Automation Technology and its Impact on Labor Markets, Factor Shares, and Productivity*

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Abstract

This article reviews the literature on automation and its impact on labor markets, wages, factor shares, and productivity. I first introduce the task model of automation and explain why this framework offers a compelling way for thinking about recent labor market trends and the effects of automation technology. The task framework clarifies that automation advances work by substituting capital for labor in a widening range of tasks. This substitution reduces costs, creating a positive productivity effect, but also reduces employment opportunities for workers displaced from automated tasks, creating a negative displacement effect. I then survey the recent empirical literature and conclude that there is wide qualitative support for the main implications of task models and the displacement effects of automation. I conclude by discussing shortcomings of the existing literature and avenues for future research.

Keywords: tasks, automation, productivity, technology, inequality, wages, robots

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This article reviews the literature on automation and its impact on labor markets and the economy. This literature studies how advances in automation technologies have impacted labor markets, the demand for workers with different skills, employment, factor shares, and productivity. In the recent past, the US economy has seen a pronounced decline of the labor share in major economic sectors (most notably, manufacturing and retail trade), a large shift away from routine occupations in both factory floors and offices, and a sizable increase in wage inequality, with wages for workers without college degree stagnating. Though these trends are more pronounced in the US, they are also visible in other advanced economies.[1] Has automation contributed to these developments?

I define automation as technological advances that facilitate the substitution of capital for labor at a widening range of tasks or productive processes. Examples include the developments of robotics, enabling the substitution of robots for workers in manufacturing; the development of computer-numerically controlled machines, which eliminated the need for machine operators; the development of specialized software systems automating clerical tasks, such as handling payroll, sales, or customer service; or the development of trashing machines in agriculture, substituting for farm labor. Not all technological developments count as automation. The creation of new goods and products does not automate existing work. Advances in material processes raise productivity but do not involve automation. Improvements in machinery already in use (i.e., more sturdy cranes, durable lathes, or conveyor belts) do not automate additional tasks.

Section 1 formalizes this definition using the *task model* of automation. The task framework captures this process of substitution of capital for labor in a widening range of tasks, as in the examples above, and works out its aggregate implications. This substitution reduces costs, creating a positive productivity effect, but also reduces employment opportunities for workers displaced from automated tasks, creating a negative displacement effect.

The framework explains how automation might have contributed to recent labor-market trends and delivers clear predictions that organize the empirical literature:

- Automation reduces the labor share of adopting firms and industries via its displacement effect.
- Automation alters the occupational structure of firms, industries, and the economy

[1] For a summary of the empirical trends regarding the US occupational and wage structure see Goldin and Katz (2008), Acemoglu and Autor (2011), and Autor (2019). For the empirical trends regarding the labor share, see Karabarbounis and Neiman (2013), Dao et al. (2019), Grossman and Oberfield (2021), and Hubmer and Restrepo (2021). The online appendix provides a summary of these trends for the US.

by substituting workers away from exposed occupations (those involving tasks that can be automated by new technologies).

- Automation allows adopting firms to expand their sales, creating an ambiguous effect on their employment level. However, firm-level employment expansions are not informative of the aggregate impacts of automation on labor demand.

- Automation reduces the relative demand for groups of workers who performed automated tasks via its displacement effects. This effect can reduce the real wages and employment of displaced groups if they cannot reallocate to non-automated tasks and the productivity gains from automation are modest.

- The impacts of automation differ from other technological advances, such as improvements in existing machinery or the development of capital needed for new goods, which do not create a displacement effect.

Section 2 reviews the growing empirical evidence with these implications in mind. Existing papers estimate the impact of specific automation technologies (most notably, industrial robots) on firms, industries, occupations, regions, and workers. My conclusion from this exercise is that there is wide qualitative support for the implications of the task framework.

Section 3 concludes by discussing limitations of this literature and areas for future work.

1 The task framework

The task framework starts from the observation that producing goods and services requires completing *tasks*. To produce a car one has to design it, procure parts, assemble them, weld them, paint them, and so on. Tasks are assigned to workers of different skill, but increasingly more tasks are produced in an automated way by software, dedicated machinery, or industrial robots, as shown in the introductory examples. The framework models this task-level substitution and derives its aggregate implications.[2]

The framework

A final good y is produced from differentiated products y_n with $n \in \{1, \dots, N\}$. Products are combined using a constant-returns to scale technology $y = f(\{y_n\}_{n \in \mathcal{N}})$ with unit cost

[2] My treatment follows Acemoglu and Restrepo (2022), and builds on Zeira (1998), Grossman and Rossi-Hansberg (2008), Acemoglu and Autor (2011), Acemoglu and Restrepo (2018), and Aghion et al. (2018). For complementary approaches see Jackson and Kanik (2020), Ocampo (2022), and Martinez (2021).

function c^u. Depending on the application, products are the output of industries or firms.

Each product requires completing a mass 1 of tasks x from disjoint sets $\mathcal{T}_n$. Task quantities y_x are aggregated with a constant elasticity of substitution $\lambda \geq 0$

$$y_n = \left(\int_{x \in \mathcal{T}_n} y_x^{\frac{\lambda - 1}{\lambda}} \cdot dx \right)^{\frac{\lambda}{\lambda - 1}}.$$

Tasks can be produced using labor or task-specific capital—software and equipment designed for this process. Workers belong to discrete groups $g \in \{1, \ldots, G\}$. Depending on the application, groups denote workers' skills, observable attributes (i.e., education and age), or region. The total quantity of task x produced is

$$y_x = \psi_{kx} \cdot k_x + \sum_g \psi_{gx} \cdot \ell_{gx},$$

where ℓ_{gx} and k_x are labor and capital allocated to x and $\psi_{gx} \geq 0$ and $\psi_{kx} \geq 0$ denote their productivity. The ψ's vary by tasks and groups and encode their comparative advantage.

I treat capital as an intermediate good, produced from the final good at a constant unit cost $1/q_x$ and used instantaneously. q_x denotes the efficiency of the investment sector. The remaining output is used for consumption so that the economy's resource constraint is

$$c + \sum_n \int_{x \in \mathcal{T}_n} (k_x / q_x) \cdot dx \leq y$$

Group g's labor supply is $\ell_g = \bar{\ell}_g \cdot w_g^{\varepsilon}$ with $\varepsilon \geq 0$ and w_g group's g wage. This labor supply can result from households optimization over consumption and leisure or from labor-market frictions as in Kim and Vogel (2021). Labor-market clearing for g requires

$$\sum_n \int_{x \in \mathcal{T}_n} \ell_{gx} \cdot dx \leq \bar{\ell}_g \cdot w_g^{\varepsilon}.$$

Firms and industries pay the same wage w_g so that there is no monopsony power or rents.[3]

A *competitive equilibrium* is given by vectors of wages $w = \{w_g\}$ and prices $p = \{p_n\}$ such that markets clear and tasks are allocated in a cost-minimizing way. Acemoglu and Restrepo (2022) provide conditions for the existence and uniqueness of equilibrium, and conditions under which each task is assigned to a unique factor (except for a zero-measure indifference set). I assume these conditions hold.

[3]See Acemoglu and Restrepo (2023) for work exploring the role of rents and monopsony in task models.

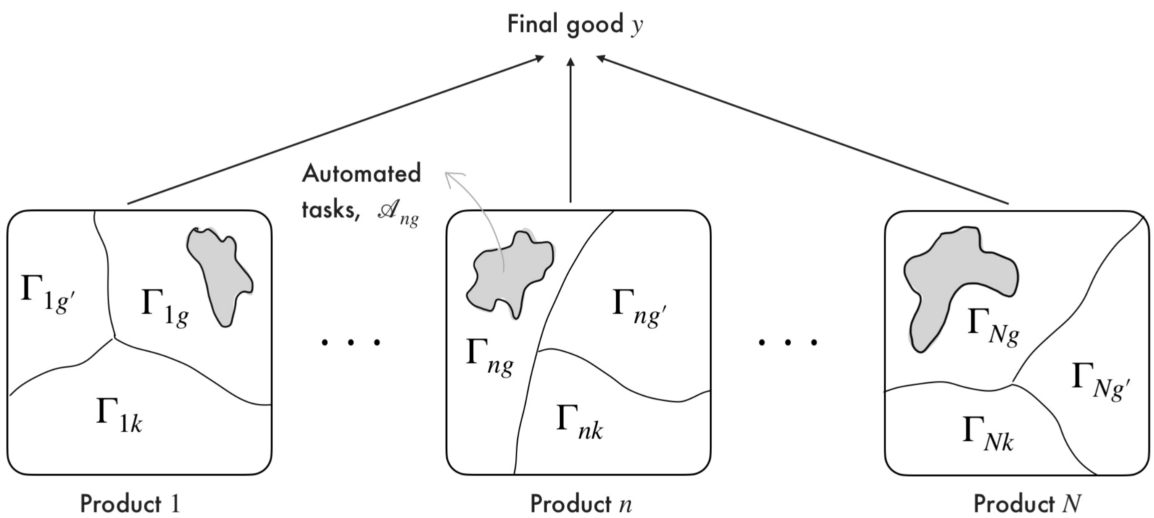

FIGURE 1: TASK ASSIGNMENT, TASK SHARES, AND AUTOMATION. The figure represents the tasks needed to complete different products $n = 1, \ldots, N$ and how these tasks are assigned to workers of different skill or produced by capital. The gray areas represent the displacement effects from automation.

The key problem in this economy is how to allocate tasks across workers and capital—a decision guided by comparative advantage. Let $\mathcal{T}_{nk}(w)$ and $\mathcal{T}_{ng}(w)$ denote the set of product-n tasks assigned to capital and labor when wages are $w = \{w_g\}$, as shown in Figure 1, and define the *task shares* of capital and group g in product n as

$$\Gamma_{nk}(w) := \int_{\mathcal{T}_{nk}(w)} (\psi_{xk} \cdot q_x)^{\lambda-1} \cdot dx, \qquad \Gamma_{ng}(w) := \int_{\mathcal{T}_{ng}(w)} \psi_{xg}^{\lambda-1} \cdot dx.$$

Task shares capture the importance of tasks assigned to capital and workers. They are functions of technology and wages encoding all information on the assignment of tasks relevant for equilibrium outcomes. In particular, equilibrium wages $w = \{w_g\}$, good prices $p = \{p_n\}$, and output y, are determined by the following conditions:

- the price of the final good is 1,

$$c^u(p) = 1; \tag{1}$$

- p_n equals the marginal cost of producing y_n

$$p_n = \left(\Gamma_{nk}(w) + \sum_g \Gamma_{ng}(w) \cdot w_g^{1-\lambda}\right)^{\frac{1}{1-\lambda}}; \tag{2}$$

- the labor market for g workers clears

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda+\varepsilon}} \cdot \left(\sum_n s_y^n \cdot p_n^{\lambda-1} \cdot \Gamma_{ng}(w) \cdot dn\right)^{\frac{1}{\lambda+\varepsilon}} \quad \text{with } s_y^n = \frac{p_n \cdot y_n}{y}. \tag{3}$$

Moreover, the equilibrium output of product n can be represented as

$$y_n = \left(\Gamma_{nk}(w)^{\frac{1}{\lambda}} \cdot k_n^{\frac{\lambda-1}{\lambda}} + \sum_g \Gamma_{ng}(w)^{\frac{1}{\lambda}} \cdot \ell_{ng}^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}. \tag{4}$$

Equations (1), (2), and (3) show how task shares determine equilibrium wages and prices. Equation (4) shows that at the product level, output aggregates to a constant elasticity of substitution (CES) production function, with task shares appearing as endogenous weights. Task shares can therefore be treated as primitives in task models. Every parameterization of the ψ's implies some task shares and two parameterizations with the same task shares produce identical outcomes. By the same token, and as I will show below, all that is needed for understanding how automation affects wages, prices, and output is knowing how it impacts task shares.

These results highlight two key features of task models that are important for modeling automation and understanding its impact:

- The endogenous weights allow for a richer pattern of substitution than in a CES model. In task models, there is substitution between tasks (governed by λ) and within tasks (governed by the derivatives of task shares, showing as shifts in weights). This determines the incidence of shocks across worker groups.

- Equation 4 highlights the possibility that automation and technological developments directly shift CES weights up and down, reducing the importance of workers from some groups in production and increasing the importance of capital or other groups. This offers a rich representation of technology capable of capturing displacement and distributional effects in an unrestricted way.[4]

[4] In contrast, most existing approaches start from production functions of the form $y = g(A_k \cdot k, \{A_g \cdot \ell_g\})$, where g is a CES (or nested CES) with exogenous weights, and represent technology by an *increase* in some or all A's (i.e., factor-augmenting improvements). This approach restricts outcomes in an arbitrary way. For example, in Katz and Murphy (1992) and Krusell et al. (2000), an increase in A_H—augmenting skilled labor—or A_K—augmenting capital in the latter—always increase unskilled workers' wages. One could extend these approaches to capture some implications of task models by having technological progress increases some A's and reduce others, mimicking a shift in weights. Yet, this reduced-form modeling opens more questions than it answers. What does it mean for some A's to decrease? How are the A's linked? What technologies move the A's in such directions? The task framework answers all these questions.

Automation advances

The defining feature of *automation advances* is that they lead to the substitution of capital for labor in specific tasks. The easiest way to capture these developments is by assuming that $q_x = 0$ for some tasks initially assigned to workers, so that the technology for producing these tasks with capital did not exist. One can then think of automation advances as exogenous events that increase q_x from zero to $q_x' > 0$ for tasks in $\mathcal{A}_{ng} \subset \mathcal{T}_{ng}$. To simplify the exposition, I assume that

$$\pi_x := \ln\left(w \cdot \frac{q_x \cdot \psi_{kx}}{\psi_{gx}}\right) > \underline{\pi},$$

for some $\underline{\pi} > 0$ for all tasks in $\bigcup_{n,g} \mathcal{A}_{ng}$ so that they all become automated.[5]

Automation advances work at the extensive margin: they displace workers from tasks in $\mathcal{A}_{ng}$, creating a *displacement effect*. I let $d \ln \Gamma_{ng}^{d}$ denote the reduction in g's task share from automating tasks in $\mathcal{A}_{ng}$, as shown in Figure 1. This is defined at the initial wages and does not account for any endogenous reassignment of tasks. Automation also lowers the cost of producing newly automated tasks by π_x, creating a *productivity effect*. I let π_{ng} denote the average cost-saving gains from automating tasks in $\mathcal{A}_{ng}$, computed at initial wages. The set of automated tasks, the productivity gains this generates, and the identity of workers displaced depend on the capabilities of the new technology and workers' comparative advantages across products and tasks. On the flip side, the change in task shares $d \ln \Gamma_{ng}^{d}$ and cost-saving gains π_{ng} brought by a specific advance in automation suffice for deriving its implications.

Implications

The next formulas summarize the impacts of automation on adopting firms and industries, worker groups and aggregates. The formulas provide first-order approximations to the effects of automation valid when the measure of automated tasks is small.

I provide two types of formulas. The first consider *direct effects*. These refer to the impact of automation on firm-level or industry-level outcomes holding wages and aggregate output y constant. These formulas are helpful for understanding how a firm or industry

[5]This can be extended in several ways. One could think of k_x as requiring skilled labor to be operated. One could also think of these advances as the realization of R&D done by firms or integrators, as in Acemoglu and Restrepo (2018) and Hubmer and Restrepo (2021). One can also think of cases where automation is endogenously adopted in some tasks but not others by having $\pi_x \lesseqgtr 0$.

adopting automation technologies change their employment, factor shares, and demand for skills relative to other firms or industries that face the same factor prices and aggregate demand. These formulas connect the theory to firm and industry estimates.

The second type incorporates *general equilibrium effects*. These formulas account for the endogenous change in wages and how this then creates a reassignment of tasks across workers. These formulas are helpful for interpreting empirical work that estimates the impact of automation on exposed workers groups (defined by skill, demographics, or regions) and for assessing the impact of automation on aggregates.

Implication 1: Declining labor shares. [6] The direct impact of automation advances in firm or industry n labor share s_n^ℓ is

$$(5)\quad d\ln s_n^\ell = \underbrace{-\sum_g \omega_n^g \cdot d\ln\Gamma_{ng}^d}_{\text{displacement effects}} + \underbrace{(1-\lambda)\cdot s_n^\ell \cdot \sum_g \omega_n^g \cdot \pi_{ng}\cdot d\ln\Gamma_{ng}^d}_{\text{task-price effects}}, \quad \left(\text{with } \omega_n^g = \frac{w_g \cdot \ell_{ng}}{\sum_{g'} w_g' \cdot \ell_{ng'}}.\right)$$

The displacement effect captures the negative contribution of automation on the labor share resulting from the extensive-margin reallocation of tasks from labor to capital. The second term captures the effect of the reduction in the price of automated tasks. When $\lambda < 1$ so that tasks are complements, the cheaper automated tasks earn a smaller share of value added, raising the labor share. When $\lambda > 1$ so that tasks are substitutes, the cheaper automated tasks earn a higher share of value added, further reducing the labor share. The displacement effect dominates for *all* values of λ. This means that automation advances reduce the labor share of adopting firms and industries relative to others.[7]

The general equilibrium effects of automation on the aggregate labor share (in the appendix) are harder to sign. On the one hand, we have the direct (negative) effect of automation due to its displacement effect on adopting firms and industries. On the other hand, this shock affects the aggregate labor share indirectly via wage levels (as in Grossman and Oberfield, 2021) and the reallocation of economic activity across firms (as in Oberfield and Raval, 2020) or industries (as in Acemoglu and Restrepo, 2022). My view is that in the case of automation these indirect effects on the labor share are small, and that automation is a plausible driver of the observed labor share decline in the aggregate and

[6] In practice, payments to capital are not treated as intermediate expenses but are part of value added. For this reason, the empirical counterpart of s_n^ℓ is the labor share in value added.

[7] This result depends on the CES task aggregator used. For other aggregators, the task-price effect might dominate and the labor share could increase for adopting firms or industries.

in manufacturing.[8]

One important point is that the direct effect of automation on firms and industry labor shares is not mediated by the elasticity of substitution between capital and labor, given by

$$\sigma_n = \lambda + \underbrace{\frac{1}{1-s_n^\ell} \cdot \sum_g \omega_n^g \cdot \left(-\sum_j \frac{\partial \ln \Gamma_{ng}(w)}{\partial \ln w_j}\right)}_{\text{substitution within marginal tasks } (\geq 0)}.$$

This elasticity is greater than or equal to λ, since firms can also respond to factor prices by substituting labor for capital at marginal tasks. But it can be well below one depending on parameters. The reason why the effects of automation on the labor share are disconnected from σ_n is that these advances take place at the extensive margin. Elasticities of substitution summarize the impact of changes in input prices (or factor-augmenting technologies) on firms' factor shares, but are not designed to capture changes in task shares at the extensive margin. The task framework thus reconciles the evidence for a negative labor share impact of automation with studies that estimate $\sigma_n < 1$ by exploiting wage variation (i.e., Oberfield and Raval, 2020).

Implication 2: Occupational structure. Occupations involve tasks with varying potential for automation. For example, middle-pay occupations such as clerical or blue-collar jobs involve routine tasks that are easier to codify and automate (Autor et al., 2003).

To capture these feature, assume that tasks can be partitioned into occupations o. Denote by $\Gamma_{nog}(w)$ the task share of group g workers in occupation o tasks in product n, and by $d\ln\Gamma^d_{nog}$ the reduction in $\Gamma_{nog}(w)$ from automating tasks in $\{\mathcal{A}_{ng}\}$. For example, if advances in automation can only substitute for routine tasks, $d\ln\Gamma^d_{nog}$ would be positive for occupations involving routine tasks and zero otherwise.

Let ω_n^o denote the share of wage payments made to workers in occupation o in the production of n (as a share of all wages paid in n). The direct impact of automation on firm or industry n occupational wage shares is

$$(6) \qquad d\ln\frac{\omega_n^o}{\omega_n^{o'}} = \underbrace{\sum_g \omega_{ng}^o \cdot d\ln\Gamma^d_{nog}}_{\text{exposure to automation, } o} - \underbrace{\sum_g \omega_{ng}^{o'} \cdot d\ln\Gamma^d_{no'g}}_{\text{exposure to automation, } o'}, \qquad \left(\text{with } \omega_{ng}^o = \frac{w_g \cdot \ell_{nog}}{\sum_{o'} w_g \cdot \ell_{no'g}}.\right)$$

[8] For example, in their quantitative exercise, Acemoglu and Restrepo (2022) estimate that automation increases wage levels by 6% and had a small impact on the sectoral composition of the economy.

This means that automation advances in an industry or firm reduce the share of wage payments (and employment) in occupations that are highly exposed to the technology, as measured by the average displacement experienced by workers in these jobs, $\sum_g \omega_{ng}^o \cdot d\ln\Gamma_{nog}^d$.

The task model thus provides a plausible explanation for the changing occupational structure of the US and other developed economies, where we have seen a decline in the share of employment and wages paid for work in routine middle-pay occupations.

Implication 3: Firm and industry sales and employment levels. Automation advances increase total-factor productivity in product n by

$$d\ln tfp_n = s_n^\ell \cdot \sum_g \omega_n^g \cdot \pi_{ng} \cdot d\ln\Gamma_{ng}^d > 0. \tag{7}$$

The direct impact of automation advances in firm or industry n sales is therefore

$$d\ln(p_n \cdot y_n) = (\epsilon_n - 1) \cdot d\ln tfp_n, \tag{8}$$

and the direct impact on firm or industry n employment is

$$d\ln\ell_{ng} = \underbrace{(\epsilon_n - \lambda) \cdot d\ln tfp_n}_{\text{Scale vs. substitution effects}} - \underbrace{d\ln\Gamma_{ng}^d}_{\text{displacement effects}}. \tag{9}$$

Here, $\epsilon_n \geq 0$ is the elasticity of demand for n.[9] When n denotes firms, we expect this elasticity to exceed one as firms to operate in elastic segments of demand. When n denotes industries, this elasticity could be below one, especially in closed economies.

Equation (9) shows that employment in industries and firms benefiting from advances in automation depend on two forces. The first term captures the usual scale vs substitution effects. The scale effect captures the expansion in quantities produced, governed by the demand elasticity ϵ_n. The substitution effect results from the fact that firms can now produce automated tasks at a lower cost, and so they will substitute away from the more expensive labor-intensive tasks that have not been automated. These are the usual effects on labor demand resulting from a change in the price of an input. The novel aspect here is that automation creates an additional negative impact due to its displacement effect.

In sum, the net impact of automation advances on firm or industry-level employment

[9] These derivations assume that products are atomistic and hold output constant. The formulas generalize to monopolistic competition. If firms or industries have an incomplete passthrough $\rho_n \in (0,1)$ of marginal cost to prices, the employment effect is $d\ln\ell_n = (\epsilon_n\rho_n - \lambda) \cdot d\ln tfp_n - \sum_g \omega_{ng} \cdot d\ln\Gamma_{ng}^d$.

is ambiguous. Employment increases if firms or industries face highly elastic demands, and decreases otherwise. The robust prediction for firms and industries is that in either case automation expands firm sales more than employment, increasing sales per worker.[10]

Implication 4: Impacts on exposed groups of workers. The impact of automation on exposed groups of workers depends on whether workers can reallocate, how much output expands, and other equilibrium considerations. Consider a shock directly changing group g wages by z_g. In equilibrium, this shock leads to a reassignment of tasks, which also impacts wages, creating a fixed point problem of the form

$$d\ln w_g = \underbrace{z_g}_{\text{direct effects}} + \underbrace{\frac{1}{\lambda+\varepsilon}\cdot \mathcal{J}_\Gamma \cdot d\ln w}_{\text{task reassignment}}.$$

In this equation, the endogenous reassignment of tasks is governed by the Jacobian $\mathcal{J}_\Gamma$, a $G \times G$ matrix where entry (g, j) is the elasticity of $\sum_n s_y^n \cdot p_n^{\lambda-1} \cdot \Gamma_{ng}(w)$ with respect to w_j. The resulting wage change accounting for the endogenous reassignment is

$$d\ln w_g = \Theta_g \cdot \text{stack}_j(z_j)$$

where $\text{stack}_j(z_j)$ is the column vector $(z_1, z_2, \ldots, z_G)$. The change in group g wages depends on the vector of shocks experienced by all other groups and mediated by the *propagation matrix* $\Theta = \left(\mathbb{I} - \frac{1}{\lambda+\varepsilon}\cdot \mathcal{J}_\Gamma\right)^{-1}$. This matrix has positive entries $\theta_{gj} \geq 0$ that capture the extent to which a shock increasing the demand for j affects g wages via the endogenous reassignment of tasks.[11] The propagation matrix has large diagonal entries and small off-diagonal ones. In this case, workers bear most of the incidence of a shock affecting them. The propagation matrix will have small diagonal entries (and larger off-diagonals) if workers can easily reallocate to other tasks, spreading the incidence of shocks to competing workers.

Using this notation, we can derive the equilibrium impact of automation on wages, product shifters, and output as a solution to the following system of equations.

[10] Not all technological advances benefiting a firm increase sales per worker, even though this is commonly used as a measure of firm productivity. For firms operating in competitive labor markets, sales per worker are an inverse measure of their labor shares. An increase in sales (or value added) per worker relative to a competitor facing the same wages means that the firm is reducing its labor share, not that it is becoming more productive.

[11] This can be because j competes directly against g for tasks, or because j competes against other groups which then compete with g. This is why Θ takes the form of a Leontief inverse aggregating these effects.

First, we have an equation for wage changes, derived by differentiating (3)

$$(10) \qquad d\ln w_g = \Theta_g \cdot \text{stack}_j\Big(\underbrace{\frac{1}{\lambda+\varepsilon}\cdot d\ln y}_{\text{productivity effect}} + \underbrace{\frac{1}{\lambda+\varepsilon}\cdot \sum_n (\omega_j^n - s_y^n)\cdot d\ln \zeta_n}_{\text{product composition}} - \underbrace{\sum_n \omega_j^n \cdot d\ln \Gamma_{jn}^d}_{\text{displacement effect}} \Big).$$

Here, $\omega_g^n = \frac{w_g \ell_{ng}}{\sum_{n'} w_g \ell_{n'g}}$ is the share of group g workers employed in product n. The equilibrium effects on employment have a similar expression, computed from $d\ln \ell_g = \varepsilon \cdot d\ln w_g$.

Second, wage level and output changes are pinned down by the dual of Solow's residual

$$(11) \qquad \sum_g s_y^g \cdot d\ln w_g = \sum_n s_y^n \cdot d\ln tfp_n \quad \Big(\text{with } s_y^g = \frac{w_g\cdot \ell_g}{y}\Big),$$

where $d\ln tfp_n$ is in equation (7) and depends on the cost-saving gains from automation, $\{\pi_{ng}\}$. This equation holds in any competitive model where production has constant returns to scale and the supply of capital and other factors of production are completely elastic. This equation shows that average wage increases across groups are always equal to the aggregate TFP gains from automation, summarized by $\{\pi_{ng}\}$.[12]

Third, we have an expression for the product shifters $d\ln\zeta_n$, computed as

$$(12) \qquad d\ln \zeta_n = (\lambda - 1)\cdot d\ln p_n + \mathcal{J}_s \cdot d\ln p, \text{ with } d\ln p_n = s_n^\ell \cdot \sum_g \omega_n^g \cdot d\ln w_g - d\ln tfp_n.$$

Here, the Jacobian J_s is an $N\times N$ matrix whose entry (n,m) is the elasticity of $\ln s_y^n$ with respect to a change in p_m.

Equations (10), (11), and (12) form a system of equations in wages, prices, and output. From these equations, we can compute the aggregate effects of automation as a function of the direct task displacement experienced by groups across products $\{d\ln\Gamma_{ng}^d\}$ and the cost-saving gains it generates $\{\pi_{ng}\}$. Equilibrium effects in turn depend on the reallocation of workers across tasks (governed by Θ and the task Jacobian $\mathcal{J}_\Gamma$), the reallocation of sales across products (governed by the Jacobian $\mathcal{J}_s$), and initial shares.

Equation (10) summarizes the channels through which automation affects wages and employment of workers from group g.

- First, we have a positive productivity effect, captured by the output expansion $d\ln y$,

[12]The logic that automation (and any improvement in technology) increases mean wages in an efficient economy goes back to Simon (1965) and was recently emphasized by Caselli and Manning (2019). Intuitively, productivity gains must accrue to labor, since this is the only fixed factor of production.

directly increasing the demand for all workers. The equilibrium output expansion is positive and depends on the productivity gains from automation, $\{\pi_{ng}\}$.

- Second, we have changes in the product composition of the economy via relative prices, captured by the product shifters $d\ln\zeta_n$. They capture the reallocation of economic activity across firms and industries with different skill intensity brought by automation. This reallocation raises the demand for workers highly demanded by expanding industries and firms. For example, automation could reallocate activity from manufacturing to high-skill service industries, increasing the relative demand for skilled labor.[13]

- Third, and most important, we have the task displacement experienced by workers from group g across all firms and industries, computed as $\sum_n \omega_j^n \cdot d\ln\Gamma_{jn}^d$. The direct impact of task displacement is to reduce the relative wages of exposed groups of workers, as they are squeezed into fewer employment opportunities.

- Finally, equation (10) shows that the incidence of automation depends on the reallocation patterns summarized by the propagation matrix Θ.

To illustrate the implications of this equation, consider a tractable case with no product shifters and where the rows of the propagation matrix Θ add up to a common value, so that all workers benefit equally from the productivity effect and the changing product composition of the economy.

Equation (10) shows that an automation shock displacing g workers from some of their tasks reduces this group wages and employment relative to non-exposed groups. This is because the propagation matrix satisfies $\theta_{gg} > \theta_{jg}$ for $j \neq q$. This makes intuitive sense: workers directly hit by a shock bear more of its incidence than other groups. The relative wage decline will be more pronounced when θ_{gg} is high, meaning that workers from group g cannot reallocate to non-automated tasks by taking small wage cuts.

Equation (10) also shows that automation can reduce group g real wages and employment levels if (i) workers cannot reallocate easily (θ_{gg} is high) and (ii) the cost-saving gains from automation π_{ng} are small—what Acemoglu and Restrepo (2019) call "so-so" automation technologies.[14]

[13] Other developments such as structural transformation, trade in final goods, and increasing sales concentration affect labor demand through this channel (see, for example, Buera et al., 2021).

[14] Both conditions are required for real wages to fall. In the limit where workers can reallocate by taking small wage cuts, $\theta_{gg} = \theta_{jg}$ for all j and all wages change by the same amount. Solow's dual in (10) then implies that all real wages must increase. Conversely, if the cost-saving gains from automation π_{ng} are

The task model thus provides a plausible explanation for the increasing wage inequality observed between groups of US workers and the wage stagnation experienced by non-college men. These can be explained as the result of the automation of tasks previously performed by non-college workers (especially men) that brought small productivity gains and left them with few opportunities to reallocate.

Implication 5: firm-level employment effects do not aggregate up. The firm-level (or industry-level) effects of automation in (9) are disconnected from the aggregate effects of automation on workers' wages and employment in (10) for two reasons.[15] First, firm or industry-level employment estimates miss the common productivity effect due to aggregate output expansions (i.e., $d \ln y$ in 10). Second, firm or industry-level employment estimates capture the reallocation of sales (and wage payments) across firms or industries. Yet, this reallocation has no clear-cut aggregate implications.

As an example, suppose that $\varepsilon_n > \lambda$, so that sales (and wage payments) at adopting firms expand at the expense of non-adopting firms. If $\omega_g^n = s_y^n$ for all g (i.e., all sectors employ workers and capital in equal proportions), reallocation washes out on aggregate, but would show up positively in firm-level estimates of employment.

Implication 6: Automation differs from other capital advances. Automation advances take place at the extensive margin: they involve an increase in the efficiency of capital at tasks previously assigned to labor, displacing workers from these tasks.

Automation differs from capital advances at the *intensive* margin or *capital deepening*: improvements in the efficiency of capital for tasks already assigned to capital. Examples of capital deepening include improvements on machinery already in use (i.e., more sturdy cranes, durable lathes, or conveyor belts), machine-learning algorithms replacing hand-coded ones, and electrical motors replacing steam engines.

The direct and aggregate impacts of capital deepening differ from those of automation. Capital deepening affects the labor share by lowering the price of capital-intensive tasks. In the relevant case where tasks are complements and $\lambda < 1$, the direct effect of capital deepening is to increase the labor share. Moreover, advances at the intensive margin do not alter the employment or occupational composition of firms or industries. Capital deepening

large, the productivity effect dominates the displacement effect for all workers, increasing wages.

[15] Firm-level estimates of the impact of automation on wages are also disconnected from aggregate effects. Firm-specific wage changes signal deviations from competitive markets, such as monopsony or rent sharing, but this has little to do with the aggregate effects of automation.

increases firm-sales too, but only affect firm-level employment via scale and substitution effects. Finally, at the aggregate level, capital deepening only affects wages and employment by expanding output and shifting the product composition of the economy. In the example discussed above with no product shifters and a common row sum for Θ, capital deepening increases all group wages and employment by the same amount.[16]

2 Empirical work on automation

This section reviews the empirical literature exploring the implications of different automation technologies for factor shares, the occupational and wage structure, and firm and industry-level outcomes.

2.1 Automation and the labor share

The prediction that automation increases sales per worker and reduces the share of labor in value added has been documented in various contexts by studies exploring the impact of automation technologies on industries and firms. Most of this literature has studied the impact of industrial robots, which provide a clear example of a technology being used for the automation of routine production tasks. But more recently, we have seen work expanding these studies to other automation technologies.

Acemoglu and Restrepo (2020) explored the introduction of industrial robots across US industries in the 1990s and 2000s. They show that the adoption of industrial robots in the US was driven by technological developments abroad (Japan, Italy, Germany, and other European countries). They document that US industries benefiting from these advances in industrial robotics saw increased value added and reduced employment. This resulted in higher output per worker and a lower labor share. Moving one industry from zero robots to 10 robots per thousand workers (the level in metalworking industries) increases value added by 12.5%, reduce employment by 6.25%, and its labor share by 5 pp.

Graetz and Michaels (2018) explored this question for a broader set of European countries with higher levels of robot adoption than the US. They show that industries intensive in tasks that can be automated via industrial robots (picking, reaching, handling, and others) adopted more robots and saw a greater increase in value added per worker from

[16] Capital advances can also lead to the introduction of *new products*, without displacing workers from their tasks. This occurs when $\psi_{xg} = 0$ for all g in a positive mass of tasks needed to produce some n and q_x jumps from zero to a positive value for these tasks. If new products demand inputs in similar proportions as the rest of the economy, these developments will increase output and all wages by the same amount.

1993 to 2007. They do not report effects on the labor share. However, they estimate that moving from the lowest (zero robots) to the highest level of adoption (the level in car manufacturing) increases value added per worker in an industry by 66–100 log points and raise average wages by 10 log points. This implies a 56-90 log point decrease in labor shares. Their appendix tables document that these results are driven by a 50–60 log point increase in value added and a 20–50 log point decrease in employment (though their employment estimates are imprecise, and cannot rule out zero or large negative effects).

The growing literature exploiting the staggered adoption of industrial robots across firms discussed below finds that this technology is associated with declining labor shares in value added and sales.

Recent work has turned to a broader range of automation technologies.

Boustan et al. (2022) studied the introduction of computer-numerically-controlled (CNC) machinery in the US, which preceded the arrival of industrial robots in manufacturing. CNC machinery (including lathes, milling machines, and others) automated the role of semi-skilled machine operators in metalworking industries. As in the case of industrial robots, the adoption of CNC machinery in the 1970s and 1980s was driven by technological developments abroad (most notably in Japan and Germany). Manufacturing industries benefiting from these developments saw declining labor shares during 1960–2010. A 10 pp increase in the share of imported CNC machinery in an industry (out of all machine tools) is associated with a 1.6 pp decline in its labor share and a 20% increase in output per worker. The increase in output per worker results from a 24% increase in output and a 4% decrease in employment, though their employment estimates cannot rule out zero effects.

Acemoglu and Restrepo (2022) considered the role of dedicated machinery (including CNC machines and other automatic machinery with specific functions, such as self-checkouts and ATMs) and specialized software systems (including custom software developed for inventory, customer, and human resource management). Using BLS detailed asset tables for 49 US industries, they compute the change in the share of dedicated machinery services and specialized software services for 1987–2016. They find that 50% of the labor share decline across US industries during this period can be explained by the increased use of dedicated machinery, specialized software services, and industrial robots. This relationship is robust to controlling for measures of the increase in markups, rising sales concentration, and declining unionization rates across industries.

Kogan et al. (2021) provide additional evidence on the impact of labor-saving technologies on the labor share using text-analysis techniques. They create a measure of similarity between the capabilities of *breakthrough innovations* (based on the text of highly-cited patents' descriptions) and tasks in an occupation (from ONET). Their analysis focuses on high-similarity breakthrough innovations, which are presumably the ones capable of substituting for worker tasks. Using data from the NBER-CES manufacturing dataset for 1958–2018, they show that a one-standard deviation increase in the number of high-similarity patents in an industry is associated with a 2.8% increase in labor productivity and a 1.25% decline in its labor share over the next five years.

The idea that automation contributed to the labor share decline also aligns with sectoral patterns.[17] In the US, most of the labor share decline concentrates in manufacturing—the sector with the greatest adoption of automation technologies (see Acemoglu et al., 2022)—and especially in capital-intensive manufacturing industries (see Hubmer, 2020).

This evidence notwithstanding, one objection to the view that automation contributed to the decline in the labor share is that the labor share of a typical firm hasn't changed much in time. Autor et al. (2020) and Kehrig and Vincent (2020) document that, while the aggregate labor share in the US declined, the labor share of the median firm and an unweighted mean of labor share changes across firms remained unchanged since the 1980s. As discussed in Hubmer and Restrepo (2021), this evidence does not contradict a role for automation since the adoption of these technologies concentrates on large firms.

2.2 Automation and the changing occupational structure

The available evidence is consistent with the idea that advances in automation have contributed to the shift away from middle-pay occupations, and in particular away from routine cognitive and manual jobs, as these tend to be highly exposed to advances in automation technologies over the last 50 years.

Autor et al. (2003) were the first to emphasize this possibility. They argued that computer capital substitutes for workers in routine cognitive and manual tasks because these follow codifiable rules. Using US data for 1960–2000, they document that the decline in routine tasks concentrated in rapidly computerizing industries and that these shifts accelerated in the 1970s as computer prices declined. Since then, a vast literature has documented a decline in routine jobs in various countries (see Goos et al., 2014).

Recent contributions have moved from the classification of occupations into routine

[17] An alternative view is that the labor share decline is due to rising markups. This runs counter to the fact that most of the decline in the US labor share is in manufacturing—the sector with the smallest increase in sales concentration and measured markups (see Hubmer and Restrepo, 2021).

and non-routine jobs and have used text analysis to measure the extent to which new technologies affect occupations. These studies produce indices of *occupational exposure* to technological advances, defined by the text similarity between tasks in an occupation (obtained from text descriptions in ONET or similar sources) and the capabilities of new technologies described in patent documents. A reasonable interpretation of these indices that aligns with the evidence is that they capture technology's capacity to substitute for worker tasks in an occupation. In line with the task fraemwork, the robust finding in these papers is that exposed occupations have seen a sizable employment decline over time, contributing to the changing US occupational structure.

Webb (2020) used this approach to create indices of occupational exposure to robotics, software, and artificial intelligence. His indices show that exposure to robotics is high for middle and low-pay blue-collar occupations, and exposure to software is high for middle-pay white-collar occupations. He then documents that occupations exposed to advances in robotics and software have seen a decline in employment and wages over time in the US. Moving from the median (technicians) to the highest (machine feeders) percentiles of robot exposure is associated with a decline in employment of 20% and wages of 15% during 1980-2010. Moving from the median (economists) to the highest (power-plant operators) percentiles of software exposure is associated with a decline in employment of 7–15% and weekly wages of 2–6.5%.

Kogan et al. (2021)'s work described above provides a measure of occupational exposure to breakthrough innovation for 1900–2000. Using this measure, they document that middle-paying occupations were more exposed to breakthrough innovations, with routine-manual jobs more exposed early on and routine-cognitive jobs more exposed after 1980. Using Census data for 1910-2010 and CPS data for 1983–2010, they show that occupations exposed to breakthrough innovations saw a subsequent decline in employment and wages. A one standard deviation increase in exposure is associated with a decrease in employment of 1% per year and wages of 0.2% per year over the next 20 years.

Autor et al. (2022) develop a measure of occupational exposure to automation technologies (constructed similarly to previous work) and a new measure of occupational exposure to labor-augmenting technological advances. They create this new measure by estimating the text similarity between patents and a list of new job titles by occupation, obtained from the *Census Alphabetical Index of Occupations and Industries*, updated in every decennial Census. The argument is that new job titles reflect the development of novel expertise in an occupation. Related patents presumably capture innovations that make novel expertise valuable. Using US data for 1940–1980 and 1980–2018, they show that the share of employment and wage payments expanded in occupations exposed to labor-augmenting innovations and contracted fro those exposed to automation innovations. Over these 40-year periods, a one standard deviation increase in automation patents is associated with an 8–16% decline in employment for exposed occupations. One important lesson from their work is that the impacts of automation differ from those brought by augmenting technologies.

The evidence from these studies aligns with work studying how the adoption of robots or CNC machinery impacted the employment composition of industries and firms. Acemoglu and Restrepo (2020) and Boustan et al. (2022) document that US manufacturing industries benefiting from advances in industrial robotics and CNC machinery, respectively, saw a decrease in the share of workers employed in blue-collar routine occupations. The evidence for firms discussed next reaches a similar conclusion.

2.3 Automation and firm-level outcomes

A growing literature has started using firm-level data to study the implications of automation technologies. This literature is growing fast and gets considerable attention.

The robust theoretical prediction from the task framework is that firms adopting automation technologies should see a decline in their labor share, a shift in their employment composition away from worker groups employed in automated tasks, and a greater expansion of sales (or value added) than in employment levels. These predictions receive considerable support from recent work exploiting the staggered adoption of industrial robots across firms in different countries.

Acemoglu et al. (2020a) use data for French manufacturing firms for 2011–2014 and document that robot adopters expand value added by 20%, employment by 10%, and see no change in average wages. This results in a 10% (or 4.3 pp) reduction in their labor share. Most papers focusing on robot adoption find similar estimates. Using data for Spanish manufacturing firms, Koch et al. (2021) find that robot adoption is associated with a 25% increase in sales, a 10% increase in employment, and a 6.5 pp decline in the labor share of value added. Using data for Danish manufacturing firms, Humlum (2020) finds that robot adoption is associated with a 20% increase in sales, a 10% increase in employment, and a 10% decline in the labor share of value added. Using data for Dutch manufacturing firms, Acemoglu et al. (2023) report similar estimates. Recent work by Bonfiglioli et al. (2020) using French data also finds a 13% increase in labor productivity associated with robot adoption, driven by a 23% increase in sales and a 10% increase in employment.

These papers also document a shift in the composition of employment away from production and routine-manual jobs and an increase in the demand for skilled labor. The work by Humlum (2020) for Danish firms stands out for having the highest quality data on employment by detailed occupation at the firm level. He shows that in the five years following the adoption of industrial robots, firms see a 20% reduction in the share of wage payments to workers in production jobs (such as assembly or welding) and a 30% increase in the share of wage payments to tech workers (such as engineers and technicians).

The firm-level evidence regarding the impact of other automation technologies on labor shares and workforce composition is not as conclusive.

Some studies support the idea that a broader set of automation technologies, including CNC machinery or specialized software, reduce firms' labor shares. Cheng et al. (2021) use data for China for 2015–2018 and exploit city-level variation in a government program subsidizing investments in industrial robots and CNC machinery for identification. Their estimates imply that a 10% subsidy for investments in robots and CNC is associated with a 2–3.5 pp decline in firms' labor shares.

Dinlersoz and Wolf (2023) use the Survey of Manufacturing Technologies (SMT) from 1991 and show that in the cross section of US manufacturing plants, those using automation technologies have lower labor shares and employ a lower share of production workers. Using the ABS technology module described above, Acemoglu et al. (2022) document that US firms using robotics, specialized software, and dedicated equipment in 2016–2018 had lower labor shares. The evidence in these last two papers is descriptive, as it relies on cross-sectional comparisons. Nonetheless, it aligns with the fact that a significant share of firms in the SMT and ABS report that automating tasks performed by workers is an important reason for adopting these technologies.

Two recent studies report weaker or no effects of investments on a broader range of equipment on firms' labor shares and workforce composition. Aghion et al. (2023) use French manufacturing data to study the implications of investments on (i) all forms of industrial equipment and (ii) imports of a broad bundle of automation equipment (as classified in previous work by Acemoglu and Restrepo, 2021). Their findings are mixed. Their event-study evidence shows that five years after an investment spike in industrial equipment firms experience an employment increase of 30% and a decrease in their labor share *in value added* of 5%. However, they find no impact on firms' labor share in sales or the share of wages paid to production and non-college workers. A second design exploits improvements in foreign suppliers' productivity as an exogenous shock causing firms to import more automation equipment. Using these supplier shocks, they estimate an expansion in firm employment but find no effects on firms' labor shares or the share of wages paid to production and non-college workers. Hirvonen et al. (2022) study a program that subsidized investments in dedicated equipment in Finland. They report an expansion in firm sales and employment but no changes in firm labor shares or workforce composition.

My view is that these studies do not necessarily contradict the view that automation advancements decrease the labor share and alter the demand for skills. Instead, they serve to reinforce the important point (both for policy and conceptually) that *not all* investments by firms in modern manufacturing technologies represent efforts to automate worker tasks.[18] As the theory clarifies, firms can make investments at the intensive margin (in tasks already automated) or in machinery for new product lines. These investments generate no displacement effects or reassignments of tasks inside firms. The subsidy program studied in Hirvonen et al. (2022) seems to work mostly by getting firms to adopt machinery for new products. Aghion et al. (2023)'s measure of investment in industrial capital necessarily includes many types of equipment that are not used for automation, such as industrial furnaces, electric switchboards, and generators. Their approach using supplier shocks exploits variation for firms that were already importing automation equipment from these suppliers, and so additional investments are likely to take place at the intensive margin.

A notable aspect of the firm-level evidence is that most papers estimate an expansion of employment at firms adopting automation technologies. Theory clarifies that this is what we should expect if adopting firms face highly elastic demand curves.[19] As the theory clarifies, firm-level effects capture the reallocation of sales across firms and the possibility that adopting firms expand at the expense of domestic competitors—as documented in Koch et al. (2021), Acemoglu et al. (2020a), and Aghion et al. (2023). This reallocation has no clear-cut aggregate implications. It could increase, decrease, or leave the demand for certain groups of workers unchanged. Because of this, firm-level effects are not informative of the aggregate impact of advances in automation on employment and wages.

In sum, firm data has been very helpful for understanding how the allocation of tasks in firms adopting automation technologies changes and how this affects their labor shares and workforce composition. But, when interpreting this literature, one should keep in mind

[18] From a policy viewpoint, these studies suggest that a blanket tax on capital and equipment imports are bad ideas for mitigating any potential adverse effects from automation, since this will distort investments at the intensive margin or associated with new products (see Acemoglu et al., 2020b; Donald, 2022).

[19] These studies find no effect of automation on firm wages, which suggest these firms operate in highly competitive labor markets.

that firm employment and wage responses tell us more about the market structure faced by firms than the aggregate impacts of automation.

2.4 Automation and exposed workers

The task framework predicts that groups of workers displaced from their tasks by automation will suffer a relative decline in wages and employment, especially if they cannot reallocate to other tasks. This prediction has been tested in three ways: by tracing individual workers, workers in exposed regions, and workers in exposed groups. The evidence is consistent with the idea that advances in automation generate a visible displacement effect on exposed workers, regions, and groups.

Evidence using panel data to trace the outcomes of individual workers exposed to automation includes work by Cortes (2016), Kogan et al. (2021), Bessen et al. (2023), and work from a unique historical context by Feigenbaum and Gross (2020). These designs isolate the incidence of displacement effects on workers directly exposed to automation and explore how they adjust.[20]

Cortes (2016) uses data from the Panel Study of Income Dynamics to explore how workers in routine occupations adjusted to the automation of these jobs. He documents that workers exposed to the automation of routine jobs suffered a sizable income loss. Although some workers reallocated, on average, workers who held routine jobs in 1980 saw a 17% income decline over the next 20 years relative to others.

Kogan et al. (2021) reach a similar conclusion using data from the US Social Security Administration tracing workers in occupations exposed to labor-replacing technologies, using their text-based measure. They document that incumbent workers in exposed occupations experienced a 2.3% income decline ten years after a one standard deviation improvement in labor-replacing technology.

Bessen et al. (2023) study the impacts of firm investments in automation technologies on incumbent workers using Dutch employer-employee matched data for 2000–2016. They use a unique survey reporting firm expenditures on *third-party automation expenditures*. These include payments made to integrators (companies offering engineering and software solutions) across various automation technologies. They document that investments in integration are lumpy and take place in spikes. These investment spikes provide a compelling

[20] One can map these designs to the theory by thinking of g as a group of workers attached to occupations, industries, or firms adopting automation technologies. These workers will bear most of the incidence from task displacement if they cannot easily reallocate, so that θ_{gg} is large.

proxy for the adoption of automation technologies at the extensive margin since significant reorganizations of production require assistance from integrators. In the five years following an investment spike in automation services, Bessen et al. document an increase in the probability of separation for incumbent workers and a cumulative labor income loss of 10% their annual income relative to non-exposed workers, driven by a decline in hours worked.

Feigenbaum and Gross (2020) study the effects of mechanizing telephone operation in the US between 1920 and 1940 on both incumbent workers and new cohorts of young women. Their exercise exploits the fact that they can identify women employed as telephone operators before this shock and trace their labor-market outcomes over time by linking decennial Censuses. They find that after a city switches to mechanical operation, the number of young women employed as operators immediately declined by 50–80%, pointing to a sizable displacement effect. Incumbent (female) workers experience a subsequent decline in employment of 8 pp. Even though some managed to reallocate to clerical jobs in other industries, they were generally forced into lower-paying occupations. New cohorts of women reallocated more swiftly and experienced no decline in employment, though some might have ended up taking lower-paying jobs.

These studies support the view that incumbent workers exposed to automation experience most of the incidence of its displacement effects, and see their income and employment prospects deteriorate (though studies vary in how much each margin matters). Workers ability to reallocate mitigate these adverse impacts to some extent, though this dampening mechanism seems most relevant for younger workers and new cohorts.

The second approach involves estimating the impact of automation on local labor markets, such as US commuting zones. One can think of this setting in the task model by letting g index the group of workers in a local labor market.[21]

Acemoglu and Restrepo (2020) use this approach to explore the implications of advances in robotics on exposed US regions. Their analysis shows that, from 1990 to 2007, US commuting zones that specialized in industries experiencing the most significant advances in industrial robots saw a relative decline in employment and wages. Their estimates imply that advances leading to the adoption of one extra industrial robot per thousand workers in a commuting zone reduce wages by 0.8 percent and the employment-to-population ratio by 0.4 pp relative to other regions, with 0.15–0.2 pp of the employment decline coming

[21]With this interpretation, the propagation matrix captures the effects of migration across regions, as in work by Borusyak et al. (2022). Due to low migration flows (at least in the US), the propagation matrix will be close to diagonal, which implies that exposed commuting zones bear most of the incidence of automation and other shocks to their labor demand.

from manufacturing. This implies a reduction of 2–3 manufacturing jobs per robot in exposed regions. The evidence in Acemoglu and Restrepo (2020) is consistent with a world where workers in exposed regions suffer the displacement effects from automation while the productivity gains are shared nationally.

Dauth et al. (2021) extend this approach to Germany. They estimate that technological advances leading to an extra robot in use at a local labor market reduce manufacturing employment by 2 jobs—a magnitude comparable to Acemoglu and Restrepo (2020). However, they find no adverse effects on total local employment, as young workers entering the labor market find employment in the expanding business services sector. One plausible interpretation is that the displacement effects from robot adoption in Germany and the US are of a similar magnitude, but in Germany, the productivity gains from automation benefit exposed labor markets the most. This could be because advances in robotics lead to the expansion of integrators and robot producers in exposed regions—a positive product shifter raising labor demand in exposed regions.

Recent work has extended this regional approach to explore the implications of a broader set of technologies.

Boustan et al. (2022) study the local-labor market effects of advances in CNC machinery from 1970 to 2000 in the US. A one standard deviation increase in exposure to CNC machinery (instrumented by advances abroad in Germany and Japan) for a commuting zone reduces the share of population employed in metal-working manufacturing industries by 3.5 pp but has no adverse effect on total manufacturing employment. This, too, points to a displacement effect in metal-working manufacturing that is offset by product shifts benefiting other local manufacturing industries.

Mann and Puttmann (2023) study the local labor market effects of a broader set of automation technologies, identified from patents they classify as automation. They find that US commuting zones that specialize in industries with a higher rate of automation patenting saw gains in employment. Coelli et al. (2019) revisit this conclusion using an updated classification of automation patents and report a negative employment effect in exposed industries and US commuting zones over the 1980-2010 period. The different findings reflect their measurement of automation patents. Mann and Puttmann (2023) classify a patent as automation if it refers to a technology capable of performing functions *independently*. This definition captures mainly innovations in computers and communications that do not involve the automation of tasks performed by workers. Because of this, their approach classifies 90% of patents in computers and communications as automation. Coelli et al. (2019) use the classification from Dechezleprêtre et al. (2021), which codes a patent as automation if it describes an innovation capable of substituting for current worker tasks. This matches the definition in the task framework.[22]

The third approach involves estimating the impact of automation on groups of workers defined by observable attributes that can be traced consistently over time. Think of skill or demographic groups indexed by g in the theory. This approach does not require panel data on individuals. All that is needed are repeated cross sections with group-level outcomes. Though these designs cannot tell us what happens to individual workers who are displaced, they are informative of the broader equilibrium effects on group-level outcomes.

Acemoglu and Autor (2011) pioneered this approach. Their work shows that groups of workers specialized in routine occupations experience a subsequent decline in wages over 1960–2010.

Acemoglu and Restrepo (2022) further developed this approach to estimate the impact of advances in automation on group-level wages and employment, using data for 500 groups of US workers. These groups are defined by gender, age, education, race, and birthplace, though they also provide robustness checks expanding the definition of their groups to account for region of residence. Their approach relies on measuring the direct task displacement experienced by each group from 1980 to 2016 and then regressing the change in group-level outcomes during this period on such measures.

They approximate the direct task displacement experienced by a group as a sum across industries of (i) their exposure to the industry, (ii) the revealed comparative advantage of that group in automatable jobs inside the industry, which apportions the task displacement in an industry equally among workers in these jobs, and (iii) a measure of the rate at which tasks have been automated in the industry, computed as the percent decline in the industry's labor share attributed to automation. They compute the first two terms using 1980 Census data and using various definitions of automatable jobs, including a dummy for the top 33% occupations with the highest routine content according to ONET, as well as the measures developed by Webb (2020) for occupations with the highest exposure to robotics and software. The last term is computed as the predicted value from the cross-industry regression described above, explaining the labor share decline on their use of dedicated machinery, specialized software services, and industrial robots.

Their measures of direct task displacement is associated with large reductions in group

[22] Coelli et al. (2019) also create a measure of non-automating patents, which is associated with increases in employment. This too distinguishes automation from other technologies.

wages and employment. A 10% increase in direct task displacement (i.e., a reduction in the task share of group g by 10% due to automation) is associated with a 15% reduction in group relative wages during 1980–2016. This effect is robust to controlling for educational dummies and industry shifters. Moreover, the direct task displacement measure explains 50–70% of the observed change in group wages during this period.

3 Areas for future work

The empirical evidence provides wide qualitative support for the implications of automation in task models. However, most of the evidence is reduced form and relies on indirect proxies for automation without clear magnitudes, such as ordinal indices of occupational exposure. For this reason, existing empirical work does not yet provide clear-cut quantitative answers to questions such as "what share of worker tasks has been automated in the last 10 years?" or "has the rate of automation accelerated since the 1980s?" To address these questions, the literature needs to improve our measures of automation and develop quantitative strategies to go beyond reduced-form evidence.

3.1 Improving our measures of automation

There are several ways to improve the measurement of automation in future research to create more direct and comprehensive measures with a clear quantitative interpretation.

The first is the use of technology surveys administered by statistical agencies. For example, the US Census recently introduced a new technology module as part of the *Annual Business Survey* (ABS) designed to measure the adoption and use of various technologies for automation across firms in all sectors (see Acemoglu et al., 2022). The ABS data shows that 30.4% of US workers in 2016–2018 were employed at firms using advanced technologies for automation. Though direct and comprehensive, the limitation of these surveys is that they only provide categorical data on adoption and the intensity of use.

The second approach involves measuring investment in automation equipment from customs data, firms balance sheets, or surveys of technology providers. The main challenge here is that investment data is coarse and pools many capital goods, some of which are not used for automation. Ideally, one would focus on a bundle of technologies that we think work by automating tasks and measure investment in these as a share of firm or industry value added. One could also add expenditures on integrators or third-party providers of automation solutions. These signal the introduction of technologies that require a major firm reorganization. Both measures have clear magnitudes that indicate how much firms and industries rely on automation technologies to produce and how this changes over time.[23]

A third approach involves using *operations data*. These data presents establishment-level information breaking the production of specific goods into tasks, and describing how each is completed (workers and tools involved, machinery if automated, power sources, time requirements, and so on). Examples include the BLS "Hand and Machine Labor Study" from the mid-1890s (analyzed in Atack et al., 2019), and hand-collected operations data for establishments producing cars and semiconductors (analyzed in Ales et al., 2023), though firms increasingly collect their operations data. These data is of course rare and hard to come by, and presumably, only available for specific sectors and products. But when available, it provides all information needed to measure task shares and identify the scope of automation advances.

Going beyond reduced-form estimates

Going beyond reduced-form evidence requires more structural approaches.

One fruitful strategy is to combine proxies for automation with accounting data to estimate the direct task displacement $\{d \ln \Gamma^d_{ng}\}$ and cost-saving gains $\{\pi_{ng}\}$ associated with the adoption of robots and other automation technologies. As explained in the theory section, these estimates provide summary measures of the scope and productivity of automation advances and is all that is needed for deriving the aggregate impact of an automation technology on output and wages.

Examples of this approach include Humlum (2020) and Acemoglu and Restrepo (2022).

Humlum (2020) assumes that firms operate a CES production function that combines workers in different occupations and allows the adoption of robots to shift CES weights and increase TFP by fixed amounts.[24] His approach then infers the direct task displacement $\{d \ln \Gamma^d_{ng}\}$ and cost-saving gains of automation $\{\pi_{ng}\}$ across occupations in adopting firms from the behavior of sales and wage shares after an investment spike in industrial robots for Dannish firms. The adoption of robots by a firm brings a $d \ln \Gamma^d_{ng} = 48\%$ decline in the

[23]These measures exist for some specific technologies, such as industrial robots. For example, an industrial-robot system can cost around \$300,000 dollars including integration costs and maintenance. This means that expenditure in industrial robots by US manufacturing firms rose from 0.07% of value added in 1990 to 0.75% of value added in 2018. The challenge is in extending these measures to a more comprehensive set of automation technologies.

[24]This is an specification of (4) where worker groups are defined by occupations and the propagation matrix is the identity. One challenge when interpreting groups as occupations is that workers change occupation over time. Humlum (2020) addresses this by modeling occupational as in Traiberman (2019).

task share of blue-collar workers and raises firm-level TFP by 6%. A back of the envelope calculation shows that this implies an average π_{ng} of 37.5%. One can plug these estimates in equations (10), (11), and (12) to compute the impact of observed robot adoption and counterfactuals (what would happen if all Danish manufacturing firms adopted robots?).

Acemoglu and Restrepo (2022) propose a method for estimating the direct task displacement experienced by different groups of US workers. Their method infers the direct task displacement experienced by group g in industry n, $d \ln \Gamma^d_{ng}$, from the percent decline in the industry labor share explained by automation proxies. This is then apportioned across groups in proportion to their revealed comparative advantage in routine (or automatable) occupations in that industry. Their measure has a clear quantitative interpretation. It shows that workers at the bottom and middle of the wage distribution lost 20–30% of their tasks since 1980 to automation, while workers with a post-college degree experienced almost zero displacement. Their paper also develops a methodology for estimating the propagation matrix, which allows them to computing the effects of automation on the US wage structure using equations (10), (11), and (12) in the theory section.[25] They find that 50% of the changes in the US wage structure between educational and demographic groups since 1980 can be explained by the uneven incidence of the displacement effects from automation.

Future work could build on these approaches by estimating the direct task displacement and productivity gains associated with different technologies, improving the modeling of ripple effects and estimates of the propagation matrix, extending these methods to account for larger shocks, or proposing flexible parameterizations of the task model suitable for a full structural analysis.[26]

Questions for future work

The data sources, theories, and methods described above pave the way for new research on many interesting open questions:

- Do countries differ in how easily workers can reallocate? Do these differences make propagation matrices less diagonal in countries with better re-training institutions?
- How do worker rents and labor market imperfections alter the impacts of automation

[25] Their work assumes that $\pi_{ng} = 30\%$, which comes from case studies of the adoption of industrial robots.

[26] For example, one could borrow from the trade literature and assume that the ψ's follows a Frechet distribution in each product which then determines task shares in a tractable way, as in Eaton and Kortum (2002). The challenge is finding a way to extend these parameterizations that can distinguish between extensive and intensive margin advances in capital—a key distinction when thinking about automation.

on wages and output?

- Why do some firms invest in automation technologies at the extensive margin and others invest in capital deepening? Can these decisions be affected by policy?
- How can the lessons from this literature be used to forecast the impacts of Artificial Intelligence? Are advances in AI extend the range of tasks that can be automated, capital deepening (by replacing existing software), or mostly enable the production of new goods?

References

Acemoglu, Daron, Gary W. Anderson, David N. Beede, Catherine Buffington, Eric E. Childress, Emin Dinlersoz, Lucia S. Foster, Nathan Goldschlag, John C. Haltiwanger, Zachary Kroff, Pascual Restrepo, and Nikolas Zolas (2022): *Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey* , U. Chicago Press.

Acemoglu, Daron and David Autor (2011): *Skills, Tasks and Technologies: Implications for Employment and Earnings*, Elsevier, vol. 4 of *Handbook of Labor Economics*, chap. 12, 1043–1171.

Acemoglu, Daron, Hans R. A Koster, and Ceren Ozgen (2023): "Robots and Workers: Evidence from the Netherlands," Working Paper 31009, National Bureau of Economic Research.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo (2020a): "Competing with Robots: Firm-Level Evidence from France," in *AEA Papers and Proceedings*, vol. 110, 383–88.

Acemoglu, Daron, Andrea Manera, and Pascual Restrepo (2020b): "Does the US Tax Code Favor Automation?" *Brookings Papers on Economic Activity*, 2020, 231–300.

Acemoglu, Daron and Pascual Restrepo (2018): "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review*, 108, 1488–1542.

——— (2019): "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33, 3–30.

——— (2020): "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128, 2188–2244.

——— (2021): "Demographics and Automation," *The Review of Economic Studies*, 89, 1–44.

——— (2022): "Tasks, automation, and the rise in US wage inequality," *Econometrica*, 90, 1973–2016.

——— (2023): "Automation and Rent Dissipation:," Tech. rep., MIMEO, Boston University.

Aghion, Philippe, Celine Antonin, Simon Bunel, and Xavier Jaravel (2023): "Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France," Tech. rep., CEPR Discussion Papers No. 1910.

Aghion, Philippe, Benjamin F Jones, and Charles I Jones (2018): "Artificial intelligence and economic growth," in *The economics of artificial intelligence: An agenda*, University of Chicago Press, 237–282.

Ales, Laurence, Christophe Combemale, Katie Whitefoot, and Erica Fuchs (2023): "How It's Made: A General Theory of the Labor Implications of Technological Change," Mimeo, Carnegie Mellon University.

Atack, Jeremy, Robert A. Margo, and Paul W. Rhode (2019): ""Automation" of Manufacturing in the Late Nineteenth Century: The Hand and Machine Labor Study," *Journal of Economic Perspectives*, 33, 51–70.

Autor, David, Caroline Chin, Anna M Salomons, and Bryan Seegmiller (2022): "New Frontiers: The Origins and Content of New Work, 1940–2018," Working Paper 30389, National Bureau of Economic Research.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen (2020): "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly Journal of Economics*, 135, 645–709.

Autor, David H. (2019): "Work of the Past, Work of the Future," *AEA Papers and Proceedings*, 109, 1–32.

Autor, David H, Frank Levy, and Richard J Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118, 1279–1333.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge (2023): "What Happens to Workers at Firms that Automate?" *The Review of Economics and Statistics*, 1–45.

Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia (2020): "Robot Imports and Firm-Level Outcomes," Tech. rep., CEPR Discussion Papers No. 14593.

Borusyak, Kirill, Rafael Dix-Carneiro, and Brian Kovak (2022): "Understanding migration responses to local shocks," Tech. rep., MIMEO, University of California, Berkeley.

Boustan, Leah Platt, Jiwon Choi, and David Clingingsmith (2022): "Automation After the Assembly Line: Computerized Machine Tools, Employment and Productivity in the United States," Working Paper 30400, National Bureau of Economic Research.

Buera, Francisco J, Joseph P Kaboski, Richard Rogerson, and Juan I Vizcaino (2021): "Skill-Biased Structural Change," *The Review of Economic Studies*, 89, 592–625.

Caselli, Francesco and Alan Manning (2019): "Robot Arithmetic: New Technology and Wages," *American Economic Review: Insights*, 1, 1–12.

Cheng, Hong, Lukasz A. Drozd, Rahul Giri, Mathieu Taschereau-Dumouchel, and Junjie Xia (2021): "The Future of Labor: Automation and the Labor Share in the Second Machine Age," Tech. rep., FRB Philadelphia.

Coelli, Federica, David Dorn, David Hémous, and Morten Olsen (2019): "Automation Threat and Wage Bargaining," Unpublished manuscript, International Monetary Fund.

Cortes, Guido Matias (2016): "Where Have the Middle-Wage Workers Gone? A Study of

Polarization Using Panel Data," *Journal of Labor Economics*, 34, 63–105.

Dao, Mai Chi, Mitali Das, and Zsoka Koczan (2019): "Why is Labour Receiving a Smaller Share of Global Income?" *Economic Policy*, 34, 723–759.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner (2021): "The adjustment of labor markets to robots," *Journal of the European Economic Association*, 19, 3104–3153.

Dechezleprêtre, Antoine, David Hémous, Morten Olsen, and Carlo Zanella (2021): "Induced automation: evidence from firm-level patent data," *University of Zurich, Department of Economics, Working Paper*.

Dinlersoz, Emin and Zoltan Wolf (2023): "Automation, labor share, and productivity: Plant-level evidence from US Manufacturing," *Economics of Innovation and New Technology*, 1–23.

Donald, Eric (2022): "Optimal Taxation with Automation: Navigating Capital and Labor's Complicated Relationship," Mimeo, Boston University.

Eaton, Jonathan and Samuel Kortum (2002): "Technology, Geography, and Trade," *Econometrica*, 70, 1741–1779.

Feigenbaum, James and Daniel P Gross (2020): "Answering the Call of Automation: How the Labor Market Adjusted to the Mechanization of Telephone Operation," Working Paper 28061, National Bureau of Economic Research.

Goldin, Claudia Dale and Lawrence F Katz (2008): *The Race Between Education and Technology*, Harvard University Press Cambridge.

Goos, Maarten, Alan Manning, and Anna Salomons (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104, 2509–26.

Graetz, Georg and Guy Michaels (2018): "Robots at Work," *The Review of Economics and Statistics*, 100, 753–768.

Grossman, Gene M and Ezra Oberfield (2021): "The Elusive Explanation for the Declining Labor Share," Working Paper 29165, National Bureau of Economic Research.

Grossman, Gene M. and Esteban Rossi-Hansberg (2008): "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*, 98, 1978–97.

Hirvonen, Johannes, Aapo Stenhammar, and Joonas Tuhkuri (2022): "MNew Evidence on the Effect of Technology on Employment and Skill Demand," Tech. rep., MIMEO, Massachusetts Institute of Technology.

Hubmer, Joachim (2020): "The Race Between Preferences and Technology," Unpublished manuscript, University of Pennsylvania.

Hubmer, Joachim and Pascual Restrepo (2021): "Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital-Labor Substitution," Working Paper 28579, National Bureau of Economic Research.

Humlum, Anders (2020): "Robot Adoption and Labor Market Dynamics," Working paper, University of Chicago.

Jackson, Matthew and Zafer Kanik (2020): "How Automation that Substitutes for Labor Affects Production Networks, Growth, and Income Inequality," Tech. rep., Stanford University.

Karabarbounis, Loukas and Brent Neiman (2013): "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 129, 61–103.

Katz, Lawrence F and Kevin M Murphy (1992): "Changes in Relative Wages, 1963–1987: Supply and Demand factors," *The Quarterly Journal of Economics*, 107, 35–78.

Kehrig, Matthias and Nicolas Vincent (2020): "The Micro-Level Anatomy of the Labor Share Decline," NBER Working Papers 25275, National Bureau of Economic Research, Inc.

Kim, Ryan and Jonathan Vogel (2021): "Trade Shocks and Labor Market Adjustment," *American Economic Review: Insights*, 3, 115–30.

Koch, Michael, Ilya Manuylov, and Marcel Smolka (2021): "Robots and Firms," *The Economic Journal*, 131, 2553–2584.

Kogan, Leonid, Dimitris Papanikolaou, Lawrence D. W Schmidt, and Bryan Seegmiller (2021): "Technology, Vintage-Specific Human Capital, and Labor Displacement: Evidence from Linking Patents with Occupations," Working Paper 29552, National Bureau of Economic Research.

Krusell, Per, Lee E. Ohanian, José-Víctor Ríos-Rull, and Giovanni L. Violante (2000): "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, 68, 1029–1053.

Mann, Katja and Lukas Puttmann (2023): "Benign Effects of Automation: New Evidence from Patent Texts," *The Review of Economics and Statistics*, 105, 562–579.

Martinez, Joseba (2021): "Putty-Clay Automation," Tech. rep., London Business School.

Oberfield, Ezra and Devesh Raval (2020): "Micro Data and Macro Technology," *Econometrica*.

Ocampo, Sergio (2022): "A task-based theory of occupations," Tech. rep., Western University.

Simon, Herbert Alexander (1965): *The shape of automation for men and management*, vol. 13, Harper & Row New York.

Traiberman, Sharon (2019): "Occupations and Import Competition: Evidence from Denmark," *American Economic Review*, 109, 4260–4301.

Webb, Michael (2020): "The Impact of Artificial Intelligence on the Labor Market," Working paper, Stanford University.

Zeira, Joseph (1998): "Workers, Machines, and Economic Growth," *The Quarterly Journal of Economics*, 113, 1091–1117.