gamma-1}{\gamma}} + (1-\phi)^{\frac{1}{\gamma}} \hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}}. \tag{9}$$

Market Structure. Before outlining the entrepreneur's solution, I discuss the product and labor market competition she faces. Entrepreneurs are price-takers in the product market

[15] Recent empirical evidence supports this specification. Using Spanish manufacturing data, Koch et al. (2021) find that robot adoption has a statistically significant positive effect on firms' Hicks-neutral total factor productivity.

and compete oligopsonistically in the labor market, which implies wage-setting power. Consequently, they face a perfectly elastic demand curve and an upward sloping labor supply curve (equation 5). This has three implications. First, trivially, it means that an entrepreneur is potentially non-atomistic in the labor market. Second, entrepreneurs will act strategically within their own local labor market. Finally, as will be shown below, occupation-specific markdowns will be endogenous and vary with firm size.

Profit Maximization. Entrepreneurs maximize profits by optimally choosing wages and, depending on whether they use automation capital, choosing the optimal level of automation.

$$\pi_i^1 = \max_{w_{iA},\, w_{iR},\, w_{iM},\, x_i} \; y_i^1 \; - \sum_{o \,\in\, \mathcal{O}} w_{io} l_{io}(w_{io}, w_{-io}, \Phi_j, \Phi) \; - \; p_x x_i, \tag{10}$$

$$\pi_i^0 = \max_{w_{iA},\, w_{iR},\, w_{iM}} \; y_i^0 \; - \sum_{o \,\in\, \mathcal{O}} w_{io} l_{io}(w_{io}, w_{-io}, \Phi_j, \Phi). \tag{11}$$

Within each occupational labor market, entrepreneurs compete á la Cournot with each other, which implies that their optimal choice of wages will also depend on their competitors posted wages within the market, as well as on the market and aggregate indexes, Φ_j and Φ, respectively.

Optimal occupational demand: Cournot Competition. Regardless of whether they use automation capital or not, all entrepreneurs choose the optimal level of labor to maximize profits. The first-order condition for profit maximization with respect to wages gives the following occupational labor demand equation:

$$w_{io} = \underbrace{\left(\frac{e_{io}}{e_{io}+1}\right)}_{\text{Markdowns}} \times \underbrace{\frac{\partial y_i^k}{\partial l_{io}}}_{\text{Marginal Product of Labor}}, \quad o \in \mathcal{O}, \;\; k \in \{0,1\}. \tag{12}$$

Equation (12) states that wages w_{io} equal the marginal product of labor multiplied by a wedge resulting from the labor market power of entrepreneurs, which I call the markdown. The markdowns in the model are firm- and occupation-specific, resulting from market power in the occupation labor market, where e_{io} is the elasticity of labor supply. In this model, the markdowns have the following analytical solution:

$$\frac{e_{io}}{e_{io}+1} \equiv \delta_{io} = \frac{\epsilon_o(1-s_{io|j}) + \eta s_{io|j}}{\epsilon_o(1-s_{io|j}) + \eta s_{io|j} + 1}, \quad s_{io|j} = \frac{T_{io} w_{io}^{\epsilon_o}}{\Phi_j}. \tag{13}$$

Equation (13) reveals that markdowns are influenced by: (1) the mobility costs parameters ϵ_o and η, which govern workers' mobility within and across markets respectively, and (2) the employment share $s_{io|j}$ of the establishment-occupation pair in its local market j.

High mobility costs, represented by low values of ϵ_o and η, result in a larger markdown. When the employment share $s_{io|j}$ is high, the establishment behaves more like a monopsonist in its local market, pushing the markdown towards its upper limit of $\frac{\eta}{\eta+1}$. Conversely, a lower employment share suggests more intra-market competition for labor, with the markdown nearing the lower bound of $\frac{\epsilon_o}{\epsilon_o+1}$. In essence, greater monopsony power arises from a combination of high employment share and low job mobility, enabling entrepreneurs to charge a higher markdown.

Optimal automation choice. Entrepreneurs adopting automation capital choose the optimal quantity by equating the marginal cost of an additional unit of automation (i.e., its price, p_X) with its marginal benefit, i.e., the marginal productivity of an additional unit of automation capital.

$$p_x = \underbrace{\left[\phi^{\frac{1}{\gamma}} \hat{l}_{iR}^{\frac{\gamma-1}{\gamma}} + \tilde{\phi}^{\frac{1}{\gamma}} \hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}} \frac{\partial z_i}{\partial x_i}}_{\text{Endogenous Productivity Effect}} + \underbrace{z_i \frac{\partial}{\partial x_i} \left[\phi^{\frac{1}{\gamma}} \hat{l}_{iR}^{\frac{\gamma-1}{\gamma}} + \tilde{\phi}^{\frac{1}{\gamma}} \hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}}}_{\text{Within-firm Substitution Effect}}. \tag{14}$$

Given the adopter's production technology, an additional unit of automation has two effects: the substitution of automation capital for routine labor and an improvement in the firm's technical efficiency (which is the first term on the right-hand side of the above equation).

4.3 Equilibrium

In this section, I aggregate the individual decisions of entrepreneurs and workers and provide the definition of the equilibrium. I also outline a computational algorithm for solving the equilibrium numerically.

Aggregation. Recall that X is the total supply of automation capital in the economy. In equilibrium, X equals the total demand for automation capital, which is the sum of the optimal adoption decisions of all entrepreneurs i:

$$X = \sum_{i=I_0+1}^{I} x_i \tag{15}$$

Aggregate output Y is either consumed by workers and entrepreneurs or used to produce automation capital X. Consumption comes from the profits of entrepreneurs and the wages paid to workers. The production of automation capital requires the fixed cost f_X per robot plus the constant marginal cost ϕ. Therefore, total output must satisfy the following aggregate resource constraint:

$$Y = \sum_{i=1}^{I_0} \pi_i^0 + \sum_{i=I_0+1}^{I} \pi_i^1 + \sum_{i\in\mathcal{I}} \sum_{o\in\mathcal{O}} w_{io} l_{io} + (p_x \times X). \tag{16}$$

Equilibrium definition. With the aggregation conditions defined, I now formally define the equilibrium of this economy.

Definition 1. *Given establishment-level productivity $\tilde{z}_i$, worker-level distributions of idiosyncratic utility shock $P(z)$ and $P(v)$, preference parameters $\{\epsilon_a, \epsilon_r, \epsilon_m, \eta\}$, and technology parameters $\{\phi, \phi_R, \phi_N, \gamma, \gamma_R, \gamma_N\}$, amenities $\{T_{ia}, T_{ir}, T_{im}\}_{i=1}^{I}$, total number of entrepreneurs adopting automation $I - I_0$, and cost of producing a unit of automation capital ϕ, an equilibrium of this economy consists of establishment-level wages $\{w_{ia}, w_{ir}, w_{im}\}_{i=1}^{I}$, labor supply $\{l_{ia}, l_{ir}, l_{im}\}_{i=1}^{I}$, output $\{y_i\}_{i=1}^{I}$, automation capital $\{x_i\}_{i=I_o+1}^{I}$, and aggregate price of automation capital p_X, and output Y such that the following conditions are satisfied:*

1. *Workers choose their occupation-establishment pair so as to maximize their utility, in accor-*

dance with equations (2)-(6).

2. *Entrepreneurs determine labor demand by setting wages, and optimize these to maximize their profits. This is subject to the labor supply constraint as defined in equation (5).*

3. *Entrepreneurs that adopt automation make optimal decisions regarding the level of adoption of automation capital, as outlined in equation (14).*

4. *The aggregate demand for automation capital is equal to its aggregate supply as outlined in equation (15).*

Computational details and the algorithm used to solve the equilibrium are provided in Appendix A.2

Model summary. Table 4 summarizes the model variables into three categories. Category I lists the primitives of the model, and categories II and III specify the endogenous objects of the model, at the establishment and aggregate levels, respectively.

Benchmark cases. The model nests two important special cases under certain parametric constraints. The first is *efficient allocation*, which is achieved when establishment-level wedges are one. This occurs when $\epsilon_o = \eta = \infty$. The second is the *atomistic monopsony* bound with constant markdowns. This requires either $I_j \to \infty$ or $\epsilon_o \to \eta$ in the labor market. In contrast to the full model, market power in these bounds determines how income is distributed between workers and entrepreneurs without loss of output due to allocative inefficiency.

4.4 Extensions

Endogenous Labor Force Participation. I endogenize labor force participation following Azkarate-Askasua and Zerecero (2020) by incorporating home production into the framework. Within each occupational labor market, I add a market that contains a single establishment that pays a home production wage w_{uo} and amenities T_{uo}. Following steps

Table 4: Summary of model variables

		I. Primitives	
η	Within-market dispersion parameter	$\gamma, \gamma_R, \gamma_N$	Elasticity of Substitution
ϵ_o	Across-market dispersion parameter	ϕ, ϕ_R, ϕ_N	Weight parameters
ϕ_X	Cost of producing a unit of automation	p_X	Price of automation capital
z_{nio}, ν_j	Idiosyncratic amenities	$\tilde{z}_i$	Firm productivity
$I - I_o$	Total # of automation adopters	I, L	Total number of estab., workers
T_{io}	Occupation-specific amenities	I_j	Number of estab. in a market
		II. Endogenous variables - Establishment	
w_{io}	Wages	l_{io}	Employment
p	Output prices	y_{io}	Output quantities
δ_{io}	Markdowns	e_{io}	Labor supply elasticity
π_i	Profits	x_i	Optimal level of automation
		III. Endogenous variables - Aggregates	
X	Aggregate level of automation	Y	Aggregate output
Π	Aggregate Profits	P_Y	Price of aggregate output, norm. to 1

outlined in Appendix A.1, we can calculate the total number of workers in occupation o who are out of the labor force as:

$$L_{uo} = \frac{T_{uo} w_{uo}^{\epsilon_o} \Gamma_o^{\eta}}{\Phi} L, \tag{17}$$

where

$$\Phi = \Phi_e + \Phi_{np}, \quad \Phi_e = \sum_{j \in \mathcal{J}} \Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}, \quad \Phi_{np} = \sum_{u \in \mathcal{O}} (T_{uo} w_{uo}^{\epsilon_o})^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}. \tag{18}$$

This extends the occupational choice model to include the option of leaving the labor force. Changes in automation costs can then affect not only occupational reallocation but also labor force participation.

Entry. To endogenize entry in the model, I proceed as follows. I assume that there are K potential entrants, where αK are potential adopters of robot technology and $(1 - \alpha)K$

are potential non-adopters of robot technology. As a result, in each local labor market there is an average of $(\alpha K)/J$ potential robot adopters and $((1-\alpha)K)/J$ potential non-adopters. The fixed operating cost incurred by non-robot firms is denoted f, while firms that choose robot technology face an additional operating cost denoted f_R. To determine the equilibrium set of entrants in each market, a refinement of Nash equilibrium, similar to the method of De Loecker et al. (2018) is employed. This approach involves selecting an equilibrium through a specific procedure, which I outline below.

I assume that all firms initially enter the labor market. Once they enter, the model's equilibrium is determined based on the computational algorithm described earlier, which allows for the calculation of the profits of each firm in the economy. Among the firms with negative profits, those with the lowest profits are eliminated first. This process results in a revised set of entrants, and the equilibrium is recalculated based on this updated composition. This algorithm iterates until a point is reached where no firm would make positive profits by entering the market.

4.5 Planner's problem

In this section, I first define measures of average and median welfare per worker in the model economy. I then formulate and solve the social planner's problem. Later, I compare the efficient allocation with the decentralized equilibrium.

Welfare. The following proposition defines the average and median welfare per worker in this framework.

Proposition 2. *The average and median welfare per worker is defined as follows:*

$$\overline{\mathbb{W}} = \mathbb{E}\left[\max_j \left\{\mathbb{E}_j(\max_i w_i z_{io}) v_j\right\}\right] = \Phi^{\frac{1}{\eta}} \Gamma\left(\frac{\eta-1}{\eta}\right), \tag{19}$$

$$\mathbb{W}^{Med} = Median\left[\max_j \left\{\mathbb{E}_j(\max_i w_i z_{io}) v_j\right\}\right] \propto \Phi^{\frac{1}{\eta}}. \tag{20}$$

where $\Phi = \sum_{j\in\mathcal{J}} \Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}$, $\overline{\mathbb{W}}$ *denotes the average welfare per worker,* $\mathbb{W}^{Med}$ *denotes median wel-*

fare and $\Gamma(\cdot)$ *denotes the Gamma function.*

Proof. See Appendix A.1.

Planner's problem. Given the definition of average welfare, I now outline the social planner's problem, which can be stated as follows:

$$\max_{l_{iA},\, l_{iR},\, l_{iM},\, c_i,\, x_i} \quad \underbrace{\Phi^{\frac{1}{\eta}}\Gamma\left(\frac{\eta-1}{\eta}\right)L}_{\text{Total welfare of workers}} \quad + \quad \underbrace{\sum_{i=1}^{I} f(c_i)}_{\text{Total welfare of entrepreneurs}} \tag{21}$$

$$\text{subject to} \quad Y = \sum_{i=1}^{I_0} c_i^0 + \sum_{i=I_0+1}^{I} c_i^1 + \sum_{i\in\mathcal{I}}\sum_{o\in\mathcal{O}} w_{io} l_{io} + (p_x \times X) \tag{22}$$

$$l_{io} = \frac{T_{io} w_{io}^{\epsilon_o}}{\Phi_j} \times \frac{\Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}}{\Phi} \times L \tag{23}$$

The planner chooses employment, consumption for entrepreneurs and the optimal level of automation capital to maximize the total welfare of workers and entrepreneurs in the economy (equation 21) subject to the economy's resource constraint (equation 22), and the inverse labor supply function (equation 23).

The planner's solution to the optimal choice of labor problem implies that she equates the marginal benefit to aggregate output of an additional unit of labor in occupation o with its marginal cost, the wage:

$$w_{io} = \frac{\partial y_i}{\partial l_{io}}. \tag{24}$$

Comparing this to the decentralized economy solution, we see that the establishment-level wedge due labor market power does not appear in equation (24). This is because the planner's decision maximizes total social welfare, including the welfare of both workers and entrepreneurs, while entrepreneurs in the decentralized economy make decisions based on private returns. The planner's optimal labor allocation implies no misallocation due to dispersion in the establishment-specific wedge across firms.

Similarly, in the case of the optimal level of automation capital for plant i, the planner equates marginal cost to marginal benefit.

$$p_x = \left[\phi^{\frac{1}{\gamma}} \hat{l}_{iR}^{\frac{\gamma-1}{\gamma}} + \tilde{\phi}^{\frac{1}{\gamma}} \hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}} \frac{\partial z_i}{\partial x_i} \quad + \quad z_i \frac{\partial}{\partial x_i} \left[\phi^{\frac{1}{\gamma}} \hat{l}_{iR}^{\frac{\gamma-1}{\gamma}} + \tilde{\phi}^{\frac{1}{\gamma}} \hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}} \tag{25}$$

Since firms do not exercise market power in the market for automation capital, the optimal condition chosen by the planner coincides with that of the decentralized economy. As shown below, this does not imply that the decentralized economy chooses the same level of automation capital as the planner. Since labor markets are misallocated and inputs are imperfect substitutes, there will also be a misallocation in the optimal amount of automation capital in the planner's economy. From the planner's point of view, automation increases aggregate output at the margin, but also incurs two social costs that are not internalized by decentralized firms: first, increased misallocation within and across firms due to higher productivity-enhancing markups and markdowns; and second, the reallocation of workers from routine to lower-paying manual occupations, where entrepreneurs exercise higher monopsony power, or non-employment. In the quantitative exercise, we try to quantify each of these channels.

Finally, for optimal entrepreneur consumption, the planner equalizes consumption across all entrepreneurs such that:

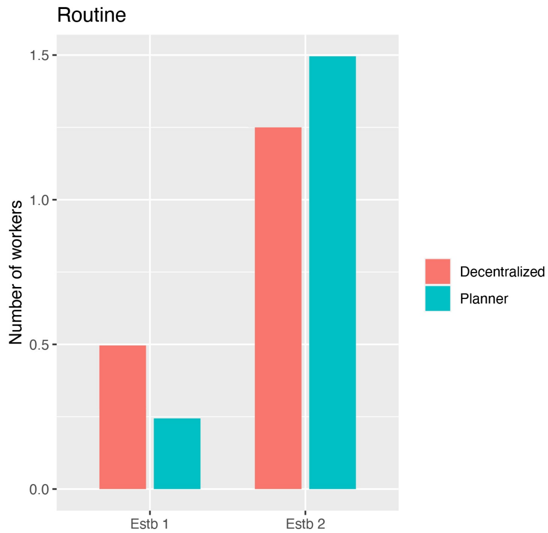
$$u'(c_i) = u'(c_j) \implies c_i = c_j = c \tag{26}$$

which implies that there is no consumption inequality between entrepreneurs in the economy.

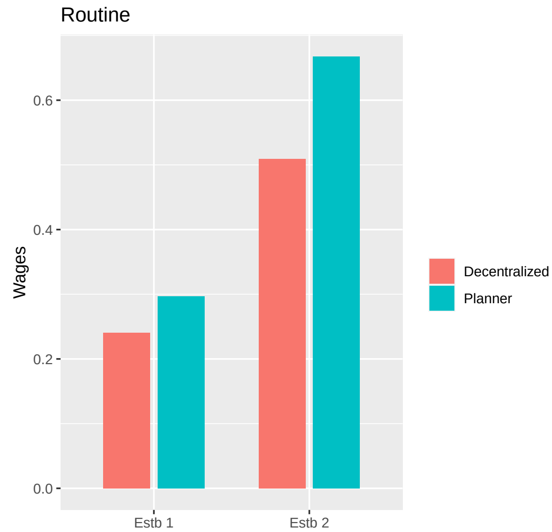
4.6 Characterization

Next, I compare the optimal allocations in the planner's economy with the allocation chosen by the planner. I then consider the implications of the misallocation in the labor market for the optimal choice of automation. Finally, I consider how automation in imperfectly competitive markets endogenously affects market power and misallocation through its effect on firm productivity.

Figure 3: Decentralized vs. Planner's Allocation: Employment and Wages



(a) Employment



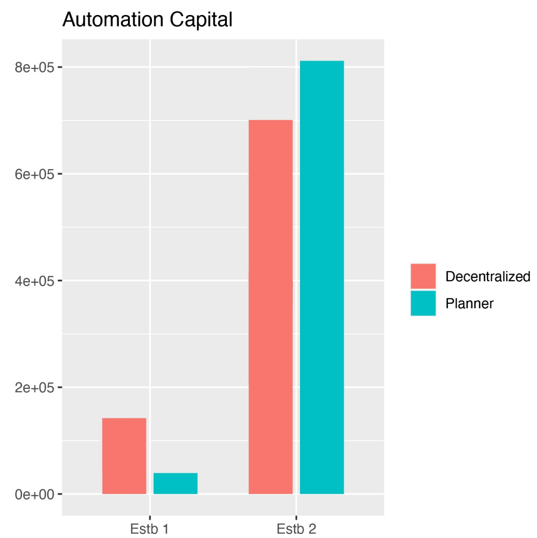
(b) Wages

Misallocation in occupational labor markets. As mentioned earlier, a comparison of the planner's first-order conditions with those of the decentralized economy shows that the establishment-specific markdowns are absent from the planner's condition. These discounts depend on the employment shares of firms within the market, which reflect productivity differences. Firms with higher shares and higher productivity can charge higher markdowns, while less productive firms with lower shares charge lower markdowns.

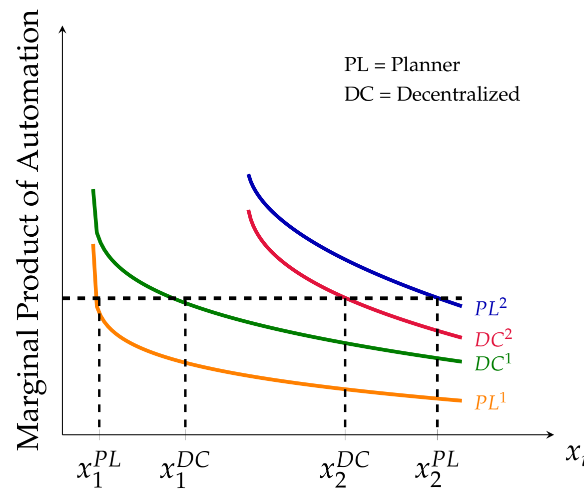
From a planner's perspective, this implies a misallocation of labor in the decentralized economy. High markdown firms are not large enough because they under-hire labor and under-produce. Meanwhile, less productive low-markdown firms overproduce relative to the planner's optimum.

Figures 3a and 3b illustrates this in a simulated duopsony model with many identical markets. Establishment 2 has higher productivity than Establishment 1. The planner allocates more labor to the more productive firm. The planner also pays higher wages in both establishments, with the more productive firm receiving even higher wages. Thus the planner's allocation deviates from the decentralized equilibrium due to establishment-level labor market power. This misallocation reduces both output and welfare in the

Figure 4: Decentralized vs. Planner's Allocation: Automation Capital



(a) Level of Automation Capital



(b) Marginal Product of Automation Capital

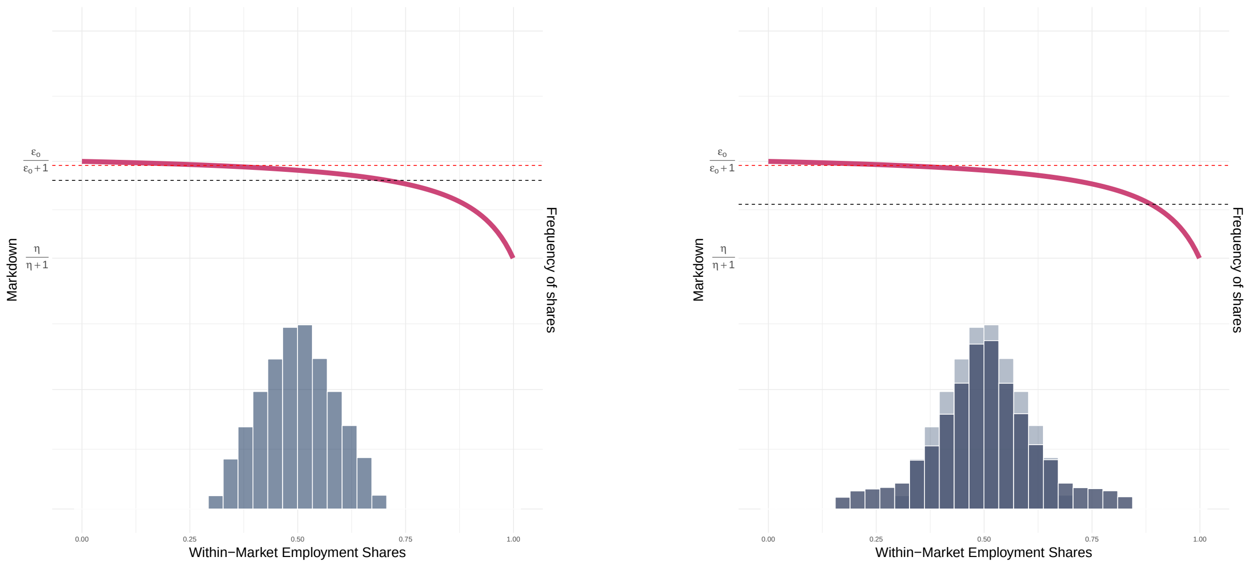
decentralized economy relative to the planner's allocation, both of which are quantified below.

Misallocation in the automation capital market. Next, let's compare the optimal allocation of automation capital between the planner and the decentralized economy. Even if the planner's first-order condition coincides with the decentralized economy, automation capital will be misallocated across establishments.

This is due to the misallocation of labor due to labor market power and the imperfect substitutability between labor and automation. Since more productive establishments will under-hire labor and less productive establishments will over-hire labor in the decentralized economy, the marginal product of automation capital will be lower than the planner's optimum. The opposite is true for less productive establishments. Therefore, more productive firms will under utilize automation capital, while less productive firms will over utilize it relative to the social optimum. Whether the use of automation in more productive firms is higher or lower than the efficient level depends on the substitutability of automation and labor.

In the current simulation in Figures 4a and 4b, automation and routine labor are as-

Figure 5: Automation's Implication on Misallocation



(a) Misallocation with high p_X

(b) Misallocation with low p_X

sumed to be gross substitutes, while non-routine labor is complementary, consistent with existing evidence. This implies that the introduction of automation reinforces the misallocation of labor. More automation further reduces labor demand in high-productivity firms, while increasing it in low-productivity firms. This lowers output and wages relative to the planner's allocation.

Automation's endogenous effect of misallocation. As emphasized earlier, labor is misallocated in the decentralized economy. The magnitude of this misallocation depends on the variance of the within-market employment share, which, together with the labor mobility parameters ϵ_o and η, constrains the variance of the distribution of markdown. By adopting robots, firms are able to endogenously improve their technical efficiency, which increases the variance of the ex-post productivity distribution, i.e. the distribution of z_i, relative to the ex-ante productivity distribution, i.e. the distribution of $\tilde{z}_i$. This widens the distribution of the within-market employment share, which widens the misallocation and lowers output and welfare relative to the socially optimal allocation.

Since empirical evidence suggests that large firms adopt automation capital and benefit from improved productivity from such adoption decisions, in the current framework this translates into a shift in the distribution of market power in the economy. Thus, in general equilibrium, automation provides them with an additional lever to restrict labor demand and under produce relative to the social optimum, highlighting the nuanced implications of automation technologies in imperfectly competitive environments with pre-existing distortions.

This is illustrated in Figures 5a and 5b, where I show the effect of falling automation prices on misallocation. The figure shows the effect of the decline in the price of automation capital on the distribution of the within-market employment share and the dispersion of discounts. We see that as the price declines, firms adopt a larger amount of automation capital, improving their productivity and scale, and increasing the dispersion of discounts.

5 Quantitative Analysis

This section provides details of the quantitative analysis used to examine the impact of robot adoption on output and welfare. First, I describe how I calibrate the baseline version of my model without labor force participation and entry, which I will include in future iterations. Finally, the section concludes with a description of the counterfactual experiments conducted using the calibrated model.

5.1 Calibration

In this iteration of the paper, I choose key parameter values based on those used in the literature to calibrate the model for the year 2019.[16] I calibrate only a limited set of parameters concerning the distribution of $\tilde{z}_i$ using French administrative data. A summary of these parameters is presented in the table 5. In ongoing work, I am structurally estimating these parameters.

The elasticity of substitution between routine and non-routine occupations, γ_R, is chosen from the recent work of Humlum (2022), who structurally estimates a production

[16] In this iteration, I consider the baseline model without endogenous labor force participation and entry.

function on the Danish data. The estimate of the elasticity of substitution between routine occupations and automation capital is chosen from Vom Lehn (2020), who calibrates this value from US data. Since the value is greater than 1, it implies that robots are gross substitutes for routine workers. I assume that $z_i = (\tilde{z}_i^{\frac{\gamma_z - 1}{\gamma_z}} + x_i^{\frac{\gamma_z - 1}{\gamma_z}})^{\frac{\gamma_z}{\gamma_z - 1}}$ where γ_z moderates the endogenous effect of automation capital on productivity z_i. I set $\gamma_z = 3.5$ in the baseline calibration.

The parameters ϵ_o, which determine the within-market mobility of workers, and the are based on the recent work of Azkarate-Askasua and Zerecero (2020), who estimate the labor supply equation using administrative data for the French manufacturing sector. For the case of η, I choose a value close to that estimated by Azkarate-Askasua and Zerecero (2020), but restrict it to be greater than 1, since this allows me to compute average welfare in my model.[17]

The share of the number of robot adopters in the French economy is chosen from the recent work by Acemoglu et al. (2020) who show that only 1% of the French manufacturing firms purchased robots between 2010 and 2015.

Finally, I calibrate the value of the cost of producing automation capital using publicly available information on Statista that provides information on the average cost of industrial automation.

5.2 Counterfactual experiments

I conduct two counterfactual experiments to quantify the welfare and output consequences of automation. First, in the *extensive margin* experiment, I compare the decentralized and planner economies with and without any automation adoption. This is done by setting the share of adopting firms to zero in both economies. Second, in the *intensive margin* experiment, I examine the effect of a 10% decline in the price of automation capital. The two experiments allow for an analysis of how automation affects output and welfare through extensive margin adoption differences and intensive margin price-driven adoption incentives. Comparing the decentralized and planned outcomes isolates the contribution

[17]The expected welfare is undefined for values of $\eta < 1$.

Table 5: Model Calibration

Parameter	Description	Value	Source
γ	EoS (R vs. NR composite)	0.49	Humlum (2022)
γ_R	EoS (R vs. Robots)	1.38	Vom Lehn (2020)
ϕ_R	Weight Parameter	0.49	Vom Lehn (2020)
ϕ_N	Weight Parameter	0.51	Humlum (2022)
ϵ_o	Within-market substitutability	4.05	AZ (2020)
$\frac{I-I_o}{I}$	Fraction of robot adopters	1%	Acemoglu et al. (2020)
p_X	Unit cost of automation	€27000	Statista
γ_Z	Effect of robots on productivity	3.5	Externally set
γ_N	EoS (A vs. M)	0.81	Externally set
η	Across-market substitutability	1.1	Externally set
T_{io}	Firm-occupation specific amenities	1.0	Externally set
$\mu_{\tilde{z}}$	Mean of $\ln(\tilde{z})$	4.15	Internally Calibrated
$\sigma^s_{\tilde{z}}$	Variance of $\ln(\tilde{z})$	0.68	Internally Calibrated
ϕ	Weight Parameter	0.55	Internally Calibrated

Notes: EoS stands for elasticity of substitution, R stands for routine occupations, NR stand for non-routine occupations, A stands for abstract occupation and M stands for manual occupations. AZ is shorthand for Azkarate-Askasua and Zerecero (2020).

Table 6: Effect of Automation on Output and Average Welfare

		Output (% Δ)	Average Welfare (% Δ)			
			All	*Abstract*	*Routine*	*Manual*
Extensive Margin	Decentralised	16.17	2.82	6.33	1.66	6.20
	Planner	18.86	4.62	8.64	3.10	8.76
Intensive Margin	Decentralised	0.85	0.29	0.20	0.12	0.40
	Planner	0.91	0.20	0.41	0.16	0.42

Table 7: Effect of Automation on Output Gap

		Homogenous Labor (a)	No Automation (b)	Extensive Margin (c)	Intensive Margin (d)	$c-b$ (e)	$d-c$ (f)
$\left(\frac{Y^{DC}-Y^{P}}{Y^{P}}\right)\times 100$		No	-1.9	-4.1	-4.2	-2.2	-0.1
		Yes	-0.9	-1.8	-1.9	-0.9	0.0
Contribution Within Misallocation			-51.9%	-55.5%	-55.6%	-	-

Notes: Y^{DC} denotes aggregate output in the decentralized economy while Y^{P} denotes aggregate output in the planner's economy.

of misallocation.

6 Results

In this section, I will examine the effects of automation on both output and welfare. I will define and analyze output and welfare gaps and discuss how automation affects these gaps. I will also address the question of how much of the loss in output and welfare can be attributed to automation-induced market power.

Implications on Output. The first result concerns the effect of automation on aggregate output. To examine this, I compare the output of a decentralized economy with and without automation. As shown in Table 6, automation leads to a 16.2% increase in output in the decentralized economy compared to an economy without automation. It's worth noting, however, that this increase is less than what I observe in the planner's economy, where automation would have increased output by 18.9%. Even at the intensive margin, automation continues to increase output, but the planner's economy maintains a higher level of output.

I then examine the impact of automation on misallocation by evaluating how it affects the output gap. This gap is defined as $(Y^{P}-Y^{DC})/Y^{P}$, which represents the percentage

Table 8: Effect of Automation on Average Welfare Gap

	Homogenous Labor (a)	No Automation (b)	Extensive Margin (c)	Intensive Margin (d)	$c-b$ (e)	$d-c$ (f)
$\left(\frac{\overline{\mathbb{W}}^{DC}-\overline{\mathbb{W}}^{P}}{\overline{\mathbb{W}}^{P}}\right)\times 100$	No	-29.3	-30.5	-30.4	-1.2	0.1
	Yes	-14.0	-14.6	-14.5	-0.6	0.0
% Contribution Within Misallocation		-52.2%	-52.3%	-52.2%	-	-

Notes: $\overline{\mathbb{W}}^{DC}$ denotes average welfare in the decentralized economy while $\overline{\mathbb{W}}^{P}$ denotes average welfare in the planner's economy.

difference in output between the planner's (Y^P) economy and the decentralized economy (Y^{DC}). The results, presented in Table 7, show that in an economy without any automation, the output gap is 1.9 percent. This suggests that the planner's economy produces 1.9 percent more output than the decentralized economy because it corrects for the misallocation due to labor market power in the decentralized economy. Column (e) of Table 7 shows that once automation is introduced in both economies, the output gap increases by 2.2 percentage points. This increase shows that automation exacerbates misallocation by increasing the variance of labor market power across firms.

A parallel pattern emerges when I consider the impact of automation on misallocation at the intensive margin, although the magnitudes are much smaller. The reduction in prices resulting from automation leads to an increase in misallocation of 0.1 percentage points. Taken together, these results provide evidence that automation has a direct impact on firms' (labor) market power.

Shifting focus, I examine the source of the misallocation. Since firms exercise labor market power over different occupations, it becomes clear that labor is misallocated not only across firms, but also within firms. To quantify the contribution of within-firm misallocation, I assume that labor is homogeneous, implying that firms do not exert different degrees of market power over workers. My analysis shows that intra-firm misallocation accounts for a substantial 51.9% of total misallocation.

Implications on Welfare. The effect of automation on average welfare reveals several important insights. First, I find that automation does indeed increase average welfare, but to a lesser extent than in the planner's economy. As shown in Table 6, the introduction of automation in the decentralized economy leads to an average welfare increase of 0.85%, compared to an increase of 0.91% in the planner's economy.

In addition, the welfare gains from automation are not evenly distributed across occupations. In particular, automation disproportionately benefits non-routine abstract and manual occupations, whose average welfare increases by 6.33% and 6.20%, respectively, compared to a more modest 1.66% increase for routine workers. This pattern of effects persists at the intensive margin, reinforcing the notion that automation has different effects on different occupational groups.

Next, I turn to the impact of automation on the welfare gap between the planner's economy and the decentralized economy, which is detailed in Table 8. I define the average welfare gap as $(\overline{\mathbb{W}}^{DC} - \overline{\mathbb{W}}^{P})/\overline{\mathbb{W}}^{P}$, where $\overline{\mathbb{W}}^{DC}$ and $\overline{\mathbb{W}}^{P}$ denote average welfare in the decentralized and the planner's economy, respectively. First, without automation, the welfare gap between these two economies shows that the average welfare in the planner's economy is 30.5% higher than in the decentralized economy. However, this gap increases with the introduction of automation. Specifically, automation increases the welfare gap by 1.2 percentage points at the extensive margin and remaining unchanged at the intensive margin. These results suggest that automation has a limited impact on the average welfare gap between the two economies. Consequently, the observed gains in average welfare appear to be driven primarily by changes at the extremes of the welfare distribution.

Finally, I show that intra-firm misallocation plays a crucial role in contributing to the average welfare gap. When labor is assumed to be homogeneous, its presence significantly reduces the average welfare gap by 52.2%. This underscores the importance of addressing within-firm misallocation to reduce the average welfare gap resulting from automation.

Table 9: Effect of Automation on Output and Welfare Loss

	Homogenous Labor	Extensive Margin	Intensive Margin
$\left(\frac{\Delta Y^P - \Delta Y^{DC}}{\Delta Y^P}\right) \times 100$	No	15.9	10.8
	Yes	8.3	5.3
$\left(\frac{\Delta \overline{\mathbb{W}}_o^P - \Delta \overline{\mathbb{W}}_o^{DC}}{\Delta \overline{\mathbb{W}}_o^P}\right) \times 100$	No	56.8	0.0
	Yes	30.6	0.0

How much output and welfare is lost due to automation-induced market power? To assess the magnitude of output and welfare losses attributable to automation-induced market power, I employ a difference-in-differences statistic. This involves calculating the difference in the change in output between the decentralized and the planner's economy, expressed as a fraction of the change in output in the planner's economy itself.

For clarity, consider an example: If the change in output resulting from automation in the planner's economy amounts to 10 units, whereas the corresponding change in the decentralized economy is 5 units, then the loss in output due to automation-induced market power would be 50%.

The findings, detailed in Table 9, reveal significant losses in both output and welfare stemming from automation, both at the extensive and intensive margins. Specifically, at the extensive margin, output loss stands at approximately 15.9%, while welfare loss reaches 56.8%.

Furthermore, consistent with previous observations, addressing differential market power over occupations leads to noteworthy improvements in mitigating these losses. In a scenario without any within-firm misallocation, output losses decrease to 8.3%, and welfare losses reduce to 30.6%. These results underscore the substantial impact of automation-induced market power on output and welfare, while also emphasizing the potential benefits of addressing within-firm misallocation.

7 Conclusion

In conclusion, this paper documents that large firms are more likely to adopt automation capital, and that adoption leads to higher productivity and increased labor market power for firms. It constructs a general equilibrium model that is consistent with the evidence from the microdata, incorporating oligopsonistic labor markets, automation adoption choice, occupational choice, labor force participation choice, and entry.

It argues that when large firms adopt automation in non-competitive markets and increase their productivity, this shifts the mean and variance of the distribution of market power across the economy. This shift, in turn, exacerbates misallocation within the economy, leading to substantial welfare and output losses relative to a socially optimal allocation. The model developed in this paper quantifies these losses and shows that automation can lead to an approximate 15.9% reduction in output and a substantial 56.8% reduction in total welfare. Furthermore, it highlights that the welfare gains are disproportionately skewed in favor of those who adopt automation capital and non-routine workers relative to routine workers.

Looking ahead, there are two promising avenues for future research. First, the current model does not explicitly model the product market power of firms. The qualitative effects of product market power may be similar to those of labor market power, but quantitatively these effects may differ significantly and warrant further investigation. Therefore, the results presented in this paper should be viewed as a lower bound on the effect of automation on efficiency losses. Analyzing how automation affects output and welfare losses in a model that accounts for both product and labor market power is an important area for future research.

Second, an important area for future research is in the area of optimal tax policy, especially when considering the impact of automation on economic efficiency. While current work has appropriately focused on the distributional consequences of automation, the results presented here underscore the need for a comprehensive approach that combines efficiency and distributional policies to effectively address the implications of the increasing prominence of robots in our economic landscape. As we continue to explore the multifaceted effects of automation, these avenues of research will be essential in shaping our understanding and policy responses in this evolving landscape.

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Appendix

A Derivations

A.1 Derivations of Propositions and Corollaries

Proposition 1. *The probability that worker n selects occupation-establishment pair (o, i) is:*

$$\chi_{io} = \frac{T_{io} w_{io}^{\epsilon_o}}{\Phi_j} \times \frac{\Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}}{\Phi}$$

where

$$\Phi_j = \sum_{i' \in j} T_{i'o} w_{i'o}^{\epsilon_o}, \quad \Phi = \sum_{o} \sum_{j \in \mathcal{J}_o} \Phi_{oj}^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}, \quad \Gamma_o = \Gamma\left(\frac{\epsilon_o - 1}{\epsilon_o}\right)$$

Proof. This proof closely follows the derivation in Appendix A.1 of Azkarate-Askasua and Zerecero (2020). I derive it again here, consistent with the notation of the model developed in Section 4, for the sake of completeness.

As highlighted in the main text, the indirect utility of worker n is given by

$$u_{nio} = c_n z_{nio} v_{nj},$$

where z_{io} and v_j are idiosyncratic utility shocks drawn from Fréchet distributions as follows:

$$P(z) = e^{-T_{io} z^{-\epsilon_o}} \text{ and } P(v) = e^{-v^{-\eta}}.$$

I assume that workers first observe the realization of the market-specific shock v_j for all local labor markets. After optimally choosing their local labor market, they observe the establishment-specific shock and choose the establishment where they supply their unit of labor. The unconditional probability of a worker going to occupation o in establishment

i of market j is thus equal to

$$\chi_{io} = \underbrace{\mathbb{P}(w_{io}z_{io|j} \geq \max_{i' \neq i} w_{i'o}z_{i'o|j})}_{\text{A. Probability of choosing } i \,|\, \text{market } j} \times \underbrace{\mathbb{P}\left[\mathbb{E}_j(\max_i w_{io}z_{io|j})v_j \geq \max_{j' \neq j} \mathbb{E}_{j'}(\max_i w_{io}z_{io|j'})v_{j'}\right]}_{\text{B. Probability of choosing market } j}.$$

In the following, I first derive the probability that a worker chooses establishment i conditional on having chosen market j. Later, I derive the probability that a worker chooses market j.

Step A. To derive the probability of choosing establishment i conditional on choosing market j, I first derive the following probability density functions and the cumulative density functions, which will be used later to calculate this probability:

$$G_i(\vartheta) = \mathbb{P}[w_{io}z_{io|j} \leq \vartheta] = \mathbb{P}\left[z_{io|j} \leq \frac{\vartheta}{w_{io}}\right] = e^{-T_{io}w_{io}^{\epsilon_o}\vartheta^{-\epsilon_o}},$$

$$\frac{dG_i(\vartheta)}{d\vartheta} \equiv g_i(\vartheta) = T_{io}\epsilon_o w_{io}^{\epsilon_o}\vartheta^{-(\epsilon_o+1)}e^{-T_{io}w_{io}^{\epsilon_o}\vartheta^{-\epsilon_o}}.$$

Assuming that $w_{io}z_{io|j} = \vartheta$, we get

$$\mathbb{P}(\max_{i' \neq i} w_{i'o}z_{i'o|j} \leq \vartheta) = \bigcap_{i' \neq i} \mathbb{P}(w_{i'o}z_{i'o|j} \leq \vartheta) = \prod_{i' \neq i} e^{-T_{i'o}w_{i'o}^{\epsilon_o}\vartheta^{-\epsilon_o}} = e^{-\Phi_j^{-i}\vartheta^{-\epsilon_o}} = G_j^{-i}(\vartheta),$$

where $\Phi_j^{-i} = \sum_{i' \neq i} T_{i'o}w_{i'o}^{\epsilon_o}$. Note that we can also write

$$G_j(\vartheta) = \mathbb{P}(\max_i w_{io}z_{io|j} \leq \vartheta) = e^{-\Phi_j\vartheta^{-\epsilon_o}},$$

where $\Phi_j = \sum_{i \in j} T_{io}w_{io}^{\epsilon_o}$. Like before, we can calculate the probability density function using the cumulative density function as follows:

$$\frac{dG_j(\vartheta)}{d\vartheta} \equiv g_j(\vartheta) = \vartheta^{-(\epsilon_o+1)}\epsilon_o\Phi_j e^{-\Phi_j\vartheta^{-\epsilon_o}}.$$

Given these distributions, the probability of choosing i given j:

$$\begin{aligned}
\mathbb{P}(\max_{i'\neq i} w_{i'o}z_{i'o|j} \leq w_{io}z_{io|j}) &= \int_0^\infty \mathbb{P}(\max_{i'\neq i} w_{i'o}z_{i'o|j} \leq \vartheta) g_i(\vartheta) d\vartheta \\
&= \int_0^\infty e^{-\Phi_j^{-i}\vartheta^{-\epsilon_o}} T_{io}\epsilon_o w_{io}^{\epsilon_o}\vartheta^{-(\epsilon_o+1)} e^{-T_{io}w_{io}^{\epsilon_o}\vartheta^{-\epsilon_o}} d\vartheta \\
&= \frac{T_{io}w_{io}^{\epsilon_o}}{\Phi_j} \int_0^\infty \vartheta^{-(\epsilon_o+1)}\epsilon_o\Phi_j e^{-\Phi_j\vartheta^{-\epsilon_o}} d\vartheta \\
&= \frac{T_{io}w_{io}^{\epsilon_o}}{\Phi_j}
\end{aligned}$$

Step B. Next, I calculate the probability of a worker optimally choosing market j. To calculate this probability, I first need to calculate $\mathbb{E}_j(\max_i w_{io}z_{io|j})$.

$$\mathbb{E}_j(\max_i w_{io}z_{io|j}) = \int_0^\infty \vartheta\Phi_j\epsilon_o\vartheta^{-(\epsilon_o+1)}e^{-\Phi_j\vartheta^{-\epsilon_o}}d\vartheta = \int_0^\infty \epsilon_o\Phi_j\vartheta^{-\epsilon_o}e^{-\Phi_j\vartheta^{-\epsilon_o}}d\vartheta.$$

To simplify the integral, we change the name of the variables as follows:

$$x = \Phi_j\vartheta^{-\epsilon_o}, \quad \frac{dx}{d\vartheta} = -\epsilon_o\Phi_j\vartheta^{-(\epsilon_o+1)} = -\epsilon_o\frac{x}{\vartheta}$$

Replacing the change of variables in the above integral, we get

$$\mathbb{E}_j(\max_i w_{io}z_{io|j}) = \int_0^\infty \epsilon_o\Phi_j\vartheta^{-\epsilon_o}e^{-\Phi_j\vartheta^{-\epsilon_o}}d\vartheta = \Phi_j^{\frac{1}{\epsilon_o}}\Gamma\left(\frac{\epsilon_o-1}{\epsilon_o}\right) = \Phi_j^{\frac{1}{\epsilon_o}}\Gamma_o$$

where $\Gamma(\cdot)$ is the Gamma function defined as $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt$. Following same steps as in Step A, we can calculate the probability of choosing market j as follows:

$$\begin{aligned}
\mathbb{P}\big(\Phi_j^{\frac{1}{\epsilon_o}}\Gamma_o v_j \geq \max_{j'\neq j}\Phi_{j'}^{\frac{1}{\epsilon_o}}\Gamma_o v_{j'}\big) &= \int_0^\infty e^{-\Phi^{-j}\vartheta^{-\eta}}\eta\Phi_j^{\frac{\eta}{\epsilon_o}}\Gamma_o^\eta\vartheta^{-(\eta+1)}e^{-\Phi_j^{\frac{\eta}{\epsilon_o}}\Gamma_o^\eta\vartheta^{-\eta}}d\vartheta \\
&= \frac{\Phi_j^{\frac{\eta}{\epsilon_o}}\Gamma_o^\eta}{\Phi}\int_0^\infty \eta\Phi\vartheta^{-(\eta+1)}e^{-\Phi\vartheta^{-\eta}}d\vartheta \\
&= \frac{\Phi_j^{\frac{\eta}{\epsilon_o}}\Gamma_o^\eta}{\Phi}
\end{aligned}$$

Hence, we can write that

$$\chi_{io} = \frac{T_{io} w_{io}^{\epsilon_o}}{\Phi_j} \times \frac{\Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}}{\Phi}.$$

Proposition 2. *The average and median welfare per worker is defined as follows:*

$$\overline{\mathbb{W}} = \mathbb{E}\left[\max_j \left\{\mathbb{E}_j(\max_i w_i z_{io}) v_j\right\}\right] = \Phi^{\frac{1}{\eta}} \Gamma\left(\frac{\eta - 1}{\eta}\right),$$

$$\mathbb{W}^{Med} = Median\left[\max_j \left\{\mathbb{E}_j(\max_i w_i z_{io}) v_j\right\}\right] \propto \Phi^{\frac{1}{\eta}}.$$

where $\Phi = \sum_{j \in \mathcal{J}} \Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}$, $\overline{\mathbb{W}}$ *denotes the average welfare per worker,* $\mathbb{W}^{Med}$ *denotes median welfare and* $\Gamma(\cdot)$ *denotes the Gamma function.*

Proof. We can calculate this object in terms of model parameters in two parts. In the first part, using the result from the proof of Proposition 1, Step B, we can calculate

$$\mathbb{E}_j(\max_i w_{io} z_{io|j}^{1}) = \Phi_j^{\frac{1}{\epsilon_o}} \Gamma\left(\frac{\epsilon_o - 1}{\epsilon_o}\right) = \Phi_j^{\frac{1}{\epsilon_o}} \Gamma_o.$$

Next, we can calculate $\mathbb{E}\left[\max_j \Phi_j^{\frac{1}{\epsilon_o}} \Gamma_o v_j\right]$ in three steps. Define the random variable $S = \max_j \Phi_j^{\frac{1}{\epsilon_o}} \Gamma_o v_j$. We can calculate the CDF of S as follows:

$$\mathbb{P}(S \leq \vartheta) = \bigcap_j (\Phi_j^{\frac{1}{\epsilon_o}} \Gamma_o v_j \leq \vartheta) = \prod_j e^{-\Phi_j^{\frac{\eta}{\epsilon_j}} \Gamma_0^{\eta} \vartheta^{-\eta}} = e^{-\Phi \vartheta^{-\eta}} \equiv K(\vartheta),$$

where $\Phi = \sum_j \Phi_j^{\frac{\eta}{\epsilon_j}} \Gamma_o^{\eta}$. We can calculate the PDF as follows:

$$\frac{\partial K(\vartheta)}{\partial \vartheta} = k(\vartheta) = \eta \Phi \vartheta^{-(\eta+1)} e^{-\Phi \vartheta^{-\eta}}.$$

From here on, we know the PDF and hence we can calculate the expectation as follows:

$$\begin{aligned}\mathbb{E}\big[\max_j \Phi_j^{\frac{1}{\epsilon_o}}\Gamma_o v_j\big] &= \int_0^\infty \vartheta\eta\Phi\vartheta^{-(\eta+1)}e^{-\Phi\vartheta^{-\eta}}d\vartheta \\ &= \int_0^\infty \eta\Phi\vartheta^{-\eta}e^{-\Phi\vartheta^{-\eta}}d\vartheta.\end{aligned}$$

To simplify the integral, we change the name of the variables

$$x = \Phi\vartheta^{-\eta}, \quad \frac{dx}{d\vartheta} = -\eta\Phi\vartheta^{-(\eta+1)} = -\eta\frac{x}{\vartheta}.$$

Replacing the change of variables in the above integral, we get

$$\begin{aligned}\mathbb{E}\big[\max_j \Phi_j^{\frac{1}{\epsilon_o}}\Gamma_o v_j\big] &= \int_0^\infty \eta\Phi\vartheta^{-\eta}e^{-\Phi\vartheta^{-\eta}}d\vartheta \\ &= \int_0^\infty \eta x e^{-x}d\vartheta = \int_\infty^0 (-\vartheta)e^{-x}dx = \Phi^{\frac{1}{\eta}}\int_0^\infty x^{-\frac{1}{\eta}}e^{-x}dx \\ &= \Phi^{\frac{1}{\eta}}\Gamma\big(\frac{\eta-1}{\eta}\big)\end{aligned}$$

A.2 Computational details

General equilibrium models with oligopsony are typically solved by relying on algorithms that exploit the block-recursive structure of these models. One first sequentially solves for the fixed point of the within-market employment share for each market in the economy, and then computes model aggregates using the shares from the first step. See the algorithms proposed by Azkarate-Askasua and Zerecero (2020) and Berger et al. (2022) for more details.

Applying such algorithms to the current model is computationally challenging because the production technology is constant elasticity of substitution (CES) and the automation choice is an endogenous outcome of the model. CES technology implies that occupational labor markets are no longer separable in the model. This means that the occupational employment share depends not only on competitors within the market but also on competitors across markets. Therefore, the dimension of the system of equations required to solve for the fixed point of the within-market employment share is quite large.

Moreover, since both occupational employment and automation are endogenous objects, one needs to solve for these quantities jointly, which further increases the dimension of the system of equations. In practice, I found it unstable to solve the large dimension of the system of equations.

To address the stability issues, I develop a nested fixed-point algorithm to compute the equilibrium. I start with an initial guess of the occupational employment share of establishment i in the aggregate, i.e. χ_{io}, for all occupations. Thus, the size of the initial guess is $3 \times I$, where, as before, I is the total number of establishments in the economy and 3 is the total number of occupations. Conditional on the guess, I compute $l_{io} = \chi_{io} \times L$. Given this, I solve for the fixed point to determine the optimal level of automation adopted for those entrepreneurs who adopt automation capital. Next, I compute the within-market occupational employment share using l_{io} and wages using the inverse labor supply equation. Finally, I update the initial estimate by calculating the occupational employment share of establishment i. I iterate until the model converges. Since the initial estimates are all bounded between 0 and 1 and sum to 1, the speed of convergence depends on the share of establishments employing automation capital and whether the initial estimate of the price of automation capital is above the limit of the marginal productivity of capital. The algorithm is stable and converges relatively quickly in practice. Below I outline it using the equations of the model:

1. Initialize the algorithm by taking a guess of χ^t_{io}, $\forall i, o$. Note that (i) $0 < \chi_{io} < 1$ and (ii) $\sum_i \sum_o \chi_{io} = 1$.

2. Compute l_{io} using the labor supply equation of the model: $l_{io} = \chi_{io} \times L$

3. Compute within market employment share for each occupationa-establishment pair using the following equation:
$$s_{io|j} = \frac{l_{io}}{\sum_{k \in j} l_{ko}}$$

4. Pin down the first order condition of automation capital for robot adopters, x_i^*, us-

ing equation 14:

$$p_x = \left[\phi^{\frac{1}{\gamma}}\hat{l}_{iR}^{\frac{\gamma-1}{\gamma}} + \tilde{\phi}^{\frac{1}{\gamma}}\hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}} \frac{\partial z_i}{\partial x_i} \quad + \quad z_i \frac{\partial}{\partial x_i}\left[\phi^{\frac{1}{\gamma}}\hat{l}_{iR}^{\frac{\gamma-1}{\gamma}} + \tilde{\phi}^{\frac{1}{\gamma}}\hat{l}_{iN}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}}$$

This step requires solving the root of the above equation.

5. Compute w_{io}, $\forall i, o$ for both adopters and non-adopters using first order conditions in equation 12:

$$w_{io} = \left(\frac{e_{io}}{e_{io}+1}\right) \times \frac{\partial y_i^k}{\partial l_{io}}, \quad o \in \mathcal{O}, \ \ k \in \{0,1\}.$$

6. Computed the model given value of χ_{io} using equilibrium wages:

$$\chi_{io} = \frac{T_{io} w_{io}^{\epsilon_o}}{\Phi_j} \times \frac{\Phi_j^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}}{\Phi},$$

where

$$\Phi_j = \sum_{i' \in j} T_{i'o} w_{i'o}^{\epsilon_o}, \quad \Phi = \sum_o \sum_{j \in \mathcal{J}_o} \Phi_{oj}^{\frac{\eta}{\epsilon_o}} \Gamma_o^{\eta}, \quad \Gamma_o = \Gamma\left(\frac{\epsilon_o - 1}{\epsilon_o}\right)$$

7. Check if convergence is achieved by verifying if the following condition is satisfied:

$$\max\left\{|\chi_{io}^t - \chi_{io}^{t+1}|\right\} \leq 1e^{-8}$$

8. If the condition is not satisfied, then update χ_{io} using the following rule:

$$\chi_{io}^{t+1} = (1-\psi)\chi_{io}^{t+1} + \psi \chi_{io}^t$$

B Production Function Estimation

To estimate Hicks-neutral productivity and firm-specific markdowns, I follow the work of Gandhi et al. (2009). In particular, I use the "inverse share equation" to separate the measurement error in the production function from Hicks-neutral productivity, as suggested by Gandhi et al. (2009), and I estimate markdowns by assuming that firms are price takers in the output market and the market for intermediate inputs.Concretely, I denote a firm's output by Y_{jt} which I define as follows:

$$Y_{jt} = Q_{jt} \times \exp(\epsilon_{jt}) = \left[\alpha_K K_{jt}^{\frac{\gamma-1}{\gamma}} + \alpha_L L_{jt}^{\frac{\gamma-1}{\gamma}} + \alpha_M M_{jt}^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\kappa\gamma}{\gamma-1}} \times \exp(\hat{\omega}_{jt}) \times \exp(\epsilon_{jt})$$

where, abusing notation, I assume that j denotes a firm and t denotes time. Assuming that firms are price-takers in the intermediate inputs market while price-setters in the output and the labor market, I get the following first-order conditions.[18] This leads to the following system of equation:

$$\begin{aligned}
\epsilon_{jt} &= \ln S_{jt} - \ln Q_{jt} + \frac{\partial Q_{jt}}{\partial M_{jt}} + \ln M_{jt} \\
\hat{\omega}_{jt} &= \log \left(\frac{Y_{jt}}{Q_{jt} e^{\epsilon_{jt}}} \right) \\
\delta_{jt} &= \frac{W_{jt}}{\kappa \alpha_L \left[\exp(\hat{\omega}_{jt}) \right]^{\frac{\gamma-1}{\kappa\gamma}} L_{jt}^{-\frac{1}{\gamma}} Q_{jt}^{\frac{\gamma(\kappa-1)+1}{\kappa\gamma}} P_t}
\end{aligned}$$

where S_{jt} denotes the inverse of the share of materials in total revenues, i.e., $S_{jt} = \frac{R_{jt}}{P_{Mt} M_{jt}}$. The estimation is currently in progress. In it, I also relax the assumption that the output market is perfectly competitive. This means that I can no longer use revenue deflated by a price index as a proxy for output. To resolve the issues with revenue production function, I rely on the French administrative data that allows me to observe prices and quantities separately. In order to construct the results presented in Section 3, I calibrate the values of the structural parameters from literature estimating production function using manufacturing data. Currently, I have used the following values in estimation: $\alpha_K = 0.25, \alpha_L = 0.50, \alpha_M = 0.25, \kappa = 0.9, \gamma = 0.7$. In order to compute the markdown, I am simply going to assume that the output market is perfectly competitive and the intermediate material market is also perfectly competitive.

[18]Note that I derive this equations assuming that firms are profit-maximizers as opposed to cost minimizers.

C Data Appendix

C.1 Occupational Classification

Every job in DADS Postes is categorized by a two-digit PCS occupational code. Following the occupational classification adopted by Albertini et al. (2017) in their work on job polarization in France, I aggregate these 22 codes into three groups: abstract, routine and manual occupations. The classification into three groups is based on following definitions:

- **Abstract**: These occupations include problem-solving and managerial tasks as primary functions on their job. Examples of occupations included in this group are engineers (PCS 38), executives (PCS 37) and scientists (PCS 34).
- **Routine**: This group includes occupations that perform cognitive or physical tasks that follow closely prescribed sets of rules and procedures and are executed in a well-controlled environment. Example includes occupations such industrial workers (PCS 62 and 67), office workers (PCS 54) and mid-level managers (PCS 46).
- **Manual**: This occupational group do not need to perform abstract problem-solving or managerial tasks but are nevertheless difficult to automate because they require some flexibility in a less than fully predictable environment. Example includes personal service workers (PCS 56), driver and security workers (PCS 53 and 64) among others.

The occupational grouping tries to capture the fact that automation and ICT capital should replace workers performing repetitive tasks. Further details concerning the assignment process, the employment share of each occupational group in 1994, and its change over time is documented in Appendix A, Table A1 (Abstract), Table A2 (Manual), Table A3 (Routine).

Next, I document the classification of occupations into three groups in Table A1 (Abstract), Table A2 (Manual), Table A3 (Routine). As mentioned in the main text, I follow the classification adopted by Albertini et al. (2017). For completeness, I also describe the representative 4-digit sub-occupations description. The main idea that this classification tries to capture is that routine occupations can be directly substituted by advances in ICT technology while non-routine occupations is only indirectly affected. Non-routine occupations are further classified based on their task content: non-cognitive are abstract occupations and non-routine manual are called manual occupations. In Figure **??**, I plot the employment share of selected PCS occupational groups and their change over time. The change in employment share for routine occupations by manufacturing and non-manufacturing industries is plotted in Figure **??**.

Table A1: **List of PCS occupations categorized as Abstract**

Title	**2-digit PCS Codes**	**Representative 4-digit sub-occupations**
Engineers	38	Technical managers for large companies, Engineers and R&D manager, Electrical chemical and materials engineers, IT R&D engineers, Purchase, planning, quality control and production managers, Telecommunications engineers and specialists
Top Managers, Executives	37	Managers of large companies, Finance, accounting, sales and advertising managers
Health Professionals, Teachers	42 + 43	High school teachers, Education counsellors, Nurse, Physiotherapist
Scientific, creative professionals	34 + 35	Professors, Public Researchers, Psychology Specialists, Pharmacists
Heads of Business	21 + 23	Heads of businesses (large and small businnes included)

Table A2: **List of PCS occupations categorized as Manual**

Title	**2-digit PCS Codes**	**Representative 4-digit sub-occupations**
Personal Service workers	56	Restaurant servers, food prep workers. Hotel employees, Barbers, Hair Stylists, Beauty shop employees, Child care providers, Home health aids, Residential building janitors, Caretakers
Drivers, Security workers	53 + 64	Truck, taxi and delivery drivers
Manual workers	63 + 68	Includes both skilled and unskilled: Gardener, Master electricians, bricklayers, carpenters, Master cooks, Bakers, butchers
Crane and forklift operator	65	Warehouse truck and forklift drivers, heavy crane and vehicle operators, Other skilled warehouse workers

Table A3: **List of PCS occupations categorized as Routine**

Title	**2-digit PCS Codes**	**Representative 4-digit sub-occupations**
Industrial workers	62 + 67	Includes both low and high-skilled: Construction workers Metalworkers, pipe fitters, wielders, Operators of electrical and electronic equipment, Shipping, moving and warehouse workers, Production workers
Mid-level managers	46	Mid-level professionals in various industries, Store, hotel and food service managers
Foremen, supervisors	48	Foremen and supervisors from manufacturing industries, food service industries
Office workers	54	Receptionist, secretaries
Technicians	47	Installation and maintenance of IT and non-IT equipments
Retail workers	55	Retails employees, cashiers