Putty-Clay Automation

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Abstract

Even as automation and AI reshape labor markets, their adoption differs significantly across firms. This paper studies the coexistence of technologies in an economy where automation capital is putty-clay so that firms cannot adjust their mix of human and automated inputs after capital is installed. It has two main findings. The first is that the effects of increased automation differ depending on which firms become more automated. Increased automation at frontier firms reduces the labor share, whereas automation among laggard firms raises wages and the labor share. I validate this theoretical finding by constructing cross-firm measures of routine employment shares as a proxy for automation and using moments of this distribution to study the equilibrium effects of greater automation among different groups of firms. Given the coexistence of diverse technologies in the economy, I then ask whether the competitive equilibrium allocation of capital across automation technologies is efficient. The second main finding is that, for a given level of frontier technology, there is overinvestment in the lowest and underinvestment in higher automation technologies. I estimate the model to match the empirical cross-firm distribution of routine shares and find that these inefficiencies lead to substantial productivity losses (1-9% in European region-industry pairs) and that wages in the decentralized social optimum are higher (1.5-14%) than in the competitive equilibrium.

Keywords: Automation, labor share, putty-clay, vintage capital, productivity

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1 Introduction

"In Sweden, if you ask a union leader, 'Are you afraid of new technology?' they will answer, 'No, I'm afraid of old technology.' "

– Ylva Johansson, Swedish Minister for Employment (2014–2019), NYT (2017)

As automation and AI advance rapidly, the implications for workers and the income distribution have emerged as defining questions of our time. Inevitably, the newest technologies garner the most attention; however, even as the frontier advances, the adoption of older technologies continues. Historical evidence clearly illustrates this pattern. Water power in British industry peaked in the 1870s, 100 years after the Watt steam engine was first commercialized (Crafts (2004)). In a more modern example, in the online grocery sector, highly automated fulfillment centers with advanced robotics and conveyor systems operate alongside smaller packing locations that rely primarily on human labor (McKinsey & Co. (2020), Markoff and Seifert (2018)). And, within six-digit US industries, there is a roughly six-fold difference in the robotics adoption rates between the highest and lowest adoption groups of firms (Acemoglu et al. (2024)).

This paper departs from the existing literature, which primarily studies the effects of advances at the technological frontier, by studying theoretically and empirically the coexistence of different technologies. I evidence, in particular, the importance of firms operating automation technologies far from the frontier in determining wages and income distribution. Why does the effect of increased automation depend on which firms become more automated? What is the empirical distribution of automation technologies across firms? And, given that different technologies coexist in the economy is the allocation of capital efficient? This paper seeks to shed light on these questions.

This study has two main parts. First, I develop a static model with heterogeneous firms that operate capital with different degrees of automation so that some firms' machines can perform more tasks and, therefore, have higher productivity. Crucially, capital is putty-clay, meaning that the tasks machines can perform and their capital-to-labor ratio is fixed after installation. The labor market clears by determining the marginal firm that is automated and, hence, productive enough to operate given the market wage, and that firm effectively acts as the wage setter. The putty-clay nature of capital implies that the marginal product of labor is not equalized across firms in equilibrium, and firms that operate supra-marginal technologies earn technological (Ricardian) rents, even though the output market is competitive.

The first finding of the paper is that the labor share, which is the proportion of income that is not paid as technological rents, does not necessarily decrease as the aggregate share of tasks performed by workers falls. Instead, the impact on income shares depends on which firms become more automated. The labor share falls if there is greater automation at the frontier because firms earn higher technological rents as the distribution "stretches out". In contrast, the labor share increases if there is greater automation at the marginal firm because increasing automation and, hence, productivity at that firm increases wages at all firms and, therefore, reduces aggregate rents in the economy.

To provide evidence for this theoretical finding, I turn to a proxy of automation for which I can measure firm-level variation: the routine share of employment. Using the Eurostat Structure of Earnings Survey, a rich cross-country worker-level data set, I measure the distribution of routine employment shares within European industry-region cells. At the industry level, I find a correlation of 0.8 between the average routine employment share and the US automation measure in Acemoglu and Restrepo (2022). Informed by the theory, I run reduced form regressions of wages and labor shares on percentiles of the corresponding routine share distribution. I find significant negative (positive) correlations between routine shares in laggard (frontier) firms and wages and labor shares, as predicted by the theory.

In the second part of the paper, I embed the static framework in a dynamic model in which firms are endowed with a technology that allows them to produce capital of a given degree of automation, with the marginal cost of capital increasing in the quantity produced at any time. Firms are perfectly competitive in the output market, but access to proprietary technology means that in equilibrium, a distribution of automation technologies emerges and endures in the long run. This implies that, as in the static model, technological rents are also present in the long-run dynamic equilibrium.

In the competitive equilibrium, there is endogenous misallocation relative to the choice of a social planner that maximizes a representative household's welfare. Misallocation arises because a firm's private benefit from operating a technology, the technological rent, is lower than the social benefit of technology, which is the productivity of any given type of capital. Firms, therefore, underinvest relative to the social optimum, resulting in lower aggregate productivity. The planning solution eliminates firms below a certain automation threshold and makes all firms above that threshold larger, increasing productivity. As a result, in the socially optimal outcome, workers perform a smaller aggregate share of tasks. In a decentralized implementation of the social optimum, wages and productivity would be higher because marginal technology is more productive in the planning solution.

To quantify the magnitude of misallocation, I estimate the model to match the cross-firm distributions of routine employment shares in the data. I find substantial productivity losses (ranging between 1-9% in European region-industry pairs) in the competitive equilibrium and that wages would be substantially higher (1.5-14%) in decentralizing the socially optimal capital allocation. Labor shares are always higher in the socially optimal outcome. Moreover, the model implies that as frontier automation increases, the effect of misallocation on aggregate productivity falls, but the effect on wages increases so that the labor share at the competitive equilibrium falls by too much (relative to the socially optimal outcome) as new automation technologies are introduced. These findings are particularly significant given the substantial empirical evidence linking automation to wage inequality and labor share declines (Acemoglu and Restrepo (2022), Bergholt et al. (2022)).

Related Literature This paper contributes to the literature on the labor market and income distribution effects of automation (Acemoglu and Restrepo (2018), Hemous and Olsen (2022), Humlum (2019), Moll et al. (2022), Ide and Talamas (2024)) by studying the effects of increased automation not just at the frontier but across different vintages of technology. Hubmer and Restrepo (2021) study an economy in which heterogeneous firms incur a fixed cost to automate and, therefore, differ in their automation choices. Their paper focuses on jointly explaining the dynamics of aggregate and firm-level labor shares in US industries in response to a shock that reduces the relative price of capital. In contrast, I focus on the determinants of the long-run distribution of automation and study misallocation. Beraja and Zorzi (2024) study an economy in which automation is inefficiently high because firms do not internalize the effects on displaced workers. This paper complements their work by studying an economy in which automation is inefficiently low because of capital misallocation across different vintages of automation technology (and therefore also relates to the extensive literature on the causes of misallocation, surveyed by Restuccia and Rogerson (2017)).

This paper studies the cross-firm distribution of routine employment shares as a proxy for the distribution of technology, following Zhang (2019), Jaimovich et al. (2024) and Blackwood et al. (2024). I contribute to this literature by explicitly relating the distribution to macroeconomic outcomes, both empirically and theoretically. Comin et al. (2025) document using firm survey data that there is significant variation in technology use across and within countries and that the most widely used technologies tend not to be at the technological frontier. Stapleton and Webb (2020) document similar patterns specifically in automation technology using firm-level data for the Spanish manufacturing sector. I find similar patterns using routine employment shares as a technological proxy.

A large literature studies the effects of increased automation at the firm (Bonfiglioli et al. (2024), Bessen et al. (2025), Aghion et al. (2020), Dechezleprêtre et al. (2020)), country-industry (Autor and Salomons (2018)) and regional (Acemoglu and Restrepo (2020), Dauth et al. (2021), Mann and Puttmann (2023)) level. This paper contributes to this literature by providing reduced form evidence of the heterogeneous equilibrium effects of increased automation at the frontier versus at laggard firms.

The dynamic version of the model features a putty-clay vintage capital structure, first introduced by Johansen (1959) and further developed by Massell (1962) and Phelps (1963). The implementation of the putty-clay technology in this model is closely related to Gilchrist and Williams (2000). As in Jovanovic and Yatsenko (2012) and Boucekkine et al. (2014), and in contrast to most vintage capital models, a crucial feature of the model in this paper is that investment occurs in both old and new vintages of capital. This paper contributes to the vintage capital and putty-clay literature by studying misallocation and bringing the models closer to data.

The rest of the paper is organized as follows. Section 2 develops a static model that characterizes the effect of increased automation at either end of the spectrum of technological advancement in a simple setting. Section 3 presents empirical evidence for the coexistence of different automation technologies in the economy and reduced form regressions that support the theoretical findings. Section 4 develops the dynamic putty-clay automation model, and Section 5 shows how misallocation arises endogenously in that framework.

2 Static Model

I start with a static model to simplify the exposition of technology and aggregation. The static economy consists of a continuum of firms, each operating a firm-specific technology to produce a homogeneous good sold in a competitive market. To produce, firms must hire labor, which homogeneous workers supply in a competitive labor market.

Firms A continuum of competitive firms produces a homogeneous final good Y. A firm i is characterized by its technology a_i, embodied in its capital stock k_i.

Technology Production of one final good requires the completion of a continuum of all tasks in an interval $[0, 1]$. Both workers and machines can perform tasks. Workers can perform all tasks, whereas a machine of type a can perform tasks in $[0, a]$, with $a < 1$[1]. So to produce one unit of the final good using a machine of type a, a worker must complete the remaining tasks $[a, 1]$. If it takes workers one unit of time to complete all tasks in $[0, 1]$, a worker-machine pair would produce $1/(1 - a)$ goods in one unit of time. I also assume

[1]Following Becker and Murphy (1992), the production function *in terms of tasks* is the Leontief function,

$$y = \min_{0<x<1} y(x)$$

with the interpretation that producing y goods requires that each task x be performed $y(x)$ times. Assuming workers can perform all tasks is not essential to the results, but it simplifies notation and algebra. What is important is that there are some tasks that only workers can perform.

that productivity gains from worker specialization are governed by a parameter $\gamma > 1$. With these assumptions, the productivity of a worker-machine team is given by:

$$z\left(a\right)=\left(\frac{1}{1-a}\right)^{\gamma} \tag{1}$$

The function $z\left(a\right)$ is related to the span of control in models in which production is organized in knowledge hierarchies as in Garicano (2000) and Garicano and Rossi-Hansberg (2006). In these papers, productivity gains arise when more knowledgeable workers are employed at higher levels in the production hierarchy. Here, productivity gains occur when workers are paired with machines because workers are essential to production ($a < 1$), and machines save workers' time by performing a portion of the required tasks. The degree of productivity gains is scaled by the parameter γ, which I interpret as capturing returns to worker specialization in the spirit of Becker and Murphy (1992).

Firm Production Function and Profit Maximization At the firm level, I assume that the number of (effective) worker hours per machine is technologically constrained to be in a fixed proportion, resulting in the following (Leontief) production function for firm i:

$$y(a_i)=z\left(a_i\right)\min\left(k_i, H\cdot n_i\right), \tag{2}$$

where k_i and n_i are the firm's capital stock and labor input. H is labor-augmenting productivity common to all workers, so that $H\cdot n_i$ is the efficiency adjusted number of hours worked by firm i's workers.

Firm-size Distribution The firm-size distribution measures capital at each level of automation a_i. I denote this measure $k\left(a\right)$, and assume that it has bounded support $a\in[a_\ell, a_h]$, so that a_ℓ and a_h are, respectively, the least and the most automated types of capital in the economy, with $0\leq a_\ell < a_h < 1$. Anticipating the discussion of aggregation in the following section, the integral of $k\left(a\right)$ is the aggregate capital stock of the economy, $K=\int_{a_\ell}^{a_h}k\left(a\right)\,\mathrm{d}a$. Normalizing the firm-size distribution by aggregate capital, I define the PDF $f\left(a\right)\equiv\frac{k(a)}{K}$, the density function of automation in the economy.

2.1 Equilibrium and Aggregation

I start by solving for aggregate labor demand. The profit maximization problem for a firm with automation a and capital stock k(a)is:

$$\max_{n}\; z\left(a\right)\min\left(k\left(a\right), H\cdot n\right)-W\cdot n \tag{3}$$

It follows that the optimal choice of hours as a function of a is:

$$n(a) = \begin{cases} \frac{k(a)}{H} & \text{if } a \geq a_w \\ 0 & \text{if } a < a_w \end{cases},$$

with $z(a_w) = w$, where for convenience I define $w \equiv \frac{W}{H}$ as the wage per effective unit of labor input. Aggregate labor demand, N, is the integral over firm labor choices, $N = \int_{a_w}^{a_h} n(a)\ \mathrm{d}a$. Substituting in the optimal choice of hours and $k(a) = K \cdot f(a)$, the integral becomes $N = \frac{K}{H}\int_{a_w}^{a_h} f(a)\ \mathrm{d}a$. Denoting by $F(\cdot)$ the CDF of a, integrating gives the aggregate labor demand as:

$$N = \frac{K}{H}\left[1 - F(a_w)\right] \tag{4}$$

Aggregate labor demand is the product of the total capital stock, divided by worker efficiency times the fraction of active firms (1 minus the CDF at a_w, the term in square brackets). I assume a labor supply function $N^s(W)$. Equating $N^s(W)$ to labor demand as in Equation 4 gives the equilibrium wage. With the equilibrium wage in hand, aggregate output Y can be solved for as the integral over firm-level output, $Y = \int_{a_w}^{a_h} z(a)\, k(a)\ \mathrm{d}a = K\int_{a_w}^{a_h} z(a) f(a)\ \mathrm{d}a$, which can be expressed as:

$$Y = K\left[1 - F(a_w)\right]\mathbb{E}\left(z(a)\,|a \geq a_w\right) \tag{5}$$

Aggregate output is the product of three terms: the capital stock, the fraction of active firms, and the average productivity of active firms, given by the third term.

2.2 Automation comparative statics

I now study comparative statics of the equilibrium wage and labor share of income for automation at the frontier, a_h, and at the margin, a_w. Because a_w is an equilibrium object, it is not strictly correct to think of this as a comparative static. Still, I do so to emphasize the association between increased automation at different points of the distribution and aggregate outcomes.

Proposition 1. *The wage is increasing in a_w, and the labor share of income is increasing in a_w and decreasing in a_h.*

Proof. The wage increasing in a_w follows from $z'(a) > 0$. Substituting in for W, N and Y, the labor share of income is given by $LS = \frac{WN}{Y} = \frac{z(a_w)}{\int_{a_w}^{a_h} z(a)f(a)\ \mathrm{d}a}$. $\frac{\partial LS}{\partial a_w} = \frac{z'(a_w)}{\left(\int_{a_w}^{a_h} z(a)f(a)\ \mathrm{d}a\right)} +$

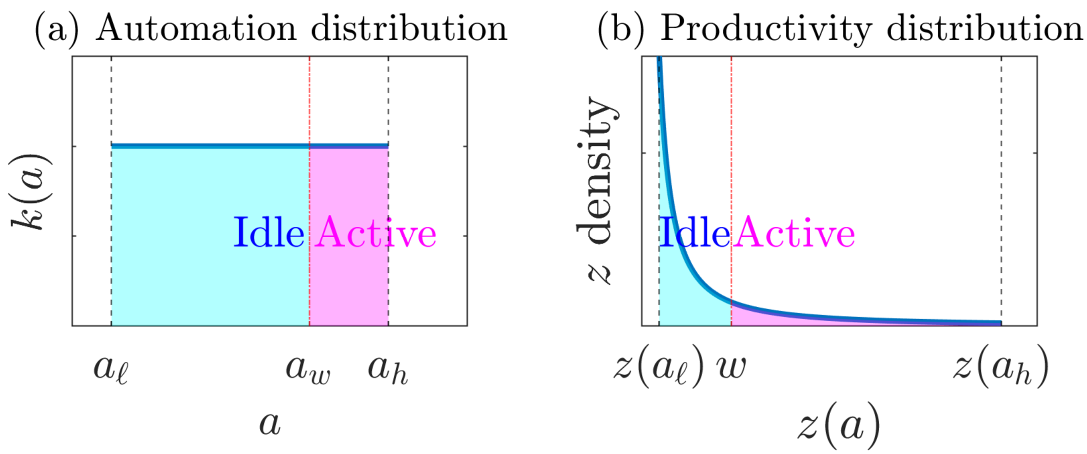


Figure 1: Illustration of static model equilibrium

Notes: (a) $f(a)$ for $\sigma = \frac{1}{2}$ (see Assumption 1), with an example of an equilibrium in which firms to the left (right) of a_w are idle (active). (b) Distribution of $z(a)$ for $\sigma = \frac{1}{2}$, with shading indicating the (in)activity regions in productivity space.

$\frac{z(a_w)^2 f(a_w)}{\left(\int_{a_w}^{a_h} z(a) f(a)\ \mathrm{d}a\right)^2} > 0$, so the labor share is increasing in marginal automation a_w. Finally, $\frac{\partial LS}{\partial a_h} = -\frac{z(a_w) z(a_h) f(a_h)}{\left(\int_{a_w}^{a_h} z(a) f(a)\ \mathrm{d}a\right)^2} < 0$, so the labor share is decreasing in marginal automation a_h. $\square$

The proposition states that comparing two economies with identical frontier automation a_h, the economy with the higher level of marginal automation will have higher wages and labor share. The relationship between automation in an economy and worker outcomes, therefore, depends not only on frontier technology but, importantly, on the entire distribution. To explain the intuition for this result in the familiar context of a CES aggregate production function, I next turn to a particularly tractable parametrization of the model.

2.3 Example: a CES Aggregate Production Function

Equation 5 expresses aggregate output as a function of the equilibrium wage. To express aggregate output in a more familiar form – as a function of capital, labor, and technology – I assume that $f(a)$ is a 3 parameter beta distribution[2] that is characterized by one shape parameter, $\frac{\sigma}{1-\sigma}$, and lower and upper bounds a_ℓ and a_h.

Assumption 1 *Assume $a \sim B\left(1, \frac{\sigma}{1-\sigma}; a_\ell, a_h\right)$ so $f(a) = \frac{\sigma}{1-\sigma} \frac{(a_h - a)^{\frac{2\sigma-1}{1-\sigma}}}{(a_h - a_\ell)^{\frac{\sigma}{1-\sigma}}}$ and that $\gamma = \frac{1}{1-\sigma}$,* so $z(a) = \left(\frac{1}{1-a}\right)^{\frac{1}{1-\sigma}}$.

[2]The standard beta distribution is bounded in $[0, 1]$ and is characterized by two shape parameters. I restrict one of the shape parameters to equal one and set the bounds to $0 < a_\ell < a_h < 1$.

The following aggregation result follows with this assumption:

Proposition 2. *Using Assumption 1, aggregate output for this economy (see Equation 5) can be represented as a CES production function with an elasticity of substitution* $0 < \sigma < 1$,

$$Y = A\left(\alpha K^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(H \cdot N)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{6}$$

where H *is labor-augmenting productivity and the capital* (K) *and labor aggregates* (N) *are* $K = \int_a k(a)\ da$ and $N = \frac{K}{H}[1 - F(a_w)]$. *The total factor productivity term* A *and the capital distribution parameter* α *are functions of parameters of the productivity distribution of the automation distribution* $F(a)$, $A = \frac{1}{(1-a_h)(1-a_\ell)^{\frac{\sigma}{1-\sigma}}}$ *and* $\alpha = \frac{a_h - a_\ell}{1-a_\ell}$. *The labor share in this economy is:*

$$LS = \frac{WN}{Y} = \frac{1-a_h}{1-a_w} \tag{7}$$

Proof. See Appendix A.1. □

Figure 1 illustrates the equilibrium of the model for the case $\sigma = \frac{1}{2}$, so $f(a)$ is uniform between a_ℓ and a_h, and $\gamma = 2$. In the left panel, firms to the left (right) of a_w are idle (active). The right panel shows the activity threshold in productivity space. The active firms, to the right of w, are those with the highest productivity levels, and the productivity distribution has a fat right tail. Proposition 2 shows that, integrating the area to the right of w using the uniform density, one can express output in this economy as exactly the familiar CES production function[3].

The aggregation result makes explicit the differences and similarities between the Acemoglu and Restrepo (2018) framework and the putty-clay approach. Here, because higher automation raises firm-level productivity, increased automation at any point in the distribution raises TFP, and A is therefore increasing in both a_h and a_ℓ. In the CES representation of the aggregate production function in Acemoglu and Restrepo (2018), the capital share parameter is an increasing function of the fraction of automated tasks. Intuitively, that means that greater automation always reduces the labor share. Here, the capital share parameter is increasing in frontier automation a_h, but *decreasing* in laggard automation a_ℓ, which is behind the putty-clay framework's implication that the effect on the labor share of greater automation depends on where in the distribution it occurs. The proposition provides an easily interpretable expression for the labor share in terms of the automation distribution: the labor share is the ratio of the fraction of non-automated tasks at the most automated

[3] This aggregation procedure was first introduced by Houthakker (1955) and generalized by Levhari (1968) and Sato (1975), and has been applied in related contexts by Jones (2005), Lagos (2006), León-Ledesma and Satchi (2018) and Oberfield and Raval (2021).

firm $1 - a_h$ over the fraction of non-automated tasks at the least automated (active) firm $1 - a_w$ (note that if capital is fully utilized, $a_\ell = a_w$).

The expression for the labor share and the general result in Proposition 1 makes explicit my model's connection to David Ricardo's theory of rent (Ricardo (1821)). In Ricardo's formulation, the profits of landowners are determined by the difference between the productivity of their land and that of the best available rent-free land because the productivity of the worst land determines the wages of landless laborers. This economic rent is not competed away because new land cannot be readily created. By analogy, in my model, the productivity of the least automated capital determines the wages of labor, and owners of supra-marginal machines earn Ricardian rents (or *quasi-rents* in the language of Phelps (1963)) from automation. These profits arise not from a lack of competition in product markets but because the fixity of capital impedes the equalization of the marginal product of labor across firms. In the static model shown above, this fixity is assumed; in the dynamic model presented below, it is sustained in equilibrium because firms operate a convex investment technology that allows them to produce capital with a certain degree of automation.

3 Empirical Evidence

This section examines the theoretical predictions of the model regarding the effects of the distribution of automation technology on workers' wages and the labor share of income, summarized in Proposition 1.

The main challenge in conducting this analysis is obtaining a measure of automation at the firm level. I use the share of routine employment within a firm as a proxy for the non-automated share of employment (corresponding to $1 - a$ in the theoretical model). This measure has been shown to contain information relevant to asset prices (Zhang (2019)) and, most relevant to this paper, cross-sectional dispersion in firm productivity within US industries (Blackwood et al. (2024)). Jaimovich et al. (2024) study the role of the firm-level distribution of routine share in explaining its aggregate decline. I show below that, aggregated to the industry level, the routine share of employment is highly correlated (0.8) with the measure of automation used by Acemoglu and Restrepo (2022).

Building on the framework introduced in the previous section, I study the association between wages and labor shares and variation in the distribution of the routine employment share. Specifically, I explore two relationships:

1. The relationship between workers' wages and automation within labor markets. The

main specification is:

$$\log w_{j,i,n,t} = \alpha_o + \alpha_i + \alpha_n + \alpha_t + \sum_{x \in (\ell,m,h)} \beta_x \log(1 - \hat{a}_{x,i,n,t}) + X_j + X_f + \varepsilon_{j,i,n,t}, \quad (8)$$

where the left-hand side is the log wage of worker j, with occupation o, in industry i, region n at time t; α_x are fixed effects; and X_x denote other controls. The main explanatory variables on the right-hand side are $\{1 - \hat{a}_{x,i,n,t}\}_{x \in (\ell,m,h)}$, which are moments of the routine employment share distribution within an industry-by-region cell. I explain below how the automation proxy is constructed, as well as the fixed effects and controls that I added to this specification. The theoretical model predicts a positive association between automation at the least automated firms and wages. This translates into a negative association between the automation proxy $(1-\hat{a}_\ell)$ and wages in the regression analysis.

2. The relationship between the labor share of value-added and automation at the country-industry level. The main specification is:

$$\log LS_{i,c,t} = \alpha_i + \alpha_c + \alpha_t + \sum_{x \in (\ell,m,h)} \beta_x \log(1 - \hat{a}_{x,i,c,t}) + X_{i,c,t} + \varepsilon_{i,c,t} \quad (9)$$

where the left-hand side is the log labor share in industry i, country c at time t; α_x are fixed effects; and $X_{i,c,t}$ denotes industry-by-country controls. The main explanatory variables on the right-hand side are $\{1 - \hat{a}_{x,i,c,t}\}_{x \in (\ell,m,h)}$, which are moments of the routine employment share distribution within a country-by-industry cell. The theoretical model predicts a positive (negative) association between increased automation at the least (most) automated firms and the labor share. This translates into a negative (positive) coefficient on $1 - \hat{a}_\ell$ $(1 - \hat{a}_h)$.

3.1 Data

The primary data source for this analysis is the Eurostat Structure of Earnings Survey (SES). SES is a quadrennial repeated cross-sectional survey that collects worker-level data on earnings, working conditions, and the characteristics of employees (e.g., gender, age, occupation, education) and their employers (e.g., industry, size, location) in 25 countries. Six waves (1995-2018) are available, varying across countries in participation and the available variables (see data appendix for further details). The sample of countries and the coverage within countries stabilized starting with the 2010 survey, so I include the three most recent waves (2010, 2014, and 2018) in the analysis. The source for country-industry level data is EU KLEMS.

Automation Proxy. I use the routine share of employment within a firm as a proxy for (one minus) the degree of automation, which I denote $1-\hat{a}_i$. The precise definition of routine occupations and classification methodology is in Table 6. At the firm level, I construct $1-\hat{a}_i$ as the count of routine employees divided by the total number of surveyed employees. The regressions relate variation in the distribution of $1-\hat{a}_i$ to worker or industry-level outcomes. For the wage regressions (Equation 8), the reference is the firm-level distribution within a NUTS1 region-by-industry cell, whereas for the labor share regressions (Equation 9) it is the distribution within a country-by-industry cell (data on labor shares is not available at region-industry level). In the main specifications, I include three descriptors of the relevant distribution, denoted $1-\hat{a}_\ell$, $1-\hat{a}_m$, and $1-\hat{a}_h$. These are computed as the average $1-\hat{a}$ among firms in the 1st, 5th, and 10th deciles of the relevant distribution. I include these averages instead of the deciles to smooth out noise in the firm-level data. I include $1-\hat{a}_m$ in the regression to parsimoniously control for other distribution features, in the spirit of Proposition 1. Table 5 shows the variation in $a_h - a_\ell$ across country-industry cells.

Worker-level variables. The SES provides worker-level data on hourly wages, as well as several worker characteristics that I include as controls in the wage regression (sex, age, full/part-time status, two-digit occupation and education).

Firm-level variables. At the firm level, the survey includes data on location (NUTS1 region), industry, firm (employment) size, and an indicator for the presence and level of collective bargaining arrangements within the firm. I use these variables as controls in the wage-level regression. Industry classification is at the two-digit level, but reporting differences across countries requires combining some two-digit industries, leaving five manufacturing and twelve non-manufacturing industries (see appendix Table 4 for details).

Country-industry variables. The country-industry labor share data is from EUKLEMS. I compute the labor share as compensation over nominal value added (COMP/VA_CP). Because data are not available for industry labor shares at the NUTS1 level, the labor share analysis is at the country-industry level.

3.2 Automation proxy

A challenge in providing evidence for the findings of the theoretical model is the lack of comprehensive, direct measures of automation at the firm level. Following a growing literature (Zhang (2019), Jaimovich et al. (2024), Blackwood et al. (2024)), I use (one minus) the routine firm employment share as a proxy. Figure 2 shows evidence for the validity of this measure and its distribution.

Panel (a) presents a scatter plot correlating the industry-level task displacement measure from Acemoglu and Restrepo (2022) with the mean $\hat{a}$ across firms, grouped by industry-NUTS1 region and averaged across NUTS1 regions. The bars denote the 10th and 90th percentiles of within-industry averages across regions. The average $\hat{a}$ has a correlation of 0.8 with the Acemoglu and Restrepo (2022) measure, with large dispersion across regions in the distribution of $\hat{a}$.

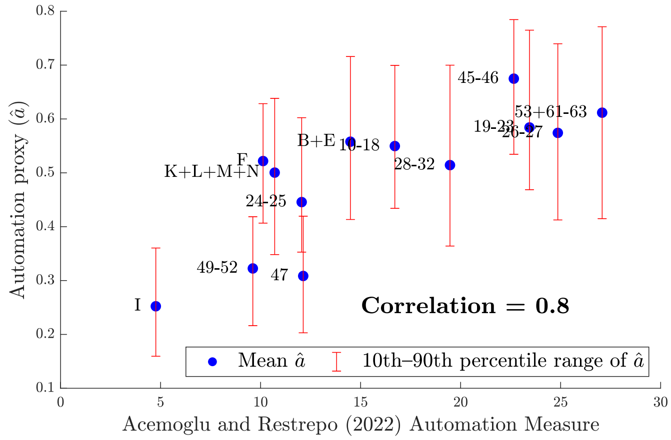
Panel (b) compares the firm-level distributions of $\hat{a}$ in machinery and vehicle manufacturing (NACE 28-32)[4] between West Germany and East Germany using employment-weighted kernel density estimates. The distribution in West Germany has significantly more mass at higher levels of $\hat{a}$, whereas the distribution in East Germany has significant mass at low levels of $\hat{a}$ and a thin tail at high levels of $\hat{a}$. Through the lens of the model in this paper, this difference in the distributions is consistent with the widely studied productivity gap between East and West Germany.

Finally, panel (c) contrasts the distributions of $\hat{a}$ within West Germany between machinery and vehicle manufacturing (NACE 28-32) and accommodation and food services (NACE I). The distribution in food and accommodation services has the most mass at low levels of automation and relatively few workers at high-$\hat{a}$ firms. This is consistent with evidence (Acemoglu et al. (2024), Acemoglu and Restrepo (2022)) showing that hospitality sectors are (at the time of writing) among the least affected by automation. In contrast, these technologies have displaced many tasks in machinery and vehicle manufacturing.

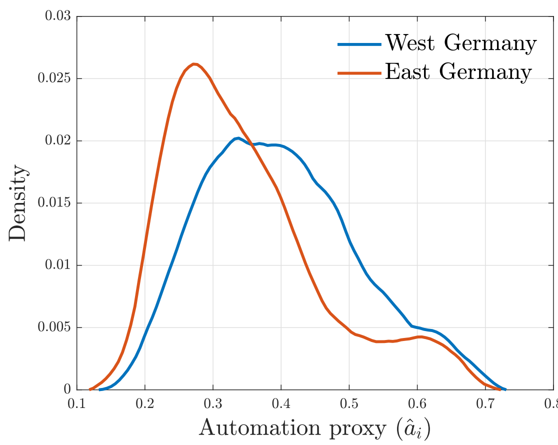
3.3 Results

Wage regressions. Table 1 shows the results of the specification in Equation 8, regressing wages on the NUTS1 region-by-industry automation distribution and controls. The regression includes three features of the automation distribution $1 - \hat{a}_\ell$, $1 - \hat{a}_h$ and $1 - \hat{a}_m$. The theory of Section 2 highlights the importance of the lower and upper bounds of the distribution in determining worker and industry-level outcomes, motivating the inclusion of $1 - \hat{a}_\ell$ and $1 - \hat{a}_h$. To parsimoniously control for other distribution features, I include $1 - \hat{a}_m$ (corresponding to the distribution median). Note that the dependent variable varies at the worker level, but the main variables of interest vary at the NUTS1-by-industry level. To isolate to the greatest extent possible the variation of interest, I also include occupation, industry,

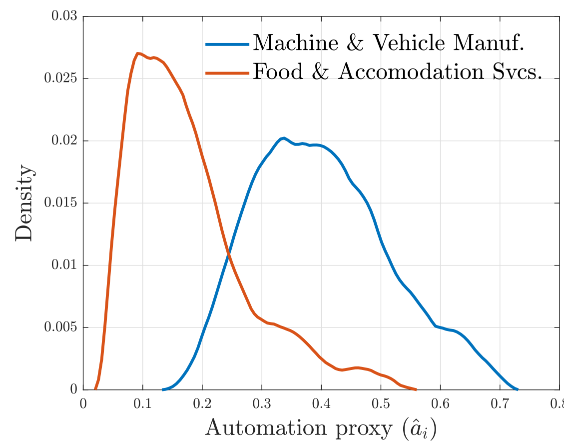
[4]NACE 28-32 also includes other types of manufacturing, but in EUKLEMS machinery and vehicles account for more than 80% of value added in these industries.



(a) Comparison to Acemoglu and Restrepo (2022) task displacement measure



(b) Cross-region comparison of $\hat{a}_i$ distribution in machine and vehicle manufacturing



(c) Cross-industry comparison of $\hat{a}_i$ distribution in West Germany

Figure 2: Descriptive evidence on the automation proxy $\hat{a}$

Notes: (a) Scatter plot of the Acemoglu and Restrepo (2022) industry-level task displacement measure against the mean of $\hat{a}$ across firms within industry-NUTS1 cells, averaged across NUTS1 regions for each industry. The bars indicate the 10th and 90th percentiles of these within-industry averages across all NUTS1 regions. The correlation between task displacement and mean $\hat{a}$ is 0.8. (b) employment-weighted Epanechnikov kernel density estimates of the distribution of $\hat{a}$ in machinery and vehicle manufacturing (NACE 28-32), comparing the distributions of West and East Germany. (c) employment-weighted Epanechnikov kernel density estimates of the distribution of $\hat{a}$ in machinery and vehicle manufacturing (NACE 28-32) and accommodation and food services (NACE I) in West Germany.

region, and time fixed effects, as well as worker (age, sex, education, and full- or part-time status) and firm controls (indicators for employment size and the presence and type of any collective bargaining arrangements). This setup, therefore, attributes observed differences in wages across region-by-industry cells to differences in automation, conditional on worker- (and firm-) level characteristics. The table presents results in three samples: manufacturing, non-manufacturing, and all industries.

The coefficient on $1 - \hat{a}_\ell$ is significantly negative in the three specifications. All things equal, the higher the routine share in the most routine-intensive firms within a NUTS1-by-industry cell, the lower the average wages in that labor market. This is consistent with the model prediction that lower automation in the least automated firms in a labor market is associated with lower wages. The partial equilibrium model of Section 2 is silent on the effect of frontier automation on wages, but the regression results suggest that – at least for non-manufacturing industries – lower frontier automation is also associated with lower wages (I study general equilibrium effects of increased frontier automation in the dynamic model of Section 4).

Table 1: Regressions of log real hourly wage on moments of the automation distribution

Dependent Variable: Log Hourly Wage

	Manufacturing Industries	Non-manufacturing Industries	All Industries
$\log(1 - \hat{a}_\ell)$	-0.63***	-0.67**	-0.53**
	(0.22)	(0.26)	(0.19)
$\log(1 - \hat{a}_m)$	-0.04	0.12**	0.07
	(0.05)	(0.06)	(0.05)
$\log(1 - \hat{a}_h)$	0.02	-0.05***	-0.03***
	(0.02)	(0.01)	(0.01)
R-squared	0.82	0.84	0.83
Observations	3.1e+06	4.7e+06	7.8e+06

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. This table reports OLS estimates associating moments of the automation distribution in NUTS1 region-by-industry cells to worker wages. Column 1 (2) reports estimates restricting the sample to 5 manufacturing (9 non-manufacturing) industries, and column 3 reports estimates for all industries (14 total). Included countries are CZ, DK, ES, HU, LT, LV, PL, PT, RO, SE, SK (a total of 36 NUTS1 regions). All specifications include time, industry, NUTS1, and occupation fixed effects, plus worker controls (age, sex, education, full-time status) and firm controls (employment size and a measure of the presence and type of collective wage agreements). All variables are described in the data appendix. Clustered (at NUTS1 level) standard errors are reported in parentheses.

Labor share regressions. Table 2 shows the results of the specification in Equation 9, regressing the country-industry labor share on the automation distribution and controls.

The regression includes the same three features of the automation distribution $1-\hat{a}_\ell$, $1-\hat{a}_h$, and $1-\hat{a}_m$. To isolate as much as possible the variation of interest, I add industry, country, and time fixed effects. I also include the intermediate input share of gross output in each country-industry and year to control for the possibility that outsourcing and offshoring of production can account for changes in the labor share (the more outsourced/offshored is production, the higher is the intermediate share in gross output, see, e.g. Giannoni and Mertens (2019) and Castro-Vincenzi and Kleinman (2024)). The table presents results in three samples: manufacturing, non-manufacturing, and all industries.

The theoretical model predicts that, all things equal, the industry labor share is increasing in the automation of laggard firms because increasing automation in these firms increases wages in all firms. The empirical estimates support this theoretical insight: the coefficient on $1-\hat{a}_\ell$ is negative in all specifications. The model also predicts that if frontier automation increases, the labor share falls. Across all industries and within non-manufacturing firms, the empirical estimates also support this conclusion (the coefficient on $1-\hat{a}_h$ is positive in these regressions). The coefficient on $1-\hat{a}_h$ is insignificant considering only manufacturing firms, but the coefficient on $1-\hat{a}_m$ is positive, showing that increasing automation is associated with a lower labor share.

Table 2: Regressions of log labor share on moments of the automation distribution

Dependent Variable: Log labor share			
	Manufacturing Industries	Non-manufacturing Industries	All Industries
$\log(1-\hat{a}_\ell)$	-0.56**	-0.13**	-0.15***
	(0.23)	(0.05)	(0.05)
$\log(1-\hat{a}_m)$	0.42***	0.00	0.02
	(0.14)	(0.04)	(0.03)
$\log(1-\hat{a}_h)$	-0.01	0.07***	0.05***
	(0.03)	(0.03)	(0.02)
R-squared	0.66	0.70	0.67
Observations	279	661	940

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports OLS estimates associating moments of the automation distribution to the labor share in country-by-industry cells. Column 1 (2) reports estimates restricting the sample to manufacturing (non-manufacturing) industries and column 3 reports estimates for all industries. Included countries are BG, CY, CZ, DE, DK, EE, EL, ES, FR, HR, HU, IT, LT, LV, MT, NL, PL, PT, RO, SE, SK. All specifications include year, industry, and country fixed effects, plus country-by-industry control (the intermediate input share of gross output). All variables are described in the data appendix. Clustered (at the country level) standard errors are reported in parentheses.

4 Dynamic Model and Balanced Growth

The static model of Section 2 predicts associations between the distribution of automation, wages, and labor shares, and Section 3 shows empirical support for these predictions. The analysis so far is silent on the determinants of the automation distribution. To shed light on this question, I make the firms' problem dynamic and introduce households that make consumption and savings decisions that determine the evolution of the capital stock and its distribution. In doing so, I purposefully simplify the model in two dimensions: labor supply is exogenous throughout, and automation technology is exogenous and fixed. This allows me to focus on the novel insights of the putty-clay automation framework.

The production and investment technologies in the dynamic model are closely related to models with putty-clay technology and irreversible investment, introduced by Johansen (1959) and further developed by Massell (1962) and Phelps (1963). The vintage capital structure in a putty-clay model of irreversible investment is a natural way to model an economy in which different types of capital coexist in the economy at any given time. In my model, a type or vintage of capital corresponds to capital with different levels of automation. The implementation of putty-clay technology in this model is closely related to that of Gilchrist and Williams (2000): the firm-level Leontief production function leads to variable utilization and old (less automated) capital is scrapped endogenously as newer (more automated) capital is installed. Importantly, as in Chari and Hopenhayn (1991) and Jovanovic and Yatsenko (2012) (but unlike most vintage capital models), here investment optimally occurs in both old and new vintages of capital.

I introduce growth into the model by assuming exogenous growth in labor augmenting technological change H_t. I assume that frontier automation a_h is exogenous and fixed at the balanced growth path[5]. The endogenous aggregate states of the dynamic economy are the aggregate capital stock K_t and the automation distribution $f_t(a)$.

4.1 Firm Life Cycle

I start by describing the production and investment decisions of an incumbent firm, followed by the endogenous scrapping and entry decisions.

Incumbent Firms A firm is characterized by its degree of automation a_i and capital stock $k_{i,t}$ (for simplicity, I refer to a unit of capital as a machine) and produces final output by combining capital and labor, $n_{i,t}$, in the Leontief production function $y_{i,t} =$

[5] An old version of this paper develops the model with growth in a_h and balanced growth (Martinez (2019)).

$z(a_i)\min[k_{i,t}, H_t \cdot n_{i,t}]$, where $z(a_i) = \left(\frac{1}{1-a_i}\right)^{\gamma}$. As in Section 2.1, the firms' optimal choice of hours is given by a cutoff rule: firms with productivity $z(a_i) < w_t \equiv \frac{W_t}{H_t}$ do not hire labor in period t, so their capital remains idle. The firm's profit function is therefore given by:

$$\pi(k_{i,t}, a_i) = k_{i,t}\pi(a_i) = k_{i,t}\max[z(a_i) - w_t, 0] \tag{10}$$

A firm's technology a_i is fixed at birth (firm entry is described below). labor augmenting technology H_t grows exponentially at rate g. At the end of each period, the firm must pay a maintenance cost $\kappa > 0$ per machine to keep a machine operational. If the firm does not pay the maintenance cost, the machine depreciates completely at the end of the period. In addition, machines fail with i.i.d. probability δ. Incumbent firms can invest irreversibly in firm-specific capital to grow their stock. I denote the value of a firm with capital $k_{i,t}$ and automation a_i by $V(k_{i,t}, a_i)$:

$$V(k_{i,t}, a_i) = \max_{\iota_{i,t}} k_{i,t}\pi_t(a_i) + \mathbb{1}\left[-\kappa k_{i,t} - \phi(\iota_{i,t}, a_i) + \Lambda_{t,t+1}V(k_{i,t+1}, a_i)\right], \tag{11}$$

$$\text{s.t. } k_{i,t+1} = (1-\delta)k_{i,t} + \iota_{i,t}, \tag{12}$$

$$\iota_{i,t} \geq 0, \tag{13}$$

where $\iota_{i,t}$ is the firm's choice of investment; $\phi(\iota_{i,t}, a_i)$ is an increasing function in both arguments that determines the marginal cost of investment; the indicator function reflects the firm's choice to either pay the maintenance cost $\kappa k_{i,t}$ or scrap its capital; and $\Lambda_{t,t+1}$ is the time t discount factor of consumption at time $t+1$. Following Abel (1983), I assume $\phi(\iota_{i,t}, a_i) = \frac{1}{2\Upsilon_t}\phi(a_i)\iota_{i,t}^2$, with $\phi(0) > 0$, $\phi' > 0$ and $\phi'' > 0$; and $\Upsilon_t > 0$ is a scaling factor that grows at the same rate as aggregate output to ensure the existence of a balanced growth path. As shown below, this formulation ensures the firm's investment is optimally always weakly positive, so the irreversibility constraint never binds. The dependence of ϕ on the level of the specific technology a captures the idea that different types of capital are differentially expensive to produce and install at any given time. This parametrization will be important when I take the model to firm-level data, but the qualitative and efficiency properties of the equilibrium do not depend on it.

Assuming for now that the firm does not scrap its capital, the first order condition for investment is

$$\frac{\phi(a_i)}{\Upsilon_t}\iota_{i,t} = \Lambda_{t,t+1}V_k(k_{i,t+1}, a_i). \tag{14}$$

Following Abel and Eberly (1997), I hypothesize that the solution to the value function $V(\cdot)$

is a linear function of the capital stock,

$$V\left(k_{i,t}, a_i\right) = v_t\left(a_i\right) k_{i,t} + \psi_t\left(a_i\right) \tag{15}$$

where $v(a)$ and $\psi(a)$ are unknown functions. With this hypothesis, the solution to the firm's investment problem is

$$\iota_{i,t} = \Upsilon_t \frac{\Lambda_{t,t+1} v_{t+1}\left(a_i\right)}{\phi\left(a_i\right)}, \tag{16}$$

which, since every term on the right-hand side is positive, confirms that investment is always weakly positive. To solve for the unknown functions $v(a)$ and $\psi(a)$, I substitute Equation 15 into Equation 11, assuming for now that the firm chooses not to scrap its capital:

$$\begin{aligned} v\left(a_i\right)_t k_{i,t} + \psi_t\left(a_i\right) = &\left(\pi_t\left(a_i\right) - \kappa + \Lambda_{t,t+1}\left(1-\delta\right) v_t\left(a_i\right)\right) k_{i,t} \\ &- \frac{1}{2\Upsilon_t}\phi\left(a_i\right)\iota_{i,t}^2 + \Lambda_{t,t+1}\left(v_{t+1}\left(a_i\right)\iota_{i,t} + \psi_{t+1}\left(a_i\right)\right) \end{aligned}$$

This equation must hold for all values of $k_{i,t}$, so the term multiplying $k_{i,t}$ on the left-hand side must equal the sum of the terms multiplying $k_{i,t}$ on the right-hand side, and similarly for the terms not multiplying $k_{i,t}$. These equalities give

$$v_t\left(a_i\right) = \pi_t\left(a_i\right) - \kappa + \left(1-\delta\right)\Lambda_{t,t+1} v_{t+1}\left(a_i\right), \tag{17}$$

and substituting in the solution to the investment problem (Equation 16),

$$\psi_t\left(a_i\right) = \frac{\Upsilon_t\left(\Lambda_{t,t+1} v_t\left(a_i\right)\right)^2}{2\phi\left(a_i\right)} + \Lambda_{t,t+1}\psi_{t+1}\left(a_i\right). \tag{18}$$

The function $v(a_i)$ is the value of each installed machine of type a_i, whereas $\psi(a_i)$ captures the present value of the rents accruing to the automation technology. For convenience, I also define the firm-specific price of installed capital as the discounted continuation value of a machine of type a_i:

$$p_{\iota,t}\left(a_i\right) \equiv \Lambda_{t,t+1} v_{t+1}\left(a_i\right). \tag{19}$$

Scrapping If firms do not pay the maintenance cost κ, their capital fully depreciates, but a firm that scraps its capital still owns its technology. The firm, therefore, chooses not to scrap if the continuation value of a machine exceeds the maintenance cost, $(1-\delta)\Lambda_{t,t+1} v_{t+1}(a_i) > \kappa$. The machine value function, incorporating the scrapping decision, is:

$$v_t\left(a_i\right) = \pi_t\left(a_i\right) + \mathbb{1}_{(1-\delta)p_{\iota,t}(a_t)>\kappa}\left[\left(1-\delta\right)\Lambda_{t,t+1} v_{t+1}\left(a_i\right) - \kappa\right]. \tag{20}$$

It follows that the scrapping threshold at the end of the period is defined implicitly by:

$$(1-\delta)\, p_{\iota,t}\,(a_i) = \kappa. \tag{21}$$

The automation level of the lowest machine installed at the beginning of time t is $a_{\ell,t}$, so the scrapping threshold condition implies that machines in $(a_{\ell,t}, a_{\ell,t+1}]$ are scrapped each period. In terms of the CDF of the automation distribution, the fraction of capital that is scrapped at the end of time t is $\varsigma_t = F_t\,(a_{\ell,t+1})$.

New Automation Technologies and Firm Entry Anticipating the discussion below, the existence of a balanced growth path in this model requires a constant a_h, and I study comparative statics of BGPs with different levels of a_h. For completeness, I describe how the economy responds to the discovery of new technologies. Starting from a steady state with $a_h = a_{h,t}$, assume that new automation technologies $(a_{h,t}, a_{h,t+1})$ are discovered in period t. Potential entrants draw technologies from the entire set and enter; consequently. a measure $a_{h,t+1} - a_{h,t}$ new firms are born with zero initial capital stock. The value function of a new firm is:

$$\begin{aligned} V\,(0, a_i) = \max_{k_{i,t+1}} & -\frac{1}{2\Upsilon_t}\phi\,(a_i)\,(k_{i,t+1})^2 + \Lambda_{t,t+1}V\,(k_{i,t+1}, a_i)\,, \\ & \text{s.t. } k_{i,t+1} \geq 0, \end{aligned} \tag{22}$$

and (similar to the above) initial investment is given by $k_{i,t+1} = \Upsilon_t \frac{\Lambda_{t,t+1} v_{t+1}(a_i)}{\phi(a_i)}$.

4.2 Households

The representative household chooses consumption C_t and savings S_{t+1} every period to solve the following intertemporal problem:

$$\max_{C_t, S_{t+1}} \sum_{t=0}^{\infty} \beta^t U(C_t), \tag{23}$$

where C is consumption, and $U\,(C)$ satisfies standard conditions. The household is subject to the following budget constraint:

$$C_t = W_t N + R_{S,t} S_t P_{S,t-1} - P_{S,t} S_{t+1}, \tag{24}$$

with $R_{S,t} = \frac{D_t + P_{s,t}}{P_{s,t-1}}$. The household saves in a mutual fund that owns the shares S_t of all firms in the economy. D_t (defined below) is the aggregate dividend (per share) of all firms, and $P_{S,t}$ is the time t price of a share in this mutual fund; W_t is the wage and N is (exogenous) labor supply. The equilibrium condition from household optimization is the standard intertemporal Euler equation:

$$1 = \Lambda_{t,t+1} R_{s,t+1}, \tag{25}$$

where $\Lambda_{t,t+1}$ is the discount factor between t and $t+1$, $\Lambda_{t,t+1} \equiv \beta \frac{U'(C_{t+1})}{U'(C_t)}$.

4.3 Aggregation

Similar to the static model of Section 2, aggregate output, labor input, and the capital stock are given by $Y_t = \int_{a_{\ell,t}}^{a_{h,t}} z(a)\, k_t(a)\ \mathrm{d}a$, $N = \int_{a_{\ell,t}}^{a_{h,t}} n_t(a)\ \mathrm{d}a$ and $K_t = \int_{a_{\ell,t}}^{a_{h,t}} k_t(a)\ \mathrm{d}a$, respectively, whereas aggregate investment and the aggregate price of investment are:

$$I_t = \int_{a_{\ell,t}}^{a_{h,t}} \iota_t(a)\ \mathrm{d}a \tag{26}$$

and

$$P_{I,t} = \int_{a_{\ell,t+1}}^{a_{h,t}} p_{\iota,t}(a)\, j_t(a)\ \mathrm{d}a \tag{27}$$

where $j_t(a)$ is the time-t density function of investment, $j_t(a) \equiv \left(\frac{\iota_t(a)}{I_t}\right)$. The dividend is the part of aggregate output that is not paid to workers in wages or used to maintain and invest in new capital, per share[6]:

$$D_t = \frac{Y_t - W_t N_t - \frac{P_{I,t}}{2} I_t - \kappa(1-\varsigma_t) K_t}{S_t}. \tag{28}$$

The aggregate capital stock of the economy evolves as follows:

$$K_{t+1} = (1-\delta)(1-\varsigma_t) K_t + I_t, \tag{29}$$

where δ is exogenous depreciation and ς_t is the fraction of capital that is scrapped in period t.

[6]Note that the aggregate resources used up in investment are given by the integral over goods used for investment at each firm, $\frac{1}{2\Upsilon_t} \int_{a_{\ell,t+1}}^{a_{h,t}} \phi(a_t)\, \iota_t(a)^2\ \mathrm{d}a = \frac{1}{2} \int_{a_{\ell,t+1}}^{a_{h,t}} p_{\iota,t}(a)\, \iota_t(a)\ \mathrm{d}a = \frac{P_{I,t}}{2} I_t$, where the second equality follows from firms' first-order condition for investment and the second from Equation 27).

4.4 Dynamics of the Automation Distribution $F(a)$

Unlike in the static model of Section 2, here the firm-size distribution $f(a)$ is an endogenous state variable, determined by the entry, ongoing investment, and scrapping decisions of firms. The law of motion for $f(a)$ is

$$f_{t+1}(a) = \begin{cases} \frac{K_t}{K_{t+1}}(1-\delta) f_t(a) + \frac{I_t}{K_{t+1}} j_t(a) & a_{\ell,t+1} < a < a_{h,t+1} \\ 0 & a \leq a_{\ell,t+1} \end{cases} \tag{30}$$

The first line is the evolution of the part of the capital stock that is not scrapped; it comes from aggregating the law of motion of capital at the firm level (Equation 12). The value of $f_{t+1}(a)$ is the weighted average of surviving capital plus new investment, where the weights are given by $\frac{K_t}{K_{t+1}}(1-\delta)$ and $\frac{I_t}{K_{t+1}}$, respectively. The second line corresponds to the part of the capital stock that is scrapped.

4.5 Equilibrium and Balanced Growth Path

An equilibrium of the dynamic model consists of sequences of: (i) aggregate allocations $\{C_t, S_t\}$; (ii) prices $\{W_t, P_{S,t}\}$; (iii) firm allocations $\{\iota_{i,t}, n_{i,t}\}$; and (iv) firm scrapping decisions, such that household and firm equilibrium conditions are satisfied, and markets for the final good savings and labor are cleared. Market clearing in final goods requires that all production (net of the cost of maintaining capital) is either consumed or invested, $Y_t = C_t + \frac{P_{I,t}}{2} I_t + \kappa(1-\varsigma_t)K_t$. Labor market clearing is $N = \int_{a_\ell}^{a_h} n(a)\, \mathrm{d}a$. The state variables of the model are the exogenous states H_t and $a_{h,t}$ (labor augmenting technology and frontier automation technology, respectively) and the endogenous states K_t, $a_{\ell,t}$ and $f_t(a)$ (the aggregate capital stock, the lower bound of technology and automation distribution).

Stationary Equilibrium and the Balanced Growth Path In analyzing the dynamic model, I focus on the stationary balanced growth path of the economy, which requires assuming that frontier automation a_h is constant along the BGP. In the Online Appendix, I present a version of the model in which automation grows in the BGP and balanced growth obtains as long as the set of tasks grows alongside it. This is very similar to the balanced growth result in Acemoglu and Restrepo (2018), and I, therefore, focus on a parametrization that highlights the novel insights of the putty-clay model.

In a stationary equilibrium with constant a_h, the lower bound a_ℓ is also constant so there is no scrapping on the BGP ($\varsigma = 0$). This also implies that capital is fully utilized, $a_w = a_\ell$, and the aggregate production function is Leontieff, $Y = AH_tN = AK_t$, where $A = \int_{a_\ell}^{a_h} z(a)f(a)\, \mathrm{d}a$.

I summarize the properties of the balanced growth path in the following proposition.

Proposition 3. *Balanced Growth. Assume labor augmenting technology H_t grows at exogenous exponential rate g and that frontier automation a_h is constant. The economy has a stationary balanced growth path with $f_t(a) = f(a)$ that satisfies the Jones and Scrimgeour (2008) definition: aggregate quantities $\{Y_t, C_t, I_t, K_t\}$ grow at rate g and factor shares are constant and strictly positive.*

Proof. See Appendix A.2. □

4.6 Analysis and long-run comparative statics

To illustrate the connection between the cost function $\phi(a)$ and the long-run equilibrium distribution $f(a)$, and to study comparative statics with respect to frontier automation a_h, I introduce a specific calibration of $\phi(a)$.

Given that the fraction of automated tasks is naturally bounded in $(0, 1)$, and considering both the empirical distributions plotted in Figure 2 and theoretical foundations developed in Section 2.3, the Beta distribution emerges as a natural modeling choice for $f(a)$. I therefore calibrate $\phi(a)$ such that the equilibrium distribution $f(a)$ is exactly Beta$(1, \rho)$ when $\gamma = 1$, $\kappa = 0$ and $a_h = 1$ (see Appendix A.4 for details of the derivation). Specifically, I calibrate ϕ as:

$$\phi(a) = \bar{\phi}\frac{a}{(1-a)^{\rho}}, \tag{31}$$

where $\bar{\phi}$ is a normalization such that $f(a)$ integrates to 1, and $\rho > 0$ maps to the Beta distribution shape parameter. The function is strictly convex and increasing, and the second derivative is increasing in ρ. This gives the interpretation that more automated machinery is more expensive to produce and install, and the higher is ρ, the faster the installation cost rises with the degree of automation.

Comparative statics with respect to ρ and γ Figure 3 illustrates equilibrium distributions for different values of ρ and γ for a fixed value of frontier technology a_h. The left panel of the figure plots two cost functions for different values of ρ. For higher ρ (the red line), the marginal cost of installation is higher for all $a > 0$. The middle panel shows the equilibrium distributions for the two parametrizations of the cost function for the case $\gamma = 1$. For $\rho = 1$, the stationary distribution $f(a)$ is uniform in (a_ℓ, a_h). With higher marginal installation cost ($\rho = 3$), the distribution is decreasing in a, with more mass on the left of the distribution. Intuitively, the more expensive it is to install more advanced capital (higher ρ), the relatively less advanced capital will be installed. In both cases, $a_\ell = 0$ so the competitive equilibrium

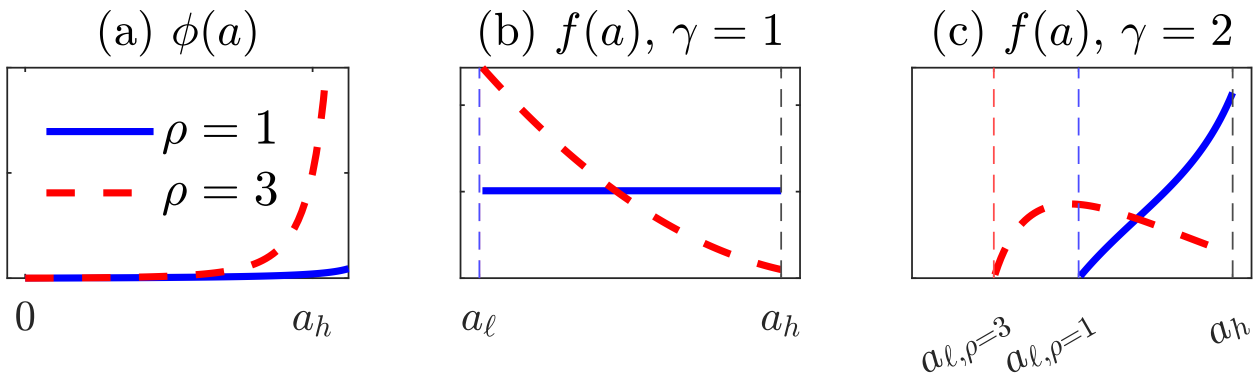


Figure 3: Illustration of stationary equilibrium distributions

Notes: (a) Cost function (Equation 31) for $\rho = 1$ (solid blue) and $\rho = 1$ (dashed red). (b) Stationary equilibrium distribution $f(a)$ for $\gamma = 1$ and $\rho = 1$ (solid blue) and $\rho = 1$ (dashed red). (b) Stationary equilibrium distribution $f(a)$ for $\gamma = 2$ and $\rho = 1$ (solid blue) and $\rho = 1$ (dashed red).

features firms with zero automation, and there will be a positive mass of firms at zero (which I do not draw in the figure to reduce clutter).

The right panel of Figure 3 illustrates equilibrium distributions for a higher value of γ, such that the productivity effects of automation are higher. With high γ and low ρ (the blue line on the right panel), the distribution is increasing in a and shifted to the right, with lower bound $a_{\ell,\rho=1}$. Intuitively, when automation is more productive (high γ) and cheap to install (low ρ), the distribution has more mass at high automation firms. The red line in the right panel illustrates a case with high γ and ρ, so automation is expensive and productive. In this case, the lower bound is above zero but lower than for the case with low ρ ($0 < a_{\ell,\rho=3} < a_{\ell,\rho=1}$), and the distribution has more mass at intermediate levels of automation.

To summarize, the equilibrium wage, productivity, and the share of automated tasks increase (decrease) in the productivity parameter γ (cost parameter ρ).

Long-run comparative statics with respect to a_h Figure 4 illustrates long-run comparative statics for wages (left column), productivity (middle), and the labor share (right) to frontier automation a_h, for different values of γ (top row) and ρ (bottom). In all cases, wages and productivity are increasing in a_h (weakly in the case of wages), and the effect of improved technology at the frontier is larger the more productive (higher γ) or cheaper to install (lower ρ) is automation technology. The increase in a_h introduces more productive technologies into the economy, which mechanically increases aggregate productivity. As labor reallocates to more automated firms, less productive firms exit, and wages increase.

The effect of higher frontier automation on the labor share depends on parameters. In most cases illustrated in Figure 4, the labor share is decreasing in a_h. The green dotted line in the top right panel shows that this is not a general property of the model. For high enough γ, the labor share is initially decreasing but eventually increasing in a_h. Intuitively, for this particular parametrization, when automation is very productive,

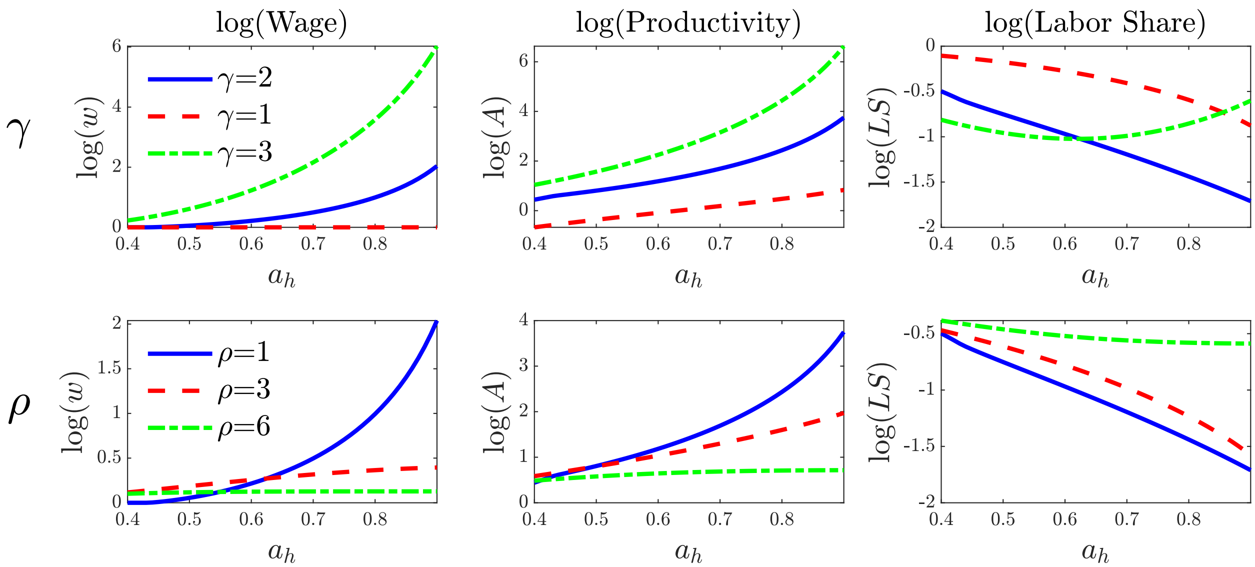


Figure 4: Comparative statics of putty-clay automation model

Notes: Comparative statics for the model. Each row corresponds to variations in a specific parameter: γ (row 1) and ρ (row 2). Each column presents the impact on a key variable: log(Wage) (left), log(Productivity) (middle), and log(Labor Share) (right). For each parameter, the plots show results for three different values (solid blue, dashed red, and dash-dotted green), illustrating how parameter changes influence these variables across the range of a_h.

5 Inefficient Rents and Automation

Although the output and labor markets in the economy of Section 4 are perfectly competitive, in equilibrium, firms earn technological (Ricardian) rents, even in the long run. In this section I examine whether the allocation of capital over automation technologies is efficient, given the presence of rents. To do so, I solve the following planning problem:

$$\max_{\iota_t(a)} \sum_{t=0}^{\infty} \beta^t U\left(C_t\right)$$

subject to the resource constraint, $Y_t = C_t + \frac{P_I}{2} I_t + \kappa K_t$, labor market clearing, $N = \int_{a_\ell}^{a_h} n(a)\ \mathrm{d}a$, and the capital accumulation equation, $k_{t+1}(a) = (1-\delta)k_t(a) + \iota_t(a)$ (the planner is also constrained by irreversibility, but as shown above this constraint does not bind in equilibrium). Expressing in terms of the automation distribution and substituting constraints into the objective function gives:

$$\max_{k_{t+1}(a)} \sum \beta^t U \left(\int_{a_\ell}^{a_h} z(a) \, k_t(a) \ \mathrm{d}a - \frac{1}{2\Upsilon_t} \int_{a_{\ell,t+1}}^{a_{h,t}} \phi(a) \left(k_{t+1}(a) - (1-\delta) \, k_t(a) \right)^2 \ \mathrm{d}a - \kappa \int_{a_{\ell,t}}^{a_{h,t}} k_t(a) \ \mathrm{d}a \right)$$

The first order condition with respect to $k_{t+1}(a)$ and in the stationary equilibrium gives:

$$f^*(a) = \frac{1}{r+\delta} \left(\frac{z(a) - \kappa}{\phi(a)} \right), \tag{32}$$

where $f^*(a)$ is the optimal $f(a)$. Intuitively, the planning solution equates the marginal social benefit, $\frac{z(a)-\kappa}{r+\delta}$, to the marginal social cost, $f^*(a)\phi(a)$, of an additional machine of type a. In contrast, the competitive equilibrium investment (Equation 16) equates private benefit and cost. The following proposition summarizes the efficiency properties of competitive equilibrium.

Proposition 4. *Above a threshold a_ℓ^*, the socially optimal distribution has more mass at higher automation than the competitive equilibrium,*

$$f^*(a) > f(a), \ \forall a \in (a_\ell^*, a_h).$$

The socially optimal minimum level of automation is higher than in the competitive equilibrium,

$$a_\ell^* > a_\ell.$$

Proof. See Appendix A.3. □

Relative to the competitive equilibrium, the socially optimal outcome removes the lowest automation firms, those below a_ℓ^*, and makes every firm above that threshold larger. In the socially optimal outcome, the fraction of tasks performed by capital is higher than in the decentralized equilibrium (since by Proposition 4, $\int_{a_\ell^*}^{a_h} af^*(a) \ \mathrm{d}a > \int_{a_\ell}^{a_h} af(a) \ \mathrm{d}a$). In this sense, the socially optimal outcome is more automated than the competitive equilibrium. In a decentralized implementation of the socially optimal outcome, both wages (because $a_\ell^* > a_\ell$) and productivity (because $f^*(a) > f(a)$) would be higher than in the competitive equilibrium, but the comparison of labor shares between the equilibria cannot be signed absent further assumptions on $f(a)$. I return to this question below using a parametrized version of the model.

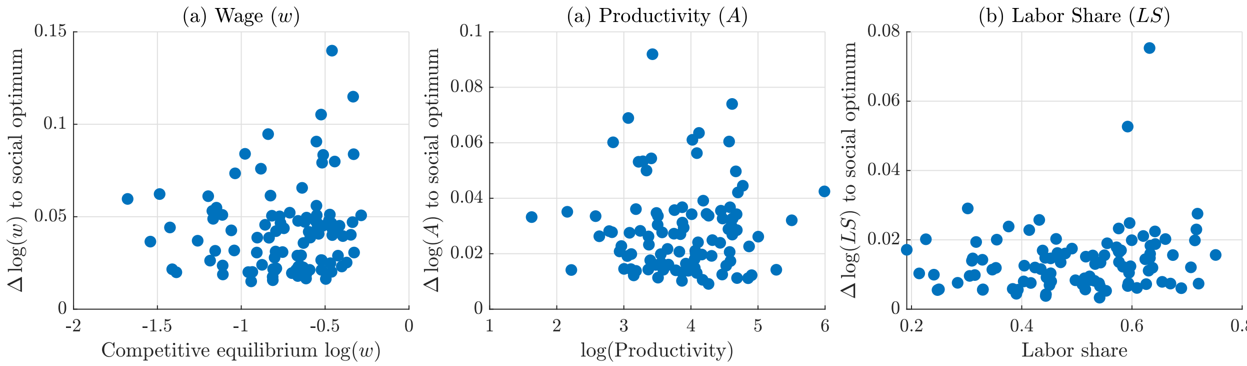


Figure 5: Comparison of competitive equilibrium and socially optimal outcomes

Notes: (a) Scatter plot of country-industry log(real wage) (source: EUKLEMS) against the model-implied log difference in wages (w) between the competitive equilibrium and socially optimal outcomes. (b) Scatter plot of country-industry log(labor productivity) (source: EUKLEMS) against the model-implied log difference in productivity (A) between the competitive equilibrium and socially optimal outcomes. (c) Scatter plot of country-industry labor share (source: EUKLEMS) against the model-implied log difference in labor share (LS) between the competitive equilibrium and socially optimal outcomes. See the text for a description of the estimation procedure.

To further understand the inefficiency, I take the ratio of the solutions:

$$\frac{f\left(a\right)}{f^{*}\left(a\right)}=\left(\frac{1}{1+r}\right)\frac{v\left(a\right)}{z(a)-\kappa}=\left(1-\frac{w}{z\left(a\right)-\kappa}\right). \tag{33}$$

The inefficiency is larger where private benefit $v(a)$ is smaller compared to social benefit $z(a)-\kappa$, which by the second inequality is the case when the profit share, net of fixed cost, $1-\frac{w}{z(a)-\kappa}$ is small (equivalently, where the labor share is high). In a relative sense, the planner wants firms with low profit shares to grow larger because underinvestment is most severe at these firms. To see this, consider the case of a firm with a very high $z(a)$ and, therefore, a very high profit margin. Because the difference between social and private benefits is negligible for that firm, it will be close to its socially optimal size in competitive equilibrium. This is not the complete story because the socially optimal outcome eliminates firms with the lowest profit shares, those between a_ℓ and a_ℓ^* in the competitive equilibrium.

There is a clear connection in this model between inefficiency and the presence of Ricardian rents, which arise because the putty-clay nature of technology prevents the marginal product of labor from being equalized across firms. In the dynamic equilibrium, these rents endure because the marginal cost of producing capital is increasing due to the convex production technology. Without adjustment costs, as in a standard vintage capital model, the investment would only go into the frontier technology, so with constant a_h, the only stationary equilibrium would be one in which all capital is at the technological frontier. In a more general model with growth in a_h, there would be a distribution of automation intensities and, therefore, Ricardian rents, but the competitive outcome would be efficient (because all investment would go into the frontier technology). The inefficient rents in this model can, therefore, be thought of as arising from the interaction of putty-clay technology and convex adjustment costs. In this particular setting, I have parametrized the marginal cost of investment, $\phi(a)$, to be type-specific, but Equation 33 shows that this is immaterial to the inefficiency result, except insofar as the marginal cost function is one of the parameters that go into determining the equilibrium wage.

5.1 Quantitative evaluation

To quantify differences between the competitive equilibrium and social optimum, I use European firm-level data from the Structure of Earnings Survey to estimate model parameters. Given that the model of Section 4 features a representative household that supplies a constant quantity of labor, I do not focus on welfare implications (which are obvious), but instead, I aim to quantify the differences in wages and productivity between the competitive equilibrium and the social optimum, and whether labor's share is "too low" in the laissez-faire equilibrium.

The automation distribution $f(a)$ is the key equilibrium object of the model, and the estimation procedure I describe below uses estimated empirical distributions to recover model parameters. In the model (Equation 36) $f(a)$ is determined by the value and cost functions, $v(a)$ and $\phi(a)$. I use the calibrated cost function introduced above (Equation 31) in the estimation procedure.

The estimation strategy is in two steps. First, I estimate the distributions of automation within industry-region cells using the routine occupation proxy described in Section 3.1. I employ kernel density estimation to approximate the empirical distribution of (one minus) this measure within country-industry cells and rescale the estimated density to bound the distribution between $\hat{a}_\ell$ and $\hat{a}_h$. Panels (b) and (c) of Figure 2 present three examples of densities estimated following this procedure.

Second, I estimate the key structural parameters. The model has 7 total parameters. I calibrate the balanced growth rate ($g = 2\%$), subjective discount factor (β, calibrated so that the steady-state interest rate is 2.5%), and depreciation rate ($\delta = 10\%$) to standard values. As to the remaining parameters, ρ determines the convexity of $\phi(a)$; the higher is $\gamma > 0$, the larger the effect of automation on firm productivity; and κ is the fixed cost of operation. The final parameter, $\bar{\phi}$, is a normalization that ensures the estimated distribution integrates to 1.

The estimation uses the model's analytical solution for the stationary distribution along the balanced growth path, derived from the optimal investment condition in Equation 36. For any candidate parameter vector, I compute the model-implied probability density function. The estimation procedure minimizes the squared deviations between the empirical and model-generated distributions, evaluated at N grid points corresponding to the support of the empirical density. This approach allows me to recover the deep parameters of the model while maintaining a tight connection between the theory and observed patterns of automation in region-industry cells.

Figure 5 illustrates the estimated effects on wages, productivity, and the labor share of moving from the competitive equilibrium to the social planner's solution. From left to right, each panel plots wages, productivity and the labor share (from KLEMS) against the estimated model-implied log difference between planner and laissez-faire in each variable. The average changes in wages and productivity are 4.3% and 2.9%, respectively, resulting in an average increase in the labor share of 1.4%. As discussed above, in principle, the labor share could be higher or lower in the socially optimal outcome, but in practice, all changes in the labor share are positive. There is substantial heterogeneity in the estimated gains in wages and productivity across country-industry cells, and in the next section, I study the reason for these differences through the model lens.

5.2 Discussion and comparative statics

Figure 5 shows substantial heterogeneity across country-industry cells in the degree to which wages and productivity are lower in the competitive equilibrium relative to the social optimum. Figure 6 illustrates comparative statics for the calibrated model for three critical parameters, γ, ρ and frontier automation a_h.

The first row illustrates the effect of increasing γ, which governs the productivity effects of automation. Since higher γ increases the productivity of all firms, the effect on aggregate productivity is mechanical. The wage increase results from increased labor demand through this productivity effect. Comparing the competitive and socially optimal outcomes, the productivity gap shrinks as γ increases, whereas the opposite is true of the wage gap. Intuitively, this is the case because as γ increases, the tail of the productivity distribution for the economy thickens, and a smaller proportion of firms produce a higher proportion of aggregate output. Because (as discussed above) firms with high productivity are closer to their optimal size, overall, a more productive economy is less distorted. However, because the economy is very productive, correcting this relatively small distortion has a large effect on labor demand and, therefore, on wages. A similar logic can be seen in the third row of the figure. Increasing frontier automation a_h raises overall productivity and, therefore, has similar effects to increasing γ.

The labor share comparative static for γ (top right panel of Figure 6) shows that when γ is low, the socially optimal labor share is lower than in laissez-faire because, in this case, the competitive equilibrium admits firms with zero automation, and the planner always eliminates such firms. The labor share gap between the equilibria increases and falls as γ grows.

The labor share is monotonically decreasing in a_h (bottom right panel of Figure 6), and the gap between the competitive and socially optimal outcomes is increasing in a_h. Since automation is a leading explanation for observed falls in labor shares across economies in the last decades, this suggests that labor shares may have fallen by *too much* relative to the socially desired outcome.

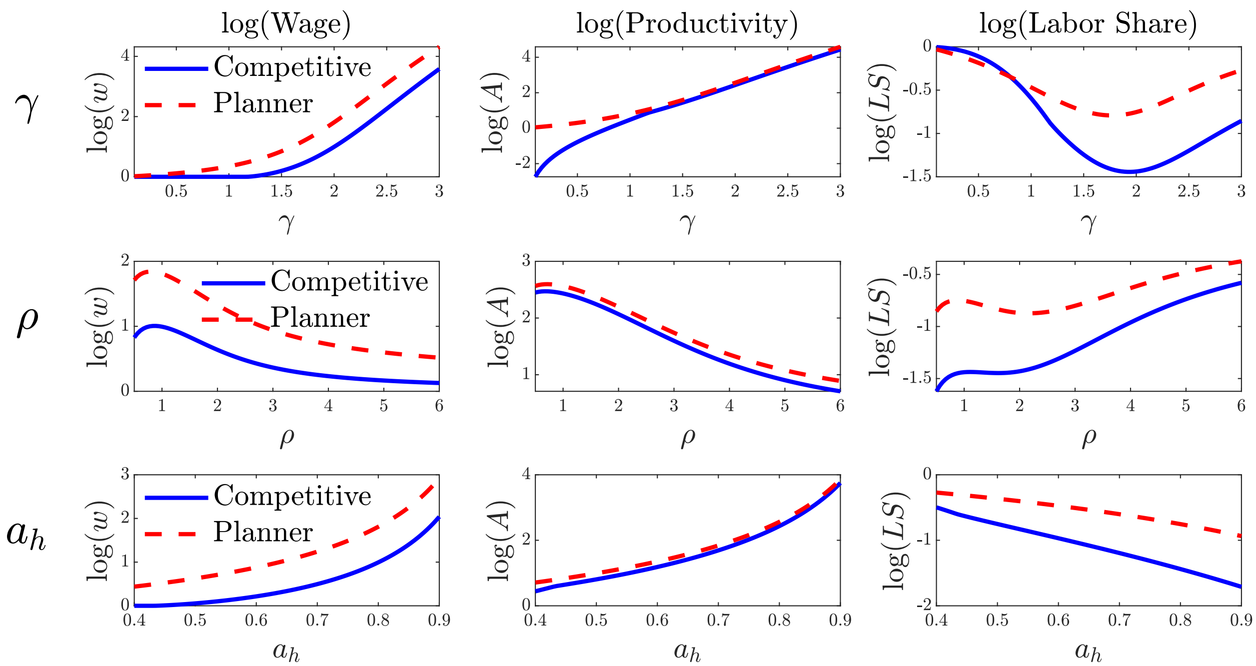


Figure 6: Comparison of the competitive and socially optimal outcomes

Notes: Long-run comparative statics for wages (column 1), productivity (column 2), and the labor share (column 3). Each row corresponds to variations in a specific parameter: γ (row 1), ρ (row 2), and a_h (row 3). Each panel plots the comparison of competitive equilibrium (solid blue line) with the socially optimal outcome (dashed red line). The baseline parametrization is $\gamma = 2$, $\rho = 1$, $a_h = 0.8$ and $\kappa = 0$.

The comparative static for ρ, in the second row of Figure 6 shows the opposite logic to those for γ and a_h. Increasing ρ increases the marginal cost of installation disproportionately for more automated capital, such that the equilibrium distribution has less automation and, therefore, lower productivity the higher is ρ. This also means that the economy is more distorted the higher is ρ, because more productive firms are smaller relative to their optimal size.

Overall, productivity gaps are larger in economies that have lower productivity from automation, either due to the level of technology (low a_h), the productivity effects of automation (low γ), or the high cost of installing advanced capital (high ρ). This suggests that policy intervention to correct the misallocation of automation capital would narrow productivity gaps across country-industry cells. The opposite is true of wage gaps, which are larger in high-wage economies, suggesting that policy intervention would increase wage differentials across country-industry cells. Moving to the socially optimal outcome would result in higher labor shares (except in economies with laggard firms with zero automation), with larger increases in labor shares in more automated economies.

6 Conclusion

The putty-clay automation model developed in this paper offers novel insights into the heterogeneous effects of increased automation at polar ends of the distribution of automation technology. In this theoretical framework, I find that increased automation at laggard firms raises wages and the labor share, while advances at the frontier reduce the labor share. Using European worker-level data, I document dispersion in firm-level routine employment shares within region-industry pairs, which I interpret as evidence of dispersion in automation technology. I use this variation in reduced-form regressions, finding evidence for the heterogeneous effects of automation at different points of the distribution predicted by the theory.

The model demonstrates that the competitive equilibrium allocation of capital across automation technologies is inefficient, with relatively high-automation firms remaining too small and too many low-automation (hence, low productivity) firms remaining active. Quantitative analysis suggests this misallocation results in significant wage and productivity losses in European country-industry pairs. Moreover, the model suggests that the gap between competitive and socially optimal labor shares widens as frontier automation advances, suggesting recent declines in labor shares may have been inefficiently large.

Automation technology is an important setting to study misallocation in a putty-clay framework. It is particularly interesting because it is possible to use routine employment shares as a proxy for technology distribution. The problem is more general, however, and a fruitful avenue for research would be to study this problem in other settings where technological rents are a prevalent feature (e.g., energy markets).

In this paper, I study the planning problem but not its decentralization. Previous literature has studied the effects of corporate taxation on the labor share (Kaymak and Schott (2023)) and automation (Acemoglu et al. (2020)), and this would be an interesting question to study in the putty-clay framework. Previous literature has also emphasized the first-order importance of heterogeneous effects on different types of workers (Beraja and Zorzi (2024), Hemous and Olsen (2022), Acemoglu and Restrepo (2022)), on which this paper is silent. A fruitful avenue of future research would be to consider jointly the effects of capital and worker heterogeneity.

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A Proofs and derivations

A.1 Proof of Proposition 2

I start by proving the following Lemma:

Lemma 1. *If $a \sim B(1,\rho;a_\ell,a_h)$, so that the PDF of a, $f(a) = \rho\frac{(a_h-a)^{\rho-1}}{(a_h-a_\ell)^\rho}$, then $z(a) = \left(\frac{1}{1-a}\right)^\gamma$ is distributed with CDF $G(z)$:*

$$G(z) = 1 - \left(1 - \frac{1-\left(\frac{z_\ell}{z}\right)^{\frac{1}{\gamma}}}{1-\left(\frac{z_\ell}{z_h}\right)^{\frac{1}{\gamma}}}\right)^\rho \tag{34}$$

and $z \in [z_\ell, z_h]$, with $z_\ell = \left(\frac{1}{1-a_\ell}\right)^\gamma$ and $z_h = \left(\frac{1}{1-a_h}\right)^\gamma$.

Proof. Start with the CDF $G(z)$, $G(z) = 1 - \left(\frac{\left(\frac{z_\ell}{z}\right)^{\frac{1}{\gamma}} - \left(\frac{z_\ell}{z_h}\right)^{\frac{1}{\gamma}}}{1-\left(\frac{z_\ell}{z_h}\right)^{\frac{1}{\gamma}}}\right)^\rho$. The random variable $\tilde{u} = G(z)$ is uniformly distributed in $[0,1]$ (by the probability integral transformation).

$$\tilde{u} = 1 - \left(\frac{\left(\frac{z_\ell}{z}\right)^{\frac{1}{\gamma}} - \left(\frac{z_\ell}{z_h}\right)^{\frac{1}{\gamma}}}{1-\left(\frac{z_\ell}{z_h}\right)^{\frac{1}{\gamma}}}\right)^\rho$$

If $\tilde{u} \sim U[0,1]$, then $u = 1-\tilde{u}$ is also $u \sim U[0,1]$. Now, express z as a function of u:

$$z = \left(\left(\frac{1}{z_h}\right)^{\frac{1}{\gamma}} + \left(\left(\frac{1}{z_\ell}\right)^{\frac{1}{\gamma}} - \left(\frac{1}{z_h}\right)^{\frac{1}{\gamma}}\right) u^{\frac{1}{\rho}}\right)^{-\gamma}$$

By the probability integral transform, the random variable $\tilde{\chi} = u^{\frac{1}{\rho}}$ is distributed $B(\rho,1)$, $\tilde{\chi} \in [0,1]$. It follows that the random variable $\chi = z_h^{-\frac{1}{\gamma}} + \left(z_\ell^{-\frac{1}{\gamma}} - z_h^{-\frac{1}{\gamma}}\right)\tilde{\chi}$ is distributed $B(\rho,1)$ with support $\chi \in \left[z_h^{-\frac{1}{\gamma}}, z_\ell^{-\frac{1}{\gamma}}\right]$. So $z = \chi^{-\gamma}$ has distribution $G(z)$. Now, let $a \equiv 1-\chi$. Since $\chi \sim B\left(\rho, 1; z_h^{-\frac{1}{\gamma}}, z_\ell^{-\frac{1}{\gamma}}\right)$, $a \sim B(1,\rho;a_\ell,a_h)$, with $a_\ell \equiv 1 - z_\ell^{-\frac{1}{\gamma}}$ and $a_h \equiv 1 - z_h^{-\frac{1}{\gamma}}$. Finally, let $\tilde{a} = qa$. Then, $\tilde{a} \sim B\left(1, \rho; \tilde{a}_\ell, \tilde{a}_h\right)$, with $a_\ell = \frac{\tilde{a}_\ell}{q}$ and $a_h = \frac{\tilde{a}_h}{q}$[7], and $z = \left(\frac{q}{q-\tilde{a}}\right)^\gamma = \left(\frac{1}{1-a}\right)^\gamma$

$\square$

Now, I show how to go from the distribution $G(z)$ to the CES aggregate production function. Aggregate output Y is:

$$Y = \int_w^{z_h} zk(z)\ \mathrm{d}z = K \int_w^{z_h} zg(z)\ \mathrm{d}z$$

Divide both sides by aggregate capital K to obtain:

$$y = \int_w^{z_h} zg(z)\ \mathrm{d}z = \int_w^{z_h} \sigma \frac{\left(\frac{z_\ell}{z}\right)^{1-\sigma}}{1-\left(\frac{z_\ell}{z_h}\right)^{1-\sigma}} \left(1 - \frac{1-\left(\frac{z_\ell}{z}\right)^{1-\sigma}}{1-\left(\frac{z_\ell}{z_h}\right)^{1-\sigma}}\right)^{\frac{\sigma}{1-\sigma}-1} \mathrm{d}z$$

Note

$$1 - G(w) = \left(\frac{\left(\frac{z_\ell}{w}\right)^{1-\sigma} - \left(\frac{z_\ell}{z_h}\right)^{1-\sigma}}{1-\left(\frac{z_\ell}{z_h}\right)^{1-\sigma}}\right)^{\frac{\sigma}{1-\sigma}} = \frac{\alpha}{\alpha + (1-\alpha)(H \cdot n)^{\frac{\sigma-1}{\sigma}}}$$

Substitute in

$$y = (z_h)^{1-\sigma} (z_\ell)^\sigma \left(\frac{1-\left(\frac{z_\ell}{z_h}\right)^{1-\sigma}}{1-\left(\frac{w}{z_h}\right)^{1-\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = A\left(\alpha + (1-\alpha)(H \cdot N)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

[7] Proof: start with $f(\chi) = \frac{\rho\left(\chi - H^{-\frac{1}{\gamma}}\right)^{\rho-1}}{\left(L^{-\frac{1}{\gamma}} - H^{-\frac{1}{\gamma}}\right)^\rho}$ and substitute in $a = 1 - \chi$

$$f(x) = \frac{\rho\left(1 - a - H^{-\frac{1}{\gamma}}\right)^{\rho-1}}{\left(L^{-\frac{1}{\gamma}} - H^{-\frac{1}{\gamma}}\right)^\rho} = \frac{\rho\left((1-a_h) - a\right)^{\rho-1}}{\left((1-a_h) - \left(1 - L^{-\frac{1}{\gamma}}\right)\right)^\rho} = \frac{\rho\left(a_h - a\right)^{\rho-1}}{\left(a_h - a_\ell\right)^\rho}$$

So $x \sim B\left(1, \rho; \ell, h, 1 - a_h\right)$. Now, let $\tilde{a} = qx$.

$$f(\tilde{a}) = \frac{1}{q} \frac{\rho\left(a_h - \frac{\tilde{a}}{q}\right)^{\rho-1}}{\left(a_h - a_\ell\right)^\rho} = \frac{1}{q^\rho} \frac{\rho\left(qa_h - \tilde{a}\right)^{\rho-1}}{\left(a_h - a_\ell\right)^\rho} = \frac{\rho\left(\tilde{a}_h - \tilde{a}\right)^{\rho-1}}{\left(\tilde{a}_h - \tilde{a}_\ell\right)^\rho}$$

Multiply both sides by K:

$$Y = A\left(\alpha K^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(H \cdot N)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

which is the CES production function with $A = (z_h)^{1-\sigma}(z_\ell)^{\sigma}$ and $\alpha = 1 - \left(\frac{z_\ell}{z_h}\right)^{1-\sigma}$. Or, expressed in terms of the parameters of the automation distribution $f(a)$, $A = \frac{(1-a_\ell)^{-\frac{\sigma}{1-\sigma}}}{1-a_h}$ and $\alpha = \frac{a_h - a_\ell}{1-a_\ell}$. The labor share expression follows from substituting for A, α and $\frac{W}{H}$ into the expression for the labor share with a CES production function, $LS = (1-\alpha)^{\sigma} A^{\sigma-1}\left(\frac{W}{H}\right)^{1-\sigma}$.

A.2 Proof of Proposition 3

I derive the detrended equilibrium conditions of the stationary balanced growth path of the model and verify that it satisfies the Jones and Scrimgeour (2008) definition. In the BGP, Y_t, C_t, I_t and K_t all grow at rate g. For notational convenience I set the steady state value of the scaling factor equal to steady state investment ($\Upsilon = I$). The equilibrium conditions are:

1. (Household) Euler equation

$$\Lambda^{-1} \equiv 1 + r = (1+g)\left(\frac{D}{P_S} + 1\right) \tag{35}$$

2. Firm investment (note that from firm capital accumulation, $f(a) = j(a)$ in the stationary BGP)

$$f(a) = \frac{1}{1+r}\frac{v(a)}{\phi(a)} \tag{36}$$

   with

$$v(a) = \left(\frac{1+r}{r+\delta}\right)(z(a) - w - \kappa) \tag{37}$$

3. Scrapping condition

$$w = z(a_\ell) - \left(\frac{1+r}{1-\delta}\right)\kappa \tag{38}$$

4. Production function

$$Y = AK = AHN \tag{39}$$

   with

$$A \equiv \int_{a_\ell}^{a_h} z(a) f(a) \; \mathrm{d}a \tag{40}$$

5. Goods market clearing

$$Y = C + \frac{P_I}{2} I + \kappa K \tag{41}$$

Or

$$C = K \left(\int_{a_\ell}^{a_h} z(a) f(a) \ \mathrm{d}a - \frac{(g+\delta)}{2} \int_{a_\ell}^{a_h} \phi(a) f^2(a) \ \mathrm{d}a - \kappa \right) \tag{42}$$

6. Labor market clearing

$$1 = \int_{a_\ell}^{a_h} f(a) \ \mathrm{d}a \tag{43}$$

The labor share is

$$LS = \frac{WN}{Y} = \frac{z(a_\ell) - \left(\frac{1+r}{1-\delta}\right)\kappa}{\int_{a_\ell}^{a_h} z(a) f(a) \ \mathrm{d}(a)} = \frac{w}{A} \tag{44}$$

From Equation 43, with constant a_h and $f(a)$, a_ℓ is constant. It follows that w (from Equation 38) and A (from Equation 40) are constant, so the labor share (Equation 44) is constant. Finally, with constant A, $\frac{K}{Y}$ (from 39) and $\frac{C}{Y}$ (from 42) are constant.

A.3 Proof of Proposition 4

Planner's problem

$$\max_{\iota_t(a)} \sum \beta^t U(C_t)$$

s.t. goods market clearing, $Y_t = C_t + \frac{P_I}{2} I_t + \kappa K_t$, labor market clearing $N = \int_{a_{\ell,t}}^{a_h} n_t(a) \ \mathrm{d}a$, and capital accumulation, $k_{t+1}(a) = (1-\delta)k_t(a) + \iota_t(a)$, with $\iota_t(a) \geq 0$ for $a \in (0, a_h)$ and $\iota_t(a) = 0$ otherwise. Rewrite goods market clearing:

$$C_t = \int_{a_\ell}^{a_h} z(a) k_t(a) \ \mathrm{d}a - \frac{1}{2\Upsilon_t} \int_{a_{\ell,t+1}}^{a_{h,t}} \phi(a) \left(k_{t+1}(a) - (1-\delta) k_t(a)\right)^2 \ \mathrm{d}a - \kappa \int_{a_{\ell,t}}^{a_{h,t}} k_t(a) \ \mathrm{d}a$$

Rearranging and substituting in the resource constraint, the planner's problem is:

$$\max_{k_{t+1}(a)} \sum \beta^t U \left(\int_{a_\ell}^{a_h} (z(a) - \kappa) k_t(a) \ \mathrm{d}a - \frac{1}{2\Upsilon_t} \int_{a_{\ell,t+1}}^{a_{h,t}} \phi(a) \left(k_{t+1}(a) - (1-\delta) k_t(a)\right)^2 \ \mathrm{d}a \right) + \mu_t \left(N - \int_{a_{\ell,t}}^{a_h} \frac{k_t(a)}{H_t} \ \mathrm{d}a \right)$$

where μ is the Lagrange multiplier on labor market clearing. The first order condition wrt $k_{t+1}(a)$ is,

$$(k_{t+1}(a)-(1-\delta)k_t(a))-(1-\delta)\frac{\Upsilon_t}{\Upsilon_{t+1}}\Lambda_{t,t+1}(k_{t+2}(a)-(1-\delta)k_{t+1}(a))=\Lambda_{t,t+1}\Upsilon_t\left(\left(\frac{z(a)-\kappa}{\phi(a)}\right)\right)$$

with complementary slackness condition $\mu_t\left(N-\int_{a_{\ell,t}}^{a_h}\frac{k_t(a)}{H_t}\,\mathrm{d}a\right)=0$. In the stationary balanced growth path, noting that $k_t=K_tf(a)$ and that quantities grow at rate g, the solution is:

$$f^*(a)=\frac{1}{r+\delta}\left(\frac{z(a)-\kappa}{\phi(a)}\right)$$

with $f^*(a)=0\;\forall a\notin(a_\ell^*,ah)$, where a_ℓ^* is defined by $1=\int_{a_\ell^*}^{a_h}f(a)\,\mathrm{d}a$. Contrast this with the competitive equilibrium (Equation 36):

$$f(a)=\frac{1}{1+r}\frac{v(a)}{\phi(a)}.$$

In the stationary competitive equilibrium, $v(a)=\left(\frac{1+r}{r+\delta}\right)(z(a)-w-\kappa)$. It follows that

$$f^*(a)>f(a),$$

because $w>0$. Further, since both distributions must integrate to 1 over their support in equilibrium, $\int_{a_\ell}^{a_h}f(a)\;\mathrm{d}a=\int_{a_\ell^*}^{a_h}f^*(a)\;\mathrm{d}a=1$, it follows that:

$$a_\ell^*>a_\ell.$$

A.4 Cost function

I derive $\phi(a)$ such that f(a) is exactly Beta in the steady state if $\kappa=0$, $a_h=1$, $a_\ell=0$ and $\gamma=1$. The first order condition for investment (Equation 36) reads:

$$f(a)=\frac{1}{1+r}\frac{v(a)}{\phi(a)}$$

Substituting in for $v(a)$ in the steady state with $\kappa=0$, $a_h=1$, $a_\ell=0$ and $\gamma=1$:

$$f(a)=\left(\frac{1}{r+\delta}\right)\frac{\left(\frac{1}{1-a}\right)-1}{\phi(a)}$$

The Beta$(1,\rho)$ distribution is:

$$f(a) = \frac{(1-a)^{\rho-1}}{B(1,\rho)}$$

Equate,

$$\frac{(1-a)^{\rho-1}}{B(1,\rho)} = \left(\frac{1}{r+\delta}\right) \frac{\left(\frac{1}{1-a}\right) - 1}{\phi(a)},$$

and solve for $\phi(a)$,

$$\phi(a) = \bar{\phi}\frac{a}{(1-a)^{\rho}}.$$

Where

$$\bar{\phi} \equiv \frac{B(1,\rho)}{r+\delta}.$$

B Data Description

B.1 Eurostat Structure of Earnings Survey

The primary data source for this analysis is the Eurostat Structure of Earnings Survey (SES), a repeated cross-sectional business survey conducted every four years. Covering 25 countries over five waves (2002-2018), the SES collects detailed micro-level data on employee earnings, working conditions, and characteristics (e.g., gender, age, occupation, education), as well as employer attributes (e.g., industry, size, location). Data are collected for enterprises with at least 10 employees across most sectors, excluding public administration, although some countries voluntarily provide additional data on smaller enterprises and public administration. Using a two-stage sampling design, the survey first selects stratified random samples of local units based on criteria such as economic activity, enterprise size, and region (NUTS 1 level) and then samples employees within those units. The gross hourly earnings data, include wages, salaries, overtime pay, bonuses, and allowances before deductions for taxes and social security contributions. This dataset provides comprehensive and comparable insights into the relationship between employee and employer characteristics and earnings across the European Union. Table 3 lists the SES variables used in the empirical analysis, Table 4 lists the industries used, and Table 6 lists the occupations and definition of routine occupation.

Table 3: Eurostat Structure of Earnings Survey variable codes and their descriptions

Variable code	**Variable label**
YEAR	Identification of the reference period (e.g.2010)
A11	Geographical location of the statistical unit (local unit) - NUTS-1
A13	Principal economic activity of the local unit (NACE Rev. 2)
A14	Form of economic and financial control
A15	Collective pay agreement
A12_CLASS	Size class category of enterprise to which the local unit belongs
B21	Sex
B22_CLASS	Age group category
B23	Occupation in the reference month (ISCO-08)
B25	Highest successfully completed level of education and training (ISCED-97)
B27	Full-time or part-time employee
B43	Average gross hourly earnings in the reference month
COUNTRY	Country code

Table 4: Industry Codes and Descriptions (NACE Rev. 2)

	Code	**Description**
1	**10-18**	**Food, beverages, tobacco, textiles, apparel, wood, paper, printing**
2	**19-23**	**Fossil fuels, chemicals, pharmaceuticals, rubber, non-metallic minerals**
3	**24-25**	**Basic metals and fabricated metal products**
4	**26-27**	**Computers, electronics, electrical equipment**
5	**28-32**	**Machinery, motor vehicles, transport equipment, other manufacturing**
6	45-46	Wholesale and retail trade; repair of motor vehicles and motorcycles
7	47	Retail trade, except of motor vehicles and motorcycles
8	49-52	Transportation and storage
9	53+61-63	Postal services, telecommunications, and information services
10	B+E	Mining, quarrying, and energy supply
11	F	Construction
12	I	Accommodation and food service activities
13	K+L+M+N	Financial, real estate, professional, administrative, and support services
14	R+S	Arts, entertainment, recreation, and other services

Notes: Industries (manufacturing in bold) included in the regressions reported in Tables 1 and 2.

Table 5: Country-Industry $\hat{a}_h - \hat{a}_\ell$ gap

	10-18	**19-23**	**24-25**	**26-27**	**28-32**	**45-46**	**47**	**49-52**	**53+61-63**	**B+E**	**F**	**I**	**K+L+M+N**	**R+S**
BG	0.8	0.71	0.72	0.68	0.75	0.78	0.67	0.67	0.9	0.74	0.73	0.51	0.85	0.82
CY	0.74	-	-	-	-	0.64	0.58	0.72	0.79	0.75	0.73	0.39	0.86	0.86
CZ	0.81	0.65	0.56	0.7	0.59	0.79	0.78	0.75	0.83	0.66	0.74	0.57	0.93	0.79
DE	0.85	0.72	0.69	0.73	0.73	0.8	0.78	0.87	0.85	0.78	0.71	0.66	0.82	0.8
DK	0.91	0.85	0.8	0.86	0.83	0.84	0.74	0.89	0.91	0.87	0.88	0.72	0.9	0.86
EE	0.83	0.75	0.75	0.85	0.76	0.78	0.71	0.85	0.87	0.75	0.84	0.56	0.88	0.85
EL	0.77	0.7	0.73	0.76	0.73	0.71	0.62	0.81	0.81	0.75	0.8	0.64	0.81	0.78
ES	0.8	0.76	0.7	0.79	0.72	0.78	0.7	0.8	0.88	0.81	0.72	0.71	0.82	0.8
FR	0.71	0.58	0.64	0.64	0.63	0.64	0.63	0.74	0.67	0.78	0.69	0.66	0.76	0.76
HR	0.88	0.79	0.77	0.87	0.86	0.81	0.76	0.84	0.82	0.72	0.8	0.63	0.89	0.89
HU	0.77	0.73	0.68	0.75	0.72	0.73	0.72	0.68	0.83	0.67	0.71	0.6	0.86	0.8
IT	0.63	0.61	0.59	0.65	0.62	0.63	0.65	0.6	0.63	0.62	0.55	0.54	0.69	0.61
LT	0.72	0.72	0.65	0.69	0.69	0.64	0.71	0.75	0.8	0.7	0.69	0.57	0.74	0.73
LV	0.79	0.68	0.72	0.74	0.63	0.75	0.73	0.81	0.87	0.73	0.82	0.67	0.9	0.75
MT	0.64	0.67	0.36	0.68	0.49	0.58	0.62	0.64	0.8	0.33	0.47	0.52	0.75	0.61
NL	0.61	0.6	0.53	0.63	0.6	0.57	0.56	0.64	0.59	0.67	0.57	0.5	0.65	0.57
NO	0.85	0.76	0.67	0.78	0.77	0.82	0.51	0.81	0.9	0.83	0.77	0.52	0.87	0.81
PL	0.83	0.76	0.66	0.77	0.68	0.8	0.72	0.78	0.78	0.72	0.84	0.69	0.89	0.76
PT	0.81	0.75	0.69	0.81	0.67	0.75	0.8	0.81	0.85	0.78	0.76	0.66	0.82	0.72
RO	0.78	0.73	0.67	0.76	0.73	0.71	0.74	0.77	0.87	0.68	0.7	0.6	0.89	0.86
SE	0.81	0.77	0.64	0.78	0.77	0.76	0.79	0.87	0.88	0.84	0.78	0.59	0.9	0.86
SK	0.8	0.73	0.61	0.78	0.66	0.75	0.8	0.8	0.83	0.72	0.73	0.54	0.93	0.87

Notes: Country-industry difference between $\hat{a}_h$ and $\hat{a}_\ell$. See Section 3.1 for descriptions of how these variables are computed and Table 4 for industry descriptions.

Table 6: ISCO Occupation Codes and Descriptions

Code	Occupation Name
11	Chief executives, senior officials, and legislators
12	Administrative and commercial managers
13	Production and specialized services managers
14	Hospitality, retail, and other services managers
21	Science and engineering professionals
22	Health professionals
23	Teaching professionals
24	Business and administration professionals
25	Information and communications technology professionals
26	Legal, social, and cultural professionals
31	Science and engineering associate professionals
32	Health associate professionals
33	**Business and administration associate professionals**
34	Legal, social, cultural, and related associate professionals
35	Information and communications technicians
41	**General clerical support workers**
42	**Customer services clerks**
43	**Numerical and material recording clerks**
44	**Other clerical support workers**
51	**Personal service workers**
52	**Sales workers**
53	Personal care workers
54	Protective services workers
62	**Market-oriented skilled forestry, fishery, and hunting workers**
71	**Building and related trades workers (excluding electricians)**
72	**Metal, machinery, and related trades workers**
73	**Handicraft and printing workers**
74	**Electrical and electronics trades workers**
75	**Food processing, woodworking, garment, and other trades workers**
81	**Drivers and mobile plant operators**
82	**Assemblers**
83	**Agricultural, forestry, and fishery laborers**
91	**Cleaners and helpers**
93	Laborers in mining, construction, manufacturing and transport
94	**Food preparation assistants**
95	**Street and related sales and service workers**
96	**Refuse workers and other elementary workers**

Notes: Occupations included in the regressions reported in Table 1. Bolded occupations are classified as routine. I classify occupations as routine by, first, classifying tasks (detailed work activities from O*NET) for US SOC 2010-coded occupations using OpenAI word embeddings, and assigning tasks to 3 digit ISCO occupations using the BLS ISCO-08 to SOC 2010 crosswalk. The classification procedure is described in detail in Martinez and Moen-Vorum (2024). Occupations in the SES are coded using 2 digits, so I map the 3 digit routine scores to 2 digits using occupation shares from the Eurostat Labor Force Survey (in which occupations are coded at 3 digits). The bolded 2-digit occupations are those with above average routine scores.