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 relative wage declines of worker groups specialized in routine tasks in industries experiencing rapid automation. We develop a conceptual framework where tasks across 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 jobs 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 wage differentials between 1980 and 2016. The negative relationship between wage changes and task displacement is unaffected when we control for changes in market power, deunionization, and other forms of capital deepening and technology unrelated to automation. We also propose a methodology for evaluating the full general equilibrium effects of automation, which incorporate induced changes in industry composition and ripple effects due to task reallocation across different groups. Our quantitative evaluation 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 inequality has risen sharply in the US and other industrialized economies over the last four decades.[1] Figure 1 depicts some of the most salient changes in the US wage structure since 1980: while the real wages of workers with a post-graduate degree rose, the real wages of low-education workers fell or remained stagnant. The real earnings of men without a high-school degree are now 15% lower than they were in 1980.

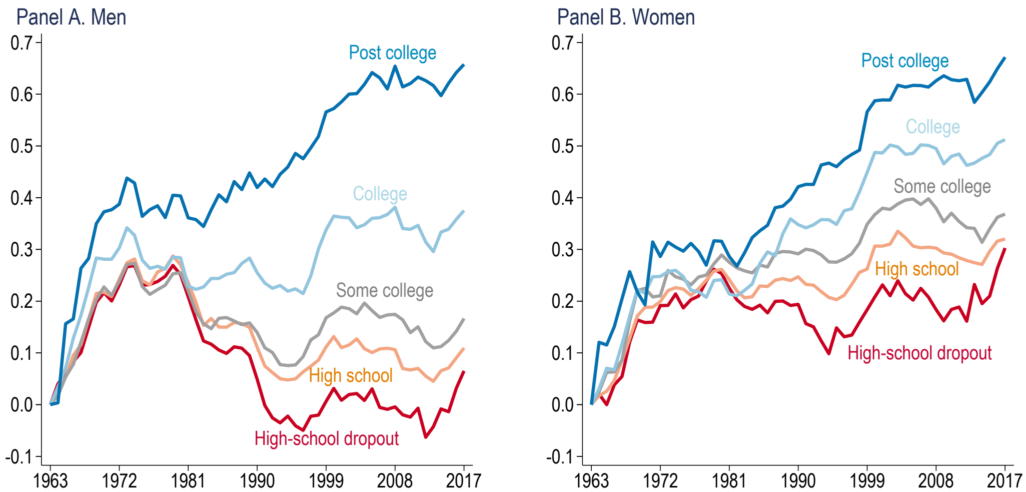

Figure 1: Cumulative growth of real hourly wages by gender and education (from Autor, 2019)

This paper proposes a new approach for thinking about wage inequality. In our theory, shifts against less skilled workers result from technologies that *automate* and thus displace workers from the tasks they used to perform. Our main contribution is to develop a general version of this theory and show how it can be applied to document and quantify the effects of automation on wages and inequality. Based on this approach, we document that between 50% and 70% of the overall changes in US wage structure are driven by automation. For example, low-education workers specialized in tasks that can be automated in industries undergoing rapid automation (e.g., those working in blue-collar jobs in manufacturing industries that introduced numerically-controlled machinery and industrial robots, or those in clerical tasks in industries that experienced software-based automation) had stagnant or even declining real wages. In contrast, worker groups that were not displaced from their tasks, such as those with a post-graduate degree or women with a college degree, enjoyed real wage gains.

Our framework models the allocation of a range of tasks across industries to capital and different demographic groups, each with a different comparative advantage. Technological progress can increase the productivity of some demographic groups (e.g., skill-biased technological change, SBTC, can augment the productivity of groups with higher education), it can raise the productivity of capital in its current tasks, and most importantly, it can automate work—which means

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

that the productivity of machines and algorithms increase in tasks previously allocated to workers and thus expanding the range of tasks performed by capital. Our model clarifies the distinct effects of these technological changes: automation displaces workers from tasks where they had comparative advantage, reducing their relative wages and even possibly their real wage levels.[2] In contrast, technologies directly improving the productivity of skilled labor do not involve any displacement and always increase the wages of unskilled workers, and in addition, their effects on inequality depend on elasticities of substitution.

The most important contribution of our framework is to provide a tractable methodology for empirically investigating these predictions. At the center of this contribution is a simple equation that relates wage changes of a worker group to the (direct) *task displacement* it experiences—a measure summarizing the share of tasks this group of workers loses directly to automation. We show that a group's task displacement can be measured as a (weighted) average of automation-driven labor share declines across industries where it specializes in tasks that can be automated.

The second part of the paper documents a robust negative reduced-form relationship between task displacement and real wages across groups of workers. For this empirical exercise, we focus on 500 demographic groups defined by education, gender, age, race and native/immigrant status. We identify tasks that can be automated with those that are routine (as classified in Acemoglu and Autor, 2011). Our first measure of (direct) task displacement exploits observed industry labor share declines, which in our framework are closely connected to automation.[3] Although we start with this simple strategy, our preferred measure of task displacement directly uses information on automation-driven industry labor share declines, which we estimate using data on the adoption of robots, specialized software, and dedicated machinery across industries. These proxies of automation account for 45% of the observed changes in industry labor shares from 1987 to 2016. Using both measures, we find a strong association between task displacement and wages. In our baseline regressions, task displacement explains 50–70% of the changes in wage structure across groups between 1980 and 2016. This is regardless of whether we control for standard forms of SBTC (for example, allowing the productivity of workers to evolve as a function of their education levels and gender). Notably, these traditional SBTC proxies account for 10% of the overall changes in the wage structure. Consistent with the notion that task displacement reflects changes in labor demand, we also estimate negative effects on employment outcomes.

The relationship between task displacement and wages is unaffected when we control for other potential determinants of industry labor shares and earnings, such as changes in industry

[2]We define automation technologies as any technology that enables machines or algorithms to perform tasks previously allocated to humans (which thus leads to 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.

[3]There are many determinants of industry labor shares, and we explore and control for their effects later. See Elsby et al. (2013), Karabarbounis and Neiman (2013), Piketty (2014), Dao et al. (2019), and Hubmer (2020) on the decline of the labor share; Acemoglu et al. (2020b) and Acemoglu and Restrepo (2020) on the role of automation in labor share declines; De Loecker et al. (2020) on the role of rising markups; and Autor et al. (2020) and Hubmer and Restrepo (2021) on superstar firms.

concentration and markups, Chinese import competition, and deunionization, and these factors themselves do not appear to play a major role in US wage inequality. Our results also remain unchanged when we control for other (non-automation) forms of capital deepening and other sources of TFP growth at the industry level. This shows that our estimates are driven by automation and not by other forms of technological progress or capital deepening. Finally, we also show that offshoring-induced task displacement has similar effects on wages, though offshoring accounts for a smaller share of the observed changes in task displacement and wage structure than automation.[4]

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

The third part of the paper undertakes a quantitative exploration of these general equilibrium mechanisms and estimates the full implications of automation for the wage structure, real wages, TFP, output, and the industry composition of the economy. Our framework provides explicit formulas to compute these general equilibrium effects as functions of task displacement as well as cost savings from automation, industry demand elasticities, and a *propagation matrix* representing 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'). We show how these ripple effects can be estimated by parametrizing group-level interactions as functions of the distance between groups. We then combine these ripple effect estimates with a standard parametrization of demand across industries, available estimates of cost savings from automation, and our measures of direct task displacement to compute the full general equilibrium implications of automation.

We find that automation—incorporating general equilibrium effects—accounts for about 50% of the changes in the wage structure during this period and explains 80% of the rise in the college premium. At the same time, we estimate that automation reduced the real wage of high-school dropout men by 8.8% and high-school dropout women by 2.3%. These sizable distributional effects are accompanied by small increases in the average wage level, GDP and TFP. For example, we find that automation accounts only for a (cumulative) 3.4% increase in TFP between 1980 and 2016. We thus conclude that stagnant and declining real wages and slow productivity growth can go hand-in-hand in the presence of rapid automation.

[4] In additional empirical exercises, we find similar results when we exploit regional variation in specialization patterns (instead of national variation in specialization patterns across groups) to compute our task displacement measures, or when we look at different sub-periods.

Our work contributes to various literatures. First, our conceptual framework builds on previous task models, in particular, Zeira (1998), Acemoglu and Zilibotti (2001), Autor et al. (2003), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2018), as well as Grossman and Rossi-Hansberg's (2008) model of offshoring. Our main innovation relative to these papers is the methodology we propose for measuring and estimating the effects of task displacement on wages and inequality. The central element of this methodology is the explicit formulas linking wage changes to task displacement, which underpin all of our empirical work. We are not aware of a counterpart to this methodology in previous work. As part of this contribution, we also develop a general version of existing models of automation and offshoring, in which there are many sectors, many tasks within each sector, and a large number of demographic groups with flexible comparative advantage across tasks and sectors.

Other empirical explorations of the consequences of automation include Autor et al. (2003), Acemoglu and Autor (2011), Graetz and Michaels (2018), and Acemoglu and Restrepo (2020). These works do not estimate the direct and/or general equilibrium effects of task displacement on the wage structure. Acemoglu and Restrepo (2020), for example, estimate the causal impacts of industrial robots on local employment and wages, but do not look at their effects on the national wage structure, which is our main focus here and its study is enabled by our new general equilibrium framework. It is also important to recall that industrial robots are only one of several automation technologies adopted in the US economy over the last four decades.[5]

Second, our work builds on but fundamentally departs from the traditional literature on SBTC. This literature starts with an aggregate production function of the form $F(A_H H, A_L L)$, where H and L are high-skill and low-skill labor, and A_H and A_L represent technologies augmenting these workers. SBTC corresponds to technology becoming more favorable to high-skill workers (e.g., a bigger increase in A_H than in A_L, provided that F has an elasticity of substitution greater than one). Several works, including Bound and Johnson (1992), Katz and Murphy (1992), Krueger (1993), Autor et al. (1998), and Card and Lemieux (2001), have explored the evolution of between-group wage inequality in response to changes in factor supplies and skill-augmenting technologies (increases in A_H). We differ from this literature in a number of ways. Most importantly, our focus is on automation technologies displacing certain groups of workers—*not* on technologies complementing high-skill workers. Our theoretical framework elucidates that task displacement has no counterpart in this literature, and our empirical results highlight the limited role that factor-augmenting technologies play in changes in the US wage structure over the last four decades.[6]

[5]Our findings also complement works on job polarization, such as Goos and Manning (2007), Goos et al. (2014), and Autor and Dorn (2013). We document that groups most affected by task displacement are in the middle of the wage distribution, thus linking task displacement to polarization. Other papers studying the decline of routine occupations and broader changes in occupational structure include, Johnson and Keane (2013), Lee and Shin (2017), Gregory et al. (2018), Bárány and Siegel (2020), Jaimovich et al. (2020), Atalay et al. (2020), and Caunedo et al. (2021).

[6]In principle, one could develop a more general form of SBTC whereby technological change increases A_H and *simultaneously* reduces A_L. This more general version would capture some displacement effects, though without

Third, our work builds on and complements the literature exploring the effects of lower equipment and computer prices on wage inequality through capital-skill complementarity. This literature posits an aggregate production function of the form $F(K, H, L)$, in which capital (or equipment capital) K directly complements skilled workers. These ideas go back to Griliches (1969), and their implications for US wage inequality have been explored in Krusell et al. (2000) and Burstein et al. (2019). As with the SBTC literature, the main mechanism via which technology and capital impact inequality in this literature is through complementarity—thus without any role for task displacement. We clarify the distinction between automation and the capital-skill complementarity studied in this literature, and show that automation has a powerful impact on inequality even when there are no direct capital-skill complementarities.

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 the reduced-form evidence. Section 5 explores the general equilibrium effects of automation. Section 6 concludes, while Appendix A contains proofs and reports our main robustness checks. Appendix B, which is available upon request, provides additional theoretical results and robustness checks for our quantitative exercise.

2 Conceptual Framework: Tasks, Wages, and Inequality

We start with a single-sector model that illustrates how automation and other technologies affect wages. We then move to our multi-sector model and formally derive the task displacement measure we use in our empirical work.

2.1 Single Sector

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

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

where x indexes tasks. For example, producing a shirt requires the completion of 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 tasks. Each task can be produced using capital or different types of labor indexed by g (where $g \in \mathcal{G} = \{1, 2, \ldots, G\}$):

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

microfoundations it is not clear why technological *progress* would make some workers *less* productive. Our theory can be viewed as providing microfoundations for this type of general SBTC model.

Here, $\ell_g(x)$ is the amount of labor of type g allocated to task x, while $k(x)$ is the amount of task-specific capital produced for and assigned to this task. The A_k and A_g terms represent standard factor-augmenting technologies, which make factors uniformly more productive at all tasks. More importantly, productivity 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 a task.

Capital for performing task x, $k(x)$, is 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:

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

Labor is supplied inelastically, and we denote the total supply of labor of type g by ℓ_g.

A *market equilibrium* is defined as an allocation of tasks to factors and a production plan for capital goods that maximizes consumption. Given a supply of labor $\boldsymbol{\ell} = (\ell_1, \ell_2, \ldots, \ell_G)$, a market equilibrium is specified by wages $\boldsymbol{w} = (w_1, w_2, \ldots, w_G)$, capital production decisions $k(x)$, and an allocation of labor to tasks, $\ell_g(x)$ such that: (i) the allocation of tasks to factors minimizes costs; (ii) capital production decisions maximize net output; and (iii) the markets for capital goods and different types of labor clear. We set the final good as the numeraire, so that the w_g's correspond to real wages. Throughout, 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, and we also assume that each factor has a strict comparative advantage for some tasks.[7]

Task shares: Cost minimization and our tie-breaking rule imply that each task is produced by a single factor. Let $\mathcal{T}_g$ represent the set of tasks allocated to labor of type g, and $\mathcal{T}_k$ the set of tasks allocated to capital. These sets are equilibrium objects that satisfy:

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

Given an allocation of tasks to factors, we define:

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

[7] The tie-breaking 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). The second part of the assumption is to ensure that an equilibrium satisfying this tie-breaking rule always exists (an equilibrium without this rule always exists). Formally, this assumption requires that for any positive measure subset of tasks $\mathcal{T}' \subset \mathcal{T}$ and for any g and g' (with the convention that $g = 0$ stands for k), $\psi_{g'}(x)/\psi_g(x)$ is not constant for all $x \in \mathcal{T}'$.

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.[8] Task shares depend on the sets $\mathcal{T}_g$ and $\mathcal{T}_k$, and thus on wages, factor-augmenting technologies, and task productivities. Consequently, they are 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 we omit this dependence when it causes no confusion.

The next proposition characterizes the equilibrium, 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-2, 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 we assume throughout that it is satisfied.

Proposition 1 (Equilibrium) *There is a unique equilibrium. In this equilibrium, output, wages, and the capital share in GDP, s^K, 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 establishes that task shares—the Γ_g' and Γ_k—are the key objects summarizing the distributional effects of technology. Equation (1) shows that output can be represented as a CES aggregate of different types of labor and capital, with elasticity of substitution λ. However, 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 are given by the task shares, the Γ_g's. They are functions of not just factor prices (via the dependence of the sets $\mathcal{T}_g$ and $\mathcal{T}_k$ on factor prices), but also technology. Second, despite appearances, the elasticity of substitution between factors is *not* equal to λ, but $\sigma \geq \lambda$. The exact value of σ 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 $1 - A_k^{\lambda-1} \cdot \Gamma_k > 0$ accounts for the roundabout nature of production.

Equation (2) is intuitive: 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 $1/\lambda$) and the factor-augmenting technology, A_g (raised to the power $(\lambda - 1)/\lambda$). More novel and central to our empirical strategy 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 its task share.

[8] 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.

Although task shares are endogenous objects, Proposition 1 is useful because it clarifies how the impact of automation technologies on equilibrium outcomes work via their influence on task shares. In particular, automation impacts equilibrium prices and quantities by reallocating tasks away from labor and thus reducing the Γ_g's. Building on this insight, we show next that the effects of automation on wages can be studied by tracing its impact on task shares.

The effects of technology: To understand the distinct effects of automation, it is useful to first contrast them with those of other technologies:

■ **Factor-augmenting technologies:** represented by higher A_g or A_k. Factor-augmenting technologies have been the focus of much of the macro and labor literatures. They are qualitatively different from automation technologies and arguably a significant abstraction, since there are no examples of technologies that increase factor productivity in *all* or even *most* tasks.

■ **Productivity-deepening technologies :** these correspond to increases in the productivity of a factor at tasks it currently performs—represented by an increase in $\psi_g(x)$ for $x \in \mathcal{T}_g$ in the case of labor or in $\psi_k(x)$ for $x \in \mathcal{T}_k$ in the case of capital. 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. Formally, we consider infinitesimal increases in $\psi_g(x)$ for $x \in \mathcal{T}_g$, and define the direct effect of these changes on group g's task share as:

$$d\ln\Gamma_g^{\text{deep}} = \frac{1}{M}\int_{\mathcal{T}_g} \frac{\psi_g(x)^{\lambda-1}}{\Gamma_g} \cdot d\ln\psi_g(x)dx. \tag{4}$$

$d\ln\Gamma_k^{\text{deep}}$ is defined similarly for capital.

■ **Automation and offshoring:** automation corresponds to increases in the productivity of capital (or reductions in the cost of producing this type of capital) at tasks previously assigned to labor and leads to the displacement of workers from these tasks. Examples of automation technologies include numerical control machinery or industrial robots taking over tasks from blue-collar workers or the introduction of specialized software automating various back-office and clerical tasks. Offshoring also leads to the displacement of workers and can be incorporated into this framework by assuming that tasks can be performed abroad and imported in exchange of $1/q(x)$ units of the final good (see also Grossman and Rossi-Hansberg, 2008).

We model automation as a discrete increase in the productivity of capital in an infinitesimal set of tasks $\mathcal{D}_g \subseteq \mathcal{T}_g$ (previously performed by workers of group g) such that capital now outperforms labor in these tasks. We define two objects that fully summarize the effects of automation. The first is the *(direct) task displacement* experienced by g:

$$d\ln\Gamma_g^{\text{auto}} = \frac{\frac{1}{M}\int_{\mathcal{D}_g}\psi_g(x)^{\lambda-1}dx}{\frac{1}{M}\int_{\mathcal{T}_g}\psi_g(x)^{\lambda-1}dx}. \tag{5}$$

This measure represents the direct reduction in group g's task share due to automation. We emphasize that this is automation's "direct" impact to highlight that it depends only on the underlying improvements in automation technology (increase in capital productivity in tasks previously performed by group g) and to distinguish it from its indirect impact that incorporates *ripple effects* that result from the reallocation of tasks across factors in response to changes in equilibrium prices. Second, we define *cost savings* from automating these tasks as

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

where $\pi_g(x)$ denotes the cost reduction from automating task $x \in \mathcal{D}_g$.[9] π_g is also a function of the underlying technology (capital productivity in the tasks in $\mathcal{D}_g$ after the change in technology).

Figure 2 depicts the effects of productivity deepening and automation on the allocation of tasks to factors. The *direct* effects in equations (4) and (5) are shown with the shaded areas (corresponding to the tasks where the productivity of capital or labor increased), while the induced ripple effects, which alter task shares of worker groups that are not themselves directly impacted by new technologies, are depicted with the dashed curves.

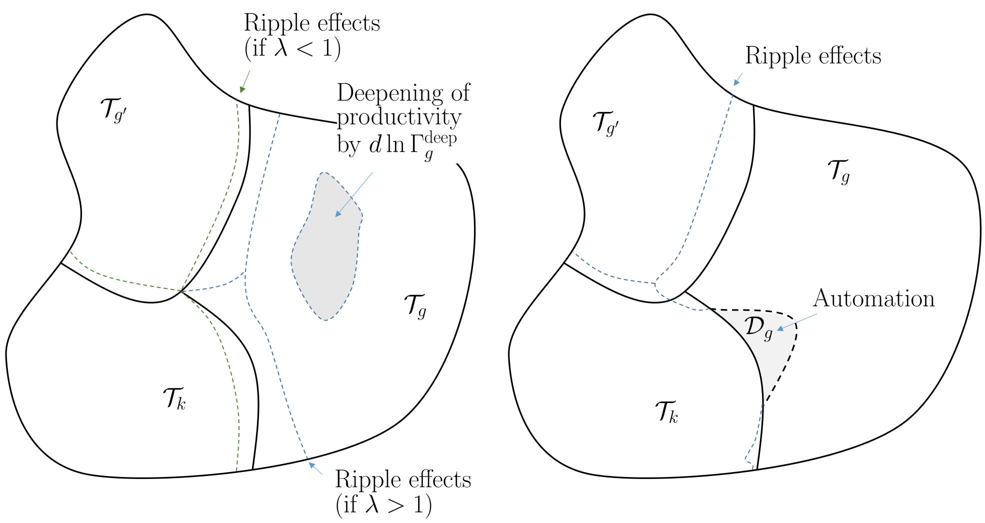

FIGURE 2: THE DIRECT EFFECTS OF TECHNOLOGY AND RIPPLE EFFECTS. The left panel shows the effects of an increase of $d\ln\Gamma_g^{\text{deep}}$ in the productivity of group g in tasks in $\mathcal{T}_g$. The right panel depicts the effects of automation technologies that reduce the task share of worker g by $d\ln\Gamma_g^{\text{auto}}$.

We now characterize the implications of these technologies, while abstracting from ripple effects, which allows us to illustrate their direct impacts and derive a simple estimating equation. The following assumption rules out ripple effects and is maintained until Section 5, where we characterize and estimate the full general equilibrium effects of automation on the wage structure:

[9] This cost saving from automating task x 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 and initial equilibrium wages.

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. $\psi_k(x) > \underline{\psi}$ and $q(x) > \overline{q}$ for all $x \in \mathcal{S} = \{x : \psi_k(x) > 0\}$, where the constants $\underline{\psi}$ and $\overline{q}$ are defined such that, in this case, $\mathcal{T}_k = \mathcal{S}$.

The first part of the assumption imposes that each task can be performed by at most 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 capital has positive productivity, will be allocated to capital, i.e., $\mathcal{T}_k = \mathcal{S}$ (see Appendix B-1 for details and a derivation of these thresholds).

The next proposition characterizes the implications of these technologies for wages, TFP, and output in terms of their direct effects on task shares and cost savings from automation.

Proposition 2 (Technology Comparative Statics) *Consider a change in technology (such as factor-augmenting, productivity-deepening, and automation). The impact on real wages, TFP, output, and the capital share are*

$$d\ln w_g = \frac{1}{\lambda} d\ln y + \frac{\lambda - 1}{\lambda} d\ln \tilde{A}_g - \frac{1}{\lambda} d\ln \Gamma_g^{auto}, \tag{6}$$

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

$$d\ln tfp = \sum_{g \in \mathcal{G}} s_g^L \cdot d\ln \tilde{A}_g + s^K \cdot d\ln \tilde{A}_k + \sum_{g \in \mathcal{G}} s_g^L \cdot d\ln \Gamma_g^{auto} \cdot \pi_g, \tag{8}$$

$$d\ln s^K = (\lambda - 1) \cdot d\ln \tilde{A}_k + \frac{1}{s^K} \cdot \sum_{g \in \mathcal{G}} s_g^L \cdot d\ln \Gamma_g^{auto} \cdot (1 + (\lambda - 1) \cdot \pi_g), \tag{9}$$

where $d\ln \tilde{A}_g = d\ln A_g + d\ln \Gamma_g^{deep}$, $d\ln \tilde{A}_k = d\ln A_k + d\ln \Gamma_k^{deep}$, and $s_g^L = w_g \cdot \ell_g / y$ is the share of group g in GDP.

Let us first consider factor-augmenting and productivity-deepening technologies that make workers (or capital) more productive at their current tasks. With no ripple effects, factor-augmenting and productivity-deepening technologies have identical implications, summarized by the terms $d\ln \tilde{A}_g$ and $d\ln \tilde{A}_k$. Equation (6) gives their impact on the wage structure. The real wage of group g increases due to productivity gains, represented by the expansion of output, $d\ln y$. These technologies further affect relative wages through the term $\frac{\lambda-1}{\lambda} \cdot d\ln \tilde{A}_g$, whose sign depends on whether the elasticity of substitution between type g labor and other factors, λ, is greater than or less than one.[10] This ambiguous impact is rooted in the fact that technologies

[10] In the presence of ripple effects, the impact of A_g on group g wages is $\frac{\sigma_g - 1}{\sigma_g} d\ln A_g$, where $\sigma_g = \lambda \cdot \frac{1}{1 + \partial \ln \Gamma_g / \partial \ln w_g}$ is the elasticity of substitution between group g and other workers. Because an increase in A_g expands the set of tasks performed by group g, $\sigma_g \geq \lambda$. Under Assumption 1, however, there are no ripple effects, and thus $\sigma_g = \lambda$.

that make workers from group g more productive simultaneously lower the price of the tasks these workers produce. When $\lambda > 1$, the first effect dominates, and technologies making a group of workers more productive will raise their relative wages. This is the standard mechanism emphasized in the SBTC literature (e.g., Katz and Murphy, 1992). Additionally, technologies increasing the productivity of group g raise the wage of all other workers (and technologies increasing the productivity of capital at its current tasks raise all wages). This is the reason theories that emphasize skill-biased technologies or capital-skill complementarities have a hard time accounting for the stagnant or decreasing wages of unskilled workers (see Acemoglu and Autor, 2011).

The impact of factor-augmenting and productivity-deepening technologies on TFP can be computed from (8) as $\sum_{g\in\mathcal{G}} s_g^L \cdot d\ln \tilde{A}_g + s^K \cdot d\ln \tilde{A}_k$. 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 s_g^L%. 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), these technologies have large productivity effects. If factor-augmenting and productivity-deepening technologies were at the root of changes in the wage structure, we should see sizable TFP gains.

These results contrast with the implications of automation, whose impact on wages in (6) is

$$\frac{1}{\lambda} d\ln y - \frac{1}{\lambda} d\ln \Gamma_g^{\text{auto}}.$$

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 shows that a group's real wage change depends on the task displacement it experiences; this is independent of whether $\lambda \lesseqgtr 1$. This negative displacement effect is the defining feature of automation technologies.

The implications of automation for TFP and factor shares are distinct from those of other technologies as well. The change in TFP is now $\sum_{g\in\mathcal{G}} s_g^L \cdot d\ln \Gamma_g^{\text{auto}} \cdot \pi_g$. If cost savings from automation, π_g, are modest, automation could have a sizable impact on the wage structure via task displacement and still bring only small aggregate productivity gains. In this case, the displacement effect can outweigh the productivity effect and the real wage for displaced groups can decline as we will see in our general equilibrium analysis.

Equation (9) also shows that automation always increases the capital share and reduces the labor share of value added—an observation that will be at the core of our measurement approach, in Section 2.4. This too is in stark contrast to what one would get from factor-augmenting and productivity-deepening technologies, whose impact on factor shares depends on whether $\lambda \lesseqgtr 1$.

2.2 Full Model: Multiple Sectors

Our full model generalizes the one-sector setup in the previous subsection. There are multiple industries indexed by $i \in \mathcal{I} = \{1, 2, \ldots, I\}$. 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 productivity term. $\mathcal{T}_{gi}$ denotes the set of tasks in industry i allocated to workers of type g, and $\mathcal{T}_{ki}$ denotes those allocated to capital. We define industry-level task shares, Γ_{gi} and Γ_{ki}, as:

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

We assume that industry outputs are combined into a single final good (aggregate output) using a constant returns to scale aggregator, $H(y_1, \dots, y_I)$. In the text, we work with the implied expenditure shares, $s_i^Y(\boldsymbol{p})$, where $\boldsymbol{p} = (p_1, p_2, \dots, p_I)$ is the vector of industry prices.[11]

The next proposition generalizes Proposition 1 to this environment and characterizes the equilibrium in terms of task shares. As before, we denote the direct impacts of productivity deepening and automation on task shares in industry i by $d\ln\Gamma_{gi}^{\text{deep}}$ and $d\ln\Gamma_{gi}^{\text{auto}}$, respectively.

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:*

$$(10) \qquad w_g = \left(\frac{y}{\ell_g} \right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi} \right)^{\frac{1}{\lambda}}$$

$$(11) \qquad p_i = \frac{1}{A_i} \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g \in \mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi} \right)^{\frac{1}{1-\lambda}}$$

$$(12) \qquad 1 = \sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}).$$

The proposition shows that task shares, the Γ_{ki}'s and Γ_{gi}'s, continue to be key determinants 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. In addition, the impact of automation technologies on equilibrium outcomes again work via their influence on task shares.

2.3 Wage Equation without Ripple Effects

Under Assumption 1, the impact of a change in technology on wages can be written as

$$(13) \qquad d\ln w_g = \frac{1}{\lambda} d\ln y + \frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_g^i \cdot d\ln \zeta_i + \frac{\lambda - 1}{\lambda} d\ln \tilde{A}_g - \frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_g^i \cdot d\ln \Gamma_{gi}^{\text{auto}},$$

[11] For example, if H is CES with elasticity η, then $s_i^Y(\boldsymbol{p}) = \alpha_i \cdot p_i^{1-\eta}$. This formulation imposes homotheticity, which can be relaxed by allowing expenditure shares to additionally depend on the level of consumption.

where $d\ln\tilde{A}_g = d\ln A_g + \sum_{i\in\mathcal{I}}\omega_g^i \cdot d\ln\Gamma_{gi}^{\text{deep}}$, $d\ln\zeta_i = d\ln s_i^Y + (1-\lambda)\cdot(d\ln p_i + d\ln A_i)$, and ω_g^i denotes the share of group g's income earned in industry i, so that $\sum_{i\in\mathcal{I}}\omega_g^i = 1$.

Equation (13) generalizes (6) to a multi-sector economy. As before, a common productivity effect increases wages. In the presence of multiple sectors, wages additionally depend on changes in industry composition that take place in response to technological shifts. The implications of these industry changes are captured by workers' exposure to industry shifters, $d\ln\zeta_i$ (the second term). Most centrally, group g's wage again depends on its direct task displacement—the automation-induced displacement it experiences, but now summed across all industries.

Equation (13) summarizes the key empirical prediction of our model: groups experiencing greater (automation-driven) task displacement should see *relative* wage declines. In what follows we use this equation, which focuses on the direct effects of automation, as the basis for our reduced-form analysis. Our general equilibrium exploration in Section 5 will allow for additional ripple effects and will incorporate the wage impacts of productivity increases and induced changes in industry composition.

2.4 Mapping the Model to Data and Measuring Task Displacement

Our reduced-form analysis estimates an empirical analogue of equation (13), relating wage changes of different worker groups to their task displacement. In this equation:

- The common expansion of output, $d\ln y$, will be absorbed by the constant term.

- The industry shifters term $\sum_{i\in\mathcal{I}}\omega_g^i \cdot d\ln\zeta_i$ will be parameterized by group g's exposure to changes in industry (log) value added shares.

- The third term, $d\ln\tilde{A}_g$, which incorporates factor-augmenting and productivity-deepening technologies, will be parameterized as in the SBTC literature. In particular, we assume that these technologies augment well-defined skills associated with education and gender, and impose:

$$\frac{\lambda-1}{\lambda}d\ln\tilde{A}_g = \alpha_{\text{edu}(g)} + \gamma_{\text{gender}(g)} + \upsilon_g,$$

where υ_g is an additional unobserved component, and $\alpha_{\text{edu}(g)}$ and $\gamma_{\text{gender}(g)}$ will be absorbed by dummies for education levels and gender. As a further refinement, we allow group-specific shifters to also depend on baseline group wages, which can be thought to proxy for skills.

- Finally, the key explanatory variable is our measure of task displacement, $\sum_{i\in\mathcal{I}}\omega_g^i \cdot d\ln\Gamma_{gi}^{\text{auto}}$. As in the single sector case, this measure corresponds to (direct) task displacement driven by advances in automation technologies.

We use two complementary strategies to measure automation-driven task displacement, both of which rely on an initial observation: displacement takes place in tasks that can be automated, which we proxy with routine tasks.[12] Formally, we impose:

[12] The idea that routine tasks are easier to automate is the main premise of Autor et al. (2003) and is in line with

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

In our reduced-form analysis, we focus on the case with $\lambda = 1$, which yields measures that are more transparent and easier to interpret. Appendix A-3 shows that when $\lambda = 1$ and Assumptions 1 and 2 hold, (direct) task displacement can be measured as:

$$\text{Task displacement}_g^{\text{direct}} = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \left(-d \ln s_i^{L,\text{auto}}\right). \tag{14}$$

This measure comprises three terms: (1) the first, ω_g^i, is the share of wages earned by group g workers in industry i (relative to their total earnings) and captures this group's exposure to industry i; (2) the second term, $\omega_{gi}^R/\omega_{gi}^R$, parameterizes the specialization of group g in routine jobs within industry i, which are the ones directly impacted by automation. This term is computed as the share of wages earned in routine jobs in industry i by workers in group g (relative to their total earnings in that industry), ω_{gi}^R, divided by the share of wages earned in routine jobs by all workers in industry i (relative to the total wage bill of the industry), ω_i^R; (3) the (percent) decline in industry i's labor share driven by automation, $-d \ln s_i^{L,\text{auto}}$. The automation-driven labor share decline quantifies the direct losses of routine tasks experienced by workers in an industry.

Our two measures of task displacement differ in how they treat this last term. Our first and simpler strategy assumes that the observed decline in the labor share of an industry, $-d \ln s_i^L$, can be entirely attributed to automation. This strategy is valid when $\lambda = 1$ (so that factor prices do not affect the labor share), there are no changes in markups, and there are no other influences on industry wages (such as changes in worker rents). We explore later the role of these factors and provide alternative measures of task displacement that adjust for each of them.

Our second and preferred approach uses data on the adoption of automation technologies at the industry level to isolate automation-driven declines in industry labor shares. Specifically, we estimate $-d \ln s_i^{L,\text{auto}}$ as the predicted change in the (log) labor share of an industry based on its adoption of automation technologies (and offshoring).

We present results using both strategies throughout the paper. Our preference for the second strategy is rooted in the fact that it exploits actual measures of automation, such as adoption of industrial robots, dedicated machinery, and specialized software. It also allows us to estimate the extent of task displacement generated by automation and offshoring. In our robustness checks and general equilibrium analysis, we use more general measures of task displacement that are valid when $\lambda \neq 1$ and Assumption 1 is relaxed.

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several studies that document a decline in routine jobs following automation, including Acemoglu and Restrepo (2020) and Humlum (2020). We present very similar results using various other measures of tasks that 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. (2020a) show that AI use takes off in the US after 2015.

3 Data, Measurement, and Descriptive Patterns

In this section, we describe our data sources and measures of task displacement, and provide a first look at the relationship between task displacement and 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 from 1987 to 2016.[13] We complement these data with three industry-level proxies for adoption of automation technologies. These are: (1) change in the value of dedicated machinery services in value added between 1987 and 2016; (2) change in the value of specialized software services in value added between 1987 and 2016;[14] (3) the adjusted penetration of robots from 1993 to 2014, which measures robot adoption driven by international advances in technology (from Acemoglu and Restrepo, 2020). We regress changes in industry (log) labor shares between 1987 and 2016 on these three proxies for automation technologies and compute the automation-driven decline in the labor share as the predicted value in this regression.[15] 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 total capital to value added ratio and industry TFP, sales concentration, estimates of markups, unionization rates, and measures of Chinese import competition.

On the worker side, we use 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 (using 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 between 1980 and 2016. In Section 4.6, we zero in on variation in labor market outcomes for demographic groups across US regions and commuting zones.

[13] These 49 industries can be consistently tracked in Census and BLS data, and cover the entire non-government sector. We have no data on our proxies of automation for the government sector. Hence, when constructing our measures of task displacement, we assume that workers in the government sector experienced no automation.

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

[15] Regressing changes in labor shares on these measures is also useful for isolating the component of investments in specialized software and dedicated machinery that are related to automation (which may differ between the two types of technologies). Our exclusion restriction does not impose that all software and dedicated machinery are automation technologies, but it requires that their non-automation component is orthogonal to other factors affecting industry labor shares.

3.2 Changes in Industry Labor Shares and Automation

Figure 3 depicts the industry-level variation in labor share declines (the basis of our first measure of task displacement, shown with the blue bars) and the component of the labor share decline driven by automation technologies (which is thus a summary measure of overall automation in the industry and the basis of our preferred task displacement variable, shown with the yellow bars) from 1987 to 2016.[16] The figure reveals considerable variation in industry labor share changes, with the largest declines taking place in mining, chemical products, petroleum, primary metals, motor vehicles, computers and electronics, computer services, and legal services. There is also a strong correlation between the blue and the yellow bars, indicating that industries with the largest labor share declines are those that have been at the forefront of automation technology adoption. Industries most affected by automation are consequently similar to those listed above and include motor vehicles, primary metals, computers and electronics, computer services, plastic and rubber products, and legal services.[17]

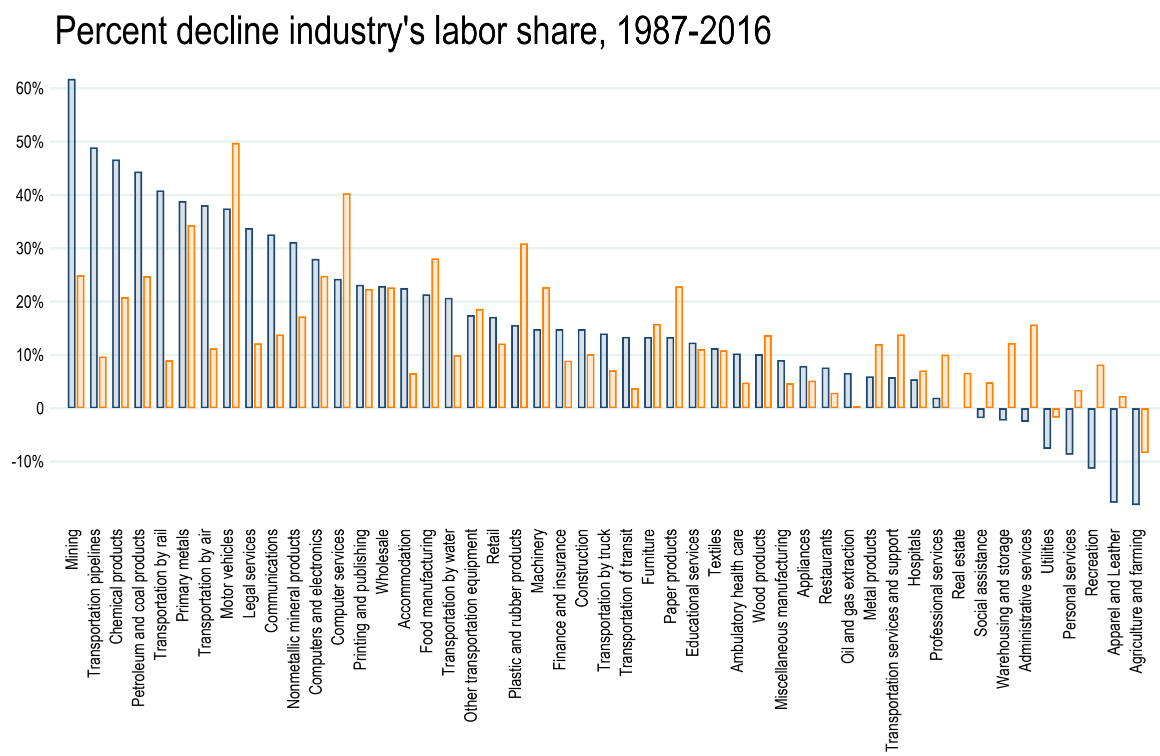

FIGURE 3: PERCENT DECLINE IN INDUSTRY LABOR SHARES (IN BLUE) AND AUTOMATION-DRIVEN LABOR SHARE DECLINES (IN ORANGE), 1987–2016. See text for variable definitions.

Figure 4 illustrates the relationship between automation and industry labor share changes.

[16]In what follows, all numbers 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 (1980–2016).

[17]Assumption 2 receives support from industry-level variation as well. Figure B-1 and Table B-2 in Appendix B-4 document a strong negative association between labor share declines, or its automation-driven component, 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).

Panel A depicts a strong negative association between labor share changes and adjusted penetration of robots ($R^2 = 0.18$). Panel B shows this association for the combined change in specialized software and dedicated machinery services ($R^2 = 0.32$). Panel C presents the relationship between observed labor share changes and the predicted labor share decline based on our three proxies of automation, which together account for 45% of the variation in industry labor share changes. Table A-1 in the Appendix further explores this relationship. It shows that offshoring matters for the labor share decline as well, but accounts for only 2% of the overall variation.

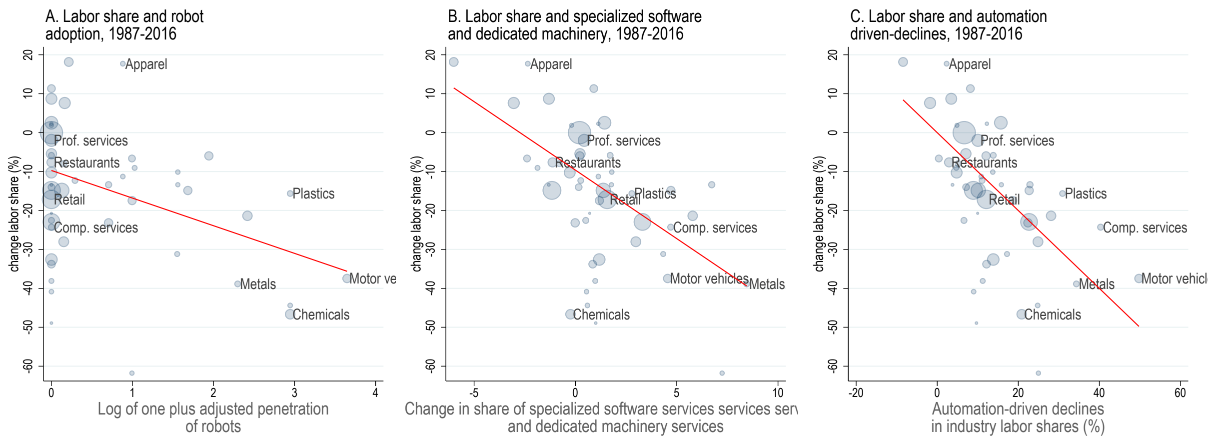

Figure 4: Relationship between automation technologies and changes in industry labor shares. See text for variable definitions. The five industries with the highest and the five industries with the lowest changes in their labor shares are identified in the figures.

Table A-1 also confirms that the inclusion of changes in total capital to value added ratio, sales concentration, markups, import competition, and unionization rates does not change the correlation between our proxies of automation and industry labor share changes. In fact, conditional on our proxies of automation, these variables do not have a sizable or statistically significant effect on industry's labor shares. Note also that changes in total capital to value added ratio are a "bad control," since our proxies of automation all contribute to the capital stock. Nevertheless, the fact that this variable has no discernible effect on our results suggests that specialized software, dedicated equipment, and industrial robots capture types of capital that lead to sizable declines in labor shares, presumably because they are used for automation, while other forms of capital are not.

3.3 Task Displacement and Wages Across Demographic Groups

We compute (direct) task displacement for our 500 demographic groups using equation (14). Specialization patterns across industries and routine jobs, the ω terms, are computed from the 1980 Census—a year that predates major advances in automation technologies—while $-d\ln s_i^{L,\text{auto}}$ corresponds to the 1987-2016 change in industry labor share or its component driven by automation technologies, as described in the previous subsection.[18]

Figure 5 presents our two measures of task displacement for the 500 groups of workers. Panel A shows that these two measures—one computed from changes in the labor share on the horizontal axis, and the other exploiting the component driven by automation on the vertical axis—are strongly correlated ($R^2 = 0.95$). This figure also reveals sizable differences in task displacement across demographic groups, using either measure: some demographic groups experienced a 25% direct reduction due to automation between 1980 and 2016, while others saw no change in their task shares.

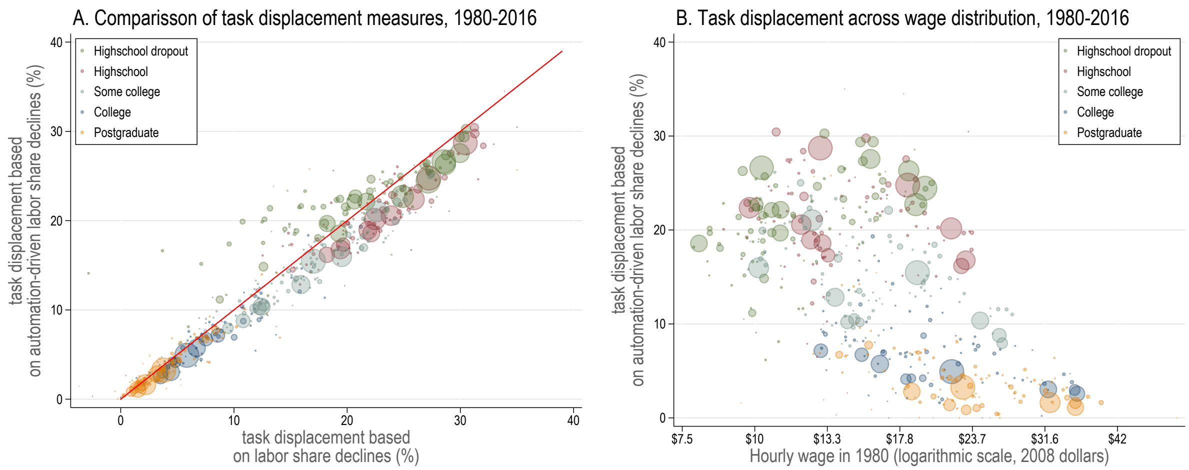

FIGURE 5: DIRECT TASK DISPLACEMENT MEASURES FOR THE 500 DEMOGRAPHIC GROUPS IN OUR SAMPLE. The left panel shows a scatter plot between our two task displacement measures. The first, computed from observed labor share declines, is on the horizontal axis, while the second, computed from automation-driven labor share declines, is on the vertical axis. The 45° line is shown in red. The right panel plots our measure of task displacement computed from automation-driven labor share declines 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.

Panel B plots our measure of task displacement based on automation-driven labor share declines for all groups sorted by their baseline wage in 1980. We see that (direct) 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.

Figure 6 provides a first glimpse of the association between (direct) task displacement and real wage changes across demographic groups. The top two panels plot the bivariate relationship between our two task displacement measures and real wage changes from 1980 to 2016. These plots reveal a strong correlation between task displacement and changes in real wages, with groups

[18] We created a consistent mapping of the 49 industries in the BEA data to the Census industry classification. For each industry, we computed the share of wages earned in routine jobs by a demographic group, using the definition of routine occupations described in Acemoglu and Autor (2011), where a third of the occupations in 1980 are classified as routine. Further details on the data used are provided in Appendix B-3. If instead we use data from the 2000 Census, the resulting task displacement measure is very similar (with a rank correlation of 0.93 with our baseline measure), confirming the strong persistence of specialization patterns.

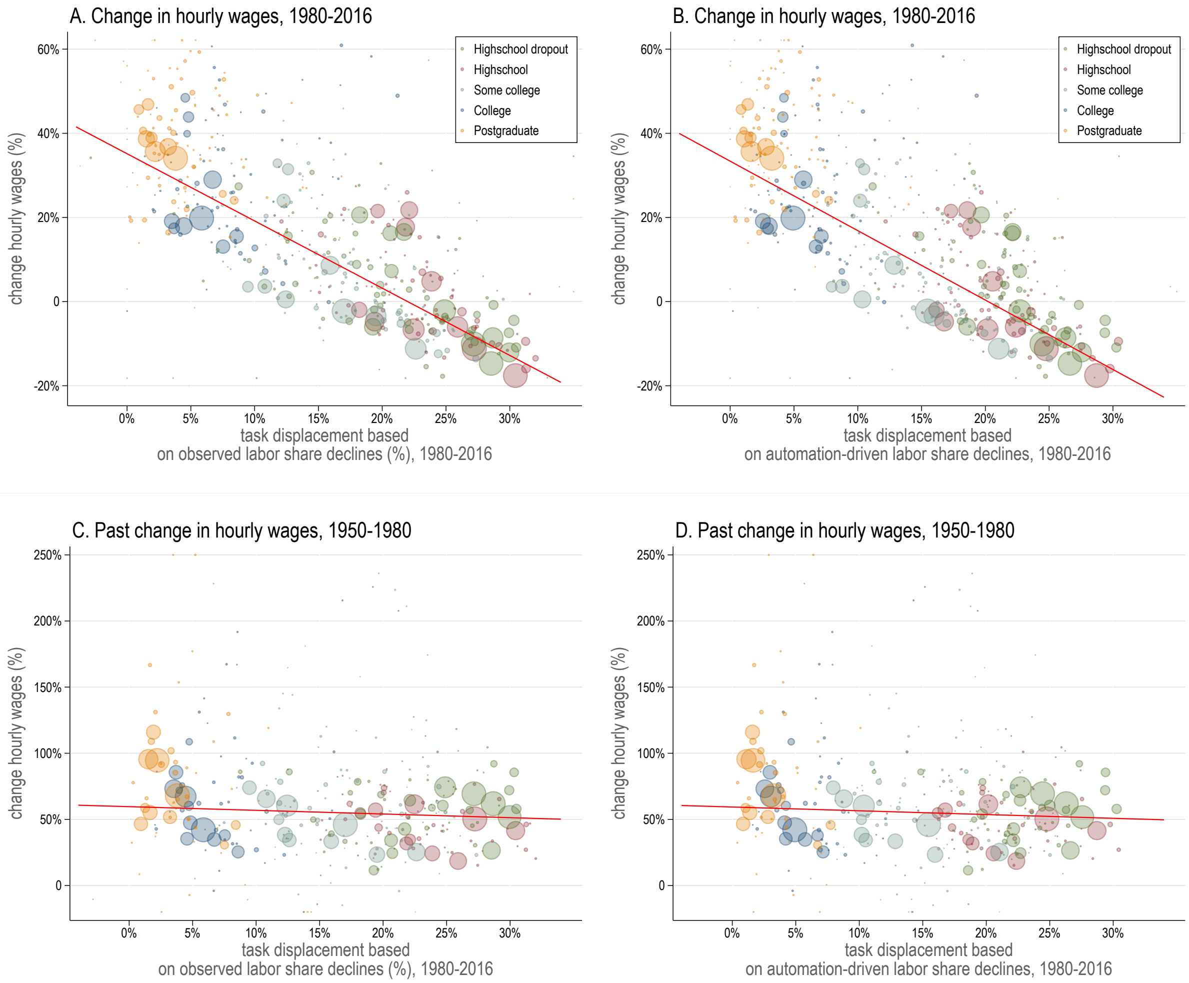

Figure 6: Reduced-form relationship between task displacement and changes in real hourly wages. Panel A plots changes in real hourly wages for 1980–2016 against our task displacement measure computed from observed labor share declines The slope of the regression line is −1.6 (standard error = 0.09). Panel B plots changes in real wages for 1980–2016 against our task displacement measure computed from automation-driven labor share declines for 1980–2016. The slope of the regression line is −1.65 (standard error = 0.10). Panels C and D plot pre-trends (changes in real hourly wages for 1950-1980) against our two task displacement measures for 1980-2016. The slopes of the regression lines in both Panels C and D are −0.28 (standard error = 0.28). Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. See text for variable definitions.

experiencing the highest levels of task displacement seeing their real wages fall or stagnate. The bottom two panels display a simple falsification exercise. They demonstrate that the relationships depicted in the top two panels are not driven by secular trends adversely affecting some groups and are not present between 1950 and 1980—a period that predates major advances in automation. Rather, all demographic groups, including those that experienced adverse task displacement after 1980, enjoyed robust real wage growth, of about 50%, between 1950 and 1980.

Both figures identify different education levels, highlighting that task displacement has been much higher for workers without a college degree. Consequently, workers without college have much lower, and in some cases negative, real wage changes. The relationship between task displacement and real wage changes is not just between education groups, however: a negative association between changes in wages and task displacement *within* education groups is visible from this figure as well.

Table A-2 in the Appendix provides descriptive statistics for the 500 demographic groups in our analysis and further corroborates these patterns. For example, it shows that workers in the top quintile of the (direct) task displacement distribution 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 automation-induced task displacement explains a large fraction of the changes in the US wage structure between 1980 and 2016. We also show that these results are not driven by changes in other forms of capital deepening and technological change, markups, industry concentration, deunionization, or import competition from China.

4.1 Baseline Results

Table 1 presents our baseline estimates from an empirical analogue of equation (13):

$$(15) \qquad \Delta \ln w_g = \beta^d \cdot \text{Task displacement}_g^{\text{direct}} + \beta^s \cdot \text{Industry shifters}_g + \alpha_{\text{edu}(g)} + \gamma_{\text{gender}(g)} + \upsilon_g.$$

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. As in all of our other results, regressions are weighted by total hours worked by each group and standard errors are robust to heteroskedasticity.

Throughout our identifying assumption is that the two (direct) task displacement measures are uncorrelated with other trends affecting wages—except through automation-driven task displacement. Later in this section, we provide extensive evidence supporting this identifying assumption.

Panel A of the table presents results with our first measure of task displacement, constructed from observed declines in industry labor shares. Panel B presents results with our second, preferred measure of task displacement, which focuses on the component of the labor share declines driven by automation technologies.

Column 1 presents a bivariate regression identical to the one shown in Figure 6. In Panel A, we see a precise and sizable relationship between task displacement and wage growth, with a coefficient of −1.6 (s.e. = 0.09). This estimate implies that a 25% increase in task displacement—which corresponds to the displacement experienced by white American men aged 26-35 with no high-school degree—is associated with a 40% (relative) wage decline. The bottom rows report the share of wage changes explained by task displacement.[19] Our measure of task displacement

[19] Following Klenow and Rodríguez-Clare (1997), we decompose the variance of y in the linear model $y = \sum_i x_i \beta_i + \varepsilon$

alone explains 67% of the variation in wage changes between 1980 and 2016.

The remaining columns document 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 share of earnings in manufacturing. These account for other demand factors favoring highly-educated workers and for the effects of 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 continues to explain 55% of the variation in wage changes during this period.

Our first task displacement measure in Panel A combines industry-level changes in labor shares with the distribution of employment of workers across industries and (routine and non-routine) occupations. Column 4 includes two more variables, corresponding to the constituent parts making up our task displacement measure. The first is the exposure of a demographic group to industry-level declines in the labor share, but without focusing on whether employment is in 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.[20] Column 4 shows that these two variables themselves do not explain real wage changes (conditional on task displacement), while task displacement remains very strongly correlated with wage changes. This result confirms that our measure of task displacement is not confounded by other industry-level changes 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. The lack of a negative impact on groups specializing in non-routine tasks also confirms that our results are not driven by a mechanical association between changes in the average wages paid in an industry and changes in its labor share.

Panel B presents results using our preferred measure of task displacement based on the component of the labor share decline driven by automation technologies. The estimates of the effects of task displacement and the shares of variance explained by this variable are, in all cases, very similar to those in Panel A. In column 3, for example, the coefficient estimate of task displacement is −1.36 (standard error = 0.21), compared to −1.31 in the same specification in Panel A. The share of wage structure changes explained by task displacement in this column is also similar:

as $\mathrm{Var}(y) = \sum_i \beta_i \cdot \mathrm{Cov}(y, x_i) + \mathrm{Cov}(y, \varepsilon)$ and compute the share of the variance in y explained by x_i as $\beta_i \cdot \frac{\mathrm{Cov}(y,x_i)}{\mathrm{Var}(y)}$. These shares add up to the R^2 of the regression, which is also reported in the table.

[20] Formally, these controls are defined as

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

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

53%, compared to 55% in Panel A.[21]

Overall, our baseline results document a strong association between task displacement and real wage changes, and support our presumption that this association is capturing the (direct) causal effect of automation-driven task displacement experienced by a demographic group. We next bolster the case that this is indeed a causal relationship and is highly robust.

4.2 Instrumental-Variables Estimates

Our preferred measure of task displacement is based on the component of the industry labor share decline that is driven by our proxies of automation. A complementary approach entails using these proxies as instruments for our first measure of task displacement based on observed labor share declines. Table 2 pursues this approach and confirms that estimating equation (15) via two-stage least squares (2SLS) yields similar results.[22]

Panel A presents 2SLS estimates for a specification analogous to column 3 of Table 1. Column 1 uses all three of our proxies as instruments. The first-stage F-statistic is very high (846.9). The 2SLS estimate for the effect of task displacement, -1.23 ($s = 0.19$) and the implied share of variance of wage changes explained by task displacement, 50%, are similar to those in column 3 of Table 1, obtained by directly using our second measure of task displacement.

The remaining columns explore the contribution of each of the proxies of automation. Column 2 uses the adjusted penetration of robots by itself. Columns 3 and 4 focus on dedicated machinery and specialized software as proxies for automation. Columns 5 and 6 include the software measure together with each one of the other two proxies for automation. The 2SLS estimates are similar across columns 1-6 and the hypothesis that they are all equal cannot be rejected. This finding is consistent with our exclusion restriction that the effects of these technologies operate through task displacement.

Finally, in column 7, we turn to offshoring—measured as the change in 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 12% of the variation in wage changes.

Panel B of the table presents estimates corresponding to the specification in column 4 of Table 1 (thus also controlling for exposure to industry labor share declines, instrumented by our automation proxies, and for relative specialization in routine jobs). The results in this panel

[21]Our main tables report robust standard errors. More conservative standard errors (for our baseline specification in column 3) are presented in Table B-3 in the Online Appendix and confirm our main findings. In particular, we compute standard errors as in Adao et al. (2019) and Borusyak et al. (2022), which are robust to the presence of unobserved industry shocks that affect all workers or workers in routine jobs in an industry. We additionally report standard errors from the single-step GMM estimation of the predicted decline in the labor share and our wage equation (see Newey, 1984), which corrects for the fact that the task displacement measure in Panel B is itself estimated from an industry-level regression.

[22]Formally, we use instruments of the form $\sum_{i \in \mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \text{Automation proxy}_i$, where our proxy is the adjusted penetration of robots, changes in the value of dedicated machinery services in value added, or changes in the value of specialized software services in value added, or combinations thereof. When we include exposure to industry labor share declines as a covariate in Panel B, we use variables of the form $\sum_{i \in \mathcal{I}} \omega_g^i \cdot \text{Automation proxy}_i$ as instruments.

are similar, though less precise in some specifications (such as in columns 2 and 3 where we use, respectively, the adjusted penetration of robots and dedicated machinery as the only instruments).

In what follows, we focus on estimates using our measure of task displacement based on automation-driven labor share declines, as in Panel B of Table 1, rather than the 2SLS models presented in this subsection.

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 2.4, these controls absorb any factor-augmenting productivity trends common to all workers with the same education level or gender. Column 1 shows that these SBTC variables are significant and have the expected signs. For example, between 1980 and 2016, the relative wage of workers with a college (but no post-graduate) degree increased by 25% relative to those with a high-school degree, and the relative wage of workers with a post-graduate degree increased by 42% relative to high-school graduates. In this model, education dummies explain 55% of the variation in wage changes during this period.

However, most of the differences between workers with different education levels disappear once our task displacement measures are included in columns 2 and 3 (these models are identical to column 3 in Panels A and B of Table 1). Notably, 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, respectively, 80% and 65% of the rise in the post-graduate premium with our two measures. Task displacement also explains more than 50% of the overall changes in the wage structure, while the education dummies explain less than 17%. In addition, task displacement accounts for 4–7 percentage points of the 17% decline in the gender wage premium during this period. These results are the basis for our claim that much of the change in the US wage structure between 1980 and 2016 is due to task displacement, with a minor role for standard (factor-augmenting) SBTC.

The next three columns go one step further and allow for differential trends that depend on the baseline wage level of each demographic group, which could proxy for dimensions of group skills that go beyond education and gender. The results of these demanding specifications are similar to those in the first three columns, and our task displacement measure explains about 40% of the observed wage changes, while differential trends by education and baseline wages explain, respectively, 18% and 7% of the variation.

In Table A-3 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 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 63%–72% of the changes in the US wage structure, while the education dummies continue to explain a small portion (4%–18%) of the variation.

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

4.4 Employment Outcomes

If task displacement leads to lower labor demand for a demographic group, we should see an impact not just on its wage but on its employment as well.[23] Table 4 presents results for the employment to population ratio 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. The first three columns use the measure of task displacement based on industry labor share declines, while the next three columns rely on our preferred measure, exploiting the component of labor share declines driven by automation technologies. Panel B reveals that most of the adjustment takes place via non-participation. For example, using the estimates from column 5 based on our preferred measure, we see that a 10 percentage point higher task displacement is associated with a 4.4 percentage point decline in employment between 1980 and 2016, and a similar 3.5 percentage point increase in non-participation. 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. Rather, as with our wage results, they are driven by task displacement. Overall, our task displacement measure explains between 16% and 38% of changes in employment and participation between 1980 and 2016.[24]

4.5 Confounding Trends: Capital, TFP, Deunionization, Imports, and Markups

The main challenge in interpreting our reduced-form estimates as the causal effect of automation on relative wages is the possibility that labor share changes or their component driven by automation technologies are confounded by other industry-level trends. We directly confront these threats to identification in this subsection.

A first concern is that our task displacement measures may capture not just the effects of automation but of other investments or other types of technological change. We already saw in Table A-1 that, conditional on our automation measures, changes in the total capital to value added ratio are not correlated with industry labor shares. Columns 1-2 and 5-6 in Panel A of Table 5 further explore the role of capital intensity and industry productivity by controlling for exposure to changes in industry capital to value added ratios and TFP growth. Consistent with

[23] Appendix B-1 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).

[24] We report results for hours per worker and the unemployment rate in Appendix Table B-4, though the responses of these margins are smaller and less robust than those of employment to population ratio and non-participation.

our interpretation that wage inequality is shaped by task displacement, rather than overall capital intensity or productivity growth resulting from non-automation technologies, exposure to these industry variables has no direct impact on wages and does not alter the relationship between task displacement and wages.[25] These results support our conceptual framework and identifying assumption.

In Appendix Table A-4 we adopt a complementary strategy for controlling for changes in capital intensity. We relax both Assumption 1 and $\lambda = 1$, so that the elasticity of substitution between capital and labor is no longer equal to one. We then adjust our task displacement measures for changes in industry capital utilization and other movements in factor prices. The results of this exercise are similar to our baseline findings.[26]

Changes in worker bargaining power can also impact industry labor shares and worker wages. To investigate this issue, in columns 3 and 7, we include 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. Finally, columns 4 and 8 include the exposure of different demographic groups to industries facing greater Chinese import competition. Although industry shifters already account for the effects of trade in final goods, this specification controls for other effects of trade with China, such as those working through changes in rent-sharing. With both controls, our task displacement measures have similar coefficients to the ones we saw in Table 1 and continue to explain about 50% of the changes in the US wage structure. We find no evidence that declining unionization rates or Chinese import competition has a direct impact on the wage structure (beyond their potential effects working through changes in industry composition).

Panel B of the table shows similar results when we allow each of these industry shocks to have a differential impact on workers specializing in routine jobs. In all cases, the effects of task displacement on wages are largely unaffected.[27]

Another important concern centers on the role of changes in industry concentration and markups, which also impact industry labor shares and might directly affect the wage structure. Table 6 explores the role of these factors. Columns 1 and 5 in Panel A control for workers' exposure to industries with rising sales concentration, and the other columns include their exposure to markup changes using three alternative estimates of industry markups. These are: markups

[25]These results are in line with our theoretical expectations. For example, when Assumption 1 holds, higher productivity of capital 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 any workers. Likewise, industry TFP growth should only affect labor demand through the industry shifters, which are already being controlled for in these regressions.

[26]When $\lambda \neq 1$ and there are ripple effects, our baseline task displacement measure in equation (14) becomes

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

where the adjusted labor share decline, $-d\ln s_i^L - s_i^K \cdot (1-\sigma_i) \cdot (d\ln w_i - d\ln R_i)$ accounts for the influence of factor prices. In this expression σ_i is the elasticity of substitution between capital and labor in industry i, and $d\ln w_i$ and $d\ln R_i$ are the observed change in factor prices faced by the industry. Table A-4 provides results using both this adjusted measure and its analogue focusing on automation-driven labor share declines.

[27]Table B-5 shows that the results are similar when we control for exposure to labor share declines and relative specialization in routine occupations as in column 4 of Table 1.

computed from accounting data; markups estimated using the (inverse of the) material share, and markup estimates following the production function approach in De Loecker et al. (2020) (see Appendix B-3 for details).

In all specifications and with either measure of task displacement, our results are similar to the baseline estimates presented in Table 1. For example, the effects of task displacement range between −1.31 and −1.42, while exposure to changes in 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 industry labor share changes driven by markups.[28] This correction does not affect our conclusions, and our point estimates for the effects of task displacement remain sizable and precise. Even with this correction, markup changes do not have a robust effect on wages 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 changes in markups or concentration. These results imply that task displacement—and not so much rising market power—has played a defining role in the surge in US wage inequality over the last four decades.

Tables 5 and 6 demonstrate that other industry trends do not confound the effects of task displacement and do not have comparable effects. They do not, however, establish that the effects of automation technologies are mainly intermediated by tasks that can be automated. Appendix A provides two sets of results that support this interpretation. First, Table A-5 reports analogous 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 constructed by Webb (2020) based on the text of new patents. Second, Table A-6 additionally controls for the exposure of workers to occupations in the bottom tercile of the overall wage distribution and the interaction between this exposure and industry automation. This has no effect on our task displacement results and these variables themselves are not significant. This robustness check thus confirms that task displacement is capturing the effects of automation on worker groups specializing in tasks that can be automated rather than on workers in low-pay occupations.

4.6 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

[28] Appendix B-1 provides an extension of our model to an economy with markups. In this more general case, denoting industry i's markup by μ_i, our baseline task displacement measure in equation (14) becomes

$$\text{Task displacement}_g^{\text{direct}} = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \left(-d\ln s_i^L - d\ln \mu_i\right),$$

which is the expression we use in Panel B of Table 6.

Table B-6 in the Appendix provides additional specifications that allow markups to have a differential impact on workers in routine jobs. Finally, Table B-7 shows the robustness of the patterns reported here to controlling for exposure to industry labor share declines and relative specialization in routine occupations.

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 results using both measures of task displacement are similar to those in Table 1.

In Panel B we separate regional and national changes by including a full set of demographic group fixed effects that 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. However, 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.[29]

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 similar to those in Panels A and B.

4.7 Further Robustness Checks

The Appendix provides a number of additional checks, all of which support our conclusions. First, in Table A-7, we provide estimates of the effects of task displacement excluding immigrants, as well as separate estimates for men and women. Second, in Table A-8 we present stacked-differences models with two periods, 1980–2000 and 2000–2016, which explore the differential patterns of task displacement between these subperiods. 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 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.[30] Finally, in Table A-9 we present comparable results when we use labor share data from the BLS, exclude extractive industries, winsorize the labor share changes, or focus only on industries with a declining labor share to construct our measure of task displacement.

[29] In the presence of migration and trade across regions, regional task displacement should have a smaller impact than national task displacement. 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, national effects are absorbed by the group fixed effects.

[30] In Appendix Table B-8, we confirm our findings for the 1980–2007 period, which avoids any persistent effects of the Great Recession.

5 General Equilibrium Effects and Quantitative Analysis

Our reduced-form evidence documented a strong negative relationship between (direct) task displacement and relative wage changes across worker groups. This evidence misses three general equilibrium effects. First, in our regressions, the common impact of productivity on real wages is in the intercept, making our estimates uninformative about wage *level* changes. Second, although our regressions control for *observed* changes in industry composition, they do not separate industry shifts *induced* by automation, missing one component of the total impact of automation. Third and most importantly, our regression estimates focus on the direct effects of automation via task displacement and do not account for the resulting ripple effects, which also impact the wage structure. In this section, we develop a methodology to quantify the effects of technological changes that accounts for these mechanisms, and for brevity, focus on automation technologies.

5.1 General Equilibrium Effects and the Propagation Matrix

We first generalize Proposition 2 to an economy with multiple sectors and with ripple effects (relaxing Assumption 1 which was imposed when we derived equation (13)). For this purpose, let us define *aggregate task shares* as

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

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

To characterize ripple effects, consider any technological change with a direct effect of z_g on the real wage of group g. For example, in the case of automation technologies, z_g corresponds to the direct task displacement of group g. Denote by $\boldsymbol{z}$ the column vector of z_g's and differentiate (2) to 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 impact of a change in wages on task allocation (which was equal to zero under Assumption 1). We refer to the $G\times G$ matrix Θ as the *propagation matrix.* Although this matrix is much lower-dimensional than the full set of task-specific productivity functions (the ψ_g's), it fully accounts for ripple effects and the general equilibrium implications of technological changes.

In Appendix A-2, we prove that Θ is well defined and has positive entries. Most importantly, $\theta_{gg'} \geq 0$ captures the extent of competition for tasks between groups g' and g. Second, we show that the row sum of Θ, which we denote by ε_g, is always between 0 and 1. Third, Θ 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 aggregate output). Finally, the entries of Θ also specify 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 $\theta_{gg'} > s^L_{g'} \cdot \varepsilon_g$ (Appendix Appendix B-1 relates these entries to common measures of elasticities of substitution). In what follows, we denote the gth row of the propagation matrix by $\Theta_g = (\theta_{g1}, \ldots, \theta_{gG})$.

The next proposition characterizes the general equilibrium effects of automation on wages, industry prices, TFP, and aggregate output (GDP).

Proposition 4 (GE Effects) *The effects of automation on wages, industry prices, and aggregates are given by the solution to the system of equations:*

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

where $d\ln \boldsymbol{\Gamma}^{auto} = \left(\sum_{i\in\mathcal{I}} \omega^i_1 \cdot d\ln \Gamma^{auto}_{1i}, \ldots, \sum_{i\in\mathcal{I}} \omega^i_G \cdot d\ln \Gamma^{auto}_{Gi}\right)$, $d\ln \boldsymbol{\zeta} = (d\ln \zeta_1, \ldots, d\ln \zeta_G)$, *and* $d\ln \boldsymbol{p} = (d\ln p_1, \ldots, d\ln p_I)$.

As before, real wage changes depend on the productivity effect ($d\ln y$), the induced shifts in industry composition ($d\ln \boldsymbol{\zeta}$), and the (direct) task displacement experienced by all groups ($d\ln \boldsymbol{\Gamma}^{\text{auto}}$). In the presence of ripple effects, these direct impacts are pre-multiplied by the gth row of the propagation matrix Θ_g. Intuitively, because of ripple effects, wage changes for a group depend on whether other groups that compete for the same tasks are being displaced from their tasks. The gth row of the propagation matrix, Θ_g, has all the necessary information for computing the effects on group g from the task displacement experienced by other groups.[31]

The proposition also shows that we can compute the full general equilibrium impact of automation on wages, industry shares and prices, TFP, GDP, and the capital share by solving

[31] Ripple effects do not affect the expressions for TFP, GDP, or industry 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.

the above system of equations. The solution to this system will be a function of the same objects we emphasized in Section 2: direct task displacement experienced by different groups (the $d\ln\Gamma_{gi}^{\text{auto}}$'s) and cost savings from automation (the π_{gi}'s). In addition, we now need two more ingredients. First, it is necessary to specify the full demand system across industries to determine how technological changes impact industry composition, which will in turn affect the wage structure. Second, we have to parametrize and estimate the propagation matrix to account for the endogenous reallocation of tasks in response to automation and the resulting ripple effects. The formulas in this proposition clarify that the direct task displacement generated by automation is the (exogenous) impulse that leads to a change in task shares, while ripple effects encoded in the propagation matrix and changes in industry composition determine the full general equilibrium implications of this task displacement.[32]

5.2 Parametrization, Calibration, and Estimation

Measuring task displacement and cost savings from automation: In this section we use our more general measures of task displacement which only require Assumption 2. We also relax the assumption that $\lambda = 1$. In this case, automation-driven task displacement experienced by group g in industry i can be measured as

$$d\ln\Gamma_{gi}^{\text{auto}} = \frac{\omega_{gi}^R}{\omega_i^R} \cdot \frac{-d\ln s_i^{L,\text{auto}}}{1+(\lambda-1)\cdot s_i^L \cdot \pi_i}, \tag{16}$$

and the (direct) task displacement for this group becomes:

$$\text{Task displacement}_g^{\text{direct}} = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \frac{-d\ln s_i^{L,\text{auto}}}{1+(\lambda-1)\cdot s_i^L \cdot \pi_i}. \tag{17}$$

where recall that $d\ln s_i^{L,\text{auto}}$ denotes the percent change in the labor share driven by automation in industry i. 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.

We continue to present results using both measures of task displacement, but for brevity, will focus on our preferred strategy that relies on the component of labor share declines driven by automation. Appendix A-3 shows that when $\lambda \neq 1$ and there are ripple effects, this component can be estimated from an industry-level regression of the *adjusted decline* in the labor share, $-d\ln s_i^L - s_i^K\cdot(1-\sigma_i)\cdot(d\ln w_i - d\ln R_i)$, on our measures of industry automation. Here, σ_i is

[32] This way of quantifying the full general equilibrium effects of technological change is a convenient alternative to approaches based on a full parameterization of the model and numerical computation of its equilibria. In our model, a full parameterization would require information on the comparative advantage schedules of 500 different demographic groups across all tasks and industries, which would have been challenging given the available data. Our alternative approach specifies a much lower-dimensional object, the propagation matrix, and enables us to obtain all of the economically relevant quantities determining the general equilibrium effects of automation (and any other direct shock to task shares) without estimating these schedules. In addition, we show that the propagation matrix can be estimated from variation in wages in response to other groups' task displacement. The drawback is that this approach is exact for small changes and is an approximation when there are larger changes.

the elasticity of substitution between capital and labor in industry i, and $d\ln w_i$ and $d\ln R_i$ are observed factor price changes facing industry i. The term $s_i^K \cdot (1-\sigma_i) \cdot (d\ln w_i - d\ln R_i)$ corrects for the endogenous changes in labor share due to factor prices and isolates the direct impact of automation on the labor share (see also Grossman and Oberfield, 2021). In the text, we also set $\sigma_i = 1$, $\lambda = 0.5$, and $\pi_{gi} = \pi_i = 30\%$, and explore robustness to variations in each one of these parameters in Table A-11).[33]

Industry demand: We use a simple CES demand system across industries as in footnote 11: $s_i^Y(\boldsymbol{p}) = \alpha_i \cdot p_i^{1-\eta}$. Following Buera et al. (2015), we set the elasticity of substitution between industries to $\eta = 0.2$.

Propagation matrix: Motivated by the symmetry property of the propagation matrix, 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 analysis, which did not find evidence of significant heterogeneities in the effects of task displacement across groups. 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 overlaps 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, wage changes from Proposition 4 can be written as:

$$\begin{aligned} d\ln w_g =& \frac{\varepsilon_g}{\lambda} \cdot d\ln y - \frac{\theta}{\lambda} \cdot \text{Task displacement}_g^{\text{direct}} \\ & - \sum_{g'\neq g} \left(\frac{1}{2}\left(\frac{\varepsilon_g}{\lambda} - \frac{\varepsilon_{g'}}{\lambda}\right) + \sum_{n\in\mathcal{N}} \frac{\beta_n}{\lambda} \cdot f(d_{g,g'}^n) \right) \cdot s_{g'}^L \cdot \text{Task displacement}_{g'}^{\text{direct}} + u_g, \end{aligned}$$

$$\text{subject to: } \varepsilon_g = \theta + \sum_{g'\neq g} \left(\frac{1}{2}(\varepsilon_g - \varepsilon_{g'}) + \sum_{n\in\mathcal{N}} \beta_n \cdot f(d_{g,g'}^n) \right) \cdot s_{g'}^L, \text{ and } \beta_n \geq 0,$$

[33] Our baseline measures of task displacement in Section 4 set $\lambda = 1$. This is consistent with our choice of the elasticity of substitution between capital and labor, $\sigma_i = 1$, here, because under Assumption 1, $\sigma_i = \lambda$ Thus in both cases we are setting the elasticity of substitution between capital and labor to unity. In the Appendix, we explore the robustness of our results to $\sigma_i = 0.8$ and $\sigma_i = 1.2$, which is consistent with the range of elasticity of substitution estimates in (Karabarbounis and Neiman, 2013; Oberfield and Raval, 2020). The estimate $\lambda = 0.5$ comes from Humlum (2020), and in the Appendix, we show robustness to $\lambda = 0.3$ and $\lambda = 0.7$. Finally, 30% cost savings from automation are in line with the estimates for industrial robots surveyed in Acemoglu and Restrepo (2020). Although cost savings may differ across technologies and industries, we do not have data to estimate such differences. We additionally report estimates from our model with endogenous labor supply in Appendix B-1.

where the second line represents the ripple effects, f is chosen as an inverted sigmoid function of the distance between two groups, and the error term u_g is derived from the unobserved wage effects for group g, denoted by υ_g in (15). Specifically, using vector notation, $\boldsymbol{u} = \Theta \cdot \boldsymbol{\upsilon}$. To estimate the parameters of this system, we impose the exclusion restriction that each group's (automation-driven) task displacement, Task displacement$_g^{\text{direct}}$, is orthogonal to $\boldsymbol{u}$, or equivalently to $\boldsymbol{\upsilon}$, which leads to the moment conditions:[34]

$$\mathbb{E}\left[\upsilon_g \cdot \left(1, \text{Task displacement}_g^{\text{direct}}, \left\{\sum_{g' \neq g} f(d^n_{g,g'}) \cdot s^L_{g'} \cdot \text{Task displacement}_{g'}^{\text{direct}}\right\}_{n \in \mathcal{N}}\right)\right] = 0 \text{ for } g = 1, \ldots, G.$$

Table A-10 in the Appendix provides GMM estimates for θ and β_n based on these moment conditions. Columns 1–3 use the task displacement measure based on the observed industry labor share declines, while columns 4–6 use our task displacement measure based on the automation-driven labor share declines. We find positive and significant estimates for ripple effects by occupation, industry, and within age×education cells. These estimates imply that demographic groups that are directly displaced by automation then compete for tasks performed by other groups that have similar age and education and that specialize in similar occupations and industries.

5.3 General Equilibrium Estimates

This subsection presents general equilibrium estimates of the consequences of automation. We use Proposition 4 to compute the full general equilibrium effects of (direct) task displacement, which we measure using equations (16) and (17).

Table 8 summarizes our findings. The first column depicts the data, while the second column presents our general equilibrium estimates when direct task displacement is given by our measure based on observed labor share declines. The third column provides our preferred estimates, feeding in direct task displacement numbers based on the automation-driven component of industry labor share declines. In what follows, we focus on the results in this last column.

The first panel of the table summarizes the effects of automation on the wage structure. This information is also displayed in Figure 7, which decomposes The contribution of the different mechanisms via which task displacement affects wages (with demographic groups sorted by their baseline wage in 1980 on the horizontal axis). Panel A of the figure plots the common productivity effect, $(1/\lambda) \cdot d \ln y$, which raises the wages for all groups by close to 45%.

Panel B adds changes in industry composition induced by automation, $(1/\lambda) \cdot d \ln \boldsymbol{\zeta}$. Because

[34] We compute distances using the dissimilarity measures $d^{\text{occupations}}_{g,g'} = \frac{1}{2}\sum_o |\omega^o_g - \omega^o_{g'}|$ and $d^{\text{industries}}_{g,g'} = \frac{1}{2}\sum_{i \in \mathcal{I}} |\omega^i_g - \omega^i_{g'}|$, where the sum runs over 330 occupations and 192 industries in the US Census, respectively. In addition, the sigmoid function takes the form

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

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 baseline estimates in Table A-10, we use a quadratic tuning parameter, $\kappa = 2$. In the Appendix, we provide analogous estimates for different values of the tuning parameter; see Tables A-10 and A-11.

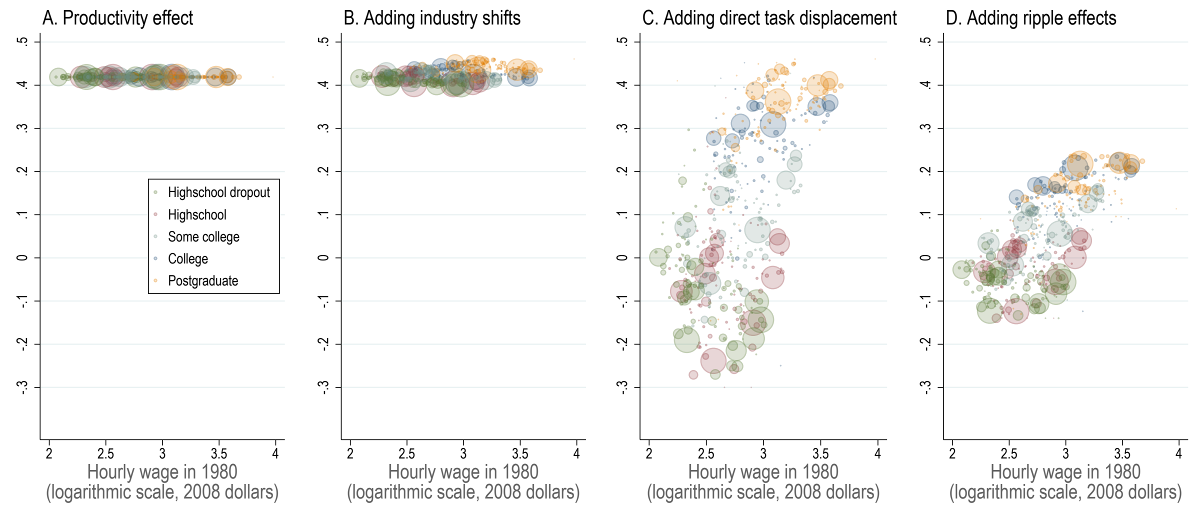

FIGURE 7: CONTRIBUTION OF PRODUCTIVITY EFFECTS, INDUSTRY SHIFTS, DIRECT DISPLACEMENT EFFECTS, AND RIPPLE EFFECTS TO THE PREDICTED CHANGE IN HOURLY WAGES, 1980–2016. Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. See text for variable definitions.

$\eta < 1$, automation induces a shift toward sectors, such as services, that have less automation and increases the demand for workers specialized in these sectors. However, this effect is modest, accounting for less than 7% of the observed changes in the US wage structure.

Panel C adds the direct task displacement effects, given by $-(1/\lambda) \cdot d \ln \mathbf{\Gamma}^{\text{auto}}$. Direct task displacement generates sizable dispersion in wage changes and causes as much as a 25% decline in the real wages of some groups. The comparison between Panels B and C shows that the main impact of automation on the wage structure is via direct task displacement. This reiterates that automation is distinct from trade in final goods and from other technologies that do not generate task displacement and impact labor demand mainly by changing industry composition.

The results in Panel C show that direct task displacement accounts for as much as 94% of the overall changes in the US wage structure between 1980 and 2016 (see the second row of Table 8). The reason why this is larger than the 50-70% estimate we obtained in Section 4 is instructive. Our reduced-form analysis did not allow for ripple effects, which were thus partially captured by our task displacement measures. Our general equilibrium framework clarifies that ripple effects enable directly-displaced demographic groups to compete for non-automated tasks performed by other groups and hence spread the impacts of task displacement across groups. This is confirmed in Panel D of Table 8, which depicts the full effects of automation on wages after accounting for ripple effects using our estimates of the propagation matrix. For example, the direct impact of automation on high-school graduate white men aged 26-35 in Panel C of Figure 7 is −13.3%. But once we allow for ripple effects in Panel D of Figure 7, this demographic group experiences a smaller, 5.5%, decline in real wages. In contrast, the direct impact on Hispanic high-school dropout women aged 36-45 is a 2.6% real wage increase, but incorporating ripple effects, this group suffers a 3.3% real wage decline.

As a summary, Figure 8 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, automation explains several other salient aspects of the labor market during this period. First, even though there is a large (close to 45%) productivity effect, real wages for 131 demographic groups (making up 42% of the 1980 population) *decline* because of automation (in the data, 121 groups, making up 53% of the 1980 population, experienced real wage declines). This result highlights how automation can generate meaningful real wage declines, which contrasts with the canonical SBTC model, where technological *progress* is predicted to increase the real wages of all groups. Second, in general equilibrium, task displacement generates a 21% increase in the college premium (80% of the observed increase) and a 22% increase in the post-graduate premium (55% of the observed increase). 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. For example, the direct effect of automation is to reduce the gender gap by 6%, but because displaced men compete for tasks previously performed by women, in general equilibrium the gender premium declines only by 2%.

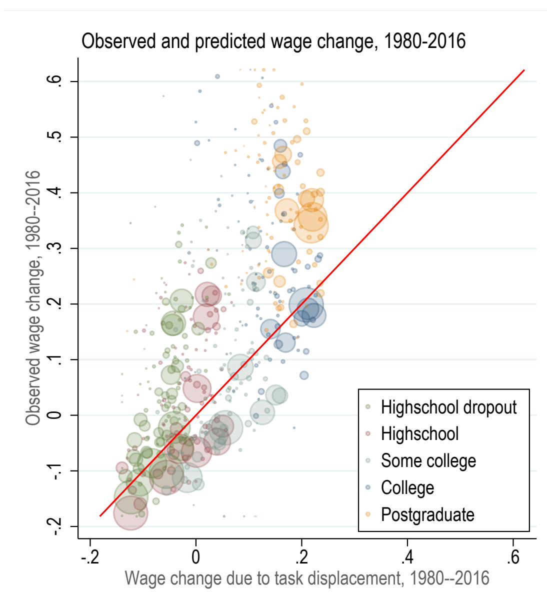

FIGURE 8: OBSERVED WAGE CHANGES (VERTICAL AXIS) VS. PREDICTED WAGE CHANGES IN GENERAL EQUILIBRIUM DUE TO AUTOMATION (HORIZONTAL AXIS). The 45° line is shown in red. Marker sizes indicate the share of hours worked by each group and different colors indicate education levels. See text for variable definitions.

Despite matching several salient aspects of the changes in the US wage structure, our model misses a significant portion of wage growth for highly-educated workers at the top of the wage distribution. This may reflect the complementarity between some of the new technologies and post-graduate workers 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 8 turns to the model's implications for aggregates. Despite the large distributional effects documented above, task displacement generates only a cumulative 3.4% TFP gain over 1980–2016, and this is the reason why average real wages are predicted to grow slowly (only by 5.2%) and many groups experience real wage declines. This small TFP increase is intuitive in light of the characterization in Proposition 4: TFP gains from automation can be approximated as the product of the share in GDP of displaced tasks ($\sum_g \sum_i s^L_{gi} \cdot d\ln\Gamma^{\text{auto}}_{gi}$), which is approximately 10%, and average cost reductions of 30%, thus yielding a $0.1 \times 0.3 \approx 3\%$ increase in TFP. In contrast to this small automation–induced increase in productivity, in the data TFP grew by 35% during this period, and average real wages rose by 29% (though two thirds of the latter is due to educational upgrading of the workforce, which is not present in our model). These numbers confirm that there were other technological advances—such as factor-augmenting and productivity-deepening technologies, industry TFP, or even new tasks—contributing to GDP, 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 due to automation accounts for the observed decline in the labor share (by construction) and the observed increase in the capital-GDP ratio over this period. This last finding implies that the amount of investment accompanying automation in our model is in the ballpark of the data.

The third panel of Table 8 summarizes the industry implications of task displacement. In line with the modest TFP gains estimated above, we see that task displacement generates small changes in industry composition and accounts for only 0.5 of the 8.8 percentage point decline in the share of manufacturing in GDP. Despite its small impact on industry composition, task displacement within manufacturing generates a large, 13%, reduction in the wage bill of that sector, accounting for a third of the decline in manufacturing labor demand for 1980–2016.

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), which displaces certain worker 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 at the expense of 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 50-70% of the changes in the 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. We also verified that our task displacement variable captures the effects of automation technologies (and to a lesser degree offshoring) rather than changes in overall capital intensity, other types of technologies, markups, industry concentration, unionization, or Chinese import competition. These alternative economic trends do not appear to play a major role in the evolution of the US wage structure between 1980 and 2016 and have negligible effects on our estimates.

Our reduced-form regressions focus on the direct effects of task displacement on wages, but miss important general equilibrium forces. We developed a methodology to quantify the general equilibrium implications 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 the 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 the US data.

There are several interesting areas for future research. First, our framework has been static, and 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, 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 another avenue for future research.

Third, our strategy exploited industry-level trends in automation and labor share. Several recent works have pointed out that labor share declines concentrate on a subset of, often largest, firms (e.g., Autor et al., 2020; Kehrig and Vincent, 2020). Acemoglu et al. (2020b) show that in French manufacturing these are the firms that adopt automation technologies and expand at the expense of their competitors, where the actual declines in labor demand take place. This pattern confirms that it is (automation-driven) reductions in the labor share at the industry level, rather than at the firm level, that are relevant for task displacement, but also suggests that modeling the competition between automating and non-automating firms is yet another interesting area for future research (see, for example, Hubmer and Restrepo, 2021).

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 our reduced-form and quantitative analyses. 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.

References

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

Acemoglu, Daron, David Autor, David Dorn, Gordon H Hanson, and Brendan Price (2016): "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34, S141–S198.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo (2020a): "AI and Jobs: Evidence from Online Vacancies," Working Paper 28257, National Bureau of Economic Research.

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

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

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

Acemoglu, Daron and Fabrizio Zilibotti (2001): "Productivity Differences*," *The Quarterly Journal of Economics*, 116, 563–606.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales (2019): "Shift-share designs: Theory and inference," *The Quarterly Journal of Economics*, 134, 1949–2010.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum (2020): "The Evolution of Work in the United States," *American Economic Journal: Applied Economics*, 12, 1–34.

Autor, David and David Dorn (2013): "The Growth of Low-skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103, 1553–97.

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

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

Autor, David H, Lawrence F Katz, and Alan B Krueger (1998): "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics*, 113, 1169–1213.

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

Bárány, Zsófia L. and Christian Siegel (2020): "Biased technological change and employment reallocation," *Labour Economics*, 67, 101930.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022): "Quasi-experimental shift-share research designs," *The Review of Economic Studies*, 89, 181–213.

Bound, John and George Johnson (1992): "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations," *American Economic Review*, 82, 371–92.

Buera, Francisco J, Joseph P Kaboski, and Richard Rogerson (2015): "Skill Biased Structural Change," Tech. rep., National Bureau of Economic Research.

Burstein, Ariel, Eduardo Morales, and Jonathan Vogel (2019): "Changes in Between-group Inequality: Computers, Occupations, and International Trade," *American Economic Journal: Macroeconomics*, 11, 348–400.

Card, David and Thomas Lemieux (2001): "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis*," *The Quarterly Journal of Economics*, 116, 705–746.

Caunedo, Julieta, David Jaume, and Elisa Keller (2021): "Occupational Exposure to Capital-Embodied Technical Change," CEPR Discussion Papers 15759, C.E.P.R. Discussion Papers.

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

David, H, David Dorn, and Gordon H Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103, 2121–68.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger (2020): "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, 135, 561–644.

Elsby, Michael WL, Bart Hobijn, and Ayşegül Şahin (2013): "The Decline of the US Labor Share," *Brookings Papers on Economic Activity*, 2013, 1–63.

Feenstra, Robert C and Gordon H Hanson (1999): "The Impact of Outsourcing and High-technology Capital on Wages: Estimates for the United States, 1979–1990," *The Quarterly Journal of Economics*, 114, 907–940.

Fernald, John (2014): "A Quarterly, Utilization-adjusted Series on Total Factor Productivity," Tech. rep., Federal Reserve Bank of San Francisco.

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

Goos, Maarten and Alan Manning (2007): "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, 89, 118–133.

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

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

Gregory, Terry, Anna Salomons, and Ulrich Zierahn (2018): "Racing With or Against the Machine? Evidence from Europe," Working Paper No. 7247, CESifo Working Paper.

Griliches, Zvi (1969): "Capital-Skill Complementarity," *The Review of Economics and Statistics*, 51, 465–468.

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

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

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

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

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

Jaimovich, Nir, Itay Saporta-Eksten, Henry E Siu, and Yaniv Yedid-Levi (2020): "The Macroeconomics of Automation: Data, Theory, and Policy Analysis," Tech. rep., National Bureau of Economic Research.

Johnson, Matthew and Michael P Keane (2013): "A dynamic equilibrium model of the US wage structure, 1968–1996," *Journal of Labor Economics*, 31, 1–49.

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

——— (2018): "Accounting for Factorless Income," NBER Working Papers 24404, National Bureau of Economic Research, Inc.

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

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

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

Klenow, Peter J. and Andrés Rodríguez-Clare (1997): "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" *NBER Macroeconomics Annual*, 12, 73–103.

Krueger, Alan B. (1993): "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989," *The Quarterly Journal of Economics*, 108, 33–60.

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

Lee, Sang Yoon (Tim) and Yongseok Shin (2017): "Horizontal and Vertical Polarization: Task-Specific Technological Change in a Multi-Sector Economy," Working Paper 23283, National Bureau of Economic Research.

Newey, Whitney K. (1984): "A method of moments interpretation of sequential estimators," *Economics Letters*, 14, 201–206.

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

Piketty, Thomas (2014): *Capital in the Twenty-First Century*, Harvard University Press, Cambridge.

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

Wright, Greg C (2014): "Revisiting the Employment Impact of Offshoring," *European Economic Review*, 66, 63–83.

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

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

	Dependent variables: Change in hourly wages, 1980–2016			
	(1)	(2)	(3)	(4)
	panel A. Task displacement based on labor share declines			
Task displacement	-1.60	-1.32	-1.31	-1.66
	(0.09)	(0.16)	(0.19)	(0.44)
Industry shifters		0.21	0.31	0.35
		(0.09)	(0.12)	(0.16)
Exposure to industry labor share decline				0.18
				(0.66)
Relative specialization in routine jobs				0.07
				(0.07)
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
	Panel B. Task displacement based on automation-driven labor share declines			
Task displacement	-1.65	-1.41	-1.36	-1.86
	(0.10)	(0.20)	(0.21)	(0.47)
Industry shifters		0.15	0.10	0.20
		(0.11)	(0.14)	(0.16)
Exposure to industry labor share decline				-0.68
				(0.80)
Relative specialization in routine jobs				0.10
				(0.08)
Share variance explained by task displacement	0.64	0.55	0.53	0.72
R-squared	0.64	0.66	0.83	0.83
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 hourly wages across 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. Panel A reports results for our measure of task displacement based on observed labor share declines. Panel B reports results for our measure of task displacement based on automation-driven labor share declines. In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table 2: 2SLS estimates using automation and offshoring as instruments.

	Dependent variable: Change in hourly wages 1980–2016						
Instruments:	Robot APR, machinery, and software	Robot APR	Dedicated machinery	Specialized Software	Robot APR and software	Machinery and software	Offshoring
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. 2SLS estimates instrumenting task displacement with our automation and offshoring proxies						
Task displacement	-1.23	-1.22	-0.83	-1.46	-1.33	-1.20	-0.81
	(0.19)	(0.25)	(0.39)	(0.36)	(0.21)	(0.18)	(0.30)
Share variance explained by task displacement	0.50	0.39	0.17	0.22	0.52	0.49	0.12
R-squared	0.84	0.84	0.83	0.84	0.84	0.84	0.82
First-stage F	846.91	98.00	29.53	68.00	432.89	716.72	30.62
Overid p-value	0.07				0.58	0.33	
Observations	500	500	500	500	500	500	500
	Panel B. 2SLS estimates controlling for industry and occupational specialization						
Task displacement	-1.56	-1.26	-0.08	-3.11	-2.06	-1.36	-2.49
	(0.50)	(0.83)	(0.97)	(1.12)	(0.56)	(0.49)	(0.71)
Exposure to industry labor share decline	0.54	0.30	-1.91	-1.19	0.15	0.30	0.06
	(0.76)	(0.91)	(1.57)	(1.63)	(0.85)	(0.77)	(0.96)
Relative specialization in routine jobs	0.06	0.01	-0.18	0.29	0.13	0.03	0.20
	(0.09)	(0.14)	(0.17)	(0.17)	(0.09)	(0.09)	(0.11)
Share variance explained by task displacement	0.63	0.41	0.02	0.47	0.80	0.55	0.37
R-squared	0.84	0.83	0.82	0.76	0.84	0.84	0.83
First-stage F	170.40	6.32	30.15	3.87	26.12	190.09	23.71
Observations	500	500	500	500	500	500	500

Notes: This table presents 2SLS estimates of the relationship between task displacement and changes in hourly wages for 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. Panel A reports 2SLS estimates using our measures of automation and offshoring to instrument for our measure of task displacement based on observed labor share declines. Formally, we use instruments of the form $\sum_{i\in\mathcal{I}} \omega_g^i \cdot (\omega_{gi}^R/\omega_i^R) \cdot \text{Automation proxy}_i$, where our proxy is either the adjusted penetration of robots, our measures of changes in dedicated machinery and specialized software services, or our measure of offshoring. Panel B provides 2SLS 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). Formally, the models in his panel also use instruments of the form $\sum_{i\in\mathcal{I}} \omega_g^i \cdot \text{Automation proxy}_i$. In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender. All regressions are weighted by total 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 hourly wages 1980–2016					
	SBTC by education level and gender			SBTC by wage level		
Task displacement measure		Labor share declines	Automation-driven declines		Labor share declines	Automation-driven declines
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: women	0.17	0.10	0.13	0.25	0.15	0.17
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Education: no high school	0.02	0.02	0.03	0.05	0.04	0.05
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Education: some college	0.05	-0.07	-0.05	0.03	-0.06	-0.03
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Education: full college	0.25	-0.02	0.03	0.18	0.01	0.05
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Education: more than college	0.42	0.08	0.15	0.29	0.09	0.16
	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
Log of hourly wage in 1980				0.23	0.12	0.11
				(0.05)	(0.04)	(0.05)
Task displacement		-1.31	-1.36		-1.03	-1.01
		(0.19)	(0.21)		(0.18)	(0.24)
Share variance explained by:						
- educational dummies	0.55	0.08	0.17	0.37	0.09	0.18
- baseline wage				0.15	0.07	0.07
- task displacement		0.55	0.53		0.43	0.39
R-squared	0.76	0.84	0.83	0.81	0.85	0.83
Observations	500	500	500	500	500	500
Other covariates:						
Industry shifters and manufacturing share	✓	✓	✓	✓	✓	✓

Notes: This table presents estimates of the relationship between SBTC proxies, task displacement, and the change in hourly 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 hourly wages for each group between 1980 and 2016. Columns 2 and 5 report results using our measure of task displacement based on observed labor share declines. Columns 3 and 6 report results using our measure of task displacement based on automation-driven labor share declines. In addition to 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. All regressions are weighted by total 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					
	Task displacement based on labor share declines			Task displacement based on automation-driven labor share declines		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Employment to population ratio					
Task displacement	-0.68	-0.46	-0.78	-0.75	-0.44	-0.82
	(0.11)	(0.14)	(0.32)	(0.11)	(0.16)	(0.39)
Share variance explained by:						
- task displacement	0.31	0.21	0.36	0.35	0.20	0.38
- educational dummies		0.10	0.12		0.15	0.15
R-squared	0.31	0.77	0.78	0.35	0.77	0.78
Observations	500	500	500	500	500	500
	Panel B. Non-participation rate					
Task displacement	0.67	0.37	0.77	0.75	0.35	0.80
	(0.12)	(0.14)	(0.31)	(0.12)	(0.16)	(0.39)
Share variance explained by:						
- task displacement	0.30	0.17	0.34	0.33	0.16	0.36
- educational dummies		0.16	0.19		0.21	0.22
R-squared	0.30	0.80	0.81	0.33	0.80	0.81
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 between 1980 and 2016. In Panel B, the dependent variable is the change in the non-participation rate between 1980 and 2016. Columns 1–3 report results using our measure of task displacement based on observed labor share declines. Columns 4–6 report results using our measure of task displacement based on automation-driven labor share declines. In addition to 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, completed high school, 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. All regressions are weighted by total 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 hourly wages 1980–2016							
	Task displacement based on labor share declines				Task displacement based on automation-driven labor share declines			
Other shocks:	Changes in K/Y ratio by industry	Changes in TFP by industry	Change in Chinese import competition	De-unionization rates	Changes in K/Y ratio by industry	Changes in TFP by industry	Change in Chinese import competition	De-unionization rates
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controlling for main effect of other shocks								
Task displacement	-1.31	-1.31	-1.26	-1.31	-1.36	-1.38	-1.28	-1.32
	(0.17)	(0.19)	(0.20)	(0.22)	(0.20)	(0.22)	(0.22)	(0.23)
Exposure to industry shock	0.01	-0.04	0.01	0.02	0.01	-0.11	0.02	-1.08
	(0.13)	(0.37)	(0.01)	(0.84)	(0.14)	(0.37)	(0.01)	(0.77)
Share variance explained by:								
- task displacement	0.55	0.55	0.53	0.55	0.53	0.54	0.50	0.51
- industry shock	0.00	0.00	-0.01	-0.00	0.00	0.01	-0.02	0.16
R-squared	0.84	0.84	0.84	0.84	0.83	0.83	0.83	0.83
Observations	500	500	500	500	500	500	500	500
Panel B. Controlling for effects on workers in routine jobs								
Task displacement	-0.87	-1.30	-1.14	-1.64	-0.75	-1.46	-1.25	-2.20
	(0.22)	(0.21)	(0.27)	(0.45)	(0.27)	(0.26)	(0.35)	(0.67)
Exposure to industry shock	0.28	-0.02	0.03	-0.32	0.36	-0.27	0.03	-2.42
	(0.18)	(0.46)	(0.03)	(0.76)	(0.18)	(0.49)	(0.03)	(0.89)
Exposure of routine jobs to industry shock	-0.28	-0.03	-0.01	0.74	-0.37	0.15	-0.00	1.71
	(0.15)	(0.21)	(0.02)	(0.82)	(0.15)	(0.23)	(0.02)	(1.18)
Share variance explained by:								
- task displacement	0.36	0.55	0.48	0.69	0.29	0.57	0.49	0.86
- industry shock	0.12	0.01	0.02	-0.16	0.15	-0.02	-0.02	-0.11
R-squared	0.84	0.84	0.84	0.84	0.84	0.83	0.83	0.83
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly 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 hourly wages for each group between 1980 and 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 results using our measure of task displacement based on observed labor share declines. Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines. In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender. All regressions are weighted by total 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 hourly wages 1980–2016							
	Task displacement based on labor share declines				Task displacement based on automation-driven labor share declines			
	Change in sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)	Change in 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	-1.37	-1.31	-1.42	-1.31	-1.40	-1.34	-1.40	-1.37
	(0.18)	(0.20)	(0.20)	(0.18)	(0.21)	(0.22)	(0.22)	(0.21)
Exposure to changes in markups or concentration	1.87	0.26	-0.77	-0.67	1.40	-0.90	-0.34	-0.67
	(1.43)	(1.44)	(0.43)	(1.00)	(1.50)	(1.37)	(0.43)	(1.08)
Share variance explained by:								
- task displacement	0.57	0.55	0.59	0.55	0.54	0.52	0.54	0.53
- markups/concetration	0.04	-0.00	-0.07	0.01	0.03	0.01	-0.03	0.01
R-squared	0.84	0.84	0.84	0.84	0.83	0.83	0.83	0.83
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-1.74	-1.71	-1.12	-1.32	-2.11	-2.11	-0.90	-1.31
	(0.22)	(0.24)	(0.15)	(0.16)	(0.34)	(0.33)	(0.14)	(0.20)
Exposure to changes in markups or concentration	0.69	-0.68	-2.09	-2.13	0.01	-1.71	-0.27	-0.49
	(1.50)	(1.40)	(0.53)	(0.75)	(1.53)	(1.35)	(0.44)	(1.12)
Share variance explained by:								
- task displacement	0.57	0.56	0.54	0.50	0.48	0.48	0.52	0.53
- markups/concetration	0.02	0.01	-0.19	0.03	0.00	0.03	-0.02	0.01
R-squared	0.83	0.83	0.85	0.86	0.82	0.82	0.82	0.82
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly 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 hourly wages for each group between 1980 and 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 et al. (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 results using our measure of task displacement based on observed labor share declines (net of markups in Panel B). Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines (net of markups in Panel B). In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender. All regressions are weighted by total 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 hourly wages 1980–2016					
	Task displacement based on labor share declines			Task displacement based on automation-driven labor share declines		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Variation across US regions					
Task displacement	-1.60	-1.07	-1.31	-1.66	-1.14	-1.41
	(0.11)	(0.12)	(0.25)	(0.11)	(0.13)	(0.29)
R-squared	0.62	0.81	0.82	0.61	0.81	0.82
Observations	2633	2633	2633	2633	2633	2633
	Panel B. Variation across US regions absorbing national trends by group					
Task displacement	-1.30	-0.26	-0.37	-1.34	-0.37	-0.51
	(0.10)	(0.08)	(0.12)	(0.06)	(0.11)	(0.15)
R-squared	0.88	0.95	0.95	0.89	0.95	0.95
Observations	2633	2633	2633	2633	2633	2633
	Panel C. Variation across commuting zones					
Task displacement	-1.23	-0.94	-1.12	-1.37	-1.23	-1.43
	(0.15)	(0.14)	(0.22)	(0.17)	(0.18)	(0.29)
R-squared	0.36	0.56	0.56	0.38	0.57	0.57
Observations	20768	20768	20768	20768	20768	20768
	Panel D. Variation across commuting zones absorbing national trends by group					
Task displacement	-0.77	-0.42	-0.41	-1.02	-0.58	-0.65
	(0.07)	(0.07)	(0.15)	(0.07)	(0.07)	(0.16)
R-squared	0.71	0.78	0.79	0.72	0.78	0.80
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 hourly wages for each cell between 1980 and 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 results using our measure of task displacement based on observed labor share declines. Columns 4–6 report results using our measure of task displacement based on automation-driven labor share declines. In addition to 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, completed high school, 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. All regressions are weighted by total 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: General Equilibrium Effects.

	Data for 1980–2016 (1)	Using task displacement based on labor share declines (2)	Using task displacement based on automation-driven labor share declines (3)
Wage structure:			
Share wage changes explained:			
-due to changes in industry composition		6.78%	6.33%
-adding direct displacement effects		100.54%	93.34%
-accounting for ripple effects		48.35%	46.88%
Rise in college premium	25.51%	21.82%	21.02%
-part due to direct displacement effect		40.92%	37.71%
Rise in postgraduate premium	40.42%	24.06%	22.42%
-part due to direct displacement effect		48.04%	43.57%
Change in gender gap	15.37%	1.83%	1.90%
-part due to direct displacement effect		6.31%	5.94%
Share with declining wages	53.10%	41.71%	42.26%
-part due to direct displacement effects		49.61%	51.52%
Wages for men with no high school	−8.21%	−7.18%	−8.41%
-part due to direct displacement effects		−13.97%	−15.11%
Wages for women with no high school	10.94%	1.24%	−3.40%
-part due to direct displacement effects		6.21%	−2.82%
Aggregates:			
Change in average wages, $d\ln w$	29.15%	5.71%	5.18%
Change in GDP per capita, $d\ln y$	70.00%	23.42%	20.95%
Change in TFP, $d\ln \text{tfp}$	35%	3.77%	3.42%
Change in labor share, ds^L	−8 p.p.	−11.69 p.p	−10.41 p.p
Change in K/Y ratio	30.00%	41.93%	38.10%
Sectoral patterns:			
Share manufacturing in GDP	−8.80 p.p	−0.41 p.p	−0.52 p.p
Change in manufacturing wage bill (per capita)	−35.00%	−8.23%	−12.85%

Notes: This table summarizes the effects of task displacement on the wage distribution, real wage levels, aggregates and industry outcomes. These 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 measure of task displacement from industry labor share declines, while column 3 computes the model predictions based on our measure of task displacement from automation-driven labor share declines. 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 industry patterns for manufacturing are from the BEA and the BLS. The TFP data is from Fernald (2014).

Appendix A: Online Appendix to "Tasks, Automation, and the Rise in US Wage Inequality"

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Appendix A-1 Glossary of Variables Used in Section 4

- (Direct) Task displacement$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \left(-d\ln s_i^{L,\text{auto}}\right)$, where $-d\ln s_i^{L,\text{auto}}$ is the observed percent decline of the labor share in industry i or the automation-driven component thereof.
- Industry shifters$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln s_i^Y$, where s_i^Y denotes the value added share of industry i.
- Exposure to industry labor share declines$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot (-d\ln s_i^{L,\text{auto}})$.
- Relative specialization in routine jobs$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R}$.
- Exposure to industry shock$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \text{Shock}_i$.
- Exposure of routine jobs to industry shock$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \text{Shock}_i$.
- Exposure to change in markups$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \text{Percent change in markups}_i$.
- Exposure of routine jobs to change in markups$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \text{Percent change in markups}_i$.
- Exposure to change in concentration$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \text{Change in concentration}_i$.
- Exposure of routine jobs to change in concentration$_g = \sum_{i\in\mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \text{Change in concentration}_i$.

Appendix A-2 Proofs of the Results in the Main Text

We first provide conditions for the single-sector and multi-sector economies to produce finite output. Let $H(y_1, \ldots, y_I)$ denote the production function for the final good, taking sectoral outputs as its inputs. Define the derived aggregate production function of the economy, depending on the total amount of capital used in production, k, and the vector of labor supplies, $\boldsymbol{\ell}$ as:

$$F(k, \boldsymbol{\ell}) = \max H(y_1, \ldots, y_I) \tag{A-1}$$

$$\text{subject to: } y_i = \left(\frac{1}{M}\int_{\mathcal{T}} (M \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx\right)^{\frac{\lambda}{\lambda-1}} \quad \forall i \in \mathcal{I},$$

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

$$\ell_g = \int_{\mathcal{T}} \ell_g(x) \cdot dx \quad \forall g \in \mathcal{G},$$

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

Proposition A-1 (Finite output) *The economy produces finite output if and only if the following Inada condition holds:*

$$\lim_{k\to\infty} F_k(k,\boldsymbol{\ell}) < 1. \tag{A-2}$$

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

Proof. A competitive equilibrium maximizes the strictly concave function $c(k) = F(k,\boldsymbol{\ell}) - k$. When the Inada condition (A-2) holds, the function $c(k)$ reaches a unique maximum at some $k^* \geq 0$. Since $c(k^*) = (1 - s^K)F(k^*,\boldsymbol{\ell})$, we also have $s^K \in [0,1)$.

Because F is concave, $\lim_{k\to\infty} F_k(k,\boldsymbol{\ell})$ exists. Suppose now that the Inada condition (A-2) fails, so that $\lim_{k\to\infty} F_k(k,\boldsymbol{\ell}) \geq 1$. Then, $c(k)$ is an increasing function on $\mathbb{R}_+$, and thus has no well-defined maximizer and the economy reaches infinite output. Since in this case $\lim_{k\to\infty} F_k(k,\boldsymbol{\ell}) \geq 1$ and F exhibits constant returns to scale, $F_k(k,\boldsymbol{\ell})$ is a decreasing function that converges to some limit $m > 1$ as $k \to \infty$. Therefore,

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

where we used l'Hôpital's rule in the third step. This implies that $s^K = 1$ as wanted.

We also note that in the single-sector case, the Inada condition (A-2) is equivalent to $A_k^{\lambda-1}\Gamma_k < 1$, as noted in the 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

$$\max_{\{k(x),\ell_1(x),\ldots,\ell_G(x)\}_{x\in\mathcal{T}}} y - \int_{\mathcal{T}} (k(x)/q(x)) \cdot dx$$

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

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

$$\ell_g = \int_{\mathcal{T}} \ell_g(x) \cdot dx \quad \forall g \in \mathcal{G}.$$

This is related to (A-1), except that it is for the single-sector case and maximizes over the production of capital inputs as well. The objective function is concave, while the constraint set is convex. Hence, this optimization problem either reaches a unique maximal value (though it might have non-unique maximizers) or has no solution (meaning that it reaches infinite output). Proposition A-1 rules out the latter case under (A-2), which we have imposed. Hence, we focus on the former case. Let w_g be the Lagrange multiplier associated with the constraint for labor of type g. Then the solution can be expressed by the following allocation of tasks to factors:

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

The tie-breaking rule described in footnote 7 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

$$y(x) = \frac{1}{M} \cdot y \cdot p(x)^{-\lambda}, \tag{A-3}$$

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

$$p(x) = \begin{cases} \dfrac{1}{A_k \cdot q(x) \cdot \psi_k(x)} & \text{if } x \in \mathcal{T}_k \\ \\ \dfrac{w_g}{A_g \cdot \psi_g(x)} & \text{if } x \in \mathcal{T}_g. \end{cases} \tag{A-4}$$

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

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

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 (A-3), we obtain the ideal price condition:

$$1 = \frac{1}{M} \int_{\mathcal{T}} p(x)^{1-\lambda} dx. \tag{A-5}$$

Substituting for the equilibrium task prices from equation (A-4) 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 rewrite this equation in terms of task shares:

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

Rearranging and using the fact that $A_k^{\lambda-1}\Gamma_k < 1$ establishes (1).

Finally, we can compute factor shares as:

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

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

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, after the technological change, will switch to capital.

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

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

The definitions of $d\ln\Gamma_g^{\text{deep}}$ and $d\ln\Gamma_g^{\text{auto}}$ in the main text, together with Assumption 1, imply

$$d\ln\Gamma_g = (\lambda-1)d\ln\Gamma_g^{\text{deep}} - d\ln\Gamma_g^{\text{auto}},$$

which yields the expression for wage changes in (6) in the text.

Let us next define changes in TFP as:

$$d\ln \text{tfp} = d\ln y - s^K\cdot d\ln k|_q$$

where $k = \int_{\mathcal{T}_k} k(x)/q(x)dx$ denotes the total capital stock and $d\ln k|_q$ denotes changes in the capital stock coming from capital quantities and not prices. For a small change in technology, this can be computed as

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

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

We now show that changes in TFP also satisfy the dual representation:

$$d\ln \text{tfp} = \sum_{g\in\mathcal{G}} s_g^L \cdot d\ln w_g - \int_{\mathcal{T}_k} s^K(x) d\ln q(x) dx, \tag{A-6}$$

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.

Equation (A-6)follows from the fact that we have competitive markets and constant returns to scale. In particular, 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 therefore have

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

We can rearrange this as

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

which is equivalent to (A-6).

We now return to the contributions of different types of technologies to TFP. For this, we use the ideal price index condition in equation (A-5), 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 a change in technology and capital prices, we obtain:

$$\begin{aligned} \sum_{g\in\mathcal{G}} s_g^L \cdot d\ln w_g - \int_{\mathcal{T}_k} s^K(x) d\ln q(x) dx =& s^K \cdot \left(d\ln A_k + d\ln \Gamma_k^{\text{deep}} \right) \\ &+ \sum_{g\in\mathcal{G}} s_g^L \cdot \left(d\ln A_g + d\ln \Gamma_g^{\text{deep}} \right) + \Delta, \end{aligned} \tag{A-7}$$

where

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

represents the reallocation of tasks from labor to capital. Using the definitions of $\pi_g(x)$ and π_g

in the main text, 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 get

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

Substituting this expression for Δ into equation (A-7) and using the dual representation of TFP in equation (A-6), we obtain (8).

Equation (7) can be obtained from (8) by using the fact that $d\ln y = d\ln\text{tfp} + s^K\cdot d\ln k$. Moreover, $k = s^K\cdot y$, which implies $d\ln k = d\ln s^K + d\ln y$. Combining this expression with the equation for $d\ln y$, we obtain

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

To derive the factor share changes, note that

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

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

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

which yields equation (9), completing the proof. ■

Proof of Proposition 3. The equilibrium of the multi-sector economy is a solution to the following optimization problem:

$$\max_{\{k(x),\ell_1(x),\dots,\ell_G(x)\}_{x\in\mathcal{T}_i,i\in\mathcal{I}}} H(y_1,\dots,y_I) - \int_{\mathcal{T}}(k(x)/q(x))\cdot dx$$

$$\text{subject to: } y_i = \left(\frac{1}{M}\int_{\mathcal{T}}(M\cdot y(x))^{\frac{\lambda-1}{\lambda}}\cdot dx\right)^{\frac{\lambda}{\lambda-1}} \quad \forall i\in\mathcal{I},$$

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

$$\ell_g = \int_{\mathcal{T}}\ell_g(x)\cdot dx \quad \forall g\in\mathcal{G}.$$

As in the proof of Proposition 1, this is a concave problem, and under the conditions of Proposition A-1, it has a solution and reaches a unique maximal value. As before, let w_g be the Lagrange multiplier for the constraint for labor of type g, and note that the allocation of tasks the factors will uniquely satisfy the following equations (under our tie-breaking rule from footnote 7):

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

$$\mathcal{T}_{ki} \subseteq \left\{x : \frac{1}{\psi_k(x)\cdot q(x)\cdot A_{ki}} \le \frac{w_g}{A_{gi}\cdot\psi_g(x)}, \text{ for all } g\right\}.$$

As in the proof of Proposition 1, the demand for task x in sector i is

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

the price of task x is

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

and the demand for capital and labor at task x is

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

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

Following the same steps as in the proof of Proposition 1, we have

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

which establishes equation (10).

To derive the industry price index in equation (11), we observe that

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

Equation (12) then follows by substituting for the equilibrium task prices to obtain:

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

Because industry shares must add up to 1, equation (12) holds, completing the proof.

Although not included in the proposition, factor shares can be computed as

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

■

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

Define the matrix

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

We now establish several properties of this matrix. 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 because $\sum_{g'} \frac{\partial \ln \Gamma_g}{\partial \ln w_{g'}} \leq 0$, 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 the 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 implies

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

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, let us denote by θ_g^r the sum of the elements of row g of Θ. Then:

$$\Theta \cdot (1, 1, \dots, 1)_1' = (\theta_1^r, \theta_2^r, \dots, \theta_G^r)' \Rightarrow \Sigma \cdot (\theta_1^r, \theta_2^r, \dots, \theta_G^r)' = (1, 1, \dots, 1)'.$$

This equality requires that

$$\text{(A-8)} \qquad \Sigma_{gg} \cdot \theta_g^r + \sum_{g' \neq g} \Sigma_{gg'} \cdot \theta_{g'}^r = 1.$$

Now, suppose without loss of generality, that $\theta_1^r > \theta_2^r > \dots > \theta_G^r > 0$ (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 $(0, 1)$). Equation (A-8) for $g = 1$ gives

$$\Sigma_{11} \cdot \theta_1^r + \sum_{g' \neq 1} \Sigma_{1g'} \cdot \theta_{g'}^r = 1,$$

and thus

$$\left(1 - \frac{1}{\lambda} \frac{\partial \ln \Gamma_1}{d \ln w_1}\right) \cdot \theta_1^r = 1 + \frac{1}{\lambda} \sum_{g' \neq 1} \frac{\partial \ln \Gamma_1}{d \ln w_{g'}} \cdot \theta_{g'}^r \leq 1 + \frac{1}{\lambda} \sum_{g' \neq 1} \frac{\partial \ln \Gamma_1}{d \ln w_{g'}} \cdot \theta_1^r.$$

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

$$\theta_1^r < 1 + \frac{1}{\lambda} \sum_{g'} \frac{\partial \ln \Gamma_1}{d \ln w_{g'}} \cdot \theta_1^r \leq 1.$$

An identical argument establishes that column sums of Θ are between 0 and 1.

We next derive the formulas characterizing the effects of technology on wages, industry prices, and TFP. First, define $w_g^e = w_g / A_g$ as the wage per efficiency unit of labor of g workers. Equation (10) 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 with respect to an automation technology, we obtain

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

Stacking these equations for all groups, we have

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

which yields

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

and thus

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

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 (12). By definition, the equilibrium task allocation $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$ solves the cost-minimization problem:

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

The envelope theorem then implies that

$$d\ln p_i = \sum_{g\in\mathcal{G}} s_{gi}^L \cdot d\ln w_g - \Delta_i,$$

where

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

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

Average cost savings from automating tasks in the set $\mathcal{D}_{gi}$ in industry i are now

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

where

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

Using these definitions, and following the same steps as in the proof of Proposition 2, we can write Δ_i as

$$\Delta_i = (A_ip_i)^{\lambda-1}\sum_{g\in\mathcal{G}}\left(\frac{w_g}{A_g}\right)^{1-\lambda}\cdot\left(\frac{1}{M_i}\int_{\mathcal{D}_{gi}}\psi_g(x)^{\lambda-1}dx\right)\cdot\pi_{gi}.$$

Again as in the proof of Proposition 2, we use $s^L_{gi} = (A_ip_i)^{\lambda-1}\left(\frac{w_g}{A_g}\right)^{1-\lambda}\cdot\left(\frac{1}{M_i}\int_{\mathcal{T}_g}\psi_g(x)^{\lambda-1}dx\right)$ to get

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

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

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

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

Our choice of numeraire, which implies that the final good has a price of 1, then implies that $1 = c^h(\boldsymbol{p})$. Log-differentiating this expression yields

$$\begin{aligned}0 &= \sum_{i\in\mathcal{I}} s^Y_i(\boldsymbol{p})\cdot d\ln p_i\\ &= \sum_{i\in\mathcal{I}} s^Y_i(\boldsymbol{p})\cdot\left(\sum_{g\in\mathcal{G}} s^L_{gi}\cdot\left(d\ln w_g - d\ln\Gamma^{\text{auto}}_{gi}\cdot\pi_{gi}\right)\right)\\ &= \sum_{g\in\mathcal{G}} s^L_g\cdot d\ln w_g - \sum_{i\in\mathcal{I}} s^Y_i(\boldsymbol{p})\sum_{g\in\mathcal{G}}\cdot s^L_{gi}\cdot\pi_{gi}.\end{aligned}$$

Rearranging this expression, and using the dual representation of TFP (which in this case is given by $d\ln\text{tfp} = \sum_{g\in\mathcal{G}} s^L_g\cdot d\ln w_g$) yields the formula for the contribution of automation to TFP in the proposition.

For aggregate output, we again have $d\ln y = d\ln\text{tfp} + s^K\cdot d\ln k$ (from the primal definition of

TFP) and $d\ln k = d\ln s^K + d\ln y$ (from $k = s^K \cdot y$). Combining these equations, we obtain

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

Finally, the change in the capital share is given by:

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

■

Appendix A-3 Measuring Task Displacement

This section derives our measures of task displacement. To derive the adjustments we perform in our empirical work, we also allow for markups and differences in the user cost of capital across industries. In the presence of these generalizations, the labor share of industry i can be written as

$$s_i^L = \frac{1}{\mu_i} \cdot \frac{\sum_g \Gamma_{gi} \cdot w_g^{1-\lambda}}{\sum_g \Gamma_{gi} \cdot w_g^{1-\lambda} + \Gamma_{ki} \cdot R_i^{1-\lambda}}, \tag{A-9}$$

where μ_i and R_i are, respectively, the markup and user cost of capital in industry i.

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 implies that only routine tasks can be automated, i.e., $\mathcal{D}_{gi} \subset \mathcal{R}_{gi}$, and also that routine tasks in a given industry will be automated at the same rate for all workers. Therefore,

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

Before continuing with our derivations, we introduce some notation that we will use in the rest of the 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:

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

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:

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

Average cost savings from automation in industry i are

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

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.

The next proposition characterizes the change in the labor share in response to automation.

Proposition A-2 (Task displacement and industry labor shares) *Suppose that Assumption 2 holds and routine tasks in industry i are automated at the rate ϑ_i. The resulting change in the labor share of industry i holding wages, markups, and other technologies constant is given by*

$$d\ln s_i^{L,auto} = -\left(1 + (\lambda-1)\cdot s_i^L \cdot \pi_i\right)\cdot \omega_i^R \cdot \vartheta_i.$$

This implies that the task displacement due to automation for group g in industry i is

$$d\ln \Gamma_{gi}^{auto} = \frac{\omega_{gi}^R}{\omega_i^R} \cdot \frac{-d\ln s_i^{L,auto}}{1 + (\lambda-1)\cdot s_i^L \cdot \pi_i}.$$

Proof. The denominator in equation (A-9) is also equal to

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

The effect of automation on s_i^L (holding prices and other technologies constant) is

$$d\ln s_i^{L,\text{auto}} = -\sum_{g\in\mathcal{G}} \omega_i^{Rg}\cdot\vartheta_i + (1-\lambda)\cdot s_i^L \cdot \sum_{g\in\mathcal{G}} \omega_i^{Rg}\cdot \vartheta_i \cdot \pi_{gi}$$

where the first term captures the effect of automation on the numerator of (A-9) and the second term the effect on the denominator of (A-9). Using the definition of π_i, this can be written as

$$d\ln s_i^{L,\text{auto}} = -\left(1 + (\lambda-1)\cdot s_i^L \cdot \pi_i\right)\cdot \omega_i^R \cdot \vartheta_i.$$

Turning to the second part of the proposition, by definition we have:

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

■

We now provide the details for our measurement of the (percent) decline in the labor share of industry i driven by automation, $d\ln s_i^{L,\text{auto}}$. Differentiating (A-9) we have

$$\text{(A-10)} \qquad -d\ln s_i^L = -d\ln s_i^{L,\text{auto}} - s_i^K \cdot \left[(1-\sigma_i^L)\cdot d\ln w_i - (1-\sigma_i^K)\cdot d\ln R_i\right] + d\ln \mu_i + \varepsilon_i.$$

Here, $d\ln \mu_i$ is the (percent) increase in industry i markups and ε_i is a residual term that captures the role of other technologies (factor-augmenting and productivity-deepening technologies on the labor share). The term $s_i^K \cdot \left[(1-\sigma_i^L)\cdot d\ln w_i - (1-\sigma_i^K)\cdot d\ln R_i\right]$ adjusts for the effect of changing factor prices on the labor share. In particular, $d\ln w_i = \sum_{g\in\mathcal{G}} \omega_i^g \cdot d\ln w_g$ denotes the average wage increase experienced by industry i, and the elasticities σ_i^L and σ_i^K give the effect of changing factor prices on the labor share. In a world with a single labor aggregate we would have $\sigma_i^L = \sigma_i^K = \sigma_i$, where σ_i is the elasticity of substitution between capital and this labor aggregate. However, with multiple types of workers, σ_i^L varies depending on whether groups experiencing a wage increase are more or less substitutable for capital at marginal tasks. Finally, ε_i denotes the influence of other technologies on the labor share. Appendix Appendix B-4 provides a full derivation of equation (A-10) and shows that the contribution of ε_i to changes in the labor share between 1987 and 2016 has been small.

Our two measures of task displacement are based on different ways of estimating $-d\ln s_i^{L,\text{auto}}$. In both cases, we approximate the discrete changes between 1987 and 2016 with our theory-based differential changes.

- Our first measure of task displacement, exploiting the observed changes in industry labor shares, is based on setting $\lambda = 1$, $d\ln\mu_i = 0$, $\varepsilon_i = 0$, and using Assumption 1 to rule out ripple effects. Under these assumptions, $\sigma_i^L = \sigma_i^K = 1$, and equation (A-10) implies

$$-d\ln s_i^{L,\text{auto}} = -d\ln s_i^L.$$

- Our second measure of task displacement, exploiting the automation-driven component of changes in industry labor share, proceeds as follows. We again set $\lambda = 1$, $d\ln\mu_i = 0$, $\varepsilon_i = 0$ and use Assumption 1 to rule out ripple effects, so that $\sigma_i^L = \sigma_i^K = 1$. However, instead of using the full observed change in industry labor shares, we use its component that is (linearly) predicted by our three proxies for automation technologies:

$$-d\ln s_i^{L,\text{auto}} = \mathbb{E}[-d\ln s_i^L | Z_i],$$

where Z_i denotes the vector of the three measures of automation technologies for industry i. This strategy also works when there are markup differences and other influences on labor shares, and in this case, relies on the formal identifying assumption: $Z_i \perp\!\!\!\perp \mu_i, \varepsilon_i$, meaning that these differences are orthogonal to our instruments (as noted in the text).

- In Section 5 and Table A-4 in the Appendix, we generalize these measures and allow for $\sigma_i^L = \sigma_i^K = \sigma_i = 0.8$ and $\sigma_i^L = \sigma_i^K = \sigma_i = 1.2$. In this case, our first measure is computed simply as

$$-d\ln s_i^{L,\text{auto}} = -d\ln s_i^L + s_i^K \cdot (1-\sigma_i) \cdot (d\ln w_i - d\ln R_i).$$

- Similarly, for our second measure, we compute $-d\ln s_i^{L,\text{auto}} = \mathbb{E}[-d\ln s_i^L + s_i^K \cdot (1-\sigma_i) \cdot (d\ln w_i - d\ln R_i)|Z_i]$ as the predicted component of a linear regression of the adjusted decline in the labor share across industries on our proxies of automation. This is again valid when there are markup differences and other influences on labor shares under the assumption that $Z_i \perp\!\!\!\perp \mu_i, \varepsilon_i$.

- In Table 6, we allow for the effects of changes in markups. In this case, we continue to set $\lambda = 1$ and abstract from ripple effects, but now adjust for the estimated change in markups. Equation (A-10) now gives

$$-d\ln s_i^{L,\text{auto}} = -d\ln s_i^L - d\ln \mu_i$$

for our first measure and

$$-d\ln s_i^{L,\text{auto}} = \mathbb{E}[-d\ln s_i^L - d\ln \mu_i|Z_i]$$

for our second measure. This is again valid when there are other influences on labor shares under the assumption that $Z_i \perp\!\!\!\perp \varepsilon_i$.

Appendix A-4 Additional Tables

This appendix includes additional tables discussed in the main text:

- Table A-1: Determinants of industry-level labor share changes, 1987–2016.
- Table A-2: Summary statistics for demographic groups.
- Table A-3: Task displacement vs. SBTC, 1980-2016—controlling for changes in relative supply.
- Table A-4: Task displacement based on adjusted labor share declines and changes in real hourly wages—measures of task displacement based on adjusted labor share decline
- Table A-5: Task displacement and changes in real hourly wages, 1980–2016—alternative measures of jobs that can be automated.
- Table A-6: Task displacement and changes in real hourly wages, 1980-2016—controlling for differential effects on low-paying jobs.

- Table A-7: Task displacement and changes in real hourly wages for men, women, and native-born workers, 1980-2016.
- Table A-8: Task displacement and changes in real hourly wages, stacked-differences models for 1980–2000 and 2000–2016.
- Table A-9: Task displacement and changes in real hourly wages, 1980–2016—alternative labor share measures.
- Table A-10: GMM estimates of the propagation matrix.
- Table A-11: Robustness checks for estimates of the general equilibrium effects.

Table A-1: Determinants of industry-level labor share changes, 1987–2016.

	Dependent variable: percent labor share changes, 1987–2016								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adjusted penetration of robots	-1.27		-0.92	-0.90	-0.93	-0.94	-1.00	-0.94	-0.73
	(0.35)		(0.42)	(0.40)	(0.42)	(0.43)	(0.42)	(0.43)	(0.53)
Change in share of dedicated machinery services		-3.32	-2.42	-2.37	-2.43	-2.40	-2.18	-2.43	-2.13
		(0.59)	(0.72)	(0.75)	(0.71)	(0.73)	(0.77)	(0.73)	(0.80)
Change in share of specialized software services	-6.33	-5.81	-6.95	-6.67	-6.99	-6.87	-6.97	-7.02	-6.84
	(1.71)	(1.87)	(1.57)	(1.71)	(1.69)	(1.75)	(1.78)	(1.64)	(1.50)
Change in share of imported intermediates				-0.56					
				(0.55)					
Change in K/Y ratio					-0.01				
					(0.03)				
Change tail index of revenue concentration						-0.06			
						(0.23)			
Change in accounting markups (%)							-0.24		
							(0.36)		
Change Chinese import competition								0.12	
								(0.25)	
De-unionization rate									-0.25
									(0.26)
F-stat technology variables	11.02	18.02	16.04	13.65	14.82	14.83	11.53	15.04	9.37
Share variance explained by technology	0.33	0.33	0.45	0.44	0.45	0.45	0.45	0.46	0.40
R-squared	0.33	0.33	0.45	0.46	0.45	0.45	0.47	0.45	0.47
Observations	49	49	49	49	49	49	49	49	49

Notes: This table presents estimates of the relationship between labor share changes (in %) between 1987 and 2016 at the industry level and automation technologies, offshoring, capital deepening, changes in market structure (proxied by markups or rising sales concentration), and changes in Chinese import competition for the 49 industries in our analysis. All regressions are weighted by industry value added in 1987. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-2: Summary statistics for demographic groups.

			Labor-market outcomes			Educational levels and gender				
Quintile	N	Task displacement	Change in hourly wages, 1980–2016	Employment to population ratio change 1980–2016	Hourly wage 1980	Completed high-school	Some college	Completed college	Postgraduate	Share male
Panel A. Quintiles of task displacement based on labor share declines										
1—Lowest	191	4.77%	26.51%	0.00 p.p.	$26.9	0.05%	12.21%	42.10%	44.84%	80.00%
2	141	15.53%	5.91%	-0.80 p.p.	$18.3	17.54%	69.15%	1.81%	0.13%	61.79%
3	63	21.01%	3.07%	-3.71 p.p.	$17.3	72.96%	13.17%	0.18%	0.00%	55.49%
4	69	24.95%	-5.06%	-8.72 p.p.	$15.1	36.93%	19.39%	0.01%	0.00%	66.33%
5—Highest	36	28.87%	-11.95%	-16.23 p.p.	$15.7	61.19%	1.19%	0.01%	0.00%	99.34%
Panel B. Quintiles of task displacement based on automation-driven labor share declines										
1—Lowest	182	3.80%	26.52%	0.01 p.p.	$27.0	0.02%	12.04%	42.71%	45.18%	80.60%
2	119	13.95%	3.21%	-2.21 p.p.	$19.3	32.43%	64.46%	1.10%	0.12%	69.30%
3	93	19.22%	5.69%	-0.84 p.p.	$15.6	77.87%	8.99%	0.26%	0.00%	38.39%
4	68	23.11%	-6.07%	-10.41 p.p.	$15.9	43.04%	13.88%	0.01%	0.00%	77.66%
5—Highest	38	27.72%	-11.98%	-18.46 p.p.	$14.5	40.26%	1.62%	0.01%	0.00%	99.86%
Panel C. All workers										
All	500	16.84%	7.18%	-4.80	$19.9	32.83%	22.28%	13.38%	13.87%	72.98%

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 (measured using the percent labor share decline in Panel A and the automation-driven labor share decline in Panel B) and reports summary statistics for all groups in panel C. See the main text and Appendix B-3 for definitions and data sources.

Table A-3: Task displacement vs. SBTC, 1980-2016—controlling for changes in relative supply.

	Dependent variable: Change in hourly wages 1980–2016					
	SBTC by education level			Allowing for SBTC by wage level		
Task displacement measure		Labor share declines	Automation-driven declines		Labor share declines	Automation-driven declines
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: women	0.19	0.09	0.13	0.25	0.16	0.18
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Education: no high school	-0.10	-0.04	-0.01	0.04	0.01	0.03
	(0.08)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)
Education: some college	0.13	-0.07	-0.04	0.03	-0.05	-0.03
	(0.06)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Education: full college	0.37	-0.03	0.04	0.19	0.01	0.06
	(0.08)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Education: more than college	0.50	0.03	0.14	0.29	0.07	0.16
	(0.07)	(0.08)	(0.06)	(0.05)	(0.07)	(0.06)
Log of hourly wage in 1980				0.25	0.14	0.13
				(0.06)	(0.05)	(0.06)
Change in supply	-0.10	-0.06	-0.04	-0.01	-0.03	-0.02
	(0.06)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Task displacement		-1.72	-1.60		-1.15	-1.06
		(0.31)	(0.28)		(0.21)	(0.25)
Share variance explained by:						
- educational dummies	0.75	0.04	0.18	0.39	0.08	0.19
- baseline wage				0.16	0.09	0.08
- supply changes	-0.28	-0.16	-0.11	-0.04	-0.07	-0.05
- task displacement		0.72	0.63		0.48	0.41
R-squared	0.43	0.75	0.77	0.80	0.83	0.82
Observations	493.00	493.00	493.00	493.00	493.00	493.00
Other covariates:						
Industry shifters and manufacturing share	✓	✓	✓	✓	✓	✓

Notes: This table presents estimates of the relationship between SBTC proxies, task displacement, and the change in hourly 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 hourly wages for each group between 1980 and 2016. Columns 2 and 5 report results using our measure of task displacement based on observed labor share declines. Columns 3 and 6 report results using our measure of task displacement based on automation-driven labor share declines. In all specifications, we measure changes in labor supply by the change in hours worked between 1980 and 2016, and instrument it using the predetermined trend in hours for 1970–1980. In addition to 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. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-4: Task displacement based on adjusted labor share declines and changes in real hourly wages—measures of task displacement based on adjusted labor share decline.

	Dependent variables: Change in wages and wage declines, 1980–2016							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Task displacement for $\lambda = 1$ and $\sigma_i = 0.8$							
Task displacement	-1.35	-1.02	-1.19	-2.05	-1.45	-1.13	-1.24	-2.70
	(0.12)	(0.15)	(0.17)	(0.38)	(0.11)	(0.17)	(0.20)	(0.47)
Share variance explained by task displacement	0.57	0.43	0.51	0.87	0.60	0.47	0.51	1.11
R-squared	0.57	0.65	0.84	0.84	0.60	0.63	0.83	0.84
Observations	500	500	500	500	500	500	500	500
	Panel B. Task displacement for $\lambda = 1$ and $\sigma_i = 1.2$							
Task displacement	-1.73	-1.53	-1.26	-0.73	-1.83	-1.71	-1.37	-0.99
	(0.09)	(0.15)	(0.17)	(0.54)	(0.10)	(0.22)	(0.21)	(0.58)
Share variance explained by task displacement	0.71	0.63	0.52	0.30	0.67	0.63	0.50	0.36
R-squared	0.71	0.73	0.83	0.83	0.67	0.67	0.82	0.82
Observations	500	500	500	500	500	500	500	500
	Panel C. Task displacement for $\lambda = 0.5$ and $\sigma_i = 0.8$							
Task displacement	-1.22	-0.92	-1.07	-1.86	-1.30	-1.02	-1.11	-2.40
	(0.10)	(0.14)	(0.16)	(0.35)	(0.10)	(0.15)	(0.18)	(0.42)
Share variance explained by task displacement	0.58	0.44	0.51	0.88	0.60	0.47	0.51	1.10
R-squared	0.58	0.65	0.84	0.84	0.60	0.63	0.83	0.84
Observations	500	500	500	500	500	500	500	500
	Panel D. Task displacement for $\lambda = 0.5$ and $\sigma_i = 1$							
Task displacement	-1.44	-1.19	-1.17	-1.47	-1.48	-1.27	-1.21	-1.64
	(0.08)	(0.14)	(0.17)	(0.40)	(0.09)	(0.18)	(0.19)	(0.43)
Share variance explained by task displacement	0.67	0.56	0.55	0.69	0.64	0.55	0.53	0.71
R-squared	0.67	0.70	0.84	0.84	0.64	0.66	0.83	0.83
Observations	500	500	500	500	500	500	500	500
	Panel E. Task displacement for $\lambda = 0.5$ and $\sigma_i = 1.2$							
Task displacement	-1.54	-1.36	-1.12	-0.63	-1.64	-1.53	-1.23	-0.87
	(0.08)	(0.14)	(0.16)	(0.49)	(0.09)	(0.20)	(0.19)	(0.52)
Share variance explained by task displacement	0.71	0.63	0.52	0.29	0.67	0.63	0.50	0.36
R-squared	0.71	0.73	0.83	0.83	0.67	0.67	0.82	0.82
Observations	500	500	500	500	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 hourly wages across demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. We measure task displacement using the general formula in equation (17). Our baseline measure sets $\lambda = \sigma_i = 1$. The panels in this table use different combinations of λ and σ_i to measure the adjusted labor share decline. Columns 1–4 report results for our measure of task displacement based on observed (and adjusted) labor share declines. Columns 5–8 report results for our measure of task displacement based on automation-driven labor share declines. In addition to the covariates reported in the table, columns 3-4 and 7–8 control for baseline wage shares in manufacturing and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, and columns 4 and 8 control for groups' exposure to industry labor share declines and groups' relative specialization in routine jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-5: Task displacement and changes in real hourly wages, 1980–2016—alternative measures of jobs that can be automated.

	Dependent variables: Change in wages and wage declines, 1980–2016							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Top 40							
Task displacement	-1.39 (0.15)	-1.02 (0.16)	-1.10 (0.19)	-2.50 (0.53)	-1.48 (0.15)	-1.04 (0.19)	-1.15 (0.22)	-2.70 (0.54)
Share variance explained by task displacement	0.52	0.38	0.41	0.93	0.51	0.36	0.39	0.92
R-squared	0.52	0.64	0.82	0.84	0.51	0.60	0.81	0.83
Observations	500	500	500	500	500	500	500	500
	Panel B. Alternative definitions							
Task displacement	-1.88 (0.08)	-1.67 (0.15)	-1.67 (0.20)	-1.79 (0.47)	-1.99 (0.09)	-1.98 (0.20)	-1.87 (0.24)	-1.54 (0.51)
Share variance explained by task displacement	0.76	0.67	0.67	0.72	0.75	0.74	0.70	0.58
R-squared	0.76	0.77	0.85	0.85	0.75	0.75	0.84	0.84
Observations	500	500	500	500	500	500	500	500
	Panel C. Occupations suitable to automation via robots							
Task displacement	-1.18 (0.08)	-1.16 (0.11)	-0.85 (0.16)	-0.66 (0.29)	-1.26 (0.09)	-1.30 (0.15)	-0.89 (0.18)	-1.41 (0.34)
Share variance explained by task displacement	0.69	0.68	0.49	0.38	0.65	0.67	0.46	0.72
R-squared	0.69	0.69	0.81	0.82	0.65	0.65	0.80	0.82
Observations	500	500	500	500	500	500	500	500
	Panel D. Occupations suitable to automation via software							
Task displacement	-1.76 (0.13)	-1.71 (0.15)	-1.46 (0.22)	-1.55 (0.51)	-1.89 (0.16)	-1.96 (0.21)	-1.50 (0.25)	-2.86 (0.63)
Share variance explained by task displacement	0.68	0.66	0.56	0.59	0.64	0.67	0.51	0.97
R-squared	0.68	0.68	0.81	0.82	0.64	0.64	0.81	0.82
Observations	500	500	500	500	500	500	500	500
	Panel E. Occupations suitable to automation via robots or software							
Task displacement	-1.46 (0.09)	-1.42 (0.12)	-1.03 (0.17)	-0.87 (0.32)	-1.50 (0.11)	-1.50 (0.15)	-1.02 (0.20)	-1.38 (0.38)
Share variance explained by task displacement	0.71	0.69	0.50	0.42	0.66	0.66	0.45	0.61
R-squared	0.71	0.71	0.81	0.82	0.66	0.66	0.80	0.81
Observations	500	500	500	500	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 hourly wages across demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 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 B-3. 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. Columns 1–4 report results for our measure of task displacement based on observed labor share declines. Columns 5–8 report results for our measure of task displacement based on automation-driven labor share declines. In addition to the covariates reported in the table, columns 3-4 and 7–8 control for baseline wage shares in manufacturing and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, and columns 4 and 8 control for groups' exposure to industry labor share declines and groups' relative specialization in routine jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-6: Task displacement and changes in real hourly wages, 1980-2016—controlling for differential effects on low-paying jobs.

	Dependent variables: Change in hourly wages, 1980–2016			
	(1)	(2)	(3)	(4)
	panel A. Task displacement based on labor share declines			
Task displacement	-1.78	-1.74	-1.51	-1.89
	(0.09)	(0.17)	(0.20)	(0.47)
Relative specialization in low-pay jobs	0.03	0.03	-0.03	-0.12
	(0.03)	(0.03)	(0.03)	(0.05)
Effect mediated through low-pay jobs	0.16	0.13	0.43	0.87
	(0.17)	(0.19)	(0.17)	(0.25)
Industry shifters		0.02	0.06	0.22
		(0.09)	(0.14)	(0.15)
Exposure to industry labor share decline				-0.95
				(0.62)
Relative specialization in routine jobs				0.08
				(0.08)
Share variance explained by task displacement	0.74	0.73	0.63	0.79
R-squared	0.76	0.76	0.85	0.86
Observations	500	500	500	500
	Panel B. Task displacement based on automation-driven labor share declines			
Task displacement	-1.79	-1.88	-1.45	-1.69
	(0.10)	(0.20)	(0.20)	(0.58)
Relative specialization in low-pay jobs	0.05	0.05	-0.01	-0.08
	(0.04)	(0.04)	(0.03)	(0.05)
Effect mediated through low-pay jobs	-0.04	-0.04	0.31	0.75
	(0.29)	(0.29)	(0.26)	(0.34)
Industry shifters		-0.05	-0.05	0.12
		(0.11)	(0.14)	(0.16)
Exposure to industry labor share decline				-1.96
				(0.74)
Relative specialization in routine jobs				0.05
				(0.10)
Share variance explained by task displacement	0.70	0.73	0.56	0.66
R-squared	0.71	0.71	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 hourly wages across 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. Panel A reports results for our measure of task displacement based on observed labor share declines. Panel B reports results for our measure of task displacement based on automation-driven labor share declines. In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender. All specifications control for groups' relative specialization in low-pay jobs (defined as occupations in the bottom tercile of the overall wage distribution in 1980) and differential effects of industry labor share declines (observed or automation-driven) on workers in low-pay jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-7: Task displacement and changes in real hourly wages for men, women, and native-born workers, 1980-2016.

	Dependent variables: Change in wages and wage declines, 1980–2016							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Change in hourly wages for native-born workers 1980–2016							
Task displacement	-1.57	-1.29	-1.48	-1.66	-1.63	-1.35	-1.56	-1.93
	(0.10)	(0.19)	(0.23)	(0.53)	(0.11)	(0.22)	(0.26)	(0.52)
Share variance explained by task displacement	0.68	0.56	0.64	0.72	0.65	0.54	0.63	0.77
R-squared	0.68	0.71	0.85	0.85	0.65	0.67	0.84	0.84
Observations	250	250	250	250	250	250	250	250
	Panel B. Change in hourly wages for men 1980–2016							
Task displacement	-1.52	-1.08	-0.83	-1.57	-1.56	-1.04	-0.79	-1.70
	(0.11)	(0.19)	(0.08)	(0.30)	(0.12)	(0.21)	(0.09)	(0.35)
Share variance explained by task displacement	0.84	0.60	0.46	0.87	0.81	0.54	0.41	0.89
R-squared	0.84	0.86	0.96	0.96	0.81	0.85	0.96	0.96
Observations	250	250	250	250	250	250	250	250
	Panel C. Change in hourly wages for women 1980–2016							
Task displacement	-1.57	-1.68	-2.66	-2.80	-1.62	-2.49	-3.86	-4.49
	(0.18)	(0.23)	(0.37)	(0.79)	(0.21)	(0.29)	(0.46)	(1.06)
Share variance explained by task displacement	0.53	0.57	0.90	0.95	0.47	0.72	1.12	1.30
R-squared	0.53	0.54	0.66	0.68	0.47	0.58	0.70	0.70
Observations	250	250	250	250	250	250	250	250
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 hourly wages across demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. Panel A provides results for native-born groups of workers. Panel B provides results for men. Panel C provides results for women. Columns 1–4 report results for our measure of task displacement based on observed labor share declines. Columns 5–8 report results for our measure of task displacement based on automation-driven labor share declines. In addition to the covariates reported in the table, columns 3-4 and 7–8 control for baseline wage shares in manufacturing and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, and columns 4 and 8 control for groups' exposure to industry labor share declines and groups' relative specialization in routine jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-8: Task displacement and changes in real hourly wages, stacked-differences models for 1980–2000 and 2000–2016.

	Dependent variable: Change in hourly wages 1980–2000, 2000–2016			
	(1)	(2)	(3)	(4)
	Panel A. Common coefficients across periods			
Task displacement	-1.31	-1.04	-0.94	-0.61
	(0.10)	(0.13)	(0.20)	(0.35)
Industry shifters		0.25	-0.44	-0.44
		(0.06)	(0.11)	(0.13)
Exposure to industry labor share decline				0.19
				(0.40)
Exposure to routine occupations				-0.06
				(0.04)
Share variance explained by				
- task displacement	0.46	0.36	0.33	0.21
- task displacement in 80s				
- task displacement in 00s				
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	-1.31	-1.21	-1.27	-1.42
	(0.10)	(0.13)	(0.14)	(0.27)
Share variance explained by				
- task displacement	0.46	0.42	0.44	0.50
- task displacement in 80s				
- task displacement in 00s				
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	-2.08	-1.33	-1.36	-2.11
	(0.28)	(0.25)	(0.25)	(0.73)
Task displacement 00–16	-1.10	-1.16	-1.22	-1.08
	(0.11)	(0.14)	(0.17)	(0.39)
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 hourly wages across 500 demographic groups using a stacked-differences specification for 1980–2000 and 2000–2016. The table uses our measure of task displacement based on observed labor share declines. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly 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. In addition to 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 total hours worked by each group at the beginning of each period. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-9: Task displacement and changes in real hourly wages, 1980–2016—alternative labor share measures.

	Dependent variable: Change in hourly wages 1980–2016			
	(1)	(2)	(3)	(4)
	Panel A. Excluding commodities			
Task displacement	-1.67	-1.32	-1.39	-2.14
	(0.12)	(0.17)	(0.20)	(0.46)
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	-1.59	-1.31	-1.34	-1.89
	(0.10)	(0.16)	(0.20)	(0.44)
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	-1.49	-1.25	-1.32	-1.96
	(0.09)	(0.16)	(0.20)	(0.42)
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	-1.39	-1.11	-0.91	-1.19
	(0.08)	(0.11)	(0.13)	(0.31)
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 hourly 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 hourly wages between 1980 and 2016. The table uses our measure of task displacement based on observed labor share declines. 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. In addition to 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 controls for relative specialization in routine jobs and groups' exposure to industry labor share declines. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table A-10: GMM estimates of the propagation matrix.

	Dependent variable: Change in wages 1980–2016					
	Task displacement measured from observed labor share declines			Task displacement measured from automation-driven labor share declines		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Baseline estimates computing the adjusted labor share decline with $\sigma_i = 1$.					
Own effect, θ/λ	0.88	0.88	0.82	0.89	0.97	0.90
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Contribution of ripple effects via occupational similarity	0.36	0.36	0.31	0.43	0.50	0.45
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)
Contribution of ripple effects via industry similarity	0.22	0.22	0.36	0.35	0.37	0.49
	(0.10)	(0.10)	(0.11)	(0.12)	(0.12)	(0.13)
Contribution of ripple effects via education–age groups	0.18	0.18	0.17	0.17	0.16	0.16
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
	Panel B. Estimates computing the adjusted labor share decline with $\sigma_i = 0.8$.					
Own effect, θ/λ	0.68	0.67	0.62	0.74	0.77	0.72
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Contribution of ripple effects via occupational similarity	0.51	0.48	0.43	0.50	0.55	0.51
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
Contribution of ripple effects via industry similarity	0.08	0.08	0.22	0.22	0.23	0.32
	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)	(0.11)
Contribution of ripple effects via education–age groups	0.20	0.20	0.19	0.18	0.17	0.17
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Panel C. Estimates computing the adjusted labor share decline with $\sigma_i = 1.2$.					
Own effect, θ/λ	1.05	1.04	0.95	1.04	1.18	1.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)
Contribution of ripple effects via occupational similarity	0.20	0.18	0.13	0.32	0.40	0.34
	(0.10)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)
Contribution of ripple effects via industry similarity	0.39	0.39	0.59	0.50	0.57	0.75
	(0.12)	(0.12)	(0.13)	(0.14)	(0.14)	(0.15)
Contribution of ripple effects via education–age groups	0.15	0.15	0.14	0.16	0.15	0.14
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Panel D. Setting $\kappa = 1$ in the sigmoid function.					
Own effect, θ/λ	0.88	0.87	0.81	0.88	0.95	0.88
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Contribution of ripple effects via occupational similarity	0.65	0.63	0.50	0.74	0.88	0.74
	(0.17)	(0.18)	(0.18)	(0.20)	(0.20)	(0.21)
Contribution of ripple effects via industry similarity	0.24	0.24	0.55	0.44	0.45	0.74
	(0.19)	(0.19)	(0.21)	(0.22)	(0.22)	(0.24)
Contribution of ripple effects via education–age groups	0.19	0.19	0.19	0.19	0.19	0.18
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
	Panel E. Setting $\kappa = 5$ in the sigmoid function.					
Own effect, θ/λ	0.91	0.90	0.85	0.92	1.00	0.95
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Contribution of ripple effects via occupational similarity	0.25	0.24	0.23	0.31	0.34	0.33
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Contribution of ripple effects via industry similarity	0.18	0.18	0.24	0.26	0.29	0.33
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
Contribution of ripple effects via education–age groups	0.16	0.16	0.15	0.15	0.14	0.13
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Covariates:						
Industry shifters		✓	✓		✓	✓
Manufacturing share			✓			✓

Notes: This table presents estimates of the propagation matrix. 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 based on observed labor share declines. Columns 4–6 provide GMM estimates using our measure of task displacement based on automation-driven labor share declines. The panels report results for different measures of the adjusted labor share decline and using different values of κ in the sigmoid function. All models are weighted by total hours worked by each group in 1980.

Table A-11: Robustness checks for estimates of the general equilibrium effects.

	Baseline	Labor supply response with Hicksian of 0.3	Setting $\lambda = 0.3$	Setting $\lambda = 0.7$	Setting $\pi = 50\%$	Setting $\kappa = 1$ in sigmoid function	Setting $\kappa = 5$ in sigmoid function	Computing adjusted labor share decline with $\sigma_i = 0.8$	Computing adjusted labor share decline with $\sigma_i = 1.2$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wage structure:									
Share wage changes explained:									
-due to industry shifts	6.33%	3.96%	3.31%	8.06%	7.38%	6.38%	6.45%	5.10%	7.50%
-adding direct displacement effects	93.34%	58.34%	142.92%	70.21%	94.38%	93.38%	93.45%	97.04%	89.57%
-accounting for ripple effects	46.88%	46.88%	43.74%	50.49%	45.04%	47.16%	47.77%	39.04%	53.68%
Rise in college premium	21.02%	21.02%	20.19%	21.96%	20.60%	20.77%	21.76%	19.68%	21.62%
-part due to direct displacement effect	37.71%	23.57%	62.86%	26.94%	37.71%	37.71%	37.71%	42.00%	33.43%
Rise in post-college premium	22.42%	22.42%	21.08%	23.96%	21.56%	22.40%	23.33%	20.51%	23.46%
-part due to direct displacement effect	43.57%	27.23%	72.62%	31.12%	43.57%	43.57%	43.57%	48.90%	38.25%
Change in gender gap	1.90%	1.90%	0.97%	2.97%	1.23%	2.25%	1.73%	-2.15%	6.43%
-part due to direct displacement effect	5.94%	3.71%	9.90%	4.24%	5.94%	5.94%	5.94%	2.19%	9.69%
Share with declining wages	42.26%	42.26%	45.82%	46.34%	35.10%	42.25%	49.04%	48.86%	42.39%
-part due to direct displacement effects	51.52%	51.52%	51.58%	48.76%	39.20%	55.30%	48.65%	55.60%	43.54%
Wages for men with no high school	-8.41%	-8.41%	-7.71%	-9.23%	-4.81%	-8.46%	-8.40%	-5.60%	-11.10%
-part due to direct displacement effects	-15.11%	-9.44%	-25.75%	-10.53%	-11.27%	-16.41%	-14.35%	-13.76%	-16.18%
Wages for women with no high school	-3.40%	-3.40%	-3.53%	-3.23%	-0.51%	-2.99%	-3.77%	-4.84%	-1.36%
-part due to direct displacement effects	-2.82%	-1.76%	-5.27%	-1.76%	1.01%	-4.13%	-2.06%	-4.94%	-0.43%
Aggregates:									
Change in average wages, $d\ln w$	5.18%	5.18%	5.18%	5.18%	8.63%	5.18%	5.18%	5.88%	4.48%
Change in GDP per capita, $d\ln y$	20.95%	20.95%	20.78%	21.13%	22.87%	20.30%	21.33%	24.13%	17.91%
Change in TFP, $d\ln \mathrm{tfp}$	3.42%	3.42%	3.42%	3.42%	5.70%	3.42%	3.42%	3.88%	2.96%
Change in labor share, ds^L	-10.41 pp	-9.38 pp	-10.30 pp	-10.53 pp	-9.40 pp	-9.98 pp	-10.66 pp	-12.04 pp	-8.87 pp
Change in K/Y ratio	38.10%	34.93%	37.77%	38.47%	34.98%	36.78%	38.87%	42.97%	33.29%
Sectoral patterns:									
Share manufacturing in GDP	-0.52 pp	-0.52 pp	-0.50 pp	-0.53 pp	-0.76 pp	-0.52 pp	-0.52 pp	-0.47 pp	-0.56 pp
Change in manufacturing wage bill	-12.85%	-12.85%	-12.93%	-12.76%	-12.30%	-13.51%	-12.49%	-11.68%	-13.88%

Notes: The table summarizes the general equilibrium effects of automation on the wage distribution, wage levels, aggregates, and industry outcomes, 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. In all cases, we use our measure of task displacement based on automation-driven labor share declines.

Appendix B: Supplemental Material for "Tasks, Automation, and the Rise in US Wage Inequality"

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Appendix B-1 Additional Theory Results

Derivation of Threshold $\bar{q}$

This section proves the existence of the threshold $\bar{q}$ introduced in Assumption 1.

Proposition B-1 (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

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

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

The left hand side of (B-1) 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 (B-1) 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 (B-1) holds and the task allocation described in Assumption 1 is the unique equilibrium. ■

Model Extensions with Markups and Endogenous Labor Supply

Proposition B-2 (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*

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \mu_i^{-\lambda} \cdot \Gamma_{gi}\right)^{\frac{1}{\lambda}} \tag{B-2}$$

$$p_i = \frac{\mu_i}{A_i} \cdot \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}} \tag{B-3}$$

$$1 = \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}). \tag{B-4}$$

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

$$d\ln w_g = \Theta_g \cdot \left(\frac{1}{\lambda} d\ln y + \frac{1}{\lambda} d\ln \boldsymbol{\zeta} - \sum_{i\in\mathcal{I}} \omega_{gi} \cdot d\ln \mu_i - \frac{1}{\lambda} d\ln \boldsymbol{\Gamma}^{auto}\right) \text{ for all } g \in \mathcal{G}.$$

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.

The demand for task $x \in \mathcal{T}_i$ can be computed as

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

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

$$y(x) = \cdot \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot p(x)^{-\lambda}, \tag{B-5}$$

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 (B-2), we add-up the demand for labor across tasks, and rearrange the resulting expression:

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

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

To derive the industry price index in equation (B-3), 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 $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$, this implies

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

which yields the expression for industry prices in the proposition.

Finally, because industry shares must add up to 1, we have equation (B-3), 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 (B-2). ∎

Proposition B-3 (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* $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$, *equilibrium wages, labor supply, industry prices, and output solve the system*

(B-6) $$w_g = y^{\frac{1}{\lambda+\varsigma}} \cdot A_g^{\frac{\lambda-1}{\lambda+\varsigma}} \cdot \left(\sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{\lambda+\varsigma}}$$

(B-7) $$\ell_g = y^{\frac{\varsigma}{\lambda+\varsigma}} \cdot A_g^{\frac{\varsigma\cdot(\lambda-1)}{\lambda+\varsigma}} \cdot \left(\sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{\varsigma}{\lambda+\varsigma}}$$

(B-8) $$p_i = \frac{1}{A_i} \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g \in \mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}}$$

(B-9) $$c = \left(1 - A_k^{\lambda-1} \cdot \sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{ki}\right) \cdot y$$

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

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

$$
\begin{aligned}
d\ln w_g =& \Theta_g \cdot \left(\frac{1}{\lambda+\varsigma} d\ln y + \frac{1}{\lambda+\varsigma} d\ln \boldsymbol{\zeta} - \frac{1}{\lambda+\varsigma} d\ln \boldsymbol{\Gamma}^{auto} \right) \text{ for all } g \in \mathcal{G}, \\
d\ln \ell_g =& \Theta_g \cdot \left(\frac{\varsigma}{\lambda+\varsigma} d\ln y + \frac{\varsigma}{\lambda+\varsigma} d\ln \boldsymbol{\zeta} - \frac{\varsigma}{\lambda+\varsigma} d\ln \boldsymbol{\Gamma}^{auto} \right) \text{ for all } g \in \mathcal{G}, \\
d\ln \zeta_g =& \sum_{i\in\mathcal{I}} \omega_{gi} \cdot \left(\frac{\partial \ln s_i^Y(\boldsymbol{p})}{\partial \ln \boldsymbol{p}} \cdot d\ln \boldsymbol{p} + (\lambda-1)\cdot d\ln p_i \right) \text{ for all } g \in \mathcal{G}, \\
d\ln p_i =& \sum_{g\in\mathcal{G}} s_{gi}^L \cdot \left(d\ln w_g - d\ln \Gamma_{gi}^{auto} \cdot \pi_{gi} \right) \text{ for all } i \in \mathcal{I}, \\
d\ln tfp =& \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \sum_{g\in\mathcal{G}} s_{gi}^L \cdot d\ln \Gamma_{gi}^{auto} \cdot \pi_{gi}, \\
d\ln y =& \frac{1}{1-s^K} \cdot \left(d\ln tfp + s^K \cdot d\ln s^K + \sum_{g\in\mathcal{G}} s_g^L \cdot d\ln \ell_g \right), \\
d\ln s^K =& -\frac{1}{s^K} \sum_{g\in\mathcal{G}} s_g^L \cdot (d\ln w_g + d\ln \ell_g - d\ln y)
\end{aligned}
$$

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

(B-11)
$$
\ell_g = w_g^{\varsigma},
$$

where ς denotes the labor supply elasticity with respect to a permanent wage change.

Plugging this labor-supply curve into the expression for wages in equation (10) 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 (B-6). In turn, plugging (B-6) into equation (B-11) yields (B-7).

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

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

Using the fact that $d\ln \ell_g = \varsigma \cdot d\ln w_g$ (from the labor-supply curve in B-11), we can rewrite this as

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

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

The derivations of the remaining expressions in the proposition parallel those in the proof of proposition 4. ■

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. In the following definitions, we use the notation $\frac{\partial y}{\partial x}\Big|_k$ to denote partial derivatives holding the current stock of capital constant (recall that k adjusts endogenously in our model).

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

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

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

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

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

$$\sigma_{\ell_{g'},\ell_g} = \frac{1}{1+\left.\dfrac{\partial\ln(s_g^L/s_{g'}^L)}{\partial\ln \ell_{g'}}\right|_k}.$$

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

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

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).

Proposition B-4 (Elasticities of substitution and Θ) *The Morishima elasticity of substitution between capital and labor is*

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

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

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

and the $q-$elasticities of substitution are

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

Proof. 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 following an increase in A_k 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

$$d\ln w_g = \Theta_g \cdot \left(\frac{1}{\lambda} d\ln y + \frac{1}{\lambda}\Sigma \cdot d\ln \boldsymbol{A_k}\right).$$

The definition of Θ implies $\Theta\frac{1}{\lambda}\Sigma = \Theta - \mathbb{1}$, and plugging this into the expression for wages, we obtain

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

Finally, holding k constant, we have that $d\ln y = s^K \cdot d\ln A_k$, which yields the formula:

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

In addition, we also have that

$$\frac{\partial \ln s^L_g}{\partial \ln A_k}\bigg|_k = \left(\frac{\varepsilon_g}{\lambda} - 1\right) \cdot s^k + (\varepsilon_g - 1) \tag{B-12}$$

Using equation (B-12), 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 (B-12), 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:

$$d\ln w_g = \frac{\varepsilon_g}{\lambda} d\ln y - \frac{\theta_{gg'}}{\lambda} d\ln \ell_{g'}. \tag{B-13}$$

Holding k constant, we have that $d\ln y = s^L_{g'} \cdot d\ln \ell_{g'}$, which yields the formula:

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

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 (B-13), 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 B-5 (Quasi-symmetry of the propagation matrix) *The propagation matrix satisfies the symmetry property*

$$\varepsilon_g - \frac{\theta_{gg'}}{s^L_{g'}} = \varepsilon_{g'} - \frac{\theta_{g'g}}{s^L_g}. \tag{B-14}$$

Proof. By definition $\sigma^Q_{\ell_{g'},\ell_g} = \sigma^Q_{\ell_g,\ell_{g'}}$, which implies the symmetry property in (B-14). ■

Appendix B-2 Measuring Task Displacement: Additional Details and Extensions

This section provides additional derivations that support our measurement of task displacement. In particular, we derive equation (A-10) and a bounding exercise for the error term ε_i.

For each type of worker g, define the elasticity σ^L_{gi} by

$$\frac{1}{\omega^g_i} \cdot \frac{\partial \ln s^L_i}{\partial \ln w_g} = s^k \cdot (1 - \sigma^L_{gi}).$$

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

Proposition B-6 (Industry labor shares) *Let s^L_i denote the labor share in industry i. Also, let $w^e_{gi} = w_g/A_{gi}$ denote the wages per efficiency unit of labor paid in industry i for workers of* *type g. Following a change in automation, factor prices (w_g, R_i), and markups μ_i, we have*

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

where

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

and

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

Proof. Given a vector of wages and technologies, we can write the labor share as in equation (A-9), where recall that the denominator is also equal to

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

The contribution of changes in markups is simply $-d\ln\mu_i$.

The contribution of automation was already derived in Proposition A-2, and is given by $d\ln s_i^{L,\text{auto}} = -\big(1 + (\lambda-1)\cdot s_i^L \cdot \pi_i\big)\cdot \omega_i^R \cdot \vartheta_i$.

We now turn to the contribution of wages. Using the definition of σ_{gi}^L, we can compute their influence on the labor share as

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

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

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

Finally, 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 (A-9). 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

$$(1 - s_i^L) \cdot (\lambda - \sigma_{gi}^L) = \sum_{g'} \sum \frac{\omega_i^{g'}}{\omega_i^g} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}}. \quad \text{(B-15)}$$

Consider a uniform change in the user cost of capital $d \ln R_i$. The effect of this change in the allocation of tasks is the same as a uniform reduction in wages of $-d \ln R_i$. Moreover, the effect of $d \ln R_i$ on the denominator of the labor share is just its direct effect—an application of the envelope theorem. Thus, we get

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

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 (A-9). Using equation (B-15), we can rewrite this expression as

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

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

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

which completes the proof of the proposition. ■

Bounding Exercise: In the general case treated in Section 5 and Tables B-1 and A-4 in the appendix, our measure of task displacement is computed from the adjusted decline in the labor share:

$$-d \ln s_i^{L,\text{auto}} = -d \ln s_i^L + s_i^K \cdot \left[(1 - \sigma_i^L) \cdot d \ln w_i - (1 - \sigma_i^K) \cdot d \ln R_i \right] - \varepsilon_i,$$

where we set $\lambda = 0.5$. and $\sigma_i^L = \sigma_i^K = \sigma_i = 0.8$ or $\sigma_i^L = \sigma_i^K = \sigma_i = 1.2$.

While our formulas for the residual decline in labor shares incorporate the effects of changes in factor prices, they miss the contribution of factor-augmenting technologies, which affect the labor share when σ_i^L or σ_i^K deviate from 1, and are therefore part of the error term, $-\varepsilon_i$.

We now provide upper bounds on the effects of this type of technological change on our measures of adjusted labor share declines by industry, which reveal that these residuals are quantitatively small.

In particular, for $\sigma_i^L, \sigma_i^K < 1$, the contribution of factor-augmenting technologies to the change in the labor share is between $-s_i^K \cdot (1 - \sigma_i^L) \cdot d\ln A_{\ell i}$ (where $d\ln A_{\ell i}$ is a weighted average of $d\ln A_{gi}$ across groups) and $s_i^K \cdot (1 - \sigma_i^K) \cdot d\ln A_{ki}$. 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

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

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

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

Figure B-2 presents our measures of the adjusted labor share decline across industries for $\sigma_i^L = \sigma_i^K = \sigma_i = 0.8$ and for $\sigma_i^L = \sigma_i^K = \sigma_i = 1.2$, 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 B-3 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 specialized software and dedicated 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 machinery used in industrial applications.

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 A-1.

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 et al. (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 et al. (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 et al., 2020b).

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). To deal with top coding, 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 4.6 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 et al., 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 A-5 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 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.

Appendix B-4 Additional Figures and Tables

This appendix includes additional tables discussed in footnotes in the main text:

- Figure B-1: Relationship between industry labor share declines and the percent change in routine wages, hours, and employment across industries.
- Figure B-2: Adjusted labor share declines
- Table B-1: Determinants of adjusted labor share changes across industries, 1987–2016.
- Table B-2: Relationship between industry labor share decline and the decline of routine jobs.
- Table B-3: Additional sets of standard errors for our baseline estimates in Column 3 of Table 1.
- Table B-4: Task displacement and additional employment outcomes, 1980–2016.
- Table B-5: 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.
- Table B-6: Task displacement and changes in real hourly wages—controlling for differential effect of markups and concentration on routine jobs.
- Table B-7: 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.
- Table B-8: Task displacement and changes in real hourly wages, 1980–2007.

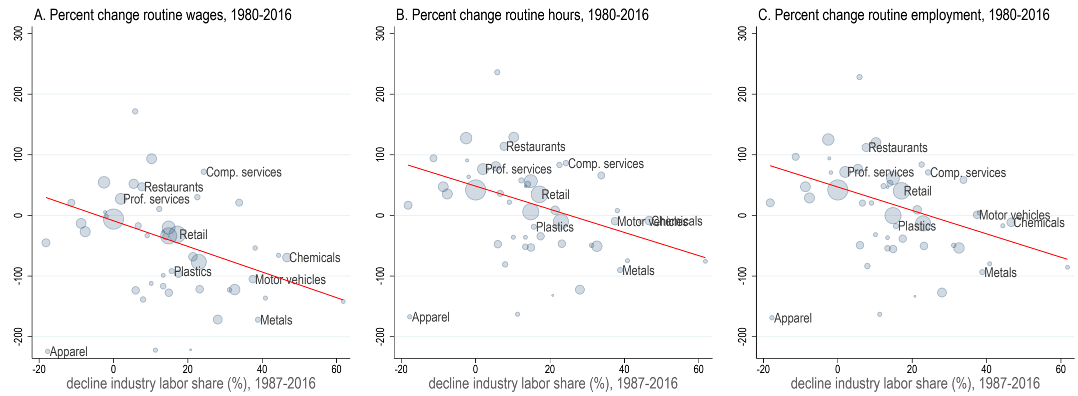

FIGURE B-1: Relationship between industry labor share declines and the percent change in routine wages, hours, and employment across industries. See text for variable definitions.

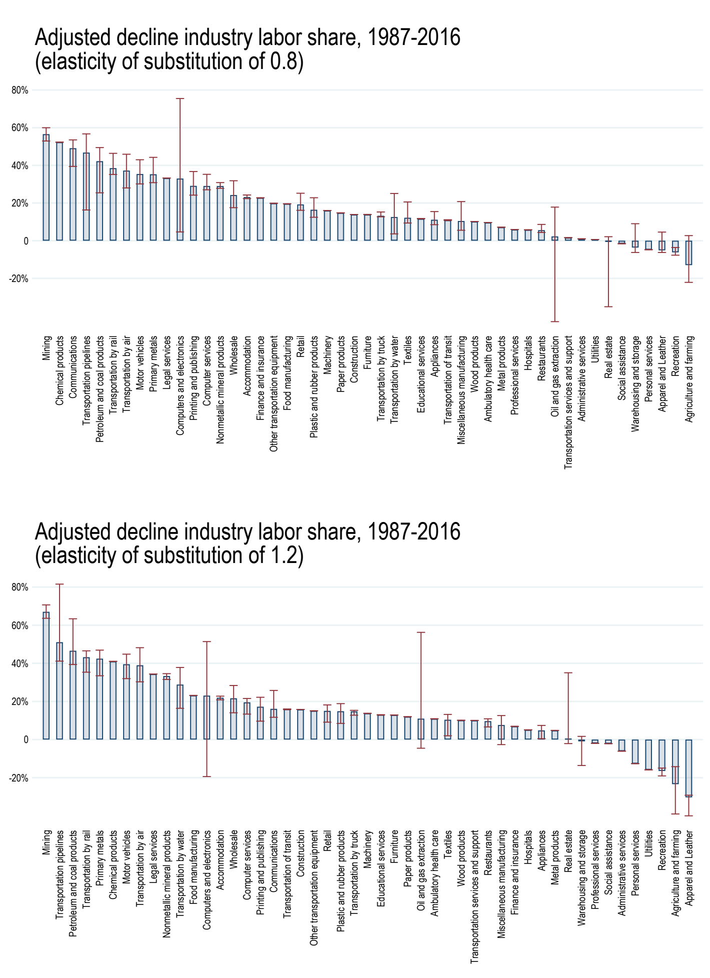

FIGURE B-2: Adjusted labor share declines. The figure provides the adjusted labor share declines for $\sigma_i = 0.8$ (top panel) and $\sigma_i = 1.2$ (bottom panel) described in Appendix A-3. The whiskers provide bounds on the decline in the adjusted labor share that cannot be explained by factor-augmenting technologies, derived in Appendix B-2.

Table B-1: Determinants of adjusted labor share changes across industries, 1987–2016.

	Dependent variable: adjusted labor share changes (in %), 1987–2016								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Adjusted labor share for $\sigma_i = 0.8$, 1987–2016								
Adjusted penetration of robots	-1.22		-0.99	-0.96	-0.99	-0.97	-1.01	-0.99	-0.59
	(0.39)		(0.47)	(0.45)	(0.46)	(0.48)	(0.48)	(0.47)	(0.63)
Change in share of dedicated machinery services		-2.57	-1.61	-1.55	-1.65	-1.64	-1.55	-1.61	-1.03
		(0.62)	(0.77)	(0.80)	(0.73)	(0.84)	(0.87)	(0.78)	(0.91)
Change in share of specialized software services	-7.89	-7.08	-8.30	-7.94	-8.40	-8.41	-8.31	-8.31	-8.07
	(1.87)	(2.16)	(1.87)	(2.03)	(2.03)	(2.10)	(1.93)	(1.93)	(1.65)
Change in share of imported intermediates				-0.71					
				(0.65)					
Change in K/Y ratio					-0.02				
					(0.03)				
Change tail index of revenue concentration						0.08			
						(0.30)			
Change in accounting markups (%)							-0.06		
							(0.35)		
Change Chinese import competition								0.01	
								(0.23)	
De-unionization rate									-0.51
									(0.34)
F-stat technology variables	11.76	12.14	12.00	10.07	11.24	10.46	9.98	11.41	8.79
Share variance explained by technology	0.35	0.27	0.40	0.38	0.40	0.40	0.40	0.40	0.31
R-squared	0.35	0.27	0.40	0.40	0.40	0.40	0.40	0.40	0.47
Observations	49	49	49	49	49	49	49	49	49
	Panel A: Adjusted labor share for $\sigma_i = 1.2$, 1987–2016								
Adjusted penetration of robots	-1.32		-0.86	-0.84	-0.86	-0.90	-0.98	-0.89	-0.86
	(0.31)		(0.37)	(0.36)	(0.38)	(0.38)	(0.37)	(0.39)	(0.44)
Change in share of dedicated machinery services		-4.07	-3.23	-3.20	-3.22	-3.15	-2.81	-3.24	-3.24
		(0.63)	(0.73)	(0.76)	(0.75)	(0.69)	(0.72)	(0.74)	(0.74)
Change in share of specialized software services	-4.78	-4.55	-5.61	-5.40	-5.58	-5.32	-5.64	-5.73	-5.61
	(1.82)	(1.71)	(1.44)	(1.60)	(1.53)	(1.54)	(1.76)	(1.53)	(1.47)
Change in share of imported intermediates				-0.41					
				(0.49)					
Change in K/Y ratio					0.00				
					(0.02)				
Change tail index of revenue concentration						-0.20			
						(0.20)			
Change in accounting markups (%)							-0.42		
							(0.39)		
Change Chinese import competition								0.24	
								(0.29)	
De-unionization rate									0.01
									(0.21)
F-stat technology variables	10.27	21.82	18.25	16.08	16.64	19.48	15.11	17.19	12.32
Share variance explained by technology	0.29	0.39	0.48	0.48	0.48	0.48	0.47	0.49	0.49
R-squared	0.29	0.39	0.48	0.49	0.49	0.49	0.54	0.49	0.48
Observations	49	49	49	49	49	49	49	49	49

Notes: This table presents estimates of the relationship between adjusted labor share changes (in %) between 1987 and 2016 at the industry level and automation technologies, offshoring, capital deepening, changes in market structure (proxied by markups or rising sales concentration), and changes in Chinese import competition for the 49 industries in our analysis. Adjusted labor share changes are computed as $d \ln s_i^L + s_i^K \cdot (1 - \sigma_i) \cdot (d \ln w_i - d \ln R_i)$, where σ_i is set to 0.8 in Panel A and to 1.2 in Panel B. All regressions are weighted by industry value added in 1987. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-2: Relationship between industry labor share decline and the decline of routine jobs.

Labor share measure:	Labor share declines			Automation-driven declines		
Dependent variable:	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 decline, 1987–2016			
Percent decline in labor share	-2.11	-1.91	-1.93	-2.85	-2.29	-2.24
	(0.54)	(0.52)	(0.52)	(0.87)	(0.80)	(0.83)
R-squared	0.21	0.20	0.20	0.17	0.13	0.12
Observations	48.00	48.00	48.00	48.00	48.00	48.00
			Panel B: Adjusted labor share decline with $\sigma_i = 0.8$, 1987–2016			
Residual decline in labor share	-2.25	-2.09	-2.13	-2.89	-2.43	-2.44
	(0.47)	(0.47)	(0.46)	(0.99)	(0.89)	(0.91)
R-squared	0.26	0.26	0.27	0.17	0.14	0.14
Observations	48	48	48	48	48	48
			Panel C: Adjusted labor share decline with $\sigma_i = 1.2$, 1987–2016			
Residual decline in labor share	-1.64	-1.42	-1.43	-2.54	-1.95	-1.87
	(0.52)	(0.50)	(0.50)	(0.70)	(0.66)	(0.69)
R-squared	0.14	0.12	0.12	0.16	0.11	0.10
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. In Panel A, columns 1–3 provide estimates using the observed indutry labor share decline (in %) as explanatory variable, while columns 4–6 provide estimates using automation-driven labor share declines (in %) as explanatory variable. In Panels B and C we provide estimates using the adjusted labor share decline obtained for $\sigma_i = 0.8$ and $\sigma_i = 1.2$. All regressions are weighted by industry value added in 1987. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-3: Additional sets of standard errors for our baseline estimates from Column 3 in Table 1.

	Standard error (1)	p–value for null $\beta = 0$ (2)	95% confidence interval (3)
	Panel A. Task displacement based on labor share declines, $\hat{\beta}^d = -1.31$		
Robust standard errors	(0.19)	[$p = 0.000$]	($-1.68, -0.94$)
Borusyak-Hull-Jaravel	(0.18)	[$p = 0.000$]	($-1.65, -0.96$)
Adao-Kolesar-Morales (correlation due to industry×routine)	(0.27)	[$p = 0.000$]	($-1.85, -0.77$)
Adao-Kolesar-Morales (correlation due to industry)	(0.44)	[$p = 0.003$]	($-2.17, -0.45$)
	Panel B. Task displacement based on automation-driven labor share declines, $\hat{\beta}^d = -1.36$		
Robust standard errors	(0.21)	[$p = 0.000$]	($-1.78, -0.94$)
Borusyak-Hull-Jaravel	(0.17)	[$p = 0.000$]	($-1.70, -1.02$)
Adao-Kolesar-Morales (correlation due to industry×routine)	(0.32)	[$p = 0.000$]	($-1.99, -0.73$)
Adao-Kolesar-Morales (correlation due to industry)	(0.49)	[$p = 0.005$]	($-2.31, -0.40$)
Adjusting for task displacement estimation using one-step GMM	(0.26)	[$p = 0.000$]	($-1.87, -0.85$)

Notes: This table provides additional sets of standard errors and confidence intervals for the estimates in column 3 from table 1. Panel A reports results using our measure of task displacement based on the observed labor share decline. The corresponding point estimate of β is -1.31 (See Table 1 column 3, Panel A). Panel B reports results using our measure of task displacement based on automation-driven labor share declines. The corresponding point estimate of β is -1.36 (See Table 1 column 3, Panel B). The tables in the paper use robust standard errors. In addition, here we report standard errors, a p–value for testing the null that task displacement had no effect on workers, and 95% confidence intervals using other procedures. *Borusyak-Hull-Jaravel:* standard errors from Borusyak et al. (2022), which are robust to unobserved industry shocks that affect workers depending on their relative specialization in routine jobs. *Adao-Kolesar-Morales:* standard errors from Adao et al. (2019). We present two sets of errors. The first allows for unobserved industry shocks that affect workers depending on their relative specialization in routine jobs. The second allows for unobserved industry shocks that affect all workers in an industry. Finally, in the last row, we provide GMM estimates where we estimate the equation that predicts the labor share decline that is due to automation (at the industry level) and the equation for wages on task displacement in a single step, as in Newey (1984). This set of standard errors account for the generated regressor problem.

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

	Dependent variable: Labor market outcomes 1980–2016					
	Task displacement measured from observed labor share declines			Task displacement measured from automation-driven labor share declines		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Unemployment rate					
Task displacement	0.11	0.17	0.02	0.12	0.20	0.03
	(0.02)	(0.04)	(0.10)	(0.02)	(0.05)	(0.12)
Share variance explained by:						
- task displacement	0.18	0.27	0.04	0.19	0.31	0.05
- educational dummies		0.00	-0.01		0.01	-0.02
R-squared	0.18	0.28	0.29	0.19	0.29	0.31
Observations	500	500	500	500	500	500
	Panel B. log hours per worker					
Task displacement	-0.86	-0.58	0.79	-0.92	-0.62	0.85
	(0.18)	(0.29)	(0.62)	(0.19)	(0.32)	(0.73)
Share variance explained by:						
- task displacement	0.31	0.21	-0.28	0.32	0.21	-0.29
- educational dummies		0.13	-0.01		0.16	-0.04
R-squared	0.31	0.47	0.50	0.32	0.47	0.51
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 between 1980 and 2016. In Panel B, the dependent variable is the change in the log of hours per worker between 1980 and 2016. Columns 1–3 report results using our measure of task displacement based on observed labor share declines. Columns 4–6 report results using our measure of task displacement based on automation-driven labor share declines. In addition to 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, completed high school, 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. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-5: 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							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
Other shocks:	Rising K/Y ratio by industry (1)	Rising TFP by industry (2)	Chinese imports' competition (3)	Declining unionization rates (4)	Rising K/Y ratio by industry (5)	Rising TFP by industry (6)	Chinese imports' competition (7)	Declining unionization rates (8)
	Panel A. Controlling for main effect of other shocks							
Task displacement	-1.67	-1.81	-1.60	-1.82	-1.85	-2.09	-1.55	-1.88
	(0.48)	(0.48)	(0.52)	(0.47)	(0.48)	(0.59)	(0.65)	(0.56)
Exposure to industry shock	-0.02	-0.16	0.00	1.14	0.02	-0.23	0.01	0.10
	(0.16)	(0.38)	(0.02)	(1.53)	(0.15)	(0.40)	(0.02)	(1.53)
Share variance explained by:								
- task displacement	0.70	0.76	0.67	0.76	0.72	0.82	0.60	0.73
- industry shock	-0.00	0.01	-0.00	-0.17	0.00	0.01	-0.01	-0.01
R-squared	0.84	0.84	0.84	0.84	0.83	0.83	0.83	0.83
Observations	500	500	500	500	500	500	500	500
	Panel B. Controlling for effects on workers in routine jobs							
Task displacement	-1.40	-1.73	-1.19	-2.66	-1.56	-2.04	-1.06	-4.06
	(0.52)	(0.44)	(0.55)	(0.85)	(0.51)	(0.54)	(0.64)	(1.14)
Exposure to industry shock	0.31	-0.00	0.04	-1.56	0.41	-0.13	0.04	-4.77
	(0.20)	(0.45)	(0.03)	(2.17)	(0.18)	(0.49)	(0.03)	(1.95)
Exposure of routine jobs to	-0.36	-0.14	-0.03	1.69	-0.44	-0.08	-0.02	3.66
industry shock	(0.15)	(0.27)	(0.02)	(1.34)	(0.14)	(0.27)	(0.02)	(1.58)
Share variance explained by:								
- task displacement	0.59	0.72	0.50	1.11	0.61	0.79	0.41	1.58
- industry shock	0.15	0.03	0.08	-0.23	0.18	0.02	0.05	-0.29
R-squared	0.85	0.84	0.84	0.84	0.84	0.83	0.83	0.84
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly 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 hourly wages for each group between 1980 and 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 results using our measure of task displacement based on observed labor share declines. Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines. In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender, relative specialization in routine jobs, and groups' exposure to industry labor share declines. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-6: 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							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	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	-0.69	-1.35	-1.17	-0.97	-0.58	-1.14	-1.09	-1.03
	(0.21)	(0.33)	(0.22)	(0.15)	(0.25)	(0.46)	(0.23)	(0.16)
Exposure to changes in markups or concentration	9.19	0.19	-1.95	-4.42	9.78	-0.37	-1.90	-4.69
	(2.22)	(1.52)	(0.55)	(1.01)	(2.22)	(1.68)	(0.58)	(0.98)
Exposure of routine jobs to changes in markups or concentration	-4.50	0.13	0.99	3.49	-5.02	-0.72	1.23	3.73
	(1.15)	(1.44)	(0.23)	(0.67)	(1.13)	(1.72)	(0.23)	(0.62)
Share variance explained by:								
- task displacement	0.29	0.57	0.49	0.41	0.22	0.44	0.43	0.40
- markups/concetration	0.25	-0.01	-0.12	-0.08	0.27	0.07	-0.09	-0.09
R-squared	0.86	0.84	0.85	0.88	0.86	0.83	0.84	0.87
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-0.90	-1.35	-1.17	-0.97	-0.75	-1.30	-0.67	-0.99
	(0.25)	(0.33)	(0.22)	(0.15)	(0.39)	(0.55)	(0.14)	(0.15)
Exposure to changes in markups or concentration	9.07	0.19	-1.95	-4.42	9.91	-0.01	-1.94	-4.61
	(2.18)	(1.52)	(0.55)	(1.01)	(2.35)	(1.64)	(0.64)	(0.99)
Exposure of routine jobs to changes in markups or concentration	-4.75	-1.22	-0.18	2.52	-5.40	-1.90	1.32	3.78
	(1.05)	(1.18)	(0.37)	(0.75)	(1.06)	(1.32)	(0.27)	(0.62)
Share variance explained by:								
- task displacement	0.30	0.44	0.57	0.37	0.17	0.30	0.38	0.40
- markups/concetration	0.25	0.11	-0.19	-0.04	0.27	0.17	-0.09	-0.09
R-squared	0.87	0.84	0.85	0.88	0.86	0.83	0.83	0.87
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly wages across 500 demographic groups controlling for changes in market structure and markups and any differential effect of these changes on routine jobs. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 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 et al. (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 results using our measure of task displacement based on observed labor share declines (net of markups in Panel B). Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines (net of markups in Panel B). In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender, relative specialization in routine jobs, and groups' exposure to industry labor share declines.. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-7: 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							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	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	-1.39	-1.61	-2.07	-1.57	-1.58	-1.85	-2.35	-1.71
	(0.46)	(0.45)	(0.46)	(0.54)	(0.45)	(0.47)	(0.54)	(0.58)
Exposure to changes in markups or concentration	1.97	0.72	-1.29	-0.40	1.80	0.20	-1.12	-0.59
	(1.56)	(1.75)	(0.55)	(1.16)	(1.53)	(1.54)	(0.58)	(1.23)
Share variance explained by:								
- task displacement	0.58	0.68	0.87	0.66	0.62	0.72	0.91	0.67
- markups/concetration	0.04	-0.01	-0.12	0.01	0.04	-0.00	-0.10	0.01
R-squared	0.84	0.84	0.85	0.84	0.83	0.83	0.84	0.83
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-1.22	-1.65	-1.24	-1.97	-1.77	-2.11	-0.69	-1.23
	(0.55)	(0.56)	(0.23)	(0.40)	(0.75)	(0.74)	(0.38)	(0.57)
Exposure to changes in markups or concentration	1.66	-0.64	-2.51	-2.04	0.42	-2.03	-0.59	-0.68
	(1.68)	(1.90)	(0.64)	(0.72)	(1.57)	(1.41)	(0.55)	(1.26)
Share variance explained by:								
- task displacement	0.40	0.54	0.60	0.74	0.41	0.49	0.40	0.50
- markups/concetration	0.04	0.01	-0.23	0.03	0.01	0.03	-0.05	0.01
R-squared	0.84	0.83	0.85	0.87	0.82	0.82	0.82	0.83
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly 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 hourly wages for each group between 1980 and 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 et al. (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 results using our measure of task displacement based on observed labor share declines (net of markups in Panel B). Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines (net of markups in Panel B). In addition to 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, completed high school, some college, college degree and postgraduate degree) and gender, relative specialization in routine jobs, and groups' exposure to industry labor share declines. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-8: Task displacement and changes in real hourly wages, 1980–2007.

	Dependent variables: Change in wages and wage declines, 1980–2007							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Change in hourly wages, 1980–2007							
Task displacement	-1.78	-1.37	-0.92	-0.33	-2.10	-1.72	-0.97	-0.24
	(0.11)	(0.14)	(0.18)	(0.56)	(0.13)	(0.22)	(0.23)	(0.66)
Share variance explained by task displacement	0.69	0.53	0.36	0.13	0.68	0.56	0.32	0.08
R-squared	0.69	0.74	0.82	0.83	0.68	0.70	0.81	0.82
Observations	500	500	500	500	500	500	500	500
	Panel B. Change in hourly wages for men, 1980–2007							
Task displacement	-1.56	-0.75	-0.57	-1.25	-1.86	-0.91	-0.70	-1.68
	(0.16)	(0.18)	(0.12)	(0.47)	(0.19)	(0.22)	(0.16)	(0.50)
Share variance explained by task displacement	0.76	0.36	0.28	0.61	0.77	0.38	0.29	0.70
R-squared	0.76	0.87	0.94	0.94	0.77	0.87	0.94	0.94
Observations	250	250	250	250	250	250	250	250
	Panel C. Change in hourly wages for women, 1980–2007							
Task displacement	-2.33	-1.99	-3.17	-1.65	-2.32	-3.31	-5.09	-1.08
	(0.34)	(0.44)	(0.60)	(0.95)	(0.35)	(0.73)	(0.87)	(1.23)
Share variance explained by task displacement	0.47	0.40	0.64	0.33	0.45	0.64	0.99	0.21
R-squared	0.47	0.50	0.66	0.72	0.45	0.48	0.64	0.71
Observations	250	250	250	250	250	250	250	250
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 hourly wages across demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2007. Panel A provides estimates for all demographic groups, while Panels B and C provide results for men and women respectively. Columns 1–4 report results for our measure of task displacement based on observed labor share declines. Columns 5–8 report results for our measure of task displacement based on automation-driven labor share declines. In addition to the covariates reported in the table, columns 3-4 and 7–8 control for baseline wage shares in manufacturing and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, and columns 4 and 8 control for groups' exposure to industry labor share declines and groups' relative specialization in routine jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.