Does Automation Lower the Labor Share?*

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Abstract

A prominent explanation for declining labor shares is automation. We test this mechanism directly at the firm level, drawing on a central prediction of the task-based model of production: firms that automate more should see larger declines in routine employment and labor share. Using administrative data from France, we find no support for this mechanism. Changes in routine employment share are uncorrelated or negatively correlated with changes in labor share. This pattern holds across sectors and specifications. Our findings do not support the notion that that automation lowers the labor share and points to mechanisms absent from the standard task model.

Keywords: labor share, automation, routinization

JEL codes: E25, J23, O33

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1 Introduction

It has been widely argued that automation is a key driver of the decline in the labor share—the share of value added accruing to labor (Karabarbounis and Neiman, 2014; Acemoglu et al., 2020; Acemoglu and Restrepo, 2022; Hubmer and Restrepo, forthcoming), and that the introduction of new labor-intensive tasks is needed to stabilize the labor share of GDP (Acemoglu and Restrepo, 2018, 2019). Existing work has examined this relationship at the industry level, assessing the implications of industry-level automation for industry and aggregate labor shares (Autor and Salomons, 2018; vom Lehn, 2018), or has used observed declines in the labor share to identify episodes of automation (Acemoglu and Restrepo, 2022).

Yet there is no direct evidence on the effects of automation on the labor share at the firm level, where automation decisions are actually made and where the displacement of routine labor by capital takes place.

We address this gap by investigating whether automation reduces the labor share within firms. We formalize this question in a variant of the task-based framework at the firm level. Our approach rests on a simple but key insight: there is broad agreement that automation displaces routine workers, that is, workers employed in occupations intensive in repetitive, rule-based tasks.[1] The change in a firm's routine employment share is therefore informative about the extent of its automation.[2] The model delivers a sharp prediction, and one that generalizes across the class of task-based models: firms that automate more should see larger declines in both their routine employment share and their labor share.

Testing this prediction requires firm-level panel data on both the occupational employment structure and the labor share. We obtain such data for France by combining matched employer-employee records with firm accounting information, covering nearly the universe of firms over

[1] Routine tasks, first defined by Autor et al. (2003), are activities that can be accomplished by following explicit rules. Automation, or routinization, is the leading explanation for labor market polarization (Autor et al., 2003, 2006; Autor and Dorn, 2013; Feng and Graetz, 2020; Michaels et al., 2014; Goos et al., 2014). An alternative explanation is that middle-skill tasks are simply the most profitable to automate (Acemoglu and Loebbing, forthcoming). In either case, automation reduces employment in routine occupations. We therefore take the view that automation directly influences a firm's routine employment share, and that the change in this share is informative about the extent of firm-level automation.

[2] While the rapid advancement of artificial intelligence may change the set of tasks and hence the occupations at risk of automation, for the period we study routine occupations are those most likely substituted by automation technologies.

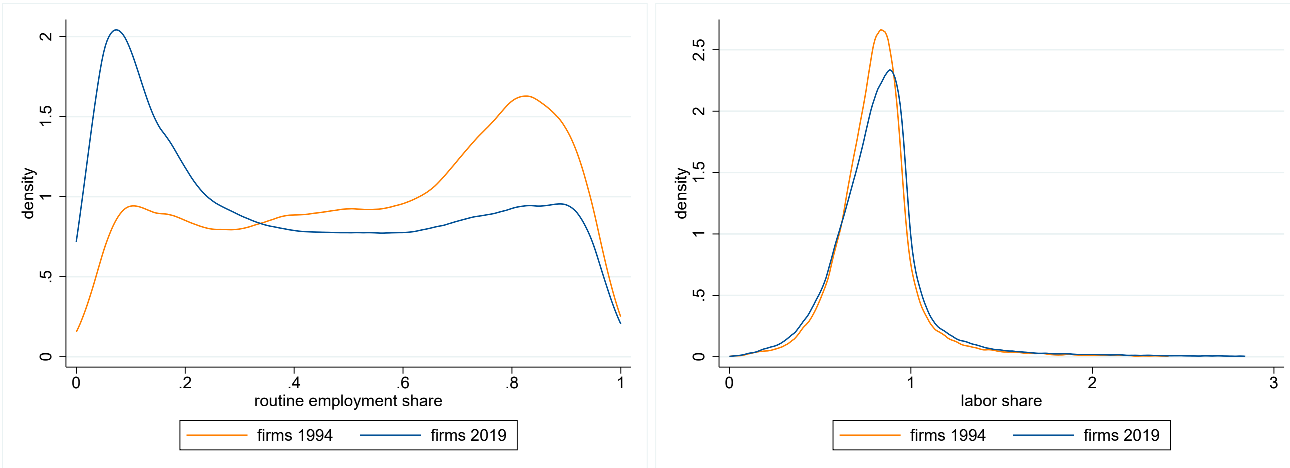

Figure 1: Routine employment share and labor share distribution across French firms

Notes: The routine employment share distribution is based on French matched employer-employee data, and the labor share distribution is based on French firm accounting data. See Section 3 for details.

1994–2019. France is a compelling setting for this test. Over this period, the median routine employment share fell from roughly 60% to 38%. This declined in routine employment is substantial and pervasive across firms, consistent with widespread automation. Similar patterns of routine employment decline have been documented across advanced economies (Autor et al., 2006; Autor and Dorn, 2013; Bárány and Siegel, 2018; Goos et al., 2014; Michaels et al., 2014). The question is whether this displacement of routine labor translated into declining labor shares within firms.

We find that it did not. Across specifications, the relationship between changes in routine employment shares and changes in labor shares is zero or significantly *negative*. This holds in the aggregate, across broad sectors, and within manufacturing, the sector most commonly associated with automation-driven labor share decline. Figure 1 illustrates this finding in its starkest form: while the distribution of routine employment shares shifted substantially between 1994 and 2019, the distribution of labor shares barely moved. Our results reject the notion that automation drives the decline in the labor share.

While the firm-level data that allows us to test this relationship directly is available for France, existing evidence from the US is consistent with our finding. Routine employment has declined widely since at least the 1980s (Jaimovich and Siu, 2020), yet the cross-firm distribution of the labor share has remained largely stable, with the aggregate decline driven by a small fraction of firms (Autor et al., 2020; Kehrig and Vincent, 2021).

Our finding suggests that automation sets in motion additional mechanisms - absent from the standard task framework - that offset its direct negative impact on the labor share. We discuss two possibilities: that automation generates overhead and platform costs through the hiring of non-routine workers needed to support automated processes, and that automation raises the wages of remaining workers through rent sharing as firm-level surplus increases.

Our findings carry two broader implications. First, routine-task displacement alone is not a sufficient explanation for (aggregate) labor share dynamics: other forces such as reallocation towards low-labor-share firms or rising markups play an important role. Second, our evidence suggests caution in using labor share movements to identify automation, since widespread routinization can coexist with stable firm-level labor shares.

The rest of the paper proceeds as follows. In Section 2 we derive the theoretical prediction. In Section 3 we test it against the French data and discuss possible mechanisms behind the lack of empirical support for the predicted co-decline. Section 4 concludes.

2 Automation, the routine share and the labor share

In this section we build on the firm-level version of the popular task-based framework, where firms differ in the set of tasks that they have automated, as in Hubmer and Restrepo (forthcoming). We augment this model by distinguishing between 'technologically automated' tasks that in principle can be automated, and technologically non-automated tasks. In line with the insights of the literature on employment polarization, we assume that 'technologically automated' tasks are rather repetitive such that workers who complete these tasks, if assigned, are employed in occupations intensive in routine tasks. Non-automatable tasks, in contrast, are done by workers employed in occupations that are not intensive in routine tasks. This distinction allows us to trace out not only the labor share in value added, but also the evolution of firm-level routine employment share, following firm-level automation.

We assume that firms, indexed by f, produce different varieties, Y_f, which are combined via a CES aggregator to produce the final output, the price of which is normalized to 1

$$Y = \left(\int_f Y_f^{\frac{\sigma-1}{\sigma}} df \right)^{\frac{\sigma}{\sigma-1}}.$$

In the above, $\sigma > 1$ denotes the elasticity of substitution across varieties. In such a setting, firms find it optimal to charge a common, constant markup $\frac{\sigma}{\sigma-1} > 1$.

We model firm-level production according to the task-based model

$$Y_f = z_f \left(\int_0^1 y_f(i)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}},$$

where z_f is firm specific TFP, $i \in [0,1]$ indexes the tasks that need to be completed for production.

Firm-level automation. We assume that in the economy tasks up to index I are technologically automated, implying that tasks $i \leq I$ can in theory be produced with capital or routine labor. We further assume that firms are heterogeneous in their automation level $I_f \leq I$, i.e., in the set of tasks that they can complete with capital. Firm f can complete tasks $i \in [0, I_f]$ with capital, where $I_f \leq I$ is determined prior to choosing the optimal production schedule at the firm. For the purpose of our analysis, we do not need to specify how I_f is determined; it is sufficient that firms with the same automation level I_f can find it optimal to change their I_f differentially.[3] Tasks above index I can only be completed with non-routine labor. Task i at firm f is produced according to

$$y_f(i) = \begin{cases} \phi_k(i)k_f(i) + \psi_r(i)l_{rf}(i) & \text{if } i \leq I_f, \\ \psi_r(i)l_{rf}(i) & \text{if } i \in (I_f, I], \\ \psi_n(i)l_{nf}(i) & \text{if } i > I. \end{cases}$$

In the above $\psi_o(i)$ is task i productivity of labor o, which is common across firms. The productivity of capital in task i $\phi_k(i)$ is also common across firms. One unit of the final good can be transformed into $q^I(i)$ units of task i capital. Let $\psi_k(i) \equiv \phi_k(i)q^I(i)$ denote the effective productivity of capital in task i. We assume that $\psi_k(i)/\psi_r(i)$ is continuous and strictly decreasing in i,

[3] This can arise for example in the specification of Hubmer and Restrepo (forthcoming). Automation entails a common fixed cost that is proportional to dI_f, leading to more productive firms (larger z_f) optimally automating more. Thus firms with the same z_f and same I_f in period $t-1$ choose the same dI_f, and enter period t with the same I_f, but different z_f because firm productivity evolves stochastically. For period $t+1$ these firms make different automation choices. Other mechanisms that would generate different optimal dI_f for firms with the same initial I_f is for example a stochastic cost of automation, or heterogeneous expectations about future productivity.

implying that (routine) labor has a comparative advantage in higher i tasks relative to capital.

Optimal production at the firm. We assume that factor markets are competitive, hence firms face the same factor prices: w_N and w_R are the wage rates of non-routine and routine workers respectively. Given that $\psi_k(i)/\psi_r(i)$ is strictly decreasing, there is a task threshold below which all firms would choose to perform the task with capital, if this was within their production possibilities. Let us denote this threshold by i^*, which is pinned down by

$$\frac{1}{\psi_k(i^*)} = \frac{w_R}{\psi_r(i^*)} \Leftrightarrow \frac{1}{w_R} = \frac{\psi_k(i^*)}{\psi_r(i^*)}.$$

For tasks i below the firm-specific automation threshold I_f, the firm can decide whether to produce it with capital or labor. If $i^* \leq I_f$, then firm f completes all tasks up to i^* with capital, and everything above i^* with labor. If, on the other hand, $i^* > I_f$, then firm f completes everything up to I_f with capital, and everything above that with labor, and the firm, if it could, would prefer to complete even more tasks with capital. The firm therefore produces tasks up to $\min\{I_f, i^*\}$ with capital, tasks in the $(\min\{I_f, i^*\}, I]$ range with routine labor, and tasks above I with non-routine labor. Following the standard steps of profit maximization, we can express firm level optimal outcomes.

Labor share in value added. The labor share in value added at the firm can be expressed as

$$\lambda_f = \frac{w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n}{\frac{\sigma}{\sigma-1}\left(\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right)}, \tag{1}$$

where $\Gamma_k(I_f) \equiv \int_0^{\min\{I_f,i^*\}} \psi_k(i)^{\eta-1}di$ and $\Gamma_r(I_f) \equiv \int_{\min\{I_f,i^*\}}^{I} \psi_r(i)^{\eta-1}di$ are endogenous and depend on the firm's automation level I_f, while $\Gamma_n \equiv \int_I^1 \psi_n(i)^{\eta-1}di$ is common to all firms, as it depends on the set of technologically automated tasks, I.

Routine employment share. Given optimal input use, the routine employment share at the firm is given by

$$\mu_f = \frac{\Gamma_r(I_f)}{\Gamma_r(I_f) + \left(\frac{w_R}{w_N}\right)^{\eta} \Gamma_n}. \tag{2}$$

Note that all firms with $I_f > i^*$ have the same labor share and the same routine employment share, as they all use capital to complete tasks up to i^*.

Firm-specific automation. We aim to analyze the firm-level implications of changes in the effective productivity of capital $\psi_k(i)$. As discussed earlier, the extent of automation, I_f, varies across firms and reflects optimal choices, and over time changes in automation, dI_f, can differ across firms that initially were similar. We aim to analyze the implications of these changes on the firm's routine employment share and on its labor share in value added. We focus on firms for which I_f is binding, that is where tasks up to I_f are optimally assigned to capital. By totally differentiating the routine employment share and the labor share in value added we obtain the following expressions:

$$d\mu_f = \underbrace{\eta \frac{-(1-\mu_f) w_R^{-\eta-1} \Gamma_r(I_f) dw_R + \mu_f w_N^{-\eta-1} \Gamma_n dw_N}{w_R^{-\eta} \Gamma_r(I_f) + w_N^{-\eta} \Gamma_n}}_{\equiv d\mu^{GE}(\mu_f)} - \underbrace{\frac{(1-\mu_f) w_R^{-\eta} \psi_r(I_f)^{\eta-1}}{w_R^{-\eta} \Gamma_r(I_f) + w_N^{-\eta} \Gamma_n}}_{\equiv d\mu^{auto}(\mu_f)} dI_f, \tag{3}$$

$$d\lambda_f = \underbrace{\frac{\sigma}{\sigma-1} \lambda_f (1-\eta) \left[\frac{(1-\lambda_f)(w_R^{-\eta} \Gamma_r(I_f) dw_R + w_N^{-\eta} \Gamma_n dw_N) + \lambda_f \int_0^{I_f} \psi_k(i)^{\eta-2} d\psi_k(i) di}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n} \right]}_{\equiv d\lambda^{GE}(\lambda_f)}$$

$$- \underbrace{\frac{\sigma}{\sigma-1} \lambda_f \frac{(1-\lambda_f) w_R^{1-\eta} \psi_r(I_f)^{\eta-1} + \lambda_f \psi_k(I_f)^{\eta-1}}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n}}_{\equiv d\lambda^{auto}(\lambda_f)} dI_f. \tag{4}$$

These expressions show that the change in both the routine employment share and in the labor share can be decomposed into two parts: the first component is driven by common changes and general equilibrium adjustments in the economy, while the second component is driven by firm specific changes in automation, dI_f.[4]

For the routine share change, the first component in (3) might be negative or positive, but it is the same for all firms with the same initial routine share, as can be seen from inspecting (2). To highlight the fact that the only firm-specific object the first term depends on is the firm's initial routine employment share, we denote it with $d\mu^{GE}(\mu_f)$. The second component is always negative and is the product of the firm-specific change in automation, dI_f and of another term that we denote with $d\mu^{auto}(\mu_f)$. This notation again highlights that the multiplier on the firm specific automation is the same for firms that have the same initial routine share.

The first component in the labor share change (4) might be negative or positive, but it is the same for all firms with the same initial labor share in value added, as can be seen from (1). We highlight this observation with the notation $d\lambda^{GE}(\lambda_f)$. The second component is negative, and is the product of the firm-specific change in automation, dI_f and of a fraction that is the same for firms with the same initial labor share. This is reflected in our notation $d\lambda^{auto}(\lambda_f)$ for this multiplier.

Based on these two expressions the model generates a testable prediction about differences in the change in the labor share across firms conditional on their initial routine share and their initial labor share.

Prediction. *Conditional on firms' initial routine share and initial labor share firms that experience larger declines in their routine share should experience larger declines in their labor share.*

Proof. We can express dI_f from the expression for $d\mu_f$ (3) and substitute it in to the expression for $d\lambda_f$ (4) to get

$$d\lambda_f = d\lambda^{GE}(\lambda_f) - d\lambda^{auto}(\lambda_f)\,\frac{d\mu^{GE}(\mu_f)}{d\mu^{auto}(\mu_f)} + \frac{d\lambda^{auto}(\lambda_f)}{d\mu^{auto}(\mu_f)}d\mu_f.$$

The first two terms are due to general equilibrium changes in the economy, and are the same for firms with the same initial routine share and same initial labor share. The last term depends

[4] As noted above, all firms for which I_f is not binding (for which $i^* < I_f$) are observationally equivalent in terms of their labor share and routine employment share. A change in the effective productivity of capital and the ensuing general equilibrium adjustment of wages leads to a common change in i^*, by di^*, and therefore these firms see common changes in labor shares and in routine employment shares over time, see Appendix section A. The formulas for the change in labor share and routine share are identical to those for firms for which I_f is binding, thus the relation of routine share change and labor share change is also the same.

on the routine employment share change $d\mu_f$, and the multiplier on it is $d\lambda^{auto}(\lambda_f)/d\mu^{auto}(\mu_f)$, which is positive, and is the same for firms with the same initial routine share and initial labor share. This proves the statement. □

The prediction essentially follows from comparing the expressions obtained for the change in the routine share and the change in the labor share, and noting that the general equilibrium adjustments and the magnitude of the impact of firm-level automation are the same across firms with the same initial labor share and initial routine share. These observations imply that among similar firms – in terms of initial routine and labor share – those with a larger decline in their routine share must have automated more, and therefore their labor share also had to decline by more.

The positive correlation of changes is quite a general result, and it hinges on the benefits of automation.[5] As capital becomes cheaper or more productive, firms use capital more, they replace routine labor with capital, and hence routine employment share goes down. As a consequence, the labor part in costs goes down more in firms that automate more. This on its own does not mean that the labor share will go down, because GE effects might push the labor share up, but it will go down more for firms that automate more among initially similar firms.

Our simple model thus provides a testable prediction regarding the within-firm change in the labor share. Conditional on firms' initial routine employment share and initial labor share, those that experience a larger decline in their routine share should experience larger declines in their labor share.

3 Empirical Test of the Model's Predictions

In this section we analyze the evolution of routine intensity and of the labor share within firms using French firm-level data.

Data. We combine two types of administrative datasets, matched employer-employee data from the *Déclaration annuelle de données sociales* (DADS Postes) and firm longitudinal data from

[5]For example it can be shown that improvements in automation technology generate the same results in a nested CES model of firm production.

Fichier complet unifié de SUSE (FICUS) and *Fichier approché des résultats d'Ésane* (FARE), which provides comprehensive balance sheet, income statement, and employment data.

In the DADS Postes data we observe the occupation (2-digit PCS codes), hours worked, and salary of each worker at a given employer for the years 1994-2019. Following the literature on routinization, we categorize occupations into two groups: routine and non-routine (see Appendix section B.1 for the detailed assignment). This allows us to compute not only firms' total employment but also their occupational employment structure.

The longitudinal administrative data from FICUS for 1994-2007 and from FARE for 2008-2019 allows us to construct the labor share at the firm level. We have information on sales, intermediates, labor compensation (salary and employer contributions), capital, investments, profits, and industry affiliation. This allows us to calculate value added for each firm and year as the difference between gross output (calculated as sales plus the change in immobilized and in stocked production) and intermediates (calculated as the sum of purchases of goods, raw materials, other purchases, the change in the stock of goods and of raw materials). We calculate the labor share as the ratio of labor compensation and value added for each firm and year. We can match this information with the DADS Postes data based on the firm's ID (SIREN).

Sample. In the following we restrict our sample to firms with at least 10 employees. We also drop firms which have any employment in clerical or public occupations, and in industries which do not have consistent coverage in the FICUS and FARE data, see Appendix section B.2.

Table 1 reports summary statistics for the number of employees, the labor share and the routine employment shares. We see that these variables are quite dispersed across firms. We also see that routine employment share has declined widely across firms between 1994 and 2019, with a leftward shift of the distribution that is apparent at the 25%, 50%, and 75% percentile. For the distribution of the labor share across firms, no similar trend is apparent between 1994 and 2019.

3.1 Empirical Analysis

The model predicts that among firms with initially identical labor shares and identical routine employment shares, subsequently the labor share should decline more when the routine em-

Table 1: Summary Statistics: Full Sample and Selected Years

Variable	Obs	Mean	Std. Dev.	p25	p50	p75
Panel A: Full Sample						
Employment	3,019,717	55.66	398.88	13.73	20.98	38.63
Labor share	3,019,717	0.817	0.251	0.686	0.813	0.917
Routine empl share	3,019,717	0.490	0.295	0.209	0.497	0.763
Panel B: Year 1994						
Employment	93,025	54.38	347.26	13.98	21.34	38.34
Labor share	93,025	0.812	0.227	0.694	0.809	0.905
Routine empl share	93,025	0.555	0.277	0.318	0.597	0.801
Panel C: Year 2019						
Employment	136,466	60.01	381.86	13.80	21.14	40.07
Labor share	136,466	0.828	0.271	0.686	0.822	0.931
Routine empl share	136,466	0.426	0.302	0.140	0.384	0.702

Notes: This table reports summary statistics computed at the firm level in the full sample as well as in the subsamples for years 1994 and 2019.

ployment share declines by more. In this section, we evaluate this prediction in our data from France.

As a first pass, we investigate the relationship between the long-run changes in these two shares. For firms active throughout our sample period 1994–2019, we construct their average labor share and their average routine employment share in the first five years (1994–1998) and in the last five years (2015–2019), and take their differences. We report these as a scatter plot in Figure 2. We see a quite dispersed cloud and no correlation between the changes in the routine employment and in the labor shares. This suggests that unconditionally there is no co-decline in labor shares and routine shares within firms.

The main prediction of the model is that among firms with identical initial routine intensity and initial labor share, those experiencing larger declines in their routine share should also experience greater declines in their labor share. We turn to data on annual changes such that the estimation sample is not restricted to only firms that were active in all years between 1994 and 2019, but includes all firms with data for at least two consecutive years. We regress the change in the labor share, $\Delta\lambda_{ft}$, on the change in the routine employment share, $\Delta\mu_{ft}$, calculated for firm

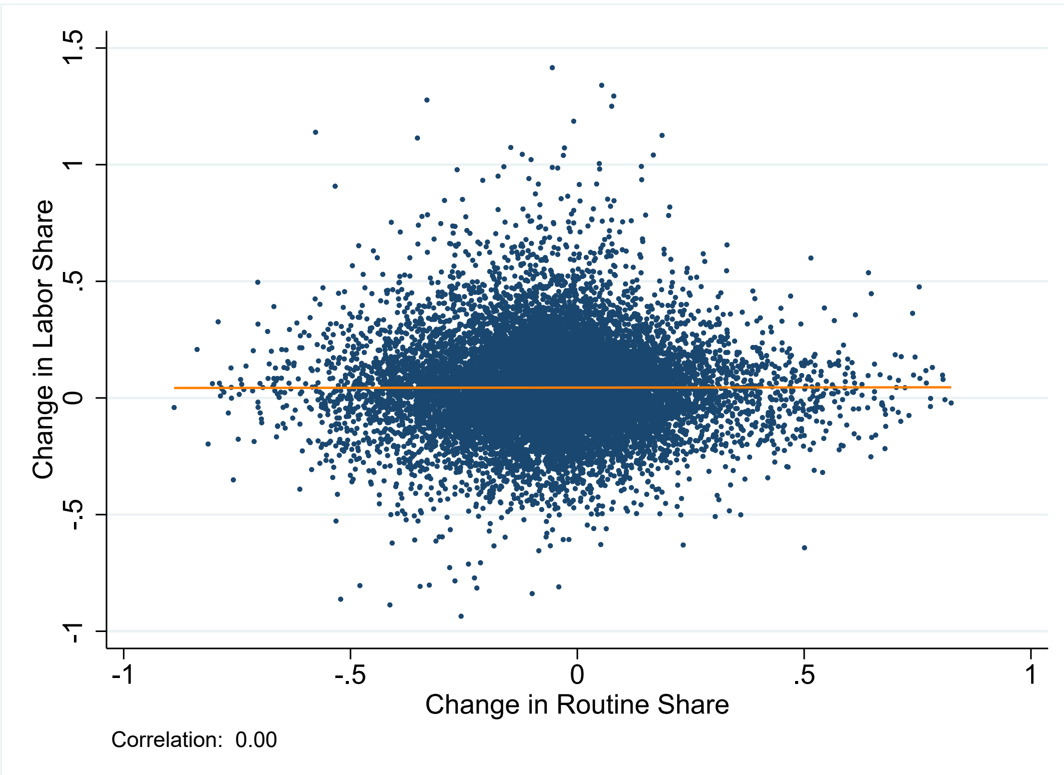

Figure 2: Long difference in routine employment share and labor share

Notes: The figure shows a scatter plot of the long-difference in firms' 5-year averaged routine employment shares and labor shares. The vertical axis shows the difference between a firm's average labor share in 2015-2019 and in 1994-1998, and the horizontal axis the corresponding change in the firm's routine employment share.

f between year t and $t-1$:

$$\Delta\lambda_{ft} = \alpha_{dt} + \beta_d \Delta\mu_{ft} + X_{ft}\gamma_d + \varepsilon_{ft}. \quad (5)$$

The theory predicts a positive relationship and therefore that $\beta_d > 0$, when comparing firms with the same initial routine share and the same initial labor share. In order to compare firms with similar initial routine shares, we run the regression by deciles of the previous period's routine employment share, indicated by subscript d. As we should be comparing firms with similar initial labor share, in our preferred specification we include a quadratic of the firms' labor share in the previous year in X_{ft}.[6] As a robustness check, we group the firms by the previous year's labor share quintile (calculated within routine share deciles), and we run the regressions by each pair of routine share decile and labor share quintile. The results in terms of the estimated βs are very similar, as shown in Appendix Figure A1.

Throughout, we include in X_{ft} additional controls to account for further heterogeneity across firms. These are all based on values from the previous year (which are predetermined) and are (i) 4-digit industry-year fixed effects to control for potential differences across industries by year, (ii) overall employment of the firm in logs to control for potential differences by firm size, and (iii) the routine employment share of the firm as within a decile the routine share still differs to some extent across firms.[7] Our main specification uses (lagged) value added weights, but we also show the baseline results from an unweighted regression. Throughout, we cluster standard errors at the (4-digit) industry-year level as firms in the same industry might be impacted by common shocks in any year.

Figure 3 reports the estimated slope, β_d, and the 95 percent confidence interval for each of the ten deciles of initial routine intensity (so "1" contains all firms in the lowest decile, "2" those in the second decile, and so on).

The empirical pattern we find starkly differs from the theoretical prediction. The theory predicts that declining routine employment should go hand in hand with declining labor shares, so

[6] Apart from being consistent with the theory, controlling for the previous labor share also helps in dealing with potential measurement error in the labor share that otherwise might bias estimates due to reversion to the mean.

[7] Including these further controls is our preferred specification. But when we estimate (5) without controls, the estimates still paint the same picture as in Figure 3, with positive β_d only in the lowest deciles bur negative elsewhere, just with some differences in the exact numbers.

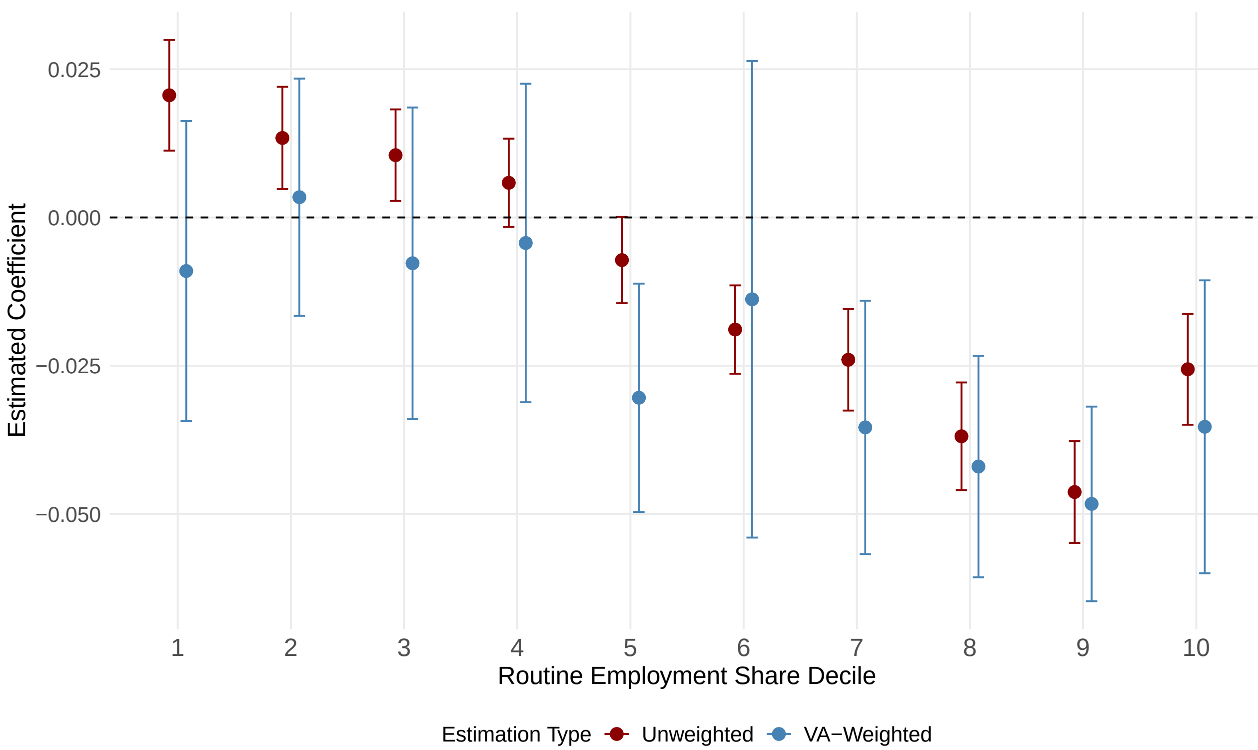

Figure 3: Routine share change and labor shares change

Notes: The figures shows point estimates and corresponding 95% confidence intervals for the estimates of the relation between the annual change in routine employment share and the annual change in labor share (β_d from equation (5)), by deciles based on the initial routine employment share of the firm.

a positive β_d. However, in the empirical results we see mostly negative relationships. Only in the unweighted regressions (in red), and then only in the lowest deciles, i.e. among the initially least routine intensive firms, is there a positive point estimate that is statistically significant.[8] While in deciles 1 to 3 based on the unweighted results, there is a statistically positive relationship between changes in routine employment shares and labor shares, the point estimate is negative from the 5th decile onward and even statistically significant at the 5 percent level from the sixth decile onward. These negative coefficients are at odds with the theoretical prediction. Even more striking are the results from the valued-added weighted regressions. Here, only the second decile's point estimate is positive, but it is not statistically significant at any conventional level, while all other β_d estimates are below zero and are statistically significant (even at the 1 percent level) for deciles 5, 7, 8, 9, and 10. Note, there are more than 230,000 observations in each of the deciles. As such, many data points correspond to rather small firms. However, for overall economic outcomes large firms matter much more. Therefore we prefer the value-added weighted regression as it gives results that are representative of each decile. These weighted regression results clearly reject the prediction of the theoretical model; there is no evidence of a positive co-movement between labor shares and routine employment shares, and for the majority of deciles the co-movement is *negative*, and highly statistically significant.

Even though we controlled for industry fixed effects when estimating (5), there might be further differences across industries. In fact, sectors differ substantially in their routine intensity (see Appendix Table A2), which might suggest differences in their production functions. We therefore conduct our analysis also by 1-digit sector (still including 4-digit industry fixed effects and all other firm-specific controls), where the deciles of the initial routine intensity are constructed within each sector.

We show the results of this disaggregated analysis based on the value-added weighted regression for the six largest sectors in Figure 4, and the results for all of the 11 broad sectors are shown in Appendix Figure A2. These plots show the point estimates and 95 percent confidence intervals by initial routine employment share deciles, defined by sector-year. There is quite substantial heterogeneity in the β_d estimates across sectors. But for the vast majority of sectors and

[8]Note, however, that in these deciles of initial routine intensity, the changes in the routine share are on average positive, such that a positive coefficient does not imply a decline in the labor share.

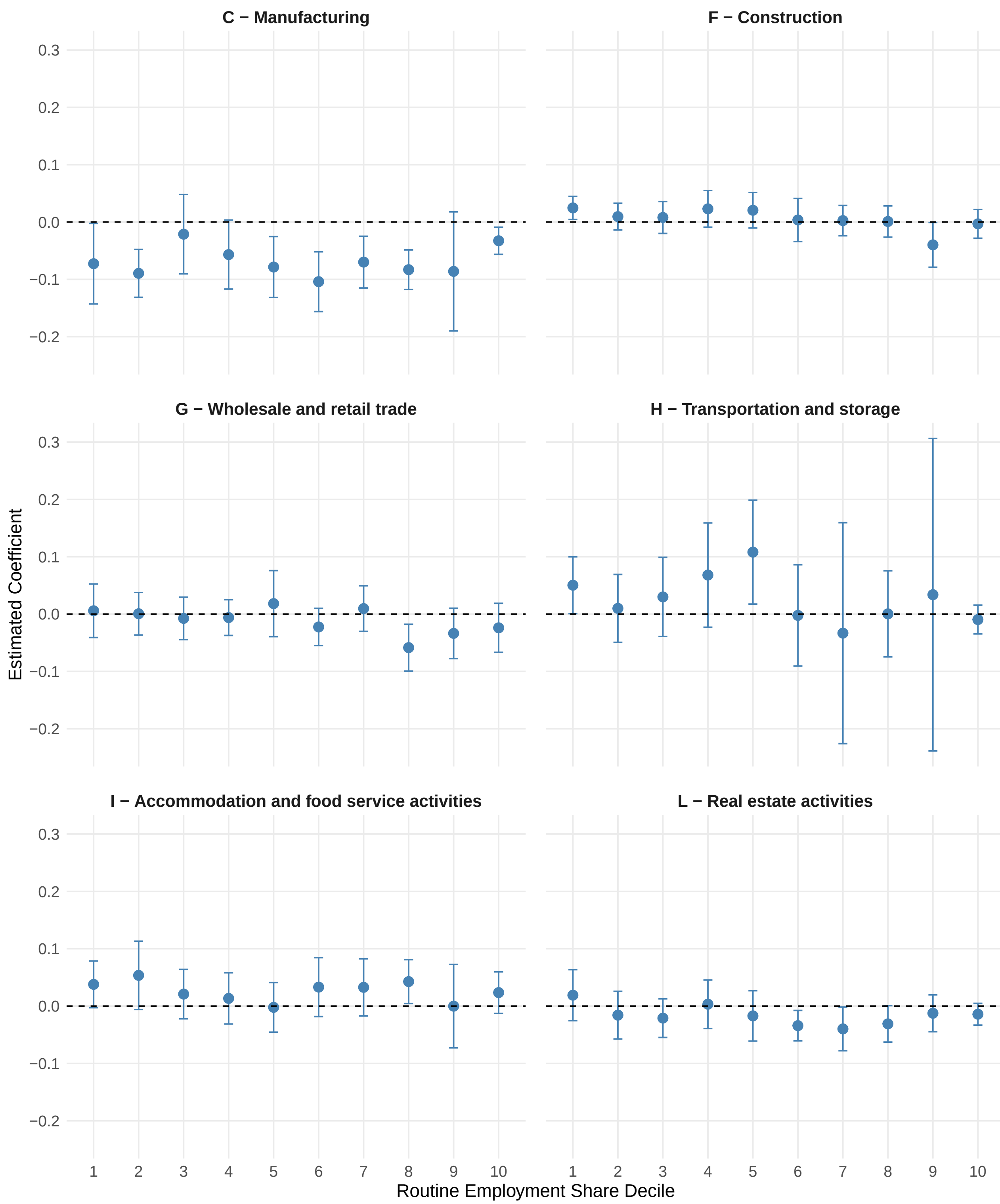

Figure 4: Routine share change and labor share change by sector

Notes: Value-added weighted estimates for β_d from equation (5) by broad sector for the largest six sectors. The results for all sectors can be found in Appendix Figure A2.

routine share deciles, the estimated relationship between changes in the routine share and in the labor share is close to zero. Contrary to the theoretical prediction, we once again see only very few positive estimates that are statistically significant (at the 5 percent level). To the contrary, where estimates are statistically different from zero, they are typically negative.[9] Interestingly, the sector with the most frequently significantly negative β_d across routine deciles is manufacturing. This is particularly noteworthy, as in the public debate and in academic research on the consequences of automation, it is the manufacturing sector that has received the most attention. But we find no evidence that a reduction in routine employment share is associated with a fall in the labor share within firms in manufacturing.

Summarizing our empirical findings, the task model's prediction of co-declining labor shares and routine employment shares does not withstand empirical scrutiny. Controlling for initial routine intensity and initial labor share, the predicted positive relationship between changes in routine employment shares and labor shares is not observed in the French data. To the contrary, this relationship is often negative.

3.2 Rationalising the Evidence

The benchmark model predicts a positive correlation between changes in routine employment share and changes in labor share: firms that automate more should see larger declines in both. Our data do not support this prediction. Across most sectors and routine intensity deciles, the correlation is indistinguishable from zero, and in manufacturing and the aggregate it is significantly negative.

What mechanisms can rationalize these patterns? For the labor share to remain stable in the face of automation, labor costs must keep pace with the rise in value added that automation generates. One possibility is that firms' market power *declines* with automation, so that a larger share of revenue accrues to workers. The available evidence, however, points in the opposite direction. On the product market side, De Loecker et al. (2020) have shown that aggregate markups have increased substantially since the 1980s, and Stiebale et al. (2024) find that European manufacturing industries with higher robot exposure see disproportionate productivity and markup gains

[9] We also see in Figure 4 that when disaggregating the analysis by sector, it is no longer the case that the β_d differ systematically across initial routine intensities, unlike in the results for the aggregate economy as seen in Figure 3.

among the most productive firms.[10] On the labor market side, Patel (2026) finds that automation increases firms' monopsony power by reducing wage markdowns. These findings suggest that automation strengthens rather than weakens market power, making it an unlikely candidate to explain the stability of the labor share.

We therefore focus on a second possibility: that automation raises labor costs through channels absent from the benchmark framework, either because firms hire additional non-routine workers or because remaining workers' wages rise. We discuss each of these channels below.

Overhead and platform costs. Automation requires supporting infrastructure: engineers to maintain systems, IT staff to manage platforms, and managers to oversee automated processes. These non-routine workers add to the firm's wage bill even as routine workers are displaced. When these opposing forces roughly offset, the labor share is unchanged; when overhead requirements are large enough, the labor share rises. We formalize this argument in Appendix C, where we show that the firm-level labor share decomposes into two components: one capturing the cost of workers directly engaged in production, which falls as routine tasks are automated, and another capturing the cost of overhead staff required to support automation, which rises with it. This logic is reinforced when platform services exhibit decreasing returns to scale, so that expanding automation capacity requires disproportionately more support staff. We formalize this extension in Appendix D.

Rising wages through rent sharing. The labor share can also be sustained if automation raises the wages of remaining workers rather than expanding headcount. In the benchmark task-based model with competitive labor markets, wages adjust through general equilibrium effects, but these affect all initially similar firms equally and therefore cannot generate heterogeneous labor share responses. What is needed is a firm-specific channel: if automation raises firm-level surplus, and workers capture a share of that surplus through rent sharing, then wages rise more in firms that automate more. In the limiting case where labor compensation equals a fixed fraction of value added, the labor share is constant by construction regardless of routine employment changes. Gans and Goldfarb (2026) provide one micro-foundation for why firm-level surplus

[10] Firooz et al. (2025), using an instrumental variable strategy for US manufacturing, similarly show that robot adoption significantly raises sales concentration.

rises with automation: in an "O-ring" production environment (Kremer, 1993), automating routine tasks allows workers to concentrate on remaining non-automated tasks, raising the value of human contributions and hence the surplus available for sharing.

Discussion. These mechanisms are not mutually exclusive and may reinforce one another. Their relevance is supported by the growth of "tech-complementary" occupations within automating firms (Harrigan et al., 2021) and case studies where automation coincided with task upgrading rather than displacement. Together, they could account for the near-zero correlations in most sectors, the negative correlations in manufacturing, and the near-absence of positive correlations that the benchmark predicts.

4 Conclusions

This paper investigates whether automation is a primary driver of the decline in the labor share, using a simple but sharp empirical test. We augment the standard task-based framework to generate a joint prediction about the firm-level co-movement of routine employment shares and labor shares: among initially similar firms, those that automate more should see larger declines in both. We test this prediction using matched employer-employee and firm accounting data covering nearly the universe of French firms over 1994–2019.

The data do not support the model's prediction. Despite widespread and well-documented declines in routine employment shares across firms, we find no evidence of a corresponding positive co-movement with labor shares. Across various specifications, the relationship is zero or significantly negative across most routine intensity deciles and broad sectors. This pattern holds in the aggregate and, notably, within manufacturing, the sector most commonly associated with automation-driven labor share decline.

We argue that the plausible explanations are that automation triggers additional labor costs, through overhead and platform activities or through rising wages of remaining workers via task complementarities, that offset the direct displacement of routine labor from production.

Our findings do not imply that automation is unimportant for labor markets. The large shift in the routine employment distribution confirms that it has profoundly reshaped the occupational structure of firms. Rather, our results suggest that the mapping from automation to the labor share is considerably more complex than the benchmark task-based framework implies. Understanding which additional mechanisms, whether overhead costs, task complementarities, or other channels, mediate this relationship is a promising direction for future research, both for refining theoretical models and for informing policy responses to technological change.

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Appendix

A Derivation of firm outcomes

In order to express the labor share and routine employment share at optimal input use, we first express the cost of producing one unit of output for firm f, by proceeding as follows. Denoting the price of task i for firm f by $p_f(i)$, the optimal relative task input for firm f is given by:

$$y_f(i') = y_f(i)\left(\frac{p_f(i)}{p_f(i')}\right)^{\eta}. \tag{A.1}$$

All tasks employing a given factor input must pay the common price for it. This implies that

$$\begin{aligned}
1 &= p_f(i)\psi_k(i) && \text{if } i \leq \min\{I_f, i^*\} \\
w_R &= p_f(i)\psi_r(i) && \text{if } i \in (\min\{I_f, i^*\}, I] \\
w_N &= p_f(i)\psi_n(i) && \text{if } i > I.
\end{aligned}$$

Using the above we can express the cost of producing 1 unit of firm f output optimally given productivity schedules and factor prices. First let's express the quantity of factor inputs needed to produce 1 unit of firm output.

$$\begin{aligned}
1 &= z_f\left(\int_0^1 y_f(i)^{\frac{\eta-1}{\eta}}di\right)^{\frac{\eta}{\eta-1}} = z_f y_f(0)\left(\int_0^1 \left(\frac{y_f(i)}{y_f(0)}\right)^{\frac{\eta-1}{\eta}}di\right)^{\frac{\eta}{\eta-1}} \\
&= z_f y_f(0)\left(\int_0^1 \left(\left[\frac{p_f(i)}{p_f(0)}\right]^{-\eta}\right)^{\frac{\eta-1}{\eta}}di\right)^{\frac{\eta}{\eta-1}} = z_f y_f(0)\left(\int_0^1 \left(\frac{p_f(i)}{p_f(0)}\right)^{1-\eta}di\right)^{\frac{\eta}{\eta-1}} \\
y_f(0) &= \frac{1}{z_f}\left(\int_0^1 \left(\frac{p_f(i)}{p_f(0)}\right)^{1-\eta}di\right)^{\frac{\eta}{1-\eta}}
\end{aligned}$$

Now we can express the cost of producing 1 unit of output

$$
\begin{aligned}
c_f &= \int_0^1 p_f(i) y_f(i) di = y_f(0) \int_0^1 p_f(i) \frac{y_f(i)}{y_f(0)} di = y_f(0) \int_0^1 p_f(i) \left[\frac{p_f(i)}{p_f(0)}\right]^{-\eta} di \\
&= \frac{p_f(0)}{z_f} \left(\int_0^1 \left(\frac{p_f(i)}{p_f(0)}\right)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}} \int_0^1 \left[\frac{p_f(i)}{p_f(0)}\right]^{1-\eta} di \\
&= \frac{p_f(0)}{z_f} \left(\int_0^1 \left(\frac{p_f(i)}{p_f(0)}\right)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}+1} \\
&= \frac{p_f(0)}{z_f} \left(\int_0^1 \left(\frac{p_f(i)}{p_f(0)}\right)^{1-\eta} di \right)^{\frac{1}{1-\eta}} = \frac{1}{z_f} \left(\int_0^1 p_f(i)^{1-\eta} di \right)^{\frac{1}{1-\eta}} \\
&= \frac{1}{z_f} \left(\int_0^{\min\{I_f, i^*\}} \psi_k(i)^{\eta-1} di + w_R^{1-\eta} \int_{\min\{I_f, i^*\}}^{I} \psi_r(i)^{\eta-1} di + w_N^{1-\eta} \int_I^1 \psi_n(i)^{\eta-1} di \right)^{\frac{1}{1-\eta}} \\
&\equiv \frac{1}{z_f} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)^{\frac{1}{1-\eta}},
\end{aligned}
$$

where $\Gamma_k(I_f) \equiv \int_0^{\min\{I_f, i^*\}} \psi_k(i)^{\eta-1} di$ and $\Gamma_r(I_f) \equiv \int_{\min\{I_f, i^*\}}^{I} \psi_r(i)^{\eta-1} di$, and $\Gamma_n \equiv \int_I^1 \psi_n(i)^{\eta-1} di$ as defined in the main text. Note that for firms where $I_f > i^*$ the expressions are common as I_f is not binding and we denote them with $\Gamma_k^* \equiv \int_0^{i^*} \psi_k(i)^{\eta-1} di$ and $\Gamma_r^* \equiv \int_{i^*}^{I} \psi_r(i)^{\eta-1} di$

To calculate the labor share, the labor costs incurred in producing 1 unit of output need to be calculated:

$$
\begin{aligned}
\text{labcost}_f &= \int_{\min\{I_f, i^*\}}^{1} p_f(i) y_f(i) di = y_f(0) \int_{\min\{I_f, i^*\}}^{1} p_f(i) \frac{y_f(i)}{y_f(0)} di \\
&= y_f(0) \int_{\min\{I_f, i^*\}}^{1} p_f(i) \left[\frac{p_f(i)}{p_f(0)} \right]^{-\eta} di \\
&= \frac{p_f(0)}{z_f} \left(\int_0^1 \left(\frac{p_f(i)}{p_f(0)} \right)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}} \int_{\min\{I_f, i^*\}}^{1} \left[\frac{p_f(i)}{p_f(0)} \right]^{1-\eta} di \\
&= \frac{1}{z_f} \left(\int_0^1 p_f(i)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}} \int_{\min\{I_f, i^*\}}^{1} p_f(i)^{1-\eta} di \\
&= \frac{1}{z_f} \left(\int_0^1 p_f(i)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}} \left(w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right).
\end{aligned}
$$

We can use a similar formulation for the unit cost:

$$
c_f = \frac{1}{z_f} \left(\int_0^1 p_f(i)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right).
$$

The labor share then can be expressed as:

$$
\begin{aligned}
\lambda_f = \frac{Y_f \text{labcost}_f}{Y_f \frac{\sigma}{\sigma-1} c_f} &= \frac{\frac{1}{z_f} \left(\int_0^1 p_f(i)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}} \left(w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)}{\frac{\sigma}{\sigma-1} \frac{1}{z_f} \left(\int_0^1 p_f(i)^{1-\eta} di \right)^{\frac{\eta}{1-\eta}} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)} \\
&= \frac{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n}{\frac{\sigma}{\sigma-1} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)}.
\end{aligned}
$$

Note that for firms where $I_f > i^*$ the labor share is the same and given by

$$
\lambda^* = \frac{w_R^{1-\eta} \Gamma_r^* + w_N^{1-\eta} \Gamma_n}{\frac{\sigma}{\sigma-1} \left(\Gamma_k^* + w_R^{1-\eta} \Gamma_r^* + w_N^{1-\eta} \Gamma_n \right)}.
$$

To express the share of routine employment at the firm, use optimal relative task input as in (A.1) we get

$$\frac{l_{rf}(i)}{l_{rf}(i')} = \left(\frac{\psi_r(i')}{\psi_r(i)}\right)^{1-\eta} \qquad \text{if } i, i' \in (\min\{I_f, i^*\}, I]$$
$$\frac{l_{nf}(i)}{l_{rf}(i')} = \left(\frac{\psi_r(i')}{\psi_n(i)}\right)^{1-\eta} \left(\frac{w_R}{w_N}\right)^{\eta} \qquad \text{if } i > I \text{ and } i' \in (\min\{I_f, i^*\}, I]$$

We can then express the routine employment share at the firm as

$$\mu_f = \frac{\int_{\min\{I_f,i^*\}}^{I} l_{rf}(i)di}{\int_{\min\{I_f,i^*\}}^{I} l_{rf}(i)di + \int_I^1 l_{nf}(i)di} = \frac{l_{rf}(I)\int_{\min\{I_f,i^*\}}^{I} \frac{l_{rf}(i)}{l_{rf}(I)}di}{l_{rf}(I)\int_{\min\{I_f,i^*\}}^{I} \frac{l_{rf}(i)}{l_{rf}(I)}di + l_{rf}(I)\int_I^1 \frac{l_{nf}(i)}{l_{rf}(I)}di}$$
$$= \frac{\int_{\min\{I_f,i^*\}}^{I} \left(\frac{\psi_r(I)}{\psi_r(i)}\right)^{1-\eta} di}{\int_{\min\{I_f,i^*\}}^{I} \left(\frac{\psi_r(I)}{\psi_r(i)}\right)^{1-\eta} di + \int_I^1 \left(\frac{\psi_r(I)}{\psi_n(i)}\right)^{1-\eta} \left(\frac{w_R}{w_N}\right)^{\eta} di} = \frac{\Gamma_r(I_f)}{\Gamma_r(I_f) + \left(\frac{w_R}{w_N}\right)^{\eta}\Gamma_n}.$$

Note that for firms for which $I_f > i*$ the routine share is the same and given by

$$\mu^* = \frac{\Gamma_r^*}{\Gamma_r^* + \left(\frac{w_R}{w_N}\right)^{\eta}\Gamma_n}.$$

To assess the change in the labor share and in the routine share, we need to totally differentiate the expressions for $\Gamma_k(I_f)$ and $\Gamma_r(I_f)$. For firms where I_f is binding we get:

$$d\Gamma_k(I_f) = \psi_k(I_f)^{\eta-1}dI_f + (\eta-1)\int_0^{I_f} \psi_k(i)^{\eta-2}d\psi_k(i)di$$
$$d\Gamma_r(I_f) = -\psi_r(I_f)^{\eta-1}dI_f$$

and for firms for which $I_f > i^*$

$$d\Gamma_k^* = \psi_k(i^*)^{\eta-1}di^* + (\eta-1)\int_0^{i^*} \psi_k(i)^{\eta-2}d\psi_k(i)di$$
$$d\Gamma_r^* = -\psi_r(i^*)^{\eta-1}di^*$$

The change in the labor share is

$$
\begin{aligned}
d\lambda_f = & \frac{w_R^{1-\eta} d\Gamma_r(I_f) + (1-\eta) w_R^{-\eta} \Gamma_r(I_f) dw_R + (1-\eta) w_N^{-\eta} \Gamma_n dw_N}{\frac{\sigma}{\sigma-1} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)} \\
& - \frac{\left[w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right] \left[d\Gamma_k(I_f) + w_R^{1-\eta} d\Gamma_r(I_f) + (1-\eta)(w_R^{-\eta} \Gamma_r(I_f) dw_R + w_N^{-\eta} \Gamma_n dw_N) \right]}{\frac{\sigma}{\sigma-1} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)^2} \\
& = \lambda_f \frac{\sigma}{\sigma-1} \left[(1-\lambda_f) \frac{w_R^{1-\eta} d\Gamma_r(I_f) + (1-\eta) w_R^{-\eta} \Gamma_r(I_f) dw_R + (1-\eta) w_N^{-\eta} \Gamma_n dw_N}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n} \right. \\
& \left. - \lambda_f \frac{d\Gamma_k(I_f)}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n} \right] \\
& = \frac{\sigma}{\sigma-1} \lambda_f (1-\lambda_f)(1-\eta) \frac{w_R^{-\eta} \Gamma_r(I_f) dw_R + w_N^{-\eta} \Gamma_n dw_N}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n} \\
& + \frac{\sigma}{\sigma-1} \lambda_f \frac{(1-\lambda_f) w_R^{1-\eta} d\Gamma_r(I_f) - \lambda_f d\Gamma_k(I_f)}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n}
\end{aligned}
$$

The above expression for a firm where I_f is binding is

$$
\begin{aligned}
d\lambda_f = & \frac{\sigma}{\sigma-1} \lambda_f (1-\lambda_f)(1-\eta) \frac{w_R^{-\eta} \Gamma_r(I_f) dw_R + w_N^{-\eta} \Gamma_n dw_N}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n} \\
& + \frac{\sigma}{\sigma-1} \lambda_f \frac{-(1-\lambda_f) w_R^{1-\eta} \psi_r(I_f)^{\eta-1} dI_f - \lambda_f \left[\psi_k(I_f)^{\eta-1} dI_f + (\eta-1) \int_0^{I_f} \psi_k(i)^{\eta-2} d\psi_k(i) di \right]}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n} \\
& = \frac{\sigma}{\sigma-1} \lambda_f (1-\eta) \frac{(1-\lambda_f)(w_R^{-\eta} \Gamma_r(I_f) dw_R + w_N^{-\eta} \Gamma_n dw_N) + \lambda_f \int_0^{I_f} \psi_k(i)^{\eta-2} d\psi_k(i) di}{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n} \\
& - \frac{\sigma}{\sigma-1} \lambda_f \frac{(1-\lambda_f) w_R^{1-\eta} \psi_r(I_f)^{\eta-1} + \lambda_f \psi_k(I_f)^{\eta-1}}{\left(w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)} dI_f
\end{aligned}
$$

The above expression for a firm where I_f is not binding, $I_f > i^*$, is

$$\begin{aligned}
d\lambda^* &= \frac{\sigma}{\sigma-1}\lambda^*(1-\lambda^*)(1-\eta)\frac{w_R^{-\eta}\Gamma_r^* dw_R + w_N^{-\eta}\Gamma_n dw_N}{w_R^{1-\eta}\Gamma_r^* + w_N^{1-\eta}\Gamma_n} \\
&+ \frac{\sigma}{\sigma-1}\lambda^*\frac{-(1-\lambda^*)w_R^{1-\eta}\psi_r(i^*)^{\eta-1}di^* - \lambda_f\left[\psi_k(i^*)^{\eta-1}di^* + (\eta-1)\int_0^{i^*}\psi_k(i)^{\eta-2}d\psi_k(i)di\right]}{w_R^{1-\eta}\Gamma_r^* + w_N^{1-\eta}\Gamma_n} \\
&= \frac{\sigma}{\sigma-1}\lambda^*(1-\eta)\frac{(1-\lambda^*)\left[w_R^{-\eta}\Gamma_r^* dw_R + w_N^{-\eta}\Gamma_n dw_N\right] + \lambda^*\int_0^{i^*}\psi_k(i)^{\eta-2}d\psi_k(i)di}{w_R^{1-\eta}\Gamma_r^* + w_N^{1-\eta}\Gamma_n} \\
&- \frac{\sigma}{\sigma-1}\lambda^*\frac{(1-\lambda^*)w_R^{1-\eta}\psi_r(i^*)^{\eta-1} + \lambda^*\psi_k(i^*)^{\eta-1}}{w_R^{1-\eta}\Gamma_r^* + w_N^{1-\eta}\Gamma_n}di^*,
\end{aligned}$$

which is the same for all firms where $I_f > i^*$ initially.

The change in the routine share

$$\begin{aligned}
d\mu_f &= \frac{w_R^{-\eta}d\Gamma_r(I_f) - \eta w_R^{-\eta-1}\Gamma_r(I_f)dw_R}{w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n} \\
&- \frac{w_R^{-\eta}\Gamma_r(I_f)(w_R^{-\eta}d\Gamma_r(I_f) - \eta w_R^{-\eta-1}\Gamma_r(I_f)dw_R - \eta w_N^{-\eta-1}\Gamma_n dw_N)}{\left(w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n\right)^2} \\
&= (1-\mu_f)\frac{w_R^{-\eta}d\Gamma_r(I_f) - \eta w_R^{-\eta-1}\Gamma_r(I_f)dw_R}{w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n} + \mu_f\frac{\eta w_N^{-\eta-1}\Gamma_n dw_N}{w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n} \\
&= (1-\mu_f)\frac{w_R^{-\eta}d\Gamma_r(I_f)}{w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n} + \eta\frac{\mu_f w_N^{-\eta-1}\Gamma_n dw_N - (1-\mu_f)w_R^{-\eta-1}\Gamma_r(I_f)dw_R}{w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n}
\end{aligned}$$

The routine share change for firms where I_f is binding is

$$d\mu_f = -\frac{(1-\mu_f)w_R^{-\eta}\psi_r(I_f)^{\eta-1}dI_f}{w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n} + \eta\frac{\mu_f w_N^{-\eta-1}\Gamma_n dw_N - (1-\mu_f)w_R^{-\eta-1}\Gamma_r(I_f)dw_R}{w_R^{-\eta}\Gamma_r(I_f) + w_N^{-\eta}\Gamma_n}.$$

For firms for which $I_f > i^*$, so I_f is not binding the change in the routine share is

$$d\mu^* = -\frac{(1-\mu^*)w_R^{-\eta}\psi_r(i^*)^{\eta-1}di^*}{w_R^{-\eta}\Gamma_r^* + w_N^{-\eta}\Gamma_n} + \eta\frac{\mu^* w_N^{-\eta-1}\Gamma_n dw_N - (1-\mu^*)w_R^{-\eta-1}\Gamma_r^* dw_R}{w_R^{-\eta}\Gamma_r^* + w_N^{-\eta}\Gamma_n},$$

which is the same for all firms.

B Data

B.1 Occupation classification

Our classification of occupations is based on 2-digit PCS occupation codes, and is as follows, with PCS codes in brackets:

1. *Routine occupations*: admin and comm intermediary professions of companies (46), foremen, supervisors (48), company admin employees (54), commercial employees (55), skilled industrial type of workers (62), unskilled industrial type workers (67).

2. *Non-routine occupations*: craftsmen (21), traders (22), company managers (23), liberal professions (31), professors, scientific professions (34), information, arts and entertainment professions (35), admin and commercial executives of companies (37), engineers and technical executives of companies (38), school teachers, teachers and similar professions (42), intermediate health and social work professions (43), technicians (except tertiary technicians) (47), supervisory officers (53), staff in direct services to individuals (56), skilled artisan type workers (63), drivers (64), skilled workers in handling, warehousing and transport (65), unskilled artisan type workers (68).

3. *Non-classified occupations*: farmers (10), public service executives (33), clergy, religious (44), admin intermediary professions of the public service (45), civilian employees and civil servants (52), agricultural and related workers (69).

B.2 Selection of firms

We do not classify agricultural occupations, civil servants and religious occupations, and drop firms with positive employment in these occupations (PCS codes 10, 33, 44, 45, 52, 69). We drop firms with no salaries paid and with negative value added. We drop firms in Finance and in Public Administration due to lack of data for some years in 1994-2019. We drop firms with less than 10 full-time equivalent workers, and we drop firms in the top 1% of the labor share distribution in each year. Finally, we drop firms that have no employment in routine or in non-routine occupations.

B.3 Industry classification

Table A1: Industry classification (NAF Rev. 2 Sections)

Code	Industry (Section)
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities

Notes: Sectors K and O are dropped from all analysis, due to lack of data for some years in the sample. Sectors E, J, M, N, S are dropped from the sectoral analysis because the sample is too small to allow for splitting it into (routine employment share) deciles.

B.4 Summary statistics by sector

B.5 Additional empirical results

As an alternative to our baseline specification, we group the firms by the previous year's labor share quintile (calculated within routine share deciles), and we run regression (5) by each pair of routine share decile and labor share quintile. We additional control the previous year's labor share of the firm as within a quintile the labor share still differs to some extent across firms.

Table A2: Summary Statistics by Sector

		Employees		Labor share		Routine empl sh	
Sector	**Obs**	Mean	SD	Mean	SD	Mean	SD
B	12,099	39.24	92.46	0.59	0.25	0.67	0.19
C	759,262	74.03	375.78	0.81	0.25	0.70	0.20
D	3,381	271.65	1342.35	0.59	0.31	0.69	0.22
E	13,701	81.02	270.15	0.77	0.33	0.43	0.24
F	453,147	35.50	122.52	0.87	0.19	0.31	0.24
G	717,511	51.69	388.03	0.78	0.25	0.60	0.24
H	199,638	66.65	1031.83	0.86	0.22	0.24	0.24
I	186,872	33.61	161.02	0.78	0.25	0.20	0.15
J	59,439	74.14	338.63	0.85	0.33	0.26	0.24
L	281,247	53.65	206.21	0.82	0.26	0.48	0.30
M	136,107	42.27	140.83	0.84	0.27	0.45	0.30
N	93,458	78.93	331.69	0.89	0.23	0.36	0.31
P	17,497	27.83	48.01	0.90	0.28	0.27	0.17
Q	20,618	32.38	61.62	0.83	0.26	0.29	0.21
R	50,678	44.33	134.29	0.82	0.36	0.35	0.22
S	15,060	38.96	100.27	0.90	0.28	0.27	0.23

Notes: This table reports means and standard deviations (SD) computed at the firm–year level, by sector.

Figure A1 shows the estimated coefficients including the 95% confidence intervals. The point estimates do not support the theory's prediction of a positive co-movement.

In the main text we show the results for the six largest sectors, In Figure A2 we show the results for all 11 broad sectors. These plots show the point estimates and 95 percent confidence intervals by initial routine employment share deciles, defined by sector-year. Even when looking at all broad sectors of the economy, we do not find support for a positive relationship between the routine share change and the labor share change within firms.

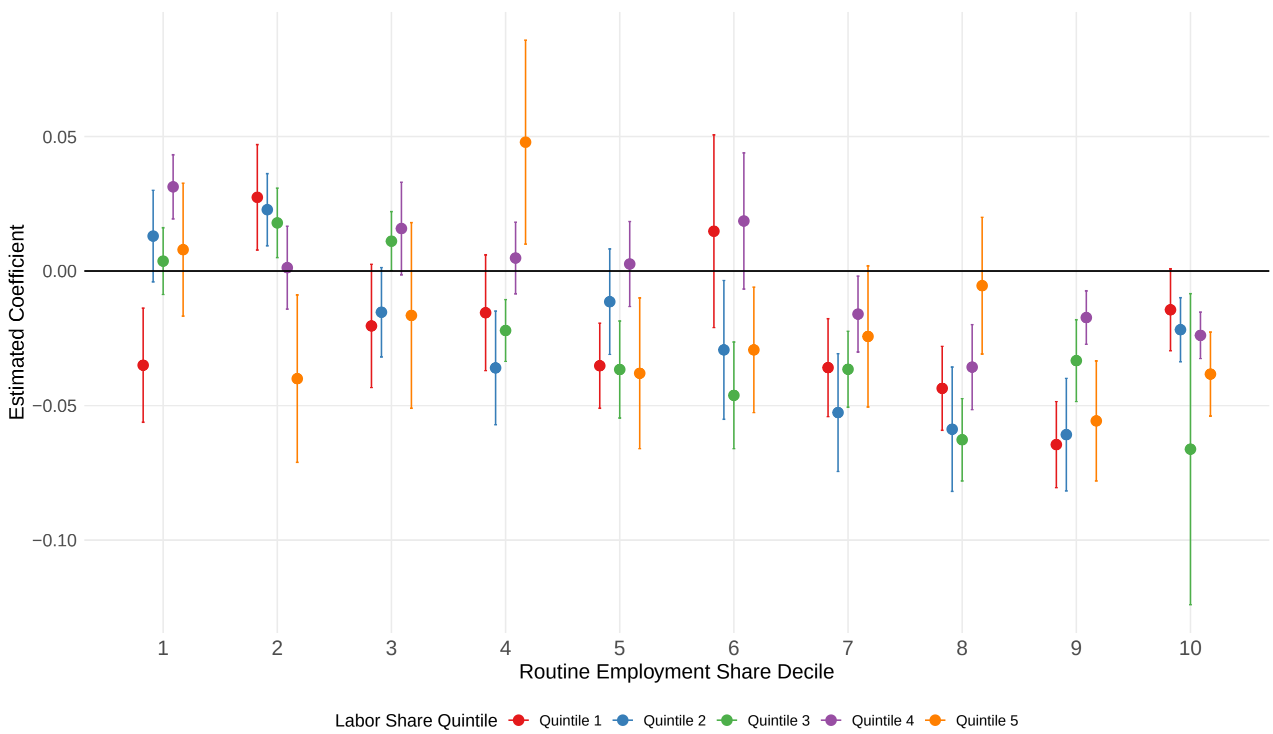
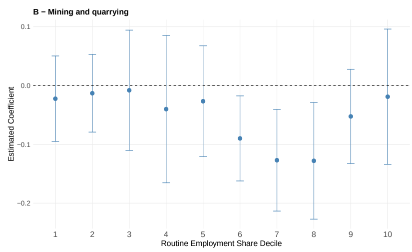
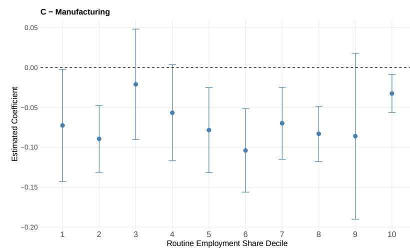


Figure A1: Routine share and labor share change by routine decile and labor quintile

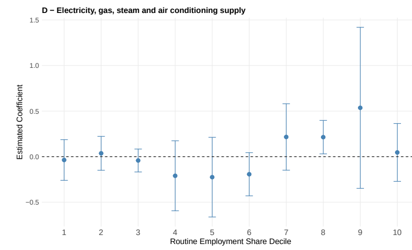
Notes: Value-added weighted estimates for β_{dq} from equation (5) run for each pair of initial labor share quintile and initial routine share decile, controlling linearly for initial labor share within a quintile.



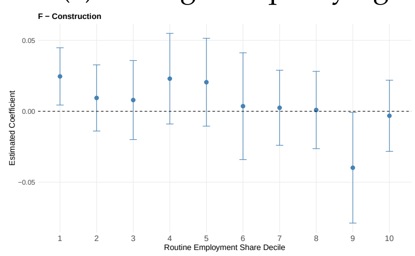
(a) Mining and quarrying



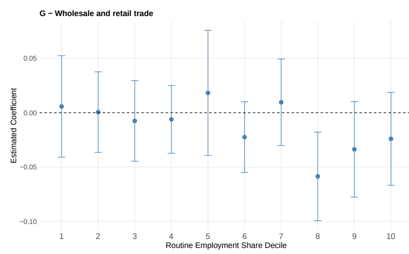
(b) Manufacturing



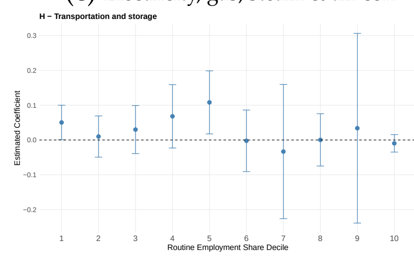
(c) Electricity, gas, steam & air con



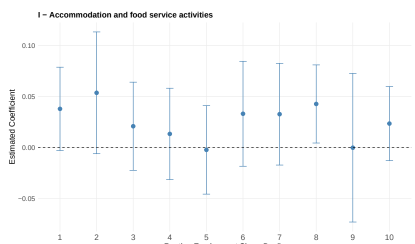
(d) Construction



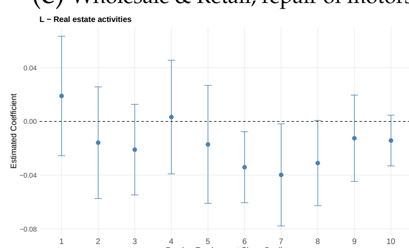
(e) Wholesale & Retail; repair of motors



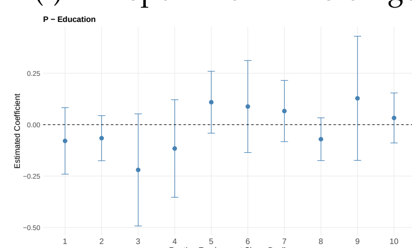
(f) Transportation and storage



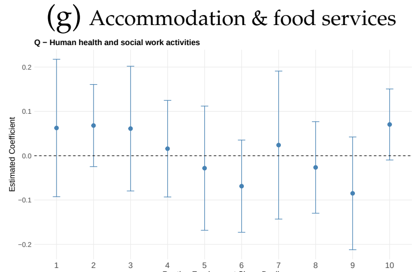
(g) Accommodation & food services



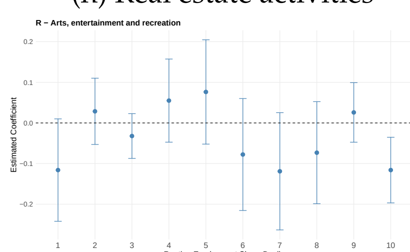
(h) Real estate activities



(i) Education



(j) Human health & social work



(k) Arts, entertainment & recreation

Figure A2: Routine share and labor share change by routine decile and sector

Notes: Value-added weighted estimates for β_d from equation (5) by broad sector.

C Derivation of the Labor Share and Routine Employment Share.

Model setup. Varieties are aggregated via a CES aggregator:

$$Y = \left(\int_f Y_f^{\frac{\sigma-1}{\sigma}} df \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1 \tag{6}$$

where σ denotes the elasticity of substitution across varieties.

Firm f produces according to a task-based production function:

$$Y_f = z_f \left(\int_0^1 y_f(i)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}}, \qquad \eta < 1 \tag{7}$$

where z_f is firm-specific TFP and η is the elasticity of substitution across tasks.

Tasks are produced according to:

$$y_f(i) = \begin{cases} \phi_k(i)k_f(i) + \psi_r(i)\ell_{rf}(i) & \text{if } i \leq I_f \\ \psi_r(i)\ell_{rf}(i) & \text{if } i \in (I_f, I] \\ \psi_n(i)\ell_{nf}(i) - I_f c(i) & \text{if } i > I \end{cases} \tag{8}$$

where I_f is the firm's automation threshold and I is the technological frontier. The term $I_f c(i)$ captures overhead costs: for each automated task, the firm must devote $c(i)$ units of non-routine task i to overhead. Total overhead labor cost is:

$$C(I_f) = \int_I^1 \frac{I_f c(i)}{\psi_n(i)} w_N \, di = I_f w_N \Psi_o, \qquad \text{where } \Psi_o \equiv \int_I^1 \frac{c(i)}{\psi_n(i)} di \tag{9}$$

Cost minimization. Firms allocate factors across tasks to minimize the cost of producing Y_f units of output. With optimal factor allocation, task prices satisfy:

$$p_f(i) = \psi_k(i)^{-1} \qquad \text{if } i \leq \min\{I_f, i^*\} \tag{10}$$

$$p_f(i) = w_R / \psi_r(i) \qquad \text{if } i \in (\min\{I_f, i^*\}, I] \tag{11}$$

$$p_f(i) = w_N / \psi_n(i) \qquad \text{if } i > I \tag{12}$$

where i^* is the threshold at which capital and routine labor are equally costly, defined by $\psi_k(i^*)/\psi_r(i^*) = 1/w_R$.

Using the CES structure, total cost of producing Y_f units of output (excluding overhead) is:

$$b(I_f)Y_f = \frac{Y_f}{z_f}\left(\int_0^1 p_f(i)^{1-\eta}di\right)^{\frac{1}{1-\eta}} \tag{13}$$

where $b(I_f)$ is the unit cost. Substituting the task prices yields:

$$b(I_f) = \frac{1}{z_f}\left(\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right)^{\frac{1}{1-\eta}} \tag{14}$$

with CES aggregates:

$$\Gamma_k(I_f) \equiv \int_0^{\min\{I_f,i^*\}} \psi_k(i)^{\eta-1}di \tag{15}$$

$$\Gamma_r(I_f) \equiv \int_{\min\{I_f,i^*\}}^{I} \psi_r(i)^{\eta-1}di \tag{16}$$

$$\Gamma_n \equiv \int_I^1 \psi_n(i)^{\eta-1}di \tag{17}$$

Profit maximization. Given CES demand, the firm faces the inverse demand function:

$$p_f = \left(\frac{Y_f}{Y}\right)^{-\frac{1}{\sigma}} \tag{18}$$

Maximizing profits $p_fY_f - b(I_f)Y_f - C(I_f)$ yields the optimal price as a constant markup over marginal cost:

$$p_f = \frac{\sigma}{\sigma-1}b(I_f) = \frac{\sigma}{\sigma-1}\frac{1}{z_f}\left(\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right)^{\frac{1}{1-\eta}} \tag{19}$$

and optimal output:

$$Y_f = Y\left(\frac{\sigma}{\sigma-1}b(I_f)\right)^{-\sigma} \tag{20}$$

Labor cost. Total labor cost consists of production labor and overhead labor:

$$\text{Labor cost} = \underbrace{\int_{\min\{I_f, i^*\}}^{1} p_f(i) y_f(i)\, di}_{\text{production labor}} + \underbrace{I_f w_N \Psi_o}_{\text{overhead labor}} \tag{21}$$

Using the CES structure, the production labor cost can be written as:

$$\text{Production labor cost} = \frac{Y_f}{z_f} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)^{\frac{\eta}{1-\eta}} \left(w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right) \tag{22}$$

Labor share derivation. The labor share is the ratio of labor cost to revenue. For the production labor component:

$$\begin{aligned}
\lambda_1(I_f) &= \frac{\text{Production labor cost}}{Y_f p_f} \\
&= \frac{\frac{Y_f}{z_f} \left(\Gamma_k + w_R^{1-\eta} \Gamma_r + w_N^{1-\eta} \Gamma_n \right)^{\frac{\eta}{1-\eta}} \left(w_R^{1-\eta} \Gamma_r + w_N^{1-\eta} \Gamma_n \right)}{\frac{\sigma}{\sigma-1} \frac{Y_f}{z_f} \left(\Gamma_k + w_R^{1-\eta} \Gamma_r + w_N^{1-\eta} \Gamma_n \right)^{\frac{1}{1-\eta}}} \\
&= \frac{w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n}{\frac{\sigma}{\sigma-1} \left(\Gamma_k(I_f) + w_R^{1-\eta} \Gamma_r(I_f) + w_N^{1-\eta} \Gamma_n \right)}
\end{aligned} \tag{23}$$

where cancellation follows from $\frac{\eta}{1-\eta} - \frac{1}{1-\eta} = -1$.

For the overhead labor component:

$$\lambda_2(I_f) = \frac{I_f w_N \Psi_o}{Y_f p_f} = \frac{I_f w_N \Psi_o}{\frac{\sigma}{\sigma-1} b(I_f) Y_f} \tag{24}$$

Substituting the expression for Y_f:

$$\begin{aligned}\lambda_2(I_f) &= \frac{I_f w_N \Psi_o}{\frac{\sigma}{\sigma-1} b(I_f) \cdot Y \left(\frac{\sigma}{\sigma-1} b(I_f)\right)^{-\sigma}} \\ &= \frac{I_f w_N \Psi_o}{Y \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} b(I_f)^{1-\sigma}} \\ &= \frac{I_f w_N \Psi_o}{\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} Y \left(\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right)^{\frac{1-\sigma}{1-\eta}}}\end{aligned} \tag{25}$$

where the final line uses $b(I_f)^{1-\sigma} = z_f^{\sigma-1}\left(\Gamma_k + w_R^{1-\eta}\Gamma_r + w_N^{1-\eta}\Gamma_n\right)^{\frac{1-\sigma}{1-\eta}}$ and the z_f terms cancel.

Routine employment share derivation. The routine employment share is defined as the ratio of routine employment to total employment at the firm:

$$\mu(I_f) = \frac{\int_{\min\{I_f,i^*\}}^{I} \ell_{rf}(i)\,di}{\int_{\min\{I_f,i^*\}}^{I} \ell_{rf}(i)\,di + \int_I^1 \ell_{nf}(i)\,di} \tag{26}$$

From optimal task input use, we have:

$$y_f(i') = y_f(i)\left(\frac{p_f(i)}{p_f(i')}\right)^{\eta} \tag{27}$$

This implies the following relative factor demands:

$$\frac{\ell_{rf}(i)}{\ell_{rf}(i')} = \left(\frac{\psi_r(i')}{\psi_r(i)}\right)^{1-\eta} \qquad \text{if } i, i' \in (\min\{I_f, i^*\}, I] \tag{28}$$

$$\frac{\ell^p_{nf}(i)}{\ell_{rf}(i')} = \left(\frac{\psi_r(i')}{\psi_n(i)}\right)^{1-\eta}\left(\frac{w_R}{w_N}\right)^{\eta} \qquad \text{if } i > I \text{ and } i' \in (\min\{I_f, i^*\}, I] \tag{29}$$

where $\ell^p_{nf}(i)$ denotes non-routine production labor in task i (excluding overhead).

Using the relative factor demands with $i' = I$ as the reference task, and noting that total non-routine employment includes both production workers $\ell^p_{nf}(i)$ and overhead workers

$I_f c(i)/\psi_n(i)$:

$$\mu(I_f) = \frac{\ell_{rf}(I)\int_{\min\{I_f,i^*\}}^{I}\frac{\ell_{rf}(i)}{\ell_{rf}(I)}di}{\ell_{rf}(I)\int_{\min\{I_f,i^*\}}^{I}\frac{\ell_{rf}(i)}{\ell_{rf}(I)}di + \ell_{rf}(I)\int_I^1\frac{\ell_{nf}^p(i)}{\ell_{rf}(I)}di + I_f\int_I^1\frac{c(i)}{\psi_n(i)}di}$$

$$= \frac{\int_{\min\{I_f,i^*\}}^{I}\left(\frac{\psi_r(I)}{\psi_r(i)}\right)^{1-\eta}di}{\int_{\min\{I_f,i^*\}}^{I}\left(\frac{\psi_r(I)}{\psi_r(i)}\right)^{1-\eta}di + \int_I^1\left(\frac{\psi_r(I)}{\psi_n(i)}\right)^{1-\eta}\left(\frac{w_R}{w_N}\right)^{\eta}di + \frac{I_f}{\ell_{rf}(I)}\Psi_o} \tag{30}$$

Recognizing that $\psi_r(I)^{1-\eta}\int_{\min\{I_f,i^*\}}^{I}\psi_r(i)^{\eta-1}di = \psi_r(I)^{1-\eta}\Gamma_r(I_f)$ and similarly for Γ_n:

$$\mu(I_f) = \frac{\Gamma_r(I_f)}{\Gamma_r(I_f) + \left(\frac{w_R}{w_N}\right)^{\eta}\Gamma_n + \psi_r(I)^{\eta-1}\frac{I_f}{\ell_{rf}(I)}\Psi_o} \tag{31}$$

To obtain a closed-form expression, we solve for routine labor employed at the boundary task I. From the CES structure:

$$\ell_{rf}(I) = \frac{Y_f p_f(I)^{-\eta}}{z_f\psi_r(I)}\left(\int_0^1 p_f(i)^{1-\eta}di\right)^{\frac{\eta}{1-\eta}} \tag{32}$$

Substituting $Y_f = Y\left(\frac{\sigma}{\sigma-1}b(I_f)\right)^{-\sigma}$ and $p_f(I) = w_R/\psi_r(I)$:

$$\psi_r(I)^{1-\eta}\ell_{rf}(I) = \frac{Y w_R^{-\eta}}{z_f^{1-\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{\sigma}}\left(\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right)^{\frac{\eta-\sigma}{1-\eta}} \tag{33}$$

Substituting into the expression for $\mu(I_f)$ yields the final expression for the routine employment share:

$$\mu(I_f) = \frac{\Gamma_r(I_f)}{\Gamma_r(I_f) + \left(\frac{w_R}{w_N}\right)^{\eta}\Gamma_n + \left(\frac{\sigma}{\sigma-1}\right)^{\sigma}\Psi_o z_f^{1-\sigma}w_R^{\eta}Y^{-1}I_f\left(\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right)^{\frac{\sigma-\eta}{1-\eta}}} \tag{34}$$

Summary: the decomposition and its properties. Collecting the results above, the total labor share decomposes into two components:

$$\lambda(I_f) = \underbrace{\frac{w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n}{\frac{\sigma}{\sigma-1}\left[\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right]}}_{\equiv\lambda_1(I_f)\text{: production labor}} + \underbrace{\frac{I_f w_N \Psi_o}{\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} Y \left[\Gamma_k(I_f) + w_R^{1-\eta}\Gamma_r(I_f) + w_N^{1-\eta}\Gamma_n\right]^{\frac{1-\sigma}{1-\eta}}}}_{\equiv\lambda_2(I_f)\text{: overhead labor}} \tag{35}$$

The production labor component $\lambda_1(I_f)$ behaves as in the benchmark model: when I_f increases, routine workers are displaced by capital, and λ_1 falls. However, the overhead component $\lambda_2(I_f)$ moves in the opposite direction; it is increasing in I_f since greater automation requires more non-routine overhead workers. The total effect on the labor share therefore depends on the relative magnitudes of these two forces:

$$\frac{d\lambda}{dI_f} = \underbrace{\frac{d\lambda_1}{dI_f}}_{<0} + \underbrace{\frac{d\lambda_2}{dI_f}}_{>0} \tag{36}$$

When these two forces roughly offset, the labor share is approximately unchanged by automation, generating the near-zero correlations we observe in most sectors. When overhead costs are sufficiently large, the second term dominates, and the labor share rises with automation, generating a negative correlation between changes in routine employment share and changes in labor share. The benchmark model, which abstracts from overhead costs, corresponds to the limiting case where the second term is absent, yielding the positive correlation that is absent in our data.

In contrast, the effect of automation on the routine employment share is unambiguous. An increase in I_f reduces the routine employment share through three channels: (i) it directly lowers $\Gamma_r(I_f)$ in the numerator as fewer tasks are performed by routine workers; (ii) it raises $\Gamma_k(I_f)$ in the denominator's CES aggregate, which enters with a positive exponent $\frac{\sigma-\eta}{1-\eta} > 0$ for $\sigma > 1$ and $\eta < 1$; and (iii) it increases the overhead employment term proportionally. All three effects work in the same direction, ensuring that $d\mu/dI_f < 0$ unambiguously. Consequently, while firms with greater automation may experience rising, falling, or unchanged labor shares depending on the magnitude of overhead costs, they will always exhibit declining routine employment shares.

D Platform Costs with Scale Effects

A related mechanism arises when platform services (monitoring, maintenance, coordination) are produced using non-routine labor with decreasing returns to scale. To see how this works, consider an automatable task $i \leq I_f$ where the firm chooses to automate. Task output is produced according to:

$$y_f(i) = \begin{cases} \psi_k(i) \min\{k_f(i), \theta(i) s_f(i)\} & \text{if } i \leq I_f \\ \psi_r(i) \ell_{rf}(i) & \text{if } i \in (I_f, I] \\ \psi_n(i) \ell_{nf}(i) & \text{if } i > I \end{cases} \tag{37}$$

where $k_f(i)$ is automation capital, $s_f(i)$ denotes platform services allocated to task i, and $\theta(i)$ governs how much platform capacity is required per unit of capital. The Leontief structure in the first line captures the idea that capital and platform services are strict complements: capital is unproductive without monitoring and support.

Let $S_f \equiv \int_0^{I_f} s_f(i)\, di$ denote the firm's total platform capacity, and let L_{Nf}^{plat} denote the non-routine labor employed to provide platform services. Suppose platform capacity is produced according to:

$$S_f = \left(L_{Nf}^{\text{plat}}\right)^{1/\chi}, \quad \chi \geq 1 \tag{38}$$

which implies that platform labor requirements are:

$$L_{Nf}^{\text{plat}} = S_f^{\chi} \tag{39}$$

The parameter χ governs the convexity of platform labor in capacity. When $\chi = 1$, doubling capacity requires doubling platform labor. When $\chi > 1$, doubling capacity requires *more than* doubling platform labor, reflecting the increasing complexity of managing larger automated systems.

Under this specification, a decline in the price of automation capital triggers competing effects on the labor share. The standard *displacement effect* reduces routine labor demand as firms automate more tasks. But a *platform expansion effect* works in the opposite direction: greater automation requires hiring more non-routine platform workers, and when $\chi > 1$, this effect is disproportionately large for firms undertaking substantial automation. When these effects are of similar magnitude, the labor share remains approximately constant even as routine employment falls, consistent with the zero correlations observed in most sectors. For firms with high initial routine intensity, precisely those experiencing the largest proportional increases in automation scale, the platform expansion effect can dominate when χ is sufficiently large, causing the labor share to rise even as routine employment falls.