Tasks, Automation, and the Rise in US Wage Inequality*

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Abstract

We document that between 50% and 70% of changes in the US wage structure over the last four decades are accounted for by the relative wage declines of worker groups specialized in routine tasks in industries experiencing rapid automation. We develop a conceptual framework where tasks across a number of industries are allocated to different types of labor and capital. Automation technologies expand the set of tasks performed by capital, displacing certain worker groups from employment opportunities for which they have comparative advantage. This framework yields a simple equation linking wage changes of a demographic group to the task displacement it experiences. We report robust evidence in favor of this relationship and show that regression models incorporating task displacement explain much of the changes in education differentials between 1980 and 2016. Our task displacement variable captures the effects of automation technologies (and to a lesser degree offshoring) rather than those of rising market power, markups or deunionization, which themselves do not appear to play a major role in US wage inequality. We also propose a methodology for evaluating the full general equilibrium effects of task displacement (which include induced changes in industry composition and ripple effects as tasks are reallocated across different groups). Our quantitative evaluation based on this methodology explains how major changes in wage inequality can go hand-in-hand with modest productivity gains.

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

JEL Classification: J23, J31, O33.

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1 Introduction

Wage and earnings inequality have risen sharply in the US and other industrialized economies over the last four decades.[1] Figure 1 depicts some salient aspects of US developments: while the real wages of workers with a post-graduate degree rose, the real wages of low-education workers declined significantly. The real earnings of men without a high-school degree are now 15% lower than they were in 1980.

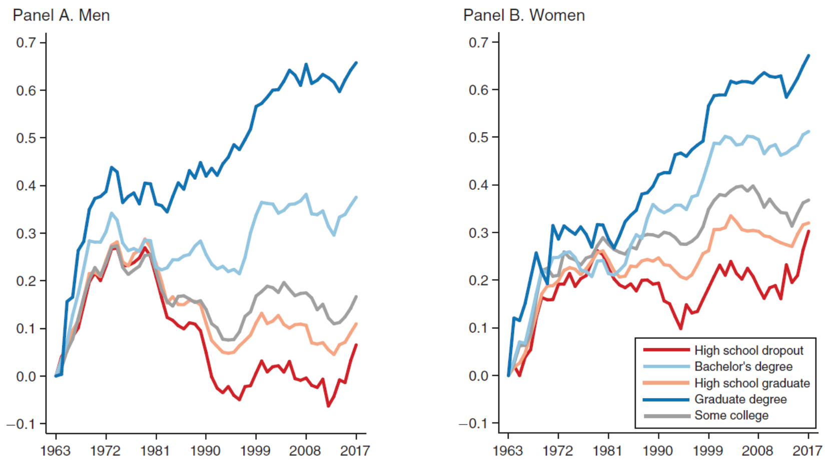

Figure 1: Cumulative growth of real wages by gender and education (from Autor, 2019)

The most popular explanation for these changes is based on skill-biased technological change (SBTC).[2] According to this framework, the demand for different types of workers comes from an aggregate production function of the form $F(A_H H, A_L L)$, where H and L are employment levels of high-skill and low-skill workers, and A_H and A_L represent technologies (or equipment) augmenting these two types of workers. SBTC corresponds to technology becoming more favorable to high-skill workers (e.g., a greater increase in A_H than in A_L, provided that F has an elasticity of substitution greater than one). One of the most powerful pieces of evidence offered in favor of SBTC in the 1990s was that increases in the demand for skills were pervasive across industries.[3] This evidence also motivated the interpretation that industry-level differences in technology played a limited role in the transformation of US wage structure.

This paper proposes an alternative approach for thinking about wage inequality. We argue that much of the changes in US wage structure are driven by the *automation* of tasks previously performed by certain types of workers in some industries (e.g., numerically-controlled machinery or industrial robots replacing blue-collar workers in manufacturing or specialized software replacing clerical workers). Workers who are not displaced from the tasks in which they have a comparative

[1] See Acemoglu and Autor (2011), Goldin and Katz (2008), and Autor (2019) for overviews.

[2] The literature has also recognized the role played by changes in labor market institutions (especially declining minimum wages and unionization) and globalization. See, for example, DiNardo, Fortin and Lemieux (1996).

[3] More precisely, the within-industry component of skill upgrading was much larger than the between-component, representing the change in employment in high-skill relative to low-skill industries (see, for example, Bound and Johnson, 1992; Berman, Bound and Griliches, 1994; Berman, Bound and Machin, 1998).

advantage, such as those with a postgraduate degree or women with a college degree, enjoyed real wage gains, while those, including low-education men, who used to specialize in tasks and industries undergoing rapid automation, experienced stagnant or declining real wages.

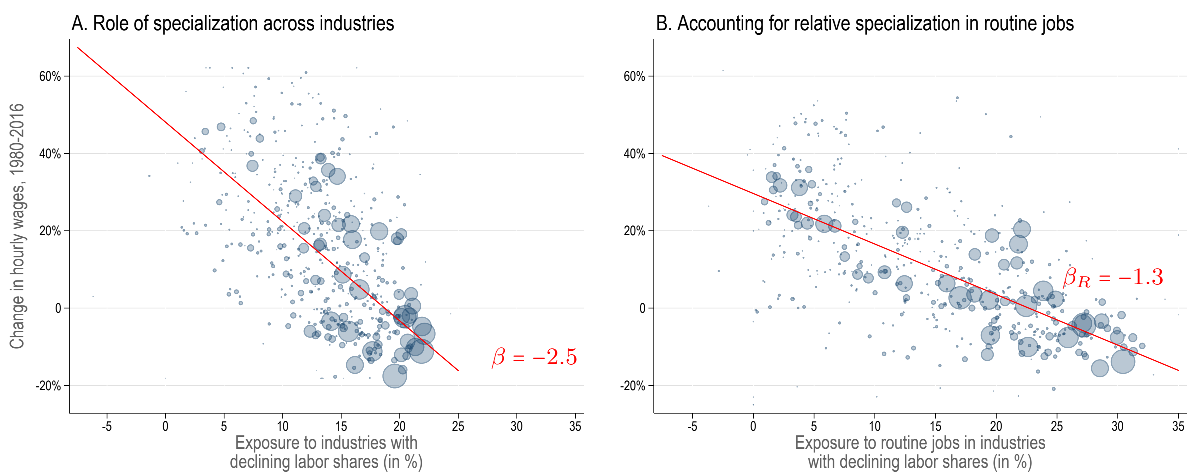

FIGURE 2: Relationship between change in real wages and a demographic group's exposure to industries with declining labor share (left panel) and exposure to routine jobs in industries with declining labor share (right panel). The dots in the figures represents 500 demographic groups, with their size indicating their share of hours worked.

Figure 2 provides motivating evidence for our explanation by revisiting the role of industry and declining labor shares—a telltale sign of automation—in US wage inequality. The left panel documents that worker groups (defined by 500 cells distinguished by gender, age, education, race, and native/immigrant status) that specialized in 1980 in industries that experienced subsequent labor share declines saw their relative wages fall between 1980 and 2016.[4] In contrast to an expectation based on the previous literature, this variation accounts for 40% of the changes in the wage structure between these groups. The right panel shows that this relationship is driven by worker groups who specialized in routine tasks—those that are easier to automate given existing technologies—within those industries. The task displacement measure in the right panel, which in addition incorporates information on whether a group specializes in routine tasks in industries with declining labor share, explains 67% of the changes in the wage structure (while the residual explanatory power of the variable used on the left falls to 10%). Put simply, a large share of the changes in the US wage structure during the last four decades are accounted for by the relative wage declines of workers that specialized in routine tasks at industries that experienced labor share declines. We will see that the same pattern holds when we focus on the component of the labor share decline driven by automation technologies.

Our framework clarifies why worker groups that specialize in tasks being automated will bear the brunt of these changes and will suffer relative and potentially absolute wage declines.

[4] This variable is defined for each group as the sum over industries of their 1980 share of employment in an industry times that industry's subsequent labor share decline. The exact construction of the right-hand side variables used in this figure and our data sources are described in Section 3.

To explain these facts, we start with a model of production in which each industry performs a range of tasks, some of which can be automated, and we identify these with "routine" tasks. There are several groups of workers, each with a different comparative advantage across tasks and industries. While we allow technology to directly complement/augment different types of workers, the innovation of our model is to allow for *automation technologies* that increase the productivity of capital in certain routine tasks that used to be produced by workers.[5]

Our framework delivers three key results. First, and in contrast to models of SBTC with factor-augmenting technologies, in our framework automation can have a negative effect on workers who are displaced from tasks they used to perform, and such changes can take place with limited increases in total factor productivity (TFP). Hence, real wage declines and slow productivity growth despite rapid automation are *not* puzzles within this framework. Second, we derive a simple equation linking wage changes of a demographic group to the task displacement it experiences, which forms the basis of our reduced-form analysis. Third, our framework implies that the task displacement experienced by a group can be measured by its employment share in routine tasks in industries undergoing automation. Moreover, the extent of automation in an industry can be inferred from declines in its labor share, thus providing an explanation for the relationship reported in the right panel of Figure 2.[6]

The second part of the paper documents a robust and negative (reduced-form) relationship between our measure of task displacement and real wages across groups of workers. Our baseline results use the decline in an industry labor share to infer the overall extent of automation and task displacement taking place in that industry. We show that close to 50% of the variation in labor shares (and measured task displacement) across industries is driven by automation technologies, including the adoption of industrial robots, specialized machinery and software. In line with this result, we find a very similar negative relationship between wage changes and task displacement using an IV strategy that exploits the component of the labor share decline driven by automation. We document that offshoring also contributes to task displacement (and conceptually, its effects on wages should be similar since it also works by displacing workers from their tasks), but quantitatively it accounts for a smaller portion of observed wage changes than automation. These results bolster our confidence that task displacement driven by automation technologies is responsible for the relationships depicted in Figure 2.

Importantly, task displacement retains its defining role when we flexibly control for various

[5]We define automation technologies as any technology that enables machines/algorithms/capital to perform tasks previously allocated to humans, which results in the displacement of workers from these tasks. Note, however, that task displacement does not need to be associated with "job loss", and can take the form of a worker being reallocated within the same firm or a decline in hiring of new workers into certain tasks.

[6] There are many determinants of industry labor shares and we discuss them and explore their effects later. It is useful to note here that we find a significant portion of industry labor share declines to be driven by the displacement of workers from (routine) tasks because of automation (and to a lesser degree offshoring). See Elsby, Hobijn and Şahin (2013), Karabarbounis and Neiman (2013), Piketty (2014), Dao, Das and Koczan (2019), and Hubmer (2020) on the decline of the labor share; Acemoglu, Lelarge and Restrepo (2020) and Acemoglu and Restrepo (2020) on the role of automation in labor share declines; De Loecker, Eeckhout and Unger (2020) on the role of rising markups; and Autor et al. (2020) on superstar firms.

forms of SBTC (for example, allowing the productivity of workers to evolve as a function of their education levels over time). Our estimates indicate that task displacement explains 50%–70% of the observed changes in wage structure between 1980 and 2016, while these traditional SBTC proxies account for less than 10%. Furthermore, the relationship between task displacement and real wages remains unchanged when we control for other potential determinants of industry labor shares and wages, such as rising concentration, markups, import competition and the decline of unions, or when we exploit regional variation in specialization patterns or focus on different sub-periods. Consistent with the notion that these trends reflect changes in labor demand, we also estimate negative effects on employment outcomes.

Although our reduced-form analysis documents a strong negative relationship between task displacement and *relative* wage changes across worker groups, it misses three indirect effects affecting real wages in general equilibrium. First, in our regressions, the common effect of productivity increases on real wages goes into the intercept, and so our results are not informative about real wage *level* changes. Second, because automation and task displacement concentrate in a handful of industries, they will change the sectoral composition of the economy, which can in turn shift the demand for different types of workers. Third, our reduced-form evidence focuses on the direct effects of task displacement, but does not account for ripple effects, which result from displaced workers competing against others for non-automated tasks, bidding down their wages and spreading negative wage effects of automation more broadly in the population.

To account for these general equilibrium effects, in the last part of the paper we turn to a quantitative exercise exploring the implications of task displacement for the wage structure, real wage levels, TFP, output, and the sectoral composition of the economy. Our model provides explicit formulas to compute all these general equilibrium effects as functions of our measure of task displacement as well as the cost savings from automation, industry demand elasticities, and a *propagation matrix* capturing the strength of ripple effects between different groups of workers (i.e., how much the displacement of group g affects the wage of group g' due to task reallocation). We show how these ripple effects can be estimated by parametrizing group-level interactions as functions of the distance between groups along a number of dimensions. We then combine these ripple effect estimates with a standard parametrization of demand across industries and available estimates of the cost savings from automation.

We find that task displacement—incorporating general equilibrium effects—accounts for about 50% of the observed relative wage changes during this period and explains 80% of the observed increase in the college premium. These sizable distributional effects are accompanied by modest increases in the average wage level, GDP and TFP. For example, technologies causing task displacement only account for a 3.8% increase in TFP between 1980 and 2016. We thus conclude that automation can explain a sizable fraction of changes in wage structure and real wage declines in the data, while having a tiny impact on productivity growth.

Our work contributes to various literatures. The first is the literature on SBTC, with papers such as Bound and Johnson (1992), Katz and Murphy (1992) and Card and Lemieux (2001) that explored the evolution of between-group wage inequality in response to changes in factor supplies and technologies augmenting the productivity of educated workers. We differ from this literature because of our distinct conceptual framework and focus on task displacement as the main driving force of changes in wage structure.

The second is the literature exploring the effects of lower equipment and computer prices on wage inequality through capital-skill complementarity. This literature goes back to Griliches (1969), and its implications for US wage inequality have been explored in Krusell et al. (2000). Relatedly, Krueger (1993) and Autor, Katz and Krueger (1998) emphasized the role of the complementarity between computers and skills. More recently, Burstein, Morales and Vogel (2019) quantify the effects of lower computer prices on inequality in a model where skilled workers have a comparative advantage in using computers. These papers quantify the effects of lower capital prices on inequality by assuming that capital directly complements skilled workers. Our framework complements this work by underscoring the role of task displacement as a separate mechanism contributing to wage inequality. We also clarify the distinction between automation and the capital-skill complementarity studied in this literature. Notably, we show that automation has a powerful impact on inequality even if there are no direct capital-skill complementarities.

Third, and most closely related to our paper is Autor, Levy and Murnane (2003), who explore the effects of technologies automating routine tasks and complementing non-routine ones on the occupational and task structure of the economy. Our paper can be seen as a generalization of their conceptual framework, enabling us to clarify the role of task displacement and quantify its effects on changes in US inequality.[7]

Finally, our conceptual framework builds on previous task models, in particular, Zeira (1998), Acemoglu and Zilibotti (2001), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2018), as well as Grossman and Rossi-Hansberg's (2008) model of offshoring. Our two main innovations relative to these papers are: (i) the general structure of comparative advantage and the flexible manner in which technologies affect the allocation of tasks to workers; (ii) our derivation of explicit formulas linking a group's wage change to its task displacement. These formulas underpin all of our empirical work.

The rest of the paper is organized as follows. The next section introduces our framework and derives the key equations for our empirical work. Section 3 presents our data sources and measurement strategy. Section 4 presents our reduced-form evidence. Section 5 presents our quantitative exercise. The Appendix contains proofs, data details, and robustness checks.

[7] Our findings complement works on job polarization, such as Goos and Manning (2007), Goos, Manning and Salomons (2014), Acemoglu and Autor (2011), and Autor and Dorn (2013). In particular, we document that groups most affected by task displacement are in the middle of the wage distribution, thus linking task displacement to polarization. Other works studying the decline of routine occupations and their macroeconomic implications include Gregory, Salomons and Zierahn (2018), Lee and Shin (2017), Jaimovich et al. (2020), and Atalay et al. (2020).

2 Conceptual Framework: Tasks, Wages, and Inequality

We start with a single-sector model, which illustrates how tasks are allocated to factors and how task displacement affects wages. We then move to our full model, including multiple sectors, and formally derive the task displacement measure we will use in our empirical work. We defer the analysis of general equilibrium effects to Section 5.

2.1 Single Sector

Environment and equilibrium: Output is produced by combining a mass M of tasks in a set $\mathcal{T}$ using a CES aggregator with elasticity of substitution $\lambda \geq 0$,

$$y = \left(\frac{1}{M}\int_{\mathcal{T}}(M \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx\right)^{\frac{\lambda}{\lambda-1}},$$

where x indexes tasks. For example, producing a shirt requires a range of tasks, including designing it; cleaning, carding, combing, and spinning the fibers; weaving, knitting, and bonding of yarn; dying, chemical processing, and finishing; marketing and advertising; transport; and various wholesale and retail tasks.

The key economic decision in this model is how to perform these different tasks. Each task can be produced using capital or different types of labor indexed by g (where $g \in \mathcal{G} = \{1, 2, \ldots, G\}$):

$$y(x) = A_k \cdot \psi_k(x) \cdot k(x) + \sum_{g \in \mathcal{G}} A_g \cdot \psi_g(x) \cdot \ell_g(x).$$

Here, $\ell_g(x)$ denotes the amount of labor of type g allocated to task x, while $k(x)$ is the amount of capital allocated to task x. In addition, A_k and the A_g's represent standard factor-augmenting technologies, which make factors uniformly more productive at all tasks. More novel and important for our purposes, productivity also has a task-specific component, represented by the functions $\psi_k(x)$ and $\{\psi_g(x)\}_{g \in \mathcal{G}}$, which determine comparative advantage and specialization patterns. Task-specific productivity is zero for factors that cannot perform the relevant task.

Capital is supplied elastically and can be produced using the final good at a constant marginal cost $1/q(x)$. Net output, which is equal to consumption, is therefore obtained by subtracting the production cost of capital goods from output:

$$c = y - \int_{\mathcal{T}}(k(x)/q(x)) \cdot dx.$$

We assume that all types of labor are supplied inelastically, and we denote the total supply of labor of type g by ℓ_g.

A *market equilibrium* in this economy is defined as an allocation of tasks to factors and a production plan for capital goods that maximize consumption. To formalize this notion, we define a critical object for the rest of our analysis: $\mathcal{T}_g$, which represents the set of tasks allocated to labor of type g, and $\mathcal{T}_k$, which is analogously the set of tasks allocated to capital. Given a supply of labor $\boldsymbol{\ell} = (\ell_1, \ell_2, \ldots, \ell_G)$, a market equilibrium is given by wages $\boldsymbol{w} = (w_1, w_2, \ldots, w_G)$, capital production decisions $k(x)$, and an allocation of tasks to factors $\{\mathcal{T}_k, \mathcal{T}_1, \ldots, \mathcal{T}_G\}$, such that: (i) the allocation of tasks to factors minimizes costs; (ii) the choice of capital maximizes net output; and (iii) the markets for capital and different types of labor clear.

Throughout, we set the final good as the numeraire, so that the w_g's correspond to real wages and the real user cost of capital is $R(x) = 1/q(x)$.

Task shares: Cost minimization implies that the sets of tasks allocated to factors satisfy:[8]

$$\mathcal{T}_g = \left\{ x : \frac{w_g}{\psi_g(x) \cdot A_g} \leq \frac{w_j}{\psi_j(x) \cdot A_j} \text{ for } j < g; \frac{w_g}{\psi_g(x) \cdot A_g} < \frac{w_j}{\psi_j(x) \cdot A_j}, \frac{1}{\psi_k(x) \cdot q(x) \cdot A_k} \text{ for } j > g \right\}$$
$$\mathcal{T}_k = \left\{ x : \frac{1}{\psi_k(x) \cdot q(x) \cdot A_k} \leq \frac{w_j}{\psi_j(x) \cdot A_j} \text{ for all } j \right\}.$$

Given an allocation of tasks to factors, we define:

$$\Gamma_g(\boldsymbol{w}, \Psi) = \frac{1}{M} \int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} \cdot dx \text{ and}$$
$$\Gamma_k(\boldsymbol{w}, \Psi) = \frac{1}{M} \int_{\mathcal{T}_k} (\psi_k(x) \cdot q(x))^{\lambda-1} \cdot dx.$$

The quantities Γ_g and Γ_k, which we refer to as the *task shares* of workers of type g and capital, respectively, give the measure of the set of tasks allocated to a factor weighted by the "importance" of the tasks.[9] Task shares depend on the sets $\mathcal{T}_g$ and $\mathcal{T}_k$, and thus on wages, factor-augmenting technologies and task productivities. Hence we write them as functions of the vectors of wages $\boldsymbol{w}$ and technology $\Psi = (\{\psi_k(x),\ \psi_g(x),\ q(x)\}_{x \in \mathcal{T}}, A_k, \{A_g\}_{g \in \mathcal{G}})$, but will omit this dependence when it causes no confusion.

The next proposition characterizes the equilibrium (all proofs are in Appendix A), and expresses factor prices, shares, and output as functions of task shares. Because production in this economy is "roundabout" (capital is produced linearly from the final good), output can be infinite. In Appendix A, we derive an Inada condition that ensures finite output (in the one-sector case, this condition implies $A_k^{\lambda-1} \cdot \Gamma_k < 1$) and assume throughout that it is satisfied.

Proposition 1 (Equilibrium) *There exists a unique equilibrium. In this equilibrium, output,*

[8] When a task can be produced at the exact same unit cost by different factors, we assume it is allocated to capital or to the type of labor with the higher index. This rule simplifies our exposition and has no substantive effect on equilibrium, except that in Proposition 1, it enables us to state that the equilibrium is unique (rather than "essentially" unique at these non-generic points of cost equality).

[9] In particular, this importance weight depends on the revenue share of the task in total costs, and hence the productivity of the factor performing the task has an exponent equal to the elasticity of substitution minus one.

wages, and factor shares can be expressed as functions of task shares:

$$y = (1 - A_k^{\lambda-1} \cdot \Gamma_k)^{\frac{\lambda}{1-\lambda}} \cdot \left(\sum_{g \in \mathcal{G}} \Gamma_g^{\frac{1}{\lambda}} \cdot (A_g \cdot \ell_g)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}, \tag{1}$$

$$w_g = \left(\frac{y}{\ell_g} \right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \Gamma_g^{\frac{1}{\lambda}} \text{ for all } g \in \mathcal{G}, \tag{2}$$

$$s^K = A_k^{\lambda-1} \cdot \Gamma_k. \tag{3}$$

The proposition shows that output can be represented as a CES aggregate of different types of labor and capital, with elasticity of substitution λ. This representation differs from the standard CES production function for three reasons. First, the distribution parameters, which are exogenous in the standard CES, are now endogenous and given by the task shares Γ_g's. They not only depend on factor prices (via the dependence of the sets $\mathcal{T}_g$ and $\mathcal{T}_k$ on factor prices), but also on technology. In particular, automation technologies impact equilibrium prices and quantities by reallocating tasks away from labor, directly changing the Γ_g's and Γ_k. Second, despite appearances, the elasticity of substitution between factors is *not* equal to λ, but depends on endogenous substitution taking place as tasks are reallocated (again captured by changes in the sets $\mathcal{T}_g$ and $\mathcal{T}_k$, or variations in the Γ_g's and Γ_k in response to factor prices). Finally, the term $1 - A_k^{\lambda-1} \cdot \Gamma_k > 0$ in front of the CES accounts for the roundabout nature of production.

Equation (2) shows that real wages are given by the marginal product of each type of labor, which is a function of output per worker (raised to the power $1/\lambda$ for standard reasons) and the factor-augmenting technology, A_g, raised to the power $(\lambda - 1)/\lambda$. This exponent captures the fact that improvements in the productivity of workers from group g reduce the price of tasks they produce, and if $\lambda < 1$ this price effect dominates. More novel is that real wages also depend directly on task shares, the Γ_g's, highlighting a key aspect of our model: the real wage of a factor is linked to the set of tasks allocated to that factor.

Proposition 1 implies that we can study and quantify the effects of technology on wages, factor shares, and output simply by tracing its impact on task shares, as we next discuss in detail.

The effects of technology: Our conceptual framework clarifies that different types of technologies have distinct impacts on wages, productivity, and output. We now discuss the effects of three types of technologies:

- **factor augmenting:** higher A_g or A_k resulting in uniform increases in productivity in all tasks. Factor-augmenting technologies have been the focus of much of the macro and labor literatures, and as we will see, they are qualitatively different from task displacement (and arguably a significant abstraction, since there are no examples of technologies that increase factor productivity in *all* tasks).

- **productivity deepening:** increases in $\psi_g(x)$ for $x \in \mathcal{T}_g$ or in $\psi_k(x)$ for $x \in \mathcal{T}_k$—which result in an increase in the productivity of a factor at the tasks it is currently performing. For example, we may have improvements in the tools used by workers to perform one of their tasks (think of GPS making drivers better at navigation, or upgrades in the capital equipment used to produce the same task). The defining feature of this type of technological progress is that it does not directly displace factors from the tasks they were performing.

- **task displacement:** increases in $\psi_k(x)$ for $x \in \mathcal{T}_g$—which therefore lead to automation and a reallocation of tasks away from workers toward capital. Well-known examples of technologies causing task displacement include the introduction of numerical control or industrial robots for blue-collar tasks previously performed by manual workers or the introduction of specialized software automating various back-office and clerical tasks. Offshoring also leads to task displacement, and one can think about it in this framework by assuming that tasks can be performed abroad and imported in exchange of the final good (see also Grossman and Rossi-Hansberg, 2008).

Figure 3 depicts the effects of productivity deepening and task displacement on the allocation of tasks to factors. The figure highlights that the total impact of a change in technology on task shares is comprised of a *direct* effect, given by the changes in the Γ_g's and Γ_k driven by productivity deepening and displacement *holding all prices* constant; and indirect or *ripple* effects, driven by the reallocation of tasks across factors in response to changes in factor prices. The direct effects are shown with the shaded areas, which indicate the tasks where productivity increases, while the induced ripple effects are depicted with the dashed curves. The ripple effects alter the task shares and prices of factors that are not themselves directly impacted by new technologies.

In this section, we provide a characterization of the implications of these three technologies abstracting from ripple effects. This allow us to illustrate the distinct direct impacts of these technologies and derive a simple equation to explore the role of these direct effects. We characterize the full general equilibrium response of wage inequality to task displacement, including ripple effects in Section 5, where we also estimate them.

The following assumption rules out ripple effects and is maintained until Section 5:

Assumption 1 *1. Workers can only produce non-overlapping sets of tasks (i.e., $\psi_g(x) > 0$ only if $\psi_{g'}(x) = 0$ for all $g' \neq g$).*

2. There exist $\underline{\psi} > 0$ and $\overline{q} > 0$ such that $\psi_k(x) > \underline{\psi}$ and $q(x) > \overline{q}$ for all $x \in \mathcal{S} = \{x : \psi_k(x) > 0\}$.

The first part of the assumption imposes that each tasks can be performed at most by one type of labor, which ensures that a group displaced from the tasks it specializes in cannot in turn displace other workers from their tasks. The second part imposes that capital productivity is high enough and the cost of capital is low enough that all tasks in the set $\mathcal{S} = \{x : \psi_k(x) > 0\}$, where

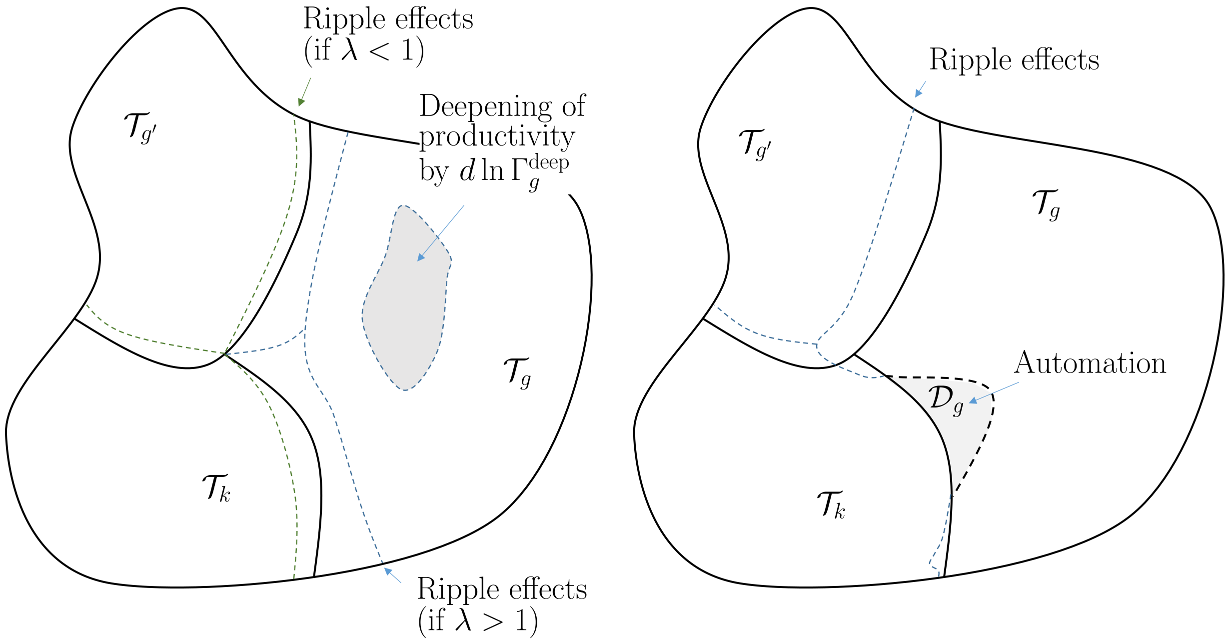

FIGURE 3: The direct effects of technology and ripple effects. The left panel shows the effects of an increase of $d \ln \Gamma_g^{\text{deep}}$ in the productivity of group g in tasks in $\mathcal{T}_g$. The right panel depicts the effects of automation technologies reducing the task share of worker g by $d \ln \Gamma_g^{\text{disp}}$.

capital has positive productivity, will be allocated to capital (see the Appendix for details and for a derivation of these thresholds).

In the next proposition, we characterize the effects of different types of technologies on factor prices, TFP, and output under Assumption 1. We present a characterization in terms of the infinitesimal changes in the direct effects of these technologies. In particular, we let $d \ln \Gamma_g^{\text{deep}} \geq 0$ denote the direct effect of productivity deepening (for capital or some types of labor) on the task share of group g; and $d \ln \Gamma_g^{\text{disp}}$ denote the direct displacement effect experienced by group g due to automation (i.e., because capital productivity $\psi_k(x)$ increases at tasks previously performed by this group).[10] These direct effects can be expressed as follows:

$$
\begin{aligned}
d \ln \Gamma_g^{\text{deep}} &= \frac{1}{M} \int_{\mathcal{T}_g} \frac{\psi_g(x)^{\lambda-1}}{\Gamma_g} \cdot d \ln \psi_g(x) dx \\
d \ln \Gamma_g^{\text{disp}} &= \frac{1}{M} \int_{\mathcal{D}_g} \psi_g(x)^{\lambda-1} dx \Bigg/ \frac{1}{M} \int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} dx,
\end{aligned}
$$

where $\mathcal{D}_g \subseteq \mathcal{T}_g$ is the subset of tasks in which, after the technological change, capital outperforms

[10]In this case, the relevant change is at the extensive margin: a discrete increase in the productivity of capital in an infinitesimal set of tasks previously performed by labor.

workers from group g (as shown in the right panel of Figure 3). Finally, we define

$$\pi_g = \frac{1}{M}\int_{\mathcal{D}_g}\psi_g(x)^{\lambda-1}\cdot\pi_g(x)dx \bigg/ \frac{1}{M}\int_{\mathcal{D}_g}\psi_g(x)^{\lambda-1}dx$$

as the average cost savings from producing the tasks in $\mathcal{D}_g$ with the now more cost effective capital. In this expression, $\pi_g(x)$ is the cost saving of automating task x previously performed by workers group g.[11]

Proposition 2 (Technology Effects) *Suppose Assumption 1 holds, so that there are no ripple effects. Consider a change in technology (including factor-augmenting, productivity deepening, and task-displacement). The impact on real wages, TFP, output, and the capital share are*

$$d\ln w_g = \frac{1}{\lambda}d\ln y + \frac{\lambda-1}{\lambda}d\ln A_g + \frac{\lambda-1}{\lambda}d\ln\Gamma_g^{deep} - \frac{1}{\lambda}d\ln\Gamma_g^{disp}, \tag{4}$$

$$d\ln TFP = \sum_{g\in\mathcal{G}} s_g^L\cdot\left(d\ln A_g + d\ln\Gamma_g^{deep}\right) + s^K\cdot\left(d\ln A_k + d\ln\Gamma_k^{deep}\right) + \sum_{g\in\mathcal{G}} s_g^L\cdot d\ln\Gamma_g^{disp}\cdot\pi_g, \tag{5}$$

$$d\ln s^K = (\lambda-1)\cdot\left(d\ln A_k + d\ln\Gamma_k^{deep}\right) + \frac{1}{s^K}\cdot\sum_{g\in\mathcal{G}} s_g^L\cdot d\ln\Gamma_g^{disp}\cdot\left(1+(\lambda-1)\cdot\pi_g\right), \tag{6}$$

$$d\ln y = \frac{1}{1-s^K}\cdot\left(d\ln TFP + s^K\cdot d\ln s^K\right). \tag{7}$$

To clarify the distinct economic forces generated by various technologies, let us first consider the implications of factor-augmenting technologies making workers of group g (or capital) more productive at all tasks—the $d\ln A_g$ and $d\ln A_k$ terms in the proposition. The real wage of group g is affected primarily by productivity gains, represented by $d\ln y$. This productivity effect raises the wages of all workers and is a consequence of the higher demand for all tasks generated by the increase in output. As a result, without ripple effects, factor-augmenting technologies increasing the productivity of group g raise the wage of all other workers (and factor-augmenting technologies increasing the productivity of capital raise all wages). Moreover, factor-augmenting technologies only affect relative wages through the term $\frac{\lambda-1}{\lambda}\cdot d\ln A_g$, whose sign depends on whether $\lambda \lesseqgtr 1$. This ambiguous impact is rooted in the fact that factor-augmenting technologies make workers from group g more productive but also lower the price of the tasks they produce. When $\lambda > 1$ the first effect dominates and improvements in the productivity of group g at tasks it currently performs lead to higher wages for this group as well. This is the standard mechanism emphasized in the SBTC literature (e.g., Bound and Johnson, 1992, Katz and Murphy, 1992).

The impact of factor-augmenting technologies on TFP can be computed from (5) as $\sum_{g\in\mathcal{G}} s_g^L\cdot d\ln A_g + s^K\cdot d\ln A_k$. This formula, which follows from Hulten's theorem, has a simple envelope logic: a 1% increase in the productivity of all workers in group g leads to an increase in TFP of

[11] This cost-saving is in turn given as $\pi_g(x) = \frac{1}{\lambda-1}\left[\left(w_g\frac{A_k\cdot q(x)\cdot\psi_k(x)}{A_g\cdot\psi_g(x)}\right)^{\lambda-1} - 1\right] > 0$, where the expression is evaluated at the new level of capital productivity.

$s_g^L\%$, where s_g^L is the share of skilled labor in GDP. Likewise, a 1% increase in the productivity of capital at all tasks leads to an increase in TFP of $s^K\%$. Thus, relative to their modest effects on the wage structure (especially for values of λ close to 1), factor-augmenting technologies have large productivity effects. If factor-augmenting technologies were at the root of changes in the wage structure, then we should see sizable TFP gains (unless there is technological regress, see Acemoglu and Restrepo, 2019). Note finally that, with no ripple effects, factor-augmenting technologies have identical effects as technologies generating a deepening of productivity—the terms $d\ln\Gamma_g^{\text{deep}}$ and $d\ln\Gamma_k^{\text{deep}}$.

These results contrast with the effects of automation, which displaces some workers from the tasks they are performing, and whose effects are captured by the term $d\ln\Gamma_g^{\text{disp}}$ in the proposition. The impact of this type of technology on wages in (4) becomes $\frac{1}{\lambda}d\ln y - \frac{1}{\lambda}d\ln\Gamma_g^{\text{disp}}$. The first term is once again the productivity effect, which raises the wages of all workers. More novel and important for our purposes is the second term, which links wage changes to task displacement and is negative (independently of whether $\lambda \lesseqgtr 1$). As we will see, this key insight generalizes to our full model and forms the basis of our empirical work.

The implications of automation for TFP and factor shares are also very different from those of factor-augmenting technologies. The change in TFP is now $\sum_{g\in\mathcal{G}} s_g^L \cdot d\ln\Gamma_g^{\text{disp}} \cdot \pi_g$. If π_g is small for groups being displaced (meaning small productivity gains from substituting capital for labor), then TFP growth could be arbitrarily small, even if there is considerable automation. As a result, the displacement effect can outweigh the productivity effect and, as a result, the real wage for displaced groups can decline despite the economy's higher productivity.

Equation (6) also shows that task displacement always results in an increase in the capital share and a reduction in the labor share of value added—an observation that will motivate our measurement approach in Section 2.3. This is also in stark contrast to what one would get from factor-augmenting technologies, whose impact on factor shares depends on whether $\lambda \lesseqgtr 1$ (with no ripple effects, λ is also the elasticity of substitution between capital and labor).

2.2 Full Model: Multiple Sectors

Our full model generalizes the one-sector setup in the previous subsection. There are multiple industries indexed by $i \in \mathcal{I} = \{1, 2, \dots, I\}$. Output in industry i is produced by combining the tasks in some set $\mathcal{T}_i$, with measure M_i, using a CES aggregator with elasticity $\lambda \geq 0$:

$$y_i = A_i \cdot \left(\frac{1}{M_i}\int_{\mathcal{T}_i} (M_i \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx\right)^{\frac{\lambda}{\lambda-1}},$$

where x again indexes tasks and A_i is a Hicks-neutral industry productivity term. As before, tasks, $\mathcal{T}_{gi}$ denotes the set of tasks in industry i allocated to workers of type g and $\mathcal{T}_{ki}$ denotes those allocated to capital. Likewise, we define industry-level task shares, Γ_{gi} and Γ_{ki}, as:

$$\Gamma_{gi}(\boldsymbol{w}, \Psi) = \frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} \cdot dx; \Gamma_{ki}(\boldsymbol{w}, \Psi) = \frac{1}{M_i} \int_{\mathcal{T}_{ki}} (\psi_k(x) \cdot q(x))^{\lambda-1} \cdot dx.$$

We assume that industry outputs are combined into a single final good using a constant returns to scale aggregator. Rather than specifying this aggregator, we work with the implied expenditure shares, $s_i^Y(\boldsymbol{p})$, where $\boldsymbol{p} = (p_1, p_2, \ldots, p_I)$ is the vector of industry prices.[12]

The next proposition generalizes Proposition 1 to this environment and characterizes the equilibrium in terms of task shares.

Proposition 3 (Equilibrium in multi-sector economy) *There is a unique equilibrium. In this equilibrium, output, wages, and industry prices can be expressed as functions of task shares defined implicitly by the solution to the system of equations:*

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{\lambda}} \tag{8}$$

$$p_i = \frac{1}{A_i} \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g \in \mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}} \tag{9}$$

$$1 = \sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}). \tag{10}$$

The proposition shows that task shares, the Γ_{ki}'s and Γ_{gi}'s, continue to be a key determinant of real wages, and we can express the equilibrium of the economy as a function of task shares, though we no longer have a closed-form solution for output. Moreover, the effects of automation technologies on equilibrium outcomes again work via their impact on task shares.

2.3 Mapping the Model to Data

In this subsection, we use Proposition 3 to derive an equation that links the change in wages to the direct effects of task displacement (and other technologies), extending (4) to this environment. This equation will form the basis of our reduced-form analysis. We will then use our model to derive a measure of task displacement that captures its direct effects across groups of workers. These equations and measures will be generalized to include ripple effects in our general equilibrium analysis in Section 5.

Task displacement and wage structure: As before, denote the effects productivity deepening and automation on task shares in industry i by $d\ln\Gamma_{gi}^{\text{deep}}$ and $d\ln\Gamma_{gi}^{\text{disp}}$, respectively. Differ-

[12]For example, a CES demand system over industries with elasticity of substitution η would imply $s_i^Y(\boldsymbol{p}) = \alpha_i \cdot p_i^{1-\eta}$. This formulation imposes homotheticity, which can be relaxed by allowing expenditure shares to also depend on the level of consumption, but this is not central to our focus.

entiating equation (8) and using Assumption 1, we obtain a generalization of (4):

$$(11)\qquad d\ln w_g = \frac{1}{\lambda} d\ln y + \frac{\lambda - 1}{\lambda}\left(d\ln A_g + \sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln \Gamma_{gi}^{\text{deep}}\right) + \frac{1}{\lambda}\sum_{i\in\mathcal{I}} \omega_g^i \cdot \left(d\ln s_i^Y + (1-\lambda)(d\ln p_i + d\ln A_i)\right) - \frac{1}{\lambda}\sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln \Gamma_{gi}^{\text{disp}},$$

where ω_g^i denotes the share of group g's wage income earned in industry i, so that $\sum_{i\in\mathcal{I}} \omega_g^i = 1$.

Equation (11) shows that wages depend on four terms, which we next explain (and also outline how they will be measured in our reduced-form empirical work):

- *The common expansion of output:* $d\ln y$, which captures the productivity effect. In our reduced-form regressions, this effect will be absorbed by the constant term.

- *Group-specific shifters:* $\frac{\lambda-1}{\lambda}\left(d\ln A_g + \sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln \Gamma_{gi}^{\text{deep}}\right)$, which represent the contribution of factor-augmenting technologies and productivity deepening. Following the SBTC literature, in our reduced-form regressions we will assume that these technologies augment certain well-defined skills associated with education and also allow them to be gender-biased. In particular, we parameterize these as:

$$\frac{\lambda - 1}{\lambda}\left(d\ln A_g + \sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln \Gamma_{gi}^{\text{deep}}\right) = \alpha_{\text{edu}(g)} + \gamma_{\text{gender}(g)} + \upsilon_g,$$

  where υ_g is an additional unobserved component, and in our regression analysis, they will be absorbed by dummies for gender and education levels. As a further refinement, we allow group-specific shifters to also depend on baseline group wages, which may proxy for skills as well.

- *Industry shifters*:

$$\text{Industry shifter}_g = \frac{1}{\lambda}\sum_{i\in\mathcal{I}} \omega_g^i \cdot \left(d\ln s_i^Y + (1-\lambda)(d\ln p_i + d\ln A_i)\right),$$

  which capture the effects coming from the expansion or contraction of industries in which a demographic group specializes (for example, due to trade in final goods, structural transformation, or the uneven effects of automation in some sectors). In our reduced-form regressions, we control for this term by including the exposure of a group to the change in value added of the sectors in which it specializes.

- *Task displacement*:

$$\text{Task displacement}_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln \Gamma_{gi}^{\text{disp}}.$$

  This term represents the direct effect of task displacement on a demographic group's wages and will be the focus of our empirical work. As equation (11) shows, the key prediction of our model is that groups exposed to taks displacement should experience a decline in their relative wages. Unlike other technologies, this effect is always negative—independently of whether the elasticity of substitution λ is above or below 1. Task displacement could come from automation or offshoring, and we will later study their contribution to this process.

Measuring task displacement: We now turn to measuring task displacement. Our measure summarizes the direct effects of task-displacing technologies on different groups of workers, and will form the basis of our reduced-form regression analysis and quantitative evaluation.

We use two complementary strategies to measure task displacement, both of which rely on an initial observation: task displacement takes place mainly in tasks that can be automated, which we initially proxy with routine tasks.[13] Formally, we impose the following assumption:

ASSUMPTION 2 *Only routine tasks are automated and, within an industry, different groups of workers are displaced from their routine tasks at a common rate.*

The next component of our measurement requires a proxy for the extent of task displacement taking place in each industry. Our two strategies take different approaches to this problem. Our first strategy develops a more comprehensive measure based on the idea that task displacement is tightly linked to declines in industry labor shares, and uses the "unexplained" portion of the change in labor share to infer task displacement at the industry level. Specifically, and as we show in Appendix E, when $\lambda = 1$ (so that the task aggregator is Cobb-Douglas) and there are no changes in industry markups, we have:

$$\text{Task displacement}_g = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \left(\omega_{gi}^R / \omega_i^R\right) \cdot (-d \ln s_i^L). \tag{12}$$

This measure comprises three terms: (1) a group's exposure to different industries, ω_g^i, which is given by the share of wages earned by workers of group g in industry i; (2) the percent decline in the labor share, $-d \ln s_i^L$, which in our framework is tightly linked to automation in industry i; (3) $\omega_{gi}^R / \omega_i^R$, which captures the relative specialization of group g in industry i's routine jobs, where displacement takes place.[14] The measure of task displacement in equation (12) is precisely the one used in the right panel of Figure 2, while the left panel focuses on exposure to industries with declining labor shares and ignores the relative specialization of workers in routine jobs.[15]

[13]The idea that routine tasks are easier to automate is the main premise of Autor, Levy and Murnane (2003) and is in line with several studies that document a decline in routine jobs following automation, including Acemoglu and Restrepo (2020) and Humlum (2020). We additionally show very similar results using various other measures of which tasks can be automated.

Although which tasks can be automated will likely change with advances in AI, AI technologies are not present for most of our sample. Acemoglu et al. (2020) show that AI use takes off in the US after 2015.

[14]Relative specialization is given by the ratio of the share of wages earned in routine jobs by workers in group g at industry i—ω_{gi}^R—to the share of wages earned in routine jobs by all workers in industry i—ω_i^R.

[15]Although we use the measure in equation (12) in most of our analysis, this formula can be extended to the more general case where $\lambda \neq 1$ and markups change over time, and we provide robustness checks using this more general formulation later in the paper.

Our second strategy uses direct measures of automation technologies (and offshoring):

$$\text{task displacement due to automation}_g = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \left(\omega_{gi}^R / \omega_i^R\right) \cdot \text{automation in industry}_i. \tag{13}$$

Although these measures can be included directly on the right-hand side of our wage regressions, we focus on specifications where they are used as instruments for the measure of task displacement based on labor share declines, which enables us to compare coefficient estimates across specifications.

These two strategies are complementary, and we present results using both throughout the paper. While the second strategy has the advantage that it exploits actual measures of automation, such as adoption of industrial robots or specialized machinery and software, it might miss other technologies generating task displacement. The more comprehensive measure exploiting the unexplained decline in industry's labor shares captures all dimensions of task displacement but may be confounded by other economic forces impacting labor shares.

3 Data, Measurement, and Descriptive Patterns

In this section, we describe our data sources, substantiate the link between task displacement and automation technologies, and provide a first look at the relationship between a demographic group's task displacement and its real wage changes.

3.1 Main Data Sources

We use data from the BEA Integrated Industry-Level Production Accounts on industry labor shares, factor prices, and value added for 49 industries that can be tracked consistently from 1987 to 2016.[16] We complement these industry data with proxies of the adoption of automation technologies, including BLS data on the change in the share of specialized machinery and software in value added from 1987 to 2016, and measures of robot adoption by industry from the International

Namely, Appendix E shows that, more generally, a measure of task displacement correcting for changes in factor prices and markups can be constructed as:

$$\text{Task displacement}_g = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \left(\omega_{gi}^R / \omega_i^R\right) \cdot \frac{-d\ln s_i^L + d\ln \mu_i - s_i^K \cdot (1-\lambda) \cdot (d\ln w_i - d\ln R_i)}{1 + (\lambda - 1) \cdot s_i^L \cdot \pi_i},$$

where $d\ln \mu_i$ is an estimate of the increase in markups in industry i. Put differently, rather than focusing on the raw decline in the labor share, we now incorporate the effects of prices and markups on the labor share and focus on the unexplained component. In addition, the term $1 + (\lambda - 1) \cdot s_i^L \cdot \pi_i$ in the denominator adjusts for the substitution toward automated tasks following a cost reduction of π_i—the average cost saving from automation in industry i. When computing this measure, we set $\pi_i = 30\%$, a choice we discuss in detail in the quantitative section. Appendix E clarifies that this expression is an approximation because it ignores the effects of augmenting technologies or productivity deepening. It also shows, however, that the contribution of these terms to changes in the labor share is small, and that the approximation is accurate.

[16]These 49 industries can be consistently tracked in Census data and BLS data and cover the entire non-government sector. When constructing our measures of task displacement, we assume that workers in the government sector experience no automation or offshoring.

Federation of Robotics (IFR).[17] In particular, we rely on the *adjusted penetration of robots* from 1993 to 2014 described in detail in Acemoglu and Restrepo (2020) as a measure of robot adoption driven by international advances in technology. We also combine these measures into a single index of automation, computed as the predicted decline in an industry's labor share from 1987 to 2016 based on its robot adoption and utilization of software and specialized equipment (specifically, this is the predicted value of industry labor share given these three measures). In addition, we look at a measure of changes in intermediate imports to proxy for offshoring (from Feenstra and Hanson, 1999). Finally, to control for other trends affecting industries, we use data on sales concentration, estimates of markups, unionization rates (from the CPS), measures of Chinese import competition and industry TFP. These covariates are described in detail in Appendix F.

On the worker side, we use US Census and American Community Survey (ACS) data to trace the labor market outcomes of 500 demographic groups defined by gender, education (less than high school, high school graduate, some college, college degree, and post-graduate degree), age (proxied by 10–year age bins, from 16–25 years to 56–65), race/ethnicity (White, Black, Asian, Hispanic, Other), and native vs. foreign-born. For each demographic group, we measure real hourly wages and other labor market outcomes in 1980 (using the 1980 US Census) and in 2016 (pooling data from the 2014–2018 ACS), and compute the change in real wages, employment, and non-participation rates from 1980 to 2016. In Section 4.7, we also zero in on variation in labor market outcomes for demographic groups across US regions and commuting zones. Further details on these data are provided in Appendix F.

We measure task displacement for these 500 demographic groups exploiting their specialization patterns across industries and in routine jobs from the 1980 Census—a year that predates major advances in automation technologies. To do so, we create a consistent mapping of the 49 industries in the BEA data to the Census industry classification, and for each industry, compute the share of wages earned in routine jobs by a demographic group, using the definition of routine occupations described in Acemoglu and Autor (2011). About a third of the occupations in the 1980 Census are classified as routine according to this measure (see Appendix F).

3.2 Task Displacement and Changes in the Labor Share across Industries

The blue bars in Figure 4 summarize our measure of task displacement at the industry level, which is given by the percent decline in an industry labor share that is not explained by changes in factor prices.[18] The whiskers indicate the range of estimates for task displacement as we vary the elasticity of substitution λ from 0.8 to 1.2 (we justify this range of elasticities in Section 5). The figure reveals considerable variation in task displacement across industries, with the largest

[17] The BLS Total Multifactor Productivity tables provide alternative series for labor share and factor prices in the 49 industries used in our analysis. These figures are based on the same underlying data as the BEA's, but use different imputations and exclude non-profit firms and firms producing services that are difficult to price. All of our results are robust to using data from the BLS Total Multifactor Productivity Tables.

[18] In what follows, all changes are re-scaled to 36-year equivalent changes, so that they match the length of the time window for which we measure real wage changes.

levels of task displacement seen in mining, chemical products, petroleum, car manufacturing, and computers and electronics. In what follows, we focus on the measure of task displacement computed for $\lambda = 1$ (in which case, industry-level task displacement is the same as the percent decline in an industry's labor share), and we use different values of λ for robustness.

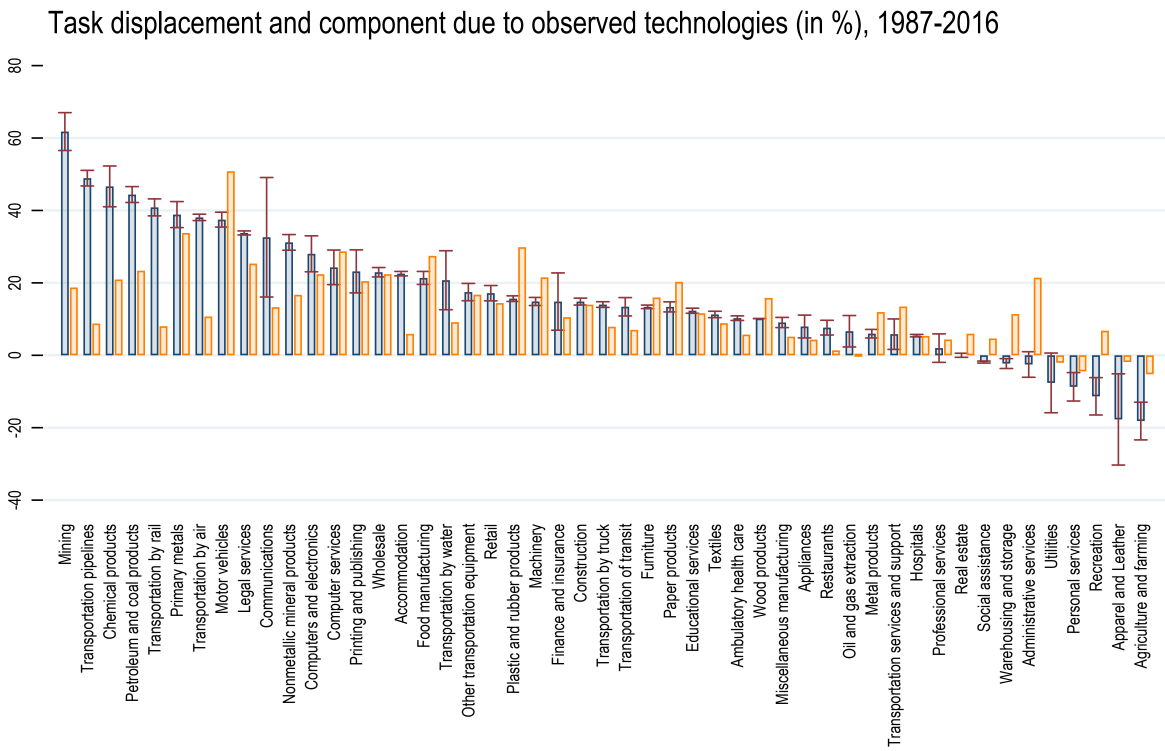

FIGURE 4: Task displacement 1987-2016 and index of automation. The blue bars provide our baseline measure of task displacement and the whiskers give the range of estimates obtained as we vary λ from 0.8 to 1.2 , while the yellow bars show the component of task displacement explained by our index of automation. See text for variable definitions.

The figure also plots our index of automation, which points to an important role of technology in generating task displacement and declining labor shares across industries. This is further confirmed in Figure 5, where we see a significant positive association between three measures of automation and industry task displacement. The first, in the left panel, is the adjusted penetration of robots; the second, in the middle panel, is the change in the share of software and specialized equipment in value added; and finally the third panel shows our single index of automation. This last summary measure explains 50% of the variation in the change in labor shares and task displacement across industries. We provide further evidence on this point in Table A1 in the Appendix, where we demonstrate that offshoring is also associated with task displacement, though it only explains 2% of the industry variation in the data. Moreover, changes in sales concentration, markups, import competition, and declining unionization rates, are not, or are only weakly, correlated with industry labor share changes and task displacement, and their inclusion does not affect the association between task displacement and our measures of automation technologies.

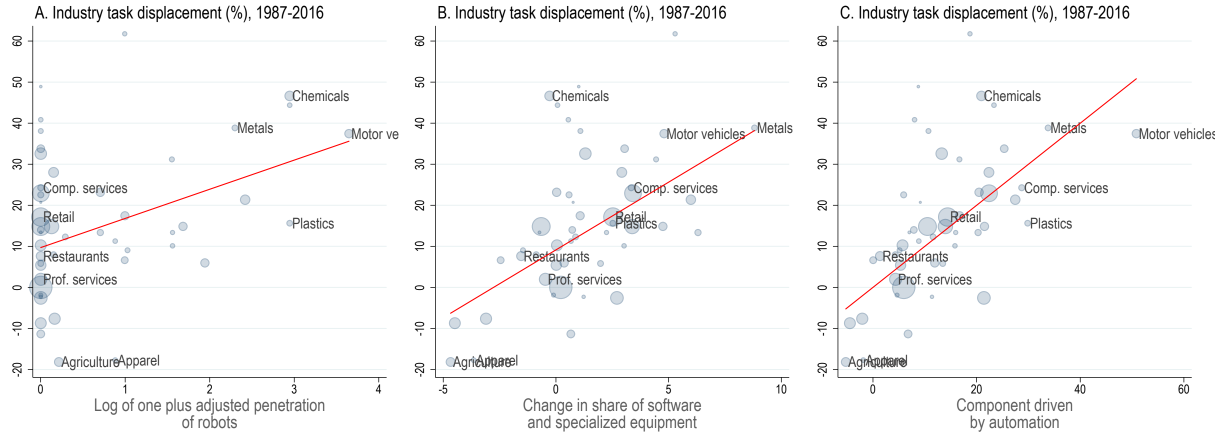

FIGURE 5: Relationship between automation technologies and task displacement across industries. See text for variable definitions. The five industries with the highest and lowest levels of task displacement are identified in the figures.

The industry-level variation in addition provides support for Assumption 2. In particular, Figure 6 depicts a strong negative association between task displacement and reductions in the demand for routine tasks across industries (measured in one of three ways: total wages in routine jobs, total hours in routine jobs, or total number of workers in routine jobs).[19] With all three measures, there is a significant decline in routine jobs in industries experiencing task displacement. Table A2 in the Appendix demonstrates the robustness of this relationship and confirms that it holds when we instrument task displacement using our index of automation.

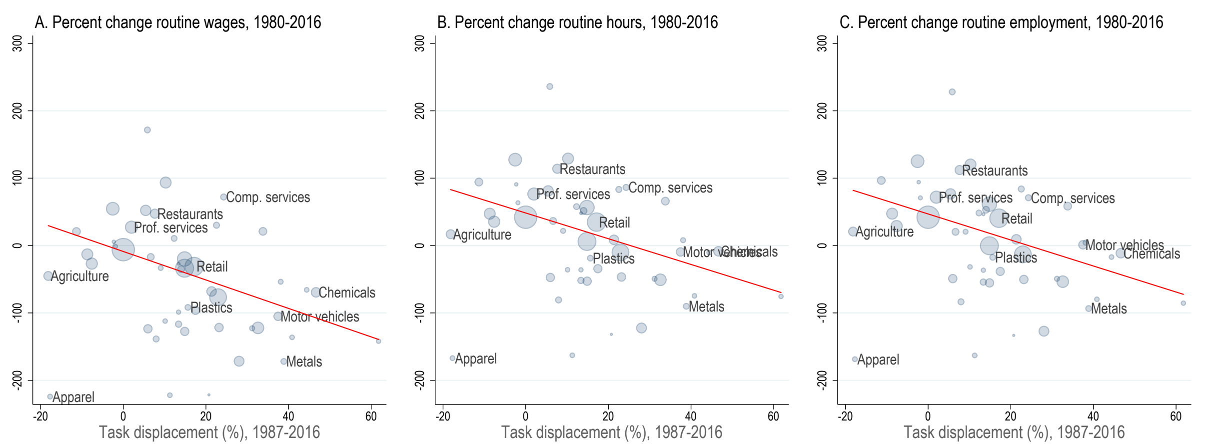

FIGURE 6: Relationship between task displacement and the decline of routine jobs across industries. See text for variable definitions. The five industries with the highest and lowest levels of task displacement are identified in the figures.

[19] To avoid changes in occupational definitions after 2016, in this exercise we focus on changes in routine jobs by industry between 1980 (from the 1980 US Census) and the 2012–2016 American Community Survey.

3.3 Task Displacement and Wages Across Demographic Groups

We now present descriptive statistics for our measure of task displacement at the level of demographic groups and take a preliminary look at its association with real wage changes. Figure 7 shows large differences across demographic groups in terms of task displacement between 1980 and 2016, with some experiencing a 25% reduction in their task shares, while others saw no change in theirs. Importantly, 95% of the variation in task displacement across groups is driven by our index of automation technologies, as can be seen from the left panel of Figure 7, which depicts task displacement by demographic group (computed using equation (12)) against the component driven by automation technologies (computed using equation (13)).

FIGURE 7: Task displacement across 500 demographic groups. The left panel shows a scatter plot between task displacement (on the vertical axis) and the component driven by the index of automation (in the horizontal axis). The 45° line is shown in red. The right panel plots our measure of task displacement against the baseline hourly wages of groups in 1980. Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. See text for variable definitions.

The right panel of Figure 7 depicts task displacement by demographic group against a group's real wage in 1980 and documents that task displacement has been particularly high during this period for groups in the middle of the wage distribution—thus playing both an unequalizing and a polarizing role.[20]

Figure 8 provides a first glimpse at the relationship between task displacement and real wage changes across demographic groups. The left panel plots the bivariate correlation between our task displacement measure and real wage changes between 1980 and 2016 (as in the right panel of Figure 2). The figure reveals a powerful negative relationship between task displacement and changes in real wages, with groups experiencing the highest levels of task displacement seeing their real wages fall or stagnate. The right panel displays a falsification exercise demonstrating that the relationship depicted in the left panel is not driven by secular declines in labor market

[20]Figure A6 in the Appendix presents similar patterns for different values of λ and also confirms that these changes are very highly correlated (over 90%) with our baseline measure in equation (12).

fortunes of some demographic groups. It confirms that there is no correlation between our task displacement measure, which only uses post-1980 information, and real wage changes between 1950 and 1980—a period that predates major advances in automation. All demographic groups, including those who later on experienced adverse task displacement after 1980, enjoyed robust real wage growth, of about 50%, between 1950 and 1980.

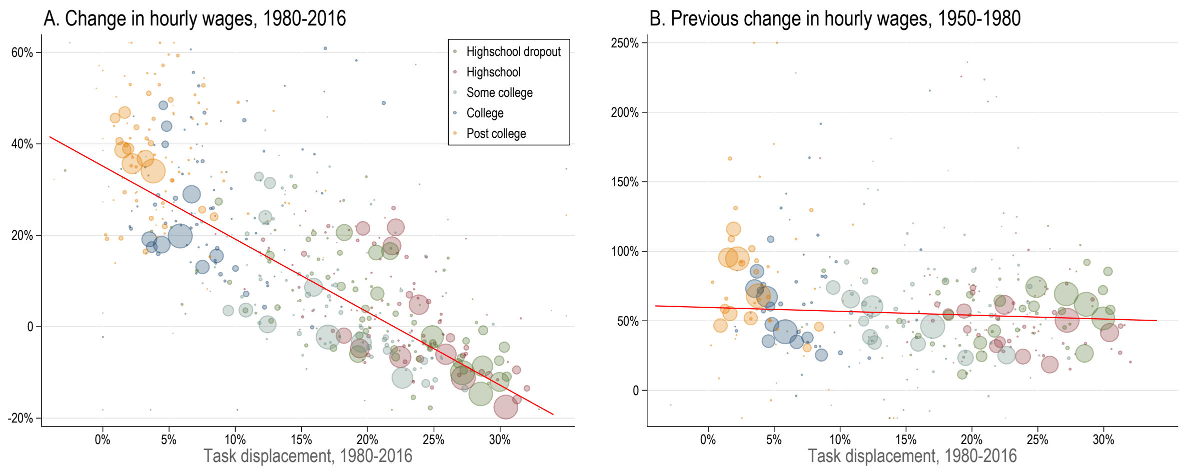

FIGURE 8: Reduced-form relationship between task displacement and real wage changes. Panel A plots changes in real wages for 1980–2016. The slope of the regression line is −1.6 (standard error = 0.09). Panel B plots pretrends in wages for 1950–1980, where the slope of the regression line is −0.2 (standard error = 0.2). Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. See text for variable definitions.

Figure 8—like Figure 7—identifies different education levels, highlighting that task displacement has been much higher for workers without a college degree. Still, the negative association between change in wages and task displacement is visible within education groups. Relatedly, Figure 9 displays average task displacement and average real wage change by gender and education. It reveals that men without college degree have experienced the highest levels of task displacement as well as substantial real wage declines, while men and women with a post-graduate degree and women with a college degree have been subject to negligible task displacement and have enjoyed robust real wage growth. Once again, these patterns are explained by the component of task displacement driven by automation technologies.

Table A3 in the Appendix provides descriptive statistics and further corroborates these patterns. For example, it shows that workers in the top quintile of the task displacement distribution—experiencing the highest task displacement—saw their real wage decline by 12%, while workers in the least exposed groups enjoyed real wage growth of about 26%.

4 Reduced-Form Evidence of the Effects of Task Displacement

This section presents our main reduced-form results. It highlights how the direct effects of task displacement explain a large fraction of the changes in the US wage structure between 1980 and 2016, and shows that task displacement is tightly linked to automation and its effects are

FIGURE 9: Task displacement, component of task displacement driven by automation, and real wage changes by education level and gender. See text for variable definitions.

not driven by changes in markups, industry concentration, import competition from China, or declining unionization rates.

4.1 Baseline OLS Results

Table 1 presents estimates from an empirical analogue of equation (11):

$$\Delta \ln w_g = \beta^d \cdot \text{Task displacement}_g + \beta^s \cdot \text{Industry shifter}_g + \alpha_{\text{edu}(g)} + \gamma_{\text{gender}(g)} + \upsilon_g. \qquad (14)$$

Here g indexes our 500 demographic groups, and $\Delta \ln w_g$ denotes the log change in real hourly wages for workers in group g between 1980 and 2016. The error term υ_g represents residual group-specific changes in supply or demand, which are assumed to be orthogonal to task displacement. As in all of our other results, regressions are weighted by the share of hours worked by each group and standard errors are robust to heteroskedasticity.

Column 1 presents a bivariate regression identical to the one shown in Figure 8. We see a precise and sizable negative relationship between task displacement and wage growth, with a coefficient of 1.6 (s.e. = 0.1). This estimate implies that a 25% increase in task displacement (or decrease in task share), which corresponds to the displacement experienced by white American men aged 26-35 with no high school degree, is associated with a 40% decline in the relative wage of the group. The bottom rows report the share of the variation in wage changes explained by task displacement as well as the R^2.[21] Our measure of task displacement alone explains 67% of the variation in wage changes between 1980 and 2016.[22]

[21] Following Klenow and Rodríguez-Clare (1997), we decompose the variance of y in the linear model $y = \sum_i x_i \beta_i + \varepsilon$ as $\text{Var}(y) = \sum_i \beta_i \cdot \text{Cov}(y, x_i) + \text{Cov}(y, \varepsilon)$ and compute the share of the variance in y explained by x_i as $\beta_i \cdot \frac{\text{Cov}(y,x_i)}{\text{Var}(y)}$. These shares add up to the R^2 of the regression, but could be negative and, as a result, some could exceed 100%.

[22] In Appendix Table A4, we show that task displacement also explains over 50% of wage declines. Thus it is not only that task displacement predicts relative wage changes, but it also predicts which groups experience wage declines—a topic to which we return in Section 5.

The rest of the table documents that this bivariate relationship is robust. Column 2 controls for industry shifters, which absorb labor demand changes coming from the expansion of industries in which a demographic group specializes. The coefficient estimate for task displacement is similar to the one in column 1, -1.32 (s.e. =0.16). Column 3, which we take as our baseline specification for the rest of the paper, controls for gender and education dummies and a group's exposure to manufacturing, thus accounting for other demand factors favoring highly-educated workers and for the secular decline of manufacturing. The coefficient estimate remains very similar to column 2, -1.31 (s.e. = 0.19). Even after the inclusion of these controls, task displacement still explains 55% of the variation in wage changes during this period.

Our task displacement measure combines industry-level changes in labor shares with the distribution of employment of workers across industries and occupations (where occupations are classified into routine and non-routine). Column 4 includes two more variables, corresponding to the constituent parts making up our task displacement measure. The first is the same variable as the one we considered in the left panel of Figure 2 in the Introduction: the exposure of a demographic group to industry-level declines in the labor share, but without focusing on whether employment is in routine or non-routine tasks in that industry. The second is a group's relative specialization in routine jobs, but this time without exploiting industry-level changes in task displacement.[23] Column 4 shows that these two variables themselves do not explain real wage changes (conditional on task displacement and covariates), while our measure of task displacement remains negatively associated with wage changes. This result confirms that our measure of task displacement is not confounded by other industry-level changes potentially impacting labor shares and wages or by other trends affecting workers specializing in routine tasks. Rather, it is demographic groups specializing in routine tasks in industries undergoing sizable labor share declines that suffer (relative) wage declines.

4.2 Baseline IV results

We now exploit information on measures of automation and offshoring to instrument for task displacement (constructed from industry labor share declines). This strategy thus focuses on the component of task displacement driven by automation technologies. Table 2 presents our findings. Panel A shows the reduced-form relationship between real wage changes and the automation measure in equation (13), focusing on our baseline specification from column 3 in Table 1.

Column 1 uses the adjusted penetration of robots from Acemoglu and Restrepo (2020). Industrial robotics is an archetypal example of automation technology, but is relevant mostly in the

[23]Formally, these controls are defined as

$$\text{exposure to industry labor share declines} = \sum_{i \in \mathcal{I}} \omega_g^i \cdot (-d \ln s_i^L)$$

$$\text{relative specialization in routine jobs} = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R}.$$

good-producing sectors, thus leaving out non-robotics, software-based automation taking place in other sectors. Columns 2 and 3 focus on, respectively, specialized machinery and software as proxies for automation. Columns 4 and 5 include the software measure together with the other two measures, while column 6 uses the index of automation constructed from all three variables. In all six specifications, we see a sizable effect of these variables on real wages. For example, the share of the variation in wage changes explained by our automation index in column 6 is of 52% (as compared to 55% for our task displacement measure in column3 of Table 1).

In column 7, we turn to offshoring, measured as the share of imported intermediates in an industry. As expected, offshoring also contributes to task displacement and depresses real wages of exposed groups, but it only explains 9% of the variation in wage changes. The results in columns 6 and 7 form the basis for our claim that the bulk of the variation in task displacement is driven by automation technologies, with a smaller contribution from offshoring.

Panel B presents our IV estimates, again focusing on the specification from column 3 of Table 1. In each column, the variables indicated at the heading are used as instrument for the measure of task displacement from equation (12). Across columns 1-6, the first-stage F-statistic is quite high, ranging from 44 to 2,357, indicating that cross-industry differences in automation provide a powerful source of variation in task displacement. The IV estimates are broadly similar to the OLS in Table 1. For example, in column 6, where we use the automation index, task displacement has a coefficient of -1.28 with a standard error of 0.19. The models in columns 4 and 5, where we have multiple instruments, pass the Hansen over-identification test, which bolsters our presumption that these measures are impacting wages via the same economic channel—the effects of automation technologies working through task displacement.

Finally, Panel C probes the robustness of our IV estimates by focusing on the specification from column 4 of Table 1, where we also control for exposure to industry labor share declines (also instrumented using our measures of automation) and relative specialization in routine jobs, which is treated as exogenous. The results are similar to those in Panel B, even if somewhat less precise. In column 6, for example, the IV estimate is -1.68 (s.e. = 0.47).

4.3 Task Displacement versus SBTC

How important is task displacement relative to other forms of SBTC? Table 3 explores this question by considering different specifications of SBTC. The first column of this table regresses wage changes on a full set of dummies for gender and education levels, but excludes our task displacement measure. As explained in Section 2.3, these controls absorb any factor-augmenting productivity trends common to all workers with the same education level or gender.[24] Column 1 shows that without controlling for task displacement, these SBTC variables are significant and have the expected signs. For example, the relative wage of workers with a college (but no

[24] This allows for a slightly more general formulation of SBTC than the one used in Katz and Murphy (1992) and Autor, Katz and Krueger (1998), who parameterize SBTC as separate productivity trends for college and non-college workers.

postgraduate) degree increased by 24.5% relative to those with high school, and the relative wage of workers with a postgraduate degree increased by 42% relative to those with high school. In this model, education dummies explain 55% of the variation in wage changes during this period.

However, most of these differences between workers with different education levels disappear once our task displacement measure is included in column 2 (which is identical to column 3 of Table 1) or when it is instrumented with our index of automation in column 3. In particular, there is no longer any differential wage growth for workers with a college degree relative to those with a high school degree. Likewise, task displacement explains 75% of the rise in the post-college premium, which goes down from 41.6% to 8.3%. In line with these findings, task displacement explains 55% of the changes in the wage structure, while the education dummies explain 8%. Task displacement also explains about 7% (out of 17%) of the change in real wages for women relative to men during this period. These results are the basis of our claim that much of the changes in wage structure in the US between 1980 and 2016 are related to task displacement, with a minor role for residual and standard forms of factor-augmenting SBTC.

The next three columns go one step further and control for other types of factor-augmenting technologies by allowing for differential trends by the baseline real wage level of the demographic group. The results are broadly similar to those in the first three columns, and our task displacement measure explains 43% of the observed wage changes while education dummies and baseline wages jointly explain 16% of the variation.

In Table A5 in the Appendix, we also control for the differential evolution of the supply (population size) of different demographic groups, which is the equivalent of the relative supply controls in Katz and Murphy (1992) and Card and Lemieux (2001). The inclusion of these controls further raises the explanatory power of our task displacement measure (because demographic shifts have gone in favor of groups experiencing task displacement). Now, task displacement explains 72% of the changes in wage structure, while the education dummies continue to explain a small portion (4%) of the variation.

In summary, these results suggest that task displacement has been at the root of the changes in the wage structure from 1980 to today, while other forms of SBTC have limited explanatory power.

4.4 Employment Outcomes

If task displacement leads to lower labor demand for a demographic group, we could see an impact not just on its wage but on its employment as well.[25] Table 4 provides results for the 1980–2016 period, focusing on the employment to population ratios in the top panel and non-participation rate in the bottom panel.

We find that task displacement is associated with lower employment to population ratios, both

[25] Appendix B provides an extension of our model that allows for endogenous supply responses and shows that task displacement will lead to a relative decline in hours worked. This decline could be involuntary if the labor market is not competitive (see, for example, Kim and Vogel, 2021).

in OLS (columns 1–3) and IV specifications using our index of automation as instrument (columns 4–6). Panel B reveals that most of the adjustment takes place via an increase in non-participation. For example, using the estimates from column 2, we see that a 10 percentage point higher task displacement is associated with a 4.6 percentage point decline in employment (s.e.=1.4) and a similar 3.7 percentage point increase in non-participation (s.e.=1.4). Additionally, columns 3 and 6 in both panels confirm that the employment effects do not reflect adverse trends against all workers specialized in routine jobs or those employed in industries with declining labor shares, but are instead driven by task displacement. Overall, our task displacement measure explains between 15% and 36% of the variation in employment and participation changes over this time period.[26]

4.5 Confounding Trends: Imports, Deunionization and Other Capital

In this and the next subsection, we control for other changes affecting the US labor market and contrast their effects with those of task displacement.

Column 1 in Panel A of Table 5 includes the exposure of different demographic groups to industries experiencing greater Chinese import competition as an explanatory variable. Although industry shifters already account for the effects of trade in final goods, this control allows for other direct effects of trade with China on the wage structure. Column 2 controls for workers' exposure to industries with declining unionization rates, which may have reduced their rents, thus contributing both to labor share declines and changes in the wage structure. In both specifications, task displacement has a very similar coefficient both in OLS and IV and continues to explain a large fraction of changes in the US wage structure. Moreover, we find no evidence that Chinese import competition or declining unionization rates have a direct effect on the wage structure.[27]

Columns 3 and 4 contrast the effects of task displacement with those of other forms of investment and technological progress. Column 3 controls for overall changes in the capital-labor ratio of industries, which will affect labor shares away from the $\lambda = 1$ benchmark. Although the CES task displacement measures we consider in the Appendix and described in footnote 15 correct for this type of capital deepening parametrically, the specifications presented here allow us to contrast the effects of task displacement to those of investments in other types of capital goods that do not involve automation. Consistent with our emphasis on the distinct effects of automation on the wage structure, we find that, conditional on task displacement, higher capital-labor ratios have no impact on wages. Finally, column 4 controls for differential wage trends for workers in industries experiencing TFP increases. Conditional on task displacement and industry shifters, we find that other technologies increasing TFP at the industry level do not affect wage inequality.

[26] Table A6 in the Appendix shows similar results for hours per worker and the unemployment rate, though the responses of these margins are somewhat less robust than for employment to population ratio and non-participation.

[27] Both variables have a small effect working through industry shifts, but no additional effect via task displacement. Note, in particular, that as Figure A5 documents, conditional on our index of automation, trade and declining unionization do not appear to be correlated with task displacement.

This reaffirms that the effects of non-automation technologies that raise TFP are very different from the task-displacing effects of automation.[28]

Columns 5–8 provide analogous IV estimates using our index of automation to instrument for task displacement, and in Panel B we go one step further and allow these shocks to have a *differential* effect on routine jobs in exposed industries. In all of these specifications, there is no evidence of a sizable role for these other forces, and task displacement's effects continue to be precisely-estimated and similar to our baseline results.[29]

4.6 Confounding Trends: Concentration and Markups

We next explore the role of rising sales concentration and markups, which impact industry labor shares and might directly affect the wage structure.[30] Table 6 provides our findings. Column 1 in Panel A controls for workers' exposure to industries with rising sales concentration, and the next three columns include their exposure to markup changes across industries using three alternative estimates of markups at the industry level. These are: markups computed from accounting data; markups estimated using the (inverse of the) material share and markup estimates following the approach in De Loecker, Eeckhout and Unger (2020) (see Appendix F for details). These specifications thus capture the possibility that workers in industries experiencing an increase in markups or concentration might suffer lower wages. Columns 5–8 provide IV estimates where we instrument task displacement using the index of automation.

In all specifications, we see that the OLS and IV estimates of the effects of our task displacement variable are very similar to before—ranging between -1.25 and -1.31—while exposure to rising concentration or markups have little explanatory power for wages.

Panel B goes one step further and uses a measure of task displacement that partials out the component of the labor share decline in an industry driven by markups (as explained in footnote 15). This correction does not affect our conclusions, and our point estimates for the effects of task displacement remain sizable and precisely estimated. Even with this correction, markup changes do not have a robust effect and explain no more than 3% of the variation in wage changes.

The findings in this table suggest that our task displacement variable is not picking up confounding effects of rising markups or concentration. Overall, it appears that it is task displacement

[28]The findings in columns 3–4 are in line with our model. For example, under Assumption 1, increases in capital productivity in tasks it is already performing will lead to greater capital utilization but will not cause any task displacement, and as such will not negatively impact workers specializing in routine tasks in these industries. Likewise, industry TFP growth should only affect labor demand through the industry shifters, which are already being controlled for in these regressions.

[29]Table A7 shows that these results are very similar when we control for exposure to labor share declines and relative specialization in routine occupations as in column 4 of Table 1.

[30]Appendix B provides an extension of our model to an economy with markups at the industry level. We explain how changes in markups can directly impact the wages of workers that specialize in sectors with rising markups and how to correct for these effects as we do in Panel B of Table 6 (see also footnote 15). Table A8 provides additional specifications that allow markups to have a differential effect on workers in routine jobs. Finally, Table A9 shows the robustness of the patterns reported here to controlling for exposure to industry labor share declines and relative specialization in routine occupations.

rather than rising market power that has played a defining role in the surge in US wage inequality over the last four decades.

4.7 Regional Variation

Task and industry composition vary greatly across regions and commuting zones in the US. To further test the association between task displacement and wages, we now investigate whether regional variation in task displacement also predicts changes in sub-national wage structures.

Table 7 provides estimates that exploit regional differences in specialization patterns. The main difference is that now the unit of observation is given by group-region cells, and we exploit differences in specialization across these cells to construct our task displacement measures. In Panel A we look at 300 demographic groups defined by gender, education, age, and race across nine US regions (giving us a total of 2,633 observations excluding empty cells). The OLS estimates in columns 1-3 and the IV estimates in columns 4–6 are very similar to those in Tables 1 and 2.

In Panel B we attempt to separate regional and national changes by including a full set of demographic group fixed effects, which absorb all national trends affecting a demographic group. We find negative and significant but smaller effects of task displacement (especially in columns 2–3 and 5–6). These estimates imply that task displacement at the regional level matters and has a precisely-estimated negative impact on wages, which is in line with our theory. Nevertheless, these results also indicate that local differences in task displacement are not as important as national changes for understanding the evolution of the wage structure.[31]

Panels C and D repeat this exercise for 54 demographic groups defined by a coarser grouping of gender, education, age, and race, but now across 722 US commuting zones (for a total of 20,768 observations). The results are very similar to those in Panels A and B.

4.8 Further Robustness Checks

The Appendix provides a number of additional checks, all of which support our main conclusions:

First, in Table A10, we provide estimates of the effects of task displacement excluding immigrants, as well as separate estimates for men and women. Second, in Table A11, we checked our results for 1980–2007, thus avoiding any persistent effects of the Great Recession, with similar results.

Third, in Table A12 we present stacked-differences models with two periods, 1980–2000 and 2000–2016, which explore the differential patterns of task displacement between these sub-periods. Panel A estimates the same specifications as in Table 1, but now using stacked differences, while Panel B allows covariates to have different coefficients in the two subperiods. The results in both

[31] In the presence of migration and trade across regions (especially relevant for manufacturing industries), regional task displacement should have a smaller impact than national trends, because the latter can cause strong ripple effects for workers in the same demographic group across different regions. For example, in the limit case where tasks can be traded across regions with no transaction or transport costs (or labor is perfectly mobile), one would expect task displacement to reduce the wages of all workers in a given group by the same amount across all regions. In Panel B, the national effect is absorbed by the group fixed effects.

panels are similar to, but smaller in some specifications than, those in Table 1. In Panel C, we report period-by-period estimates of the effects of task displacement on wage changes, and confirm that our estimates are comparable across the 1980–2000 and 2000–2016 periods.

Fourth, Table A13 verifies that our results are similar when we compute the task displacement measure using different values of the elasticity of substitution to account for changes in factor prices using the formulas in footnote 15. Table A14 confirms that the results are robust to using labor share data from the BLS, excluding extractive industries, winsorizing the labor share changes, or focusing only on industries with a declining labor share to construct our measure of task displacement (rather than our baseline measure which exploited both declines and increases in industry labor shares). Table A15 reports similar results when we utilize several alternative measures of which jobs can be automated. Most importantly, the results are similar when we rely on the measure of automatable jobs from Webb (2020).

5 General Equilibrium Effects and Quantitative Analysis

Our reduced-form evidence documented a strong negative relationship between task displacement and relative wage changes. This evidence misses three general equilibrium effects, however. First, in our regressions the common effect of productivity on real wages is included in the intercept, making our estimates uninformative about wage *level* changes. Second, our regression estimates focus on the direct effects of task displacement and do not account for the resulting ripple effects, which also impact the wage structure. Third, although our regressions control for *observed* industry changes, they do not separate out industry shifts *induced* by task displacement, thus missing one component of the total effect of automation and offshoring. In this section, we develop our full general equilibrium model, which enables us to quantify these mechanisms.

5.1 General Equilibrium Effects and the Propagation Matrix

We first generalize Proposition 2 to the case in which Assumption 1 is relaxed and there are ripple effects. For this purpose, let us define *aggregate task shares* as

$$\Gamma_g(\boldsymbol{w}, \boldsymbol{\zeta}, \Psi) = \sum_{i \in \mathcal{I}} \underbrace{s_i^Y(\boldsymbol{p}, c) \cdot (A_i \cdot p_i)^{\lambda - 1}}_{= \zeta_i} \cdot \underbrace{\frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda - 1} \cdot dx}_{= \Gamma_{gi}},$$

$$\Gamma_k(\boldsymbol{w}, \boldsymbol{\zeta}, \Psi) = \sum_{i \in \mathcal{I}} \underbrace{s_i^Y(\boldsymbol{p}, c) \cdot (A_i \cdot p_i)^{\lambda - 1}}_{= \zeta_i} \cdot \underbrace{\frac{1}{M_i} \int_{\mathcal{T}_{ki}} \psi_k(x)^{\lambda - 1} \cdot dx}_{= \Gamma_{ki}},$$

which are given by a weighted sum of industry-specific task shares, Γ_{gi} (or Γ_{ki}), and also depend on industry shifters, $\boldsymbol{\zeta} = (\zeta_1, \ldots, \zeta_I)$. Because worker groups now compete for tasks, task shares in each industry are a function of both wages and technology.

To characterize ripple effects, consider any technological change with a direct effect of z_g on the real wage of group g, and denote by $\boldsymbol{z}$ the column vector of z_g's. Differentiating (2), we obtain:

$$d\ln \boldsymbol{w} = \boldsymbol{z} + \frac{1}{\lambda}\frac{\partial \ln \Gamma(\boldsymbol{w},\boldsymbol{\zeta},\Psi)}{\partial \ln \boldsymbol{w}} \cdot d\ln \boldsymbol{w} \Rightarrow d\ln \boldsymbol{w} = \underbrace{\left(\mathbb{1} - \frac{1}{\lambda}\frac{\partial \ln \Gamma(\boldsymbol{w},\boldsymbol{\zeta},\Psi)}{\partial \ln \boldsymbol{w}}\right)^{-1}}_{\Theta} \cdot \boldsymbol{z},$$

where $\partial \ln \Gamma(\boldsymbol{w},\boldsymbol{\zeta},\Psi)/\partial \ln \boldsymbol{w}$ is the $G \times G$ Jacobian of the function $\ln \Gamma(\boldsymbol{w},\boldsymbol{\zeta},\Psi) = (\ln \Gamma_1(\boldsymbol{w},\boldsymbol{\zeta},\Psi),$ $\ln \Gamma_2(\boldsymbol{w},\boldsymbol{\zeta},\Psi), \ldots, \ln \Gamma_G(\boldsymbol{w},\boldsymbol{\zeta},\Psi))$ with respect to the vector of wages $\boldsymbol{w}$. This Jacobian summarizes the effect of a change in wages on the task allocation. We refer to the $G \times G$ matrix Θ as the *propagation matrix* . The propagation matrix summarizes the general equilibrium effects of a vector of shocks $\boldsymbol{z}$ once we account for ripple effects.

In the Appendix, we prove that Θ is well defined and has positive entries. In particular $\theta_{gg'} \geq 0$ captures the extent to which workers of type g' compete for marginal tasks against workers of type g. Second, we show that the row sum of Θ, which we label by ε_g, is always between 0 and 1. Third, the propagation matrix satisfies the following symmetry property: $\varepsilon_g - \theta_{gg'}/s^L_{g'} = \varepsilon_{g'} - \theta_{g'g}/s^L_g$ for any two groups g and g' (where s^L_g is the labor share of group g in output). Finally, the propagation matrix tells us whether different workers are q–complements or q–substitutes: an increase in the supply of workers of type g' reduces the real wage of type g if and only if $\theta_{gg'} > s^L_{g'} \cdot \varepsilon_g$ (see Appendix C for additional properties of the propagation matrix). In what follows, we denote the row g of the propagation matrix by $\Theta_g = (\theta_{g1}, \ldots, \theta_{gG})$.

The next proposition characterizes the general equilibrium effects of task displacement on wages, industry prices, TFP, and output. We use $d\ln \boldsymbol{x}$ to designate the column vector of $(d\ln x_1, \ldots, d\ln x_G)$ across groups of workers, and with some abuse of notation, we denote the vector of industry prices by $d\ln\ \boldsymbol{p} = (d\ln p_1, d\ln p_2, \ldots, d\ln p_I)$.

Proposition 4 (Counterfactuals) *The effect of task displacement on wages, industry prices, and aggregates is given by the solution to the system of equations:*

$$\begin{aligned}
d\ln w_g =& \Theta_g \cdot \left(\frac{1}{\lambda} \cdot d\ln y + \frac{1}{\lambda} d\ln \boldsymbol{\zeta} - \frac{1}{\lambda} d\ln \boldsymbol{\Gamma}^{disp}\right) \text{ for all } g \in \mathcal{G},\\
d\ln \zeta_g =& \sum_{i\in\mathcal{I}} \omega_{gi} \cdot \left(\frac{\partial \ln s^Y_i(\boldsymbol{p})}{\partial \ln \boldsymbol{p}} \cdot d\ln \boldsymbol{p} + (\lambda - 1) \cdot d\ln p_i\right) \text{ for all } g \in \mathcal{G},\\
d\ln p_i =& \sum_{g\in\mathcal{G}} s^L_{gi} \cdot \left(d\ln w_g - d\ln \Gamma^{disp}_{gi} \cdot \pi_{gi}\right) \text{ for all } i \in \mathcal{I},\\
d\ln TFP =& \sum_{i\in\mathcal{I}} s^Y_i(\boldsymbol{p}) \sum_{g\in\mathcal{G}} s^L_{gi} \cdot d\ln \Gamma^{disp}_{gi} \cdot \pi_{gi},\\
d\ln y =& \frac{1}{1 - s^K} \cdot \left(d\ln TFP + s^K \cdot d\ln s^K\right),\\
d\ln s^K =& -\frac{1}{s^K} \sum_{g\in\mathcal{G}} s^L_g \cdot (d\ln w_g - d\ln y).
\end{aligned}$$

This proposition generalizes Proposition 2 to an economy with multiple sectors and ripple effects, but for notational simplicity, focuses on task-displacing technologies.[32] The expression for wages transparently illustrates the general equilibrium forces described above: real wage changes depend on the expansion of output, induced shifts in sectoral composition, and the ripple effects summarized by the propagation matrix. It is because of ripple effects that a demographic group's real wage now depends on the task displacement experienced by other groups.

The formulas in this proposition provide the basis for our quantitative exercise. In particular, the proposition shows that one can use our measures of task displacement across groups and industries, together with a demand system for industries, estimates of the propagation matrix, and estimates of the cost savings from automation, to compute the full general equilibrium effects of these technologies.

5.2 Parametrization, Calibration, and Estimation

This subsection describes our measurement of task displacement in the presence of ripple effects. It also explains how we parametrize the model and estimate the propagation matrix.

Measuring task displacement and the cost savings from automation: Recall that λ is the elasticity of substitution between capital and labor in an industry holding the task allocation constant, while the elasticity of substitution incorporating task reallocation, σ_i, exceeds λ. As a result, when we incorporate ripple effects and task reallocation, the task displacement experienced by group g in industry i can be expressed as

$$d\ln\Gamma_{gi}^{\text{disp}} = \left(\omega_{gi}^R/\omega_i^R\right)\cdot\frac{-d\ln s_i^L - s_i^K\cdot(1-\sigma_i)\cdot(d\ln w_i - d\ln R_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}, \tag{15}$$

and the task displacement measure in equation (12) becomes

$$\text{Task displacement}_g = \sum_{g\in\mathcal{G}}\omega_g^i\cdot\left(\omega_{gi}^R/\omega_i^R\right)\cdot\frac{-d\ln s_i^L - s_i^K\cdot(1-\sigma_i)\cdot(d\ln w_i - d\ln R_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}. \tag{16}$$

To compute these measures, we set $\sigma_i = 1$, which is in the spirit of our baseline assumption in Section 2.3. We explore the robustness of our results to $\sigma_i = 0.8$ and $\sigma_i = 1.2$ in the Appendix. This range for the elasticity of substitution between capital and labor aligns with the available empirical estimates (see Oberfield and Raval, 2020; Karabarbounis and Neiman, 2013). For the elasticity of substitution between tasks, which should be lower than σ_i, we choose $\lambda = 0.5$, which is in line with the estimates in Humlum (2020).[33]

[32] The proposition also shows that ripple effects do not affect our expressions for TFP, output, or sectoral prices. This is thanks to the envelope theorem: in an efficient economy, induced worker reallocation has only second-order effects on TFP and industry prices, even though it has a first-order impact on labor demand and wages.

[33] The reason why we choose a different value of λ here than in the reduced-form analysis is that, in the absence of ripple effects, the task allocation of factors is constant and λ gives the elasticity of substitution between factors. In contrast, in the presence of ripple effects, the relevant elasticity is σ_i, which is greater than λ. For σ_i we use the same range of values explored in the reduced-form analysis—from 0.8 to 1.2. The Appendix also provides results for $\lambda = 0.625$, which is the value implied by our reduced-form regression evidence, where the coefficient estimate for

Finally, we set the cost savings from automation to $\pi_i = 30\%$ for all industries, which is in line with estimates for industrial robots surveyed in Acemoglu and Restrepo (2020).[34]

Industry demand: We use a simple CES demand system across industries as in footnote 12: $s_i^Y(\boldsymbol{p}) = \alpha_i \cdot p_i^{1-\eta}$. Following Buera, Kaboski and Rogerson (2015), we set the elasticity of substitution between industries to $\eta = 0.2$.

Propagation matrix: Motivated by the symmetry property of the propagation matrix described above, we parameterize the extent of competition for tasks between two demographic groups g and g' as a function of their distance (dissimilarity) across $n \in \mathcal{N}$ dimensions. In particular, we assume that

$$\theta_{gg'} = \frac{1}{2}(\varepsilon_g - \varepsilon_{g'}) \cdot s_{g'}^L + \sum_{n \in \mathcal{N}} \beta_n \cdot f(d_{gg'}^n) \cdot s_{g'}^L \text{ for all } g' \neq g \text{ and } \theta_{gg} = \theta \text{ for all } g,$$

where f is a decreasing function of the distance along a given dimension n between groups g' and g, denoted here by $d_{gg'}^n$. The assumption of common diagonal term is consistent with our reduced-form evidence, which did not find major heterogeneities across groups.[35] The parameter $\beta_n \geq 0$ gives the importance of dimension n in mediating ripple effects. We choose the following dimensions along which we measure distance between groups: occupational and industry employment shares (which account for similarity in the types of tasks performed), and education by age (which allows for the possibility that, among workers with or without college, workers of similar ages might be more substitutable than those of different ages; see Card and Lemieux (2001)).

Using this parameterization, the wage effects from Proposition 4 can be written as:

$$\begin{aligned} d\ln w_g = & \frac{\varepsilon_g}{\lambda} \cdot d\ln y - \frac{\theta}{\lambda} \cdot \text{Task displacement}_g \\ & - \sum_{g' \neq g} \left(\frac{1}{2}\left(\frac{\varepsilon_g}{\lambda} - \frac{\varepsilon_{g'}}{\lambda} \right) + \sum_{n \in \mathcal{N}} \frac{\beta_n}{\lambda} \cdot f(d_{g,g'}^n) \right) \cdot s_{g'}^L \cdot \text{Task displacement}_{g'} + \upsilon_g, \\ \text{subject to: } \varepsilon_g = & \theta + \sum_{g' \neq g} \left(\frac{1}{2}(\varepsilon_g - \varepsilon_{g'}) + \sum_x \beta_n \cdot f(d_{g,g'}^n) \right) \cdot s_{g'}^L, \text{ and } \beta_n \geq 0, \end{aligned} \tag{17}$$

where f is chosen as an inverted sigmoid function of the distance between two groups.[36] The

task displacement, -1.6, corresponds to $-1/\lambda$ in the absence of ripple effects.

[34] In practice, cost savings might be different across industries, but we do not have separate estimates.

[35] Appendix D provides an alternative parametrization that assumes a common row sum $\varepsilon_g = \varepsilon$, with similar results.

[36] We compute distances using the dissimilarity measures $d_{g,g'}^{\text{occupations}} = \frac{1}{2}\sum_o |\omega_g^o - \omega_{g'}^o|$ and $d_{g,g'}^{\text{industries}} = \frac{1}{2}\sum_{i \in \mathcal{I}} |\omega_g^i - \omega_{g'}^i|$, where the sum runs over 330 occupations and 192 industries in the US Census, respectively. In addition, the sigmoid function takes the form

$$f(d_{g,g'}^n) = \frac{1}{1 + \left(1/d_{g,g'}^n - 1\right)^{-\kappa}},$$

where $\kappa \geq 1$ is a tuning parameter governing the decay of the function. For $\kappa = 1$ we get $f(d) = 1 - d$. More generally, the sigmoid function has a maximum of 1 when there is no dissimilarity between two groups. In our parameters of this system can be estimated by GMM exploiting the moment conditions

$$\mathbb{E}\left[\upsilon_g \cdot \left(1, z_g, \sum_{g' \neq g} f(d^1_{g,g'}) \cdot s^L_{g'} \cdot z_{g'}, \ldots, \sum_{g' \neq g} f(d^N_{g,g'}) \cdot s^L_{g'} \cdot z_{g'}\right)\right] = 0,$$

where z_g is either our measure of task displacement, or alternatively, our index of automation (so that we only exploit automation-induced changes in demand).

Table 8 provides our estimates for θ/λ and β_n/λ in equation (17). Columns 1–3 use our task displacement measure in equation (16) to form moment conditions, while columns 4–6 use the index of automation. The estimates in Panel A of Table 8 provide evidence of significant ripple effects by occupation, industry, and within age×education cells, and suggest that these are all of comparable importance.[37] These estimates also imply that demographic groups suffering displacement will compete for tasks performed by other groups that have similar age and education and specialize in similar occupations and industries.

5.3 Quantitative Results

This subsection presents our quantitative results using the estimates of the propagation matrix from column 1 of Table 8. We use Proposition 4 to compute the effects of task displacement across workers and industries. We treat task displacement, as measured in equations (15) and (16), as the driving force affecting the wage structure. Thus, this exercise leaves out other forms of technological progress (including factor-augmenting technologies, productivity deepening, new tasks, and sectoral TFPs) and changes in factor supplies driven by education and demographics.

Table 9 summarizes our findings. The first column depicts the data, while the second column presents the model-implied numbers when we feed in industry-level labor share changes as the driving force. Finally, the third column, instead, feeds in the component of industry labor share changes driven by our index of automation (with very similar results to those in column 2). The first panel of the table presents the effects on wage inequality. This information is also displayed in Figure 10, which decomposes the effects of the various mechanisms via which task displacement affects the wage structure.

Panel A of the figure plots the productivity effect $(1/\lambda) \cdot d\ln y$, which raises the wages for all demographic groups by close to 45%. Panel B adds the implications of industry shifts caused by task displacement, $(1/\lambda) \cdot d\ln \boldsymbol{\zeta}$. Because task displacement concentrates and reduces costs in manufacturing, mining, and retail, it induces an expansion of the service sector (similar to a

baseline estimates in Table 8, we use a quadratic tuning parameter, $\kappa = 2$. In the Appendix, we provide very similar estimates for different values of the tuning parameter; see Appendix D.

[37] The table reports the average contribution of ripple effects along dimension $n \in \mathcal{N}$ to the off-diagonal terms of the propagation matrix, which is computed as

$$\text{Contribution of ripple effects}_n = \frac{\beta_n}{\lambda} \cdot \left(\frac{1}{s^L} \sum_g \sum_{g' \neq g} f(d^n_{gg'}) \cdot s^L_g \cdot s^L_{g'}\right).$$

Baumol effect), boosting the demand for workers specializing in services. Quantitatively, however, this effect is small, accounting for less than 7% of the observed changes in the US wage structure.[38]

Panel C adds the direct effects of task displacement, $-(1/\lambda)\cdot d\ln\mathbf{\Gamma}^{\text{disp}}$ and confirms the pattern documented in our reduced-form analysis: direct task displacement plays a dominant role in changes in the US wage structure between 1980 and 2016. We also see in this panel that the direct impact of task displacement causes as much as a 25% decline in the real wages of some groups. There are, nonetheless, some notable differences from the reduced-form evidence. While in the reduced-form regressions, task displacement accounted for 50%-70% of the changes in the US wage structure, the second row of Table 9 shows that it accounts for as much as 100% of the variation here. This, however, overstates the full impact of task displacement, because of the ripple effects shown in the next row of the table and in Panel D of Figure 10.

Once ripple effects are added (row 3 in Table 9), task displacement, with its full general equilibrium effects, is predicted to explain about 48% of changes in the US wage structure. The reason why this is significantly less than the direct impact of task displacement shown in row 2 is because ripple effects spread ("democratize") the negative consequences of displacement across demographic groups and also reduce the burden on directly-affected groups. For example, the impact on high school-graduate white men aged 26-35 in Panel C of Figure 10 is -14%. But once we allow for the ripple effects—which incorporate the fact that they now compete for non-automated tasks performed by other demographic groups—we find the total effect on this group in Panel D of Figure 10 to be -5.3%. In contrast, without the ripple effects, white high school-dropout women aged 26-35 are predicted to experience a 4% real wage increase, but incorporating the ripple effects, they suffer a 1% decline in their real wage.

The consequences of ripple effects are further illustrated in Figure 11. The figure plots the direct effects of task displacement against the baseline wage of demographic groups (marker sizes are proportional to hours worked by each group). For each group, we also include an arrow indicating the direction of change due to ripple effects: the red markers designate groups that benefit from ripple effects, while blue markers highlight those losing out from ripple effects. Two features standout from this figure. First, 153 directly affected groups (accounting for 34% of hours worked) that would have suffered larger wage losses due to task displacement are helped by ripple effects, while 347 groups that are, on the whole, less impacted by direct task displacement themselves share in the relative wage declines because of the ripple effects. Second, while the directly-affected groups are typically among those that already had lower wages in 1980, the

[38] This finding reiterates that most of the effects of task displacement are "within-industry": they are caused by reduced demand for affected demographic groups depressing their wages and thus their earnings in all of the industries in which they are employed, even though this reduced labor demand originates in the subset of industries undergoing rapid automation.

The fact that ("between") industry shifts induced by task displacement are playing a minor role in our context does not rule out the possibility that industry shifts generated by secular structural transformation and trade could have bigger effects on the wage structure. See, for example, Buera, Kaboski and Rogerson (2015) and Galle, Rodríguez-Clare and Yi (2017) for recent contributions quantifying the distributional effects of structural transformation and trade.

indirectly-affected groups are more evenly spread in terms of their 1980 wage distribution.

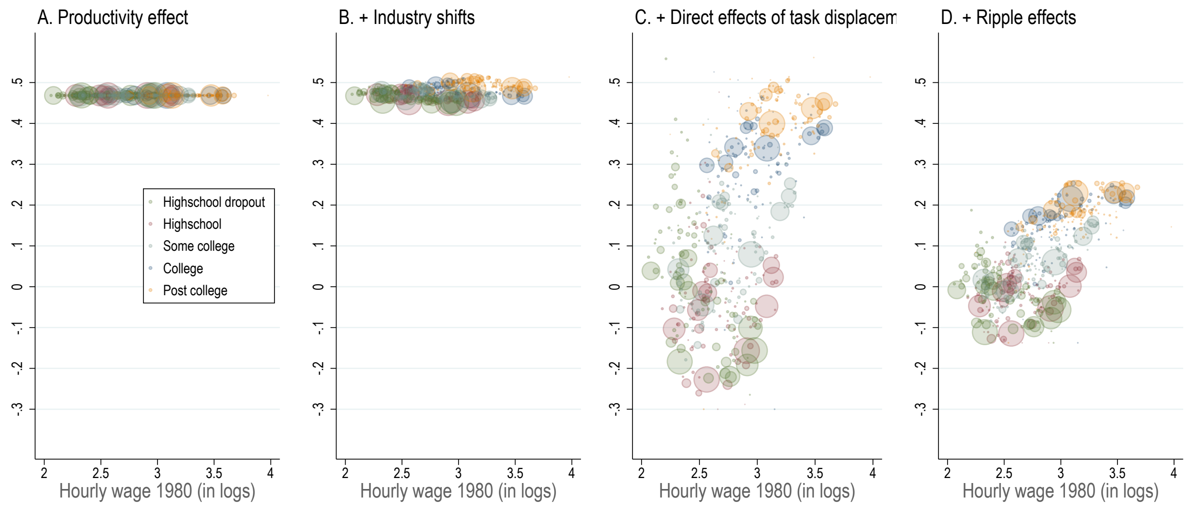

FIGURE 10: Contribution of productivity effects, industry shifts, direct displacement effects, and ripple effects to the predicted change in wages for 1980–2016. Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. See text for variable definitions.

A final feature of the predicted wage changes in Panel D of Figure 10 is worth noting: even though there is a large (close to 45%) productivity effect, the real wage level of 131 demographic groups (making up 42% of the 1980 population) *declines* because of task displacement (in the data, 121 groups, making up 53% of the 1980 population, experienced real wage declines). This result highlights how task displacement can generate meaningful real wage declines. In contrast, the canonical SBTC model cannot explain real wage declines.

As a summary, Figure 12 plots the predicted wage changes in the model and the observed real wage changes between 1980 and 2016. In addition to accounting for a large fraction of the variation in US wage structure, task displacement can explain several other salient aspects of the labor market this period. First, our quantitative results imply a 6.7% decline in the real wage of low-education men compared to a 8.2% decline in the data. Second, in general equilibrium, task displacement generates a 21% increase in the college premium and a 23% increase in the post-college premium (over high school graduates)—accounting for 80% and 55% of the observed increases, respectively. Finally, task displacement alone closes the gender gap by about 2%. Interestingly, in all these cases, the direct effects of task displacement are dampened once we account for ripple effects. It is also worth noting, however, that our model misses a significant portion of wage growth coming from highly-educated workers at the top of the wage distribution. This may reflect the complementarity between some of the new technologies and post-graduate skills or other forces, such as winner-take-all dynamics in some high-skill professions, which are both absent from our model.

The second panel of Table 9 turns to the model's implications for aggregates. Despite the large distributional effects documented above, task displacement generates only a 3.8% TFP gain

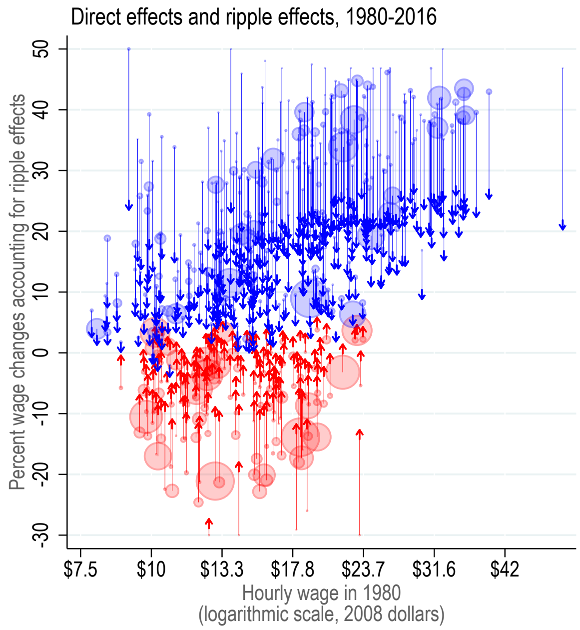

FIGURE 11: Direct effects of task displacement compared to general equilibrium effects after accounting for ripple effects. Marker sizes indicate the share of hours worked by each group. The red markers identify groups for which ripple effects dampened the effect of task displacement on their wages. The blue markers identify groups for which ripple effects reduced their wages. See text for variable definitions.

in the aggregate, and this is the reason why average real wages are predicted to grow slowly (only by 5.7%) and many groups experience real wage declines.[39] In contrast, in the data, TFP grew by 35% during this period, and average real wages rose by 29% (though two thirds of this is due to changes in the composition of the workforce, which are not present in our model). These numbers confirm our earlier conclusion that there were other technological advances—such as productivity deepening, factor augmenting, sectoral TFP, or even new tasks—contributing to output, wage growth, and productivity between 1980 and 2016. However, the congruence between the model-implied changes in wage structure and the data suggests that these other technological changes had small effects on inequality, except possibly at the top of the wage distribution. Finally, task displacement accounts for the observed decline in the labor share (by construction) and the observed increase in the capital-output ratio over this period. This suggests that the amount of investment accompanying automation in our model is in the ballpark of the data.

The third panel of Table 9 summarizes the sectoral implications of task displacement. In line with the small TFP gains estimated above, we see that task displacement generates small changes in industry composition and accounts for only 0.4 of the 8.8 percentage point decline in the share of manufacturing in value added. The results in this panel and in Panel B of Figure 10 further reinforce the view that automation and offshoring affect the economy and inequality through very

[39]In a competitive economy with elastic supply of capital (as in our model), $d \ln \text{TFP} = \sum_g s_g^L \cdot d \ln w_g$, which shows that average wage growth equals $(1/s^L) \cdot d \ln \text{TFP} > 0$. Thus the modest wage gains are directly linked to the small TFP gains generated by automation. While the model predicts a larger increase in output per worker, this is driven not by higher TFP, but by growing investment (the rising capital-output ratio).

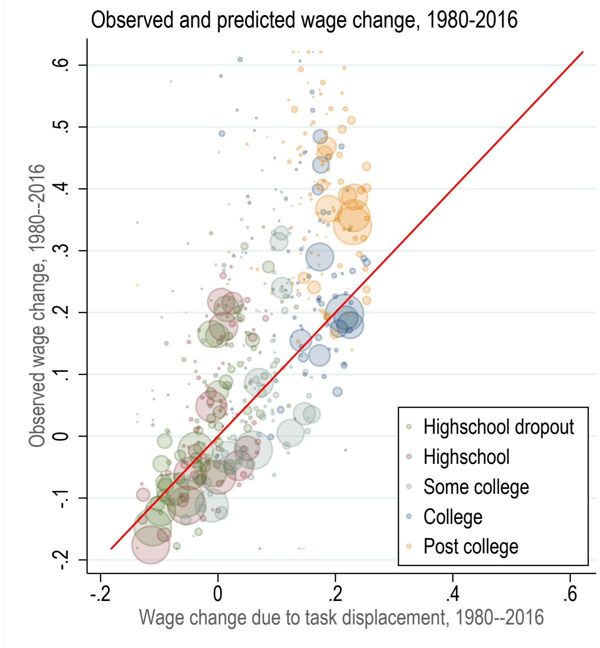

FIGURE 12: Predicted (horizontal axis) vs. observed (vertical axis) wage changes. The 45° line is shown in red. Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. See text for variable definitions.

different channels than structural transformation or trade in final goods.[40]

6 Concluding Remarks

This paper argued that a significant portion of the rise in US wage inequality over the last four decades has been driven by automation (and to a lesser extent offshoring) displacing certain work-groups from employment opportunities for which they had comparative advantage. To develop this point, we proposed a conceptual framework where tasks are allocated to different types of labor and capital, and automation technologies expand the set of tasks performed by capital and displace workers previously employed in these tasks. We derived a simple equation linking wage changes of a demographic group to the task displacement it experiences.

Our reduced-form evidence is based on estimating this equation and reveals a number of striking new facts. Most notably, we documented that between 50% and 70% of the changes in US wage structure between 1980 and 2016 are accounted for by the relative wage declines of worker groups specialized in routine tasks in industries experiencing rapid automation. In our first set of regression models, industry level task displacement is approximated by (the unexplained component of) labor share declines. We also estimate very similar results using explicit measures of industry-level automation and offshoring, confirming that our task displacement variable captures the effects of automation technologies (and to a lesser degree offshoring) rather than increasing markups,

[40] Despite its small effect on sectoral shares, task displacement taking place within manufacturing generates a large 8.2% reduction in the wage bill of that sector, which accounts for 25% of the decline in manufacturing labor demand for 1980–2016.

industry concentration, or import competition. These alternative economic trends themselves do not appear to play a major role in the evolution of the US wage structure.

Our reduced-form regressions estimate the direct effects of task displacement on relative wages, but miss important general equilibrium forces. We developed a methodology to quantify the general equilibrium effects of task displacement, which can account for the implications of automation working through productivity gains, ripple effects and changes in industry composition. Our full quantitative evaluation shows that task displacement explains close to 50% of the observed changes in US wage structure. Most notably, task displacement leads to sizable increases in wage inequality, but only small productivity gains—thus providing a possible resolution to a puzzling feature of US data.

There are several interesting areas for future research. First, our framework has been static, and thus any effects from capital accumulation, dynamic incentives for the development of new technologies and education and skill acquisition are absent. Incorporating those is an important direction for future research. Second, and relatedly, we did not attempt to model and estimate the effects of technologies introducing new labor-intensive tasks (which we argued to have been important in previous work, Acemoglu and Restrepo, 2018). This is yet another avenue for future research. Finally, our empirical work has been confined to the US and the 1980-2016 period, for which we have all the data components necessary for implementing our reduced-form and structural estimation. Expanding these data sources and the empirical exploration of the role of task displacement to earlier periods and other economies is an important direction for research that may help us understand the technological and institutional reasons why the US wage structure was quite stable for the three decades leading up to the mid-1970s.

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Table 1: Task displacement and changes in real hourly wages, 1980-2016.

	Dependent variables: Change in wages and wage declines, 1980–2016			
	(1)	(2)	(3)	(4)
Task displacement	-1.598	-1.323	-1.307	-1.659
	(0.094)	(0.158)	(0.188)	(0.444)
Industry shifters		0.210	0.310	0.347
		(0.091)	(0.120)	(0.158)
Exposure to industry labor share decline				0.178
				(0.664)
Relative specialization in routine jobs				0.072
				(0.073)
Share variance explained by task displacement	0.67	0.55	0.55	0.70
R-squared	0.67	0.70	0.84	0.84
Observations	500	500	500	500
Other covariates:				
Manufacturing share, and education and gender dummies			✓	✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. Besides the covariates reported in the table, columns 3 and 4 control for baseline wage shares in manufacturing and dummies for education (for no high school degree, some college, college degree and postgraduate degree) and gender. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table 2: IV estimates instrumenting task displacement with automation and offshoring measures.

	Dependent variable: Change in wages 1980–2016						
Instrument:	Robot APR	Specialized machinery	Software	Robot APR and software	Machinery and software	Combined measure	Offshoring
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Reduced-form estimates							
Routine at industries adopting robots	-2.014			-2.029			
	(0.451)			(0.439)			
Routine at industries adopting specialized machinery		-0.969			-1.352		
		(0.430)			(0.315)		
Routine at industries adopting software			-4.076	-4.097	-4.645		
			(0.823)	(0.880)	(0.918)		
Routine at automating industries						-1.334	
						(0.210)	
Routine at offshoring industries							-2.243
							(1.009)
Share variance explained by task displacement	0.30	0.16	0.17	0.47	0.42	0.52	0.09
R-squared	0.79	0.77	0.80	0.83	0.82	0.83	0.76
Observations	500	500	500	500	500	500	500
Panel B. IV estimates							
Task displacement	-1.216	-0.894	-1.480	-1.345	-1.216	-1.279	-0.813
	(0.246)	(0.317)	(0.357)	(0.214)	(0.184)	(0.193)	(0.299)
Share variance explained by task displacement	0.51	0.38	0.62	0.56	0.51	0.54	0.34
R-squared	0.84	0.83	0.83	0.84	0.84	0.84	0.82
First-stage F	98.00	44.98	67.40	439.92	831.72	785.80	30.62
Overid p-value				0.56	0.31		
Observations	500	500	500	500	500	500	500
Panel C. Role of industry and occupation in driving results							
Task displacement	-1.265	-0.186	-2.951	-2.075	-1.425	-1.677	-2.494
	(0.830)	(0.934)	(1.003)	(0.534)	(0.462)	(0.466)	(0.714)
Exposure to industry labor share decline	0.302	-1.656	-0.857	0.103	0.362	0.310	0.063
	(0.913)	(1.558)	(1.346)	(0.792)	(0.743)	(0.686)	(0.959)
Relative specialization in routine jobs	0.011	-0.165	0.269	0.137	0.037	0.075	0.201
	(0.143)	(0.161)	(0.147)	(0.088)	(0.080)	(0.081)	(0.110)
R-squared	0.83	0.82	0.79	0.83	0.84	0.84	0.83
First-stage F	6.32	33.72	5.46	32.80	229.90	156.33	23.71
Observations	500	500	500	500	500	500	500

Notes: This table presents reduced-form and IV estimates of the relationship between task displacement and changes in real wages for 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. Panel A provides reduced-form estimates, where the instruments are indicated at the column headers and described in detail in the text and Appendix F. Panel B provides IV estimates. Panel C provides IV estimates where we also control for relative specialization in routine jobs and exposure to industry labor share declines (this last term instrumented too using our proxies for technology and offshoring). Besides the covariates reported in the table, all specifications control for industry shifters, group's baseline wage share in manufacturing, and dummies for education (for no high school degree, some college, college degree and postgraduate degree) and gender. When using our index of automation as an instrument, we report first-stage F–statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table 3: Task displacement vs. SBTC, 1980–2016.

	Dependent variable: Change in real wages 1980–2016					
	SBTC by education level			Allowing for SBTC by wage level		
	OLS (1)	OLS (2)	IV (3)	OLS (4)	OLS (5)	IV (6)
Gender: women	0.173	0.104	0.105	0.245	0.154	0.165
	(0.019)	(0.020)	(0.020)	(0.024)	(0.026)	(0.027)
Education: no high school	0.016	0.023	0.023	0.051	0.039	0.040
	(0.024)	(0.020)	(0.019)	(0.023)	(0.018)	(0.018)
Education: some college	0.053	-0.070	-0.068	0.027	-0.057	-0.046
	(0.031)	(0.032)	(0.033)	(0.024)	(0.031)	(0.031)
Education: full college	0.245	-0.019	-0.013	0.180	0.005	0.027
	(0.039)	(0.050)	(0.052)	(0.036)	(0.049)	(0.050)
Education: more than college	0.416	0.083	0.090	0.292	0.093	0.118
	(0.046)	(0.062)	(0.064)	(0.048)	(0.061)	(0.061)
Log of hourly wage in 1980				0.235	0.115	0.130
				(0.046)	(0.043)	(0.046)
Task displacement		-1.307	-1.279		-1.028	-0.902
		(0.188)	(0.193)		(0.185)	(0.194)
Share variance explained by:						
- educational dummies	0.55	0.08	0.09	0.37	0.09	0.12
- baseline wage				0.15	0.07	0.08
- task displacement		0.55	0.54		0.43	0.38
R-squared	0.76	0.84	0.84	0.81	0.85	0.84
First-stage F			785.80			562.20
Observations	500	500	500	500	500	500
Other covariates:						
Industry shifters and manufacturing share	✓	✓	✓	✓	✓	✓

Notes: This table presents estimates of the relationship between task displacement and different proxies of skill-biased technical change and the change in real wages across 500 demographic groups. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. Columns 1–2 and 4–5 report OLS estimates. In columns 3 and 6 we report IV estimates instrumenting task displacement using our index of automation. Besides the covariates reported in the table, all specifications control for industry shifters and baseline wage shares in manufacturing. The bottom rows of the table report the share of variance explained by task displacement and the different proxies of skill biased technical change. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table 4: Task displacement and employment outcomes, 1980-2016.

	Dependent variable: Labor market outcomes 1980–2016					
	OLS Estimates			IV Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Employment to population ratio					
Task displacement	-0.676 (0.112)	-0.465 (0.141)	-0.785 (0.317)	-0.720 (0.112)	-0.422 (0.149)	-0.729 (0.366)
Share variance explained by:						
- task displacement	0.31	0.21	0.36	0.33	0.19	0.34
- educational dummies		0.10	0.12		0.12	0.12
R-squared	0.31	0.77	0.78	0.31	0.77	0.78
First-stage F				3246.45	785.80	156.33
Observations	500	500	500	500	500	500
	Panel B. Non-participation rate					
Task displacement	0.668 (0.120)	0.374 (0.138)	0.772 (0.312)	0.718 (0.120)	0.337 (0.149)	0.747 (0.361)
Share variance explained by:						
- task displacement	0.30	0.17	0.34	0.32	0.15	0.33
- educational dummies		0.16	0.19		0.18	0.19
R-squared	0.30	0.80	0.81	0.30	0.80	0.81
First-stage F				3246.45	785.80	156.33
Observations	500	500	500	500	500	500
Covariates:						
Industry shifters, manufacturing share, education and gender dummies		✓	✓		✓	✓
Exposure to labor share declines and relative specialization in routine jobs			✓			✓

Notes: This table presents estimates of the relationship between task displacement and labor market outcomes for 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. In Panel A, the dependent variable is the change in the employment to population ratio from 1980 to 2016. In Panel B, the dependent variable is the change in the non-participation rate from 1980 to 2016. Columns 1–3 report OLS estimates. Columns 4–6 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table, columns 2–3 and 5–6 control for industry shifters, baseline wage shares in manufacturing, and dummies for education (for no high school degree, some college, college degree and postgraduate degree) and gender. Columns 3 and 6 control for relative specialization in routine jobs and groups' exposure to industry labor share declines. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table 5: Task displacement and changes in real hourly wages—controlling for other trends, 1980-2016.

	Dependent variable: Change in wages 1980–2016							
	OLS estimates				IV estimates			
	Chinese imports' competition	Decline in unionization rates	Rising K/L ratio by industry	Rising TFP by industry	Chinese imports' competition	Decline in unionization rates	Rising K/L ratio by industry	Rising TFP by industry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Controlling for main effect of other shocks							
Task displacement	-1.259	-1.308	-1.306	-1.314	-1.235	-1.277	-1.274	-1.285
	(0.203)	(0.219)	(0.189)	(0.187)	(0.203)	(0.210)	(0.193)	(0.189)
Effect of other shocks by industry	0.012	0.017	0.014	-0.042	0.012	-0.032	0.015	-0.031
	(0.013)	(0.841)	(0.078)	(0.371)	(0.012)	(0.821)	(0.078)	(0.367)
Share variance explained by task displacement	0.53	0.55	0.55	0.55	0.52	0.54	0.53	0.54
R-squared	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
First-stage F					851.32	1126.35	883.48	952.66
Observations	500	500	500	500	500	500	500	500
	Panel B. Controlling for effects on workers in routine jobs							
Task displacement	-1.312	-1.629	-1.128	-1.299	-1.285	-1.580	-1.055	-1.267
	(0.184)	(0.451)	(0.221)	(0.199)	(0.185)	(0.523)	(0.264)	(0.208)
Effect of other shocks on routine jobs	0.001	0.678	-0.049	-0.035	0.001	0.601	-0.059	-0.044
	(0.006)	(0.806)	(0.054)	(0.196)	(0.006)	(0.899)	(0.059)	(0.197)
Share variance explained by task displacement	0.55	0.68	0.47	0.54	0.54	0.66	0.44	0.53
R-squared	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
First-stage F					929.19	224.85	362.42	686.25
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups controlling for trade in final goods, declining unionization rates, other forms of capital investments, and other technologies leading to productivity growth in an industry. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. In Panel A, we control for the main effect of these shocks on workers in exposed industries. In Panel B, we allow these shocks to have a differential impact on workers in routine jobs in exposed industries. Columns 1–4 report OLS estimates. Columns 5–8 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table, all specifications control for industry shifters, baseline wage share in manufacturing, and dummies for education (for no high school degree, some college, college degree and postgraduate degree) and gender. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table 6: Task displacement and changes in real hourly wages—controlling for changes in markups and industry concentration, 1980-2016.

	Dependent variable: Change in wages 1980–2016							
	OLS estimates				IV estimates			
	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controlling for main effect of markups and concentration								
Task displacement	-1.368	-1.315	-1.417	-1.314	-1.339	-1.283	-1.365	-1.286
	(0.178)	(0.204)	(0.204)	(0.183)	(0.186)	(0.204)	(0.205)	(0.187)
Exposure to rising markups or concentration	1.874	0.261	-0.767	-0.670	1.835	0.211	-0.721	-0.663
	(1.429)	(1.442)	(0.425)	(1.005)	(1.433)	(1.419)	(0.417)	(1.000)
Share variance explained by:								
- task displacement	0.57	0.55	0.59	0.55	0.56	0.54	0.57	0.54
- markups/concetration	0.04	-0.00	-0.07	0.01	0.04	-0.00	-0.07	0.01
R-squared	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
First-stage F					747	798	704	784
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-1.738	-1.712	-1.122	-1.323	-1.809	-1.759	-1.090	-1.177
	(0.223)	(0.238)	(0.149)	(0.161)	(0.257)	(0.277)	(0.164)	(0.151)
Exposure to rising markups or concentration	0.694	-0.684	-2.089	-2.127	0.721	-0.654	-2.016	-1.930
	(1.503)	(1.397)	(0.528)	(0.748)	(1.482)	(1.377)	(0.535)	(0.794)
Share variance explained by:								
- task displacement	0.57	0.56	0.54	0.50	0.60	0.58	0.53	0.44
- markups/concetration	0.02	0.01	-0.19	0.03	0.02	0.01	-0.19	0.03
R-squared	0.83	0.83	0.85	0.86	0.83	0.83	0.85	0.86
First-stage F					471	405	301	197
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups controlling for changes in market structure and markups. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. In Panel A, we control for groups' specialization in industries with changes in market structure leading to higher markups. In column 1, we proxy changes in market structure by rising sales concentration in the industry. In columns 2–4, we directly control for changes in markups. These are computed as the ratio of revenue to costs in column 2, the inverse of the materials' share in gross output in column 3, and markups estimated using a production function approach as in De Loecker, Eeckhout and Unger (2020) in column 4. In Panel B, we also subtract the percent increase in markups from the percent decline in the labor share when computing our measure of task displacement (using the accounting markup in columns 1 and 5). Columns 1–4 report OLS estimates. Columns 5–8 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table, all specifications control for industry shifters, baseline wage shares in manufacturing, and dummies for education (for no high school degree, some college, college degree and postgraduate degree) and gender. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table 7: Task displacement and changes in real hourly wages, 1980-2016: regional variation.

	Dependent variable: Change in real wages 1980–2016					
	OLS estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Variation across US regions					
Task displacement	-1.601	-1.070	-1.307	-1.650	-1.134	-1.497
	(0.111)	(0.118)	(0.252)	(0.107)	(0.121)	(0.285)
R-squared	0.62	0.81	0.82	0.62	0.81	0.81
First-stage F				1548.83	893.34	146.35
Observations	2633	2633	2633	2633	2633	2633
	Panel B. Variation across US regions absorbing national trends by group					
Task displacement	-1.296	-0.263	-0.373	-1.714	-0.412	-0.601
	(0.100)	(0.082)	(0.119)	(0.097)	(0.112)	(0.171)
R-squared	0.88	0.95	0.95	0.26	0.70	0.71
First-stage F				293.03	546.96	150.16
Observations	2633	2633	2633	2633	2633	2633
	Panel C. Variation across commuting zones					
Task displacement	-1.234	-0.943	-1.119	-1.385	-1.225	-1.472
	(0.146)	(0.140)	(0.221)	(0.189)	(0.180)	(0.286)
R-squared	0.36	0.56	0.56	0.35	0.55	0.54
First-stage F				558.65	487.63	92.12
Observations	20768	20768	20768	20768	20768	20768
	Panel D. Variation across commuting zones absorbing national trends by group					
Task displacement	-0.767	-0.418	-0.414	-1.169	-0.522	-0.567
	(0.070)	(0.065)	(0.147)	(0.097)	(0.061)	(0.188)
R-squared	0.71	0.78	0.79	0.10	0.36	0.39
First-stage F				694.53	137.33	69.31
Observations	20768	20768	20768	20768	20768	20768
Covariates:						
Industry shifters, manufacturing share, education and gender dummies		✓	✓		✓	✓
Exposure to labor share declines and relative specialization in routine jobs			✓			✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across demographic groups × region cells. In panels A and B, we focus on 300 demographic groups defined by gender, education, age, and race across 9 Census regions. In panels C and D, we focus on 54 demographic groups defined by gender, education, age, and race across 722 commuting zones. The dependent variable is the change in real wages for each cell from 1980 to 2016. In Panels B and D we provide estimates controlling for group fixed effects, which account for all national trends affecting a specific group. Columns 1–3 report OLS estimates and Columns 4–6 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table and the panel headers, columns 2–3 and 4–5 control for industry shifters, baseline wage shares in manufacturing, regional dummies, and dummies for education (for no high school degree, some college, college degree and postgraduate degree) and gender. Columns 3 and 6 control for relative specialization in routine jobs and groups' exposure to industry labor share decline. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group-region cell in 1980. Standard errors robust to heteroskedasticity and correlation within demographic group (in Panels A and B) or commuting zone (in Panels C and D) are reported in parentheses.

Table 8: Estimates of the propagation matrix.

	Dependent variable: Change in wages 1980–2016					
	GMM estimates			GMM using automation index		
	(1)	(2)	(3)	(4)	(5)	(6)
Own effect, θ/λ	0.885	0.881	0.818	0.878	0.872	0.800
	(0.047)	(0.050)	(0.053)	(0.048)	(0.050)	(0.054)
Contribution of ripple effects via	0.362	0.357	0.310	0.366	0.360	0.321
occupational similarity	(0.087)	(0.090)	(0.091)	(0.087)	(0.091)	(0.091)
Contribution of ripple effects via	0.221	0.222	0.363	0.225	0.225	0.366
industry similarity	(0.105)	(0.105)	(0.113)	(0.105)	(0.105)	(0.113)
Contribution of ripple effects via	0.179	0.179	0.170	0.178	0.179	0.167
education–age groups	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Observations	500	500	500	500	500	500
Covariates:						
Industry shifters		✓	✓		✓	✓
Manufacturing share			✓			✓

Notes: This table presents estimates of the propagation matrix using the parametrization in equation (17). Here, ripple effects are parametrized as functions of the similarity of groups in terms of their 1980 occupational distribution, industry distribution, and education×age groups. The table reports our estimates of the common diagonal term θ and a summary measure of the strength of ripple effects operating through each of these dimensions, defined by

$$\text{Contribution of ripple effects}_n = \frac{\beta_n}{\lambda} \cdot \left(\frac{1}{s^L} \sum_g \sum_{g' \neq g} f(d^n_{gg'}) \cdot s^L_g \cdot s^L_{g'} \right),$$

which equals the average sum of the off diagonal terms of the propagation matrix explained by each dimension of similarity. Estimates and standard errors are obtained via GMM. Columns 1–3 provide GMM estimates using our measure of task displacement to construct the instruments used in the moment conditions. Columns 4–6 provide GMM estimates using our index of automation to construct the instruments used in the moment conditions. All models are weighted by the share of hours worked by each group in 1980.

Table 9: Results from quantitative exercise.

	Data for 1980–2016 (1)	Model prediction computed using Proposition 4 (2)	Variation due to automation index (3)
Wage structure:			
Share wage changes explained:			
-due to industry shifts		6.78%	5.72%
-adding direct displacement effects		100.54%	84.21%
-accounting for ripple effects		48.35%	41.10%
Rise in college premium	25.51%	21.82%	18.29%
-part due to direct displacement effect		40.92%	33.91%
Rise in post-college premium	40.42%	24.06%	19.88%
-part due to direct displacement effect		48.04%	39.11%
Change in gender gap	15.37%	1.83%	1.75%
-part due to direct displacement effect		6.31%	5.38%
Share with declining wages	53.10%	41.71%	44.89%
-part due to direct displacement effects		49.61%	49.62%
Wages for men with no high school	-8.21%	-7.18%	-7.09%
-part due to direct displacement effects		-13.97%	-13.52%
Wages for women with no high school	10.94%	1.24%	-1.47%
-part due to direct displacement effects		6.21%	-0.06%
Aggregates:			
Change in average wages, $d \ln w$	29.15%	5.71%	4.61%
Change in GDP per capita, $d \ln y$	70.00%	23.42%	18.93%
Change in TFP, $d \ln \text{tfp}$	35%	3.77%	3.04%
Change in labor share, ds^L	-8 p.p.	-11.69 p.p	-9.45 p.p
Change in K/Y ratio	30.00%	41.93%	35.15%
Sectoral patterns:			
Share manufacturing in GDP	-8.80 p.p	-0.41 p.p	-0.43 p.p
Change in manufacturing wage bill	-35.00%	-8.23%	-9.98%

Notes: This table summarizes the effects of task displacement on the wage distribution, wage levels, aggregates and sectoral outcomes. All these objects are computed using the formulas in Proposition 4 and the parametrization and estimates for the industry demand system and the propagation matrix in Section 5.2. Column 2 computes the model predictions based on our baseline measure of task displacement (constructed from industry labor share declines), while column 3 computes the model predictions due to variation in the index of automation. The wage data reported in column 1 are from the 1980 US Census and 2014–2018 ACS. The data for GDP, the labor share, the capital-output ratio data, and the sectoral patterns for manufacturing are from the BEA and the BLS. The TFP data is from Fernald (2014).

Online Appendix to "Tasks, Automation, and the Rise of US Wage Inequality"

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Appendix A Theory Appendix

Proofs of results in the main text

Proof of Proposition 1. We first show that an equilibrium exists and is unique. The equilibrium of this economy solves the following optimization problem

$$\begin{aligned}\max_{\{k(x),\ell_1(x),\dots,\ell_G(x)\}_{x\in\mathcal{T}}} & y - \int_{\mathcal{T}} (k(x)/q(x)) \cdot dx \\ \text{subject to: } y &= \left(\frac{1}{M}\int_{\mathcal{T}} (M \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx\right)^{\frac{\lambda}{\lambda-1}}, \\ y(x) &= A_k \cdot \psi_k(x) \cdot k(x) + \sum_{g\in\mathcal{G}} A_g \cdot \psi_g(x) \cdot \ell_g(x) \ \ \forall x \in \mathcal{T}, \\ \ell_g &= \int_{\mathcal{T}} \ell_g(x) \cdot dx \ \ \forall g \in \mathcal{G}.\end{aligned}$$

This involves the maximization of a concave objective function subject to a convex constraint set. As a result, this optimization problem is i. unbounded or ii. has a unique solution (up to a set of measure zero). Suppose the problem is not unbounded (Proposition A2 in this appendix provides conditions under which the maximization problem is bounded). Let w_g be the Lagrange multiplier associated with the constraint for labor of type g. It follows that the solution to this optimization problem is given by an allocation of tasks to factors such that

$$\begin{aligned}\mathcal{T}_g &\subseteq \left\{x : \frac{w_g}{A_g \cdot \psi_g(x)} \leq \frac{w_{g'}}{A_{g'} \cdot \psi_{g'}(x)}, \frac{1}{\psi_k(x) \cdot q(x) \cdot A_k} \text{ for all } g'\right\}, \\ \mathcal{T}_k &\subseteq \left\{x : \frac{1}{\psi_k(x) \cdot q(x) \cdot A_k} \leq \frac{w_g}{A_g \cdot \psi_g(x)}, \text{ for all } g\right\}.\end{aligned}$$

The tie-breaking rule described in footnote 8 then selects a unique equilibrium allocation. This argument shows that, when the maximization problem is bounded, there is a unique equilibrium, where the task allocation is as described in the main text. In what follows, we characterize the equilibrium as a function of this unique task allocation.

The demand for task x is

$$y(x) = \frac{1}{M} \cdot y \cdot p(x)^{-\lambda}, \tag{A1}$$

where $p(x)$ is this task's price. Given the allocation of tasks $\{\mathcal{T}_k, \mathcal{T}_1, \dots, \mathcal{T}_G\}$, this price is

$$p(x) = \begin{cases} \dfrac{1}{A_k \cdot q(x) \cdot \psi_k(x)} & \text{if } x \in \mathcal{T}_k \\ \\ \dfrac{w_g}{A_g \cdot \psi_g(x)} & \text{if } x \in \mathcal{T}_g. \end{cases} \tag{A2}$$

This implies that the demand for capital and labor at the task level is given by:

$$k(x)/q(x) = \begin{cases} \dfrac{1}{M} \cdot y \cdot (A_k \cdot q(x) \cdot \psi_k(x))^{\lambda-1} & \text{if } x \in \mathcal{T}_k \\ \\ 0 & \text{if } x \notin \mathcal{T}_k. \end{cases}$$

$$\ell_g(x) = \begin{cases} \dfrac{1}{M} \cdot y \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} & \text{if } x \in \mathcal{T}_g \\ \\ 0 & \text{if } x \notin \mathcal{T}_g. \end{cases}$$

To derive equation (2), we integrate over the demand for labor across tasks in the previous expression and rearrange to obtain:

$$\ell_g = \int_{\mathcal{T}_g} \frac{1}{M} \cdot y \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} \cdot dx \Rightarrow w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\frac{1}{M} \int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}}.$$

Equation (1) follows by noting that by definition gross output y is

$$y = \int_{\mathcal{T}} y(x) p(x) dx.$$

Substituting for $y(x)$ from equation (A1), we obtain the ideal price condition:

$$1 = \frac{1}{M} \int_{\mathcal{T}} p(x)^{1-\lambda} dx. \tag{A3}$$

Substituting for the equilibrium task prices from equation (A2) yields

$$1 = A_k^{\lambda-1} \cdot \left(\frac{1}{M} \int_{\mathcal{T}_k} (q(x) \cdot \psi_k(x))^{\lambda-1} dx\right) + \sum_{g \in \mathcal{G}} \left(\frac{w_g}{A_g}\right)^{1-\lambda} \cdot \left(\frac{1}{M} \int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} dx\right).$$

Next substituting for w_g from equation (2), we can rewrite this equation in terms of task shares as

$$1 = A_k^{\lambda-1} \cdot \Gamma_k + \sum_{g \in \mathcal{G}} \Gamma_g^{\frac{1}{\lambda}} \cdot \left(\frac{y}{A_g \cdot \ell_g}\right)^{\frac{1-\lambda}{\lambda}}.$$

Rearranging this equation and using the fact that $A_k^{\lambda-1} \Gamma_k < 1$ yields the expression for output in equation (1).

Finally, we can compute factor shares as:

$$s^K = \frac{1}{M}\int_{\mathcal{T}_k} y \cdot p(x)^{1-\lambda}dx \Big/ y = A_k^{\lambda-1}\cdot\Gamma_k.$$

Because of constant-returns to scale, we must have $s^L = 1 - s^K$.

To conclude, note that in any competitive equilibrium we have $s^L, s^K \in [0,1]$, and so

$$1 \geq A_k^{\lambda-1}\cdot\Gamma_k,$$

as claimed in the main text. ∎

Proof of Proposition 2. We now characterize the effects of a small change in technology. As in the text, we use $\mathcal{D}_g \subset \mathcal{T}_g$ to denote the set of tasks that used to be performed by group g and where, after the technological change, capital now outperforms labor. The definitions of $d\ln\Gamma_g^{\text{deep}}$ and $d\ln\Gamma_g^{\text{disp}}$ in the main text imply

$$d\ln\Gamma_g = (\lambda-1)d\ln\Gamma_g^{\text{deep}} - d\ln\Gamma_g^{\text{disp}}. \tag{A4}$$

To characterize the effects of technology on wages, we first log-differentiate equation (2):

$$d\ln w_g = \frac{1}{\lambda}d\ln y + \frac{\lambda-1}{\lambda}d\ln A_g + \frac{1}{\lambda}d\ln\Gamma_g.$$

Plugging the formula for $d\ln\Gamma_g$ in (A4) yields the expression for wage changes in (4).

Let us next define changes in TFP, which are:

$$d\ln\text{TFP} = d\ln y - s^K\cdot d\ln k,$$

where $k = \int_{\mathcal{T}_k} k(x)/q(x)dx$. This definition corresponds to gross TFP, defined as the change in gross output that is not explain by the change in capital and intermediate inputs, k. This can also be written in its dual representation as:

$$d\ln\text{TFP} = \sum_{g\in\mathcal{G}} s_g^L\cdot d\ln w_g - \int_{\mathcal{T}_k} s^K(x)d\ln q(x)dx, \tag{A5}$$

where $s^K(x)$ denotes the share of capital $k(x)$ in gross output and s_g^L denote the share of labor of type g in gross output.

To obtain this expression, note that because of constant returns to scale, Euler's theorem implies

$$y = \sum_{g \in \mathcal{G}} w_g \ell_g + \int_{\mathcal{T}_k} k(x)/q(x) dx.$$

For any small change in technology, we have

$$d \ln y = \sum_{g \in \mathcal{G}} s_g^L \cdot d \ln w_g + \int_{\mathcal{T}_k} s^K(x) d \ln k(x) dx - \int_{\mathcal{T}_k} s^K(x) d \ln q(x) dx + \frac{1}{y} \sum_{g \in \mathcal{G}} \int_{\mathcal{D}_g} (k^{\text{new}}(x)/q^{\text{new}}(x)) dx,$$

where the $k^{\text{new}}(x)$ and $q^{\text{new}}(x)$ denote the new capital usage and prices in the newly-automated tasks. Rearranging, we have

$$d \ln y - \left(\int_{\mathcal{T}_k} s^K(x) d \ln k(x) dx + \frac{1}{y} \sum_{g \in \mathcal{G}} \int_{\mathcal{D}_g} (k^{\text{new}}(x)/q^{\text{new}}(x)) dx \right) = \sum_{g \in \mathcal{G}} s_g^L \cdot d \ln w_g - \int_{\mathcal{T}_k} s^K(x) d \ln q(x) dx.$$

Finally, using the fact that

$$s^K d \ln k = \frac{1}{y} dk = \int_{\mathcal{T}_k} s^K(x) d \ln k(x) dx + \frac{1}{y} \sum_{g \in \mathcal{G}} \int_{\mathcal{D}_g} (k^{\text{new}}(x)/q^{\text{new}}(x)) dx,$$

we obtain the dual representation of TFP.

We now return to determining the contribution of different types of technologies to TFP. For this, we use the ideal price index condition in equation (A3), which we can rewrite as

$$1 = A_k^{\lambda-1} \cdot \left(\frac{1}{M} \int_{\mathcal{T}_k} (q(x) \cdot \psi_k(x))^{\lambda-1} dx \right) + \sum_{g \in \mathcal{G}} \left(\frac{w_g}{A_g} \right)^{1-\lambda} \cdot \left(\frac{1}{M} \int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} dx \right).$$

Log-differentiating this equation following an arbitrary change in technology and capital prices, we obtain:

$$\text{(A6)} \qquad \sum_{g \in \mathcal{G}} s_g^L \cdot d \ln w_g - \int_{\mathcal{T}_k} s^K(x) d \ln q(x) dx = s^K \cdot \left(d \ln A_k + d \ln \Gamma_k^{\text{deep}} \right) + \sum_{g \in \mathcal{G}} s_g^L \cdot \left(d \ln A_g + d \ln \Gamma_g^{\text{deep}} \right) + \frac{1}{\lambda - 1} \left[s^K \cdot d \ln \Gamma_k^{\text{disp}} - \sum_{g \in \mathcal{G}} s_g^L \cdot d \ln \Gamma_g^{\text{disp}} \right].$$

Let us define the last line as

$$\Delta = \frac{1}{\lambda - 1} \left[s^K \cdot d \ln \Gamma_k^{\text{disp}} - \sum_{g \in \mathcal{G}} s_g^L \cdot d \ln \Gamma_g^{\text{disp}} \right],$$

which represents the reallocation of tasks from labor to capital.

To develop this expression further, let us recall the definition of the *cost-saving gains* from automating task x:

$$\pi_g(x) = \frac{1}{\lambda - 1}\left[\left(w_g \frac{A_k \cdot q(x) \cdot \psi_k(x)}{A_g \cdot \psi_g(x)}\right)^{\lambda-1} - 1\right] > 0.$$

Averaging this across tasks, we obtain the *average cost-saving gains* from automating tasks in $\mathcal{D}_g$ (which was also defined in the text):

$$\pi_g = \frac{1}{M}\int_{\mathcal{D}_g} \psi_g(x)^{\lambda-1} \cdot \pi_g(x) dx \Bigg/ \frac{1}{M}\int_{\mathcal{D}_g} \psi_g(x)^{\lambda-1} dx.$$

Using these definitions, Δ can be rewritten as

$$\begin{aligned}
\Delta &= \sum_{g \in \mathcal{G}} \frac{1}{\lambda - 1}\left[A_k^{\lambda-1} \cdot \frac{1}{M}\int_{\mathcal{D}_g} (q(x) \cdot \psi_k(x))^{\lambda-1} dx - \left(\frac{w_g}{A_g}\right)^{1-\lambda} \cdot \frac{1}{M}\int_{\mathcal{D}_g} \psi_g(x)^{\lambda-1} dx\right] \\
&= \sum_{g \in \mathcal{G}} \frac{1}{M}\int_{\mathcal{D}_g} \frac{1}{\lambda - 1}\left[(A_k \cdot q(x) \cdot \psi_k(x))^{\lambda-1} - \left(\frac{w_g}{A_g}\right)^{1-\lambda} \cdot \psi_g(x)^{\lambda-1}\right] dx \\
&= \sum_{g \in \mathcal{G}} \frac{1}{M}\int_{\mathcal{D}_g} \left(\frac{w_g}{A_g}\right)^{1-\lambda} \cdot \psi_g(x)^{\lambda-1} \cdot \pi_g(x) dx \\
&= \sum_{g \in \mathcal{G}} \left(\frac{w_g}{A_g}\right)^{1-\lambda} \cdot \left(\frac{1}{M}\int_{\mathcal{D}_g} \psi_g(x)^{\lambda-1} dx\right) \cdot \pi_g.
\end{aligned}$$

Next, using the fact that $s_g^L = \left(\frac{w_g}{A_g}\right)^{1-\lambda} \cdot \left(\frac{1}{M}\int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} dx\right)$, we can rewrite Δ as:

$$\Delta = \sum_{g \in \mathcal{G}} s_g^L \cdot \frac{\frac{1}{M}\int_{\mathcal{D}_g} \psi_g(x)^{\lambda-1} dx}{\frac{1}{M}\int_{\mathcal{T}_g} \psi_g(x)^{\lambda-1} dx} \cdot \pi_g = \sum_{g \in \mathcal{G}} s_g^L \cdot d\ln\Gamma_g^{\text{disp}} \cdot \pi_g.$$

Substituting this expression for Δ into equation (A6) and using the dual representation of TFP in equation (A5), we obtain the TFP expressions in equation (5) as desired.

The output equation, (7), can be obtained from the TFP equation, (5). Note that by definition we have

$$d\ln y = d\ln \text{TFP} + s^K \cdot d\ln k.$$

Moreover, $k = s^K \cdot y$, which implies

$$d\ln k = d\ln s^K + d\ln y.$$

Combining these two equations yields

$$d\ln y = \frac{1}{1-s^K}\left(d\ln \mathrm{TFP} + s^K \cdot d\ln s^K\right)$$
$$d\ln k = \frac{1}{1-s^K}\left(d\ln \mathrm{TFP} + d\ln s^K\right).$$

To obtain the factor share changes, note that

$$d\ln s^K = (\lambda-1)\cdot\left(d\ln A_k + d\ln \Gamma_k^{\mathrm{deep}}\right) + d\ln \Gamma_k^{\mathrm{disp}},$$

which follows from the fact that $s^K = A_k^{\lambda-1}\cdot\Gamma_k$. We can rewrite this expression as follows:

$$\begin{aligned} d\ln s^K =& (\lambda-1)\cdot\left(d\ln A_k + d\ln \Gamma_k^{\mathrm{deep}}\right) + \frac{1}{s^K}\cdot\left((\lambda-1)\cdot\Delta + \sum_{g\in\mathcal{G}} s_g^L \cdot d\ln \Gamma_g^{\mathrm{disp}}\right) \\ =& (\lambda-1)\cdot\left(d\ln A_k + d\ln \Gamma_k^{\mathrm{deep}}\right) + \frac{1}{s^K}\cdot\sum_{g\in\mathcal{G}} s_g^L \cdot d\ln \Gamma_g^{\mathrm{disp}}\cdot(1+(\lambda-1)\cdot\pi_g), \end{aligned}$$

which yields equation (6) in the proposition. ■

Proof of Proposition 3. We first show that an equilibrium exists and is unique. Denote the aggregator of industry output by $H(y_1,\ldots,y_I)$. The equilibrium of this economy solves the following optimization problem

$$\max_{\{k(x),\ell_1(x),\ldots,\ell_G(x)\}_{x\in\mathcal{T}_i,i\in\mathcal{I}}} H(y_1,\ldots,y_I) - \int_{\mathcal{T}}(k(x)/q(x))\cdot dx$$
$$\text{subject to: } y_i = \left(\frac{1}{M}\int_{\mathcal{T}}(M\cdot y(x))^{\frac{\lambda-1}{\lambda}}\cdot dx\right)^{\frac{\lambda}{\lambda-1}} \quad \forall i\in\mathcal{I},$$
$$y(x) = A_k\cdot\psi_k(x)\cdot k(x) + \sum_{g\in\mathcal{G}} A_g\cdot\psi_g(x)\cdot\ell_g(x) \quad \forall x\in\mathcal{T},$$
$$\ell_g = \int_{\mathcal{T}}\ell_g(x)\cdot dx \quad \forall g\in\mathcal{G}.$$

This involves the maximization of a concave objective function subject to a convex constraint set. As a result, this optimization problem is i. unbounded or ii. has a unique solution (up to a set of measure zero). Suppose the problem is not unbounded (Proposition A2 in this appendix provides conditions under which the maximization problem is bounded). Let w_g be the Lagrange multiplier associated with the constraint for labor of type g. It follows that the solution is given by an allocation of tasks to factors such that

$$\mathcal{T}_{gi} \subseteq \left\{x : \frac{w_g}{A_{gi}\cdot\psi_g(x)} \le \frac{w_{g'}}{A_{g'i}\cdot\psi_{g'}(x)}, \frac{1}{\psi_k(x)\cdot q(x)\cdot A_{ki}} \text{ for all } g'\right\},$$
$$\mathcal{T}_{ki} \subseteq \left\{x : \frac{1}{\psi_k(x)\cdot q(x)\cdot A_{ki}} \le \frac{w_g}{A_{gi}\cdot\psi_g(x)}, \text{ for all } g\right\}.$$

The tie-breaking rule described in footnote 8 then selects a unique equilibrium allocation. This argument shows that, when the maximization problem is bounded, there is a unique equilibrium, where the task allocation is as described in the main text. In what follows, we characterize the equilibrium as a function of this unique task allocation (we provide a sufficient condition for finite output at the end of the proof).

The demand for task x in sector i is

$$y(x) = \frac{1}{M_i} \cdot y \cdot s_i^Y(\boldsymbol{p}) \cdot p(x)^{-\lambda} \cdot (A_i p_i)^{\lambda-1}.$$

Given $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$, the price of task x is

$$p(x) = \begin{cases} \dfrac{1}{A_k \cdot q(x) \cdot \psi_k(x)} & \text{if } x \in \mathcal{T}_{ki} \\ \\ \dfrac{w_g}{A_g \cdot \psi_k(x)} & \text{if } x \in \mathcal{T}_{gi}. \end{cases}$$

The demand for capital and labor at task x can be written as

$$k(x)/q(x) = \begin{cases} \dfrac{1}{M_i} \cdot y \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_k \cdot q(x) \cdot \psi_k(x))^{\lambda-1} & \text{if } x \in \mathcal{T}_{ki} \\ \\ 0 & \text{if } x \notin \mathcal{T}_k. \end{cases}$$

$$\ell_g(x) = \begin{cases} \dfrac{1}{M_i} \cdot y \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} & \text{if } x \in \mathcal{T}_g \\ \\ 0 & \text{if } x \notin \mathcal{T}_g. \end{cases}$$

Integrating these demands, as in the proof of Proposition 1, and rearranging, we have

$$\begin{aligned} \ell_g &= \sum_{i \in \mathcal{I}} \int_{\mathcal{T}_{gi}} \frac{1}{M_i} \cdot y \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} \cdot dx \\ \Rightarrow w_g &= \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}}, \end{aligned}$$

which thus establishes equation (8) as desired.

To derive the industry price index in equation (9), we observe that

$$p_i \cdot y_i = \int_{\mathcal{T}_i} p(x) \cdot y(x) dx \Rightarrow p_i = \frac{1}{A_i} \left(\frac{1}{M_i} \int_{\mathcal{T}_i} p(x)^{1-\lambda} dx\right)^{\frac{1}{1-\lambda}}.$$

Using the allocation of tasks $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$, this implies

$$\begin{aligned} p_i =& \frac{1}{A_i}\left(\frac{1}{M_i}\int_{\mathcal{T}_i} p(x)^{1-\lambda}dx\right)^{\frac{1}{1-\lambda}} \\ =& \frac{1}{A_i}\left(A_k \cdot \left(\frac{1}{M_i}\int_{\mathcal{T}_{ki}} (q(x)\cdot\psi_k(x))^{\lambda-1}dx\right) + \sum_{g\in\mathcal{G}} w_g^{1-\lambda}\cdot A_g^{\lambda-1}\cdot\left(\frac{1}{M_i}\int_{\mathcal{T}_{gi}}\psi_g(x)^{\lambda-1}dx\right)\right)^{\frac{1}{1-\lambda}}, \end{aligned}$$

which yields equation (10) in the proposition.

Finally, because industry shares must add up to 1, equation (10) holds, completing the proof.

Although not reported, factor shares can be computed as

$$s^K = A_k^{\lambda-1}\cdot\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p})\cdot(A_i p_i)^{\lambda-1}\cdot\Gamma_{ki} \tag{A7}$$

$$s^L = 1 - A_k^{\lambda-1}\cdot\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p})\cdot(A_i p_i)^{\lambda-1}\cdot\Gamma_{ki}. \tag{A8}$$

■

Proof of Proposition 4. We first provide a proof for the existence and some of the properties of the propagation matrix Θ.

Define the matrix

$$\Sigma = \mathbb{1} - \frac{1}{\lambda}\frac{\partial \ln \Gamma(\boldsymbol{w}, \boldsymbol{\zeta}, \Psi)}{\partial \ln \boldsymbol{w}}.$$

This matrix satisfies several properties. First, because $\partial\Gamma_g/\partial w_{g'} \geq 0$, all of its off-diagonal entries are negative. This implies that Σ is a $Z-$matrix.

Second, Σ has a positive dominant diagonal. This follows from the fact that

$$\Sigma_{gg} = 1 - \frac{1}{\lambda}\frac{\partial \ln \Gamma_g}{\partial \ln w_g} > 0,$$

and

$$\Sigma_{gg} - \sum_{g'\neq g} |\Sigma_{gg'}| = 1 - \sum_{g'} \frac{1}{\lambda}\frac{\partial \ln \Gamma_g}{\partial \ln w_{g'}} > 1.$$

This last inequality follows from the fact that $\sum_{g'} \frac{\partial \ln \Gamma_g}{\partial \ln w_{g'}} \leq 0$, which is true since when all wages rise by the same amount, workers lose tasks to capital but do not experience task reallocation among them.

Third, all eigenvalues of Σ have a real part that exceeds 1. This follows from an application of Gershgorin circle theorem, which states that for each eigenvalue ε of Σ, we can find a dimension g such that

$$\|\varepsilon - \Sigma_{gg}\| < \sum_{g'\neq g} |\Sigma_{gg'}|.$$

This inequality requires that

$$\Re(\varepsilon) \in \left[\Sigma_{gg} - \sum_{g' \neq g} |\Sigma_{gg'}|, \Sigma_{gg} + \sum_{g' \neq g} |\Sigma_{gg'}|\right].$$

Because $\Sigma_{gg} - \sum_{g' \neq g} |\Sigma_{gg'}| > 1$ for all g, as shown above, all eigenvalues of Σ have a real part that is greater than 1.

Fourth, since Σ has negative off diagonal elements and all of its eigenvalues have a positive real part, we can conclude that it is an $M-$matrix.

Because Σ is an $M-$matrix, its inverse Θ exists and has positive and real entries, $\theta_{gg'} \geq 0$, as desired. Moreover, each eigenvalue of Θ has a real part that is positive and less than 1. Finally, the row and column sums of Θ are also less than 1. In particular, denote by θ^r_g the sum of the elements of row g of Θ. Then:

$$\Theta \cdot (1, 1, \ldots, 1)'_1 = (\theta^r_1, \theta^r_2, \ldots, \theta^r_G)' \Rightarrow \Sigma \cdot (\theta^r_1, \theta^r_2, \ldots, \theta^r_G)' = (1, 1, \ldots, 1)'.$$

This equality requires that

$$\Sigma_{gg} \cdot \theta^r_g + \sum_{g' \neq g} \Sigma_{gg'} \cdot \theta^r_{g'} = 1.$$

Now, suppose without loss of generality, that $\theta^r_1 > \theta^r_2 > \ldots > \theta^r_G > 0$ (all rows must have strictly positive sums, since $\theta_{gg'} = 0$ for all g' would imply that Θ is singular, contradicting the fact that all its eigenavlues have real parts in $(0, 1)$). We have

$$\Sigma_{11} \cdot \theta^r_1 + \sum_{g' \neq 1} \Sigma_{1g'} \cdot \theta^r_{g'} = 1,$$

which implies that

$$\left(1 - \frac{1}{\lambda} \frac{\partial \ln \Gamma_1}{d \ln w_1}\right) \cdot \theta^r_1 = 1 + \frac{1}{\lambda} \sum_{g' \neq 1} \frac{\partial \ln \Gamma_1}{d \ln w_{g'}} \cdot \theta^r_{g'} \leq 1 + \frac{1}{\lambda} \sum_{g' \neq 1} \frac{\partial \ln \Gamma_1}{d \ln w_{g'}} \cdot \theta^r_1.$$

Because $\sum_{g'} \frac{\partial \ln \Gamma_1}{d \ln w_{g'}} \leq 0$, we can rewrite this inequality as

$$\theta^r_1 < 1 + \frac{1}{\lambda} \sum_{g'} \frac{\partial \ln \Gamma_1}{d \ln w_{g'}} \cdot \theta^r_1 \leq 1.$$

An identical argument establishes that column sums of Θ lie in $(0, 1)$.

Having introduced the propagation matrix Θ, we are now in a position to derive the formulas characterizing the effects of technology on wages, sectoral prices, and TFP.

First, define $w^e_g = w_g / A_g$ as the wage per efficiency unit of labor of g workers. Equation (8) then implies

$$w_g^e = \left(\frac{y}{A_g \cdot \ell_g}\right)^{\frac{1}{\lambda}} \cdot \Gamma_g(\boldsymbol{w}, \boldsymbol{\zeta}, \Psi)^{\frac{1}{\lambda}}.$$

Log-differentiating this equation in response to an automation (task-displacing) technology, we obtain:

$$d\ln w_g^e = \frac{1}{\lambda} d\ln y - \frac{1}{\lambda} d\ln \Gamma_g^{\text{disp}} + \frac{1}{\lambda}\sum_{i\in\mathcal{I}} \omega_{gi} \cdot d\ln\zeta_i + \frac{1}{\lambda}\frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}} \cdot d\ln \boldsymbol{w}.$$

Stacking these equations for all groups, we can write:

$$\begin{pmatrix} d\ln w_1^e \\ d\ln w_1^e \\ \dots \\ d\ln w_G^e \end{pmatrix} = \frac{1}{\lambda}\begin{pmatrix} d\ln y \\ d\ln y \\ \dots \\ d\ln y \end{pmatrix} + \frac{1}{\lambda}\begin{pmatrix} \sum_{i\in\mathcal{I}} \omega_{1i} \cdot d\ln\zeta_i \\ \sum_{i\in\mathcal{I}} \omega_{2i} \cdot d\ln\zeta_i \\ \dots \\ \sum_{i\in\mathcal{I}} \omega_{Gi} \cdot d\ln\zeta_i \end{pmatrix} - \frac{1}{\lambda}\begin{pmatrix} d\ln\Gamma_1^{\text{disp}} \\ d\ln\Gamma_2^{\text{disp}} \\ \dots \\ d\ln\Gamma_G^{\text{disp}} \end{pmatrix} + \frac{1}{\lambda}\frac{\partial \ln \Gamma}{\partial \ln \boldsymbol{w}} \cdot \begin{pmatrix} d\ln w_1^e \\ d\ln w_1^e \\ \dots \\ d\ln w_G^e \end{pmatrix}.$$

We can solve this system of equations as

$$\begin{pmatrix} d\ln w_1^e \\ d\ln w_1^e \\ \dots \\ d\ln w_G^e \end{pmatrix} = \frac{1}{\lambda}\Theta \cdot \begin{pmatrix} d\ln y \\ d\ln y \\ \dots \\ d\ln y \end{pmatrix} + \frac{1}{\lambda}\Theta \cdot \begin{pmatrix} \sum_{i\in\mathcal{I}} \omega_{1i} \cdot d\ln\zeta_i \\ \sum_{i\in\mathcal{I}} \omega_{2i} \cdot d\ln\zeta_i \\ \dots \\ \sum_{i\in\mathcal{I}} \omega_{Gi} \cdot d\ln\zeta_i \end{pmatrix} - \frac{1}{\lambda}\Theta \cdot \begin{pmatrix} d\ln\Gamma_1^{\text{disp}} \\ d\ln\Gamma_2^{\text{disp}} \\ \dots \\ d\ln\Gamma_G^{\text{disp}} \end{pmatrix},$$

which implies

$$d\ln w_g = \frac{\varepsilon_g}{\lambda} d\ln y + \frac{1}{\lambda}\Theta_g \cdot d\ln\zeta - \frac{1}{\lambda}\Theta_g \cdot d\ln \Gamma^{\text{disp}},$$

where

$$d\ln\zeta_g = \sum_{i\in\mathcal{I}} \omega_{gi} \cdot d\ln\zeta_i = \sum_{i\in\mathcal{I}} \omega_{gi} \cdot \left(\frac{\partial \ln s_i^Y(\boldsymbol{p})}{\partial \ln \boldsymbol{p}} \cdot d\ln\ \boldsymbol{p} + (\lambda - 1) \cdot d\ln p_i\right).$$

Turning to industry prices, note that these are given by equation (10). By definition, the equilibrium task allocation $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \dots, \mathcal{T}_{Gi}\}$ solves the cost-minimization problem:

$$p_i = \min_{\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \dots, \mathcal{T}_{Gi}\}} \frac{1}{A_i}\left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}}.$$

The envelope theorem then implies that

$$d\ln p_i = \sum_{g\in\mathcal{G}} s_{gi}^L \cdot d\ln w_g - (A_i p_i)^{\lambda-1}\frac{1}{\lambda-1}\left[A_k^{\lambda-1} \cdot d\Gamma_{ki}^{\text{disp}} - \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot d\Gamma_{gi}^{\text{disp}}\right],$$

since the reallocation of tasks across factors in response to changes in factor prices has a second-order effect on industry prices. Here, the term

$$\Delta_i = (A_i p_i)^{\lambda-1} \frac{1}{\lambda-1}\left[A_k^{\lambda-1}\cdot d\Gamma_{ki}^{\text{disp}} - \sum_{g\in\mathcal{G}} w_g^{1-\lambda}\cdot A_g^{\lambda-1}\cdot d\Gamma_{gi}^{\text{disp}}\right]$$

is a generalization of the term Δ in the proof of Proposition 2, and again corresponds to cost savings from the reallocation of tasks from labor to capital, but now in industry i.

Similarly, we define the industry versions of cost savings at the task level (when tasks in the set $\mathcal{D}_{gi}$ in industry i previous to perform by factor g are automated):

$$\pi_{gi}(x) = \frac{1}{\lambda-1}\left[\left(w_g \frac{A_k\cdot q(x)\cdot\psi_k(x)}{A_g\cdot\psi_g(x)}\right)^{\lambda-1} - 1\right] > 0,$$

and *average percent cost-saving gains* in industry i as

$$\pi_{gi} = \frac{1}{M_i}\int_{\mathcal{D}_{gi}} \psi_g(x)^{\lambda-1}\cdot\pi_{gi}(x)dx \bigg/ \frac{1}{M_i}\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx.$$

Using these definitions, we can write Δ_i as

$$\begin{aligned}
\Delta_i =&(A_i p_i)^{\lambda-1}\sum_{g\in\mathcal{G}}\frac{1}{\lambda-1}\left[A_k^{\lambda-1}\cdot\frac{1}{M_i}\int_{\mathcal{D}_{gi}}(q(x)\cdot\psi_k(x))^{\lambda-1}dx - \left(\frac{w_g}{A_g}\right)^{1-\lambda}\cdot\frac{1}{M_i}\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx\right]\\
=&(A_i p_i)^{\lambda-1}\sum_{g\in\mathcal{G}}\frac{1}{M_i}\int_{\mathcal{D}_{gi}}\frac{1}{\lambda-1}\left[(A_k\cdot q(x)\cdot\psi_k(x))^{\lambda-1} - \left(\frac{w_g}{A_g}\right)^{1-\lambda}\cdot\psi_g(x)^{\lambda-1}\right]dx\\
=&(A_i p_i)^{\lambda-1}\sum_{g\in\mathcal{G}}\frac{1}{M_i}\int_{\mathcal{D}_{gi}}\left(\frac{w_g}{A_g}\right)^{1-\lambda}\cdot\psi_g(x)^{\lambda-1}\cdot\pi_{gi}(x)dx\\
=&(A_i p_i)^{\lambda-1}\sum_{g\in\mathcal{G}}\left(\frac{w_g}{A_g}\right)^{1-\lambda}\cdot\left(\frac{1}{M_i}\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx\right)\cdot\pi_{gi}.
\end{aligned}$$

Again as in the proof of Proposition 2, using the fact that $s_{gi}^L = (A_i p_i)^{\lambda-1}\left(\frac{w_g}{A_g}\right)^{1-\lambda}\cdot\left(\frac{1}{M_i}\int_{\mathcal{T}_g}\psi_g(x)^{\lambda-1}dx\right)$, we get

$$\Delta_i = \sum_{g\in\mathcal{G}} s_{gi}^L\cdot\frac{\frac{1}{M_i}\int_{\mathcal{A}_{gi}}\psi_g(x)^{\lambda-1}dx}{\frac{1}{M_i}\int_{\mathcal{T}_g}\psi_g(x)^{\lambda-1}dx}\cdot\pi_{gi} = \sum_{g\in\mathcal{G}} s_{gi}^L\cdot d\ln\Gamma_{gi}^{\text{disp}}\cdot\pi_{gi},$$

which yields the desired formula for $d\ln p_i$ in the proposition.

We now turn to TFP. As before, we use the dual definition of TFP, which now implies

(A9) $$d\ln\text{TFP} = \sum_{g\in\mathcal{G}} s_g^L\cdot d\ln w_g.$$

To derive a formula for TFP, first note that given a price vector $\boldsymbol{p}$, we can define the cost of producing the final good as $c^h(\boldsymbol{p})$. Moreover, Shephard's lemma implies that

$$s_i^Y(\boldsymbol{p}) = \frac{\partial c^h(\boldsymbol{p})}{\partial p_i}\frac{p_i}{c^h}.$$

Our choice of numeraire, which implies that the final good has a price of 1, then implies

$$1 = c^h(\boldsymbol{p}).$$

Log-differentiating this expression yields

$$\begin{aligned}
0 &= \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot d\ln p_i \\
&= \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot \left(\sum_{g\in\mathcal{G}} s_{gi}^L \cdot \left(d\ln w_g - d\ln \Gamma_{gi}^{\text{disp}} \cdot \pi_{gi}\right)\right) \\
&= \sum_{g\in\mathcal{G}} s_g^L \cdot d\ln w_g - \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \sum_{g\in\mathcal{G}} \cdot s_{gi}^L \cdot \pi_{gi}
\end{aligned}$$

Rearranging this expression, and using the dual definition of TFP in equation (A9), yields the formula for the contribution of automation to TFP in the proposition.

Turning to output, the primal definition of TFP implies

$$d\ln y = d\ln \text{TFP} + s^K \cdot d\ln k.$$

Moreover, $k = s^K \cdot y$, which implies

$$d\ln k = d\ln s^K + d\ln y.$$

Combining these two equations yields

$$\begin{aligned}
d\ln y &= \frac{1}{1-s^K}\left(d\ln \text{TFP} + s^K \cdot d\ln s^K\right) \\
d\ln k &= \frac{1}{1-s^K}\left(d\ln \text{TFP} + d\ln s^K\right).
\end{aligned}$$

Finally, we provide a derivation for the change in the capital share. Recall that the capital share is given by

$$d\ln s^K = -\frac{1-s^K}{s^K} d\ln s^L = -\frac{1}{s^K}\sum_{g\in\mathcal{G}} s_g^L \cdot (d\ln w_g - d\ln y).$$

■

Additional results and lemmas

This section proves the existence of the threshold $\bar{q}$ introduced in Assumption 1 and provides primitive conditions under which the economy will produce finite output.

Proposition A1 (Existence of $\bar{q}$) *Suppose that workers can only produce non-overlapping sets of tasks (i.e., $\psi_g(x) > 0$ only if $\psi_{g'}(x) = 0$ for all $g' \neq g$). Consider the set of tasks where capital has positive productivity, $\mathcal{S} = \{x : \psi_k(x) > 0\}$. Suppose that there exists $\underline{\psi} > 0$, such that for all $x \in \mathcal{S}$ we have $\psi_k(x) > \underline{\psi}$. Then there exists a threshold $\bar{q}$ such that, if $q(x) > \bar{q}$ for all $x \in \mathcal{S}$, all the tasks in $\mathcal{S}$ are allocated to capital.*

Proof. Consider an allocation with $\mathcal{T}_k = \mathcal{S}$ and where $\mathcal{T}_g = \{x : \psi_g(x) > 0, x \notin \mathcal{S}\}$. This allocation is the unique equilibrium of the economy if and only if

$$\frac{w_g}{A_g \cdot \psi_g(x)} \geq \frac{1}{q(x) \cdot A_k \cdot \psi_k(x)} \text{ for all } x \in \mathcal{S} \text{ and } g \in \mathcal{G}.$$

Using the formula for wages in equation (2) and the fact that $\psi_k(x) > \underline{\psi}$, it follows that a sufficient condition for this inequality is that

$$\text{(A10)} \qquad \frac{\left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\frac{1}{M}\int_{x:\psi_g(x)>0, x\notin\mathcal{S}} \psi_g(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}}}{A_g \cdot \psi_g(x)} \geq \frac{1}{q_0 \cdot A_k \cdot \underline{\psi}} \text{ for all } x \in \mathcal{S} \text{ and } g \in \mathcal{G},$$

where $q_0 = \inf_{x\in\mathcal{S}} q(x)$.

The left hand side of (A10) is increasing in q_0 (since output increases in $q(x)$ and the candidate task allocation remains unchanged); while the right-hand side is decreasing in q_0 and converges to zero as q_0 goes to infinity. Let $\bar{q}$ denote the point at which (A10) holds with equality. It follows that if $q_0 \geq \bar{q}$ (that is, $q(x) \geq \bar{q}$ for all $x \in \mathcal{S}$), inequality (A10) holds and the task allocation described in Assumption 1 is the unique equilibrium. ■

Finally, we provide conditions under which the economy produces final output. To do so, it is convenient to introduce the derived production function of the economy as

$$\begin{aligned}
F(k, \boldsymbol{\ell}) &= \max H(y_1, \ldots, y_I) \\
\text{subject to: } y_i &= \left(\frac{1}{M}\int_{\mathcal{T}} (M \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx\right)^{\frac{\lambda}{\lambda-1}} \quad \forall i \in \mathcal{I}, \\
y(x) &= A_k \cdot \psi_k(x) \cdot k(x) + \sum_{g\in\mathcal{G}} A_g \cdot \psi_g(x) \cdot \ell_g(x) \quad \forall x \in \mathcal{T}, \\
\ell_g &= \int_{\mathcal{T}} \ell_g(x) \cdot dx \quad \forall g \in \mathcal{G}, \\
k &= \int_{\mathcal{T}} (k(x)/q(x)) \cdot dx.
\end{aligned}$$

This gives a standard constant-returns to scale production function that depends on the supply of labor and the total resources used to produce capital, k.

Proposition A2 (Finite output) *The economy produces finite output if and only if the following Inada condition holds:*

$$\lim_{k \to \infty} F_k(k, \boldsymbol{\ell}) < 1. \tag{A11}$$

Moreover, in any equilibrium with positive and finite consumption, we have that $s^K \in [0, 1)$. *Instead, in any equilibrium with infinite output,* $s^K = 1$.

Proof. A competitive equilibrium maximizes $c(k) = F(k, \boldsymbol{\ell}) - k$.

When the Inada condition (A11) holds, we have that $c(k)$ reaches a unique maximum at some $k^* \geq 0$. Moreover, $c(k^*) = (1 - s^K)F(k^*, \boldsymbol{\ell})$, which requires $s^K \in [0, 1)$.

When the Inada condition fails, $c(k)$ is an increasing function and the economy achieves infinite output. Moreover, because $\lim_{k \to \infty} F_k(k, \boldsymbol{\ell}) > 1$, we have that $\lim_{k \to \infty} F_k(k, \boldsymbol{\ell}) = m > 1$. Thus, the capital share is given by

$$s^K = \lim_{k \to \infty} \frac{F_k(k, \boldsymbol{\ell}) \cdot k}{F(k, \boldsymbol{\ell})} = m \cdot \lim_{k \to \infty} \frac{k}{F(k, \boldsymbol{\ell})} = m \cdot \lim_{k \to \infty} \frac{1}{F_k(k, \boldsymbol{\ell})} = 1,$$

where we used l'Hôpital's rule in the third step. ■

Proposition A3 (Extension with markups) *Given labor-supply levels $\ell = (\ell_1, \ell_2, \ldots, \ell_G)$ and industry markups $\mu = (\mu_1, \mu_2, \ldots, \mu_I)$, and conditional on an allocation of tasks $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$, equilibrium wages, industry prices, and output are a solution to the system of equations*

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \mu_i^{-\lambda} \cdot \Gamma_{gi}\right)^{\frac{1}{\lambda}} \tag{A12}$$

$$p_i = \frac{\mu_i}{A_i} \cdot \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}} \tag{A13}$$

$$1 = \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}). \tag{A14}$$

Moreover, following advances in automation or changes in markups, the change in the real wage of group g is given by

$$d\ln w_g = \frac{\varepsilon_g}{\lambda} \cdot d\ln y + \frac{1}{\lambda}\Theta_g \cdot d\ln \boldsymbol{\zeta} - \frac{1}{\lambda}\Theta_g \cdot d\ln \boldsymbol{\Gamma}^{disp} \text{ for all } g \in \mathcal{G},$$

where the industry shifters are now given by

$$d\ln \zeta_g = \sum_{i\in\mathcal{I}} \omega_{gi} \cdot \left(\frac{\partial \ln s_i^Y(\boldsymbol{p})}{\partial \ln \boldsymbol{p}} \cdot d\ln \boldsymbol{p} + (\lambda - 1) \cdot d\ln p_i - d\ln \mu_i\right) \text{ for all } g \in \mathcal{G}.$$

Proof. Let

$$\mu_i : \frac{p}{\text{mc}_i}$$

denote the markup charged in industry i, where p_i is the industry price and mc_i the marginal cost. Production optimality requires that

$$\text{mc}_i = p(x) \Big/ \frac{\partial y}{\partial y(x)} \Rightarrow p(x) = \frac{p_i}{\mu_i} \cdot \frac{\partial y}{\partial y(x)}.$$

Using this last equation, we can solve for the quantity of task x used in sector i as

$$y(x) = \cdot \frac{1}{M_i} \cdot y \cdot s_i^Y(\boldsymbol{p}) \cdot (\mu \cdot p(x))^{-\lambda} \cdot (A_i p_i)^{\lambda-1} \cdot \mu_i^{-\lambda}, \tag{A15}$$

where $p(x)$ is the price of task x. Following the same steps as in the proof of Proposition 3, we can therefore compute the demand for capital and labor at task x as

$$k(x)/q(x) = \begin{cases} \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_k \cdot q(x) \cdot \psi_k(x))^{\lambda-1} & \text{if } x \in \mathcal{T}_{ki} \\ 0 & \text{if } x \notin \mathcal{T}_k. \end{cases}$$

$$\ell_g(x) = \begin{cases} \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} & \text{if } x \in \mathcal{T}_g \\ 0 & \text{if } x \notin \mathcal{T}_g. \end{cases}$$

To derive equation (A12), we add-up the demand for labor across tasks, and rearrange the resulting expression:

$$\begin{aligned} \ell_g =& \sum_{i\in\mathcal{I}} \int_{\mathcal{T}_{gi}} \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} \cdot dx \\ \Rightarrow w_g =& \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i\in\mathcal{I}} \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}}. \end{aligned}$$

To derive the industry price index in equation (A14), note that due to constant returns to scale and the presence of markups, we must have

$$\frac{1}{\mu_i} \cdot p_i \cdot y_i = \int_{\mathcal{T}_i} p(x) \cdot y(x) dx \Rightarrow p_i = \frac{\mu_i}{A_i} \left(\frac{1}{M_i} \int_{\mathcal{T}_i} p(x)^{1-\lambda} dx\right)^{\frac{1}{1-\lambda}}.$$

Using the allocation of tasks $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \dots, \mathcal{T}_{Gi}\}$, this implies

$$\begin{aligned} p_i =& \frac{\mu_i}{A_i} \left(\frac{1}{M_i} \int_{\mathcal{T}_i} p(x)^{1-\lambda} dx\right)^{\frac{1}{1-\lambda}} \\ =& \frac{1}{A_i} \left(A_k \cdot \left(\frac{1}{M_i} \int_{\mathcal{T}_{ki}} (q(x) \cdot \psi_k(x))^{\lambda-1} dx\right) + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \left(\frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx\right)\right)^{\frac{1}{1-\lambda}}, \end{aligned}$$

which yields the expression for industry prices in the proposition.

Finally, because industry shares must add up to 1, we have equation (A14), which is equivalent to a price-index condition for industries.

The expressions for wage changes and industry shifters are derived using the same steps as in the proof of Proposition 4, but now accounting for the markup term in equation (A13). ■

PROPOSITION A4 (EXTENSION WITH LABOR SUPPLY) *Suppose that households choose their labor supply and consumption to maximize*

$$\max_{\ell_g, c_g} \frac{c_g^{1-\varsigma_c}}{1-\varsigma_c} - \frac{\ell_g^{1+\varsigma_\ell}}{1+\varsigma_\ell} \text{ subject to: } c_g \leq w_g \cdot \ell_g,$$

and let $\varsigma = (1-\varsigma_c)/(\varsigma_c + \varsigma_\ell)$. *Conditional on an allocation of tasks* $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \dots, \mathcal{T}_{Gi}\}$, *equilibrium* *wages, labor supply, industry prices, and output solve the system*

$$w_g = y^{\frac{1}{\lambda+\varsigma}} \cdot A_g^{\frac{\lambda-1}{\lambda+\varsigma}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi} \right)^{\frac{1}{\lambda+\varsigma}} \tag{A16}$$

$$\ell_g = y^{\frac{\varsigma}{\lambda+\varsigma}} \cdot A_g^{\frac{\varsigma\cdot(\lambda-1)}{\lambda+\varsigma}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi} \right)^{\frac{\varsigma}{\lambda+\varsigma}} \tag{A17}$$

$$p_i = \frac{1}{A_i} \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi} \right)^{\frac{1}{1-\lambda}} \tag{A18}$$

$$c = \left(1 - A_k^{\lambda-1} \cdot \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{ki} \right) \cdot y \tag{A19}$$

$$1 = \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}). \tag{A20}$$

Moreover, the effect of task displacement on wages and employment is given by

$$d\ln w_g = \frac{\varepsilon_g}{\lambda+\varsigma} \cdot d\ln y + \frac{1}{\lambda+\varsigma}\Theta_g \cdot d\ln \boldsymbol{\zeta} - \frac{1}{\lambda+\varsigma}\Theta_g \cdot d\ln \boldsymbol{\Gamma}^{disp} \text{ for all } g\in\mathcal{G},$$
$$d\ln \ell_g = \frac{\varepsilon_g\cdot\varsigma}{\lambda+\varsigma} \cdot d\ln y + \frac{\varsigma}{\lambda+\varsigma}\Theta_g \cdot d\ln \boldsymbol{\zeta} - \frac{\varsigma}{\lambda+\varsigma}\Theta_g \cdot d\ln \boldsymbol{\Gamma}^{disp} \text{ for all } g\in\mathcal{G},$$

where the propagation matrix now becomes

$$\Theta = \left(\mathbb{1} - \frac{1}{\lambda+\varsigma} \frac{\partial \ln \Gamma(\boldsymbol{w},\boldsymbol{\zeta},\Psi)}{\partial \ln \boldsymbol{w}} \right)^{-1}$$

Proof. The household problem gives the labor-supply curve

$$\ell_g = w_g^{\varsigma}. \tag{A21}$$

Plugging this labor-supply curve into the expression for wages in equation (8) yields

$$w_g = \left(\frac{y}{w_g^{\varsigma}} \right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi} \right)^{\frac{1}{\lambda}}.$$

Using this equation to solve for w_g yields equation (A16). In turn, plugging (A16) into equation (A21) yields (A17).

The derivations of the remaining expressions in the proposition are identical to those in the proof of proposition 3.

Turning to the effect of technologies on wage changes, and following the same steps as in the derivation of Proposition 4, we obtain

$$d\ln w_g = \frac{1}{\lambda} d\ln y - \frac{1}{\lambda} d\ln \ell_g - \frac{1}{\lambda} d\ln \Gamma_g^{\text{disp}} + \frac{1}{\lambda} \sum_{i\in\mathcal{I}} \omega_{gi} \cdot d\ln \zeta_i + \frac{1}{\lambda} \frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}} \cdot d\ln \boldsymbol{w}.$$

Using the fact that $d\ln\ell_g = \varsigma \cdot d\ln w_g$ (from the labor-supply curve in A21), we can rewrite this as

$$d\ln w_g = \frac{1}{\lambda+\varsigma} d\ln y - \frac{1}{\lambda+\varsigma} d\ln \Gamma_g^{\text{disp}} + \frac{1}{\lambda+\varsigma} \sum_{i\in\mathcal{I}} \omega_{gi} \cdot d\ln\zeta_i + \frac{1}{\lambda+\varsigma} \frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}} \cdot d\ln \boldsymbol{w}.$$

Solving this system for wage changes gives the formula for the propagation matrix in the proposition. ■

Appendix C Propagation Matrix and Elasticities of Substitution

This section provides additional properties of the propagation matrix and relates it to traditional definitions of elasticities of substitution.

First, let us recall that the *Morishima elasticity of substitution* between capital and labor of type g can be defined as

$$\sigma_{k,\ell_g} = \frac{1}{1 + \left. \frac{\partial \ln(s^L_g / s^k)}{\partial \ln A_k} \right|_k}.$$

Similarly, the *Morishima elasticity of substitution* between capital and labor can be defined as

$$\sigma_{k,\ell} = \frac{1}{1 + \left. \frac{\partial \ln(s^L / s^k)}{\partial \ln A_k} \right|_k},$$

and the *Morishima elasticity of substitution* between labor of type g' and g can be defined as

$$\sigma_{\ell_{g'},\ell_g} = \frac{1}{1 + \left. \frac{\partial \ln(s^L_g / s^L_{g'})}{\partial \ln \ell_{g'}} \right|_k}.$$

The Morishima elasticities tell us about changes in factor shares as one factor becomes more abundant or productive. In the presence of multiple factors, these elasticities need not be symmetric, as is the case with only two factors of production.

Also, define the *$q-$elasticity of substitution* between capital and labor of type g by the identity

$$\sigma^Q_{k,\ell_g} = \frac{1}{\left. \frac{1}{s^k} \frac{\partial \ln w_g}{\partial \ln A_k} \right|_k},$$

and the *$q-$elasticity of substitution* between labor of type g' and g by

$$\sigma^Q_{\ell_{g'},\ell_g} = \frac{1}{\left. \frac{1}{s^L_{g'}} \frac{\partial \ln w_g}{\partial \ln \ell_{g'}} \right|_k}.$$

The $q-$elasticities of substitution tell us whether factors are $q-$complements (a positive elasticity) or $q-$substitutes (a negative elasticity), and are symmetric in a competitive economy by definition (a corollary of Young's theorem).

Note that in all these definitions we are holding k—the resources devoted to produce capital—constant.

Proposition A5 (Elasticities of substitution and Θ) *The Morishima elasticity of substitution between capital and labor is*

$$\sigma_{k,\ell} = \frac{1}{\frac{\bar{\varepsilon}}{\lambda} + \frac{1}{s^k} \cdot (\bar{\varepsilon} - 1)} \qquad \text{where: } \bar{\varepsilon} := \sum_{g \in \mathcal{G}} \frac{s_g^L}{s^L} \varepsilon_g \in (0,1).$$

Moreover, the Morishima elasticities of substitution between pairs of factors are

$$\sigma_{k,\ell_g} = \frac{1}{\frac{\varepsilon_g}{\lambda} s^k + \frac{\bar{\varepsilon}}{\lambda} s^L + (\varepsilon_g - 1) + \frac{s^L}{s^k}(\bar{\varepsilon} - 1)} \qquad \sigma_{\ell_{g'},\ell_g} = \frac{1}{1 + \frac{s_{g'}^L}{\lambda} \cdot \left(\varepsilon_g - \varepsilon_{g'} - \left(\frac{\theta_{gg'}}{s_{g'}^L} - \frac{\theta_{g'g'}}{s_{g'}^L}\right)\right)},$$

and the q−elasticities of substitution are

$$\sigma^Q_{k,\ell_g} = \frac{1}{\frac{\varepsilon_g}{\lambda} + \frac{1}{s^k} \cdot (\varepsilon_g - 1)} \qquad \sigma^Q_{\ell_{g'},\ell_g} = \frac{1}{\frac{1}{\lambda} \cdot \left(\varepsilon_g - \frac{\theta_{gg'}}{s_{g'}^L}\right)}.$$

Proof. First, note that we can rewrite the definition of the set $\mathcal{T}_g$ as

$$\mathcal{T}_g = \left\{ x : \frac{1}{\psi_g(x)} \cdot \frac{w_g \cdot A_k}{A_g} \le \frac{1}{\psi_{g'}(x)} \cdot \frac{w_{g'} \cdot A_k}{A_{g'}}, \frac{1}{\psi_k(x) \cdot q(x)} \forall g' \right\}$$
$$\mathcal{T}_k = \left\{ x : \frac{1}{\psi_k(x) \cdot q(x)} \le \frac{1}{\psi_{g'}(x)} \cdot \frac{w_{g'} \cdot A_k}{A_{g'}} \forall g' \right\}.$$

These expressions imply that the effect of an increase in A_k on the allocation of tasks is equivalent to a uniform rise in wages. That is:

$$\frac{\partial \ln \Gamma_g}{\partial \ln A_k} = \sum_{g'} \frac{\partial \ln \Gamma_g}{\partial \ln w_{g'}}.$$

Using this property, we can compute the change in wages as

$$d \ln w_g = \frac{1}{\lambda} d \ln y + \frac{1}{\lambda} \frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}} \cdot d \ln \boldsymbol{w} + \frac{1}{\lambda} \frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}} \cdot d \ln \boldsymbol{A_k}.$$

We can then solve for the change in wages as

$$d \ln w = \frac{1}{\lambda} \Theta d \ln y + \Theta \frac{1}{\lambda} \Sigma \cdot d \ln \boldsymbol{A_k}.$$

Moreover, using the definition of Θ, we get

$$\Theta \frac{1}{\lambda} \Sigma = \Theta - \mathbb{1}.$$

Plugging this into the expression for wages, we obtain

$$d \ln w_g = \frac{\varepsilon_g}{\lambda} \cdot d \ln y + (\varepsilon_g - 1) d \ln A_k.$$

Finally, holding k constant, we have that $d \ln y = s^K \cdot d \ln A_k$. Therefore

$$\text{(A22)} \qquad \frac{1}{\sigma^Q_{k,\ell_g}} = \frac{1}{s^k} \frac{\partial \ln w_g}{\partial \ln A_k}\bigg|_k = \frac{\varepsilon_g}{\lambda} + \frac{1}{s^k} \cdot (\varepsilon_g - 1).$$

In addition, we also have that

$$\text{(A23)} \qquad \frac{\partial \ln s^L_g}{\partial \ln A_k}\bigg|_k = \left(\frac{\varepsilon_g}{\lambda} - 1\right) \cdot s^k + (\varepsilon_g - 1)$$

Using equation (A23), we can compute the Morishima elasticity of substitution between capital and labor as

$$\begin{aligned}
\frac{1}{\sigma_{k,\ell}} =& 1 + \frac{\partial \ln(s^L/s^k)}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{1}{s^k} \cdot \frac{\partial \ln s^L}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{1}{s^k} \sum_{g \in \mathcal{G}} \frac{s^L_g}{s^L} \frac{\partial \ln s^L_g}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{1}{s^k} \sum_{g \in \mathcal{G}} \frac{s^L_g}{s^L} \cdot \left(\left(\frac{\varepsilon_g}{\lambda} - 1\right) \cdot s^k + (\varepsilon_g - 1) \right) \\
=& 1 + \frac{1}{s^k} \left(\left(\frac{\bar{\varepsilon}}{\lambda} - 1\right) \cdot s^k + (\bar{\varepsilon} - 1) \right) \\
=& \frac{\bar{\varepsilon}}{\lambda} + \frac{1}{s^k} \cdot (\bar{\varepsilon} - 1)
\end{aligned}$$

Similarly, using equation (A23), we can compute the Morishima elasticity of substitution between capital and labor of type g as

$$\begin{aligned}
\frac{1}{\sigma_{k,\ell_g}} =& 1 + \frac{\partial \ln(s^L_g/s^k)}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{\partial \ln s^L_g}{\partial \ln A_k}\bigg|_k + \frac{s^L}{s^k} \frac{\partial \ln s^L}{\partial \ln A_k}\bigg|_k \\
=& 1 + \left(\frac{\varepsilon_g}{\lambda} - 1\right) \cdot s^k + (\varepsilon_g - 1) + \frac{s^L}{s^k} \left(\left(\frac{\bar{\varepsilon}}{\lambda} - 1\right) \cdot s^k + (\bar{\varepsilon} - 1) \right) \\
=& \frac{\varepsilon_g}{\lambda} s^k + \frac{\bar{\varepsilon}}{\lambda} s^L + (\varepsilon_g - 1) + \frac{s^L}{s^k} (\bar{\varepsilon} - 1).
\end{aligned}$$

We now turn to the elasticities involving chnages in $\ell_{g'}$. Following a change in $\ell_{g'}$, we have:

$$d \ln w_g = \frac{\varepsilon_g}{\lambda} d \ln y - \frac{\theta_{gg'}}{\lambda} d \ln \ell_{g'}. \tag{A24}$$

Holding k constant, $d \ln y = s^L_{g'} \cdot d \ln \ell_{g'}$. Therefore,

$$\frac{1}{\sigma^Q_{\ell_{g'},\ell_g}} = \frac{1}{s^L_{g'}} \frac{\partial \ln w_g}{\partial \ln \ell_{g'}}\bigg|_k = \frac{1}{\lambda} \cdot \left(\varepsilon_g - \frac{\theta_{gg'}}{s^L_{g'}} \right).$$

Finally, we can write the Morishima elasticity of substitution between labor of type g' and g as

$$\frac{1}{\sigma_{\ell_{g'},\ell_g}} = 1 + \frac{\partial \ln(s^L_g / s^L_{g'})}{\partial \ln \ell_{g'}}\bigg|_k = 1 + \frac{\partial \ln w_g}{\partial \ln \ell_{g'}}\bigg|_k - \frac{\partial \ln w_{g'}}{\partial \ln \ell_{g'}}\bigg|_k.$$

Using the formula for the change in wages in equation (A24), we obtain

$$\frac{1}{\sigma_{\ell_{g'},\ell_g}} = 1 + \frac{s^L_{g'}}{\lambda} \cdot \left(\varepsilon_g - \varepsilon_{g'} - \left(\frac{\theta_{gg'}}{s^L_{g'}} - \frac{\theta_{g'g'}}{s^L_{g'}} \right) \right),$$

which completes proof of the proposition. ■

Proposition A6 (Quasi-symmetry of the propagation matrix) *The propagation matrix satisfies the symmetry property*

$$\varepsilon_g - \frac{\theta_{gg'}}{s^L_{g'}} = \varepsilon_{g'} - \frac{\theta_{g'g}}{s^L_g}. \tag{A25}$$

Proof. By definition $\sigma^Q_{\ell_{g'},\ell_g} = \sigma^Q_{\ell_g,\ell_{g'}}$, which implies the symmetry property in (A25). ■

Appendix D Estimating the Propagation Matrix

This appendix provides additional details regarding the estimation of the propagation matrix. It also describes an alternative parametrization.

Common diagonal $\theta_{gg} = \theta$

Our baseline estimation strategy makes two assumptions:

- The propagation matrix has a common diagonal term $\theta_{gg} = \theta \geq 0$. This is motivated by the strong reduced form evidence between task displacement and the observed change in real wages.
- The extent of competition for tasks between groups is determined by their similarity across a set of characteristics $\mathcal{N}$. We operationalize this by assuming that

$$\frac{\theta_{gg'}}{s^L_{g'}} + \frac{\theta_{g'g}}{s^L_g} = 2\sum_{n\in\mathcal{N}} \beta_n \cdot f(d^n_{g,g'}).$$

Using these two assumptions, and combining them with the theoretical restriction that

$$\varepsilon_g - \frac{\theta_{gg'}}{s^L_{g'}} = \varepsilon_{g'} - \frac{\theta_{g'g}}{s^L_g},$$

yields the parametrization used in the main text.

Common elasticities ε_g

Our baseline estimates allow ε_g to vary across groups but fixes θ_{gg} to a common value. We now outline an estimation approach based on the alternative assumption that

$$\sum_{g'} \theta_{gg'} = \varepsilon_g = \varepsilon \text{ for all } g,$$

which implies that all wages rise by the same amount in response to a factor-neutral increase in output.

With this assumption, the symmetry property derived in Proposition A6 becomes:

$$\frac{\theta_{gg'}}{s^L_{g'}} = \frac{\theta_{g'g}}{s^L_g},$$

which motivates a parametrization where the extent of competition between g' and g depends on how similar these groups are along several characteristics $n \in \mathcal{N}$. In particular, we assume

$$\begin{aligned}\theta_{gg'} &= \sum_{n \in \mathcal{N}} \beta_n \cdot f(d^n_{g,g'}) \cdot s^L_{g'} \text{ for all } g' \neq g \\ \theta_{gg} &= \varepsilon - \sum_{g' \neq g} \sum_{n \in \mathcal{N}} \beta_n \cdot f(d^n_{g,g'}) \cdot s^L_{g'},\end{aligned}$$

where f is a decreasing function of the distance along a given dimension n between groups g' and g, denoted here by $d^n_{g,g'}$.

Thus, For a given set of characteristics $n \in \mathcal{N}$, we estimate $\{\beta_n\}_{n \in \mathcal{N}}$ and ε using the equation

$$\begin{aligned}\text{(A26)} \qquad d \ln w_g =& \varepsilon \cdot d \ln y - \varepsilon \cdot \text{Task displacement}_g \\ & - \sum_{n \in \mathcal{N}} \beta_n \cdot \sum_{g' \neq g} f(d^n_{g,g'}) \cdot s^L_{g'} \cdot \left(\text{Task displacement}_{g'} - \text{Task displacement}_g\right) + v_g,\end{aligned}$$

imposing the restriction that $\beta_n \geq 0$.

Additional estimates and robustness

Besides the exercises summarized in the main text, we conducted several robustness checks regarding our estimation of the propagation matrix. In particular, Table A16 provides estimates using a tuning parameter of $\kappa = 1$ and $\kappa = 5$ (recall that our baseline uses a quadratic decay with $\kappa = 2$). This table also summarizes the results obtained using our alternative estimation approach, described in the previous section, and assuming a common row sum $\varepsilon_g = \varepsilon$.

Appendix E Measuring Task Displacement

Theoretical derivations

This section derives our measures of task displacement in the extended version of our model that allows for markups.

We assume that tasks can be partitioned into routine tasks $\mathcal{R}_i$ and non-routine tasks $\mathcal{N}_i$, whose union equals $\mathcal{T}_i$. Moreover, let $\mathcal{R}_{gi}$ and $\mathcal{N}_{gi}$ denote the (disjoint) sets of routine and non-routine tasks allocated to workers of type g.

Assumption 2 is equivalent to:

i Only routine tasks have been automated, which implies that $\mathcal{D}_{gi} \subset \mathcal{R}_{gi}$

ii Routine tasks in a given industry have been automated at the same rate for all workers, which implies that

$$\frac{\int_{\mathcal{D}_{gi}} \psi_g(x)^{\lambda-1} dx}{\int_{\mathcal{R}_{gi}} \psi_g(x)^{\lambda-1} dx} = \vartheta_i \geq 0 \text{ for all } g.$$

Before continuing with our derivations, we introduce some notation that we will use throughout this appendix. Define by ω_X^Y the share of wages in some cell X earned within another sub-cell Y. For example, define ω_g^i as the share of wages earned by members of group g in industry i as a fraction of their total wage income:

$$\omega_g^i = \frac{s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi}}{\sum_{g'} s_{g'}^Y(\boldsymbol{p}) \cdot (A_{g'} p_{g'})^{\lambda-1} \cdot \Gamma_{gg'}}.$$

Define ω_{gi}^R as the share of wages earned by members of group g in industry i in routine jobs as a fraction of the total wage income earned by workers of group g in industry i:

$$\omega_{gi}^R = \frac{\int_{\mathcal{R}_{gi}} \psi_g(x)^{\lambda-1} dx}{\int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx}.$$

And define ω_i^R as the share of wages earned by workers in industry i in routine jobs as a fraction of the total wage income earned by workers in industry i:

$$\omega_i^R = \frac{\sum_{g \in \mathcal{G}} w_g^{1-\lambda} \int_{\mathcal{R}_{gi}} \psi_g(x)^{\lambda-1} dx}{\sum_{g \in \mathcal{G}} w_g^{1-\lambda} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx}.$$

We next define the average cost-saving gains from automating tasks in sector i as

$$\pi_i = \sum_{g \in \mathcal{G}} \frac{\omega_i^{Rg}}{\omega_i^R} \cdot \pi_{gi},$$

where ω_i^{Rg} is the share of wages in industry i paid to g workers in routine jobs, and ω_i^R is the share of wages in industry i paid to workers in routine jobs.

Finally, for each type of worker g, define the elasticity σ_{gi}^L by

$$\frac{1}{\omega_i^g} \cdot \frac{\partial \ln s_i^L}{\partial \ln w_g} = s^k \cdot (1 - \sigma_{gi}^L).$$

When $\sigma_{gi}^L > 1$, an increase in w_g reduces the labor share. Instead, when $\sigma_{gi}^L < 1$, an increase in w_g increases the labor share.

The following proposition characterizes the change in the labor share as a function of various driving forces:

1. task displacement generated by automation or offshoring, $d \ln \Gamma_{gi}^{\text{disp}}$ generating productivity gains $\pi_{gi} > 0$;

2. productivity deepening and factor augmenting technologies taking place in that industry, and denoted by $d \ln \Gamma_{gi}^{\text{deepp}}$ and $d \ln A_{gi}$. Note that, in this proposition, factor-augmenting technologies may vary by industry;

3. changes in markups at the industry level, denoted by $d \ln \mu_i$;

4. changes in wages, $d \ln w_g$ due to other shocks in the economy or changes in factor supplies;

5. and changes in the user cost of capital. In particular, we assume there are two types of technologies increasing the productivity of capital or reducing its price. On the one hand we have the task displacement technologies introduced above. And on the other hand, we have uniform declines in the user cost of capital driven by lower capital prices at all tasks or cheap access to credit. Formally, we write $q(x) = \frac{1}{R_i} \cdot q_0(x)$ and consider changes in $q_0(x)$ leading to task displacement or changes in R_i common to all uses of capital in a given industry.

Proposition A7 (Industry labor shares) *Let s_i^L denote the labor share in industry i. Also, let $q(x) = \frac{1}{R_i} \cdot q_0(x)$, where R_i captures uniform changes in the price of capital at all tasks in industry i, and let $w_{gi}^e = w_g / A_{gi}$ denote the wages per efficiency unit of labor paid in industry i for workers of type g. Following a change in technology (task displacement, productivity deepening,*

A_{ki}, A_{gi}, and A_i) factor prices (w_g, R_i), and markups μ_i, we have

$$d\ln s_i^L = -d\ln\mu_i - \left(1 + (\lambda - 1)\cdot s_i^L \cdot \pi_i\right)\cdot \omega_i^R \cdot \vartheta_i$$
$$+ (1 - s_i^L)\cdot(\lambda - 1)\cdot\left(\sum_{g\in\mathcal{G}} \omega_i^g \cdot d\ln\Gamma_{gi}^{deep} - d\ln\Gamma_{ki}^{deep}\right)$$
$$+ (1 - s_i^L)\cdot(1 - \sigma_i^L)\cdot d\ln w_i^e - (1 - s_i^L)\cdot(1 - \sigma_i^K)\cdot d\ln(R_i/A_{ki}),$$

where

$$\sigma_i^L := \sum_{g\in\mathcal{G}} \frac{\omega_i^g \cdot d\ln w_g^e}{\sum_{g'} \omega_i^{g'}\cdot d\ln w_{g'}^e}\cdot \sigma_{gi}^L \qquad\qquad \sigma_i^K := \sum_{g\in\mathcal{G}} \omega_i^g \cdot \sigma_{gi}^L,$$

and

$$d\ln w_i^e = \sum_{g\in\mathcal{G}} \omega_i^g \cdot d\ln w_{gi}^e.$$

Proof. Given a vector of wages and technologies, we can write the labor share as

$$s_i^L = \frac{1}{\mu_i}\cdot \frac{\sum_{g\in\mathcal{G}} {w_{gi}^e}^{1-\lambda}\cdot \Gamma_{gi}}{A_k^{\lambda-1}\cdot\Gamma_{ki} + \sum_{g\in\mathcal{G}} {w_{gi}^e}^{1-\lambda}\cdot\Gamma_{gi}}, \tag{A27}$$

where recall that the denominator is also equal to

$$p_i^{1-\lambda} = A_k^{\lambda-1}\cdot\Gamma_{ki} + \sum_{g\in\mathcal{G}} {w_{gi}^e}^{1-\lambda}\cdot\Gamma_{gi}.$$

We can decompose changes in the labor share into four terms:

$$d\ln s_i^L = \begin{matrix}\text{contribution of}\\ \text{markups}\end{matrix} + \begin{matrix}\text{contribution of}\\ \text{task displacement}\end{matrix} + \begin{matrix}\text{contribution of}\\ \text{prod. deepening}\end{matrix}$$
$$+ \begin{matrix}\text{contribution of}\\ \text{eff. wage changes}\end{matrix} + \begin{matrix}\text{contribution of}\\ \text{price of capital}\end{matrix},$$

which we now derive in detail.

1. **Contribution of markups:** this is simply given by $-d\ln\mu_i$.
2. **Contribution of task displacement:** we can compute this as

$$\begin{matrix}\text{contribution of}\\ \text{task displacement}\end{matrix} = -\sum_{g\in\mathcal{G}} \omega_i^{Rg}\cdot\vartheta_i + (1-\lambda)\cdot s_i^L \cdot \sum_{g\in\mathcal{G}} \omega_i^{Rg}\cdot\vartheta_i\cdot\pi_{gi}$$

where the first term captures the effect of task displacement on the numerator and the second term the effect on the denominator of the labor share expression in equation (A27). Using the definition of π_i, this can be simplified as

$$\begin{matrix}\text{contribution of} \\ \text{task displacement}\end{matrix} = -\left(1 + (\lambda - 1) \cdot s_i^L \cdot \pi_i\right) \cdot \omega_i^R \cdot \vartheta_i.$$

3. Contribution of productivity deepening: we can compute this as

$$\begin{matrix}\text{contribution of} \\ \text{prod. deepening}\end{matrix} = (\lambda - 1) \cdot \sum_{g \in \mathcal{G}} \omega_i^g \cdot d \ln \Gamma_{gi}^{\text{deep}} - (\lambda - 1) \cdot \left(s_g^L \cdot \sum_{g \in \mathcal{G}} \omega_i^g \cdot d \ln \Gamma_{gi}^{\text{deep}} + s_i^k \cdot d \ln \Gamma_{ki}^{\text{deep}}\right),$$

where the first term captures the effect of task displacement on the numerator and the second term the effect on the denominator of the labor share expression in equation (A27). We can rewrite this as

$$\begin{matrix}\text{contribution of} \\ \text{prod. deepening}\end{matrix} = (\lambda - 1) \cdot (1 - s_i^L) \cdot \left(\sum_{g \in \mathcal{G}} \omega_i^g \cdot d \ln \Gamma_{gi}^{\text{deep}} - d \ln \Gamma_{ki}^{\text{deep}}\right)$$

4. Contribution of wages per efficiency unit of labor: We now turn to the contribution of wages per efficiency unit of labor. Using the definition of σ_{gi}^L, we can compute their effect as

$$\begin{matrix}\text{contribution of} \\ \text{wage changes}\end{matrix} = \sum_{g \in \mathcal{G}} \omega_i^g \cdot (1 - s_i^L) \cdot (1 - \sigma_{gi}^L) \cdot d \ln w_{gi}^e.$$

Using the definition of σ_i^L and $d \ln w_i$, we obtain

$$\begin{matrix}\text{contribution of} \\ \text{wage changes}\end{matrix} = (1 - s_i^L) \cdot (1 - \sigma_i^L) \cdot d \ln w_i.$$

5. Contribution of price of capital: To compute the effects of a uniform change in capital prices, we first provide explicit formulas for σ_{gi}^L, which we will use in our derivations below. We have that

$$\frac{1}{\omega_i^g} \cdot \frac{\partial \ln s_i^L}{\partial \ln w_g} = \frac{1}{\omega_i^g} \cdot \left(\omega_i^g \cdot (1 - \lambda) + \sum_{g'} \omega_i^{g'} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}} - s^L \cdot \omega_i^g \cdot (1 - \lambda)\right),$$

where the first two terms capture the effect of task displacement on the numerator and the third term the effect on the denominator of the labor share expression in equation (A27). Here, we used the fact that the effect of wages on the denominator equals the direct effect holding the task allocation constant—an implication of the envelope theorem. We can rewrite this expression as

$$\frac{1}{\omega_i^g} \cdot \frac{\partial \ln s_i^L}{\partial \ln w_g} = (1 - s_i^L) \cdot (1 - \lambda) + \sum_{g'} \frac{\omega_i^{g'}}{\omega_i^g} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}},$$

which implies that

$$\sigma_{gi}^{L} = \lambda - \frac{1}{1-s_i^L} \cdot \sum_{g'} \frac{\omega_i^{g'}}{\omega_i^g} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}},$$

and

$$(1-s_i^L)\cdot(\lambda-\sigma_{gi}^L) = \sum_{g'}\sum \frac{\omega_i^{g'}}{\omega_i^g} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}}. \tag{A28}$$

Consider a uniform change in the cost per efficiency unit of capital $d\ln(R_i/A_{ki})$ on the labor share of industry i. The effect of this change in the allocation of tasks is the same as a uniform reduction in wages of $d\ln(R_i/A_{ki})$. Moreover, the effect of $d\ln(R_i/A_{ki})$ on the denominator of the labor share is just its direct effect—an application of the envelope theorem. Thus, we get

$$\begin{array}{l}\text{contribution of}\\ \text{price of capital}\end{array} = -\sum_{g\in\mathcal{G}}\sum_{g'} \omega_i^{g'} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_g} \cdot d\ln(R_i/A_{ki}) - s_i^k \cdot (1-\lambda)\cdot d\ln(R_i/A_{ki}),$$

where the first term captures the effect of task changes on the numerator and the second term the effect on the denominator of the labor share expression in equation (A27). Using equation (A28), we can rewrite this expression as

$$\begin{array}{l}\text{contribution of}\\ \text{price of capital}\end{array} = -\sum_{g\in\mathcal{G}} \omega_i^g \cdot (1-s_i^L)\cdot(\lambda-\sigma_{gi}^L)\cdot d\ln(R_i/A_{ki}) - s_i^k \cdot (1-\lambda)\cdot d\ln(R_i/A_{ki}).$$

Finally, using the definition of σ_i^K, we can rewrite this as

$$\begin{array}{l}\text{contribution of}\\ \text{price of capital}\end{array} = -(1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln(R_i/A_{ki}),$$

which completes the proof of the proposition ∎

We are now in a position to derive the measures of task displacement used in the text. We start with the case with no ripple effects, no change in markups, and $\lambda = 1$, which gives the baseline measure in equation (12).

PROPOSITION A8 *Suppose that Assumptions 1 and 2 hold. Suppose also that $\lambda = 1$ and there are no markups. Then $\sigma_i^L = \sigma_i^K = 1$ and task displacement can be computed as*

$$d\ln\Gamma_g^{disp} = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R}\cdot(-d\ln s_i^L) \quad \text{and} \quad d\ln\Gamma_{gi}^{disp} = \frac{\omega_{gi}^R}{\omega_i^R}\cdot(-d\ln s_i^L).$$

Moreover, total task displacement taking place in industry i is given by

$$d\ln\Gamma_i^{disp}=\sum_{i\in\mathcal{I}}\omega_i^g\cdot d\ln\Gamma_{gi}^{disp}=(-d\ln s_i^L).$$

PROOF. Proposition A7 implies that

$$d\ln s_i^L=-\omega_i^R\cdot\vartheta_i\Rightarrow\vartheta_i=\frac{(-d\ln s_i^L)}{\omega_i^R}.$$

Moreover, by definition

$$d\ln\Gamma_{gi}^{\text{disp}}=\frac{\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{T}_{gi}}\psi_g(x)^{\lambda-1}dx}=\frac{\int_{\mathcal{R}_{gi}}\psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{T}_{gi}}\psi_g(x)^{\lambda-1}dx}\cdot\frac{\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{R}_{gi}}\psi_g(x)^{\lambda-1}dx}=\omega_{gi}^R\cdot\vartheta_i=\frac{\omega_{gi}^R}{\omega_i^R}\cdot(-d\ln s_i^L).$$

and task displacement for worker groups is given by

$$d\ln\Gamma_g^{\text{disp}}=\sum_{i\in\mathcal{I}}\omega_g^i\cdot d\ln\Gamma_{gi}^{\text{disp}}=\sum_{i\in\mathcal{I}}\omega_g^i\frac{\omega_{gi}^R}{\omega_i^R}\cdot(-d\ln s_i^L).$$

■

The next Proposition derives the more general measure in footnote 15.

PROPOSITION A9 *Suppose that Assumptions 1 and 2 hold. Then, $\sigma_i^L=\sigma_i^K=\lambda$. In the absence of productivity deepening or factor-augmenting technologies affecting the labor share, task displacement can be computed as*

$$d\ln\Gamma_g^{disp}=\sum_{i\in\mathcal{I}}\omega_g^i\cdot\frac{\omega_{gi}^R}{\omega_i^R}\cdot\frac{-d\ln s_i^L-d\ln\mu_i+(1-s_i^L)\cdot(1-\lambda)\cdot(d\ln w_i-d\ln R_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}$$
$$d\ln\Gamma_{gi}^{disp}=\frac{\omega_{gi}^R}{\omega_i^R}\cdot\frac{-d\ln s_i^L-d\ln\mu_i+(1-s_i^L)\cdot(1-\lambda)\cdot(d\ln w_i-d\ln R_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.$$

Moreover, total task displacement taking place in industry i is given by

$$d\ln\Gamma_i^{disp}=\sum_{i\in\mathcal{I}}\omega_i^g\cdot d\ln\Gamma_{gi}^{disp}=\frac{-d\ln s_i^L-d\ln\mu_i+(1-s_i^L)\cdot(1-\lambda)\cdot(d\ln w_i-d\ln R_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.$$

PROOF. Proposition A7 implies that

$$d\ln s_i^L=-d\ln\mu_i-(1+(\lambda-1)\cdot s_i^L\cdot\pi_i)\cdot\omega_i^R\cdot\vartheta_i+(1-s_i^L)\cdot(1-\lambda)\cdot(d\ln w_i-d\ln R_i),$$

which gives

$$\vartheta_i=\frac{-d\ln s_i^L-d\ln\mu_i+(1-s_i^L)\cdot(1-\lambda)\cdot(d\ln w_i-d\ln q_i)}{(1+(\lambda-1)\cdot s_i^L\cdot\pi_i)\cdot\omega_i^R}.$$

Moreover, following the same steps as in the proof of Proposition A8, we get

$$
\begin{aligned}
d\ln\Gamma_{gi}^{\text{disp}} &= \frac{\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{T}_{gi}}\psi_g(x)^{\lambda-1}dx} \\
&= \frac{\int_{\mathcal{R}_{gi}}\psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{T}_{gi}}\psi_g(x)^{\lambda-1}dx}\cdot\frac{\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{R}_{gi}}\psi_g(x)^{\lambda-1}dx} \\
&= \omega_{gi}^R\cdot\vartheta_i \\
&= \frac{\omega_{gi}^R}{\omega_i^R}\cdot\frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\lambda)\cdot(d\ln w_i - d\ln R_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.
\end{aligned}
$$

and task displacement for worker groups is given by

$$
d\ln\Gamma_g^{\text{disp}} = \sum_{i\in\mathcal{I}}\omega_g^i\cdot d\ln\Gamma_{gi}^{\text{disp}} = \sum_{i\in\mathcal{I}}\omega_g^i\cdot\frac{\omega_{gi}^R}{\omega_i^R}\cdot\frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\lambda)\cdot(d\ln w_i - d\ln R_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.
$$

■

Our final Proposition derives a version of our measure of task displacement that allows for ripple effects. Equation (16) corresponds to the special case of this formula when there are no changes in markups and $\sigma_i^L = \sigma_i^K$.

Proposition A10 *Suppose that Assumptions 2 holds. In the absence of productivity deepening or factor-augmenting technologies affecting the labor share, task displacement can be computed as*

$$
\begin{aligned}
d\ln\Gamma_g^{disp} &= \sum_{i\in\mathcal{I}}\omega_g^i\cdot\frac{\omega_{gi}^R}{\omega_i^R}\cdot\frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i - (1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln R_i}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i} \\
d\ln\Gamma_{gi}^{disp} &= \frac{\omega_{gi}^R}{\omega_i^R}\cdot\frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i - (1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln R_i}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.
\end{aligned}
$$

Moreover, total task displacement taking place in industry i is given by

$$
d\ln\Gamma_i^{disp} = \sum_{i\in\mathcal{I}}\omega_i^g\cdot d\ln\Gamma_{gi}^{disp} = \frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i - (1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln R_i}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.
$$

Proof. Proposition A7 implies that

$$
d\ln s_i^L = -d\ln\mu_i - (1+(\lambda-1)\cdot s_i^L\cdot\pi_i)\cdot\omega_i^R\cdot\vartheta_i + (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i - (1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln R_i,
$$

which gives

$$
\vartheta_i = \frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i - (1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln R_i}{(1+(\lambda-1)\cdot s_i^L\cdot\pi_i)\cdot\omega_i^R}.
$$

Following the same steps as in the proof of Proposition A8, we get

$$\begin{aligned}
d\ln\Gamma_{gi}^{\text{disp}} &= \frac{\int_{\mathcal{D}_{gi}} \psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1}dx} \\
&= \frac{\int_{\mathcal{R}_{gi}} \psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1}dx} \cdot \frac{\int_{\mathcal{D}_{gi}} \psi_g(x)^{\lambda-1}dx}{\int_{\mathcal{R}_{gi}} \psi_g(x)^{\lambda-1}dx} \\
&= \omega_{gi}^R \cdot \vartheta_i \\
&= \frac{\omega_{gi}^R}{\omega_i^R} \cdot \frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i - (1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln R_i}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.
\end{aligned}$$

and task displacement for worker groups is given by

$$\begin{aligned}
d\ln\Gamma_g^{\text{disp}} &= \sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln\Gamma_{gi}^{\text{disp}} \\
&= \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \frac{-d\ln s_i^L - d\ln\mu_i + (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i - (1-s_i^L)\cdot(1-\sigma_i^K)\cdot d\ln R_i}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}.
\end{aligned}$$

■

Empirical implementation and bounding exercise

The empirical implementation of our measures of task displacement in Propositions A8 and A9 is straightforward. However, the formulas in Proposition A10 depend on two elasticities of substitution, σ_i^K and σ_i^L, which may differ due to the fact that we have different types of workers, and that when wages rise in one industry, we may be capturing the substitution of different worker groups for capital in marginal tasks. When implementing these formulas, we will assume that $\sigma_i^K = \sigma_i^L$, and use empirical estimates of the elasticity of substitution between capital and labor at the industry level, σ_i, to discipline their common value. This is motivated by the fact that empirical estimates of the elasticity of substitution between capital and labor are also estimating some combination of the group-specific elasticities, σ_{gi}^L's.

In addition, when computing task displacement, we will use empirical estimates of $d\ln w_i$ and $d\ln R_i$ from the BLS, which account for changes in wages, the quality of workers, and quality-adjusted prices of capital used in an industry. We note also that, although our model has common wages for a given skill across industries, the expressions in Propositions A9 and A10 apply without modification to the case in which wages are industry-specific. In addition, our formula is not affected by factor-neutral improvements in TFP in industry i, since these do not affect an industry's labor share.

While our formulas incorporate the effects of changes in factor prices, they miss the contribution of general factor-augmenting technologies. Now we provide upper bounds on the effects of this type of technological change on our estimates of task displacement, which will reveal that this type of technological change tends to have a very small effect on our inferred task displacement measure.

We focus on our measures in Proposition A10 obtained for $\lambda = 0.5$ and σ_i ranging from 0.8 to 1.2 (these technologies do not affect our measures if $\sigma_i = 1$). In particular, for $\sigma_i < 1$, the contribution of factor-augmenting technologies to the change in the labor share is between $-s_i^K \cdot (1-\sigma_i) \cdot d\ln A_{\ell i}$ (where $d\ln A_{\ell i}$ is a weighted average of $d\ln A_{gi}$ across workers) and $s_i^K \cdot (1-\sigma_i) \cdot d\ln A_{ki}$. Moreover, assuming no technological regress, we have that the total increase in (gross output) TFP in industry i must exceed both $\tilde{s}_i^L \cdot d\ln A_{Li}$ and $\tilde{s}_i^K \cdot d\ln A_{ki}$, where now $\tilde{s}_i^L$ and $\tilde{s}_i^K$ denote the share of labor and capital in gross output (an application of Hulten's theorem). As a result, we can bound the contribution of factor-augmenting technologies to lie in the interval

$$\left[-\frac{s_i^K}{\tilde{s}_i^L} \cdot (1-\sigma_i) \cdot d\ln \mathrm{TFP}_i, \frac{s_i^K}{\tilde{s}_i^K} \cdot (1-\sigma_i) \cdot d\ln \mathrm{TFP}_i\right].$$

Likewise, for $\sigma_i > 1$, the contribution of factor-augmenting technologies to the change in the labor share is between $-s_i^K \cdot (\sigma_i - 1) \cdot d\ln A_{ki}$ and $s_i^K \cdot (\sigma_i - 1) \cdot d\ln A_{\ell i}$, which we can bound by

$$\left[-\frac{s_i^K}{\tilde{s}_i^K} \cdot (\sigma_i - 1) \cdot d\ln \mathrm{TFP}_i, \frac{s_i^K}{\tilde{s}_i^L} \cdot (\sigma_i - 1) \cdot d\ln \mathrm{TFP}_i\right].$$

Figure A4 presents our measures of task displacement across industries and worker groups using equation (16) for $\sigma_i = 0.8$ and for $\sigma_i = 1.2$, depicting the bounds on the contribution of factor-augmenting technologies using the whiskers. When constructing these bounds, we assume that industries with declining TFP between 1987 and 2016, experienced no factor-augmenting improvements. Except for a handful of IT-intensive industries with vast increases in TFP (electronics, computers, and communications), our bounds exclude anything other than very small effects of factor-augmenting technologies on the decline in labor shares and our task displacement measure. This is because these technologies have limited distributional effects but generate large TFP gains. Through the lens of our model, and given the pervasive lack of productivity growth observed across industries, these technologies cannot play a key role in explaining the decline in the labor share.

Appendix F Data Appendix

Industry data: Our main source of industry-level data are the BEA Integrated industry accounts for 1987–2016. These data contain information on industry value added, labor compensation, industry prices and factor prices for 61 NAICS industries. We aggregated these data to the 49 industries used in our analysis, which we could track consistently both in the BEA and the worker-level data from the 1980 US Census. Finally, when computing changes in industry's labor shares, we winsorized labor shares in value added at 20% to reduce noise in our measures of task displacement coming from industries with low and volatile labor shares.

Besides the BEA data, we also used data from the BLS multifactor productivity tables for 1987–2016. These data are also available for 61 NAICS industries which we aggregated to the 49 industries used in our analysis.

We complement the industry data with proxies for the adoption of automation technologies across industries. First, we use the measure of *adjusted penetration of robots* from Acemoglu and Restrepo (2020), which is available for 1993–2014. These measure is constructed using data from the International Federation of Robotics, and is defined for each industry i as

$$\text{APR}_i = \frac{1}{5}\sum_{e=1}^{5}\left[\frac{\text{robots}_{e,i,2014} - \text{robots}_{e,i,1993}}{\ell_{e,i,1993}} - \text{output growth}_{e,i,2004-1993} \cdot \frac{\text{robots}_{e,i,1993}}{\ell_{e,i,1993}}\right],$$

where the right-hand side is computed as an average among five European countries, e, leading the US in the adoption of industrial robots (see Acemoglu and Restrepo, 2020, for details). These measure is available for all of our manufacturing industries, but has a coarser resolution outside of manufacturing.

Finally, we also use the share of software and specialized machinery in value added from the BLS multifactor productivity tables. In particular, we use the detailed capital tables from the BLS, which provide the compensation for different assets (computed as the user cost of each asset multiplied by its stock). For software, we add custom-made software or software developed in house—which are more relevant for automation than pre-packaged software like Stata or Word. For specialized machinery, we add metalworking machinery (typically numerically controlled machines capable of automatically producing a pre-specified task), agricultural machinery other than tractors, specialized machinery used in the service sector, specialized machinery used in industry applications (which should also include industrial robots), construction machinery, and material handling equipment used in industrial applications. Although not all software and dedicated machinery necessarily involve the automation of tasks previously performed by labor, the component of these measures associated with significant declines in the labor share helps isolate the automation component.

For offshoring, we use a measure from Feenstra and Hanson (1999) recently updated by Wright (2014) for 1990–2007. This measure captures changes in the share of imported intermediates across industries, and is only available for the manufacturing sector. When using it, we set it to zero outside of manufacturing.

When using these proxies of automation and offshoring, we rescale the coefficients on our reduced-form estimates by the first-stage relationship between each of these variables and task displacement at the industry level reported in Panel B of Table A1.

Turning to our proxies for changes in market structure, we use changes in sales concentration and several estimates of markups aggregated at the industry level. Our data for sales concentration comes from the Census Statistics of U.S. Businesses (SUSB) and is only available for 1997–2016. Using these data, we computed the tail index of the sales distribution for all the industries in our sample. The SUSB data can also be used to compute tail indices for the employment distribution going back to 1992. Using this alternative proxy of concentration available over a longer period didn't alter our findings.

For markups, we provide three different estimates.

First, we compute markups in a given industry using an accounting approach, which measures markups by the ratio of output to costs:

$$\mu_i = \frac{\text{gross output}_i}{R_i K_i + \text{Variable inputs}_i}.$$

This approach requires constant returns to scale and assumes there are no adjustment costs. This approach also requires a measurement of the unobserved user cost of capital R_i. We follow Karabarbounis and Neiman (2018) and compute R_i using a user-cost formula accounting for changes in taxes. We do this using data on capital stocks and prices from NIPA's Fixed Asset Tables. We also set the internal rate of return to 6% and keep it constant over time. As shown in Karabarbounis and Neiman (2013), the alternative approach of using bond rates to proxy for firms' and investors' internal rates of return yields large, volatile, and unreasonable estimates of aggregate markups. More relevant for our exercise is the fact that different values of the internal rate of return do not affect the variation in relative trends in markups across industries.

Second, we compute the change in markups by looking at the percent decline in the share of materials in gross output. That is:

$$\Delta \ln \mu_i = -\Delta \ln \text{share materials}_i.$$

This approach assumes that the share of materials in total costs is constant, and that a decline in the share of materials thus reveals higher markups. We use the BEA data described above to measure the share of materials in gross output. Outside of manufacturing, we focus on the share of materials and intermediate services, since raw materials play a smaller role in the service sector.

Finally, we compute markups using a production function approach as in De Loecker, Eeckhout and Unger (2020). In this approach, markups are computed for firms in industry i as

$$\mu_{i,f} = \frac{\text{elasticity variable inputs}_{i,f}}{\text{share variable inputs}_{i,f}}.$$

The share of variable inputs is typically observed from the data while the elasticity of output to variable input has to be estimated. Following De Loecker, Eeckhout and Unger (2020), we estimate these markups using Compustat data, but deviate from their approach in two important aspects. First, when aggregating markups at the industry level, we use an harmonic sales-weighted mean, rather than a sales-weighted mean. As shown in Hubmer and Restrepo (2021), this is the relevant notion of an aggregate markup that matters for industry factor shares. Second, and following Hubmer and Restrepo (2021), we allow the production function to vary flexibly over time, by firm, and by firm-size quintile within each industry, which accounts for the fact that the adoption of automation technologies typically concentrates among large firms (see also Acemoglu, Lelarge and Restrepo, 2020).

Census data We use the 1980 US Census to measure group-level outcomes and specialization patterns by industry and routine occupations. In addition, we also use the 2000 US Census to measure group-level outcomes for the year 2000. Finally, and to maximize our sample size, we use data from the pooled 2014–2018 American Community Survey to measure outcomes around the year 2016.

To measure real hourly wages we follow standard cleaning procedures (see for example Acemoglu and Autor, 2011). First, the wage data are top coded. To deal with this, we replace top coded observations by 1.5 times the value of the top code. Second, we convert hourly wages to 2007 dollars using the Personal Consumption Expenditure deflator from the BEA. Third, we winsorized real hourly wages from below at 2 dollars per years and from above at 180 dollars per year.

Regional variation Our estimates in Section 4.7 also exploit variation in specialization patterns across regions. In particular, we use two different groupings. First, we look at workers in 300 different demographic groups across 9 Census regions. To maintain a reasonable cell size, in this exercise we define demographic groups by gender, education, age (now defined by 16–30 years of age, 31–50 years, and 51–65 years) and race. Second, we look at workers in 54 different demographic groups across 722 commuting zones (see David, Dorn and Hanson, 2013, for a description of commuting zones). To maintain a reasonable cell size, in this exercise we define demographic groups by gender, education (completed college and less than completed college), age (now defined by 16–30 years of age, 31–50 years, and 51–65 years), and race (Whites, Blacks, and others).

Routine occupations Following Acemoglu and Autor (2011), we use $ONET$ to define routine jobs. In particular, for each Census occupation o, we compute a routine index given by

$$\text{routine index}_o = \text{routine manual input}_o + \text{routine cognitive input}_o - \text{average task input}_o.$$

Here, $\text{routine manual input}_o$ denotes the intensity of routine manual tasks in occupation o, the term $\text{routine cognitive input}_o$ denotes the intensity of routine cognitive tasks, and the term $\text{average task input}_o$ denotes the average task intensity (capturing the extent to which workers also conduct manual and analytical tasks). As is common practice in the literature, we define an occupation as routine if it is the top 33% of the routine index distribution.

Table A15 explores the robustness of our results to using different thresholds and alternative formulations of the routine index. In particular, in Panel A we define an occupation as routine if it is the top 40% of the routine index distribution, and In Panel B we use an alternative index of the form

$$\text{routine index}_o = \text{routine manual input}_o + \text{routine cognitive input}_o.$$

Panels C–E probed the robustness of our results to using Webb (2020) indices of suitability for automation via robots and software and a combination of both of them. These measures provide a ranking of occupations depending on their suitability for automation, and we define an occupation as routine if it lies in the top 33% of each measure.

Other covariates Table 5 uses additional covariates. These include industries exposure to rising Chinese imports for 1990–2011, which we obtained from Acemoglu et al. (2016); the decline in the unionization rates by industry, which we computed for 1984–2016 using union membership by industry from the CPS; and industry-level changes in the quantity of capital per worker and TFP from the BEA Integrated Industry Accounts.

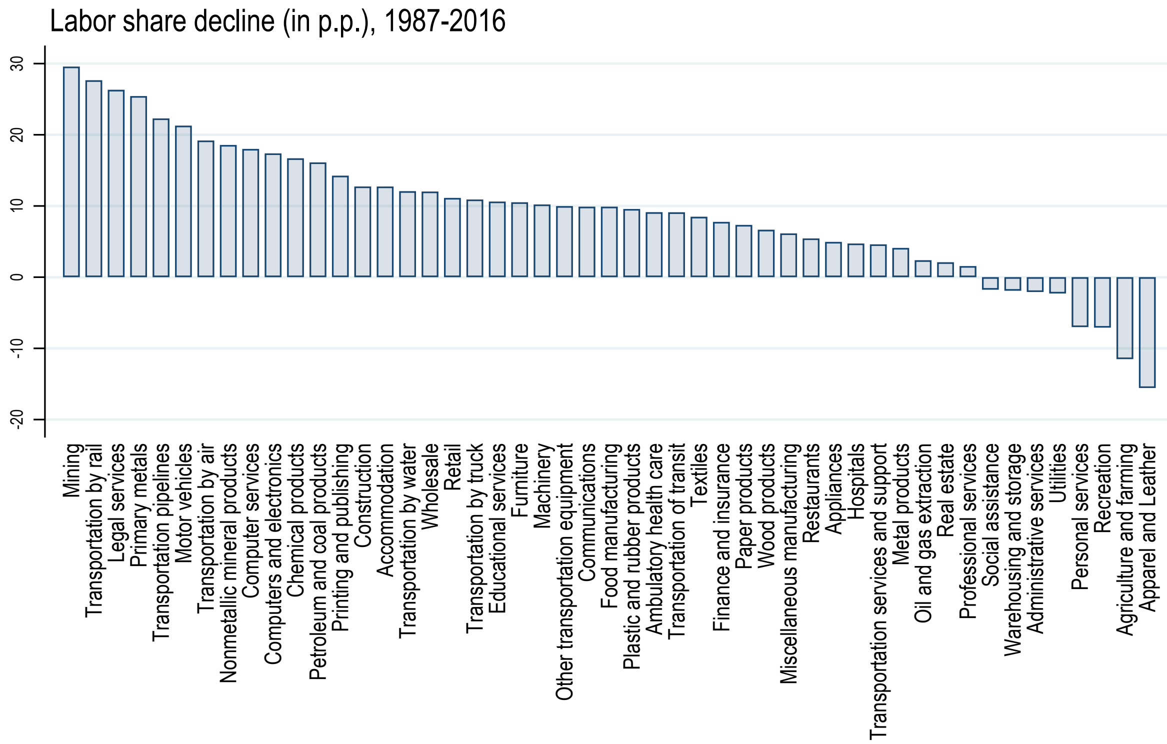


Figure A1: Labor share decline for 1987–2016 across industries from the 1987–2016 BEA Integrated Industry Accounts.

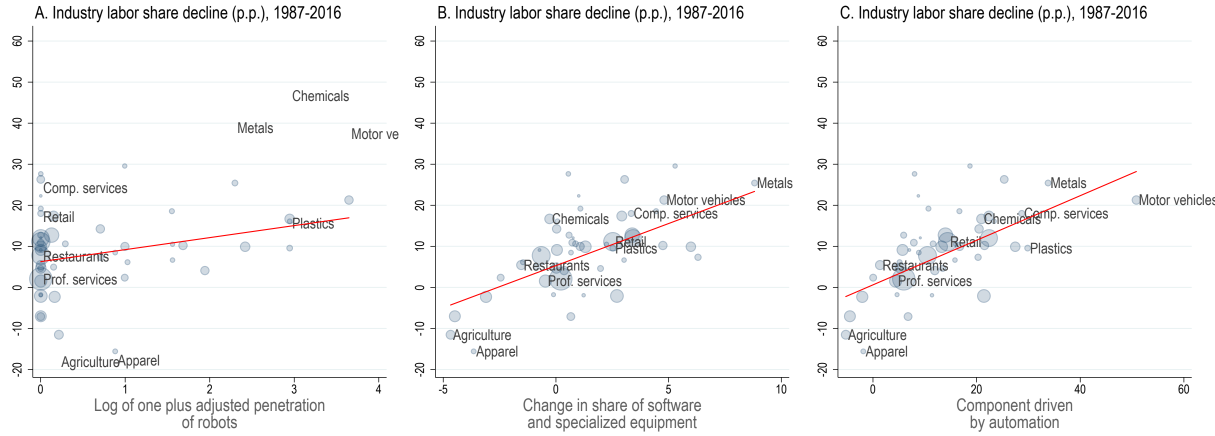


FIGURE A2: Relationship between automation technologies and labor share declines across industries. Note that the vertical axis provides the decline in industry's labor share from 1987 to 2016 (given by minus their change).

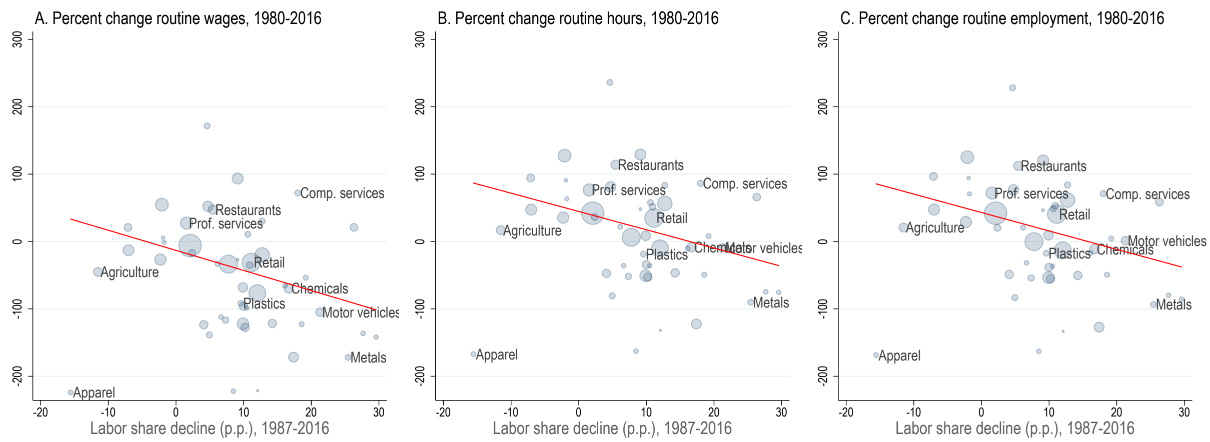
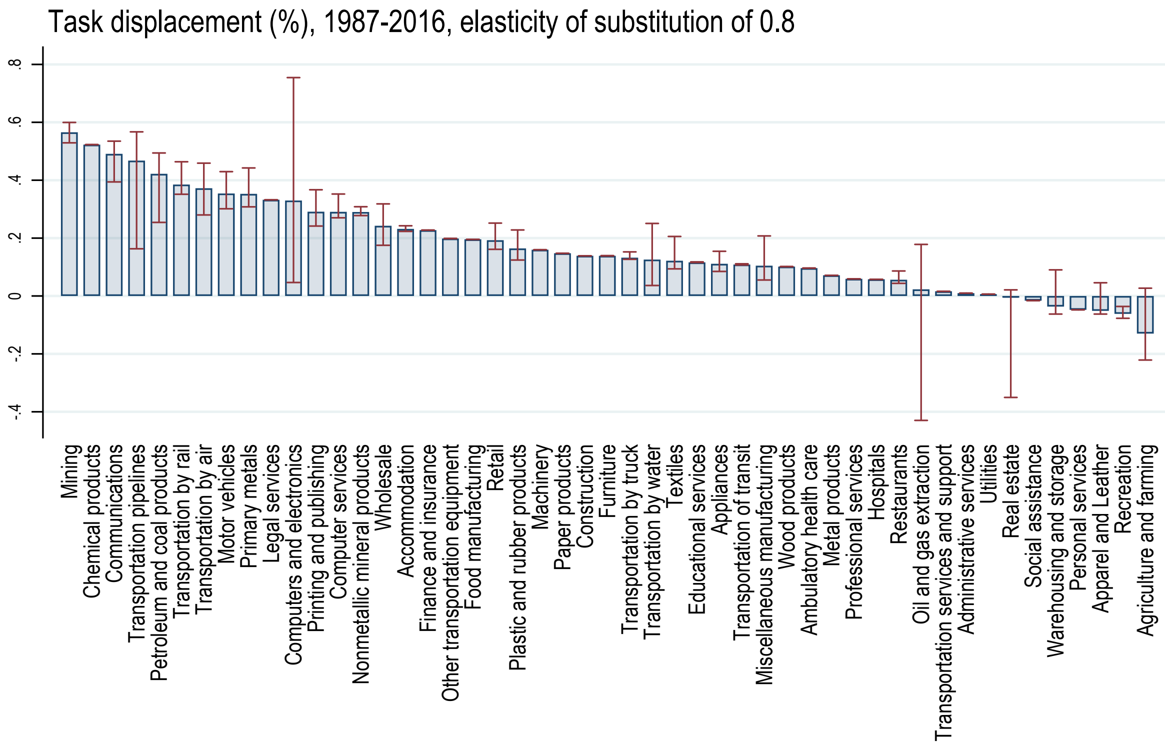


FIGURE A3: Relationship between labor share declines and reductions in the demand for routine jobs across industries. See text for variable definitions.



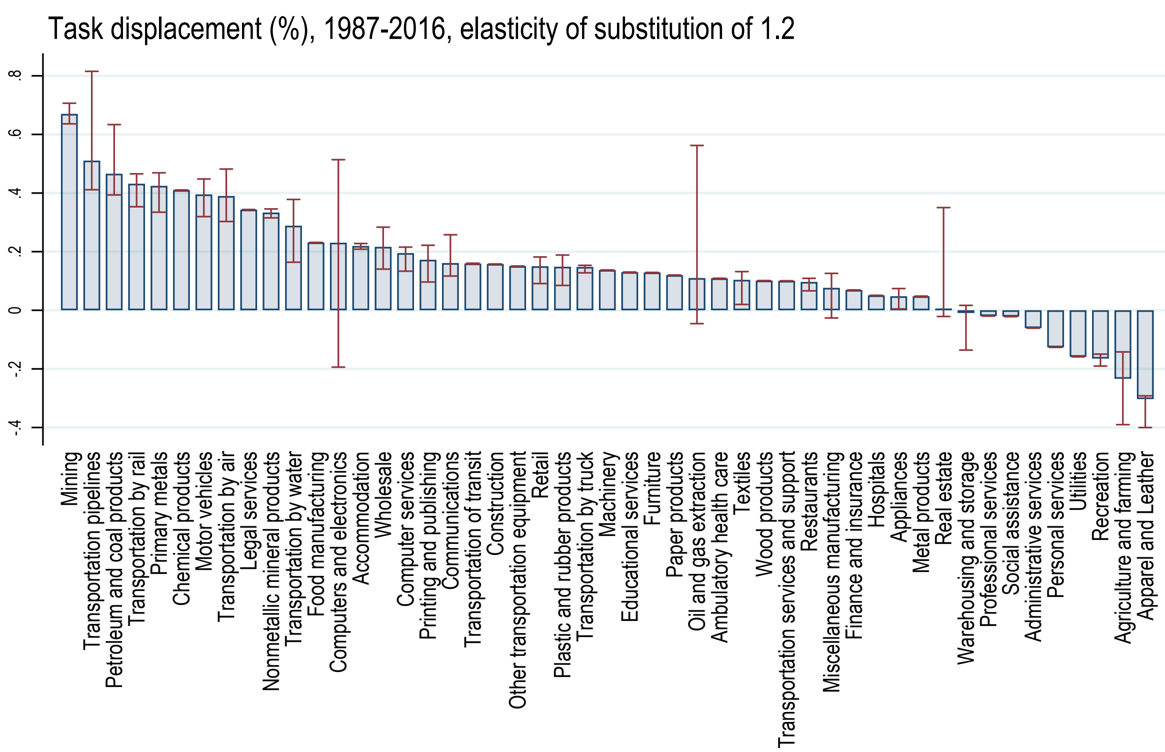


FIGURE A4: Bounds on measures of task displacement for $\sigma_i = 0.8$ (top panel) and $\sigma_i = 1.2$ (bottom panel) described in Appendix E.

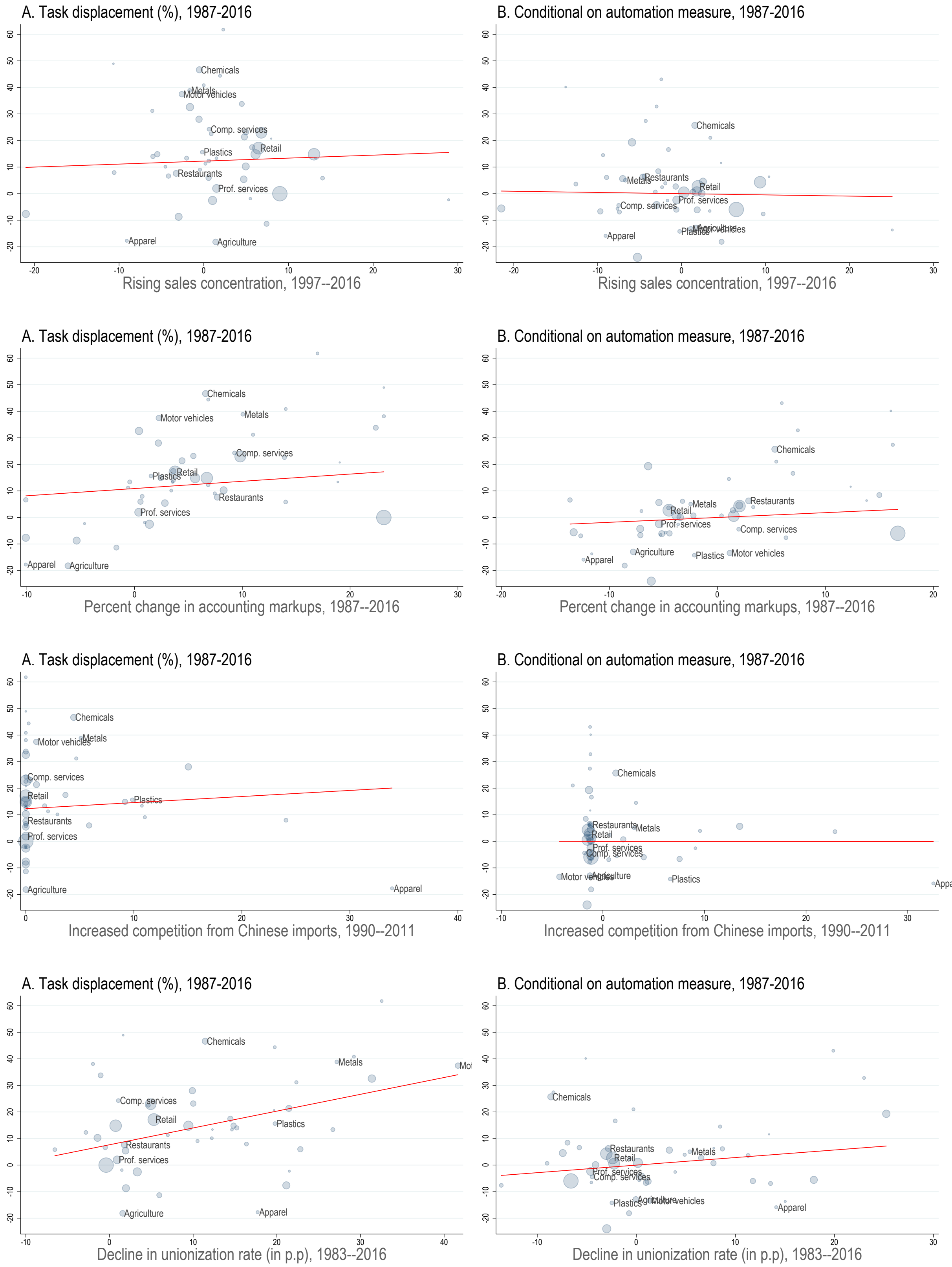


FIGURE A5: Relationship between task displacement 1987-2016 and sales concentration (first panel), rising markups (second panel), Chinese import penetration (third panel) and declining unionization (fourth panel). In all cases, Panel A provides the bivariate relationship and Panel B controls for our index of automation.

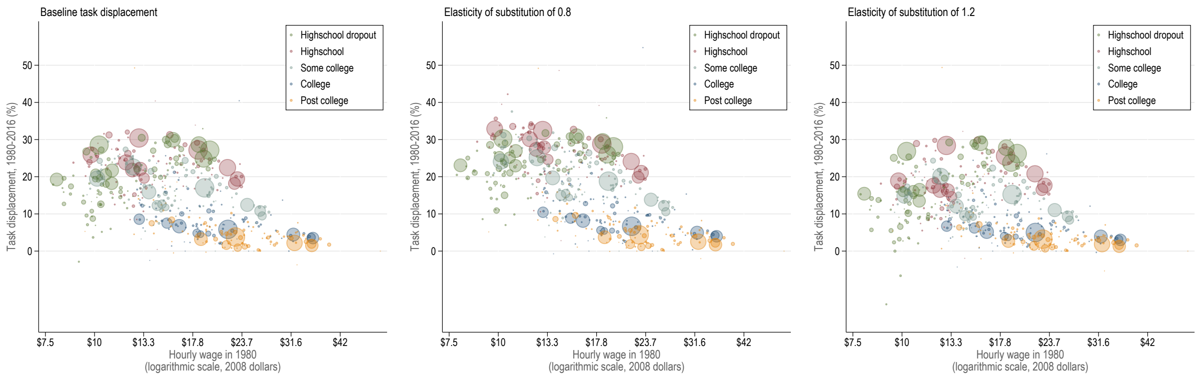


FIGURE A6: Task displacement across 500 demographic groups sorted by their hourly wage in 1980. The figure plots task displacement for each of the 500 demographic groups used in our analysis against their baseline hourly wage in 1980. Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. The left panel uses our baseline measure of task displacement in equation (12). The middle and right panels use the CES version in footnote 15 for $\lambda = 0.8$ and $\lambda = 1.2$ respectively.

Table A1: Determinants of task displacement and labor share declines across industries, 1987–2016.

	Dependent variable: task displacement and labor share declines, 1987–2016							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Labor share decline, 1987–2016							
Adjusted penetration of robots	0.582		0.341	0.323	0.340	0.388	0.345	0.307
	(0.103)		(0.122)	(0.115)	(0.125)	(0.121)	(0.123)	(0.157)
Change in share of specialized machinery		1.940	1.655	1.629	1.659	1.484	1.654	1.611
		(0.301)	(0.330)	(0.340)	(0.354)	(0.365)	(0.333)	(0.340)
Change in share of software	3.157	3.072	3.489	3.323	3.501	3.419	3.493	3.489
	(1.206)	(1.247)	(1.206)	(1.274)	(1.345)	(1.262)	(1.231)	(1.210)
Change in share of imported intermediates				0.496				
				(0.295)				
Change tail index of revenue concentration					-0.008			
					(0.112)			
Percent change in accounting markups						0.174		
						(0.180)		
Chinese imports penetration							-0.027	
							(0.170)	
Decline in unionization rate								0.045
								(0.084)
F-stat technology variables	15.88	21.21	19.07	17.41	18.41	15.85	17.88	11.25
Share variance explained by technology	0.27	0.45	0.50	0.49	0.51	0.49	0.51	0.49
R-squared	0.27	0.45	0.50	0.51	0.51	0.54	0.51	0.51
Observations	49	49	49	49	49	49	49	49
	Panel B: Task displacement, 1987–2016							
Adjusted penetration of robots	1.298		0.967	0.936	0.957	1.016	0.967	0.745
	(0.353)		(0.414)	(0.398)	(0.425)	(0.420)	(0.419)	(0.533)
Change in share of specialized machinery		3.089	2.282	2.238	2.307	2.104	2.282	2.001
		(0.502)	(0.579)	(0.599)	(0.638)	(0.659)	(0.585)	(0.657)
Change in share of software	5.943	5.222	6.401	6.124	6.474	6.328	6.402	6.403
	(1.956)	(2.176)	(1.925)	(2.038)	(2.195)	(2.073)	(1.957)	(1.881)
Change in share of imported intermediates				0.829				
				(0.559)				
Change tail index of revenue concentration					-0.046			
					(0.253)			
Pecrent change in accounting markups						0.182		
						(0.327)		
Chinese imports penetration							-0.003	
							(0.244)	
Decline in unionization rate								0.284
								(0.252)
F-stat technology variables	9.35	19.10	15.27	13.50	13.51	11.08	14.65	6.52
Share variance explained by technology	0.35	0.35	0.48	0.46	0.48	0.47	0.48	0.42
R-squared	0.35	0.35	0.48	0.49	0.48	0.49	0.48	0.50
Observations	49	49	49	49	49	49	49	49

Notes: This table presents estimates of the relationship between automation technologies, offshoring, and changes in market structure (proxied by markups or rising sales concentration) on task displacement across the 49 industries in our analysis. In Panel A, the dependent variable is the decline in the labor share from 1987–2016. In Panel B, the dependent variable is the task displacement measure from equation (12) computed at the industry level (or equivalently, the percent decline in the labor share). All regressions are weighted by the share of industry value added in 1987. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A2: Relationship between task displacement and the decline of routine jobs across industries.

Dependent variable:	OLS Estimates			IV Estimates		
	Change in log wages in routine jobs 1980–2016	Change in log hours in routine jobs 1980–2016	Change in log employment in routine jobs 1980–2016	Change in log wages in routine jobs 1980–2016	Change in log hours in routine jobs 1980–2016	Change in log employment in routine jobs 1980–2016
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Labor share declines, 1987–2016						
Labor share decline	-2.981	-2.715	-2.735	-4.427	-3.275	-3.135
	(1.187)	(1.152)	(1.150)	(1.471)	(1.292)	(1.288)
R-squared	0.12	0.12	0.12	0.09	0.11	0.12
First-stage F				32.92	32.92	32.92
Observations	48	48	48	48	48	48
Panel B: Task displacement, 1987–2016						
Task displacement	-2.113	-1.910	-1.931	-2.403	-1.778	-1.702
	(0.537)	(0.518)	(0.517)	(0.744)	(0.673)	(0.674)
R-squared	0.21	0.20	0.20	0.20	0.20	0.20
First-stage F				37.47	37.47	37.47
Observations	48	48	48	48	48	48
Panel C: Task displacement with elasticity of substitution 0.8, 1987–2016						
Task displacement	-2.250	-2.092	-2.129	-2.559	-1.893	-1.812
	(0.470)	(0.469)	(0.464)	(0.777)	(0.698)	(0.693)
R-squared	0.26	0.26	0.27	0.25	0.25	0.26
First-stage F				27.63	27.63	27.63
Observations	48	48	48	48	48	48
Panel D: Task displacement with elasticity of substitution 1.2, 1987–2016						
Task displacement	-1.641	-1.423	-1.426	-2.266	-1.676	-1.604
	(0.518)	(0.498)	(0.501)	(0.732)	(0.660)	(0.664)
R-squared	0.14	0.12	0.12	0.12	0.11	0.12
First-stage F				42.39	42.39	42.39
Observations	48	48	48	48	48	48

Notes: This table presents estimates of the relationship between task displacement and the demand for routine jobs across industries (Transportation pipelines are excluded due to lack of ACS data). The dependent variable is indicated at the column headers. Columns 1–3 provide OLS estimates, and columns 4–6 instrument task displacement (or the decline in the labor share) using our index of automation. In Panel A, the explanatory variable is the decline in the labor share from 1987–2016. In Panel B, the explanatory variable is the task displacement measure from equation (12) computed at the industry level (or equivalently, the percent decline in the labor share). In Panel C, the explanatory variable is the task displacement measure from footnote 15 for $\lambda = 0.8$ at the industry level. In Panel D, the explanatory variable is the task displacement measure from footnote 15 for $\lambda = 1.2$ at the industry level. All regressions are weighted by the share of industry value added in 1987. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A3: Summary statistics for demographic groups by quintiles of task displacement.

Quintile	N	Task displacement	Labor-market outcomes: Wage change 1980–2016	Labor-market outcomes: Wage change 1980–2007	Labor-market outcomes: Employment to population ratio change 1980–2016	Labor-market outcomes: Hourly wage 1980	Educational levels: Completed high-school	Educational levels: Some college	Educational levels: Completed college	Educational levels: Post-college	Share male
1—Lowest	191	4.8%	26.5%	24.2%	0.00 pp	$26.9	0.0%	12.2%	42.1%	44.8%	80.0%
2	141	15.5%	5.9%	7.1%	-0.80 pp	$18.3	17.5%	69.2%	1.8%	0.1%	61.8%
3	63	21.0%	3.1%	3.6%	-3.71 pp	$17.3	73.0%	13.2%	0.2%	0.0%	55.5%
4	69	24.9%	-5.1%	-3.4%	-8.72 pp	$15.1	36.9%	19.4%	0.0%	0.0%	66.3%
5—Highest	36	28.9%	-12.0%	-8.5%	-16.23 pp	$15.7	61.2%	1.2%	0.0%	0.0%	99.3%
All	500	16.8%	7.2%	7.6%	-4.80 pp	$19.9	32.8%	22.3%	13.4%	13.9%	73.0%

Notes: This table presents summary statistics for the 500 demographic groups used in our analysis. These groups are defined by gender, education, age, race, and native/immigrant status. The table breaks down these groups by quintiles of exposure to task displacement and provides summary statistics for groups in each quintile and for all groups pooled together. See the main text and Appendix F for definitions and data sources.

Table A4: Task displacement and real wage declines, 1980–2016.

	Dependent variables: Change in wages and wage declines, 1980–2016			
	(1)	(2)	(3)	(4)
	Panel A. Dummy for declining real wages 1980–2016			
Task displacement	4.071	3.691	4.164	6.586
	(0.265)	(0.639)	(1.062)	(1.614)
Industry shifters		-0.290	-0.495	-0.317
		(0.383)	(0.641)	(0.789)
Exposure to industry labor share decline				-2.880
				(2.499)
Relative specialization in routine jobs				-0.446
				(0.266)
Share variance explained by task displacement	0.48	0.44	0.49	0.78
R-squared	0.48	0.49	0.65	0.66
Observations	500	500	500	500
	Panel B. Real wage declines, 1980–2016			
Task displacement	-0.445	-0.418	-0.647	-1.149
	(0.072)	(0.080)	(0.074)	(0.166)
Industry shifters		0.021	0.272	0.185
		(0.025)	(0.077)	(0.069)
Exposure to industry labor share decline				0.789
				(0.208)
Relative specialization in routine jobs				0.087
				(0.023)
Share variance explained by task displacement	0.50	0.47	0.73	1.30
R-squared	0.50	0.51	0.78	0.80
Observations	500	500	500	500
Other covariates:				
Manufacturing share, and education and gender dummies			✓	✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. In Panel A, the dependent variable is a dummy for real wage declines from 1980 to 2016. In Panel B, the dependent variable is given by the negative component of real wage changes from 1980 to 2016, defined by the minimum of the observed wage change and zero. Besides the covariates reported in the table, columns 3 and 4 control for baseline wage shares in manufacturing and education and gender dummies. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A5: Task displacement vs. SBTC—controlling for changes in relative supply, 1980-2016.

	Dependent variable: Change in real wages 1980–2016					
	SBTC by education level			Allowing for SBTC by wage level		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: women	0.193	0.094	0.099	0.254	0.159	0.175
	(0.029)	(0.020)	(0.019)	(0.028)	(0.026)	(0.028)
Education: no high school	-0.098	-0.041	-0.044	0.039	0.014	0.018
	(0.076)	(0.050)	(0.051)	(0.034)	(0.033)	(0.032)
Education: some college	0.128	-0.066	-0.056	0.035	-0.052	-0.038
	(0.063)	(0.034)	(0.036)	(0.025)	(0.030)	(0.031)
Education: full college	0.375	-0.027	-0.008	0.192	0.006	0.037
	(0.084)	(0.054)	(0.055)	(0.036)	(0.049)	(0.049)
Education: more than college	0.499	0.026	0.049	0.292	0.070	0.107
	(0.067)	(0.079)	(0.076)	(0.047)	(0.067)	(0.063)
Log of hourly wage in 1980				0.254	0.137	0.156
				(0.055)	(0.049)	(0.053)
Change in supply	-0.104	-0.060	-0.062	-0.014	-0.026	-0.024
	(0.062)	(0.035)	(0.036)	(0.024)	(0.023)	(0.023)
Task displacement		-1.718	-1.634		-1.152	-0.962
		(0.312)	(0.297)		(0.208)	(0.201)
Share variance explained by:						
- educational dummies	0.75	0.04	0.08	0.39	0.08	0.13
- baseline wage				0.16	0.09	0.10
- supply changes	-0.28	-0.16	-0.17	-0.04	-0.07	-0.06
- task displacement		0.72	0.69		0.48	0.40
R-squared	0.43	0.75	0.74	0.80	0.83	0.83
First-stage F	9.98	18.73	2.96	34.42	34.96	5.82
Observations	493	493	493	493	493	493
Other covariates:						
Industry shifters and manufacturing share	✓	✓	✓	✓	✓	✓

Notes: This table presents estimates of the relationship between task displacement, changes in labor supply, and different proxies of skill-biased technical change and the change in real wages across 500 demographic groups. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. In all specifications, we measure changes in labor supply by the change in hours worked from 1980 to 2016, and instrument it using the predetermined trend in hours for 1970–1980. In addition, in columns 3 and 6 we also instrument task displacement with our index of automation. Besides the covariates reported in the table, all specifications control for industry shifters and baseline wage shares in manufacturing. The bottom rows of the table report the share of variance explained by task displacement and the different proxies of skill biased technical change. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A6: Task displacement and hours per worker and unemployment rates, 1980-2016.

	Dependent variable: Labor market outcomes 1980–2016					
	OLS Estimates			IV Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Unemployment rate					
Task displacement	0.113	0.171	0.024	0.120	0.183	0.018
	(0.019)	(0.044)	(0.097)	(0.021)	(0.049)	(0.107)
Share variance explained by:						
- task displacement	0.18	0.27	0.04	0.19	0.29	0.03
- educational dummies		0.00	-0.01		-0.00	-0.02
R-squared	0.18	0.28	0.29	0.18	0.28	0.29
First-stage F				3246.45	785.80	156.33
Observations	500	500	500	500	500	500
	Panel B. log hours per worker					
Task displacement	-0.862	-0.581	0.790	-0.896	-0.611	0.693
	(0.180)	(0.292)	(0.619)	(0.186)	(0.299)	(0.665)
Share variance explained by:						
- task displacement	0.31	0.21	-0.28	0.32	0.22	-0.25
- educational dummies		0.13	-0.01		0.11	-0.03
R-squared	0.31	0.47	0.50	0.31	0.47	0.50
First-stage F				3246.45	785.80	156.33
Observations	500	500	500	500	500	500
Covariates:						
Industry shifters, manufacturing share, education and gender dummies		✓	✓		✓	✓
Exposure to labor share declines and relative specialization in routine jobs			✓			✓

Notes: This table presents estimates of the relationship between task displacement and labor market outcomes for 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. In Panel A, the dependent variable is the change in the unemployment rate from 1980 to 2016. In Panel B, the dependent variable is the percent change in hours per worker from 1980 to 2016. Columns 1–3 report OLS estimates. Columns 4–6 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table, columns 2–3 and 5–6 control for industry shifters, baseline wage shares in manufacturing, and education and gender dummies. Columns 3 and 6 control for relative specialization in routine jobs and groups' exposure to industry labor share declines. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A7: Task displacement and changes in real hourly wages—controlling for other trends and for exposure to industry labor share declines and relative specialization in routine jobs.

	Dependent variable: Change in wages 1980–2016							
	OLS estimates				IV estimates			
	Chinese imports' competition	Decline in unionization rates	Rising K/L ratio by industry	Rising TFP by industry	Chinese imports' competition	Decline in unionization rates	Rising K/L ratio by industry	Rising TFP by industry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Controlling for main effect of other shocks							
Task displacement	-1.601	-1.816	-1.767	-1.813	-1.483	-1.753	-1.672	-1.763
	(0.524)	(0.467)	(0.574)	(0.476)	(0.669)	(0.520)	(0.640)	(0.586)
Effect of other shocks by industry	0.003	1.136	-0.028	-0.164	0.006	1.065	-0.017	-0.149
	(0.019)	(1.532)	(0.094)	(0.380)	(0.022)	(1.560)	(0.097)	(0.411)
Share variance explained by task displacement	0.67	0.76	0.74	0.76	0.62	0.73	0.70	0.74
R-squared	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
First-stage F					206.62	277.15	210.06	187.47
Observations	500	500	500	500	500	500	500	500
	Panel B. Controlling for effects on workers in routine jobs							
Task displacement	-1.730	-2.388	-1.785	-1.726	-1.675	-2.447	-1.828	-1.695
	(0.459)	(0.715)	(0.444)	(0.438)	(0.512)	(0.905)	(0.478)	(0.496)
Effect of other shocks on routine jobs	-0.008	1.013	-0.127	-0.144	-0.007	1.060	-0.128	-0.141
	(0.012)	(0.854)	(0.064)	(0.247)	(0.012)	(0.983)	(0.063)	(0.252)
Share variance explained by task displacement	0.73	1.00	0.75	0.72	0.70	1.03	0.77	0.71
R-squared	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
First-stage F					291.82	90.39	272.01	268.17
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups controlling for trade in final goods, declining unionization rates, other forms of capital investments, and other technologies leading to productivity growth in an industry. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. In Panel A, we control for the main effect of these shocks on workers in exposed industries. In Panel B, we allow these shocks to have a differential impact on workers in routine jobs in exposed industries. Columns 1–4 report OLS estimates. Columns 5–8 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table, all specifications control for industry shifters, baseline wage share in manufacturing, education and gender dummies, relative specialization in routine jobs, and groups' exposure to industry labor share declines. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A8: Task displacement and changes in real hourly wages—controlling for differential effect of markups and concentration on routine jobs.

	Dependent variable: Change in wages 1980–2016							
	OLS estimates				IV estimates			
	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controlling for effects of markups and concentration on workers in routine jobs								
Task displacement	-1.200	-1.363	-1.290	-1.106	-1.152	-1.238	-1.249	-1.082
	(0.196)	(0.354)	(0.237)	(0.171)	(0.218)	(0.440)	(0.240)	(0.174)
Effects of rising markups or	-0.526	0.207	0.041	1.870	-0.603	-0.146	0.074	1.891
concentration on routine jobs	(0.798)	(1.354)	(0.221)	(0.535)	(0.815)	(1.551)	(0.217)	(0.523)
Share variance explained by:								
- task displacement	0.50	0.57	0.54	0.46	0.48	0.52	0.52	0.45
- markups/concetration	0.01	-0.02	0.00	-0.08	0.01	0.01	0.00	-0.08
R-squared	0.84	0.84	0.84	0.85	0.84	0.84	0.84	0.85
First-stage F					515	178	723	721
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-1.499	-1.363	-1.290	-1.106	-1.440	-1.238	-1.249	-1.082
	(0.238)	(0.354)	(0.237)	(0.171)	(0.270)	(0.440)	(0.240)	(0.174)
Effects of rising markups or	-1.101	-1.157	-1.249	0.764	-1.155	-1.384	-1.176	0.809
concentration on routine jobs	(0.745)	(1.064)	(0.419)	(0.609)	(0.757)	(1.169)	(0.419)	(0.593)
Share variance explained by:								
- task displacement	0.49	0.45	0.63	0.42	0.47	0.41	0.61	0.41
- markups/concetration	0.01	0.10	-0.08	-0.03	0.01	0.12	-0.08	-0.03
R-squared	0.84	0.84	0.84	0.85	0.84	0.84	0.84	0.85
First-stage F					348	178	723	721
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups controlling for changes in market structure and markups. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. In Panel A, we control for groups' relative specialization in routine jobs at industries with changes in market structure leading to higher markups. In column 1, we proxy changes in market structure by rising sales concentration in the industry. In columns 2–4, we directly control for changes in markups. These are computed as the ratio of revenue to costs in column 2, the inverse of the materials' share in gross output in column 3, and markups estimated using a production function approach as in De Loecker, Eeckhout and Unger (2020) in column 4. In Panel B, we also subtract the percent increase in markups from the percent decline in the labor share when computing our measure of task displacement (using the accounting markup in columns 1 and 5). Columns 1–4 report OLS estimates. Columns 5–8 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table, all specifications control for industry shifters, baseline wage shares in manufacturing, and education and gender dummies. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A9: Task displacement and changes in real hourly wages—controlling for changes in markups and concentrations and for exposure to industry labor share declines and relative specialization in routine jobs.

	Dependent variable: Change in wages 1980–2016							
	OLS estimates				IV estimates			
	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controlling for main effect of markups and concentration								
Task displacement	-1.389	-1.614	-2.074	-1.573	-1.374	-1.584	-2.131	-1.499
	(0.461)	(0.454)	(0.460)	(0.542)	(0.481)	(0.486)	(0.527)	(0.584)
Exposure to rising markups or concentration	1.969	0.721	-1.290	-0.404	1.984	0.749	-1.312	-0.468
	(1.556)	(1.754)	(0.552)	(1.159)	(1.485)	(1.766)	(0.576)	(1.163)
Share variance explained by:								
- task displacement	0.58	0.68	0.87	0.66	0.58	0.66	0.89	0.63
- markups/concetration	0.04	-0.01	-0.12	0.01	0.04	-0.01	-0.12	0.01
R-squared	0.84	0.84	0.85	0.84	0.84	0.84	0.85	0.84
First-stage F					326	385	252	214
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-1.216	-1.651	-1.244	-1.970	-1.722	-1.881	-1.378	-1.228
	(0.554)	(0.560)	(0.229)	(0.401)	(0.605)	(0.574)	(0.345)	(0.436)
Exposure to rising markups or concentration	1.662	-0.640	-2.511	-2.045	0.951	-1.042	-2.731	-1.935
	(1.677)	(1.903)	(0.645)	(0.719)	(1.670)	(2.013)	(0.805)	(0.786)
Share variance explained by:								
- task displacement	0.40	0.54	0.60	0.74	0.57	0.62	0.67	0.46
- markups/concetration	0.04	0.01	-0.23	0.03	0.02	0.02	-0.25	0.03
R-squared	0.84	0.83	0.85	0.87	0.83	0.83	0.85	0.86
First-stage F					236	355	108	47
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups controlling for changes in market structure and markups. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for each group from 1980 to 2016. In Panel A, we control for groups' specialization in industries with changes in market structure leading to higher markups. In column 1, we proxy changes in market structure by rising sales concentration in the industry. In columns 2–4, we directly control for changes in markups. These are computed as the ratio of revenue to costs in column 2, the inverse of the materials' share in gross output in column 3, and markups estimated using a production function approach as in De Loecker, Eeckhout and Unger (2020) in column 4. In Panel B, we also subtract the percent increase in markups from the percent decline in the labor share when computing our measure of task displacement (using the accounting markup in columns 1 and 5). Columns 1–4 report OLS estimates. Columns 5–8 report IV estimates using our index of automation to instrument task displacement. Besides the covariates reported in the table, all specifications control for industry shifters, baseline wage shares in manufacturing, education and gender dummies, relative specialization in routine jobs, and groups' exposure to industry labor share declines. When using our index of automation as an instrument, we report first-stage F statistics that are adjusted for the degrees of freedom lost in the construction of the index. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A10: Task displacement and changes in real hourly wages for men, women, and native-born workers, 1980-2016.

	Dependent variables: Change in wages, 1980–2016			
	(1)	(2)	(3)	(4)
	Panel A. Change in real wages for native-born workers 1980–2016			
Task displacement	-1.573	-1.288	-1.482	-1.660
	(0.099)	(0.191)	(0.231)	(0.526)
Industry shifters		0.212	0.113	0.213
		(0.115)	(0.176)	(0.292)
Share variance explained by task displacement	0.68	0.56	0.64	0.72
R-squared	0.68	0.71	0.85	0.85
Observations	250	250	250	250
	Panel B. Change in real wages for men 1980–2016			
Task displacement	-1.515	-1.083	-0.827	-1.570
	(0.107)	(0.193)	(0.085)	(0.302)
Industry shifters		0.374	0.604	0.520
		(0.158)	(0.124)	(0.123)
Share variance explained by task displacement	0.84	0.60	0.46	0.87
R-squared	0.84	0.86	0.96	0.96
Observations	250	250	250	250
	Panel C. Change in real wages for women 1980–2016			
Task displacement	-1.568	-1.676	-2.657	-2.805
	(0.182)	(0.234)	(0.367)	(0.790)
Industry shifters		-0.077	0.754	0.240
		(0.084)	(0.282)	(0.358)
Share variance explained by task displacement	0.53	0.57	0.90	0.95
R-squared	0.53	0.54	0.66	0.68
Observations	250	250	250	250
Other covariates:				
Manufacturing share, and education and gender dummies			✓	✓
Exposure to labor share declines and relative specialization in routine jobs				✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups. These groups are defined by gender, education, age, race, and native/immigrant status. In all panels, the dependent variable is the change in real wages from 1980 to 2016. Panel A presents estimates for native-born workers. Panel B presents estimates for men. Panel C presents estimates for women. Besides the covariates reported in the table, column 3 controls for each group's baseline wage share in manufacturing and by Census region, and column 4 controls for relative specialization in routine jobs and groups' exposure to industry labor share declines. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A11: Task displacement and changes in real hourly wages, 1980-2007.

	Dependent variables: Change in wages and wage declines, 1980–2007			
	(1)	(2)	(3)	(4)
	Panel A. Change in real wages 1980–2007			
Task displacement	-1.777	-1.371	-0.920	-0.333
	(0.110)	(0.136)	(0.179)	(0.558)
Industry shifters		0.322	0.505	0.492
		(0.088)	(0.143)	(0.208)
Exposure to industry labor share decline				-0.784
				(0.832)
Relative specialization in routine jobs				-0.085
				(0.075)
Share variance explained by task displacement	0.69	0.53	0.36	0.13
R-squared	0.69	0.74	0.82	0.83
Observations	500	500	500	500
	Panel B. Real wage declines, 1980–2007			
Task displacement	-0.467	-0.486	-0.488	-0.896
	(0.057)	(0.070)	(0.098)	(0.182)
Industry shifters		-0.016	0.137	0.121
		(0.019)	(0.078)	(0.088)
Exposure to industry labor share decline				0.618
				(0.233)
Relative specialization in routine jobs				0.056
				(0.015)
Share variance explained by task displacement	0.65	0.68	0.68	1.26
R-squared	0.65	0.66	0.77	0.79
Observations	500	500	500	500
Other covariates:				
Manufacturing share, and education and gender dummies			✓	✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. In Panel A, the dependent variable is the change in real wages for each group from 1980 to 2007. In Panel B, the dependent variable is given by the negative component of real wage changes from 1980 to 2007, defined by the minimum of the observed wage change and zero. Besides the covariates reported in the table, columns 3 and 4 control for baseline wage shares in manufacturing and education and gender dummies. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A12: Task displacement and changes in real hourly wages, stacked-differences models, 1980-2000 and 2000-2016.

	Dependent variable: Change in real wages 1980–2000, 2000–2016			
	(1)	(2)	(3)	(4)
	Panel A. Common coefficients across periods			
Task displacement	-1.310	-1.045	-0.938	-0.612
	(0.102)	(0.130)	(0.204)	(0.352)
Industry shifters		0.248	-0.438	-0.438
		(0.058)	(0.112)	(0.132)
Exposure to industry labor share decline				0.191
				(0.402)
Exposure to routine occupations				-0.056
				(0.041)
Share variance explained by				
- task displacement	0.46	0.36	0.33	0.21
- task displacement in 80s	0.26	0.21	0.19	0.12
- task displacement in 00s	0.59	0.47	0.42	0.27
R-squared	0.42	0.46	0.56	0.57
Observations	1000	1000	1000	1000
	Panel B. Allow covariates to have period-specific coefficients			
Task displacement	-1.310	-1.205	-1.273	-1.419
	(0.102)	(0.132)	(0.144)	(0.275)
Share variance explained by				
- task displacement	0.46	0.42	0.44	0.50
- task displacement in 80s	0.26	0.24	0.26	0.29
- task displacement in 00s	0.59	0.54	0.57	0.64
R-squared	0.42	0.58	0.74	0.74
Observations	1000	1000	1000	1000
	Panel C. Period specific estimates of task displacement			
Task displacement 80–00	-2.081	-1.333	-1.364	-2.109
	(0.277)	(0.248)	(0.252)	(0.728)
Task displacement 00–16	-1.100	-1.159	-1.220	-1.077
	(0.113)	(0.141)	(0.169)	(0.391)
Share variance explained by				
- task displacement	0.45	0.42	0.44	0.45
- task displacement in 80s	0.42	0.27	0.27	0.42
- task displacement in 00s	0.49	0.52	0.55	0.48
R-squared	0.46	0.58	0.74	0.74
Observations	1000	1000	1000	1000
Covariates:				
Industry shifters		✓	✓	✓
Manufacturing share, gender and education dummies			✓	✓
Exposure to labor share declines and relative specialization in routine jobs				✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups using a stacked-differences specification for 1980–2000 and 2000–2016. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages for 1980–2000 and 2000–2016. Panel A provides estimates assuming common coefficients across periods. Panel B allows covariates to have period-specific coefficients. Panel C provides period-specific estimates of task displacement. Besides the covariates reported in the table, column 2 controls for industry shifters, column 3 controls for groups' baseline wage share in manufacturing at the beginning of each period and for education and gender dummies, and column 4 controls for relative specialization in routine jobs and groups' exposure to industry labor share declines. Observations are weighted by the share of hours worked by each group at the beginning of each period. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A13: Task displacement and changes in real hourly wages—alternative price adjustments for task displacement.

	Dependent variable: Change in real wages 1980–2016			
	(1)	(2)	(3)	(4)
	Panel A. Task displacement for $\lambda = 1$ and $\sigma_i = 0.8$			
Task displacement	-1.349	-1.016	-1.188	-2.050
	(0.118)	(0.152)	(0.173)	(0.381)
Share variance explained by task displacement	0.57	0.43	0.51	0.87
R-squared	0.57	0.65	0.84	0.84
Observations	500	500	500	500
	Panel B. Task displacement for $\lambda = 1$ and $\sigma_i = 1.2$			
Task displacement	-1.729	-1.527	-1.263	-0.734
	(0.086)	(0.152)	(0.175)	(0.541)
Share variance explained by task displacement	0.71	0.63	0.52	0.30
R-squared	0.71	0.73	0.83	0.83
Observations	500	500	500	500
	Panel C. Task displacement for $\lambda = 0.5$ and $\sigma_i = 0.8$			
Task displacement	-1.220	-0.924	-1.074	-1.858
	(0.104)	(0.136)	(0.156)	(0.347)
Share variance explained by task displacement	0.58	0.44	0.51	0.88
R-squared	0.58	0.65	0.84	0.84
Observations	500	500	500	500
	Panel D. Task displacement for $\lambda = 0.5$ and $\sigma_i = 1$			
Task displacement	-1.436	-1.192	-1.172	-1.468
	(0.083)	(0.141)	(0.168)	(0.402)
Share variance explained by task displacement	0.67	0.56	0.55	0.69
R-squared	0.67	0.70	0.84	0.84
Observations	500	500	500	500
	Panel E. Task displacement for $\lambda = 0.5$ and $\sigma_i = 1.2$			
Task displacement	-1.545	-1.362	-1.125	-0.631
	(0.077)	(0.135)	(0.156)	(0.487)
Share variance explained by task displacement	0.71	0.63	0.52	0.29
R-squared	0.71	0.73	0.83	0.83
Observations	500	500	500	500
Covariates:				
Industry shifters		✓	✓	✓
Manufacturing share, gender and education dummies			✓	✓
Exposure to labor share declines and relative specialization in routine jobs				✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups using different price adjustments in our measurement of task displacement. The general formula for task displacement is given in equation (16). Our baseline measure sets $\lambda = \sigma_i = 1$. The panels in this table use different combinations of λ and σ. Besides the covariates reported in the table, column 2 controls for industry shifters, column 3 controls for each group's baseline wage share in manufacturing and dummies for education level and gender, and column 4 control for relative specialization in routine jobs and groups' exposure to industry labor share declines. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A14: Task displacement and changes in real hourly wages—alternative labor share measures.

	Dependent variable: Change in real wages 1980–2016			
	(1)	(2)	(3)	(4)
	Panel A. Excluding commodities			
Task displacement	-1.675	-1.323	-1.394	-2.144
	(0.120)	(0.174)	(0.201)	(0.456)
Share variance explained by task displacement	0.63	0.50	0.52	0.80
R-squared	0.63	0.67	0.83	0.84
Observations	500	500	500	500
	Panel B. Winsorized labor share changes			
Task displacement	-1.592	-1.312	-1.345	-1.891
	(0.098)	(0.165)	(0.195)	(0.444)
Share variance explained by task displacement	0.66	0.54	0.56	0.78
R-squared	0.66	0.69	0.84	0.84
Observations	500	500	500	500
	Panel C. Excluding industries with rising labor shares			
Task displacement	-1.491	-1.250	-1.322	-1.959
	(0.090)	(0.163)	(0.196)	(0.419)
Share variance explained by task displacement	0.66	0.55	0.58	0.86
R-squared	0.66	0.68	0.84	0.84
Observations	500	500	500	500
	Panel D. Gross labor share changes			
Task displacement	-1.393	-1.113	-0.909	-1.190
	(0.082)	(0.105)	(0.126)	(0.310)
Share variance explained by task displacement	0.66	0.53	0.43	0.57
R-squared	0.66	0.74	0.83	0.83
Observations	500	500	500	500
Covariates:				
Industry shifters		✓	✓	✓
Manufacturing share, gender and education dummies			✓	✓
Exposure to labor share declines and relative specialization in routine jobs				✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups using different measures of the labor share decline. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages from 1980 to 2016. In Panel A, we exclude sectors producing commodities. In Panel B, we winsorized the observed labor share changes at the 5th and 95th percentiles when constructing the task displacement measure. In Panel C, we exclude industries with rising labor shares. In Panel D, we use the percent decline in the labor share of gross output to construct our measure, which also accounts for substitution of labor for intermediates. Besides the covariates reported in the table, column 2 controls for industry shifters, column 3 controls for each group's baseline wage share in manufacturing and dummies for education level and gender, and column 4 control for relative specialization in routine jobs and groups' exposure to industry labor share declines. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A15: Task displacement and changes in real hourly wages—alternative measures of jobs that can be automated.

	Dependent variable: Change in real wages 1980–2016 (1)	(2)	(3)	(4)
	Panel A. Top 40			
Task displacement	-1.391	-1.016	-1.100	-2.496
	(0.147)	(0.164)	(0.193)	(0.534)
Share variance explained by task displacement	0.52	0.38	0.41	0.93
R-squared	0.52	0.64	0.82	0.84
Observations	500	500	500	500
	Panel B. Alternative definitions			
Task displacement	-1.875	-1.674	-1.673	-1.793
	(0.082)	(0.148)	(0.197)	(0.469)
Share variance explained by task displacement	0.76	0.67	0.67	0.72
R-squared	0.76	0.77	0.85	0.85
Observations	500	500	500	500
	Panel C. Occupations suitable to automation via robots			
Task displacement	-1.184	-1.163	-0.848	-0.658
	(0.080)	(0.111)	(0.157)	(0.291)
Share variance explained by task displacement	0.69	0.68	0.49	0.38
R-squared	0.69	0.69	0.81	0.82
Observations	500	500	500	500
	Panel D. Occupations suitable to automation via software			
Task displacement	-1.757	-1.709	-1.456	-1.546
	(0.132)	(0.150)	(0.222)	(0.513)
Share variance explained by task displacement	0.68	0.66	0.56	0.59
R-squared	0.68	0.68	0.81	0.82
Observations	500	500	500	500
	Panel E. Occupations suitable to automation via robots or software			
Task displacement	-1.459	-1.417	-1.027	-0.869
	(0.092)	(0.116)	(0.173)	(0.324)
Share variance explained by task displacement	0.71	0.69	0.50	0.42
R-squared	0.71	0.71	0.81	0.82
Observations	500	500	500	500
Covariates:				
Industry shifters		✓	✓	✓
Manufacturing share, gender and education dummies			✓	✓
Exposure to labor share declines and relative specialization in routine jobs				✓

Notes: This table presents estimates of the relationship between task displacement and the change in real wages across 500 demographic groups using different definitions of routine jobs. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in real wages from 1980 to 2016. In Panel A, we define routine occupations as the top 40% in the routine index distribution (as opposed to the top 30%). In Panel B, we use an alternative construction of the routine index described in Appendix F. In Panel C, we use a measure of occupational suitability to automation via robots from Webb (2020). In Panel D, we use a measure of occupational suitability to automation via software from Webb (2020). In Panel E we combine these two indices in a single one. Besides the covariates reported in the table, column 2 controls for industry shifters, column 3 controls for each group's baseline wage share in manufacturing and dummies for education level and gender, and column 4 control for relative specialization in routine jobs and groups' exposure to industry labor share declines. All regressions are weighted by the share of hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A16: Alternative estimates of the propagation matrix.

	Dependent variable: Change in wages 1980–2016					
	GMM estimates			GMM using automation index IVs		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Decay parameter $\kappa = 1$.					
Own effect, θ/λ	0.875	0.872	0.806	0.867	0.860	0.786
	(0.049)	(0.052)	(0.054)	(0.050)	(0.052)	(0.055)
Contribution of ripple effects via occupational similarity	0.646	0.631	0.496	0.661	0.647	0.526
	(0.175)	(0.181)	(0.184)	(0.175)	(0.182)	(0.184)
Contribution of ripple effects via industry similarity	0.241	0.245	0.553	0.237	0.238	0.547
	(0.192)	(0.192)	(0.210)	(0.192)	(0.193)	(0.210)
Contribution of ripple effects via education–age groups	0.194	0.194	0.186	0.194	0.194	0.182
	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)
Observations	500	500	500	500	500	500
	Panel B. Decay parameter $\kappa = 5$.					
Own effect, θ/λ	0.910	0.900	0.849	0.904	0.888	0.828
	(0.046)	(0.049)	(0.052)	(0.047)	(0.050)	(0.053)
Contribution of ripple effects via occupational similarity	0.250	0.244	0.233	0.250	0.244	0.238
	(0.048)	(0.050)	(0.050)	(0.049)	(0.050)	(0.050)
Contribution of ripple effects via industry similarity	0.184	0.182	0.236	0.191	0.187	0.242
	(0.060)	(0.059)	(0.062)	(0.060)	(0.059)	(0.062)
Contribution of ripple effects via education–age groups	0.160	0.160	0.152	0.159	0.160	0.149
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Observations	500	500	500	500	500	500
	Panel C. Alternative parametrization, $\kappa = 2$.					
Common row sum, ε	2.856	2.716	2.767	2.890	2.717	2.771
	(0.109)	(0.153)	(0.156)	(0.110)	(0.156)	(0.159)
Contribution of ripple effects via occupational similarity						
Contribution of ripple effects via industry similarity	1.564	1.443	1.549	1.626	1.475	1.604
	(0.134)	(0.163)	(0.177)	(0.135)	(0.165)	(0.179)
Contribution of ripple effects via education–age groups	0.398	0.407	0.377	0.381	0.395	0.355
	(0.048)	(0.049)	(0.052)	(0.049)	(0.049)	(0.053)
Observations	500	500	500	500	500	500
Covariates:						
Industry shifters		✓	✓		✓	✓
Manufacturing share			✓			✓

Notes: This table presents estimates of the propagation matrix using the parametrization in equation (17) (Panels A and B) and the parametrization in Appendix D (Panel C). Ripple effects are parametrized as functions of the similarity of groups in terms of their 1980 occupational distribution, industry distribution, and education×age groups. Panels A and B vary the tuning parameter used to compute the ripple effects. The table reports our estimates of the common diagonal term θ and a summary measure of the strength of ripple effects operating through each of these dimensions, defined by

$$\text{Contribution of ripple effects}_n = \frac{\beta_n}{\lambda} \cdot \left(\frac{1}{s^L} \sum_g \sum_{g' \neq g} f(d^n_{gg'}) \cdot s^L_g \cdot s^L_{g'} \right),$$

which equals the average sum of the off diagonal terms of the propagation matrix explained by each dimension of similarity. Estimates and standard errors are obtained via GMM. Columns 1–3 provide GMM estimates using our measure of task displacement to construct the instruments used in the moment conditions. Columns 4–6 provide GMM estimates using our index of automation to construct the instruments used in the moment conditions. All models are weighted by the share of hours worked by each group in 1980.

Table A17: Alternative estimates of the propagation matrix (Continued).

	Dependent variable: Change in wages 1980–2016					
	GMM estimates			GMM using automation index IVs		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Setting $\sigma_i = 0.8$.			
Own effect, θ/λ	0.682	0.668	0.615	0.706	0.692	0.639
	(0.040)	(0.042)	(0.045)	(0.042)	(0.043)	(0.046)
Contribution of ripple effects via	0.509	0.477	0.426	0.537	0.519	0.475
occupational similarity	(0.079)	(0.082)	(0.084)	(0.079)	(0.083)	(0.084)
Contribution of ripple effects via	0.080	0.083	0.216	0.076	0.077	0.200
industry similarity	(0.096)	(0.096)	(0.104)	(0.096)	(0.096)	(0.104)
Contribution of ripple effects via	0.198	0.197	0.189	0.182	0.182	0.171
education–age groups	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Observations	500	500	500	500	500	500
			Panel B. Setting $\sigma_i = 1.2$.			
Own effect, θ/λ	1.045	1.038	0.949	1.121	1.125	1.022
	(0.058)	(0.061)	(0.064)	(0.061)	(0.064)	(0.067)
Contribution of ripple effects via	0.195	0.184	0.130	0.081	0.084	0.057
occupational similarity	(0.104)	(0.107)	(0.106)	(0.106)	(0.108)	(0.107)
Contribution of ripple effects via	0.391	0.391	0.592	0.460	0.461	0.627
industry similarity	(0.123)	(0.123)	(0.130)	(0.124)	(0.124)	(0.130)
Contribution of ripple effects via	0.152	0.153	0.141	0.169	0.169	0.156
education–age groups	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)	(0.027)
Observations	500	500	500	500	500	500
Covariates:						
Industry shifters		✓	✓		✓	✓
Manufacturing share			✓			✓

Notes: This table presents estimates of the propagation matrix using the parametrization in equation (17). Ripple effects are parametrized as functions of the similarity of groups in terms of their 1980 occupational distribution, industry distribution, and education×age groups. Panel A uses our measure of task displacement from equation (16) setting $\lambda = 0.5$ and $\sigma_i = 0.8$. Panel B uses our measure of task displacement from equation (16) setting $\lambda = 0.5$ and $\sigma_i = 1.2$. The table reports our estimates of the common diagonal term θ and a summary measure of the strength of ripple effects operating through each of these dimensions, defined by

$$\text{Contribution of ripple effects}_n = \frac{\beta_n}{\lambda} \cdot \left(\frac{1}{s^L} \sum_g \sum_{g' \neq g} f(d^n_{gg'}) \cdot s^L_g \cdot s^L_{g'} \right),$$

which equals the average sum of the off diagonal terms of the propagation matrix explained by each dimension of similarity. Estimates and standard errors are obtained via GMM. Columns 1-3 provide GMM estimates using moment conditions based on our measure of task displacement, while columns 4-6 use moment conditions based on the index of automation. All models are weighted by the share of hours worked by each group in 1980.

Table A18: Robustness checks for estimates of full general equilibrium effects.

	Data for 1980–2016 (1)	Baseline calibration but setting $\lambda = 0.625$ (2)	Baseline calibration but setting $\sigma_i = 0.8$ (3)	Baseline calibration but setting $\sigma_i = 1.2$ (4)	Baseline calibration but setting $\pi = 0.5$ (5)	Estimates of propagation matrix for $\kappa = 1$ (6)	Estimates of propagation matrix for $\kappa = 5$ (7)	Assuming common row sum of propagation (8)
Wage structure:								
Share wage changes explained:								
-due to industry shifts		7.99%	4.85%	8.40%	8.08%	6.82%	6.88%	12.01%
-adding direct displacement effects		83.00%	99.88%	100.90%	101.84%	100.58%	100.64%	105.77%
-accounting for ripple effects		50.61%	34.75%	58.59%	46.40%	48.63%	49.17%	89.87%
Rise in college premium	25.51%	22.40%	19.38%	22.31%	21.33%	21.63%	22.45%	30.51%
-part due to direct displacement effect		32.74%	45.96%	35.89%	40.92%	40.92%	40.92%	40.92%
Rise in post-college premium	40.42%	25.00%	20.54%	25.21%	23.19%	24.01%	24.87%	46.14%
-part due to direct displacement effect		38.43%	54.06%	42.01%	48.04%	48.04%	48.04%	48.04%
Change in gender gap	15.37%	2.53%	-4.45%	8.52%	1.17%	2.13%	1.73%	12.90%
-part due to direct displacement effect		5.05%	-0.19%	12.81%	6.31%	6.31%	6.31%	6.31%
Share with declining wages	53.10%	44.66%	48.97%	34.20%	26.49%	40.84%	46.24%	54.86%
-part due to direct displacement effects		49.48%	55.52%	38.49%	34.58%	51.41%	48.83%	61.03%
Wages for men with no high school	-8.21%	-7.67%	-2.74%	-11.32%	-3.16%	-7.27%	-7.13%	-12.19%
-part due to direct displacement effects		-11.02%	-10.02%	-17.50%	-9.32%	-15.32%	-13.25%	-18.21%
Wages for women with no high school	10.94%	1.47%	-2.18%	5.38%	4.66%	1.52%	1.07%	3.82%
-part due to direct displacement effects		5.13%	2.48%	10.37%	10.86%	4.86%	6.93%	1.97%
Aggregates:								
Change in average wages, $d\ln w$	29.15%	5.71%	6.41%	5.02%	9.52%	5.71%	5.71%	5.72%
Change in GDP per capita, $d\ln y$	70.00%	23.52%	26.72%	20.34%	25.75%	22.75%	23.78%	21.31%
Change in TFP, $d\ln \text{tfp}$	35%	3.77%	4.23%	3.31%	6.29%	3.77%	3.77%	3.77%
Change in labor share, ds^L	-8 p.p.	-11.75 p.p	-13.40 p.p	-10.11 p.p.	-10.71 p.p	-11.24 p.p	-11.93 p.p.	-10.29 p.p
Change in K/Y ratio	30.00%	42.12%	46.83%	37.21%	39.01%	40.62%	42.62%	37.74%
Sectoral patterns:								
Share manufacturing in GDP	-8.80 p.p	-0.42 p.p	-0.36 p.p.	-0.46 p.p.	-0.60 p.p.	-0.42 p.p.	-0.42 p.p.	-0.62 p.p
Change in manufacturing wage bill	-35.00%	-8.19%	-7.36%	-8.84%	-6.93%	-8.91%	-7.89%	-11.51%

Notes: This table summarizes the effects of task displacement on the wage distribution, wage levels, aggregates, and sectoral outcomes. All these objects are computed using the formulas in Proposition 4 and the parametrization and estimates for the industry demand system and the propagation matrix described in the column headers. The wage data reported in column 1 are from the 1980 US Census and 2014–2018 ACS. The data for GDP, the labor share, the capital-output ratio data, and the sectoral patterns for manufacturing are from the BEA and the BLS. The TFP data is from Fernald (2014).