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Automation and Rent Dissipation: Implications for Wages, Inequality, and Productivity
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ABSTRACT

This paper studies the effects of automation in economies with labor market distortions that generate worker rents—wages above opportunity cost—in some jobs. We show that automation targets high-rent tasks, dissipating rents and amplifying wage losses from automation. It also reduces within-group wage dispersion for exposed groups. Automation-driven rent dissipation is inefficient and reduces (and could even negate) the productivity gains from automation. Using data for the US from 1980 to 2016, we find evidence of sizable rent dissipation and reduced within-group wage dispersion due to automation. Using these estimates and accounting for equilibrium effects, we estimate that automation accounts for 52% of the increase in between-group inequality in the US since 1980, with rent dissipation being responsible for a fifth of this contribution. We also estimate that inefficient rent dissipation offset 60–90% of the productivity gains from automation since 1980.

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1 Introduction

The US labor market has undergone significant changes since 1980: not only has inequality increased sharply, but real wages for workers without a college degree have stagnated or declined. Although many factors may have contributed to rising inequality, the automation of tasks performed by less-educated workers appears to have played an important role.[1]

This paper examines the implications of automation for wages, productivity, and welfare in economies with imperfect labor markets, where workers earn rents—wages above their outside options or opportunity costs. While the presence of worker rents is well-documented, the literature has not reached consensus on how changes in these rents have shaped the wage structure, and little is known about how the interplay between automation and labor market imperfections has affected inequality.[2] Our contribution is to develop a new framework for analyzing, estimating and quantifying the effects of automation in the presence of worker rents.

We consider an economy where firms allocate tasks to workers of different skills or decide to automate them. Worker rents distort hiring and automation decisions by creating a wedge between the wage firms must pay workers in some tasks and their opportunity cost. This wedge may be due to efficiency wages, bargaining, regulations (such as licensing requirements), or norms. These wedges artificially inflate the cost of hiring workers, reducing employment in high-rent tasks below the efficient level and encouraging excessive automation of these tasks.[3]

Our first theoretical contribution is to identify a novel *rent dissipation* mechanism. All else equal, automation targets and displaces workers from high-rent tasks. This targeting has important implications for wages and productivity:

1. *Average group wages.* In competitive labor markets, automation depresses the relative demand for exposed workers via a *displacement effect*—by reducing the share of tasks allocated to them. Rent dissipation amplifies wage losses by pushing exposed groups away from high-rent tasks toward lower-wage jobs.
2. *Within-group wage dispersion.* By reallocating workers away from high-rent jobs,

[1] See Goldin and Katz (2008), Acemoglu and Autor (2011), and Autor (2019) for a review of US inequality trends, and Acemoglu and Restrepo (2022) for estimates of the impact of automation on US inequality.

[2] The presence of worker rents receives support from the literature on wage losses following job displacement (Gibbons and Katz, 1992; Jacobson et al., 1993; Schmieder et al., 2023), earnings differentials (Krueger and Summers, 1988; Katz and Summers, 1989; Card et al., 2018), and wage premia associated with unions and licenses (Kleiner and Krueger, 2013; Gittleman and Kleiner, 2016; Farber et al., 2021).

[3] This definition of rents excludes compensating differentials, paid to compensate workers for differences in amenities or hazards, and high wages accruing to workers with specialized skills.

automation reduces within-group wage dispersion. This results in a U-shaped profile of wage changes across percentiles of exposed groups.

3. *Productivity and welfare.* In competitive labor markets, automation increases TFP by reducing the cost of producing automated tasks. In our economy, rent dissipation is inefficient. Tasks targeted for automation are not those where worker wages are high due to rents, not due to scarcity or skills. A planner would have preferred to allocate more—rather than less—labor to these tasks. Inefficient rent dissipation offsets some (or all) of the cost-saving gains from automation.

Our second contribution is to provide reduced-form evidence on rent dissipation using US data from 1980 to 2016. In a first strategy, we document that the negative impact of automation on wages within detailed demographic groups follows the distinctive U-shaped pattern predicted by theory, with the largest effects between the 70th and 95th percentiles of the within-group distribution. This is indicative of automation leading to a loss of high-rent jobs.

In a second complementary strategy, we directly show that automation displaced exposed groups of workers from high-rent jobs, using various proxies of rents proposed in the literature (see Krueger and Summers, 1988; Katz and Summers, 1989; Gibbons and Katz, 1992). These include: wage differentials across industries and occupations (controlling for worker characteristics), wage losses after job displacement, and quit rates (an inverse measure of rents, since workers leave attractive jobs less often). Using these proxies, we document that the US workforce has over time shifted away from high-rent to lower-paying jobs, with the shift being more pronounced for groups exposed to automation.

Both strategies yield robust results, including when we control for compensating wage differentials and other factors, such as minimum wages. They also imply a sizable role for rent dissipation: on average, automation displaced workers from jobs where wages exceeded their opportunity cost by about 35%. This loss of rents accounts for one-fifth of the overall relative wage decline experienced by groups exposed to automation.

Our third contribution is to quantify the general equilibrium implications of automation for wages and productivity in the presence of labor market distortions. We derive formulas that express the effects of automation in terms of task displacement (the share of tasks automated for a demographic group), the extent of rent dissipation, and cost savings from automation. In general equilibrium, the automation of tasks performed by a group impacts other groups via *ripple effects*—as the displaced group competes against others for marginal tasks more intensively. Our formulas summarize these ripple effects using two matrices, which can be estimated using US data: the *propagation matrix*, which encodes this competition for marginal tasks, and the *rent-impact matrix*, which encodes information on how task reallocation changes rents across groups.

We find that automation accounts for 52% of the rise in between-group wage inequality since 1980. 42 percentage points of the 52 are due to the baseline effects of automation working through labor demand. The remaining 10 percentage points are due to rent dissipation. We also estimate that the cost savings from automation increased TFP by 3% between 1980 and 2016. However, the inefficient targeting of high-rent tasks offsets 60–90% of these gains. On net, automation increased aggregate TFP by only 0.3–1.3% and aggregate consumption by just 0.45–1.95% during this period.

Literature: Our primary contribution is to develop a framework for analyzing the effects of automation on labor markets with rents. Several papers study the interplay between technology and labor market imperfections (e.g., Aghion and Howitt, 1994; Acemoglu, 1997; Caballero and Hammour, 1998; Mortensen and Pissarides, 1998), but they do not explore the effects of automation. Recent exceptions include Arnoud (2019) and Leduc and Liu (2022), who focus on how automation affects wages via bargaining.

Our framework extends the task model in Acemoglu and Restrepo (2022) to incorporate worker rents.[4] We model rents as exogenous wedges, following the misallocation literature (e.g. Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008; Hsieh et al., 2019). This choice preserves comparability with prior analyses in competitive markets and isolates the differences due to rents. We also provide formulas for the effects of automation on wages and productivity in distorted economies, which relate to work by Baqaee and Farhi (2020); Basu et al. (2022) and Dávila and Schaab (2023).

Our work contributes to the literature on the rise in US wage inequality (e.g., Katz and Murphy, 1992; Card and Lemieux, 2001), in particular to papers examining the impact of computers and automation on inequality, including Krueger (1993); Autor et al. (1998, 2003), to the literature on capital-skill complementarity (e.g., Krusell et al., 2000; Burstein et al., 2019), and to our previous work Acemoglu and Restrepo (2022), which modeled and quantified the effects of automation on the US wage structure. In relation to these papers, our contribution is to examine the interplay between automation and worker rents.

Our emphasis on technology and rents is closer to work by Bound and Johnson (1992) and Borjas and Ramey (1995). Bound and Johnson (1992) decompose changes in the wage structure between 1979 and 1988 into technology, supply, and rents (modeled as exogenous

[4]These models build on prior works exploring the effects of technologies and trade in task models, including 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.

industry wedges), finding that 10–20% of between-group wage changes reflect the loss of rents. Borjas and Ramey (1995) estimate that, between 1976 and 1990, trade increased the college premium by 1.3–2.6 log points, with 15–33% of the effect being due to loss of rents from trade-exposed jobs. Both estimates are comparable to ours, though Bound and Johnson's estimates include all factors affecting rents. Recent work by Stansbury and Summers (2020) also documents a decline in worker rents, but does not explore the role of automation.

We also contribute to this literature by documenting the implications of automation for between- and within-group inequality. We find that groups exposed to automation have experienced lower wage growth on average and more within-group wage compression—a phenomenon explained by a shift away from high-rent jobs. This pattern contrasts with the standard view that inequality is fractal, rising at all levels of aggregation (e.g., Katz, 1994), due to higher skill demand (see Acemoglu, 2002). Our theory points to a more nuanced pattern: automation can increase wage inequality between groups while reducing it within affected groups, especially among non-college workers who have been more exposed to automation. This mechanism helps explain the divergent trends in within-group wage inequality, which has steadily risen for college workers since the 1980s while remaining flat and then declining for non-college workers since the 1990s (see Goldin and Katz, 2007).

Our exploration of the effect of technology on within-group inequality relates to recent work by Kogan et al. (2021) and Danieli (2024). These papers have little overlap with our approach, as they do not model or estimate the effects of automation via rents.

Finally, our work contributes to the literature on worker rents and their implications for efficiency. This literature proposes several reasons why workers earn rents, ranging from efficiency wages (Akerlof, 1984; Shapiro and Stiglitz, 1984; Stiglitz, 1985; Bulow and Summers, 1986) to search, bargaining (Grout, 1984; Pissarides, 2000), and labor market regulations. This literature shows that worker rents can be distortionary, leading to insufficient employment in high-rent jobs. These distortions can also justify second-best policy interventions and imply that technology or trade can reduce welfare (see, for example, Katz and Summers, 1989; Bhagwati, 1968), a point related to the automation inefficiencies we emphasize.

Organization: Section 2 presents our theoretical framework. Section 3 documents reduced-form evidence of rent dissipation. Section 4 outlines our approach for estimating the general equilibrium effects of automation. The Appendix includes the main proofs, while the (online) Supplement provides the remaining proofs, robustness checks, and data details.

2 Theory: Automation and Labor Market Distortions

This section presents our framework and derives theoretical results. We study a one-sector model and extend to a multi-sector one in Section 4.

2.1 Single-Sector Model

Description: A unique final good y is produced by combining complementary tasks $x \in \mathcal{T}$ (where the set of tasks $\mathcal{T} \subset \mathbb{R}^d$ has mass M). Task quantities, y_x, are aggregated with a constant elasticity of substitution $\lambda \in (0,1)$:[5]

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

There is a finite set of labor groups (demographic groups in our application) indexed by g, where $g \in \mathbb{G} = \{1, 2, \ldots, G\}$. Tasks can also be produced using task-specific capital, equipment, or software, denoted by k_x for task x. The total production of task x is

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

where ℓ_{gx} is the amount of labor of type g allocated to task x; k_x is the amount of task-specific capital used for this task; and ψ_{gx} and ψ_{kx} represent their productivity in task x. In our baseline model, workers in a group share the same productivity profile across tasks, but differ from other groups in their comparative advantage.

There is an inelastic supply ℓ_g of workers of type g to be allocated across tasks, so that

$$\int_{\mathcal{T}} \ell_{gx}\, dx \le \ell_g.$$

We treat task-specific machines, $\{k_x\}_{x \in \mathcal{T}}$, as intermediate goods. They are produced within the same period using the final good at the constant unit cost $1/q_x$. This implies that total consumption equals net output:

$$c = y - \int_{\mathcal{T}} (k_x / q_x)\, dx.$$

If $q_x = 0$, task x cannot be automated (or produced by capital).

[5] The set $\mathcal{T}$ is assumed measurable and $\int f_x\, dx$ denotes the Lebesgue integral of f_x in $\mathbb{R}^d$.

Labor market distortions and equilibrium: We model labor market distortions using task-specific wedges. A firm that employs labor of type g to perform task x pays a wage

$$w_{gx} = w_g \, \mu_{gx},$$

where $w_g > 0$ is the *base wage* of group g, and $\mu_{gx} \geq 1$ is an exogenous wedge that varies across tasks. The wedge μ_{gx} captures worker rents: how much more task x pays workers from group g relative to their base wage. We assume $\mu_{gx} = 1$ for some of the tasks assigned to group g, so that base wages are equal to what workers earn in tasks that pay no rents.

The wedges $\{\mu_{gx}\}$ represent distortions that force firms to pay wages above what workers could earn in other tasks. For example, μ_{gx} may capture rents from efficiency wages or bargaining, as shown in Supplement S2. The wedges may also capture constraints imposed by national union contracts, licensing boards, or regulations.[6]

We treat labor wedges as fixed, a convenient simplification that implies they do not adjust in response to changes elsewhere in equilibrium. Our results only require that wedges are rigid and do not fully adjust to restore efficiency—a common feature of many sources of distortions. For example, in the micro-foundations given in the Supplement, wedges depend on the monitoring technology, bargaining parameters, or irreversible investments, and do not adjust in response to automation or broader market conditions.[7]

The labor market operates as follows. Firms take base wages w_g and wedges μ_{gx} as given and decide how many g workers to hire for task x at a wage w_{gx}. Workers prefer higher-rent jobs, but these are *rationed* in equilibrium: firms hire until the value of the marginal product of labor (VMPL) equals the wage w_{gx}. Workers are then randomly assigned to tasks until labor demand is met, and the base wage w_g adjusts to ensure full employment.

Formally, a *market equilibrium* is given by base wages $w = \{w_g\}_{g \in \mathbb{G}}$, output (real GDP) y, an allocation of tasks $\{\mathcal{T}_g\}_{g \in \mathbb{G}}, \mathcal{T}_k$, task prices $\{p_x\}_{x \in \mathcal{T}}$, hiring plans $\{\ell_{gx}\}_{gx \in \mathbb{G} \times \mathcal{T}}$, and capital $\{k_x\}_{x \in \mathcal{T}}$ such that:

[6]Monopsony power generates similar implications as our wedges. This is because monopsony acts like a tax on firm hiring (the cost of hiring a new worker exceeds the wage because it raises wages for all existing workers). As a result, monopsony distortions reduce employment and create incentives for excessive automation.

[7]An exception is efficient bargaining models, where workers and firms are on their contract curve, ensuring an efficient level of employment.

E1 Task prices equal the minimum unit cost of performing them:

$$p_x = \min\left\{\frac{1}{q_x\,\psi_{kx}}, \left\{\frac{w_g\,\mu_{gx}}{\psi_{gx}}\right\}_g\right\}.$$

E2 The task allocation minimizes costs. Workers from group g perform tasks in

$$\mathcal{T}_g = \left\{x : p_x = \frac{w_g\,\mu_{gx}}{\psi_{gx}}\right\}$$

and capital performs the remaining tasks in

$$\mathcal{T}_k = \left\{x : p_x = \frac{1}{q_x\,\psi_{kx}}\right\}.$$

E3 Workers in g are rationed across tasks in $\mathcal{T}_g$. Firms hire ℓ_{gx} for task x, at the wage $w_{gx} = w_g \mu_{gx}$. The base wage adjusts to ensure the labor market clears $\int_{\mathcal{T}_g} \ell_{gx} dx = \ell_g$.

E4 For every $x \in \mathcal{T}_k$, firms use capital until its marginal product value equals its cost.

E5 The price of the final good is normalized to one, which requires:

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

To ensure the existence of a unique equilibrium, we impose the following assumption:

Assumption 1 (Restrictions on the task space)

- *For each task* $x \in \mathcal{T}$, *there exists at least one* $g \in \mathbb{G}$ *such that* $\psi_{gx} > 0$.
- *For each* $g \in \mathbb{G}$, *the set* $\{x \in \mathcal{T}$ *st:* $\psi_{gx} > 0$, $\psi_{g'x} = 0$ *for all* $g' \neq g$ *and* $\psi_{kx} = 0$ *or* $q_x = 0\}$ *has positive measure.*
- *For each* $g \in \mathbb{G}$, $\int_{\{x:\psi_{gx}>0\}} \psi_{gx}^{\lambda-1}\,\mu_{gx}^{-\lambda}\,dx$ *and* $\int_{\{x:\psi_{gx}>0\}} \psi_{gx}^{\lambda-1}\,\mu_{gx}^{1-\lambda}\,dx$ *are bounded.*
- *Comparative advantage is strict: for any two groups* $g \neq g'$ *and constants* $a, b > 0$, *the set of tasks for which* $\psi_{gx}/\mu_{gx} = a\,\psi_{g'x}/\mu_{g'x}$ *and* $\psi_{gx}/\mu_{gx} = b\,q_x\,\psi_{kx}$ *has measure zero.*

Strict comparative advantage ensures that labor demand is smooth and groups are imperfect substitutes in aggregate. Combined with the other conditions, this guarantees the existence of a unique equilibrium where each group g performs a positive share of tasks.

2.2 Equilibrium with Labor Market Rents

Following Acemoglu and Restrepo (2022), we characterize the equilibrium in terms of task shares. Define the *task shares* of worker group g and capital as

$$\Gamma_g(w) = \frac{1}{M} \int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{-\lambda} \, dx \text{ for } g \in \mathbb{G},$$

$$\Gamma_k(w) = \frac{1}{M} \int_{\mathcal{T}_k(w)} (\psi_{kx} \, q_x)^{\lambda-1} \, dx.$$

The integrals are computed over the set of tasks allocated to worker groups and capital, denoted by $\mathcal{T}_g(w)$ and $\mathcal{T}_k(w)$, when base wages are w. Task shares summarize how the range of tasks assigned to workers and capital varies as a function of base wages. Assumption 1 ensures task shares are bounded, positive, and differentiable.

In addition, define the *average group rent* earned by g workers in tasks in $\mathcal{T}_g(w)$ as

$$\mu_g(w) = \frac{1}{M \, \Gamma_g(w)} \int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{1-\lambda} \, dx \text{ for } g \in \mathbb{G}.$$

Proposition 1 (Equilibrium representation) *Under Assumption 1, the market equilibrium exists and is unique. The base wage vector w and output level y solve the equations*

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \Gamma_g(w)^{\frac{1}{\lambda}} \text{ for } g \in \mathbb{G}, \tag{1}$$

$$1 = \left(\Gamma_k(w) + \sum_g \Gamma_g(w) \, \mu_g(w) \, w_g^{1-\lambda}\right)^{1/(1-\lambda)}. \tag{2}$$

In addition, group average wages are given by $\bar{w}_g = w_g \, \mu_g(w)$.

Equation (1) ensures that base wages clear the labor market. Equation (2) is the ideal price index condition. These equations resemble the equilibrium conditions of an aggregate CES production function that combines capital and labor. The difference is that the CES shares are endogenous and given by task shares, which depend on technology and rents. We denote equilibrium task shares and average group rents by Γ_g and μ_g, respectively.

Our next proposition explains how rents distort equilibrium allocations.

Proposition 2 (Inefficiency) *The equilibrium is inefficient:*

- (intensive margin) *it features too little employment in high-rent tasks;*

- (extensive margin) *it involves inefficient automation of tasks for which*

$$\frac{w_g \, \mu_{gx}}{\psi_{gx}} > \frac{1}{\psi_{kx} \, q_x} > \frac{w_g \, \mu_g}{\psi_{gx}}. \tag{3}$$

Efficiency requires that VMPLs be equalized across tasks within a group (intensive margin), and that this common VMPL exceed what workers could generate in automated tasks (extensive margin). Worker rents distort both margins.[8]

At the intensive margin, firms hire workers until the VMPL equals the task wage $w_g \, \mu_{gx}$. As a result, the VMPL in high-rent tasks exceeds the VMPL in lower-rent tasks. The distortion at the intensive margin depends on the dispersion of rents across tasks within groups—as emphasized in the misallocation literature (e.g., Hsieh and Klenow, 2009).

The extensive margin inefficiency is more novel: tasks for which (3) holds are inefficiently automated and allocated to capital. Reallocating g workers from non-automated tasks to producing one unit of task x raises output by $\frac{1}{\psi_{kx} \, q_x} - \frac{w_g \mu_g}{\psi_{gx}}$ (the value of task x minus workers' opportunity cost). Firms automate these tasks inefficiently because the wage they face is inflated by rents and exceeds workers' opportunity cost. This inefficiency arises whenever the wage for task that can be automated exceeds what workers could earn elsewhere in the economy, and can persist even when rents are identical among all tasks left to workers.

2.3 Automation

We now study how automation impacts wages and productivity. We start with the invention of new automation technologies driven by an exogenous increase in q_x from zero to a positive level $q'_x > 0$ for tasks in $\mathscr{A}_g^T$ in $\mathcal{T}_g$ across $g \in \mathbb{G}$. The sets $\{\mathscr{A}_g^T\}_{g \in \mathbb{G}}$ contain tasks that were initially infeasible to automate, but can now be automated thanks to new technologies. For example, advances in robotics in the 1980s and 1990s made it possible to automate industrial tasks such as welding and painting, previously performed by blue-collar workers. The development of enterprise software systems made it feasible to automate clerical tasks performed by clerks and assistants.

Endogenous targeting of high-rent tasks: Following the arrival of new opportunities for automating tasks in $\mathscr{A}_g^T$, firms *endogenously* decide which tasks to automate and which ones to continue producing with labor. We first study this question in partial equilibrium

[8] Apart from worker rents, there are no distortions in this economy. The market equilibrium is therefore efficient if rents are absent (as in Acemoglu and Restrepo, 2022) or when $\mu_{gx} = \mu_g$ for all $g \in \mathbb{G}$ and $x \in \mathcal{T}$.

(taking initial base wages as given) and then turn to the equilibrium implications of these choices, which includes how wages change in response to automation.

From cost minimization, firms choose to automate all tasks in

$$\mathscr{A}_g = \left\{ x \in \mathscr{A}_g^T : \frac{w_g\, \mu_{gx}}{\psi_{gx}} \geq \frac{1}{q'_x\, \psi_{kx}} \right\}. \tag{4}$$

Intuitively, this set contains the tasks for which the cost of production using the new automation technologies is less than the cost of producing with labor (inclusive of rents).

The set of automated tasks $\mathscr{A}_g$ depends both on what technology permits (assumed exogenous and summarized by $\mathscr{A}_g^T$ and q'_x) and the endogenous targeting of high-wage tasks: among the entire set of tasks that can be automated, firms have a stronger incentive to target high-rent tasks. This is because by automating these tasks, firms save more in terms of labor costs, due to the higher wage, $w_g\, \mu_{gx}$.

To isolate the role of the endogenous targeting of high-rent tasks, which is at the root of all of our remaining results, we first consider a benchmark scenario where opportunities for automation are "neutral." This is important, since if the opportunities for automation were biased toward high- or low-rent tasks, this bias could drive what is automated in equilibrium. By choosing a neutral configuration, we focus on the forces that guide the endogenous automation of tasks in our model.

Assumption 2 (Neutral Inventions) *Let $F_g(\mu|\mathcal{S})$ denote the "counter cdf" corresponding to the share of group g employment in tasks in $\mathcal{S}$ that pay rents above μ. Then for each group $g \in \mathbb{G}$, we have:*

(i) the rent distribution among tasks that can now be automated is the same as in all tasks:

$$F_g(\mu \mid \mathscr{A}_g^T) = F_g(\mu \mid \mathcal{T}_g) \quad \forall\, \mu \geq 1;$$

(ii) among tasks that can be automated, rents are independent of task-level productivities:

$$F_g\big(\mu \mid \mathscr{A}_g^T,\, q'_x\psi_{kx} \leq a,\, \psi_{gx} \leq b\big) = F_g(\mu \mid \mathscr{A}_g^T) \quad \forall\, \mu \geq 1, a > 0, b > 0.$$

The assumption imposes neutrality in the sense that, within each group g, opportunities for automation are independent of rents and independent of comparative advantage. These conditions are imposed within groups, so that some groups of workers can still be more exposed to advances in automation than others. We also assume throughout this section that the sets $\mathscr{A}_g^T \setminus \mathscr{A}_g$ and $\mathscr{A}_g$ have positive measure, so that some but not all tasks in $\mathscr{A}_g^T$

are automated, which means there is a meaningful adoption decision. Given the neutrality assumption, any bias in which tasks are automated will be entirely driven by the economic forces in our model, as shown in the next proposition.

Proposition 3 (Targeting of high-rent tasks)
For $g \in \mathbb{G}$, suppose $\mathscr{A}_g^T \setminus \mathscr{A}_g$ and $\mathscr{A}_g$ have positive measure and Assumption 2 holds. Then,

$$F_g(\mu \mid \mathscr{A}_g) > F_g(\mu \mid \mathcal{T}_g) \quad \forall \mu > 1,$$

meaning that the rent distribution in $\mathscr{A}_g$ first-order stochastically dominates the rents distribution in $\mathcal{T}_g$.

The proposition establishes that, when opportunities for automation are neutral, endogenous adoption decisions are tilted toward high-rent tasks. While Assumption 2 provides sufficient conditions for this result, one can see that even with non-neutral inventions, adoption may still be biased toward high-rent tasks. Naturally, this requires that automation possibilities are not too skewed toward low-rent tasks.

Proposition 3 has two important implications. The first is that automation dissipates worker rents. Because adoption endogenously targets high-rent tasks, it reduces the average rents earned by workers. The second is that automation compresses wages within exposed groups. By displacing workers out of high-rent tasks, it reduces within-group inequality and generates a distinctive U-shaped pattern of wage changes inside exposed groups.

To state this second implication formally, assume each worker performs a single task, so that the wage distribution across workers in a group is well defined, and let $\ln w_g(p)$ denote the p-th quantile of the log wage distribution within group g ($p \in [0,1]$).

Proposition 4 (Automation and within-group wage compression)
For $g \in \mathbb{G}$, suppose $F_g(\mu \mid \mathscr{A}_g) \geq F_g(\mu \mid \mathcal{T}_g)$ for all $\mu > 1$ and let $M_g > 0$ measure group g employment in no-rent tasks. The automation of tasks in $\mathscr{A}_g$ has the following effects:

- *For $p \in [0, M_g]$, $\Delta \ln w_g(p) = \Delta \ln w_g$, where $\Delta \ln w_g$ gives the change in base wages.*
- *For $p \in (M_g, 1)$, $\Delta \ln w_g(p) < \Delta \ln w_g$, which reflects the loss of rents at higher percentiles.*
- *Suppose moreover that Assumption 2(i) holds. Then, at the top, $\Delta \ln w_g(1) = \Delta \ln w_g$.*

Figure 1 depicts the U-shaped pattern of within-group wage changes described in the proposition. Workers at the lowest percentiles hold tasks with no rents. They earn the base wage w_g, and their wages change only through adjustments in the base wage for group g in equilibrium. Above M_g, wages fall more sharply due to the loss of high-rent jobs, which are more often automated. At the top, two scenarios are possible: either $\Delta \ln w_g(1) < \Delta \ln w_g$ or $\Delta \ln w_g(1) = \Delta \ln w_g$. The second case arises when some of the highest-rent tasks assigned to g cannot be automated, which is the case under Assumption 2(i).

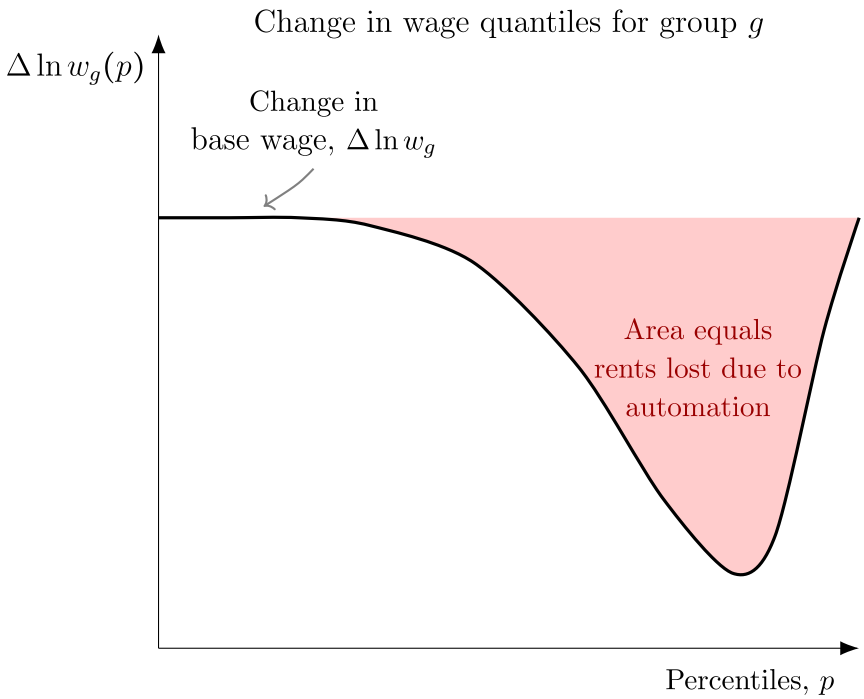

FIGURE 1: PREDICTED CHANGES IN WITHIN-GROUP WAGE PERCENTILES DUE TO AUTOMATION.

The results in Proposition 4 offer new empirical predictions, as they contrast with the common view that technological progress increases inequality in a fractal way—both between and within groups. Our theory predicts that automation can reduce within-group inequality for exposed groups and identifies this outcome as a telltale sign of rent dissipation. This novel implication motivates our first empirical strategy for measuring rent dissipation.

Equilibrium effects: We now characterize the equilibrium effects of automation on wages and productivity. We derive formulas for the first-order effects, assuming the sets $\{\mathcal{A}_g^T\}_{g\in\mathbb{G}}$ are small and lie in the interior of $\mathcal{T}_g$.[9]

[9]Formally, we assume $\mathscr{A}_g^T$ has measure less than ϵ for some small $\epsilon > 0$ and apply the appropriate notion of "differential" given in Acemoglu et al. (2024). With rents, additional technical conditions are required. These and the full derivations appear in the Online Supplement.

We describe the effects of automation in three steps. First, we take the set of new automation possibilities $\{\mathcal{A}_g^T\}_{g\in\mathbb{G}}$ and the underlying changes in $\{q_x'\}_{x\in\mathcal{A}_g^T}$ as given. Second, we compute the set of automated tasks $\{\mathcal{A}_g\}_{g\in\mathbb{G}}$ using equation (4) at the initial equilibrium wages. These sets determine the following key objects—all computed at the initial equilibrium allocation—that are sufficient to characterize the effects of automation:

- The task displacement experienced by group g:

$$\delta_g = \frac{\int_{\mathscr{A}_g} \ell_{gx}\, dx}{\int_{\mathcal{T}_g} \ell_{gx}\, dx}.$$

  This is the reduction in g's task share due to automation of tasks in $\mathscr{A}_g$, and is given by the share of group g employment in these tasks at the initial allocation.

- The average cost savings from automating tasks in $\mathscr{A}_g$:

$$\pi_g = \frac{\int_{\mathscr{A}_g} \ell_{gx}\, \mu_{gx}\, \pi_{gx}\, dx}{\int_{\mathscr{A}_g} \ell_{gx}\, \mu_{gx}\, dx},$$

  where π_{gx} denotes the cost savings from automating task x in $\mathscr{A}_g$:

$$\pi_{gx} = \frac{1}{\lambda - 1}\left[\left(\frac{q_x'\, \psi_{kx}\, w_g\, \mu_{gx}}{\psi_{gx}}\right)^{\lambda-1} - 1\right] \geq 0.$$

- The average rent earned by group g workers in newly-automated tasks:

$$\mu_{\mathscr{A}_g} = \frac{\int_{\mathscr{A}_g} \ell_{gx}\, \mu_{gx}\, dx}{\int_{\mathscr{A}_g} \ell_{gx}\, dx}.$$

  While we provide sufficient conditions under which automation targets high-rent tasks and identify economic forces ensuring $\mu_{\mathscr{A}_g} > \mu_g$, the characterization of automation's effects below does not rely on Assumption 2. We invoke this assumption only when a sufficient condition is needed to guarantee $\mu_{\mathscr{A}_g} > \mu_g$.

The quantities $\left\langle \{\delta_g\}_{g\in\mathbb{G}}, \{\pi_g\}_{g\in\mathbb{G}}, \{\{\mu_{\mathscr{A}_g}\}_{g\in\mathbb{G}}\} \right\rangle$ summarize the *direct* impact of new automation technologies on task shares, costs, and average group rents holding the allocation of non-automated tasks constant.

The final step incorporates the reassignment of marginal tasks across groups in response to these direct effects, tracing the resulting *ripple effects*. Figure 2 illustrates both direct and ripple effects: the left panel shows the initial allocation of tasks to g, g', and capital, while the right panel introduces the new automation technologies $\mathscr{A}_g^T$ and the subset of tasks automated, $\mathscr{A}_g$. The displacement of g workers from $\mathscr{A}_g$ triggers an endogenous reassignment of tasks from other factors toward g, as its relative base wage declines. These ripple effects are depicted with the dashed curves, indicating how tasks are reallocated.

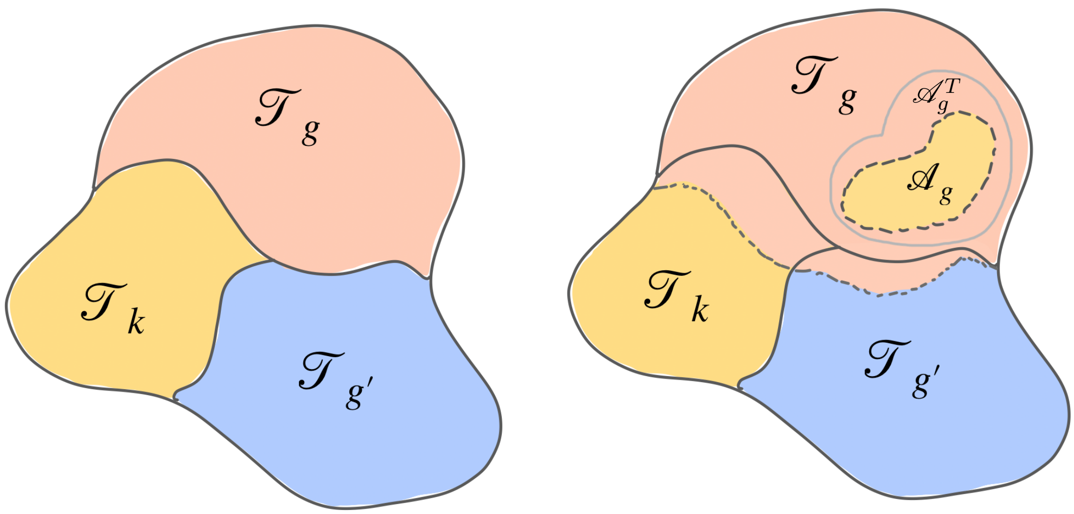

FIGURE 2: THE TASK ALLOCATION AND THE EFFECTS OF AUTOMATION. The left panel shows the assignment of tasks across factors in the initial equilibrium. The right panel illustrates new automation possibilities, the subset of tasks automated, and the resulting task displacement and ripple effects.

To characterize the consequences of ripple effects, we follow Acemoglu and Restrepo (2022) and differentiate (1) to obtain:

$$d\ln w_g = \frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_g + \frac{1}{\lambda}\sum_{g'} \frac{\partial \ln \Gamma_g(w)}{\partial \ln w_{g'}}\, d\ln w_{g'} \quad \text{for } g \in \mathbb{G}.$$

The term δ_g represents the task displacement from automation experienced by group g, and the third term captures ripple effects. Stacking these equations and solving for $d\ln w_g$, we obtain:

$$d\ln w_g = \frac{1}{\lambda}\,\Theta_g\,\text{stack}\left(d\ln y - \delta_j\right), \qquad \text{with } \Theta = \left(\mathbb{1} - \frac{1}{\lambda}\,\mathcal{J}_\Gamma\right)^{-1}.$$

Here stack(x_j) denotes the column vector $(x_1, x_2, \ldots, x_{\mathbb{G}})$, and $\mathcal{J}_\Gamma$ is the $G \times G$ Jacobian with entries $\mathcal{J}_{\Gamma,g,g'} = \partial \ln \Gamma_g(w)/\partial \ln w_{g'}$. As in Acemoglu and Restrepo (2022), we refer to Θ as the *propagation matrix* (because it propagates an initial direct impact across the economy). Each entry $\theta_{gg'}$ is non-negative and captures the extent to which shocks that reduce the base wage of group g' affect group g via ripple effects.[10]

[10]The propagation matrix takes the form of a Leontief inverse because it accumulates successive rounds of task reassignment. This inverse exists, has positive entries, and its eigenvalues are in $[0,1]$. This means

In the presence of distortions, we also need to keep track of how ripple effects influence average group rents. This information is summarized by the *rent-impact matrix*:

$$\mathcal{M} = \mathcal{J}_\mu \left(\mathbb{1} - \frac{1}{\lambda}\mathcal{J}_\Gamma\right)^{-1},$$

where $\mathcal{J}_\mu$ is a $G \times G$ Jacobian with entries $\mathcal{J}_{\mu,g,g'} = \partial \ln \mu_g(w)/\partial \ln w_{g'}$. The entries in this matrix indicate whether competition between group g' and g occurs at tasks where g workers earn above-average rents (positive entries) or below-average rents (negative entries).

The following proposition provides our formulas for the first-order equilibrium effects of new automation technologies on wages, rents, and productivity.

Proposition 5 (Equilibrium effects of automation)
Consider new automation technologies represented by (small interior) sets $\{\mathscr{A}_g^T\}_{g\in\mathbb{G}}$. Let $\{\mathcal{A}_g\}_{g\in\mathbb{G}}$ be given by equation (4) and the corresponding direct effects of automation be given by $\left\langle\{\delta_g\}_{g\in\mathbb{G}}, \{\pi_g\}_{g\in\mathbb{G}}, \{\{\mu_{\mathscr{A}_g}\}_{g\in\mathbb{G}}\}\right\rangle$. The first-order equilibrium effects of automation on base wages and output are given by the formulas

$$d\ln w_g = \Theta_g \; stack\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_j\right) \quad \text{for } g \in \mathbb{G} \tag{5}$$

$$\sum_g s_g \, d\ln w_g = \sum_g s_g \, \delta_g \, \frac{\mu_{\mathscr{A}_g}}{\mu_g}\, \pi_g, \tag{6}$$

where s_g is the share of g's earnings in output. Moreover, the change in group rents is

$$d\ln \mu_g = \mathcal{M}_g \; stack\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_j\right) - \left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1\right)\delta_g. \tag{7}$$

and the change in aggregate consumption is $d\ln c = \frac{1}{s_L}\, d\ln \text{TFP}$, where s_L is the labor share in output and $d\ln \text{TFP}$ is the change in TFP from automation:

$$d\ln \text{TFP} = \sum_g s_g \, \delta_g \, \frac{\mu_{\mathscr{A}_g}}{\mu_g}\, \pi_g + \sum_g s_g \, d\ln \mu_g \tag{8}$$

Proof. We sketch the proof and provide details in the Appendix. Equation (5) was derived above. Equation (6) follows from differentiating the price index condition in (2). Together with (5), it forms a system of equations that pins the change in output.

Define $d\ln \text{TFP} = d\ln y - s_K\, d\ln k$. With constant returns to scale, we obtain the dual

that ripple effects play an equalizing role and dampen the direct effects of automation. The entries of the propagation matrix also summarize how substitutable groups of workers are in the aggregate.

version of the Solow residual: $d\ln \text{TFP} = \sum_g s_g(d\ln w_g + d\ln \mu_g)$. Substituting $\sum_g s_g \, d\ln w_g$ from (6) yields (8). The fact that $d\ln c = \frac{1}{s_L} d\ln \text{TFP}$ follows from the resource constraint $c = y - k$. ■

Using the formulas in the proposition, we obtain the impact of automation on average group wages $\bar{w}_g = w_g \, \mu_g$ as follows:

$$(9) \qquad d\ln \bar{w}_g \; = \; (\Theta_g + \mathcal{M}_g) \; \text{stack}\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\, \delta_j\right) - \left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1\right) \delta_g.$$

To gain intuition for this equation, consider an economy where groups can only produce disjoint tasks and capital produces all tasks with $q_x > 0$, so there are no ripple effects, the propagation matrix is the identity, and all of the entries of the rent-impact matrix are zero.[11] Equation (9) then becomes:

$$(10) \qquad d\ln \bar{w}_g \; = \; \underbrace{\frac{1}{\lambda}\, d\ln y}_{\text{productivity effect}} \; - \; \underbrace{\frac{1}{\lambda}\, \delta_g}_{\text{displacement effect}} \; \underbrace{-\left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1\right) \delta_g}_{\text{rent dissipation}}.$$

Without ripple effects, the change in average group wages depends on three forces. The first two operate in models with competitive labor markets, such as Acemoglu and Restrepo (2022), and capture the effects of automation working via labor demand and base wages. These include a positive *productivity effect* (cost reductions due to automation expand output and increase the demand for all workers) and a negative *displacement effect* (automation reduces the share of tasks employing workers from group g by δ_g).

The third term captures the new *rent dissipation* channel. This force amplifies wage losses for exposed groups whenever $\mu_{\mathscr{A}_g} > \mu_g$—because automation displaces workers from higher-rent tasks and pushes them into lower-wage jobs. As noted above, Assumption 2 is sufficient but not necessary for this pattern. In general, the strength of rent dissipation depends on the magnitude of $\mu_{\mathscr{A}_g}/\mu_g$—how high average rents were in newly-automated tasks relative to the average.

When ripple effects are present in (9), group g's average wages additionally depend on whether other groups competing with it are displaced by automation. The propagation matrix contains all the information about how these ripple effects work, while the rent impact matrix adjusts for how this reassignment changes group-level average rents.

[11] Formally, one can shut down ripple effects by assuming that: (i) for all x, $\psi_{gx} > 0$ implies $\psi_{g'x} = 0$ for all $g' \neq g$; and (ii) for all x, $\psi_{kx} > 0$ implies $\psi_{kx} > \underline{\psi}_k$ for some threshold $\underline{\psi}_k > 0$.

One important difference between the displacement effect and rent dissipation is in their propagation. Automation reduces the (relative) base wage of exposed groups, and this enables exposed groups of workers to gain some marginal tasks, propagating the incidence of the shock to others and dampening its initial adverse effects on them. This is the reason why the effects of task displacement are mediated by the matrices Θ and $\mathcal{M}$. In contrast, rent dissipation works by reducing group wages in excess of base wages, and does not generate additional task reassignments. Consequently, exposed groups bear the full incidence of rent dissipation, which does not propagate via Θ and $\mathcal{M}$.

We next discuss the implications of automation for productivity and welfare. In our economy, changes in TFP are proportional to changes in consumption and the average change in wages paid to workers: $d\ln \text{TFP} = s_L\, d\ln c = \sum_g s_g\, d\ln \bar{w}_g$. It is therefore sufficient to derive the impact of automation on TFP, from which the effects on consumption and average wage levels can be seen.

In the absence of ripple effects, the formula for changes in TFP in equation (8) simplifies to

$$d\ln \text{TFP} = \underbrace{\sum_g s_g\, \delta_g\, \frac{\mu_{\mathscr{A}_g}}{\mu_g}\, \pi_g}_{\text{direct gains à-la Hulten}} - \underbrace{\sum_g s_g \left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1\right) \delta_g}_{\text{changes in allocative efficiency}} . \tag{11}$$

This formula relates to Baqaee and Farhi (2020), who decompose the impact of technology in inefficient economies into a direct effect plus changes in *allocative efficiency*. The first term in (11) represents the direct benefits from reducing the cost of producing automated tasks. This term is positive and has the same envelope logic as Hulten's theorem in competitive economies: it is the product of (i) the cost share of automated tasks in output, given by their Domar weights, $s_g\, \delta_g\, \frac{\mu_{\mathscr{A}_g}}{\mu_g}$; and (ii) average cost savings from automation, $\pi_g > 0$. The second term, in turn, reflects changes in allocative efficiency from automation. This term captures how changes in the allocation of labor across tasks affect output. In a competitive economy, an envelope argument implies that this term is zero—the initial allocation of labor already maximized output and thus small changes only have second-order consequences. This is no longer true in the presence of labor market distortions.

A key observation in our economy is that automating jobs that pay above-average rents ($\mu_{\mathscr{A}_g} > \mu_g$) worsens allocative efficiency. At first this may seem paradoxical, since one might expect that eliminating high-rent jobs improves efficiency. This intuition is incorrect. Automation reallocates labor from high-rent to low-rent jobs, where workers' VMPL is lower.

By pushing workers into lower-VMPL jobs, automation *reduces* allocative efficiency.[12]

A complementary interpretation of the TFP formula in (11) views the first term as firms' and consumers' willingness to pay for the new technology. This value is positive and equals the consumer surplus from reallocating tasks in $\mathscr{A}_g$ from labor (produced at cost $\frac{w_g \mu_{gx}}{\psi_{gx}}$) to capital (produced at the lower cost $\frac{1}{q'_x \psi_{kx}}$). This surplus, however, overstates the social value of new automation technologies because it ignores the first-order cost to workers of losing high-rent jobs, captured by the rent dissipation term.[13]

The TFP formula in (11) establishes that rent dissipation offsets part of the productivity gains from automation and can even reduce aggregate productivity, average real wages, and welfare. This happens when new automation technologies are adopted in tasks where workers earn high rents but yield only small cost savings, so that automation saves on rents more than it improves efficiency. By contrast, in competitive labor markets automation always raises TFP, consumption, and average wages (even if it reduces the real wages of exposed groups), because allocative efficiency is unaffected.

In the general case with ripple effects, the TFP expression in equation (8) shows that allocative efficiency may deteriorate either through rent dissipation (as discussed above) or because ripple effects reallocate workers away from high-rent tasks. These second force is summarized by the matrix $\mathcal{M}$ in the term $\sum_g s_g \, d\ln \mu_g$.

This discussion also clarifies the role of fixed wedges in our theory. Rent dissipation is inefficient because automation displaces workers from high-rent tasks, which occurs due to the presence of fixed wedges. More generally, the same inefficiency would arise even if wedges adjusted partially, as long as they do not fully adjust to ensure an efficient level of hiring and separations. Our empirical analysis in the next section shows that automation has indeed shifted US workers *away* from high-rent jobs, supporting the view that wedges do not fully adjust and that automation inefficiently dissipates rents.

[12]Not all forms of technological progress reduce allocative efficiency. An improvement in capital productivity in tasks already assigned to this factor (e.g., a better automatic drill or copying machine) has no direct impact on allocative efficiency. Nor do labor-augmenting technological advances at the *intensive margin* (meaning improvements in productivity for a group in tasks already assigned to that group). The fact that automation operates at the *extensive margin*, shifting high-rent tasks away from labor, is responsible for its direct impact on allocative efficiency.

[13]In our model, firms' and consumers' willingness to pay coincide because there are no product market distortions. If labor market rents were linked to producer markups, automation would also affect allocative efficiency through its impact on the economy's product mix.

2.4 Incorporating Additional Within-Group Differences

Our base model assumes that all workers within a demographic group are identical in terms of their absolute and comparative advantages, and the only source of wage differences within groups is due to rents. In practice, there are additional sources of within-group heterogeneity, and we now show how two of these—within group productivity differences and compensating differentials—can be incorporated into our framework. These extensions show that such forms of heterogeneity do not alter our key results, and they also provide guidance on how empirical work can control for these differences. The details for both extensions are in Supplement S3.

Within-group productivity differences: In our baseline model, all workers in group g have identical task-level productivities. We now relax this by assuming that workers from group g have productivity $\psi_{gx}\, z$ in task x, where z is an individual-specific productivity level. This formulation assumes that workers in a group share the same *comparative advantage*, but differ in their *absolute advantages*, given by their productivity level z.

This generalization affects only within-group wages. A worker from group g with individual productivity z performing task x is paid

$$w_{gx}(z) = w_g\, \mu_{gx}\, z,$$

where w_g is the base wage for workers with $z = 1$. This wage equation follows from firms' indifference across workers of different skill levels, which equates wages per efficiency unit within each group. Put differently, this wage rule ensures that the cost of producing one unit of task x with group g labor is $\frac{w_g \mu_{gx}}{\psi_{gx}}$, exactly as in the baseline model, regardless of the individual productivity z of the worker performing that task.

Given this wage rule, the equilibrium mirrors the baseline model, except that there is now within-group wage differences as well. Firms take wages as given and allocate tasks in order to minimize costs, and this leads to the same assignment of tasks to factors as before.

The only complication arises from rationing, which is again present since only some workers will get the high-rent jobs. Rationing can now condition on individual skill (though there is no reason for firms to prefer to do so, since they make the same profits from all workers in the same demographic group). We assume that the rationing protocol *preserves ranks*, so that rents do not alter relative wages in a group. That is, we assume that for any two workers from group g with individual skills $z > z'$, we have $w_{gx}(z) > w_{gx}(z')$. This requirement is automatically satisfied when rationing is orthogonal to individual skill.

The Supplement shows that all our theoretical results remain valid in this extension. In particular, automation still targets high-rent tasks regardless of the skill level of the workers performing them, since adoption decisions depend only on wages per efficiency unit of labor, which are the same as in the baseline model. This targeting generates the same U-shaped pattern for wage changes described in Proposition 4 and Figure 1, because differences in z cancel out with our rationing rule.

The key implication of this extension is that there may be *level* differences in productivity and wages across workers within the same group, including possibly across the lower percentiles of the within-group wage distribution. Nevertheless, all our results and the U-shaped pattern depicted in Figure 1 for wage *changes* is unaffected.

Compensating differentials: The baseline model ignores the possibility that wage differences may reflect compensating differentials. Some jobs may pay more than others because they are unpleasant or difficult to perform. To capture this, we assume that workers from group g derive utility

$$u_{gx} = \frac{w_{gx}}{\zeta_{gx}}$$

from employment in task x. The numerator represents utility from consumption, which depends on the wage w_{gx}. The denominator is a disutility from performing task x, denoted by $\zeta_{gx} > 0$. This parameter captures task attributes such as hazardous conditions, long shifts, or monotony, and is allowed to vary across groups and tasks (for example, construction jobs may be harder for all workers, but particularly for older ones). This specification implies that worker utility depends on *net wages*, given by w_{gx}/ζ_{gx}.

We assume the following wage rule in this extension:

$$w_{gx} = w_g \, \mu_{gx} \, \zeta_{gx},$$

where w_g is the base utility level of g workers in jobs that pay no rents, and w_{gx} again denotes the wage of workers from group g in task x. In the Supplement, we show that this wage rule follows from our micro-foundations, where net wages must exceed the base utility w_g by a rent μ_{gx} due to either efficiency wages or bargaining.[14]

Two important results follow from this extension (both established in the Supplement).

[14] Two additional points. First, measured wages within a group can also vary due to in-kind payments, such as a company car or accommodation. Nevertheless, to the extent that these are merely transfers between the firm and the worker, they will not affect allocations or incentives for automation. Second, in some models of labor market imperfections, part of the amenity value of a job could be captured by the employer. This possibility would complicate the analysis but would not affect our conclusions.

First, because wages depend on the composite term $\mu_{gx}\zeta_{gx}$, compensating differentials and rents have the same *positive* implications, with automation targeting high-rent and/or high-compensating differential jobs. In essence, a job with high ζ_{gx} is more expensive for the employer and thus more profitable to automate. However, these two features have different *normative* implications. While automating high-rent jobs can be inefficient, this is not the case for jobs with high compensating differentials. A planner would also choose to automate unpleasant or dangerous jobs, since they impose a greater burden on workers.

Second, given these distinct normative consequences, our empirical analysis pays close attention to separating rents from compensating differentials. In this regard, the extension shows that Propositions 4 and 5 now hold for *net wages* (as defined above), rather than raw wages. This means that when compensating differentials are present, estimates of automation's impact on rents should control for these differentials (or be based on wages purged of their influence). This is the strategy we adopt in the next section.

3 Reduced-Form Evidence

This section presents reduced-form evidence on the impact of automation on group-level wages, within-group wage dispersion, and worker rents in the US between 1980 and 2016.

We focus on 500 detailed demographic groups, defined by five education levels, gender, five age groups, five race and ethnicity groups and native/immigrant status. We estimate group-level specifications of the form

$$\text{Change in group } g \text{ outcome 1980–2016} = \beta \, \text{Task displacement}_g + X_g \, \gamma + u_g, \tag{12}$$

where Task displacement$_g$ is the empirical analogue of δ_g and measures the task displacement due to automation experienced by group g between 1980 and 2016. Additionally, X_g includes covariates, and u_g denotes the residual. When estimating this equation, we weigh groups by their share of US employment in 1980 and report standard errors that are robust to heteroscedasticity.

Our outcomes include changes in group average real hourly wages and changes in the p-th percentile of the within-group wage distribution, $\Delta \ln w_g(p)$ for $p = 5, 10, \ldots, 95, 99$. These are computed from the 1980 Census and by pooling 2015-2017 American Community Survey (ACS) data. We use the cleaning procedures from Acemoglu and Restrepo (2022).

We also use the Basic Monthly and Displaced Worker Supplement from the Current Population Survey (CPS) to create proxies for worker rents, and the 1977 Quality of Employment Survey to construct proxies for workplace amenities and compensating differentials. This survey asked a cross-section of respondents across all US industries about working conditions and job satisfaction. We aggregate answers at the industry level (using the 49 industries in our sample) and create four measures which we use to purge wage differences from compensating wage differentials:

1. A measure of *job amenities*, summarizing the extent to which respondents perceive their jobs as having desirable conditions (ease of travel, good hours, generous benefits, autonomy, security, and comfort).
2. A measure of *job meaning*, summarizing the extent to which respondents believe their work is meaningful and important.
3. A measure of *willingness to pay for improved working conditions*, giving the extent to which respondents would take a wage cut to improve conditions in their job.
4. A composite *job quality index*, defined as the first principal component of the three measures above.

3.1 Measuring Task Displacement

Our strategy for measuring task displacement follows Acemoglu and Restrepo (2022) and is based on the following assumption:

ASSUMPTION 3 (MEASUREMENT ASSUMPTION) *During 1980–2016, only routine tasks were automated, and within an industry, automation displaced all groups of workers from routine tasks at a common rate.*

Supplement S4.7 shows that, in the multi-sector version of our model (described in Section 4) and under Assumption 3, task displacement across groups can be estimated as

$$\text{Task displacement}_g = \sum_i \frac{\ell_{gi}}{\ell_g} \text{RCA}_{gi}^{\text{routine}} \frac{-\Delta \ln s_{\ell i}^{\mathcal{A}}}{(1 + s_{\ell i}\,(\lambda - 1)\,\pi_i)\;\mu_{\mathscr{A}_i}/\mu_i}. \tag{13}$$

This measure is the product of three terms:

1. The term ℓ_{gi}/ℓ_g represents group g's exposure to industry i. It accounts for groups' specialization in sectors that automated more tasks.
2. The term $\text{RCA}_{gi}^{\text{routine}}$ is a measure of the "revealed comparative advantage" of group g in routine jobs in industry i. It apportions the incidence of automation in the industry based on who performs routine tasks. This term is the reason why, for example, managers and blue-collar workers in the manufacturing industry are not equally impacted by the introduction of industrial robots.

3. The term $-\Delta \ln s_{\ell i}^{\mathcal{A}}$ is the percent reduction of the labor share of industry i caused by automation between 1980 and 2016. In our framework, there is a direct relationship between the rate at which tasks are automated in an industry and the resulting decline in its labor share, $-\Delta \ln s_{\ell i}^{\mathcal{A}}$. This term is divided by $1 + s_{\ell i}(\lambda - 1)\pi_i$ to adjust for the effects of automation on the labor share working via substitution across tasks, and by the term $\mu_{\mathscr{A}_i}/\mu_i$ —the average (relative) rent in tasks automated in industry i—to adjust for the effects of automation operating through worker rents (this last adjustment is not present in competitive markets).

We measure task displacement using data for 49 industries from the BEA Integrated Industry-Level Production Accounts. We compute employment shares by industry, ℓ_{gi}/ℓ_g, and revealed comparative advantages $\text{RCA}_{gi}^{\text{routine}}$ for the 500 demographic groups from the 1980 Census. We define routine jobs as the 33% occupations with the highest routine content according to O*NET. As in Acemoglu and Restrepo (2022), we estimate $-\Delta \ln s_{\ell i}^{\mathcal{A}}$ as the predicted labor share decline from a cross-industry regression of percent labor share changes by industry (from the BEA, between 1987 and 2016, and re-scaled to a 36-year change) against three proxies for automation: the adjusted penetration of industrial robots (from Acemoglu and Restrepo, 2020), the increase in the share of specialized software services in value added, and the increase in the share of dedicated machinery in value added (from the BLS Total Multifactor Productivity Tables). For the adjustment term, we set $\lambda = 0.5$, $\pi_i = 30\%$ and $\mu_{\mathscr{A}_i}/\mu_i = 1.35$ for all industries. These choices are motivated in Section 4.

The left panel of Figure 3 summarizes the industry labor share trends. The blue bars show the observed percent labor share declines. The orange bars depict the component attributed to our proxies of automation, which jointly explain 50% of cross-industry changes in labor shares since 1987.

The right panel of Figure 3 depicts our measure of task displacement from automation over 1980–2016, for 500 US demographic groups, plotted against their baseline hourly wages in 1980 in the horizontal axis. Groups with post-college degrees saw few of their tasks automated between 1980 and 2016, while workers in the middle and lower middle of the wage distribution lost 15%–20% of their tasks to automation.[15]

[15]The measure in (13) is the same as in Acemoglu and Restrepo (2022), except for the term $\mu_{\mathscr{A}_i}/\mu_i$, since our previous work did not consider the role of rents. There are also minor differences in weights outlined in Supplement S4. These explain the small differences in magnitudes and estimates between papers.

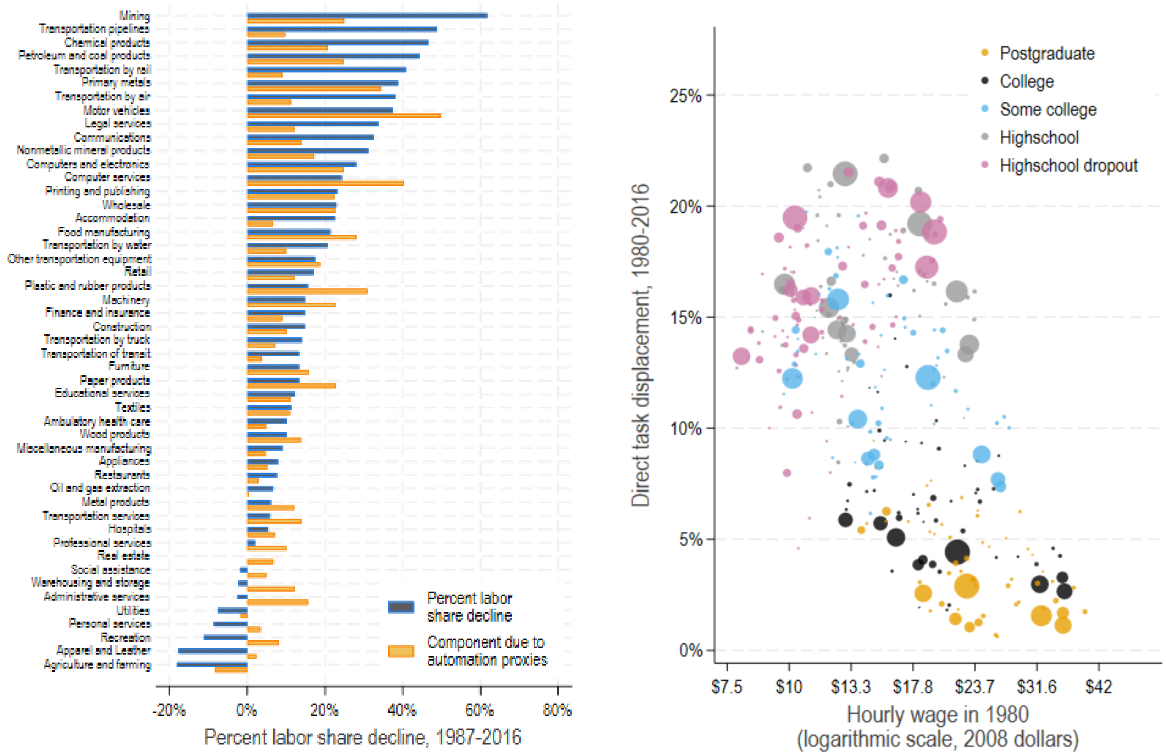

FIGURE 3: TASK DISPLACEMENT FROM AUTOMATION ACROSS INDUSTRIES AND GROUPS. The left panel shows labor share declines across US industries from 1987 to 2016 (positive values indicate declines). Orange bars mark the decline explained by automation, using our three proxies. The right panel reports direct task displacement for 500 demographic groups between 1980 and 2016, as measured by equation (13).

3.2 The Effect of Automation on Average Group Wages

We first examine the reduced-form relationship between automation and average group wages. We estimate equation (12) using the change in group log average wages between 1980 and 2016 as the dependent variable, following Acemoglu and Restrepo (2022).

The left panel of Figure 4 shows the relationship between changes in average group wages and exposure to automation. The point estimate indicates that a 10 percentage point increase in task displacement is associated with a 24% decline in group-level relative wages. This single measure of exposure explains 66% of the variation in wage changes among US demographic groups since 1980.

The right panel of Figure 4 depicts this relationship after controlling for our baseline covariates, including: (i) gender and education dummies, which capture other forms of skill-biased technological change affecting college and post-college groups, as well as social or technological changes affecting women relative to men; and (ii) three measures of changes

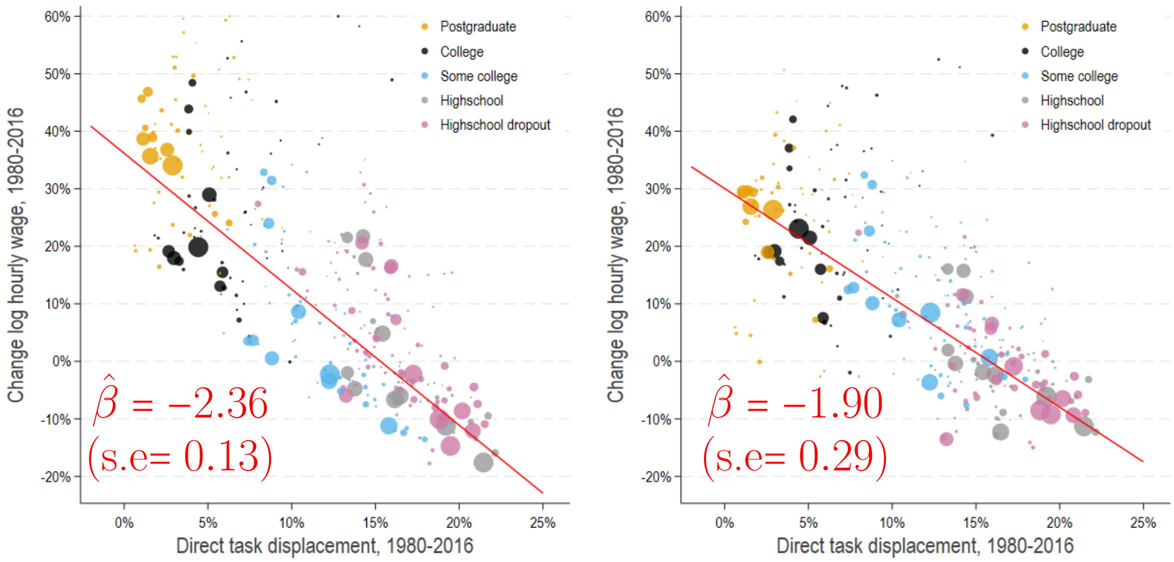

FIGURE 4: REDUCED-FORM RELATIONSHIP BETWEEN WAGE CHANGES AND TASK DISPLACEMENT. The left panel shows the relationship between changes in group wages (in logs) and task displacement. The right controls for gender, education, and sectoral demand and rent shifters.

in the economy's sectoral composition, which influence labor demand and worker rents. These measures are: the employment shares of groups in manufacturing in 1980, which controls for shocks affecting this sector;

$$\text{Sectoral demand shifts}_g = \sum_i \frac{\ell_{gi}}{\ell_g} \Delta \ln \text{value added}_i,$$

which accounts for exposure to expanding sectors (in terms of value added); and

$$\text{Sectoral rent shifts}_g = \sum_i \frac{\ell_{gi}}{\ell_g} \left(\frac{\bar{w}_{gi}}{\bar{w}_g} - 1 \right) \Delta \ln \text{value added}_i,$$

which incorporates the effects of expansions (or contractions) of sectors where workers earn high rents. In this expression, $\bar{w}_{gi}/\bar{w}_g$ is the ratio between the average wage earned by a group in industry i and that group's average wage.[16]

The point estimate in the right panel is $\hat{\beta} = -1.9$, implying that a 10 percentage point increase in task displacement from automation is associated with a 20% decline in average group wages. With these additional controls, differences in exposure to automation explain 53% of the variation in wage changes among US demographic groups since 1980.

[16]For these covariates, we measure ℓ_{gi}/ℓ_g and $\bar{w}_{gi}/\bar{w}_g$ from the 1980 Census, and the change in value added from the BEA industry accounts for 1987–2016.

3.3 Rent Dissipation

The relationships shown in Figure 4 are similar to the results reported in Acemoglu and Restrepo (2022). Our framework, however, recognizes that this relationship reflects both the direct displacement effects of automation (present even in competitive labor markets) and rent dissipation (which arises when labor market rents exist and automation targets high-rent tasks). The goal of this section is to decompose this relationship into these two components, using two complementary strategies.

The first strategy exploits within-group wage changes associated with automation. As implied by our theory, these changes follow a U-shaped pattern, which we use to infer the magnitude of rents in jobs displaced by automation. The second strategy relies on explicit proxies for rents at the industry and occupation levels to show that automation shifts exposed groups of workers away from high-rent jobs. In both strategies, we pay special attention to controlling for the role of compensating differentials.

Estimates of rent dissipation from within-group wage changes: In our theory, automation affects wages at the bottom percentiles of the within-group distribution exactly by the change in the base wage, $\Delta \ln w_g$, since these workers earn no rents. Any further wage declines beyond this level reflect the loss of rents, as workers are displaced from high-rent tasks. We can therefore estimate the contribution of rent dissipation by comparing the larger wage declines at higher within-group percentiles to those at lower percentiles.

We implement this strategy by estimating a variant of equation (12) with the dependent variable as the change in log wages at the p-th percentile of the within-group wage distribution between 1980 and 2016, $\Delta \ln w_g(p)$, for $p = 5, 10, \ldots, 95, 99$:

$$(14) \qquad \Delta \ln w_g(p) \;=\; \beta(p) \text{ Task displacement}_g + X_g\, \gamma(p) + u_g^p,$$

This is an unconditional group-quantile regression, as in Chetverikov et al. (2016), which estimates the effect of automation at each percentile.

Figure 5 plots our estimates of $\beta(p)$ from a parsimonious specification that controls only for sectoral shifts. A clear U-shape is visible. Groups exposed to automation experienced a more pronounced decline in wages between the 70th and 90th percentiles of the within-group distribution, with estimates of $\beta(p)$ ranging from -2.5 to -3. This implies that wages at these percentiles fell by 25–30% for every 10 percentage point increase in task displacement. In contrast, the estimates of $\beta(p)$ are fairly uniform between the 5th and 40th percentiles, ranging from -1.6 to -1.75. Wages at these bottom percentiles fell by only 16% for every

10 percentage point increase in task displacement.

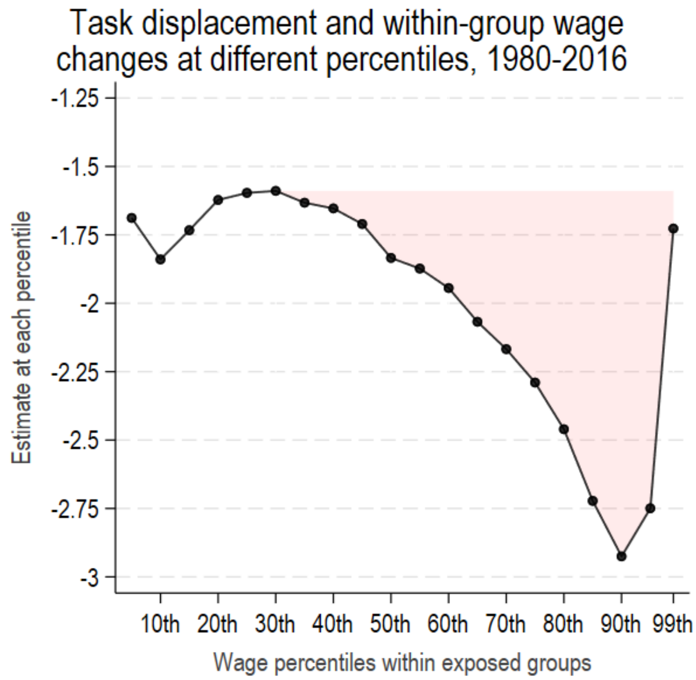

FIGURE 5: REDUCED-FORM RELATIONSHIP BETWEEN WITHIN-GROUP WAGE CHANGES AND TASK DISPLACEMENT. The figure shows estimates from an unconditional quantile regression of $\Delta \ln w_g(p)$ on task displacement for percentiles p from the 5th to the 99th (see equation (14)), controlling for sectoral shifts.

This is the pattern predicted by our theory. In light of Proposition 4, workers below the 30th (or the 40th) percentiles of the within-group wage distribution earn no rents, and the common decline in wages below the 30th or 40th percentile reflects the fall in group *base* wages via equilibrium effects. The more pronounced declines between the 50th and 95th percentiles (shown in red) capture the loss of rents. We also see that wages at the 99th percentile fall by a similar amount as at the bottom, consistent with the proposition.[17]

Figure 6 demonstrates the robustness of the U-shaped pattern. The left panel reports estimates of $\beta(p)$ relative to the 30th percentile, showing how much wages decline beyond this base level. The black line shows estimates from our baseline specification, which controls only for sectoral shifts. The remaining lines add controls for sectoral rent shifts (orange line), gender and education dummies (blue line), and exposure to manufacturing (pink line). The last specification is conservative, since part of what we seek to explain is the loss of high-rent jobs in manufacturing. In all specifications, wages decline by similar

[17] This refers to the 99th percentile of the within-group wage distribution, not the overall wage distribution. The upward-sloping portion of the U-shape is therefore not driven by top-coded Census wages.

amounts between the 5th and 40th percentiles (the differences below the 30th percentile, when controlling for manufacturing, are not statistically different from zero) and show more pronounced declines at higher percentiles (except at the very top).

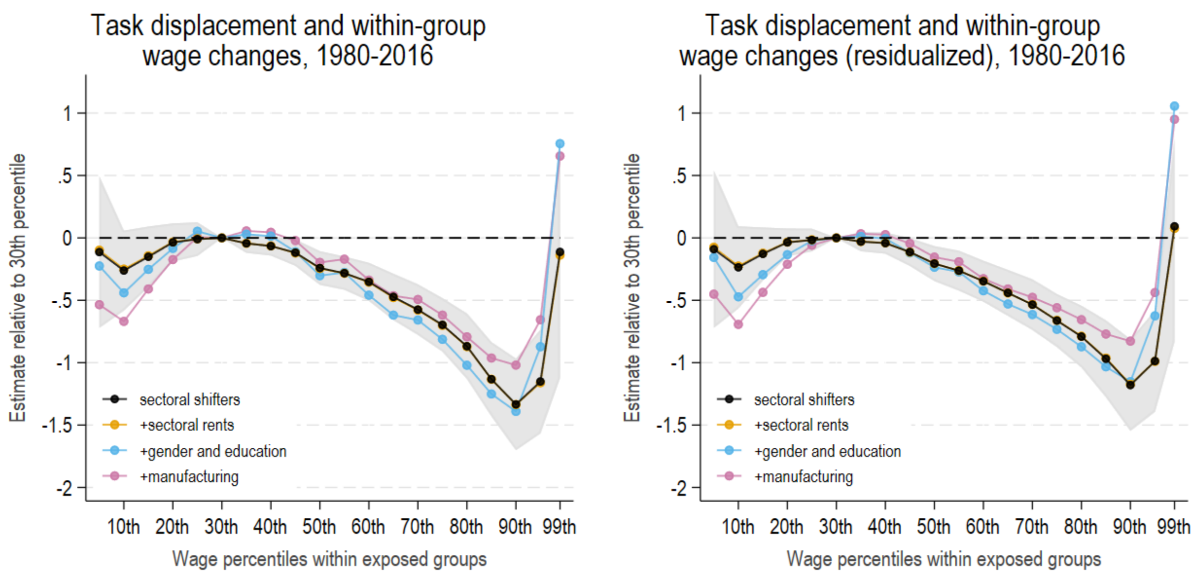

Figure 6: Robustness of the reduced-form relationship between within-group wage changes and task displacement. The figure shows estimates from an unconditional quantile regression of $\Delta \ln w_g(p)$ on task displacement for percentiles p from the 5th to the 99th (equation (14)), relative to the 30th percentile. The colors indicate different specifications. The left panel uses observed wages, while the right panel uses wages purged of job-quality measures.

The interpretation of the U-shape as reflecting rent dissipation due to automation does not require us to assume away other sources of within-group wage differences. As discussed in Section 2.4, even if workers differ in productivity levels, automation would still generate the same U-shaped pattern of wage changes. Although workers at different percentiles differ in productivity and thus baseline wage levels, the quantile regression in (14) continues to identify *changes* in base wages and rents, provided automation does not alter the ranking of workers within a group.

The U-shape pattern is also not explained by compensating wage differentials. The right panel of Figure 6 shows that the same U-shape is visible for net wage changes. To compute net wages, we use the job quality index from the 1977 Job Quality Survey described above. In a first stage, we regress wages on job quality to purge wages of compensating differentials. We then re-estimate (14) using net (or residual) wage changes at each percentile of the within-group distribution as the dependent variable. The resulting pattern is similar, though slightly less pronounced, suggesting that the bulk of the U-shape is driven by the loss of rents rather than compensating differentials.

Motivated by the robust U-shaped pattern, our first strategy for measuring rent dissipation decomposes the average wage change of exposed groups, $\Delta \ln \bar{w}_g$, into two components: a base wage change, given by the decline at the 30th percentile, $\Delta \ln w_g(30\text{th})$, and a rent dissipation component, given by the more pronounced decline above the 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$, attributed to automation. This latter component corresponds to the shaded red area in Figure 5.

Figure 7 uses these components, estimated from equation (12) with $\Delta \ln w_g(30\text{th})$ and $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$ as dependent variables. Both specifications control for baseline covariates. The left-most panel shows estimates of the decline in base wages. A 10 percentage point increase in task displacement is associated with a 15.3% decline in the base wages of exposed groups. The remainder of the average wage effect is due to rent dissipation, shown in the middle panel. A group with 10 percentage points more task displacement experiences an additional 3.5% decline in wages above the 30th percentile, which our theory interprets as the loss of rents from automation. The point estimate of $\beta = -0.37$ (s.e. $= 0.11$) implies a rent dissipation rate of 37% (corresponding to $\mu_{\mathcal{A}_g}/\mu_g - 1$ in the theory). Overall, this means that one-fifth of the average wage decline in Figure 4 is due to rent dissipation, with the rest driven by base wage changes.

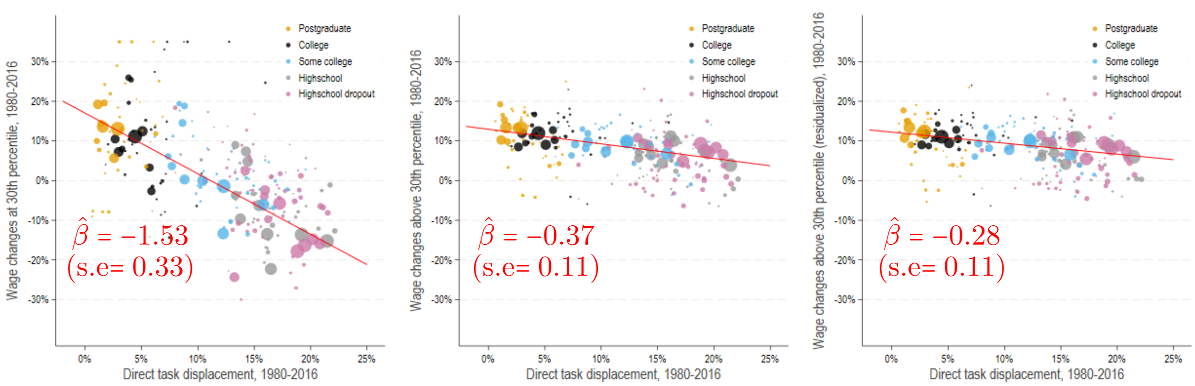

FIGURE 7: REDUCED-FORM: CHANGES IN BASE WAGES AND RENTS FROM AUTOMATION. The left panel plots the relationship between task displacement and changes in base wages, measured by the change at the 30th percentile, $\Delta \ln w_g(30\text{th})$. The middle panel plots the relationship between task displacement and rent losses, measured by the additional wage decline above the 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$. The right panel repeats the exercise but purges wages of job-quality differences. All specifications include our baseline controls: gender and education dummies, sectoral demand and rent shifts, and exposure to manufacturing.

The right-most panel shows estimates of rent dissipation, as in the middle panel, but now also controlling for compensating differentials. Namely, the dependent variable $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$ is constructed after purging wages of job quality. The point estimate of $\beta = -0.28$ (s.e=0.11) implies a rate of rent dissipation of 28%, which is similar to the estimate in the middle panel. This shows that accounting for compensating wage differentials does not affect our estimates of rent dissipation from automation.

Tables S2 and S3 in Supplement S4 confirm that these results are not sensitive to the use of the 30th percentile as our measure of base wages: we obtain similar estimates when using the 20th and 40th percentiles, or when we use the average wage decline between the 10th and 40th percentile to estimate the change in base wage changes due to automation. We also report similar point estimates for the rate of rent dissipation among non-college and college workers, pointing to the pervasiveness of this phenomenon (and confirming that the loss of high-rent jobs is not confined to non-college workers, even if the extent of this loss is significantly larger for non-college groups).[18]

Estimates of rent dissipation from employment shifts away from high-rent jobs: In our theory, rent dissipation arises because automation displaces workers from high-rent tasks. Our second strategy uses proxies for rents to directly measure rent dissipation from these shifts in employment away from high-rent jobs.

We start with time-invariant measures of rents, denoted Rents_{gn}, which capture the extent of rents in job n (defined at the industry or industry×occupation level) for demographic group g. We then compute a second measure of rent dissipation as $\sum_n \text{Rents}_{gn} \Delta\ell_{gn}$, where $\Delta\ell_{gn}$ is the change in the share of hours worked by group g in job n between 1980 and 2016. A negative value for this measure indicates that workers from group g moved out of high-rent jobs and into low-rent jobs.

With these measures, we estimate a variant of equation (12):

$$\sum_n \text{Rents}_{gn} \Delta\ell_{gn} = \beta \text{ Task displacement}_g + X_g \gamma + u_g. \tag{15}$$

The coefficient on task displacement captures the extent to which automation shifts exposed groups away from high-rent jobs, providing a direct estimate of rent dissipation and the associated decline in allocative efficiency.

While this strategy requires proxies of job rents, it provides a more direct test of the core mechanism in our theory. In our model with fixed wedges, all rent dissipation comes from the inefficient displacement of workers from high-rent jobs, and this is exactly what

[18] Another concern is that minimum wages or other regulations may explain the weaker effects at the bottom percentiles of the within-group wage distribution in Figure 5. Supplement S4 shows this is not the case: the U-shape is robust to controlling for minimum wage incidence or restricting the sample to groups with average real wages above \$10 in 1980. If anything, these strategies remove the imprecise negative effects at the bottom, suggesting that the slightly stronger declines at the 5th or the 10th percentiles likely reflect wage floors compressing low wages more in 1980 than in 2016.

this strategy measures. Comparing these estimates of rent dissipation to those from our first strategy thus serves as a check on our assumption that wedges are fixed and that rent dissipation operates through worker displacement. Under this hypothesis, this second strategy should yield the same magnitude of rent dissipation as the first.

We estimate equation (15) using four proxies for rents.

Our first proxy uses inter-industry and occupation wage differentials in 1980. This approach builds on the inter-industry wage differentials literature, which documents that such differences are persistent and cannot be explained solely by worker characteristics or job amenities (see Krueger and Summers, 1988; Katz and Summers, 1989). We measure the relative rent paid to workers from group g in industry i and occupation o as $\bar{w}_{gio}/\bar{w}_g$, where $\bar{w}_{gio}$ is the average wage of group g in industry i and occupation o in 1980..[19]

The top-left panel of Figure 8 reports results using this first proxy. We estimate that a 10 percentage point increase in task displacement reduces group rents by 3.9%, reflecting a reallocation of workers away from higher-wage industries and occupations. The point estimate implies a rate of rent dissipation due to automation ($\mu_{\mathcal{A}_g}/\mu_g - 1$ in the theory) of 39%—very close to the magnitude obtained with our first strategy, as hypothesized.

One concern with our first proxy is that part of the wage differentials could be due to differences in worker productivity across industry-occupation cells. Our second proxy addresses this issue by building on Gibbons and Katz (1992) and focusing on wage losses after job displacement. Because these compare the same worker before and after displacement, they are not affected by unobserved heterogeneity.[20] We compute wage losses for workers with at least one year of tenure pre-displacement who subsequently found a new job, using the CPS Displaced Worker Supplement. Given the small sample of displaced workers, we estimate wage losses by industry and six broad occupations, allowing losses to vary by gender and education (rather than at the more granular level of 500 demographic groups). We average these estimates over 1984–2022 to obtain our second proxy for Rents_{gn}.[21]

[19] This is equivalent to measuring worker rents by a group-specific industry×occupation intercept in a Mincer regression, while controlling for a full set of interactions between age, gender, education, race and birthplace. Our baseline results use wage differentials for the 49 industries in our analysis and 300 detailed Census occupations. Table S6 in Supplement S4 shows that the results are robust to using wage differentials computed for broader occupational groups or only across industries.

[20] The estimates of rent dissipation using this proxy for rents also rule out other potential explanations for the U-shape in Figures 5 and 6. For example, an alternative explanation for the U-shaped pattern based on within-group heterogeneity in both absolute and comparative advantage could not explain why automation shifts workers out of high-rent jobs, when rents are measured by wage losses from job displacement. This advantage is also shared by our third strategy using quit rates to measure rents.

[21] A higher tenure threshold reduces the sample of displaced workers, but does not affect our estimates. Table S6 in Supplement S4 establishes the robustness of our results to using varying levels of aggregation for this rent measure.

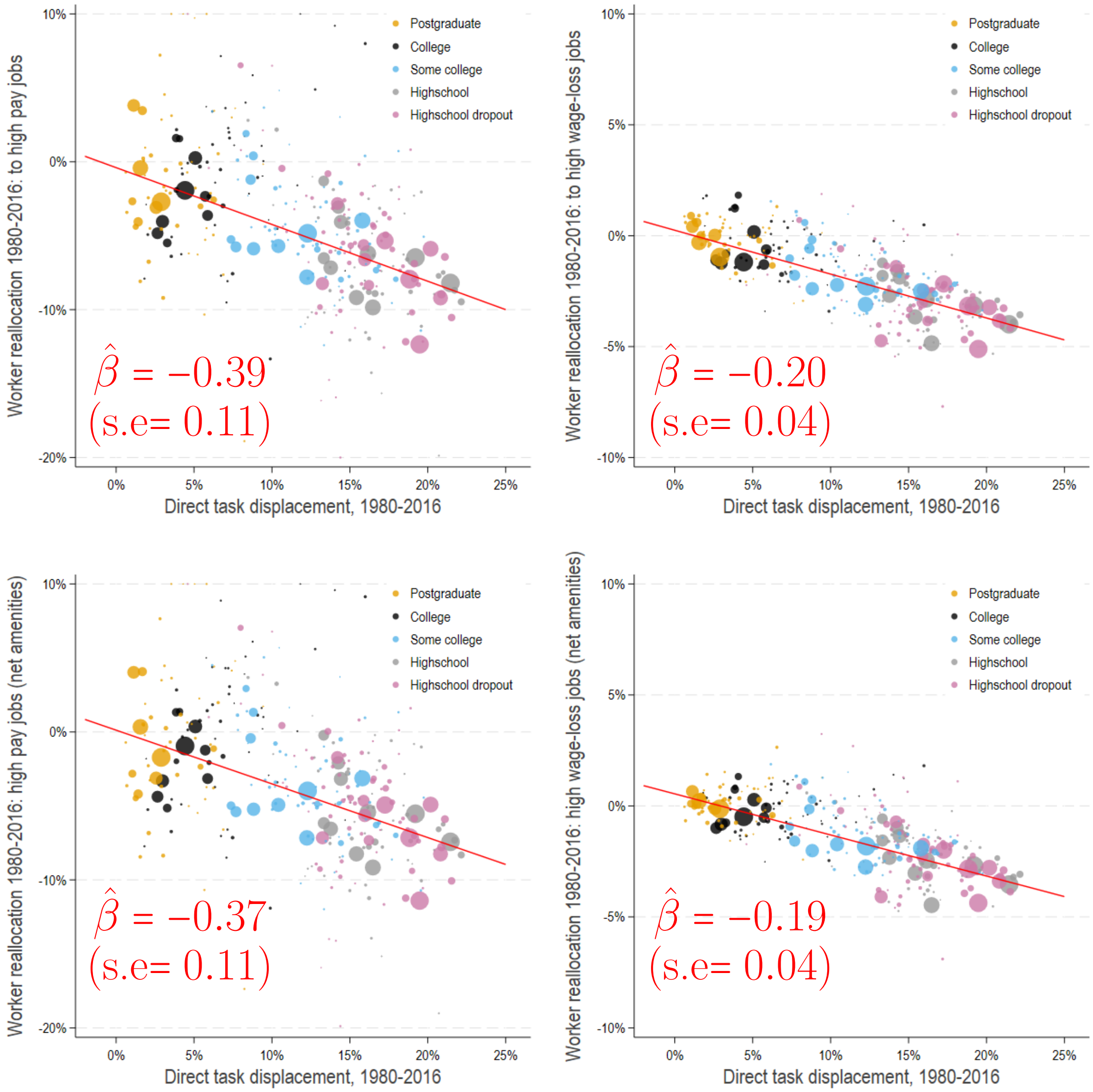

FIGURE 8: REDUCED-FORM: AUTOMATION AND SHIFTS AWAY FROM HIGH-RENT JOBS. The figure plots the relationship between automation and worker shifts away from high-rent jobs, measured as $\sum_n \text{Rents}_{gn} \Delta\ell_{gn}$. The top-left panel uses industry and occupation wage differentials in 1980 as the proxy for rents. The top-right panel uses wage losses after job displacement from the CPS Displaced Worker Supplement. The bottom panels repeat these analyses after purging job-quality differences from the rent proxies. All specifications include baseline controls: gender and education dummies, sectoral demand and rent shifts, and exposure to manufacturing.

The top-right panel of Figure 8 presents the results using this second proxy. A 10 percentage point increase in task displacement is estimated to reduce group rents by 2%, as workers are reallocated away from jobs with higher rents. This estimate implies a rent dissipation rate from automation of 20%, once again close to the magnitudes obtained from our first strategy.

One drawback of our first two proxies is that they may capture compensating differentials. We address this concern in two ways. First, building on our previous analysis, we purge both rent proxies of differences in job quality, measured using the job quality index from the 1977 Quality of Employment Survey. This index explains 9% of the variation in wage differentials and 14% of the variation in wage losses from displacement across industries. The bottom panels of Figure 8 report estimates using these residualized rent proxies. We obtain slightly smaller but very similar estimates of rent dissipation: 0.37 (s.e.=0.11) using our first proxy and 0.19 (s.e.=0.04) using our second proxy based on wage losses after displacement.

Our second approach is to use two additional proxies for rents which we expect to be unrelated to compensating differentials. This approach exploits differences in worker quit behavior, based on the idea that workers should be less likely to quit jobs that pay rents, but not those that pay higher wages as compensating differential. We compute two (time-invariant) proxies for quits from the CPS, as average employment-to-employment (EE) and voluntary employment-to-unemployment (EU) monthly quit rates by industry, occupation, gender and education. The EE measure is averaged over 1994–2023 and the EU measure is average over 1976–2023.[22] Consistent with our interpretation, quit rates are inversely associated with industry-occupation wage differentials (correlation of -0.72) and with wage losses after displacement (correlation of -0.54).

Figure 9 reports estimates of a variant of equation (12) with $\text{Rents}_{gn} = -\text{ Quit rate}_{gn}$, where the quit rate is computed either from the EE or the EU rates. In both cases, we see a clear negative relationship, suggesting that automation displaced workers from jobs with low quit rates. A 10 pp increase in task displacement pushes workers to jobs with a 0.15 percentage point higher EE rate and a 0.03 percentage point higher voluntary EU rate per month. This pattern suggests that automation is not shifting workers out of jobs with high compensating differentials, but from jobs that they prefer to hold—hence jobs that used to pay higher rents.

To facilitate the interpretation of these point estimates, we convert them into implied rents by using the empirical relationship between intra-industry wage differentials and quit rates. In our data, a 1 pp lower EE rate is associated with an 18.9% higher wage differential. Our estimates in the left panel of Figure 9 then imply a rate of rent dissipation of $1.5 \times 18.9\% = 28.4\%$. Likewise, in our data, a 1 pp lower voluntary EU rate is associated with a 149% higher wage differential. Our estimates in the right panel of Figure 9 then

[22]Our data cleaning procedure follows Fujita et al. (2024). We compute average quit rates for the 49 industries and 300 detailed occupations. We also partial out time trends in the CPS from these industry×occupation averages. Table S7 in Supplement S4 reports very similar results when we use average quit rates at different levels of aggregation.

imply a rate of rent dissipation of $0.3 \times 149\% = 44.8\%$. These estimates are similar to those from our other two rent proxies and our first strategy.[23]

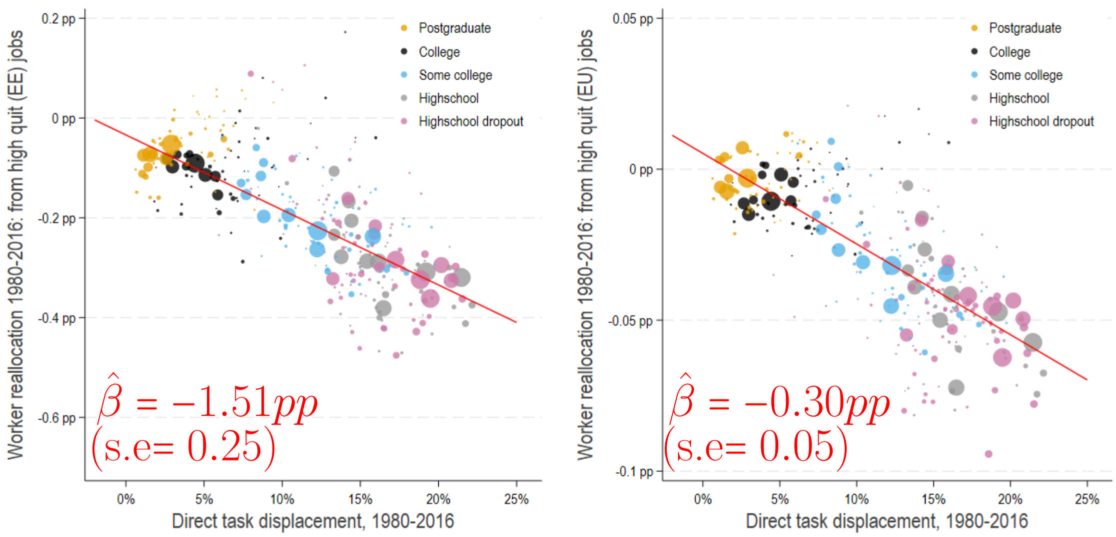

FIGURE 9: REDUCED-FORM: AUTOMATION AND SHIFTS AWAY FROM HIGH-RENT JOBS (AS REVEALED BY QUITS). The figure plots the relation between automation and worker shifts away from high-rent jobs, measured as $-\sum_n \text{Quit rate}_{gn} \Delta\ell_{gn}$. The left panel presents results using the employment-to-employment monthly transition rate as an inverse proxy for rents (computed from the Basic Monthly CPS). The right panel presents results using the voluntary employment-to-unemployment monthly transition rate as an inverse proxy for rents (computed from the Basic Monthly CPS). All specifications include baseline controls: gender and education dummies, sectoral demand and rent shifts, and exposure to manufacturing.

The results from our second strategy confirm that automation caused significant rent dissipation, displacing exposed groups of workers from high-rent jobs.[24] Our estimates imply a rate of rent dissipation between 19% and 44.5%, with a central estimate of 35%.

Further empirical results and checks: Our framework implies that automation is partially motivated by a desire to dissipate rents. Hence, all else equal, industries with higher rents should witness more automation. We provide evidence supporting this prediction in Supplement S4, Tables S12 and S13. Using our four proxies of rents, we show

[23] We obtain similar results if we use estimates of the elasticity of separation rates with respect to wages from Bassier et al. (2022) to do this conversion. Their paper estimates an elasticity of 2.1 of separation rates (into unemployment or other jobs) with respect to job-level wage differentials. Converted to a semi-elasticity, this implies that a 1 percentage point lower separation rate is associated with a 17% higher wage. Pooling the estimates from Figure 9 for EE and EU quits, we obtain a 1.8 percentage point higher overall quit rate, which implies a rate of rent dissipation of $1.8 \times 17\% = 30.6\%$.

[24] All of our rent proxies point to a pervasive overall shift away from high-rent jobs for most demographic groups since 1980. The reduced-form evidence in this section shows that automation has been an important driver of this trend. For example, automation explains 33% (in the top left panel of Figure 8) to 68% (in the left panel of Figure 9) of the extent to which different groups shifted away from high-rent jobs.

that high-rent industries exhibit larger declines in labor share and task displacement due to automation.[25]

Supplement S4 also provides additional results exploring the robustness of our findings. Besides providing tables summarizing all the estimates presented in figures here (see Table S1), we demonstrate the robustness of these estimates to different sets of covariates and also provide estimates using different definitions of routine jobs when measuring task displacement (see Tables S8 and S9). The Supplement additionally presents estimates for different sub-periods (see Tables S10 and S11). We find some suggestive (but not conclusive) evidence in support of the view that rent dissipation was stronger early on in our sample period and has weakened over time. This pattern is consistent with a dynamic version of our theory. The same logic as in our model implies that highest-rent tasks should be automated first, and rent dissipation should be stronger early on and start declining as further advances in automation move on to displacing workers from medium-rent jobs.

4 General Equilibrium Effects of Automation

This section explores the general equilibrium effects of automation in the US labor market between 1980 and 2016 by estimating the ripple effects from automation and incorporating the sectoral reallocation of employment and output induced by automation. To do this, we first extend our model to a multi-sector economy and derive formulas describing the general equilibrium implications of automation in this context.

4.1 Multi-Sector Economy

Consider an economy with multiple sectors $i \in \mathbb{I}$. Sector i produces output y_i with price p_i. Sectoral outputs are combined into a unique final good via an aggregator with a constant elasticity of substitution $\eta > 0$. Each of these goods is produced as in our single-sector economy, with good y_i produced by combining complementary tasks $x \in \mathcal{T}_i$,

$$y_i = \left(\frac{1}{M_i} \int_{\mathcal{T}_i} (M_i \, y_x)^{\frac{\lambda-1}{\lambda}} \, dx \right)^{\lambda/(\lambda-1)} .$$

The sets $\{\mathcal{T}_i\}_{i \in \mathbb{I}}$ are sector-specific, which is without loss since tasks can be relabeled.

[25] This evidence aligns with work by Acemoglu and Restrepo (2021), and Hémous et al. (2025), which establish that higher wages (driven by demographic changes in the former paper and by labor market reforms in the latter paper) induce more automation. Our exercise additionally highlights the role of rents, which can induce inefficient automation. These results also align with Doms et al. (1997), who show that establishments that pay higher wages subsequently adopt more automation technologies, though in practice there may be several different reasons than worker rents that account for this association.

The rest of the model is unchanged, and turns on how tasks in these industries are allocated to worker groups and capital. The details are provided in Supplement S1. The definition of equilibrium is a direct generalization of the one in Section 2, with the only difference that sectoral prices are determined in equilibrium.

As before, new automation technologies are modeled as an exogenous increase in q_x from zero to q'_x for tasks in $\{\mathscr{A}^T_{gi}\}_{i\in\mathbb{I},g\in\mathbb{G}}$, where $\mathscr{A}^T_{gi}$ denotes tasks that are feasible to automate (among those assigned to group g in industry i) and $\mathscr{A}_{gi}$ corresponds to the subset of tasks that are automated. We use δ_{gi} to denote the task displacement for group g in industry i and $\delta_g = \sum_i \frac{\ell_{gi}}{\ell_g} \delta_{gi}$ for the total task displacement across all industries, where ℓ_{gi} is group g's employment in industry i. In addition, π_{gi} measures the cost savings from automating tasks in $\mathscr{A}_{gi}$, $\mu_{\mathscr{A}_{gi}}$ is the average rent in these tasks and $\mu_{\mathscr{A}_g}$ the average across industries.

The next proposition characterizes the general equilibrium effects of automation in the multi-sector economy.

Proposition 6 (General Equilibrium Effects of Automation)
Consider new automation technologies represented by (small interior) sets $\{\mathscr{A}^T_{gi}\}_{i\in\mathbb{I},g\in\mathbb{G}}$. Let $\{\mathscr{A}_{gi}\}_{i\in\mathbb{I},g\in\mathbb{G}}$ be given by equation (4) and the corresponding direct effects of automation be given by $\left\langle\{\delta_{gi}\}_{i\in\mathbb{I},g\in\mathbb{G}}, \{\pi_{gi}\}_{i\in\mathbb{I},g\in\mathbb{G}}, \{\{\mu_{\mathscr{A}_{gi}}\}_{i\in\mathbb{I},g\in\mathbb{G}}\}\right\rangle$. The first-order impact on base wages w_g, sectoral prices p_i, and output y are given by the solution to the system of equations:

$$d\ln w_g = \Theta_g \; stack\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_j + \frac{1}{\lambda}\sum_i \frac{\ell_{ji}}{\ell_j}\,(\lambda-\eta)\, d\ln p_i\right) \quad \text{for } g\in\mathbb{G} \tag{16}$$

$$d\ln p_i = \sum_g s_{gi}\, d\ln w_g - \sum_g s_{gi}\,\frac{\mu_{\mathscr{A}gi}}{\mu_{gi}}\,\delta_{gi}\,\pi_{gi} \quad \text{for } i\in\mathbb{I} \tag{17}$$

$$\sum_g s_g\, d\ln w_g = \sum_i s_{y_i} \sum_g s_{gi}\,\frac{\mu_{\mathscr{A}gi}}{\mu_{gi}}\,\delta_{gi}\,\pi_{gi}, \tag{18}$$

where s_{gi} is the share of group g's earnings in industry i's output and s_{y_i} is the output share of industry i in GDP. Moreover, the change in group rents is given by

$$d\ln \mu_g = \mathcal{M}_g \; stack\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_j + \frac{1}{\lambda}\sum_i \frac{\ell_{ji}}{\ell_j}\,(\lambda-\eta)\, d\ln p_i\right) \tag{19}$$

$$-\left(\frac{\mu_{\mathscr{A}_g}}{\mu_g}-1\right)\delta_g + \sum_i\left(\frac{\mu_{gi}}{\mu_g}-1\right)\frac{\ell_{gi}}{\ell_g}\,(\lambda-\eta)\, d\ln p_i \quad \text{for } g\in\mathbb{G} \tag{20}$$

and the change in aggregate consumption is $d\ln c = \frac{1}{s_L}\, d\ln \text{TFP}$, where s_L is the economy-

wide labor share and $d\ln \text{TFP}$ *is the contribution of automation to* TFP*, given by*

$$d\ln \text{TFP} \;=\; \sum_i s_{y_i} \sum_g s_{gi} \frac{\mu_{\mathscr{A}gi}}{\mu_{gi}}\, \delta_{gi}\, \pi_{gi} + \sum_g s_g\, d\ln \mu_g. \tag{21}$$

From this proposition, the general equilibrium effects of automation on group wages can be summarized as:

$$\begin{aligned} d\ln \bar{w}_g \;=\; (\Theta_g + \mathcal{M}_g)\;\; \text{stack}\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_j + \frac{1}{\lambda}\sum_i \frac{\ell_{ji}}{\ell_j}\,(\lambda-\eta)\, d\ln p_i\right) \\ -\left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1\right)\delta_g + \sum_i \left(\frac{\mu_{gi}}{\mu_g} - 1\right)\frac{\ell_{gi}}{\ell_g}\,(\lambda-\eta)\, d\ln p_i. \end{aligned} \tag{22}$$

Relative to Proposition 5, these formulas account for the impact of automation on sectoral prices and the resulting changes in sectoral composition of the economy (for example, automation in one industry can now reallocate expenditure away from that industry). Equation (17) shows that changes in sectoral prices depend on base wage changes (from Shephard's lemma) and cost savings from automation. Induced changes in sectoral composition affect wages because sectors differ in terms of their labor demands. This is measured by the term $\sum_i \frac{\ell_{ji}}{\ell_j}\,(\lambda-\eta)\, d\ln p_i$ in equations (16) and (22). The sectoral reallocation also influences the distribution of rents, as captured by the term $\sum_i \left(\frac{\mu_{gi}}{\mu_g} - 1\right)\frac{\ell_{gi}}{\ell_g}\,(\lambda-\eta)\, d\ln p_i$ in equations (19) and (22).

4.2 Measurement and Estimation

The formulas in Proposition 6 allow us to compute the first-order effects of automation in terms of the following objects:

i. the task displacement of automation across industries δ_{gi} and on aggregate δ_g.
ii. the rent dissipation due to automation, $\mu_{\mathscr{A}_{gi}}/\mu_g$ and $\mu_{\mathscr{A}_g}/\mu_g$;
iii. the cost savings from automation, π_{gi};
iv. the propagation matrix, Θ, and the rent-impact matrix, $\mathcal{M}$;

In addition, the formulas involve initial factor shares, which we compute from the BEA and Census data, and the elasticities of substitution between tasks, λ, and sectors, η, which we set as $\lambda = 0.5$ from Humlum (2020) and $\eta = 0.2$ from Buera et al. (2015).

The rest of our approach requires three simplifying choices. First, we impose Assumption 3. Second, we assume that cost savings from the adoption of industrial robots in manufacturing—about 30% in Acemoglu and Restrepo (2020)—applies across the board and set $\pi_{gi} = 30\%$ for all industries and groups.[26] Third, we assume the rate of rent dissipation $\mu_{\mathscr{A}_{gi}}/\mu_{gi}$ is the same across industries and groups. In particular, we set $\mu_{\mathscr{A}_{gi}}/\mu_{gi} = 1 + \rho$ and treat ρ—the common rate of rent dissipation—as a parameter to be estimated.

Under these assumptions, aggregate task displacement δ_g is again given by equation (13), as in our reduced-form analysis. The only difference now is that in the reduced form we imposed the value of ρ, whereas here we estimate it directly.[27]

Estimating $\rho, \Theta, \mathcal{M}$: Our model delivers two equations in terms of changes in base wages and rents as a function of task displacement and other equilibrium objects (such as other groups' wage changes):

$$\Delta \ln w_g = \beta_0 - \frac{1}{\lambda}\,\delta_g + \beta\, X_g + \frac{1}{\lambda}\,\mathcal{J}_{\Gamma,g}\,\text{stack}(\Delta \ln w_j) + u_g \tag{23}$$

$$\Delta \ln \mu_g = \beta_0^{\mu} - \rho\,\delta_g + \beta^{\mu}\,X_g^{\mu} + \mathcal{J}_{\mu,g}\,\text{stack}(\Delta \ln w_j) + e_g. \tag{24}$$

The first equation describes the change in base wages in terms of common shifts β_0 (such as the expansion of GDP, $\Delta \ln y$), the task displacement from automation δ_g, other shifts in technology X_g (such as sectoral productivity shifts), and ripple effects. These are captured by $\mathcal{J}_{\Gamma,g}\,\text{stack}(\Delta \ln w_j)$, where $\mathcal{J}_{\Gamma}$ is the Jacobian summarizing how task shares adjust in response to wage changes, and $\mathcal{J}_{\Gamma,g}$ is its g-th row. The error term u_g represents other changes in technology or labor supply.

The second equation describes changes in group rents in terms of a constant β_0^{μ}, rent dissipation from automation, $\rho\delta_g$, the direct impact on rents of other shifts in technology, X_j^{μ}, and ripple effects, $\mathcal{J}_{\mu,g}\,\text{stack}(\Delta \ln w_j)$, now with $\mathcal{J}_{\mu}$ representing the rent impact Jacobian. The error term e_g corresponds to omitted factors affecting rents (for example, due to changes in wedges coming from other sources).

In essence, these equations define a factor demand system, describing how the base wage and average rent of a group are impacted by wage changes of other groups and demand shifters, including task displacement and sectoral composition terms. The key unknowns in these equations can be written in the form of the propagation and rent-impact matrices:

[26] We do this because we lack disaggregated data on the costs of and productivity gains from other automation technologies. This feature can be improved in future work leveraging industry-specific estimates.

[27] Consistent with this, the industry-level task displacement for group g in industry i, which is needed to compute change in sectoral prices in Proposition 6, is measured as (see Supplement S4.7 for the derivation):

$$\delta_{gi} = \text{RCA}_{gi}^{\text{routine}}\,\frac{-d\ln s_{\ell i}^{\mathcal{A}}}{1 + s_{\ell i}\,(\lambda - 1)\,\pi}\,\frac{1}{1+\rho}.$$

$\Theta = \left(\mathbb{1} - \frac{1}{\lambda}\,\mathcal{J}_{\Gamma}\right)^{-1}$ and $\mathcal{M} = \mathcal{J}_{\mu}\,\left(\mathbb{1} - \frac{1}{\lambda}\mathcal{J}_{\Gamma}\right)^{-1}$. These matrices, which fully summarize the ripple effects, can be estimated under similar assumptions to those we made in our reduced-form analysis. However, without further restrictions, each one of the matrices Θ and $\mathcal{M}$ include 500×500 entries—since the effects of task displacement experienced by g on group g' could be very different than its effect on group g''.

To make progress, we put some structure and parameterize the entries of the Jacobian matrices in terms of job and demographic group-level similarities. For the diagonal terms, we suppose that

$$\mathcal{J}_{\Gamma,g,g} = (s_g - 1)\,\varphi - \sum_n \sum_{g' \neq g} \frac{\ell_{gn}}{\ell_g}\, s_{g'n} \left[\theta + \theta_{\text{job}}\,\text{job similarity}_{gg'} + \theta_{\text{edu-age}}\,\text{edu-age similarity}_{gg'}\right]$$

and the off-diagonal terms, for $g' \neq g$, are assumed to take the form:

$$\mathcal{J}_{\Gamma,g,g'} = s_{g'}\,\varphi + \sum_n \frac{\ell_{gn}}{\ell_g}\, s_{g'n} \left[\theta + \theta_{\text{job}}\,\text{job similarity}_{gg'} + \theta_{\text{edu-age}}\,\text{edu-age similarity}_{gg'}\right].$$

This parameterization imposes that competition between groups for marginal tasks takes place within job categories, defined in the data at the level of 16 industries and six occupations (and denoted by n). The effects of competition from demographic group g' on group g in job category n are then assumed to depend on the importance of this job category for group g, ℓ_{gn}/ℓ_g, and on the extent of group g''s impact on this job category, represented by the share of earnings in job category n accruing to group g', $s_{g'n}$. (We measure both of these from the 1980 Census). This captures the intuitive notion that groups with greater shares should generate more competitive pressure on other groups in the same job category.

The parameters θ, θ_{job}, $\theta_{\text{edu-age}} \geq 0$ summarize the extent of competition for marginal tasks across groups. Specifically, θ represents competition for tasks common to all workers in a job category. For example, if worker productivity for all tasks in job category n were drawn from independent Frechet distributions with shape parameter ν, then we would have $\theta = \nu + 1 - \lambda$. The parameters θ_{job} and $\theta_{\text{edu-age}}$ then allow competition to be more intense among groups that hold similar jobs elsewhere in the economy (suggesting a greater overlap in their skills) or that are of a similar age and education (as in Card and Lemieux, 2001).[28]

Note also that in these specifications, the constant $\varphi \geq 0$ controls the extent of competition between capital and workers for marginal tasks. In this parameterization, the

[28]We measure job similarity$_{gg'}$ by the *cosine* similarity in job categories performed by groups g' and g in the 1980 Census. For edu-age similarity$_{gg'}$, we first run a Mincer wage regression, and then compute this quantity as one minus the difference in regression coefficients of experience and education for the education and experience of groups g and g'.

aggregate elasticity of substitution between capital and labor is $\sigma = \lambda + \varphi$ (capturing the sum of the elasticities of substitution between tasks and between demographic groups in marginal tasks). We set $\varphi = 0.1$ externally to match estimates of $\sigma = 0.6$ from Oberfield and Raval (2021).

For the rent Jacobian, we follow a similar strategy and parameterize it as

$$\mathcal{J}_{\mu,g,g} = -\sum_n \sum_{g' \neq g} \left(\frac{\bar{w}_{gn}}{\bar{w}_g} - 1 \right) \frac{\ell_{gn}}{\ell_g} \, s_{ng'} \left[\theta + \theta_{\text{job}} \text{ job similarity}_{gg'} + \theta_{\text{edu-age}} \text{ edu-age similarity}_{gg'} \right],$$

and the off-diagonal terms, for $g' \neq g$, as

$$\mathcal{J}_{\mu,g,g'} = \sum_n \left(\frac{\bar{w}_{gn}}{\bar{w}_g} - 1 \right) \frac{\ell_{gn}}{\ell_g} \, s_{ng'} \left[\theta + \theta_{\text{job}} \text{ job similarity}_{gg'} + \theta_{\text{edu-age}} \text{ edu-age similarity}_{gg'} \right].$$

The term $\left(\frac{\bar{w}_{gn}}{\bar{w}_g} - 1 \right)$ proxies for rents earned by group g in job category n, and accounts for whether competition from demographic group g' takes place at jobs where g workers earn above average rents. We compute this from observed wages in the 1980 Census as well. The rows of the rent Jacobian sum to zero, which imposes the restriction that substitution of capital for labor at marginal tasks does not affect group rents on average.

With these parametric forms, the system of equations (23) and (24) enable us to estimate ρ, θ, θ_{job} and $\theta_{\text{edu-age}}$ using GMM. As in our reduced-form analysis, we measure the change in base wages $\Delta \ln w_g$ by the change at the 30th percentile of the within-group distribution, and take the decline in wages above the 30th percentile of exposed groups as a measure for the change in average rents, $\Delta \ln \mu_g$. Formally, the orthogonality conditions for the GMM estimation are essentially the same as in our reduced-form analysis:

$$\delta_g, X_g, X_g^{\mu} \perp u_j, e_j \text{ for all } g,$$

except that we are now simultaneously estimating the ripple effects.[29] Once these parameters are estimated, the propagation and rent-impact matrices can be recovered from their definitions: $\Theta = \left(\mathbb{1} - \frac{1}{\lambda} \, \mathcal{J}_\Gamma \right)^{-1}$ and $\mathcal{M} = \mathcal{J}_\mu \, \left(\mathbb{1} - \frac{1}{\lambda} \mathcal{J}_\Gamma \right)^{-1}$.

Table S14 in Supplement S4 reports our GMM estimates for $\rho, \theta, \theta_{\text{job}}, \theta_{\text{edu-age}}$. Here we summarize the main findings:

1. The common rent dissipation coefficient is estimated as $\hat{\rho} = 0.35$ (s.e.=0.12). This

[29] Recall that equation (23) is in essence a factor demand system, which can be estimated using various demand shifters. In the trade literature, these shifters come from changes in trade costs, for example induced by the evolution of tariffs (see, for example, Adao et al., 2017). Our approach instead uses different groups' uneven exposure to automation, but operates with the same logic.

aligns with our reduce-form estimates in Section 3.

2. The propagation matrix has an average diagonal of 0.34, and the row sum of the off-diagonal terms is 0.6. This implies that exposed workers bear 40% of the incidence of automation, with the rest shifted to others via ripple effects.

3. The entries of the rent-impact matrix are small, which implies that ripple effects on group rents are small.

4.3 General Equilibrium Effects of Automation

This section reports our estimates of the effects of automation on wages, rents, and TFP in the US between 1980 and 2016. The calculations use the formulas from Proposition 6, our measures of task displacement, and the parameter estimates from the previous subsection. Column 1 of Table 1 summarizes the data, while column 2 presents our estimates.

Effects on wages and group rents: Panel A of Table 1 reports our estimates for wages, which are also depicted in Figure 10. Using equation (22), the figure decomposes the change in average wages for the 500 demographic groups into the different channels through which automation operates. The vertical axis shows wage changes over 1980–2016, while the horizontal axis orders groups by their average hourly wages in 1980.

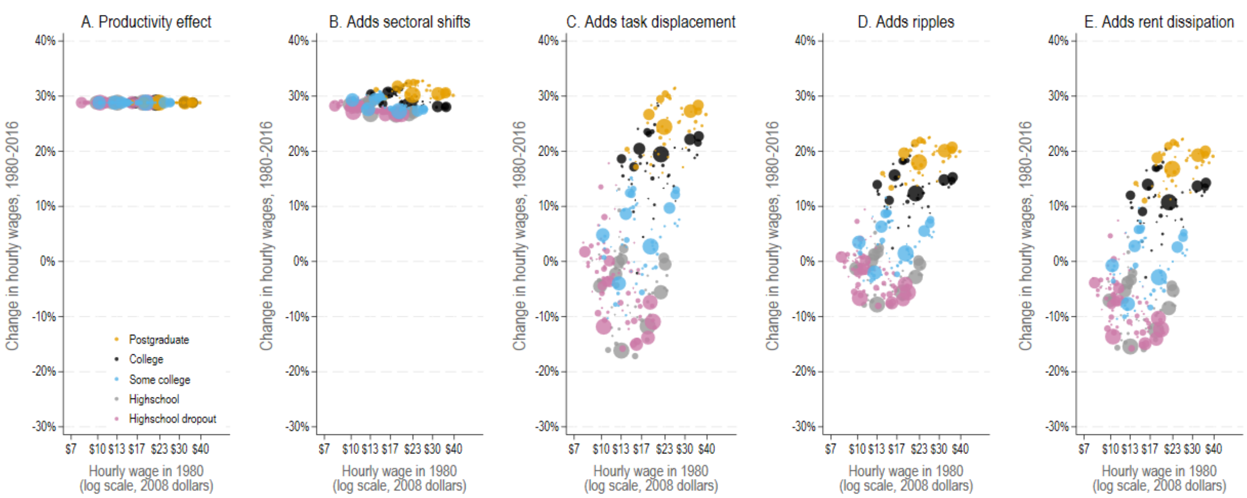

FIGURE 10: WAGE EFFECTS OF AUTOMATION. The figure shows estimates of automation's impact on between-group wage changes through different channels, beginning with the productivity effect in Panel A and adding components cumulatively until Panel E. In all panels, the horizontal axis sorts groups by their hourly wage in 1980.

Panel A of Figure 10 shows only the productivity effect of automation, given by $(1/\lambda)\, d\ln y$.

We estimate that aggregate output increased by 14.4% over 1980–2016 due to automation, and this raised wages by 28.8% for all demographic groups. We estimate that automation increased aggregate output by 14.4% between 1980 and 2016, raising wages by 28.8% for all demographic groups. Panel B adds the effects of sectoral shifts induced by automation, computed as $(1/\lambda)\ d\ln y + (1/\lambda)\ \sum_i (\ell_{ji}/\ell_j)\ (\lambda - \eta)\ d\ln p_i$. The modest dispersion of wages across groups in this panel indicates that the overall contribution of automation-driven sectoral shifts to wage inequality was limited.

Panel C adds the direct displacement effects from automation, thus plotting $(1/\lambda)\ d\ln y + (1/\lambda)\ \sum_i (\ell_{ji}/\ell_j)\ (\lambda - \eta)\ d\ln p_i - (1/\lambda)\ \delta_g$. Consistent with the reduced-form evidence, task displacement has significant effects on the wage structure and generates much greater dispersion compared to Panels A and B. While groups less exposed to automation experience real wage gains, we see large declines in the real wages of highly exposed groups.

Panel D illustrates the role of ripple effects, by plotting Θ_g stack $((1/\lambda)\ d\ln y - (1/\lambda)\ \delta_j + (1/\lambda)\ \sum_i (\ell_{ji}/\ell_j)\ (\lambda - \eta)\ d\ln p_i)$. Ripple effects play an equalizing role, as can be seen from the fact that the dispersion in wage changes across groups is less pronounced than in Panel C. This is because automation lowers the relative wages of displaced groups, triggering a reassignment of marginal tasks toward them and away from others. Ripple effects are sizable and spread about two-thirds of the incidence of automation across groups.

Panel E completes the picture by adding changes in group rents, $d\ln\mu_g$, so we can now see the full effects of automation. The figure shows sizable rent dissipation, which reduces wages among highly exposed groups by about 10%.[30] In contrast to ripple effects, rent dissipation plays an unequalizing role. This is because, as explained in the theory, exposed groups bear the full incidence of rent dissipation.

To quantify and further illustrate the contribution of rent dissipation, Figure 11 plots actual group-level wage changes against our estimates of wage changes due to automation between 1980 and 2016. The left panel shows the effects of automation working only through base wages, omitting rent dissipation. The right panel depicts the full impact, including rent dissipation. Changes in base wages alone explain 42% of observed wage changes, while estimates incorporating rent dissipation explain a total of 52%. These results imply that automation accounts for 52% of the rise in between-group wage inequality over this period, with about one-fifth of the effect being due to rent dissipation.[31]

[30] Most of the decline in rents across groups reflects direct rent dissipation—automation targeting jobs with above-average rents—rather than indirect effects working through the rent-impact matrix.

[31] The 42% number is lower than the 50% estimate in Acemoglu and Restrepo (2022), which used a model with fully competitive labor markets. If data are generated with imperfect labor markets but we impose a fully competitive model to interpret it, rent dissipation effects can load on the direct displacement term, exaggerating its role.

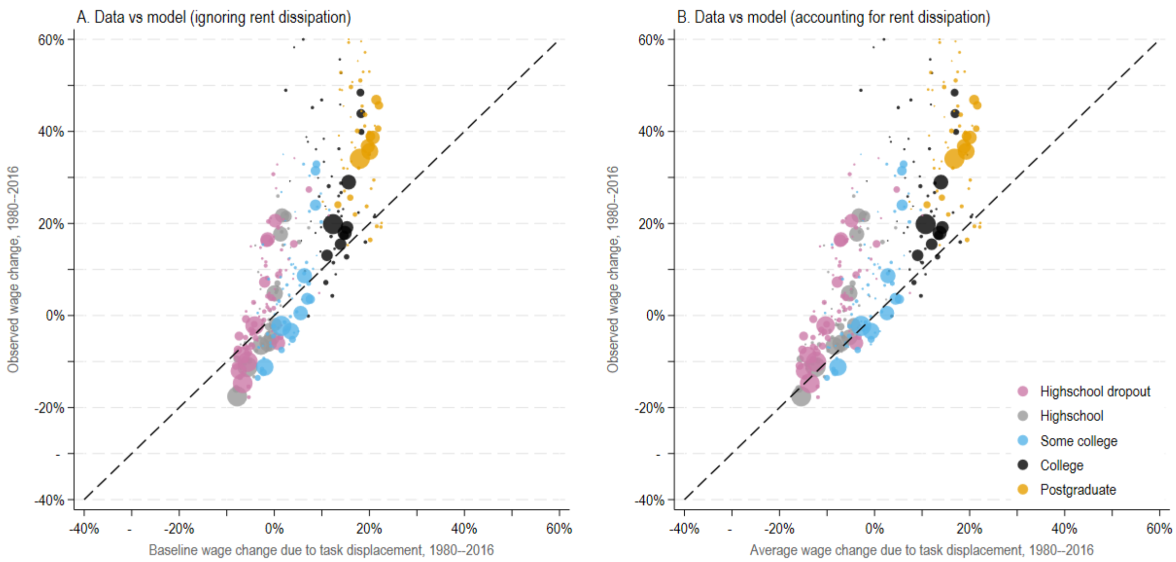

FIGURE 11: WAGE EFFECTS OF AUTOMATION: MODEL VS. DATA. The left panel compares predicted wage changes, excluding rent dissipation, to observed changes from 1980–2016. The right one includes rent dissipation and shows the full model-predicted wage changes against data.

The effects of rent dissipation are especially important for explaining the lack of real wage growth among low-education groups. On the left panel, several demographic groups lie below the 45° line, but far fewer do so on the right. Without accounting for rent dissipation, automation cannot explain the real wage declines experienced by many low-education groups between 1980 and 2016. Once rent dissipation is included, our estimates account for most of the observed real wage stagnation and decline over this period.

As a further illustration, Table 1 reports our estimates of the change in wages and rents for non-college men and women. Without rent dissipation, automation would have led to a 2.4% decline in the real wage of non-college men during 1980–2016 (compared to 6.5% in the data) and a 2.4% increase in the real wage of women. Once rent dissipation is factored in, we estimate an 8% decline for non-college men and a 2.2% decline for non-college women.

Rent dissipation also implies that automation generated virtually no aggregate wage gains during this period. Absent rent dissipation, automation would have raised the average real wage of US workers by about 4.5% between 1980 and 2016. Once rent dissipation is taken into account, the predicted gain falls to 0.5%.

Effects on productivity and consumption: Panel B in Table 1 reports our estimates for aggregate output, consumption and TFP. Our benchmark value for cost savings of $\pi = 30\%$, combined with the extent of automation estimated in the data, implies that automation generated a 3% increase in TFP. However, our estimate for $\mu_{\mathscr{A}_g}/\mu_g$ of 35% also means that this automation created inefficient rent dissipation. Overall, our estimates imply that automation worsened allocative efficiency by about 2.7% during this period. This inefficiency offset 90% of potential cost savings and led to a net contribution of automation to TFP of only 0.3% between 1980 and 2016.[32]

Turning to consumption, and using the formula $d\ln c = \frac{1}{s_L}\, d\ln \text{TFP}$, we estimate that automation increased aggregate consumption by about 0.46% during 1980–2016. This is smaller than the estimated increase in GDP of 14.4%, because GDP growth also includes the effects of greater investment required for producing capital equipment. Indeed, according to our estimates, automation raised the capital-output ratio by 27.9%. The increase in investment is in line with BLS data, which indicate a 30% increase in the aggregate capital stock relative to GDP.

Robustness: Table 1 also reports a number of robustness checks. Column 3 depicts estimates obtained by assuming a rate of rent dissipation of $\mu_{\mathscr{A}_g}/\mu_g = 20\%$, as opposed to our baseline estimate of 35%. The impact of rent dissipation on wages and TFP is less pronounced in this case, but it still offsets 60% of the cost savings and average wage gains from new automation between 1980 and 2016. Column 4 goes in the other direction and reports the consequences of a rate of rent dissipation of $\mu_{\mathscr{A}_g}/\mu_g = 50\%$. At this rate, we estimate that automation would have reduced average wages by 0.7%, the wages of non-college men by 9%, and the wages of non-college women by 3.3%. We also estimate that the worsening allocative efficiency due to rent dissipation would have overwhelmed the cost saving gains from automation, reducing aggregate TFP by 0.47% during 1980–2016.

Column 5 reports estimates from a specification of the Jacobians setting $\theta = 1.6 - \lambda$, $\theta_{\text{job}} = \theta_{\text{edu-age}} = 0$, which imposes a common elasticity of substitution between groups of 1.6 as in Katz and Murphy (1992). We continue to assume the baseline rate of rent dissipation of 35%. The effects of automation on wages and productivity are similar to the baseline.

Column 6 reports estimates obtained by using a larger elasticity of substitution between sectoral outputs, $\eta = 0.75$. This parameter does not affect our conclusions, in part because sectoral shifts are not a major channel via which automation affects the wage structure, as shown in Figure 10.

[32] In the data, US TFP increased by 30% over this time period. Our estimates therefore imply that almost all of this increase was due to other technologies—not due to automation. These other technologies include those that create new tasks for workers or new products for consumers, those that provide better information or tools to workers, raising their productivity in tasks already assigned to them, or improvements in capital productivity in tasks that were already automated (see Acemoglu and Restrepo, 2018).

5 Conclusion

This paper developed a framework in which labor market rents shape the consequences of automation. Our main insight is that firms tend to automate high-rent tasks first. Consequently, compared to a competitive benchmark, automation amplifies wage declines for exposed groups, reduces within-group wage dispersion, and can worsen allocative efficiency, offsetting much of the direct cost savings from automation and potentially lowering TFP and welfare.

Using US data, we documented that in the US data between 1980 and 2016, there is a robust pattern indicating the predicted U-shaped within-group wage response and a reallocation of workers away from high-rent jobs. A quantitative exercise exploiting the structure of our theoretical framework implies that automation, overall, explains 52% of the rise in between-group inequality since 1980, but only 42 percentage point of this is driven by competitive forces, with the remaining 10 percentage points being accounted for by rent dissipation. The efficiency losses from rent dissipation offset nearly all of the cost savings from automation, leaving close to zero gains in TFP, average wages, and consumption due to automation since the 1980s.

Our analysis centers on the interplay between automation and labor market rents. There are several interesting areas for future work, including: (i) how automation interacts with other distortions, such as monopsony, product market power, financial frictions and investment taxes/subsidies (see, for example, Acemoglu et al., 2020); (ii) how other shocks, such as outsourcing, international trade, and immigration, reshape the wage structure—not only through competitive labor demand channels but also via rent dissipation, which can be analyzed using our theoretical framework; (iii) how matched employer-employee data, together with information on technology adoption, balance sheets, and product and labor market power of firms, can be leveraged to test additional implications of automation in the presence of labor market distortions; and (iv) how labor market institutions and imperfections shape firms' incentives to adopt different types of technologies, beyond automation, including those introducing new tasks and collaborative tools for workers.

Appendix: Proofs of Propositions 1–5

We first provide a lemma characterizing the Jacobian of task shares.

Lemma 1 *Let $\Sigma = \mathbb{1} - \frac{1}{\lambda}\frac{\partial \ln \Gamma(w)}{\partial \ln w}$. For all $w > 0$, the matrix Σ is non-singular. Moreover, Σ is a $P-$matrix of the Leontief type (meaning that it has non-positive off-diagonal entries)* *and has a well-defined inverse Θ whose entries are all non-negative.*

PROOF. Assumption 1 ensures that task shares are a continuous and differentiable function of wages. We now establish the properties of Σ.

First, because $\partial\Gamma_g/\partial w_{g'} \geq 0$ for $g' \neq g$, Σ is a $Z-$matrix (it has negative off diagonals).

Second, Σ has a positive dominant diagonal. This follows from the fact that $\Sigma_{gg} = 1 - \frac{1}{\lambda}\frac{\partial \ln \Gamma_g}{\partial \ln w_g} > 0$, and $\Sigma_{gg} - \sum_{g' \neq g} |\Sigma_{gg'}| = 1 - \sum_{g'} \frac{1}{\lambda}\frac{\partial \ln \Gamma_g}{\partial \ln w_{g'}} > 1$. This last inequality follows from $\sum_{g'} \frac{\partial \ln \Gamma_g}{\partial \ln w_{g'}} \leq 0$: 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 real parts that exceed 1. This follows from Gershgorin's circle theorem: for each eigenvalue e of Σ, we can find a dimension g such that $\|e - \Sigma_{gg}\| < \sum_{g' \neq g} |\Sigma_{gg'}|$. This inequality implies $\Re(e) \in \left[\Sigma_{gg} - \sum_{g' \neq g} |\Sigma_{gg'}|, \Sigma_{gg} + \sum_{g' \neq g} |\Sigma_{gg'}|\right]$. Because $\Sigma_{gg} - \sum_{g' \neq g} |\Sigma_{gg'}| > 1$ for all g, all eigenvalues of Σ have real parts greater than 1.

Fourth, since Σ is a $Z-$matrix whose eigenvalues have positive real part, it is also an $M-$matrix and a $P-$matrix of the Leontief type. The inverse of such matrices exists and has non-negative real entries, $\theta_{gg'} \geq 0$. ∎

Proof of Proposition 1. We first prove that equilibrium wages and output solve (1) and (2). Task level demands for capital and labor described are: $\ell_{gx} = y \, \frac{1}{M} \, \psi_{gx}^{\lambda-1} \, (w_g \, \mu_{gx})^{-\lambda}$ for $x \in \mathcal{T}_g$ and $k_x = y \, \frac{1}{M} \, \psi_{kx}^{\lambda-1} \, q_x^{\lambda}$ for $x \in \mathcal{T}_k$ Aggregating the labor demand equation over tasks in $\mathcal{T}_g(w)$, we obtain $\ell_g = y \, \Gamma_g(w) \, w_g^{-\lambda}$. This can be rewritten as the market clearing condition in (1). Likewise, using the definitions of $\Gamma_g(w)$, $\Gamma_k(w)$, and $\mu_g(w)$, we can re-write E5 as (2).

To establish that (1) and (2) admit a unique solution, we first prove that, given a level for output y, there is a unique set of wages $\{w_g(y)\}_{g\in\mathbb{G}}$ that satisfies the market clearing conditions in (1). We then show there is a unique level of output that satisfies (2) (evaluated at $\{w_g(y)\}_{g\in\mathbb{G}}$).

For the first step, Assumption 1 implies that $\Gamma_g(w)$ lies in a compact set $[\underline{\Gamma}, \bar{\Gamma}]$. Then note that $\mathbb{T} : w \to (\mathbb{T}w_1, \ldots, \mathbb{T}w_G)'$ defined by $\mathbb{T}w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \, \Gamma_g(w)^{\frac{1}{\lambda}}$ for $g = 1, 2, \ldots, G$ is a continuous mapping from the compact convex set $\mathbb{X} = \prod_{g=1}^{G} [(y/\ell_g)^{\frac{1}{\lambda}} \, \underline{\Gamma}^{\frac{1}{\lambda}}, (y/\ell_g)^{\frac{1}{\lambda}} \, \bar{\Gamma}^{\frac{1}{\lambda}}]$ onto itself. The existence of a positive wage vector $\{w_g(y)\}_{g\in\mathbb{G}}$ solving this fixed point problem follows from Brouwer's fixed point theorem.

We now turn to uniqueness of $\{w_g(y)\}_{g\in\mathbb{G}}$. Rewrite the system of equations $\{w_g(y)\}_{g\in\mathbb{G}}$ defining $\{w_g(y)\}_{g\in\mathbb{G}}$ in logs as $F(x) = \frac{1}{\lambda} \, \text{stack}(\ln y - \ln \ell_j)$, where $x = (\ln w_1, \ldots, \ln w_G)$ and $F(x) = (f_1(x), \ldots, f_G(x))$ with $f_g(x) = x_g - \frac{1}{\lambda} \, \ln \Gamma_g(x)$. The Jacobian of F is given by

Σ, which is an M−matrix and thus a P−matrix of the Leontief type. Theorem 5 from Gale and Nikaido (1965) implies that the solution to the system $F(x) = a$ is unique if the Jacobian of F is a P−matrix of the Leontief type. The theorem also shows that the unique solution $x(a)$ is increasing in a. As a result, the unique solution to the system of equations in (1) is$\{w_g(y)\}_{g\in\mathbb{G}}$ and each $w_g(y)$ is strictly increasing in y. We also note that $(y/\ell_g)^{1/\lambda}\ \underline{\Gamma}^{1/\lambda} \leq w_g(y) \leq (y/\ell_g)^{1/\lambda}\ \bar{\Gamma}^{1/\lambda}$, so that $w_g(y) \to \infty$ as $y \to \infty$, and $w_g(y) \to 0$ as $y \to 0$.

To conclude, we prove that there is a unique y that satisfies the ideal price index equation (2). This condition can be written as $I(y) = 1$, where

$$I(y) = \left(\frac{1}{M}\int_{\mathcal{T}}\left[\min\left\{\min_g\left\{w_g(y)\ \frac{\mu_{gx}}{\psi_{gx}}\right\}, \frac{1}{q_x\ \psi_{kx}}\right\}\right]^{1-\lambda} dx\right)^{1/(1-\lambda)}.$$

Because wages are strictly increasing in y, $I(y)$ increases in y. Assumption 1 also ensures that a positive measure of tasks must be allocated to labor at any wage level, which implies that $I(y)$ is strictly increasing in y. The function $I(y)$ can then be written as $I(y) = \left(\Gamma_k(w(y)) + \sum_g \Gamma_g(w(y))\ \mu_g(w(y))\ w_g(y)^{1-\lambda}\right)^{1/(1-\lambda)}$. As $y \to \infty$, $\Gamma_g(w)\ \mu_g(w)\ w_g(y)^{1-\lambda} \to \infty$ (since $\Gamma_g(w)$ is bounded from below, $\mu_g(w) \geq 1$, and $\lambda < 1$) and $\Gamma_k(w(y)) \geq 0$. This implies $I(y) \to \infty$. Moreover, as $y \to 0$, $\Gamma_g(w)\ \mu_g(w)\ w_g(y)^{1-\lambda} \to 0$ (since $\Gamma_g(w)$ and $\mu_g(w)$ are bounded from above and $\lambda < 1$) and $\Gamma_k(w(y)) = 0$ (since, by Assumption 1, all tasks can be produced by at least one type of worker). Hence, $I(y) \to 0$. Because $I(y)$ is strictly increasing in y, there is a unique $y \in (0, \infty)$ for which $I(y) = 1$ and, therefore, a unique equilibrium with wages $w_g = w_g(y)$. The equilibrium wages and the tie-breaking rule for tasks where there is indifference uniquely determine equilibrium task allocation.

Our argument for uniqueness also establishes that, under Assumption 1, the unique equilibrium features finite output, positive wages, and positive task shares for all workers. Moreover, from $I(y) = 1$, we obtain that, in equilibrium, $1 - \Gamma_k > 0$. ■

Proof of Proposition 2.

Starting at the equilibrium allocation, consider the reallocation of a mass $\epsilon > 0$ of g workers from task x to task x' where both x and x' are in $\mathcal{T}_g$ and $\mu_{gx'} > \mu_{gx}$. This perturbation raises aggregate output and consumption by $[p_{x'}\ \psi_{gx'} - p_x\ \psi_{gx} = w_g\ (\mu_{gx'} - \mu_{gx})] \cdot \epsilon > 0$. This establishes that there is underemployment and high-rents tasks.

We now show that tasks x that satisfy (3) are inefficiently automated. The right-hand side of the inequality implies that these tasks are automated in equilibrium. Starting at the equilibrium allocation, reallocate a mass $\epsilon > 0$ of g workers drawn proportionally from tasks in $\mathcal{T}_g$ to task x. This perturbation raises aggregate output and consumption by $\left[p_x\,\psi_{gx} - \int_{\mathcal{T}_g} p_x\,\psi_{gx}\,\frac{\ell_{gx}}{\ell_g}\,dx\right]\cdot\epsilon = \left[\frac{\psi_{gx}}{q_x\,\psi_{kx}} - w_g\,\mu_g\right]\cdot\epsilon > 0$, establishing the claim. ■

Proof of Proposition 3. Let $f_g(.\mid\mathcal{S})$ be the derivative of $F_g(.\mid\mathcal{S})$. We first establish an intermediate inequality, proving that for all ϱ and $\mu \geq 1$, we have

$$\frac{\int_{\max\{\mu,\varrho\}}^{\infty} f_g(u|\mathscr{A}_g^T)\,du}{\int_{\max\{1,\varrho\}}^{\infty} f_g(u|\mathscr{A}_g^T)\,du} \geq \frac{\int_{\mu}^{\infty} f_g(u|\mathscr{A}_g^T)\,du}{\int_{1}^{\infty} f_g(u|\mathscr{A}_g^T)\,du}, \tag{25}$$

with strict inequality if $\varrho, \mu > 1$. This can be done by considering three possible cases:

1. When $\varrho \leq 1$ both sides in (25) are equal to 1.
2. When $\varrho \in (1,\mu]$, (25) becomes

$$\frac{\int_{\mu}^{\infty} f_g(u|\mathscr{A}_g^T)\,du}{\int_{\varrho}^{\infty} f_g(u|\mathscr{A}_g^T)\,du} > \frac{\int_{\mu}^{\infty} f_g(u|\mathscr{A}_g^T)\,du}{\int_{1}^{\infty} f_g(u|\mathscr{A}_g^T)\,du} \Leftrightarrow \int_{1}^{\infty} f_g(u|\mathscr{A}_g^T)\,du > \int_{\varrho}^{\infty} f_g(u|\mathscr{A}_g^T)\,du,$$

which holds as a strict inequality for $\varrho > 1$.

3. Finally, when $\varrho > \mu$, (25) becomes

$$1 > \frac{\int_{\mu}^{\infty} f_g(u|\mathscr{A}_g^T)\,du}{\int_{1}^{\infty} f_g(u|\mathscr{A}_g^T)\,du} \Leftrightarrow \int_{1}^{\infty} f_g(u|\mathscr{A}_g^T)\,du > \int_{\mu}^{\infty} f_g(u|\mathscr{A}_g^T)\,du,$$

which holds as a strict inequality for $\mu > 1$.

Let $\varrho_{gx} = \frac{1}{w_g}\,\frac{\psi_{gx}}{q'\,\psi_{kx}}$. For any set $\mathcal{S} \subseteq \mathcal{T}$, define the cdf of ϱ_{gx} in $\mathcal{S}$ by $H(\varrho|\mathcal{S}) = \int_{\mathcal{S}\cap\{x:\frac{1}{w_g}\,\frac{\psi_{gx}}{q'_x\,\psi_{kx}}\leq\varrho\}} dx / \int_{\mathcal{S}} dx$ and denote its probability density function by $h(\varrho|\mathcal{S})$.

For all $\mu \geq 1$, we have

$$F_g(\mu|\mathscr{A}_g^T) = \frac{\int_{\varrho}\int_{\mu}^{\infty} f_g(u|\varrho,\mathscr{A}_g^T)\,h(\varrho|\mathscr{A}_g^T)\,du\,d\varrho}{\int_{\varrho}\int_{1}^{\infty} f_g(u|\varrho,\mathscr{A}_g^T)\,h(\varrho|\mathscr{A}_g^T)\,du\,d\varrho} = \frac{\int_{\mu}^{\infty} f_g(u|\mathscr{A}_g^T)\,du}{\int_{1}^{\infty} f_g(u|\mathscr{A}_g^T)\,du},$$

where the last equality follows from condition (ii), which ensures that μ_{gx} is independent from ϱ_{gx} inside of $\mathcal{A}_g^T$, and so $f_g(u|\varrho,\mathscr{A}_g^T) = f_g(u|\mathscr{A}_g^T)$

Turning to $F_g(\mu|\mathscr{A}_g)$, we have

$$F_g(\mu|\mathscr{A}_g) = \frac{\int_\varrho \int_{\max\{\mu,\varrho\}}^\infty f_g(u|\varrho,\mathscr{A}_g^T)\, h(\varrho|\mathscr{A}_g^T)\, du\, d\varrho}{\int_\varrho \int_{\max\{1,\varrho\}}^\infty f_g(u|\varrho,\mathscr{A}_g^T)\, h(\varrho|\mathscr{A}_g^T)\, du\, d\varrho}.$$

Here, the numerator accounts for the fact that only tasks for which $\mu_{gx} \geq \varrho_{gx}$ will be automated. Using condition (ii) once more, we can write this as

$$F_g(\mu|\mathscr{A}_g) = \frac{\int_\varrho \int_{\max\{\mu,\varrho\}}^\infty f_g(u|\mathscr{A}_g^T)\, h(\varrho|\mathscr{A}_g^T)\, du\, d\varrho}{\int_\varrho \int_{\max\{1,\varrho\}}^\infty f_g(u|\mathscr{A}_g^T)\, h(\varrho|\mathscr{A}_g^T)\, du\, d\varrho}.$$

To conclude the proof, re-write (25) as $\int_{\max\{\mu,\varrho\}}^\infty f_g(u|\mathscr{A}_g^T)\, du \geq F_g(\mu|\mathscr{A}_g^T)\ \int_{\max\{1,\varrho\}}^\infty \bar{f}_g(u|\mathscr{A}_g^T)\, du$. Integrating over ρ in $\mathscr{A}_g^T$, we get

$$\int_\varrho \int_{\max\{\mu,\varrho\}\}}^\infty f_g(u|\mathscr{A}_g^T)\, h(\varrho|\mathscr{A}_g^T)\, du\, d\varrho$$
$$> F_g(\mu|\mathscr{A}_g^T)\ \int_\varrho \int_{\max\{1,\varrho(\varrho)\}}^\infty f_g(u|\mathscr{A}_g^T)\, h(\varrho|\mathscr{A}_g^T)\, du\, d\varrho.$$

The inequality is strict because not all tasks in $\mathscr{A}_g^T$ are automated, which means that $\varrho > 1$ for a positive measure of tasks in $\mathscr{A}_g^T$ for which (25) holds with strict inequality. This inequality can be rearranged as $F_g(\mu|\mathscr{A}_g) > F_g(\mu|\mathscr{A}_g^T)$. From condition (i), it follows that $F_g(\mu|\mathscr{A}_g) > F_g(\mu|\mathcal{T}_g)$, as desired. ■

Proof of Proposition 4. We have $\ln w_g(p) = \ln w_g + \ln \mu_g(p)$, where $\mu_g(p)$ is the p–th quantile of the rent distribution in group g. This implies $\Delta \ln w_g(p) = \Delta \ln w_g + \Delta \ln \mu_g(p)$. We now show that $\Delta \ln \mu_g(p) = 0$ at the bottom, $\Delta \ln \mu_g(p) < 0$ at the top, and $\Delta \ln \mu_g(p) \leq 0$ (possibly with equality) at the very top.

The automation of tasks in $\mathscr{A}_g$ shifts the distribution of rents for workers in group g from $F_g(\mu|\mathcal{T}_g)$ to $F_g(\mu|\mathcal{T}_g \setminus \mathscr{A}_g)$. Consider the old quantile functions for rents in $\mathcal{T}_g$, denoted by $\ln \mu_g(p)$ and the new quantile function for rents in $\mathcal{T}_g \setminus \mathscr{A}_g$, denoted by $\ln \mu_{g,\text{new}}(p)$. Because $F_g(\mu|\mathscr{A}_g) > F_g(\mu|\mathcal{T}_g)$, the distribution of rents in $\mathcal{T}_g$ dominates their new distribution in $\mathcal{T}_g \setminus \mathscr{A}_g$, in the first order stochastic sense.

Below M_g, both quantile functions equal 0, since the share of workers earning no rents in $\mathcal{T}_g \setminus \mathscr{A}_g$ is greater than or equal to the share of workers earning no rents in $\mathcal{T}_g$. This shows that $\Delta \ln \mu_g(p) = \ln \mu_{g,\text{new}}(p) - \ln \mu_g(p) = 0$ for $p \in [0, M_g]$.

First-order stochastic dominance also implies that the quantile function for rents in

$\mathcal{T}_g \setminus \mathscr{A}_g$ is strictly below the quantile function for rents in $\mathcal{T}_g$ for all $\mu > 1$. This shows that $\Delta \ln \mu_g(p) = \ln \mu_{g,\text{new}}(p) - \ln \mu_g(p) < 0$ for all $p \in (M_g, 1)$.

To conclude, we characterize the behavior of $\Delta \ln \mu_g(p)$ as $p \to 1$ when not all high-rent tasks can be automated. Initially, $\lim_{p\to 1} \ln \mu_g(p) = \ln \bar{\mu}_g$, where $\bar{\mu}_g < \infty$ is the supremum of rents earned by group g workers (recall that by assumption these are bounded). Moreover, for $p = 1 - \epsilon$, we had a mass ϵ of workers earning a rent above $\ln \mu_g^{1-\epsilon}$. Of these, a fraction δ still earns a rent above $\ln \mu_g(p)$ after all tasks in $\mathscr{A}_g$ are automated. This implies $\ln \mu_g^{1-\epsilon} \leq \ln \mu_{g,\text{new}}^{1-\epsilon\,\delta} \leq \ln \bar{\mu}_g$. Taking limits as $\epsilon \to 0$, we obtain $\lim_{p\to 1} \ln \mu_{g,\text{new}}(p) = \ln \bar{\mu}_g$. Finally, note that Assumption 2 is sufficient to ensure that $p \to 1$ when not all high-rent tasks can be automated, hence the desired conclusion follows. ■

Proof of Proposition 5. Consider a small interior set of new automation technologies given by $\{\mathscr{A}_g^T\}_{g\in\mathbb{G}}$.

Derivation of equation (5): Recall that $\ln \Gamma_g(w) = \ln\left(\frac{1}{M}\int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1}\ \mu_{gx}^{-\lambda}\ dx\right)$ Totally differentiating (using our notion of total derivatives), we obtain

$$d \ln \Gamma_g = -\underbrace{\frac{\int_{\mathcal{A}_g} \psi_{gx}^{\lambda-1}\ \mu_{gx}^{-\lambda}\ dx}{\int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1}\ \mu_{gx}^{-\lambda}\ dx}}_{\delta_g} + \frac{\partial \ln \Gamma_g(w)}{\partial \ln w}\,\text{stack}(d\ln w_j).$$

Taking logs in (1), totally differentiating, and using this formula for $d\ln\Gamma_g$, yields

$$d\ln w_g = \frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_g + \frac{1}{\lambda}\,\frac{\partial \ln \Gamma_g(w)}{\partial \ln w}\,\text{stack}(d\ln w_j).$$

Lemma 1 implies that this system has the unique solution as in equation (5): $d\ln w_g = \Theta_g\,\text{stack}\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_j\right)$.

Derivation of equation (6): We use the final good price index. Let

$$\mathcal{C}(\{\Gamma_g(w)\}_{g\in\mathbb{G}}, \Gamma_k(w), w) = \left(\Gamma_k(w) + \sum_g \Gamma_g(w)\,\mu_g(w)\,w_g^{1-\lambda}\right)^{1/(1-\lambda)}.$$

Totally differentiating this relationship:

$$d\ln\mathcal{C} = \frac{1}{1-\lambda}\,\frac{1}{\mathcal{C}}\,\sum_g \frac{1}{M}\int_{\mathscr{A}_g}\left[(q_x'\,\psi_{kx})^{\lambda-1} - (\psi_{gx}/\mu_{gx})^{\lambda-1}\,{w_g}^{1-\lambda}\right]dx \;+\; \sum_g s_g\,d\ln w_g,$$

where the last term is from Shephards' lemma, $\frac{\partial \ln C}{\partial \ln w_g} = s_g$, where s_g is the share of group g in total labor income.

To derive (6), use the fact that $\mathcal{C} = 1$ in equilibrium, which implies $d \ln \mathcal{C} = 0$ and thus

$$\sum_g s_g \, d \ln w_g = \frac{1}{\lambda - 1} \sum_g \frac{1}{M} \int_{\mathscr{A}_g} \left[(q'_x \, \psi_{kx})^{\lambda-1} - (\psi_{gx}/\mu_{gx})^{\lambda-1} \, w_g{}^{1-\lambda} \right] dx$$
$$= \sum_g s_g \, \delta_g \, \frac{\mu_{\mathscr{A}_g}}{\mu_g} \underbrace{\frac{\frac{1}{M} \int_{\mathscr{A}_g} (\psi_{gx}/\mu_{gx})^{\lambda-1} \, \frac{1}{\lambda-1} \left[\left(\frac{q'_x \, \psi_{kx} \, w_g \, \mu_{gx}}{\psi_{gx}} \right)^{\lambda-1} - 1 \right] dx}{\frac{1}{M} \int_{\mathscr{A}_g} (\psi_{gx}/\mu_{gx})^{\lambda-1} \, dx}}_{\pi_g}.$$

Derivation of equation (7)*:* Recall that

$$\ln \mu_g(x) = \ln \Big(\int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{1-\lambda} \, dx \Big) - \ln \Big(\int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{-\lambda} \, dx \Big).$$

Totally differentiating yields

$$d \ln \mu_g = \underbrace{- \frac{\int_{\mathcal{A}_g} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{1-\lambda} \, dx}{\int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{1-\lambda} \, dx} + \frac{\int_{\mathcal{A}_g} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{-\lambda} \, dx}{\int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{-\lambda} \, dx}}_{-\left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1 \right) \delta_g} + \frac{\partial \ln \mu_g(w)}{\partial \ln w} \, \text{stack}(d \ln w).$$

Substituting the expression for the change in base wages in (5), this becomes

$$d \ln \mu_g = - \left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1 \right) \delta_g + \mathcal{M}_g \, \text{stack} \left(\frac{1}{\lambda} \, d \ln y - \frac{1}{\lambda} \, \delta_j \right).$$

Derivation of equation (8)*:* We first prove the dual of the Solow residual. Because all income accrues to capital and labor, we have $y = \sum_g \bar{w}_g \, \ell_g + k$. Total differentiation yields

$$d \ln y = s_k \, d \ln k + \sum_g s_g \, d \ln \bar{w}_g \quad \Rightarrow \underbrace{d \ln y - s_k \, d \ln k}_{\equiv d \ln \text{TFP}} = \sum_g s_g \, d \ln \bar{w}_g.$$

From this we obtain the dual Solow residual: $d \ln \text{TFP} = \sum_g s_g \, d \ln w_g + \sum_g s_g \, d \ln \mu_g$. Substituting the formula for $\sum_g s_g \, d \ln w_g$ into equation (6) yields equation (8) in the proposition, as desired.

Turning to consumption, we have $c = y - k$, and therefore $d \ln c = (1/c) \, (dy - dk) = (1/s^L) \, (d \ln y - (k/y) d \ln k) = (1/s^L) \, d \ln \text{TFP}$. The last step uses the fact that $s_L = c/y$. ■

Finally, we note that our characterization of the equilibrium effects of automation uses a technical lemma, proven in the Supplement, which formally shows how to "totally differentiate" functions of the task space over small and interior sets. This lemma builds on and extends a similar result in Acemoglu et al. (2024). Here we only remark that with this lemma at hand, all of the differentials we use here are well-defined, though there is a second order approximation term, which is characterized in the Supplement.

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Table 1: Estimated effects of new automation technology, 1980–2016.

	Data 1980–2016	Baseline estimates	Low rent dissipation (20%)	High rent dissipation (50%)	Imposing aggregate elasticity of substitution of 1.6 between groups	Higher elasticity of substitution between industries ($\eta = 0.75$)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Wage structure:						
Change in average wages, $d\ln \bar{w}_g$	29.15%	0.456%	1.91%	-0.705%	0.497%	0.61%
Change in base wages, $d\ln w_g$	.	4.54%	4.54%	4.54%	4.54%	4.54%
Change in group rents, $d\ln \mu_g$	.	-4.08%	-2.63%	-5.24%	-4.04%	-3.92%
Wage changes for non-college men	-6.5%	-8.0%	-6.8%	-9.0%	-6.9%	-6.5%
- base wage changes		-2.4%	-3.2%	-1.7%	-1.3%	-0.9%
- rent dissipation		-5.6%	-3.6%	-7.3%	-5.6%	-5.4%
Wage changes for non-college women	10.6%	-2.2%	-0.8%	-3.3%	-1.5%	-2.6%
- base wage changes		2.4%	2.1%	2.6%	3.0%	1.9%
- rent dissipation		-4.6%	-2.9%	-5.9%	-4.6%	-4.5%
Between-group wage changes explained						
-due to changes in industry composition		6.72%	7.30%	6.26%	5.92%	-4.76%
-adding direct displacement effects		63.49%	71.16%	57.35%	62.68%	52.00%
-accounting for ripple effects		41.79%	46.84%	37.75%	35.08%	34.23%
-accounting for rent dissipation		51.87%	53.38%	50.66%	45.39%	44.13%
Panel B. Aggregates:						
Change in GDP per capita, $d\ln y$	70%	14.41%	15.90%	13.22%	14.50%	14.02%
Change in TFP, $d\ln \text{TFP}$	35%	0.304%	1.27%	-0.47%	0.331%	0.41%
-cost-saving gains		3.02%	3.02%	3.02%	3.02%	3.02%
-changes in allocative efficiency		-2.72%	-1.75%	-3.49%	-2.69%	-2.61%
-inefficient rent dissipation		-2.70%	-1.73%	-3.47%	-2.7%	-2.7%
Change in consumption, $d\ln c$	70%	0.456%	1.91%	-0.705%	0.497%	0.61%
Change in k/y ratio	30.0%	27.9%	28.0%	27.8%	28.0%	26.8%

Notes: This table summarizes the estimated effects of automation on group wages and aggregates from 1980 to 2016. The estimates are computed using the formulas in Proposition 6. Column 1 reports data for the US for comparison. The wage data is from the US Census and the ACS. The data on GDP and capital are from the BLS. The data on consumption is from the BEA and the data for TFP is from Fernald (2014). Column 2 provides our baseline estimates. Column 3 assumes a lower rate of rent dissipation of 20%. Column 4 assumes a higher rate of rent dissipation of 50%. Column 5 assumes $\theta = 1.6 - \lambda$ and sets $\theta_{\text{job}} = \theta_{\text{edu-age}} = 0$, imposing an aggregate elasticity of substitution between worker groups of 1.6. Column 6 uses the baseline specification from Column 2 but sets the elasticity of substitution between industries η to 0.75.

Supplementary Materials for "Automation and Rent Dissipation"

Daron Acemoglu and Pascual Restrepo

S1 Proofs and details for the multi-sector model.

Throughout this appendix, we maintain Assumption 1.

S1.1 Description of multi-sector model and preliminaries

Description: There are multiple sectors indexed by $i \in \mathbb{I}$ (where $\mathbb{I}$ denotes the set of sectors). Sectoral production functions are given by

$$y_i = \left(\frac{1}{M_i} \int_{\mathcal{T}_i} (M_i \, y_x)^{\frac{\lambda-1}{\lambda}} \, dx \right)^{\lambda/(\lambda-1)}.$$

The sets of tasks across sectors $\{\mathcal{T}_i\}_{i\in\mathbb{I}}$ are sector-specific, which is without loss of generality since tasks can be relabeled.

Sectoral outputs are combined into a final good that can be used for consumption or to build productive capital. The transformation of sectoral output into the final good y is described by a CES production function with an elasticity of substitution $\eta > 0$:

$$y = \left(\sum_i \alpha_i^{\frac{1}{\eta}} \, y_i^{\frac{\eta-1}{\eta}} \, dx \right)^{\eta/(\eta-1)}.$$

We denote sectoral prices by $\{p_i\}_{i\in\mathbb{I}}$ and normalize the price of the final good to 1.

The total quantity produced of task x is

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

Here, ℓ_{gx} is the amount of labor of type g allocated to task x, while k_x is the amount of task-specific capital used for this task.

A fixed supply ℓ_g of workers of type g is allocated across tasks and industries, so that

$$\sum_i \int_{\mathcal{T}_i} \ell_{gx} \, dx \le \ell_g.$$

We treat task-specific capital, $\{k_x\}_{x\in\mathcal{T}}$, as intermediate goods. They are produced within the same period using the final good at a constant unit cost $1/q_x$. If $q_x = 0$, task x cannot be performed by capital. This implies that total consumption equals net output:

$$c = y - \sum_i \int_{\mathcal{T}_i} (k_x/q_x)\, dx.$$

As in the single-sector model, we assume there are task specific rents μ_{gx}.

A *market equilibrium* is given by a vector of base wages $\{w_g\}$, output y, sectoral prices p_i, an allocation of tasks $\{\mathcal{T}_{gi}\}_{i,g}, \{\mathcal{T}_{ki}\}_i$, task prices p_x, hiring plans ℓ_{gx}, and capital production plans k_x such that:

E1' Tasks prices equal the minimum unit cost of producing the task

$$p_x = \min\left\{\frac{1}{q_x\, \psi_{kx}}, \left\{w_g\, \frac{\mu_{gx}}{\psi_{gx}}\right\}_g\right\}.$$

E2' Tasks are allocated in a cost-minimizing way. The set of tasks

$$\mathcal{T}_{gi} = \left\{x \in \mathcal{T}_i : p_x = w_g\, \frac{\mu_{gx}}{\psi_{gx}}\right\}$$

will be produced by workers of type g, and the set of tasks

$$\mathcal{T}_{ik} = \left\{x \in \mathcal{T}_i : p_x = \frac{1}{q_x\, \psi_{kx}}\right\}$$

will be produced by capital.

E3' Task-level demands for labor and capital are given by

$$\ell_{gx} = y\, s_{y_i}\, p_i^{\lambda-1}\, \frac{1}{M_i}\, \psi_{gx}^{\lambda-1}\, (w_g\, \mu_{gx})^{-\lambda} \text{ for } x \in \mathcal{T}_{gi},$$
$$k_x = y\, s_{y_i}\, p_i^{\lambda-1}\, \frac{1}{M_i}\, \psi_{kx}^{\lambda-1}\, q_x^{\lambda} \qquad \text{for } x \in \mathcal{T}_{ki}.$$

Here $s_{y_i} = \alpha_i\, p_i^{1-\eta}$ is the share of industry i in output.

E4' Sectoral prices are given by

$$p_i = \left(\frac{1}{M_i} \int_{\mathcal{T}_i} p_x^{1-\lambda}\, dx\right)^{1/(1-\lambda)}$$

E5' The ideal-price index condition holds

$$1 = \left(\sum_i \alpha_i \, p_i^{1-\eta} \right)^{1/(1-\eta)}.$$

Remark: For completeness, we explain how to derive equilibrium conditions E3' and E4'. The production of the final good is perfectly competitive, and so tasks are priced at their marginal product. This implies $p_x = p_i \, M_i^{-\frac{1}{\lambda}} \, (y_i/y_x)^{\frac{1}{\lambda}}$, which can be rearranged as

$$y_x = \frac{1}{M_i} \, y \, s_{y_i} \, p_i^{\lambda-1} \, p_x^{-\lambda}. \tag{S1}$$

For tasks in $\mathcal{T}_g$, equation (S1) implies

$$\ell_{gx} \, \psi_{gx} = \frac{1}{M_i} \, y \, s_{y_i} \, p_i^{\lambda-1} \left(w_g \, \frac{\mu_{gx}}{\psi_{gx}} \right)^{-\lambda},$$

which can be rearranged into the labor demand equation in E3'.

For tasks in $\mathcal{T}_k$, equation (S1) implies

$$k_x \, \psi_{kx} = \frac{1}{M_i} \, y \, s_{y_i} \, p_i^{\lambda-1} \left(\frac{1}{q_x \, \psi_{kx}} \right)^{-\lambda},$$

which can be rearranged into the capital demand equation in E3'.

Finally, multiplying equation (S1) by p_x and integrating over $\mathcal{T}_i$ yields

$$s_{y_i} \, y = \int_{\mathcal{T}_i} p_x \, y_x \, dx = \frac{1}{M_i} \, s_{y_i} \, y \, p_i^{\lambda-1} \int_{\mathcal{T}_i} p_x^{1-\lambda} \, dx.$$

Canceling $s_{y_i} \, y$ on both sides of this equation yields the sectoral-price index condition E4'.

Equilibrium representation: Before deriving the effects of new automation technology, we extend the representation result in Proposition 1 to the multi-sector economy. As in the single-sector economy, define

$$\Gamma_{gi}(w) = \frac{1}{M_i} \int_{\mathcal{T}_{gi}(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{-\lambda} \, dx \text{ for each } g \in \mathbb{G} \text{ and } i \in \mathbb{I},$$

$$\Gamma_{ki}(w) = \frac{1}{M_i} \int_{\mathcal{T}_{ki}(w)} (\psi_{kx} \, q_x)^{\lambda-1} \, dx \text{ for each } i \in \mathbb{I}.$$

The integrals are computed over the set of tasks in industry i allocated to different groups and capital when base wages are w, denoted by $\mathcal{T}_{gi}(w)$ and $\mathcal{T}_{ki}(w)$. In addition, define

$$\mu_{gi}(w) = \frac{1}{M_i \, \Gamma_{gi}(w)} \int_{\mathcal{T}_{gi}(w)} \psi_{gx}^{\lambda-1} \, \mu_{gx}^{1-\lambda} \, dx \text{ for each } g \in \mathbb{G} \text{ and } i \in \mathbb{I}.$$

Proposition S1 *The equilibrium base wages $\{w_g\}$, industry prices $\{p_i\}$, and output y solve the system of equations*

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \left[\sum_i \alpha_i \, p_i^{\lambda-\eta} \, \Gamma_{gi}(w)\right]^{\frac{1}{\lambda}}, \tag{S2}$$

$$p_i = \left(\Gamma_{ki}(w) + \sum_g \Gamma_{gi}(w) \, \mu_g(w) \, w_g^{1-\lambda}\right)^{1/(1-\lambda)}, \tag{S3}$$

$$1 = \left(\sum_i \alpha_i p_i^{1-\eta}\right)^{1/(1-\eta)}. \tag{S4}$$

Proof of Proposition S1. Aggregating the labor demand equation in E3' over tasks in $\mathcal{T}_{gi}$ for all industries, we obtain

$$\ell_g = y \left[\sum_i \alpha_i \, p_i^{\lambda-\eta} \, \Gamma_{gi}(w)\right] w_g^{-\lambda}.$$

This can be rewritten as (S2).

Equation E4' implies that sectoral prices satisfy

$$p_i = \left(\frac{1}{M_i} \int_{\mathcal{T}_i} p_x^{1-\lambda} \, dx\right)^{\frac{1}{1-\lambda}} = \left(\Gamma_{ki}(w) + \sum_g \Gamma_{gi}(w) \, \mu_{gi}(w) \, w_g^{1-\lambda}\right)^{\frac{1}{1-\lambda}}.$$

Finally, equation E5' is the same as (S4). ∎

S1.2 Effects of new automation technologies

Our derivations on the equilibrium effects of automation use the next technical lemma, proven in the Supplement. The lemma shows how to "totally differentiate" functions of the task space, after advances in automation over small and interior sets. This builds on the treatment by Acemoglu et al. (2024).

Lemma S1 *Suppose $\mathcal{T}$ is a subset of $\mathbb{R}^d$ with $d \geq 2$, $\mathscr{A}_{gi}^T$ is in the interior of $\mathcal{T}_{gi}$, and:*

1. *The d—dimensional sets* $\mathscr{A}_{gi}^T$ *are measurable and have measure* $\mathcal{O}(\epsilon)$.

2. *The* $d-1$*—dimensional hyper-surfaces*

$$\mathcal{B}_{gi}(w_g) = \left\{ x \in \mathscr{A}_{gi}^T : \frac{w_g\, \mu_{gx}}{\psi_{gx}} = \frac{1}{q'_x\, \psi_{kx}} \right\}$$

are smooth, measurable, and have surface area $\mathcal{O}(\epsilon^{1-1/d})$ *for all* g.

3. *The rate of change in* $\mathcal{B}_{gi}(w_g)$ *is bounded from above by* $\bar{D}$. *That is:*

$$D_{gi}(x) = \lim_{h\to 0} \frac{1}{h} \min_{x' \in \mathcal{B}_{gi}(w_g+h)} \|x - x'\| < \bar{D} \text{ for all } x \in \mathcal{B}_{gi}(w_g).$$

Suppose also the equilibrium is locally unique. Then:

i *The change in equilibrium wages* $d\boldsymbol{w}$ *and sectoral prices* $d\boldsymbol{p}$ *from these automation technologies is* $\mathcal{O}(\epsilon)$.

ii *Let* $\Lambda_{gi}(w) = \int_{\mathcal{T}_{gi}(w)} h_{xg}\, dx$, *with* h_{xg} *continuous and bounded. The total change in this function due to automation satisfies*

$$\text{Total change } \Lambda_{gi} \; = \; -\int_{\mathcal{A}_{gi}} h_{xg}\, dx \; + \; \frac{\partial \Lambda_{gi}(w)}{\partial w} \cdot d\boldsymbol{w} \; + \; o(\epsilon)$$

(i.e., the approximation error goes to zero faster than ϵ*).*

- *Let* $\Lambda_{ki}(w) = \int_{\mathcal{T}_{ki}(w)} h_{xk}\, dx$, *with* h_{xk} *continuous and bounded. The total change in this function due to automation satisfies*

$$\text{Total change } \Lambda_{ki} \; = \; \sum_g \int_{\mathcal{A}_{gi}} h'_{xk}\, dx \; + \; \frac{\partial \Lambda_{ki}(w)}{\partial w} \cdot d\boldsymbol{w} \; + \; o(\epsilon),$$

where h'_{xk} *is the new value of* h_{xk} *after the automation shock.*

iii *For any differentiable function* f, *the total change in* $f(\{\Lambda_{gi}(w)\}_{g\in\mathbb{G}, i\in\mathbb{I}}, \{\Lambda_{ki}(w)\}_{i\in\mathbb{I}}, w, p)$ *due to automation satisfies*

$$\begin{aligned} \text{Total change } f \; = & \sum_{g,i} \frac{\partial f}{\partial \Lambda_{gi}} \Big(-\int_{\mathcal{A}_{gi}} h_{xg}\, dx \; + \; \frac{\partial \Lambda_{gi}(w)}{\partial w} \cdot d\boldsymbol{w} \Big) \; + \\ & \sum_{i} \frac{\partial f}{\partial \Lambda_{ki}} \Big(\sum_g \int_{\mathcal{A}_{gi}} h'_{xk}\, dx \; + \; \frac{\partial \Lambda_{ki}(w)}{\partial w} \cdot d\boldsymbol{w} \Big) \; + \; \frac{\partial f}{\partial w} d\boldsymbol{w} \; + \; \frac{\partial f}{\partial p} d\boldsymbol{p} \; + \; o(\epsilon), \end{aligned}$$

with all partial derivatives evaluated at the initial equilibrium values.

PROOF. We first prove (i). Let ω be a vector with equilibrium wages w, industry prices p, and output y. The equilibrium of the model is defined by a set of equations of the form

$$0 = F(\omega) = H(\Lambda(w), \omega) = 0,$$

where H is a continuous and differentiable function and F has a non-singular Jacobian $\frac{\partial F}{\partial \omega}$ (we showed this explicitly for the single sector economy and assume this is the case for the multi-sector model). Here, Λ is a finite vector of functions of the form

$$\Lambda_{gi} = \int_{\mathcal{T}_{gi}(w)} h_{xg}\, dx$$

or

$$\Lambda_{ki} = \int_{\mathcal{T}_{ki}(w)} h_{xg}\, dx.$$

Following the arrival of new automation technology, the new equilibrium vector ω satisfies

$$0 = F'(w') = H(\Lambda'(w'), \omega') = 0,$$

where Λ' is the same vector of functions as before, but now re-defined as

$$\Lambda'_{gi} = \int_{\mathcal{T}'_{gi}(w)} h_{xg}\, dx$$

or

$$\Lambda'_{ki} = \int_{\mathcal{T}'_{ki}(w)} h'_{xg}\, dx,$$

where $\mathcal{T}'_{gi}(w)$ and $\mathcal{T}'_{ki}(w)$ is the task allocation obtained after the automation technology arrives at a given vector of base wages w.

Because $F(w) = F'(w')$, we have

$$H(\Lambda'(w), \omega) - H(\Lambda(w), \omega) = -\big(H(\Lambda'(w'), \omega') - H(\Lambda'(w), \omega)\big).$$

A Taylor expansion of the left side with respect to $\Lambda(w)$ yields

$$\frac{\partial H}{\partial \Lambda}\, (\Lambda'(w) - \Lambda(w)) + o(\epsilon) = F'(\omega') - F'(\omega).$$

As $\epsilon \to 0$, the left side goes to zero. Since (we assume) the equilibrium is unique, w' must converge to w, which means that $d\omega \to 0$ too.

We now show that both quantities converge to zero at the same rate, which shows that

$d\omega$ is $\mathcal{O}(\epsilon)$ as wanted. Suppose by way of contradiction this is not the case, and $\frac{\epsilon}{||dw||} \to 0$ as $\epsilon \to 0$.

A Taylor expansion of both sides, the left with respect to $\Lambda(w)$ and the right with respect to ω now yields

$$\frac{\partial H}{\partial \Lambda}\left(\Lambda'(w) - \Lambda(w)\right) + R_1 = \frac{\partial F'(\omega)}{\partial \omega}\, d\omega \;+\; R_2,$$

where dω=$\omega' - \omega$, $R_1 = o(\epsilon)$ and $R_2 = o(d\omega)$. Dividing by $||d\omega||$, we can write this as

$$\frac{\partial H}{\partial \Lambda}\,\frac{\left(\Lambda'(w) - \Lambda(w)\right)}{\epsilon}\,\frac{\epsilon}{||d\omega||} + \frac{R_1}{\epsilon}\,\frac{\epsilon}{||d\omega||} = \frac{\partial F'(\omega)}{\partial \omega}\,\frac{d\omega}{||d\omega||} \;+\; \frac{R_2}{||d\omega||}.$$

Taking limits as $\epsilon \to 0$, we obtain $0 = \frac{\partial F(\omega)}{\partial \omega}\frac{d\omega}{||d\omega||}$—a contradiction, since $\frac{\partial F(\omega)}{\partial \omega}$ is assumed non-singular. This shows that the change in all equilibrium variables is also $\mathcal{O}(\epsilon)$, as wanted.

We now turn to (ii). Let

$$\Lambda'_{gi}(w) \;=\; \int_{\mathcal{T}'_{gi}(w)} h_{xg}\, dx,$$

where $\mathcal{T}'_{gi}(w)$ is the task allocation obtained after the automation technology arrives at a given vector of base wages w. Let $w' = w + dw$ be the new equilibrium wage vector. The total change in $\Lambda_{gi}(w)$ is then

$$\Lambda'_{gi}(w') - \Lambda_{gi}(w) = \underbrace{\Lambda'_{gi}(w) - \Lambda_{gi}(w)}_{-\int_{\mathcal{A}_{gi}} h_{xg} dx} + \Lambda'_{gi}(w') - \Lambda'_{gi}(w).$$

Assumption 1 ensures that $\Lambda'_{gi}(w)$ is a continuous and differentiable function of w. Taylor's theorem implies that this can be approximated as

$$\Lambda'_{gi}(w') - \Lambda'_{gi}(w) = \frac{\partial \Lambda'_{gi}}{\partial w} d\boldsymbol{w} + o(\epsilon),$$

where we use the fact that the change in wages is $\mathcal{O}(\epsilon)$, which implies an approximation error $o(\epsilon)$.

We now show that

$$\frac{\partial \Lambda'_{gi}}{\partial w} = \frac{\partial \Lambda_{gi}}{\partial w} + \mathcal{O}(\epsilon^{1-1/d}).$$

First, observe that, because the set $\mathcal{A}_{gi}^T$ is in the interior of $\mathcal{T}_{gi}(w)$, we can write

$$\frac{\partial \Lambda'_{gi}}{\partial w} = \frac{\partial \Lambda_{gi}}{\partial w} - \frac{\partial \int_{\mathcal{A}_{gi}(w_g)} h_{xg} dx}{\partial w_g},$$

where $\mathcal{A}_{gi}(w_g)$ is the set of tasks automated when the group wage is w_g. Using Leibniz integral rule, we can write this second term as an integral over boundary tasks $B_{gi}(w_g)$:

$$\frac{\partial \Lambda'_{gi}}{\partial w} = \frac{\partial \Lambda_{gi}}{\partial w} - \int_{\mathcal{B}_{gi}(w_g)} h_{ug} \, D_{gi}(u) \, du,$$

where $D_{gi}(u) \, du$ is the induced Lebesgue measure over the hyper-surface $\mathcal{B}_{gi}(w_g)$. The claim above follows from the fact that $D_{gi}(u)$ and h_{ug} are assumed bounded and $\mathcal{B}_{gi}(w_g)$ is assumed to have measure $\mathcal{O}(\epsilon^{1-1/d})$.

We conclude that the total change in $\Lambda_{gi}(w)$ satisfies

$$\Lambda'_{gi}(w') - \Lambda_{gi}(w) = -\int_{\mathcal{A}_{gi}} h_{xg} dx + \frac{\partial \Lambda_{gi}}{\partial w} + \mathcal{O}(\epsilon^{2-1/d}) + o(\epsilon).$$

For $d \geq 2$, this also implies

$$\Lambda'_{gi}(w') - \Lambda_{gi}(w) = -\int_{\mathcal{A}_{gi}} h_{xg} dx + \frac{\partial \Lambda_{gi}}{\partial w} + o(\epsilon).$$

Following the exact same steps, we conclude that the total change in $\Lambda_{ki}(w)$ satisfies

$$\Lambda'_{ki}(w') - \Lambda_{ki}(w) = \sum_g \int_{\mathcal{A}_{gi}} h'_{xk} dx + \frac{\partial \Lambda_{ki}}{\partial w} + o(\epsilon).$$

For (iii), consider a differentiable function $f(\{\Lambda_{gi}(w)\}_{g\in\mathbb{G},i\in\mathbb{I}}, \{\Lambda_{ki}(w)\}_{i\in\mathbb{I}}, w, p)$. Let $p' = p + d\boldsymbol{p}$ be the new industry price vector. A Taylor expansion of this function shows that we can write its change as

$$\begin{aligned} f(\{\Lambda'_{gi}(w')\}_{g\in\mathbb{G},i\in\mathbb{I}}, &\{\Lambda'_{ki}(w')\}_{i\in\mathbb{I}}, w', p') \\ - f(\{\Lambda_{gi}(w)\}_{g\in\mathbb{G},i\in\mathbb{I}}, \{\Lambda_{ki}(w)\}_{i\in\mathbb{I}}, w, p) \; &= \; \sum_g \frac{\partial f}{\partial \Lambda_g} \Big(-\int_{\mathcal{A}_g} h_{xg} \, dx \; + \; \frac{\partial \Lambda_g(w)}{\partial w} \cdot d\boldsymbol{w} \Big) \\ &\quad + \; \frac{\partial f}{\partial \Lambda_k} \Big(\sum_g \int_{\mathcal{A}_g} h'_{xk} \, dx \; + \; \frac{\partial \Lambda_k(w)}{\partial w} \cdot d\boldsymbol{w} \Big) \\ &\quad + \; \frac{\partial f}{\partial w} d\boldsymbol{w} \; + \; \frac{\partial f}{\partial p} d\boldsymbol{p} + o(\epsilon). \end{aligned}$$

Here we used the fact that all differences in arguments are $\mathcal{O}(\epsilon)$, which implies an approximation error $o(\epsilon)$. ■

Motivated by the lemma, we define the total derivatives of $\Lambda_{gi}(w)$ as

$$d\Lambda_{gi} = -\int_{\mathcal{A}_{gi}} h_{xg}\, dx \;+\; \frac{\partial \Lambda_{gi}(w)}{\partial w} \cdot d\boldsymbol{w},$$

and the total derivative of $f(\{\Lambda_{gi}(w)\}_{g\in\mathbb{G},i\in\mathbb{I}}, \{\Lambda_{ki}(w)\}_{i\in\mathbb{I}}, w, p)$ via the chain rule as

$$\begin{aligned} df \;&=\; \sum_g \frac{\partial f}{\partial \Lambda_g}\left(-\int_{\mathcal{A}_g} h_{xg}\, dx \;+\; \frac{\partial \Lambda_g(w)}{\partial w}\cdot d\boldsymbol{w}\right) \\ &\quad+\; \frac{\partial f}{\partial \Lambda_k}\left(\sum_g \int_{\mathcal{A}_g} h'_{xk}\, dx \;+\; \frac{\partial \Lambda_k(w)}{\partial w}\cdot d\boldsymbol{w}\right) \;+\; \frac{\partial f}{\partial w} d\boldsymbol{w}. \end{aligned}$$

Lemma S1 shows that total derivatives give the *infinitesimal change* in the relevant equilibrium objects following an infinitesimal change in wages and task sets due to automation.

Remark 1: The dimension of the task space must be at least two. Otherwise, the advances in $\mathcal{A}^T_{gi}$ introduce a new set of marginal tasks that change substitution patterns (i.e., the Jacobian $\frac{\partial \Lambda_g(w)}{\partial w}$) in a discontinuous way. In Acemoglu and Restrepo (2022), this requirement was not needed because we assumed all tasks for which advances in automation occurred where automated, and so $\mathcal{A}^T_{gi}$ contained no marginal tasks.

Remark 2: The requirement that advances in automation are interior can be relaxed by imposing bounds on the hyper-surfaces at the intersection of $\mathscr{A}^T_{gi}$ and the initial set of boundary tasks, but this requires additional notation.

Proof of Proposition 6. Consider a small interior automation shock in $\{\mathscr{A}^T_{gi}\}_{g\in\mathbb{G},i\in\mathbb{I}}$.

Derivation of equation (16): Let

$$\Gamma_g(w,p) \;=\; \sum_i \alpha_i\, p_i^{\lambda-\eta}\, \Gamma_{gi}(w)$$

Total differentiation of this expression (in logs) yields

$$d\ln\Gamma_g \;=\; -\sum_i \frac{\ell_{gi}}{\ell_g}\,\delta_{gi} + (\lambda-\eta)\sum_i \frac{\ell_{gi}}{\ell_g}\, d\ln p_i + \frac{\partial \ln\Gamma_g(w)}{\partial \ln w}\,\text{stack}(d\ln w).$$

Taking logs in (S2), totally differentiating, and using the above expression for $d\ln\Gamma_g$ yields

$$\text{(S5)}\quad d\ln w_g = \frac{1}{\lambda}\, d\ln y + \frac{1}{\lambda}\underbrace{\left(-\sum_i \frac{\ell_{gi}}{\ell_g}\,\delta_{gi} + (\lambda-\eta)\sum_i \frac{\ell_{gi}}{\ell_g}\, d\ln p_i + \frac{\partial \ln\Gamma_g(w)}{\partial \ln w}\,\text{stack}(d\ln w)\right)}_{d\ln\Gamma_g}.$$

Lemma 1 implies that this system has the unique solution

$$\text{(S6)}\qquad d\ln w_g = \Theta_g \,\text{stack}\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\,\delta_j + \frac{1}{\lambda}\,\sum_i \frac{\ell_{ji}}{\ell_j}\,(\lambda-\eta)\, d\ln p_i\right).$$

Derivation of equation (17)*:* Equation (S3) can be written as

$$p_i = \mathcal{C}(\{\Gamma_g(w)\}_{g\in\mathbb{G}}, \Gamma_k(w), w).$$

Totally differentiating this expression in logs yields

$$d\ln p_i \;=\; \frac{1}{1-\lambda}\,\frac{1}{p_i}\,\sum_g \frac{1}{M_i}\int_{\mathscr{A}_{gi}} \left[(q_x'\,\psi_{kx})^{\lambda-1} - (\psi_{gx}/\mu_{gx})^{\lambda-1}\,{w_g}^{1-\lambda}\right] dx \;+\; \sum_g s_{gi}\, d\ln w_g.$$

The last term is from Shephards' lemma $\frac{\partial \ln C}{\partial \ln w_g} = s_{gi}$, where s_{gi} are sector i income shares.

Following the same steps in the proof of Proposition 5, the first term can be written as

$$d\ln p_i \;=\; -\sum_g s_{gi}\,\delta_{gi}\,\frac{\mu_{\mathscr{A}_{gi}}}{\mu_{gi}}\;\underbrace{\frac{\frac{1}{M_i}\int_{\mathscr{A}_{gi}}(\psi_{gx}/\mu_{gx})^{\lambda-1}\,\frac{1}{\lambda-1}\left[\left(\frac{q_x'\,\psi_{kx}\,w_g\,\mu_{gx}}{\psi_{gx}}\right)^{\lambda-1}-1\right]dx}{\frac{1}{M_i}\int_{\mathscr{A}_{gi}}(\psi_{gx}/\mu_{gx})^{\lambda-1}\,dx}}_{\pi_{gi}} \;+\; \sum_g s_{gi}\, d\ln w_g.$$

Derivation of equation (18)*:* The envelope theorem applied to the production of the final good implies

$$0 = \sum_i s_{y_i}\, d\ln p_i,$$

where s_{y_i} are sectoral shares in GDP. Substituting the expression for $d\ln p_i$ in (17) and rearranging yields

$$\sum_g s_g\, d\ln w_g = \sum_i s_{y_i}\,\sum_g s_{gi}\,\delta_{gi}\,\frac{\mu_{\mathscr{A}_{gi}}}{\mu_{gi}}\,\pi_{gi}.$$

Derivation of equation (19)*:* In the multi-sector economy, average rents are given by

$$\ln\mu_g(w,p) \;=\; \ln\Big(\sum_i \alpha_i p_i^{\lambda-\eta}\,\int_{\mathcal{T}_{gi}(w)} \psi_{gx}^{\lambda-1}\mu_{gx}^{1-\lambda}dx\Big) - \ln\Big(\sum_i \alpha_i p_i^{\lambda-\eta}\,\int_{\mathcal{T}_{gi}(w)} \psi_{gx}^{\lambda-1}\mu_{gx}^{-\lambda}dx\Big)$$

Totally differentiating yields

$$d\ln\mu_g = \overbrace{\frac{\sum_i \alpha_i p_i^{\lambda-\eta}\int_{\mathcal{A}_{gi}}\psi_{gx}^{\lambda-1}\mu_{gx}^{1-\lambda}dx}{\sum_i \alpha_i p_i^{\lambda-\eta}\int_{\mathcal{T}_{gi}(w)}\psi_{gx}^{\lambda-1}\mu_{gx}^{1-\lambda}dx} - \frac{\sum_i \alpha_i p_i^{\lambda-\eta}\int_{\mathcal{A}_{gi}}\psi_{gx}^{\lambda-1}\mu_{gx}^{-\lambda}dx}{\sum_i \alpha_i p_i^{\lambda-\eta}\int_{\mathcal{T}_{gi}(w)}\psi_{gx}^{\lambda-1}\mu_{gx}^{-\lambda}dx}}^{-\left(\frac{\mu_{\mathscr{A}_g}}{\mu_g}-1\right)\delta_g} + \frac{\partial\ln\mu_g(w,p)}{\partial\ln w}\,\text{stack}(d\ln p) + \frac{\partial\ln\mu_g(w,p)}{\partial\ln w}\,\text{stack}(d\ln w)$$

The effects of sectoral prices on group rents can in turn be computed as

$$\frac{\partial\ln\mu_g(w,p)}{\partial\ln p}\,d\ln p = \sum_i\left(\frac{\mu_{gi}}{\mu_g}-1\right)\frac{\ell_{gi}}{\ell_g}\,(\lambda-\eta)\,d\ln p_i,$$

Plugging this and the expression for the change in base wages in (16), we obtain (19).

Derivation of equation (21): As in the single-sector economy, the dual version of Solow implies $d\ln \text{TFP} = \sum_g s_g\ d\ln\bar{w}_g = \sum_g s_g\ d\ln w_g + \sum_g s_g\ d\ln\mu_g$. Plugging the formula for $\sum_g s_g\, d\ln w_g$ in equation (18) yields equation (21) in the proposition.

Turning to consumption, we have $c = y - k$. Differentiating, we get $d\ln c = (1/c)\ (dy - dk) = (1/s^L)\ (d\ln y - (k/y)d\ln k) = (1/s^L)\ d\ln \text{TFP}$. Note that $s_L = c/y$ since there is no net capital income in our model, as capital is produced linearly from the final good. ■

S2 Microfoundations for wedges.

S2.1 Efficiency wage considerations

We consider a static version of an efficiency wage model (i.e. Shapiro and Stiglitz, 1984; Bulow and Summers, 1986).

On the one hand, there is a positive mass of tasks where workers earn a wage w_g and do not have to be monitored or receive extra incentives to work. Workers can always take these jobs freely.

On the other hand, there is a positive mass of tasks where workers need to be monitored and are paid an efficiency wage w_{gx}. In these tasks, workers have two options. They can stick to their duties, produce, and obtain a wage w_{gx}. Or they can shirk. In this case they put no effort on their main job and collect some income $e\ w_g$ by moonlighting in the no-rent sector. If not found, they obtain an income $w_{gx} + e\ w_g$. However, workers who shirk are detected with probability P_{gx}, fired, and forced to take a job that pays no rents. The no shirking condition is then

$$w_{gx} \geq (1 - P_{gx})\,(w_{gx} + e\,w_g) + P_{gx}\,w_g.$$

This can be rearranged as

$$w_{gx} = \left(e\,\frac{1 - P_{gx}}{P_{gx}} + 1\right) w_g.$$

This model thus provides a micro-foundation for wedges $\mu_{gx} = e\,\frac{1-P_{gx}}{P_{gx}} + 1$ derived from efficiency wage considerations. Our treatment assumes there are no other contracts that can solve the monitoring problem.

S2.2 Bargaining models

Consider a one-shot model where firms must make an investment to create a position before matching with a worker, as in Grout (1984).

A firm producing task x can create ℓ_{gx} positions for workers of type g. Creating each position takes up $\kappa \in (0,1)$ units of labor, which implies that the total amount of labor available for production is $\ell_{gx}\,(1-\kappa)$. The firm must pay this cost in advance, which implies that once workers are matched to their positions, there is a surplus to bargain over.

The firm obtains a surplus of $p_x\,\psi_{gx} - w_{gx}$ if the negotiation succeeds and 0 otherwise. The worker obtains a surplus of w_{gx} if the negotiation succeeds and w_g otherwise. As before, we assume that there is a positive mass of jobs that pay no rents at which workers can always access. The wage w_{gx} is determined by Nash bargaining, with workers' bargaining power given by $\beta_{gx} \in (0, 1-\kappa)$.

Lemma S2 (Representation result) *The equilibrium of the bargaining economy coincides with that of our baseline model by taking $\widetilde{\psi}_{gx} = \psi_{gx}\,(1-\kappa)$ and $\mu_{gx} = \frac{(1-\kappa)\,(1-\beta_{gx})}{1-\kappa-\beta_{gx}} \geq 1$.*

Proof. Free entry for firms implies

$$(1 - \beta_{gx})\;(p_x\,\psi_{gx} - w_g) \leq \kappa\,p_x\,\psi_{gx}.$$

This can be written as

$$p_x \leq \frac{w_g}{\psi_{gx}\,(1-\kappa)}\;\underbrace{\frac{(1-\kappa)\,(1-\beta_{gx})}{1-\kappa-\beta_{gx}}}_{\mu_{gx}},$$

which coincides with E1 and E2 for $\widetilde{\psi}_{gx} = \psi_{gx}\,(1-\kappa)$. Thus, the bargaining model gives the same rule for allocating tasks across workers and capital than our baseline model with exogenous wedges.

Moreover market clearing for task $x \in \mathcal{T}_g$ requires

$$\psi_{gx}\,(1-\kappa)\,\ell_{gx} = y\,\frac{1}{M}\,(\psi_{gx}\,(1-\kappa))^{\lambda}\,(w_g\,\mu_{gx})^{-\lambda}$$

which coincides with E3 for $\widetilde{\psi}_{gx} = \psi_{gx}\,(1-\kappa)$. Thus, the bargaining model gives the same allocation of labor by tasks as our baseline model with exogenous wedges.

Turning to wages paid to workers, we have

$$w_{gx} = \beta_{gx}\,p_x\,\psi_{gx} + (1-\beta_{gx})\,w_g \quad \Rightarrow \quad w_{gx} = w_g\,\underbrace{\frac{(1-\kappa)\,(1-\beta_{gx})}{1-\kappa-\beta_{gx}}}_{\mu_{gx}}.$$

This implies the bargaining model gives the same wage payments by task as our baseline model with exogenous wedges. ■

S3 Extensions: Unmeasured Worker Productivity and Compensating Differentials

S3.1 Worker differences in productivity

This sub-section introduces a variant of our benchmark single-sector model with unmeasured differences in productivity levels within groups. As before, a unique final good y is produced by combining complementary tasks $x \in \mathcal{T}$ (where the set of tasks $\mathcal{T} \subset \mathbb{R}^d$ has mass M). Task quantities, y_x, are aggregated with a constant elasticity of substitution $\lambda \in (0,1)$.

The main difference is that workers in a group differ in their individual productivity level z, with $z \sim G$ and $\mathbb{E}[z|g]$ normalized to 1 for every group. As a result, the total production of task x is now

$$y_x \;=\; \psi_{kx}\,k_x + \sum_g \psi_{gx}\;\int_z z\,\ell_{gx}(z)\,dz,$$

where $\ell_{gx}(z)$ is the quantity of g workers of skill level z employed in task x, who produce $\psi_{gx}\,z$ units of task x. Market clearing now requires that for every g and z

$$\int_{\mathcal{T}} \ell_{gx}(z)\,dx \;\le\; G(z)\,\ell_g.$$

The rest of the model is the same, with task wedges μ_{gx} assumed independent of z.

The equilibrium is defined in the same way as before. The main difference is that now, a firm performing task x using labor of type g and productivity level z must pay a group-, skill-, and task-specific wage:

$$w_{gx}(z) = w_g \, \mu_{gx} \, z.$$

$w_g > 0$ is now the *base wage per efficiency-unit of labor* in group g, and $\mu_{gx} \geq 1$ an exogenous wedge that varies across tasks. This is because firms are indifferent between hiring z workers of skill 1 from group g or one worker of skill z from the same group. In particular, at these wages, the cost of producing one unit of task x with workers from group g is the same as before, and given by

$$\frac{w_g \, \mu_{gx}}{\psi_{gx}},$$

which is irrespective of the skill level of the worker being employed.

As in the baseline model, the equilibrium, can be characterized in terms of task shares for workers $\{\Gamma_g(w)\}_{g\in\mathbb{G}}$, capital $\Gamma_k(w)$, and average group rents $\mu_g(w)$, all written as functions of base wages per efficiency-unit of labor. We obtain the exact same formulas from our baseline model, showing that the structure of the equilibrium and the effects of automation on average and base group wages are the same.

Proposition S2 (Equilibrium representation) *There is a unique equilibrium vector of wages per efficiency unit of labor w and output level y. These solve equations (1) and (2). In addition, group average wages are still given by $\bar{w}_g = w_g \, \mu_g(w)$.*

Proof. For every task $x \in \mathcal{T}_g$, firms are indifferent between producing with workers from group g of different skill level z, and hire workers until the total efficiency-units of labor used equal those needed:

$$\int_z z \, \ell_{gx}(z) \, dz = y \, \frac{1}{M} \, \psi_{gx}^{\lambda-1} \, (w_g \, \mu_{gx})^{-\lambda} \text{ for } x \in \mathcal{T}_g(w).$$

Adding across all tasks in $\mathcal{T}_g(w)$, and using the fact that we normalized $\mathbb{E}[z|g] = 1$ yields

$$\ell_g = y \, \Gamma_g(w) w_g^{-\lambda}.$$

Solving for w_g yields equation (1).

Using the fact that we normalized the price of the final good to one, we obtain

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

Moreover, task prices equal the minimum unit cost of performing the relevant task:

$$p_x \;=\; \min\left\{\frac{1}{q_x\,\psi_{kx}},\left\{\frac{w_g\,\mu_{gx}}{\psi_{gx}}\right\}_g\right\}.$$

Substituting the expression for p_x above yields (2).

The existence and uniqueness of the equilibrium vector $\{w, y\}$ is then established as in the baseline model.

We conclude by deriving the expression for average wages. These are given by

$$\begin{aligned}\frac{\int_{\mathcal{T}_g(w)}\int_z \ell_{gx}(z)\,w_{gx}(z)\,dz\,dx}{\ell_g} &= \frac{\int_{\mathcal{T}_g(w)}\int_z z\,\ell_{gx}(z)\,w_g\,\mu_{gx}\,dz\,dx}{\ell_g}\\ &= \frac{\int_{\mathcal{T}_g(w)} y\,\frac{1}{M}\,\psi_{gx}^{\lambda-1}\,(w_g\,\mu_{gx})^{-\lambda}\,w_g\,\mu_{gx}\,dx}{y\,\Gamma_g(w)\,w_g^{-\lambda}}\\ &= w_g\,\underbrace{\frac{1}{M\,\Gamma_g(w)}\int_{\mathcal{T}_g(w)}\psi_{gx}^{\lambda-1}\,\mu_{gx}^{1-\lambda}\,dx}_{\mu_g(w)}.\end{aligned}$$

The first line uses the fact that $w_{gx}(z) = w_g\,\mu_{gx}\,z$. The second line uses the equilibrium demand for efficiency-units of labor in task x (for $x \in \mathcal{T}_g(w)$). The third line rearranges and cancels terms. ■

We now show that Propositions 3 and 4 continue to hold in this environment.

Proposition S3 (Targeting of high-rent tasks)
Suppose $\mathscr{A}_g^T \smallsetminus \mathscr{A}_g$ and $\mathscr{A}_g$ have positive mass. Under Assumption 2,

$$F_g(\mu\,|\,\mathscr{A}_g) \;>\; F_g(\mu\,|\,\mathcal{T}_g) \quad \forall\,\mu > 1,$$

i.e., the rent distribution in $\mathscr{A}_g$ first-order stochastically dominates that in $\mathcal{T}_g$.

Proof. The set of automated tasks is

$$\mathscr{A}_g \;=\; \left\{x \in \mathscr{A}_g^T : \frac{w_g\,\mu_{gx}}{\psi_{gx}} \geq \frac{1}{q'_x\,\psi_{kx}}\right\}.$$

This set is the same as in our baseline model, which implies that $F_g(\mu\,|\,\mathcal{A}_g)$ satisfies the same properties shown in Proposition 3. ■

As discussed in the text, the result that the automation of high-rent tasks generates a U-shape pattern for wage changes within a group extends to the model with differences in skill levels z. This requires the following rank-preservation assumption.

Assumption S1 (Rank preservation) *For any two workers from group g with productivity levels $z > z'$, the first earns a higher wage in equilibrium.*

Proposition S4 (Automation and within-group wage compression) *Suppose $F_g(\mu \mid \mathscr{A}_g) \geq F_g(\mu \mid \mathcal{T}_g)$ for all $\mu > 1$ and let $M_g > 0$ be the mass of employment in no-rent jobs. If each worker performs one task and Assumption S1 holds, automation has the following effects:*

- *For $p \in [0, M_g]$, $\Delta \ln w_g^p = \Delta \ln w_g$, with $\Delta \ln w_g$ the change in base wages.*
- *For $p \in (M_g, 1)$, $\Delta \ln w_g^p < \Delta \ln w_g$, reflecting the loss of rents at higher percentiles.*
- *For $p \to 1$, $\Delta \ln w_g^p \leq \Delta \ln w_g$, with equality if there exists $\epsilon > 0$ such that, for all $\mu > 1$, a positive share of at least ϵ tasks with rent $\mu_{gx} = \mu$ are not in $\mathscr{A}_g^T$.*

Proof. Assumption S1 implies that

$$\ln w_g^p = \ln z^p + \ln w_g + \ln \mu_g^p,$$

where $\ln z^p$ is the p-th quantile of the productivity distribution within a group and $\ln \mu_g^p$ is the p-th quantile of the rent distribution.

Taking changes over time, we get

$$\Delta \ln w_g^p = \underbrace{\Delta \ln z^p}_{=0} + \Delta \ln w_g + \Delta \ln \mu_g^p.$$

That is, the change in wage quantiles is the same as the change in base wages plus the change in rent quantiles. It follows that all properties shown for the change in rent quantiles in Proposition 4 apply here. ■

S3.2 Compensating differentials

Let's return to the baseline model with no unmeasured differences in productivity levels in a group. Let's suppose now that g workers' utility from working in task x is

$$\ln u_{gx} = \ln w_{gx} - \ln \zeta_{gx}.$$

The first term is the utility from consumption, which depends on the wage w_{gx}. The second term is a disutility from the job, $\zeta_{gx} > 0$, which varies by group and task. This formulation implies that the wage earned by workers from group g in task x is

$$w_{gx} = w_g \, \mu_{gx} \, \zeta_{gx},$$

where w_g is the utility level reached by g workers in a job that pays no rents.

As discussed in the text, the equilibrium is the same as before and characterized by Proposition 1, with μ_{gx} replaced by a composite term $\mu_{gx} \, \zeta_{gx}$. In particular, the equilibrium is still given by Proposition 1, where now

$$\Gamma_g(w) = \int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \zeta_{gx}^{-\lambda} \, \mu_{gx}^{-\lambda} \, dx$$

and

$$\mu_g(w) = \frac{1}{M \, \Gamma_g(w)} \int_{\mathcal{T}_g(w)} \psi_{gx}^{\lambda-1} \, \zeta_{gx}^{-\lambda} \, \mu_{gx}^{1-\lambda} \, dx.$$

We now extend Propositions 3 and 4 to this environment. In the presence of the disutility term ζ_{gx}, Assumption 2 has to be modified as follows.

Assumption S2 (Neutral Inventions) *Within group g,*

i the rent distribution among newly automatable tasks is the same as in all tasks:

$$F_g(\mu \mid \mathscr{A}_g^T) = F_g(\mu \mid \mathcal{T}_g) \quad \forall \, \mu \geq 1,$$

ii conditional on automability, rents are independent of task-level productivities and worker disutility

$$F_g\big(\mu \mid \mathscr{A}_g^T, \, q_x' \psi_{kx} \leq a, \, \psi_{gx} \leq b, \zeta_{gx} \leq z\big) = F_g(\mu \mid \mathscr{A}_g^T) \quad \forall \, \mu \geq 1, a, b, z > 0.$$

The assumption plays the same role as before. In addition, it prevents a situation where rents μ_{gx} and compensating differentials negatively co-vary, which could lead to the automation of tasks with high ζ_{gx} but low μ_{gx}.

Proposition S5 (Targeting of high-rent tasks)
Suppose $\mathscr{A}_g^T \setminus \mathscr{A}_g$ and $\mathscr{A}_g$ have positive mass. Under Assumption S2,

$$F_g(\mu \mid \mathscr{A}_g) > F_g(\mu \mid \mathcal{T}_g) \quad \forall \, \mu > 1,$$

i.e., the rent distribution in $\mathscr{A}_g$ first-order stochastically dominates that in $\mathcal{T}_g$.

Proof. The proof is the same as that of Proposition 3, with $\varrho_{gx} = \frac{1}{w_g} \frac{1}{\zeta_{gx}} \frac{\psi_{gx}}{q'_x \psi_{kx}}$. ■

The targeting of high-rent tasks also predicts increased wage compression for wages purged of compensating differentials. In what follows, we let $w_{\text{net}} = w/\zeta$ denote wages net of compensating differentials, or net wages for short. We also let $\ln w_{g,\text{net}}(p)$ denote the p-th quantile of the distribution of log (net) wages among workers in group g.

Proposition S6 (Automation and within-group wage compression)
Suppose $F_g(\mu \mid \mathscr{A}_g) \geq F_g(\mu \mid \mathcal{T}_g)$ for all $\mu > 1$ and let $M_g > 0$ be the mass of employment in no-rent jobs. If each worker performs one task, automation has the following effects:

- *For $p \in [0, M_g]$, $\Delta \ln w^p_{g,net} = \Delta \ln w_g$, with $\Delta \ln w_g$ the change in base wages.*
- *For $p \in (M_g, 1)$, $\Delta \ln w^p_{g,net} < \Delta \ln w_g$, reflecting the loss of rents at higher percentiles.*
- *For $p \to 1$, $\Delta \ln w^p_{g,net} \leq \Delta \ln w_g$, with equality if there exists $\epsilon > 0$ such that, for all $\mu > 1$, a positive share of at least ϵ tasks with rent $\mu_{gx} = \mu$ are not in $\mathscr{A}^T_g$.*

Proof. Net wages are the product of base wages and rents. This implies that

$$\Delta \ln w^p_{g,\text{net}} = \Delta \ln w_g + \Delta \ln \mu^p_g.$$

That is, the change in wage quantiles is the same as the change in rent quantiles (plus the base wage). It follows that all properties shown for the change in wage quantiles in Proposition 4 apply here. ■

To conclude, we show that the impact of automation on average net wages is described by similar formulas to those developed in Proposition 5. As in the baseline model, the formulas are derived in terms of:

- The task displacement experienced by group g, δ_g defined as before.
- The average cost savings from automating tasks in $\mathscr{A}_g$, now defined as

$$\pi_g = \frac{\int_{\mathscr{A}_g} \ell_{gx}\, \mu_{gx}\, \zeta_{gx}\, \pi_{gx}\, dx}{\int_{\mathscr{A}_g} \ell_{gx}\, \mu_{gx}\, dx},$$

where the π_{gx}'s are cost savings from automating task x in $\mathscr{A}_g$,

$$\pi_{gx} = \frac{1}{\lambda - 1}\left[\left(\frac{q'_x\, \psi_{kx}\, w_g\, \mu_{gx}\, \zeta_{gx}}{\psi_{gx}}\right)^{\lambda-1} - 1\right] \geq 0.$$

- The average rent earned by group g workers in newly-automated tasks

$$\mu_{\mathscr{A}_g} = \frac{\int_{\mathscr{A}_g} \ell_{gx}\, \mu_{gx}\, dx}{\int_{\mathscr{A}_g} \ell_{gx}\, dx}.$$

- The average wage differential (inclusive of rents) earned by group g workers in newly-automated tasks, relative to their average task:

$$\Omega_{\mathcal{A}_g} = \frac{\int_{\mathscr{A}_g} \ell_{gx}\, \mu_{gx}\, \zeta_{gx} dx}{\int_{\mathscr{A}_g} \ell_{gx}\, dx} \Bigg/ \frac{\int_{\mathscr{T}_g} \ell_{gx}\, \mu_{gx}\, dx}{\int_{\mathscr{T}_g} \ell_{gx}\, dx}$$

(note this equals $\mu_{\mathcal{A}_g}/\mu_g$ in our baseline model.)

Proposition S7 (Equilibrium effects of automation)
Consider new automation technologies in small interior sets $\{\mathscr{A}_g^T\}_{g\in\mathbb{G}}$ with direct effects $\left\langle\{\delta_g\}_{g\in\mathbb{G}}, \{\pi_g\}_{g\in\mathbb{G}}, \{\{\mu_{\mathscr{A}_g}\}_{g\in\mathbb{G}}\}, \{\{\Omega_{\mathscr{A}_g}\}_{g\in\mathbb{G}}\}\right\rangle$. The first-order impacts on base wages and output are given by the formulas

$$d\ln w_g = \Theta_g\ stack\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\, \delta_j\right) \quad \text{for } g \in \mathbb{G} \tag{S7}$$

$$\sum_g s_g\, d\ln w_g = \sum_g s_g\, \delta_g\, \Omega_{\mathcal{A}_g}\, \pi_g. \tag{S8}$$

Moreover, the change in average group rents (employment weighted) is

$$d\ln \mu_g = \mathcal{M}_g\ stack\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\, \delta_j\right) - \left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1\right) \delta_g. \tag{S9}$$

and the change in net wages for group g is

$$d\ln \bar{w}_{g,net} = (\Theta_g + \mathcal{M}_g)\ stack\left(\frac{1}{\lambda}\, d\ln y - \frac{1}{\lambda}\, \delta_j\right) - \left(\frac{\mu_{\mathscr{A}_g}}{\mu_g} - 1\right) \delta_g. \tag{S10}$$

Finally, the change in average net consumption (adjusted for the disutility of labor) is

$$d\ln c_{net} = \sum_g s_g\, \delta_g\, \Omega_{\mathcal{A}_g}\, \pi_g + \sum_g s_g\, d\ln \mu_g. \tag{S11}$$

Proof. Equations (S7), (S8), and (S9) are derived following the same steps as in the proof of Proposition 5.

To derive (S10), note that

$$\bar{w}_{g,\text{net}} = \frac{\int_{\mathcal{T}_g} \ell_{gx} \, (w_{gx}/\zeta_{gx}) \, dx}{\ell_g} = \frac{\int_{\mathcal{T}_g} \ell_{gx} \, w_g \, \mu_{gx} \, dx}{\ell_g} = w_g \, \mu_g.$$

Thus, $d \ln \bar{w}_{g,\text{net}} = d \ln w_g + d \ln \mu_g$ and (S10) is obtained by substituting (S7) and (S9).

To derive (S11), note that

$$c_{\text{net}} = \sum_g \frac{\ell_g}{\ell} \frac{\int_{\mathcal{T}_g} \ell_{gx} \, (w_{gx}/\zeta_{gx}) \, dx}{\ell_g} = \sum_g \frac{\ell_g}{\ell} \frac{\int_{\mathcal{T}_g} \ell_{gx} \, w_g \, \mu_{gx} \, dx}{\ell_g} = \sum_g \frac{\ell_g}{\ell} \, w_g \, \mu_g.$$

It follows that $d \ln c_{\text{net}} = \sum_g s_g \, d \ln w_g + \sum_g s_g \, d \ln \mu_g$, and (S11) is obtained by substituting the expression for average wage changes in (S8). ■

Propositions S5, S6 and S7 show that the effects of automation on net wages are the same as in our baseline model, both in terms of within-group changes and between groups.

Proposition 5 also shows that the effects of automation on aggregate consumption, appropriately adjusted for the disutility of work, are the same as before. Thus, the efficiency and normative implications of rent dissipation are the same as our baseline model.

The formula for aggregate net consumption in (S11) also highlights the key normative difference between rents and compensating differentials. The formula shows that the automation of high- compensating differential jobs does not have a negative impact on allocative efficiency. It is only the automation of high-rent jobs that reduces allocative efficiency and offsets (and could flip) the aggregate welfare gains from automation.

S3.3 Deriving the wage rule with compensating differentials

The text assumes that in the presence of compensating differentials, wages are

$$w_{gx} = w_g \, \mu_{gx} \, \zeta_{gx}.$$

We now show this is the unique equilibrium wage in our micro-foundations for rents.

In the efficiency-wage micro-foundation, worker utility if they do not shirk is

$$u_{gx}^{\text{no shirking}} = \frac{w_{gx}}{\zeta_{gx}}.$$

Their utility if they shirk is

$$u_{gx}^{\text{shirking}} \;=\; (1-P_{gx})\left(\frac{w_{gx}}{\zeta_{gx}}+e\,w_g\right) \;+\; P_{gx}\,w_g,$$

where recall that w_g are the additional *utils* they receive from working in a no rent job.

The no shirking condition then implies

$$u_{gx}^{\text{shirking}} \;\geq\; u_{gx}^{\text{shirking}},$$

which holds if and only if workers are paid a wage

$$w_{gx} \;=\; w_g \underbrace{\left(e\,\frac{1-P_{gx}}{P_{gx}}+1\right)}_{\mu_{gx}}\zeta_{gx}.$$

In the hold-up microfoundation, we now have that the firm receives a surplus $p_x\,\psi_{gx}-w_{gx}$ if the negotiation succeeds and 0 otherwise. The worker obtains a surplus of $\frac{w_{gx}}{\zeta_{gx}}$ if the negotiation succeeds and w_g otherwise. As before, we assume that there is a positive mass of jobs that pay no rents and workers can always access. The wage w_{gx} is determined by Nash bargaining, with workers' bargaining power given by $\beta_{gx}\in(0,1-\kappa)$. The Nash bargaining solution therefore solves

$$\max_{w_{gx}}\;\left(p_x\,\psi_{gx}-w_{gx}\right)^{1-\beta_{gx}}\left(\frac{w_{gx}}{\zeta_{gx}}-w_g\right)^{\beta_{gx}}.$$

The surplus received by the firm is then $(1-\beta_{gx})\left(p_x\,\psi_{gx}-w_g\,\zeta_{gx}\right)$, and the free entry condition reads

$$(1-\beta_{gx})\left(p_x\,\psi_{gx}-w_g\,\zeta_{gx}\right)\leq\kappa p_x\psi_{gx}.$$

This can be rewritten as

$$p_x\leq\;\frac{w_g}{\psi_{gx}\,(1-\kappa)}\underbrace{\frac{(1-\kappa)\,(1-\beta_{gx})}{1-\kappa-\beta_{gx}}}_{\mu_{gx}}\zeta_{gx},$$

Finally, wage payments are given by

$$\frac{w_{gx}}{\zeta_{gx}}=\beta_{gx}\,\frac{p_x\,\psi_{gx}}{\zeta_{gx}}+(1-\beta_{gx})\,w_g\quad\Rightarrow\quad w_{gx}=w_g\underbrace{\frac{(1-\kappa)\,(1-\beta_{gx})}{1-\kappa-\beta_{gx}}}_{\mu_{gx}}\zeta_{gx}.$$

S4 Empirical Appendix.

S4.1 Data sources and details

Our main data sources are the same used in Acemoglu and Restrepo (2022), and we refer readers to this paper for details. This paper brings in new proxies for rents, described in detail below.

Wage differentials: our first proxy for job-specific rents is the inter-industry and occupation wage differentials. As explained in the text, we compute this using 1980 Census data as $\bar{w}_{gio}/\bar{w}_g$. In this expression, $\bar{w}_{gio}$ is the average wage earned by group g in industry i and occupation o in 1980. This is computed for the 49 industries in our analysis and 300 detailed Census occupations.

Wage losses from job displacement: our second proxy for job-specific rents is the industry-specific wage loss from job displacement, computed separately for workers by gender and education. As explained in the text, we compute this using the CPS Displaced Worker Supplement as the average change in (log) wages before and after a displacement event. We restrict the sample of displaced workers to those with at least a year of tenure before the displacement episode who have since then found a new job. The resulting sample contains 37,355 displaced workers, observed between 1984 and 2022. We winsorize previous job and current job wages from below at 100 dollars per week and we also winsorize the change in log wages at the 5th and 95th percentiles to avoid outliers.

We compute the average wage loss for these workers for the 49 industries in our analysis and in sic broad occupations. We allow these to vary by worker education (grouping only college vs non-college groups) and gender. We do not compute this measure by detailed worker demographic characteristics because the resulting cells would be too small.

Quit rates: our last proxy for job-specific rents is the (inverse of the) monthly quit rate from jobs in an industry and occupation. This is computed from the panel component of the Basic Monthly CPS.

We consider two forms of quits. First, we compute the EE rate, following the cleaning procedure in Fujita et al. (2024). EE transitions are identified using a new question added to the CPS in 1994, and so this measure is only available for 1994–2023. As pointed out in Fujita et al. (2024), there is a growing share of workers reporting "not knowing" if they still work for the same employer, which we treat as missing observations.

Second, we compute voluntary EU transitions per month. For this, we consider a separation into unemployment as voluntary if workers report that the reason for being unemployed is that they are "job leavers". This measure is available for the 1976–2023 period. For our analysis, we average EE and voluntary EU rates over these years and by industry, occupation, and group (only in terms of gender and for college vs non-college workers). We use the 49 industries in our analysis and 300 detailed Census occupations, which we match to the CPS.

In addition, we use measures of job quality to purge wages of compensating differentials.

Job quality measures: We use data from the *Quality of Employment Survey* from 1977. The survey asked a cross-section of respondents across all US industries about working conditions and job satisfaction. We aggregate answers at the industry level (using the 49 industries in our sample) and create the four measures described in the text. The exact construction of these measures and the questions used can be accessed in our replication kit. Our measures of job quality are only available at the industry level because the Quality of Employment Survey has limited coverage of occupations within industries.

S4.2 Summary of main estimates in the paper

Table S1 provides a summary of the reduced-form evidence in the paper. The panels report estimates of the reduced form equation (12) for different outcome variables. The specification in column 1 reports a bivariate regression. The specification in column 2 adds sectoral demand shifts, gender and education dummies as covariates. The specification in column 3 adds sectoral rent shifts as a covariate. The specification in column 4 adds the share of employment in manufacturing from the 1980 Census as a covariate. This last specification is conservative, as part of what we are trying to explain is the removal of highly paid manufacturing jobs.

Table S1: Summary of reduced-form evidence, 1980-2016.

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: percent change in group average wage, $\Delta \ln \bar{w}_g$			
Direct task displacement	-2.36	-2.06	-2.06	-1.90
	(0.13)	(0.25)	(0.27)	(0.29)
R^2 for task displacement	0.67	0.58	0.58	0.54
Observations	500	500	500	500
	Panel B. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$			
Direct task displacement	-0.35	-0.53	-0.50	-0.37
	(0.06)	(0.13)	(0.11)	(0.11)
R^2 for task displacement	0.23	0.34	0.32	0.24
Observations	500	500	500	500
	Panel C. Dependent variable: wage changes at 30th percentile, $\Delta \ln w_g(30\text{th})$			
Direct task displacement	-2.01	-1.53	-1.55	-1.53
	(0.14)	(0.29)	(0.30)	(0.33)
R^2 for task displacement	0.57	0.43	0.44	0.44
Observations	500	500	500	500
	Panel D. Dependent variable: change in group rents due to reallocation—wage differentials from Census			
Direct task displacement	-0.46	-0.36	-0.35	-0.39
	(0.06)	(0.10)	(0.11)	(0.11)
R^2 for task displacement	0.39	0.31	0.30	0.33
Observations	496	496	496	496
	Panel E. Dependent variable: change in group rents due to reallocation—wage loss due to displacement from CPS			
Direct task displacement	-0.17	-0.19	-0.18	-0.20
	(0.02)	(0.03)	(0.03)	(0.04)
R^2 for task displacement	0.47	0.53	0.51	0.56
Observations	500	500	500	500
	Panel F. Dependent variable: change in group rents due to reallocation—(minus) EE rates from CPS			
Direct task displacement	-1.276	-1.273	-1.332	-1.506
	(0.085)	(0.278)	(0.255)	(0.253)
R^2 for task displacement	0.58	0.57	0.60	0.68
Observations	500	500	500	500
	Panel G. Dependent variable: change in group rents due to reallocation—(minus) voluntary EU rates from CPS			
Direct task displacement	-0.223	-0.292	-0.286	-0.300
	(0.023)	(0.043)	(0.045)	(0.050)
R^2 for task displacement	0.43	0.56	0.55	0.58
Observations	500	500	500	500
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and various group-level outcomes. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

S4.3 Estimates of rent dissipation: additional results and checks

Acemoglu and Restrepo (2022) report several robustness checks for the reduced-form relationship between average wage changes and the task displacement due to automation across groups. Here, we provide robustness checks for the relationship between automation and within-group wage dispersion and rents, which is the novel empirical aspect in this paper.

S4.3.1 Strategy 1: Within-group wage changes.

Our first strategy for estimating the role of rent dissipation is described in Section 3.3 and focuses on within-group wage changes.

We first asses the robustness of the U-shape pattern in Figure 6. Figure S1 shows the U-shape pattern is robust to including additional controls or restricting the sample to high-wage groups. The left panel reports estimates constraining the estimation sample to groups with an average real wage in 1980 above $10 dollars. For these groups, wage changes become flat below the 30th percentile. We continue to see a clear U-shape pattern of withing-group wage changes, with a more pronounced decline between the 30th and 95th percentiles. The right panel shows that this pattern is also robust to controlling for the incidence of the minimum wage and declining unionization rates across industries. For the minimum wage, we control for the share of workers in each group earning an hourly wage below 3.1 dollars in 1980 (the Federal minimum wage). For unionization, we control for groups' exposure to industries with declining unionization rates. These are computed from the CPS as in Acemoglu and Restrepo (2022).

We now explore the robustness of our estimates of rent dissipation, obtained from the first strategy in Section 3.3. In this section, we use wage changes at the 30th percentile inside each group to measure the effects of automation on base wages. We then attributed any wage losses above this point to rent dissipation.

Table S2 shows that our main results are robust when using different thresholds and procedures to measure base wages and rents.

- Panels A and B provide estimates of the decline in wages within exposed groups above their 20th and 40th percentiles, instead of the 30th percentile used in the text.
- Panel C provides estimates for groups with an average wage above $10 in 1980, where concerns about minimum wages or other forces keeping wages from falling at the bottom are less salient.

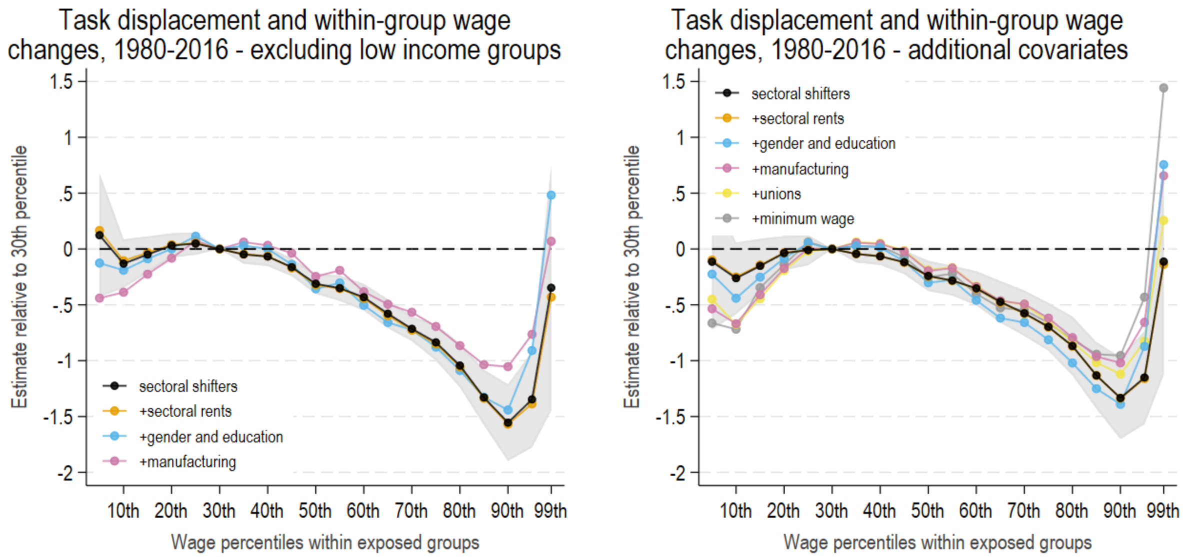

FIGURE S1: REDUCED-FORM RELATIONSHIP BETWEEN WAGE CHANGES ACROSS PERCENTILES OF THE WITHIN-GROUP WAGE DISTRIBUTION AND TASK DISPLACEMENT. The figure plots estimates from a group-level quantile regression of changes in $d \ln w_g(p)$ against task displacement for percentiles p ranging from the 5th to the 99th relative to the 30th percentile. Different colors represent estimates from different specifications.

- Panels D and E report separate estimates for groups without and with college degrees.
- Panels F and G report estimates where we use the average wage change between the 10th and 95th percentiles minus the average wage change between the 10th and 30th percentiles (or the 10th and 40th percentiles) in each group to measure rent dissipation. The advantage of these measures is that they are not sensitive to changes at the extremes of the within-group distribution, where wage ceilings and censoring could be problematic.

The estimates point to a rent dissipation rate of 19–60% due to automation for 1980–2016.

Table S3 reproduces these estimates but now purging wages of differences in job quality (measured by the composite job quality index). As shown in the text, this leads to smaller but still large and significant estimates of rent dissipation due to automation. In Panel A, for example, which uses our baseline measure of rents (change in wages above 30th percentile), we estimate a rate of rent dissipation due to automation of 28% to 41%

Table S2: Rent dissipation and within-group wage changes.

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: wage change above 20th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g^{20th}$			
Direct task displacement	-0.42	-0.45	-0.42	-0.19
	(0.08)	(0.20)	(0.18)	(0.16)
R^2 for task displacement	0.20	0.21	0.20	0.09
Observations	500	500	500	500
	Panel B. Dependent variable: wage change above 40th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g^{40th}$			
Direct task displacement	-0.31	-0.56	-0.52	-0.41
	(0.07)	(0.15)	(0.13)	(0.11)
R^2 for task displacement	0.21	0.38	0.35	0.28
Observations	500	500	500	500
	Panel C. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$—only groups with average wage above $10 in 1980			
Direct task displacement	-0.36	-0.60	-0.55	-0.44
	(0.06)	(0.13)	(0.10)	(0.11)
R^2 for task displacement	0.25	0.42	0.38	0.31
Observations	460	460	460	460
	Panel D. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$—includes only groups without a college degree			
Direct task displacement	-0.19	-0.54	-0.47	-0.32
	(0.10)	(0.15)	(0.13)	(0.13)
R^2 for task displacement	0.04	0.10	0.09	0.06
Observations	300	300	300	300
	Panel E. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$—includes only groups with a college degree			
Direct task displacement	-0.63	-0.35	-0.37	-0.38
	(0.22)	(0.28)	(0.33)	(0.34)
R^2 for task displacement	0.12	0.07	0.07	0.07
Observations	200	200	200	200
	Panel F. Dependent variable: Average wage change in 95th–10th minus average wage change in 30th–10th percentiles.			
Direct task displacement	-0.57	-0.55	-0.54	-0.28
	(0.08)	(0.15)	(0.14)	(0.13)
R^2 for task displacement	0.34	0.34	0.33	0.17
Observations	500	500	500	500
	Panel G. Dependent variable: Average wage change in 95th–10th minus average wage change in 40th–10th percentiles.			
Direct task displacement	-0.53	-0.60	-0.59	-0.38
	(0.06)	(0.13)	(0.12)	(0.11)
R^2 for task displacement	0.42	0.47	0.46	0.29
Observations	500	500	500	500
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and various group-level outcomes. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

Table S3: Rent dissipation and within-group wage changes, residualized.

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$			
Direct task displacement	-0.31	-0.41	-0.39	-0.28
	(0.06)	(0.11)	(0.10)	(0.11)
R^2 for task displacement	0.20	0.26	0.25	0.18
Observations	500	500	500	500
	Panel B. Dependent variable: wage change above 20th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g^{20th}$			
Direct task displacement	-0.35	-0.27	-0.26	-0.07
	(0.07)	(0.14)	(0.13)	(0.14)
R^2 for task displacement	0.16	0.12	0.12	0.03
Observations	500	500	500	500
	Panel C. Dependent variable: wage change above 40th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g^{40th}$			
Direct task displacement	-0.27	-0.42	-0.39	-0.30
	(0.06)	(0.12)	(0.10)	(0.10)
R^2 for task displacement	0.19	0.29	0.27	0.21
Observations	500	500	500	500
	Panel D. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$—only groups with average wage above $10 in 1980			
Direct task displacement	-0.32	-0.47	-0.43	-0.33
	(0.06)	(0.11)	(0.10)	(0.10)
R^2 for task displacement	0.22	0.32	0.30	0.23
Observations	460	460	460	460
	Panel E. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$—includes only groups without a college degree			
Direct task displacement	-0.13	-0.41	-0.36	-0.23
	(0.09)	(0.13)	(0.12)	(0.13)
R^2 for task displacement	0.02	0.05	0.05	0.03
Observations	300	300	300	300
	Panel F. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$—includes only groups with a college degree			
Direct task displacement	-0.62	-0.39	-0.35	-0.36
	(0.22)	(0.26)	(0.32)	(0.33)
R^2 for task displacement	0.11	0.07	0.06	0.07
Observations	200	200	200	200
	Panel G. Dependent variable: Average wage change in 95th–10th minus average wage change in 30th–10th percentiles.			
Direct task displacement	-0.46	-0.40	-0.40	-0.18
	(0.08)	(0.13)	(0.12)	(0.13)
R^2 for task displacement	0.27	0.23	0.23	0.10
Observations	500	500	500	500
	Panel H. Dependent variable: Average wage change in 95th–10th minus average wage change in 40th–10th percentiles.			
Direct task displacement	-0.43	-0.46	-0.46	-0.28
	(0.06)	(0.11)	(0.10)	(0.11)
R^2 for task displacement	0.33	0.35	0.35	0.22
Observations	500	500	500	500
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and various group-level outcomes. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

S4.3.2 Strategy 2: Use explicit proxies for worker rents.

Our second strategy for estimating the importance of rent dissipation uses explicit proxies for rents at the occupation and industry level. The strategy is explained in Section 3.3, where we also show that groups automation has displaced exposed groups of workers away from high rent jobs.

Figure 8 in Section 3.3 already presented estimates of the shift away from high rent jobs that purged our rent proxies of differences in the composite job quality index. For completeness, this section shows results obtained after purging our proxies for worker rents of each of the different measures of job quality.

Table S4 report estimates using wage differentials as our proxy for rents. Panel A residualizes the composite job quality index. Panel B residualizes job amenities, Panel C residualizes job meaning, and Panel D residualizes willingness to pay for job improvements. Table S5 report estimates using wage losses after displacement as our proxy for rents. Panel A residualizes the composite job quality index. Panel B residualizes job amenities, Panel C residualizes job meaning, and Panel D residualizes willingness to pay for job improvements.

Level of aggregation of our rent proxies: One challenge with our second strategy is that our proxies for rents in Section 3.3 are available at varying levels of aggregation, due to sample limitations. This appendix section explores the implications of this shortcoming. We also provide some exercises addressing the possibility that wage differentials may reflect differences in wages across regions, due to varying costs of living.

Table S6 and S7 report our estimates. For these tests, we focus on a specification that includes all our baseline covariates.

Panel A in Table S6 provides robustness checks for our measure of rent reallocation based on inter-industry and occupation wage differentials (obtained from the 1980 Census):

- Column 1 reports our baseline estimates.
- Column 2 uses a measure of wage differentials that partials out differences in wages across states. This accounts for the possibility that jobs are located in areas with different costs of living, which would generate wage variation in the form of compensating differentials.
- Column 3 uses a broader occupational grouping with 6 occupations in total (instead of the 300 in our baseline).

- Column 4 also uses this broader occupational grouping and partials out regional wage differences.
- Column 5 computes a common inter-industry and occupation wage differential averaging across all groups.
- Column 6 uses this common differential and also partials out regional wage differences.

Panel B in Table S6 provides robustness checks for our measure of rent reallocation based on wage losses from displacement (obtained from the CPS, job displacement supplement).

- Column 1 reports our baseline estimates.
- Column 2 uses a common wage-loss measure averaging across all workers, and not only across workers of the same gender and education of a group.
- Column 3 also uses a common wage-loss measure averaging across all workers, but controls for the observable characteristics of displaced workers when computing these losses. For these columns, we compute wage losses for the 49 industries in our analysis and six broad occupational groups.
- Columns 4–6 report analogous specifications, where we compute wage losses at the industry level.

Panels C and D in Table S7 provide robustness checks for our measure of rent reallocation based on (the inverse of) monthly quit rates (both into other jobs— Panel C—or non-employment—Panel D).

- Column 1 reports our baseline estimates.
- Column 2 uses a common quit rate averaging across all workers, and not only across workers of the same gender and education of a group. Here we only control for differences in EE rates and voluntary EU rates over time, to account for trends in EE and EUV rates.
- Column 3 also uses a common wage loss measure averaging across all workers, but controls for the observable characteristics of displaced workers across industries and occupations when computing monthly transition rates.
- Columns 4–6 report similar specifications but now compute wage losses by industry and broad occupational group. For these we use the 49 industries in our analysis and 6 occupational groups.

Table S4: Robustness checks on reduced-form evidence, partial out measures of job quality from the Quality of Employment Survey, 1977.

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: change in group rents due to reallocation—wage differentials partialing out job quality index			
Direct task displacement	-0.44	-0.36	-0.35	-0.36
	(0.06)	(0.11)	(0.11)	(0.11)
R^2 for task displacement	0.35	0.29	0.28	0.29
Observations	496	496	496	496
	Panel B. Dependent variable: change in group rents due to reallocation—wage differentials partialing out job amenities			
Direct task displacement	-0.46	-0.37	-0.36	-0.39
	(0.06)	(0.10)	(0.11)	(0.11)
R^2 for task displacement	0.39	0.31	0.30	0.33
Observations	496	496	496	496
	Panel C. Dependent variable: change in group rents due to reallocation—wage differentials partialing out job meaning			
Direct task displacement	-0.40	-0.38	-0.37	-0.37
	(0.06)	(0.10)	(0.10)	(0.11)
R^2 for task displacement	0.32	0.31	0.29	0.30
Observations	496	496	496	496
	Panel D. Dependent variable: change in group rents due to reallocation—wage differentials partialing out willingness to pay to improve working conditions			
Direct task displacement	-0.44	-0.31	-0.30	-0.32
	(0.07)	(0.11)	(0.11)	(0.11)
R^2 for task displacement	0.34	0.24	0.23	0.25
Observations	496	496	496	496
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between the automation's task displacement from 1980 to 2016 and the shift away from high-rent jobs, measured by wage differentials in the 1980s purged of measures of job quality. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. Panel A residualizes the job quality index; Panel B residualizes job amenities; Panel C residualizes job meaning; and Panel D residualizes willingness to pay for job improvements. The measures of job quality residualized are from the *Quality of Employment Survey* from 1977. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

Table S5: Robustness checks on reduced-form evidence, partial out measures of job quality from the Quality of Employment Survey, 1977.

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: change in group rents due to reallocation—wage loss due to displacement from CPS partialing out job quality index			
Direct task displacement	-0.14	-0.19	-0.18	-0.19
	(0.02)	(0.03)	(0.03)	(0.04)
R^2 for task displacement	0.38	0.51	0.49	0.50
Observations	500	500	500	500
	Panel B. Dependent variable: change in group rents due to reallocation—wage loss due to displacement from CPS partialing out job amenities			
Direct task displacement	-0.16	-0.19	-0.19	-0.20
	(0.02)	(0.03)	(0.04)	(0.04)
R^2 for task displacement	0.45	0.54	0.52	0.56
Observations	500	500	500	500
	Panel C. Dependent variable: change in group rents due to reallocation—wage loss due to displacement from CPS partialing out job meaning			
Direct task displacement	-0.12	-0.19	-0.19	-0.18
	(0.02)	(0.03)	(0.03)	(0.04)
R^2 for task displacement	0.34	0.54	0.52	0.50
Observations	500	500	500	500
	Panel D. Dependent variable: change in group rents due to reallocation—wage loss due to displacement from CPS partialing out willingness to pay to improve working conditions			
Direct task displacement	-0.14	-0.15	-0.15	-0.16
	(0.02)	(0.03)	(0.03)	(0.04)
R^2 for task displacement	0.37	0.41	0.39	0.42
Observations	500	500	500	500
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and the shift away from high-rent jobs, using wage losses from displacement as our proxy for rents and purging-out measures oj job quality. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. Panel A residualizes the job quality index; Panel B residualizes job amenities; Panel C residualizes job meaning; and Panel D residualizes willingness to pay for job improvements. The measures of job quality residualized are from the *Quality of Employment Survey* from 1977. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

Table S6: Robustness checks: reallocation away from high-rent jobs of exposed workers (I)

	Panel A. Dependent variable: reallocation to high rent jobs, measured by wage differentials in 1980 Census					
	Baseline	Partial out state differences	Broader occupational groups	Broader occupational groups and partial out state differences	Common wage differences	Common wage differences and partial out state differences
	(1)	(2)	(3)	(4)	(5)	(6)
Direct task displacement	-0.385	-0.368	-0.380	-0.363	-0.505	-0.488
	(0.108)	(0.104)	(0.095)	(0.091)	(0.093)	(0.088)
R^2 for task displacement	0.33	0.32	0.37	0.36	0.51	0.52
Observations	496	496	499	499	500	500

	Panel B. Dependent variable: reallocation to high rent jobs, measured by wage loss from job separation in CPS					
	Wage losses by industry, broad occupation, gender, and education	Common wage losses by industry and broad occupation	Common wage losses by industry and broad occupation (adjusted for demographics)	Wage losses by industry, gender, and education	Common wage losses by industry	Common wage losses by industry (adjusted for demographics)
	(1)	(2)	(3)	(4)	(5)	(6)
Direct task displacement	-0.198	-0.227	-0.229	-0.183	-0.190	-0.203
	(0.038)	(0.031)	(0.032)	(0.034)	(0.028)	(0.029)
R^2 for task displacement	0.56	0.71	0.67	0.53	0.66	0.68
Observations	500	500	500	500	500	500

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and the reallocation of exposed groups away from high-rent jobs. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. The different columns present results varying the measurement of rents across jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses. All specifications control for sectoral demand shifters, sectoral rent shifters, gender and education dummies, and the share of employment in manufacturing in 1980.

Table S7: Robustness checks: reallocation away from high-rent jobs of exposed workers (II)

	Panel C. Dependent variable: reallocation to high rent jobs, measured by (minus) EE rates from CPS					
	Quit rates by industry, occupation, gender, and education	Common quit rate by industry and occupation	Common quit rate by industry and occupation (adjusted by demographics)	Quit rates by industry, broad occupation, gender, and education	Common quit rate by industry and broad occupation	Common quit rate by industry and broad occupation (adjusted by demographics)
	(1)	(2)	(3)	(4)	(5)	(6)
Direct task displacement	-1.506	-2.152	-1.849	-1.506	-1.645	-1.457
	(0.253)	(0.305)	(0.301)	(0.253)	(0.292)	(0.283)
R^2 for task displacement	0.68	0.66	0.58	0.68	0.65	0.60
Observations	500	498	498	500	500	500

	Panel D. Dependent variable: reallocation to high rent jobs, measured by (minus) voluntary EU rates from CPS					
	Quit rates by industry, occupation, gender, and education	Common quit rate by industry and occupation	Common quit rate by industry and occupation (adjusted by demographics)	Quit rates by industry, broad occupation, gender, and education	Common quit rate by industry and broad occupation	Common quit rate by industry and broad occupation (adjusted by demographics)
	(1)	(2)	(3)	(4)	(5)	(6)
Direct task displacement	-0.300	-0.382	-0.354	-0.300	-0.305	-0.282
	(0.050)	(0.061)	(0.057)	(0.050)	(0.048)	(0.044)
R^2 for task displacement	0.58	0.65	0.63	0.58	0.68	0.68
Observations	500	500	500	500	500	500

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and the reallocation of exposed groups away from high-rent jobs. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. The different columns present results varying the measurement of rents across jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses. All specifications control for sectoral demand shifters, sectoral rent shifters, gender and education dummies, and the share of employment in manufacturing in 1980.

S4.4 Additional Robustness Checks

Alternative measures of task displacement due to automation: Our baseline empirical results assume that only the top 33% jobs with the highest routine content are exposed to automation. In Acemoglu and Restrepo (2022), we presented a series of robustness checks showing that the exact threshold used did not impact our findings on the relationship between task displacement and average group wages. Tables S8 and S9 show the same holds for the new reduced-form findings pertaining rent dissipation. Table S8 constructs the task displacement measure assuming the top 25% jobs with highest routine content are exposed. Table S9 constructs the task displacement measure assuming the top 40% jobs with highest routine content are exposed.

Timing Our baseline estimates measure outcomes for the entire 1980–2016 period. Table S10 reports estimates for outcomes over 1980–1990 and Table S11 reports estimates for 1990–2016. Most of the rent dissipation over our sample period concentrates in the early years. The exact magnitude varies depending on the proxy used. The estimates from Panel B suggest that 80% of the rent dissipation due to automation over our study period took place in 1980–1990. The estimates from Panels D-G suggest that 60% of the rent dissipation due to automation over our study period took place in 1980–1990.

Table S8: Robustness checks on reduced-form evidence, assuming top 25% jobs with highest routine content exposed to automation

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: percent change in group average wage, $\Delta \ln \bar{w}_g$			
Direct task displacement	-1.71	-1.57	-1.57	-1.53
	(0.08)	(0.15)	(0.15)	(0.17)
R^2 for task displacement	0.77	0.70	0.70	0.69
Observations	500	500	500	500
	Panel B. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$			
Direct task displacement	-0.24	-0.35	-0.33	-0.24
	(0.04)	(0.08)	(0.07)	(0.07)
R^2 for task displacement	0.22	0.32	0.31	0.22
Observations	500	500	500	500
	Panel C. Dependent variable: wage changes at 30th percentile, $\Delta \ln w_g(30\text{th})$			
Direct task displacement	-1.47	-1.22	-1.24	-1.29
	(0.09)	(0.19)	(0.18)	(0.20)
R^2 for task displacement	0.67	0.56	0.57	0.59
Observations	500	500	500	500
	Panel D. Dependent variable: change in group rents due to reallocation— wage differentials from Census			
Direct task displacement	-0.31	-0.28	-0.28	-0.32
	(0.04)	(0.07)	(0.07)	(0.07)
R^2 for task displacement	0.39	0.36	0.35	0.40
Observations	496	496	496	496
	Panel E. Dependent variable: change in group rents due to reallocation— wage loss due to displacement from CPS			
Direct task displacement	-0.12	-0.13	-0.13	-0.15
	(0.01)	(0.02)	(0.02)	(0.02)
R^2 for task displacement	0.49	0.57	0.55	0.63
Observations	500	500	500	500
	Panel F. Dependent variable: change in group rents due to reallocation— (minus) EE rates from CPS			
Direct task displacement	-0.915	-0.982	-1.021	-1.205
	(0.064)	(0.188)	(0.168)	(0.155)
R^2 for task displacement	0.65	0.70	0.72	0.85
Observations	500	500	500	500
	Panel G. Dependent variable: change in group rents due to reallocation— (minus) voluntary EU rates from CPS			
Direct task displacement	-0.147	-0.223	-0.221	-0.242
	(0.016)	(0.031)	(0.032)	(0.034)
R^2 for task displacement	0.41	0.62	0.61	0.67
Observations	500	500	500	500
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and various group-level outcomes. Differently from our baseline measure of task displacement, the one used here assumes the top 25% jobs with the highest routine content are exposed. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

Table S9: Robustness checks on reduced-form evidence, assuming top 40% jobs with highest routine content exposed to automation

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: percent change in group average wage, $\Delta \ln \bar{w}_g$			
Direct task displacement	-1.57	-1.29	-1.28	-1.17
	(0.15)	(0.22)	(0.22)	(0.23)
R^2 for task displacement	0.52	0.43	0.42	0.39
Observations	500	500	500	500
	Panel B. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(\text{30th})$			
Direct task displacement	-0.28	-0.36	-0.35	-0.29
	(0.04)	(0.11)	(0.09)	(0.09)
R^2 for task displacement	0.26	0.33	0.32	0.26
Observations	500	500	500	500
	Panel C. Dependent variable: wage changes at 30th percentile, $\Delta \ln w_g(\text{30th})$			
Direct task displacement	-1.29	-0.92	-0.93	-0.88
	(0.15)	(0.24)	(0.25)	(0.26)
R^2 for task displacement	0.41	0.30	0.30	0.28
Observations	500	500	500	500
	Panel D. Dependent variable: change in group rents due to reallocation— wage differentials from Census			
Direct task displacement	-0.36	-0.28	-0.27	-0.28
	(0.05)	(0.08)	(0.08)	(0.08)
R^2 for task displacement	0.43	0.33	0.32	0.33
Observations	496	496	496	496
	Panel E. Dependent variable: change in group rents due to reallocation— wage loss due to displacement from CPS			
Direct task displacement	-0.12	-0.14	-0.14	-0.14
	(0.01)	(0.03)	(0.03)	(0.03)
R^2 for task displacement	0.45	0.53	0.52	0.53
Observations	500	500	500	500
	Panel F. Dependent variable: change in group rents due to reallocation— (minus) EE rates from CPS			
Direct task displacement	-0.886	-0.991	-1.009	-1.052
	(0.075)	(0.200)	(0.194)	(0.190)
R^2 for task displacement	0.49	0.55	0.56	0.58
Observations	500	500	500	500
	Panel G. Dependent variable: change in group rents due to reallocation— (minus) voluntary EU rates from CPS			
Direct task displacement	-0.186	-0.217	-0.214	-0.214
	(0.018)	(0.036)	(0.036)	(0.038)
R^2 for task displacement	0.53	0.61	0.60	0.60
Observations	500	500	500	500
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1980 to 2016 and various group-level outcomes. Differently from our baseline measure of task displacement, the one used here assumes the top 40% jobs with the highest routine content are exposed. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

Table S10: Robustness checks on reduced-form evidence, outcomes constructed for 1980–1990 period.

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: percent change in group average wage, $\Delta \ln \bar{w}_g$			
Direct task displacement	-1.38	-1.20	-1.16	-0.96
	(0.12)	(0.21)	(0.19)	(0.18)
R^2 for task displacement	0.68	0.59	0.57	0.47
Observations	499	499	499	499
	Panel B. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$			
Direct task displacement	-0.17	-0.43	-0.42	-0.30
	(0.05)	(0.08)	(0.07)	(0.07)
R^2 for task displacement	0.13	0.34	0.33	0.24
Observations	499	499	499	499
	Panel C. Dependent variable: wage changes at 30th percentile, $\Delta \ln w_g(30\text{th})$			
Direct task displacement	-1.21	-0.77	-0.74	-0.67
	(0.11)	(0.19)	(0.19)	(0.19)
R^2 for task displacement	0.59	0.38	0.36	0.33
Observations	499	499	499	499
	Panel D. Dependent variable: change in group rents due to reallocation—wage differentials from Census			
Direct task displacement	-0.32	-0.23	-0.21	-0.22
	(0.03)	(0.05)	(0.05)	(0.05)
R^2 for task displacement	0.51	0.36	0.34	0.34
Observations	492	492	492	492
	Panel E. Dependent variable: change in group rents due to reallocation—wage loss due to displacement from CPS			
Direct task displacement	-0.12	-0.13	-0.12	-0.12
	(0.01)	(0.02)	(0.02)	(0.02)
R^2 for task displacement	0.51	0.56	0.53	0.52
Observations	499	499	499	499
	Panel F. Dependent variable: change in group rents due to reallocation—(minus) EE rates from CPS			
Direct task displacement	-0.594	-0.841	-0.846	-0.883
	(0.053)	(0.113)	(0.111)	(0.117)
R^2 for task displacement	0.49	0.69	0.69	0.73
Observations	499	499	499	499
	Panel G. Dependent variable: change in group rents due to reallocation—(minus) voluntary EU rates from CPS			
Direct task displacement	-0.099	-0.154	-0.148	-0.139
	(0.010)	(0.018)	(0.017)	(0.019)
R^2 for task displacement	0.45	0.70	0.67	0.63
Observations	499	499	499	499
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship automation's task displacement from 1980 to 1990 and various group-level outcomes. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

Table S11: Robustness checks on reduced-form evidence, outcomes constructed for 1990–2016 period.

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: percent change in group average wage, $\Delta \ln \bar{w}_g$			
Direct task displacement	-0.98	-0.86	-0.90	-0.94
	(0.08)	(0.22)	(0.22)	(0.23)
R^2 for task displacement	0.42	0.37	0.38	0.40
Observations	499	499	499	499
	Panel B. Dependent variable: wage change above 30th percentile, $\Delta \ln \bar{w}_g - \Delta \ln w_g(30\text{th})$			
Direct task displacement	-0.18	-0.10	-0.08	-0.07
	(0.05)	(0.11)	(0.11)	(0.11)
R^2 for task displacement	0.09	0.05	0.04	0.03
Observations	499	499	499	499
	Panel C. Dependent variable: wage changes at 30th percentile, $\Delta \ln w_g(30\text{th})$			
Direct task displacement	-0.80	-0.76	-0.81	-0.87
	(0.10)	(0.26)	(0.25)	(0.26)
R^2 for task displacement	0.29	0.27	0.29	0.31
Observations	499	499	499	499
	Panel D. Dependent variable: change in group rents due to reallocation—wage differentials from Census			
Direct task displacement	-0.14	-0.14	-0.14	-0.17
	(0.05)	(0.08)	(0.08)	(0.08)
R^2 for task displacement	0.07	0.07	0.07	0.09
Observations	491	491	491	491
	Panel E. Dependent variable: change in group rents due to reallocation—wage loss due to displacement from CPS			
Direct task displacement	-0.05	-0.06	-0.06	-0.08
	(0.01)	(0.02)	(0.02)	(0.03)
R^2 for task displacement	0.13	0.15	0.15	0.20
Observations	499	499	499	499
	Panel F. Dependent variable: change in group rents due to reallocation—(minus) EE rates from CPS			
Direct task displacement	-0.681	-0.432	-0.487	-0.623
	(0.083)	(0.211)	(0.190)	(0.187)
R^2 for task displacement	0.42	0.27	0.30	0.38
Observations	499	499	499	499
	Panel G. Dependent variable: change in group rents due to reallocation—(minus) voluntary EU rates from CPS			
Direct task displacement	-0.125	-0.138	-0.138	-0.160
	(0.019)	(0.034)	(0.034)	(0.036)
R^2 for task displacement	0.29	0.32	0.33	0.38
Observations	499	499	499	499
Covariates:				
Education and gender		✓	✓	✓
Sectoral demand shifters		✓	✓	✓
Sectoral rent shifters			✓	✓
Manufacturing share				✓

Notes: This table presents estimates of the reduced-form relationship between automation's task displacement from 1990 to 2016 and various group-level outcomes. The sample includes 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is indicated in the panel headers. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

S4.5 Industry-level association between rents and automation

The reduced-evidence in the text focuses on the group-level relation between wages, rents, and the exposure fo groups to automation. This appendix section provides a complementary exercise showing that automation concentrates in high worker-rent industries.

Table S12 presents estimates of the equation

$$\text{(S12)} \qquad \text{Percent labor share decline 1987–2016}_i = \beta \text{ Proxies for rents}_i + u_i,$$

where we take the labor share decline to be indicative of more automation in an industry. The panels report estimates for one of our four proxies for rents:

- Panel A uses wage differentials from the 1980 Census.
- Panel B uses displacement wage losses from the CPS.
- Panel C uses the job-to-job transition rates from the CPS (an inverse measure of rents).
- Panel D uses the quit rate into non-employment from the CPS (an inverse measure of rents).

The columns report different specifications:

- Column 1 reports bivariate regression estimates.
- Column 2 controls for the composite industry index of job quality, obtained from the *Quality of Employment Survey*.
- Column 3 controls for industry-level measures of job amenities, from the *Quality of Employment Survey*.
- Column 4 controls for industry-level measures of job meaning, from the *Quality of Employment Survey*.
- Column 5 controls for industry-level measures of willingness to pay for improved conditions, from the *Quality of Employment Survey*.
- Column 6 controls for a manufacturing dummy, which explores the extent to which our findings are unique to this sector.

In columns 2–5, we adjust the sign of our compensating differential measures, so that higher values mean more wage compensation is required.

Table S13 follows the same format but present estimates of the equation

$$\text{Task displacement 1987–2016}_i = \beta \,\text{Proxies for rents}_i + u_i, \tag{S13}$$

where the left variable is now the percent labor share decline in an industry attributed to automation.

In both cases, we find that industries that pay high worker rents were more likely to automate their processes between 1987 and 2016. This is true even after controlling for different proxies of compensating differentials and holds even within manufacturing.

Table S12: Industry-level association between rent proxies and labor share declines

		Control for compensating differentials				Control for manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Rent proxy on right-hand side of (S12): wage differentials from 1980 Census					
Wage differentials	0.56	0.56	0.56	0.56	0.53	0.57
	(0.11)	(0.13)	(0.12)	(0.14)	(0.12)	(0.13)
Proxy for compensating differentials		0.00	-0.01	0.01	0.04	
		(0.02)	(0.02)	(0.05)	(0.04)	
R^2	0.40	0.40	0.40	0.40	0.41	0.40
Observations	49	49	49	49	49	49
	Panel B. Rent proxy on right-hand side of (S12): Displacement wage losses from CPS					
Wage decline from job loss	0.86	0.86	0.90	0.82	0.77	0.88
	(0.30)	(0.35)	(0.31)	(0.37)	(0.32)	(0.38)
Proxy for compensating differentials		0.00	-0.02	0.02	0.05	
		(0.02)	(0.02)	(0.07)	(0.05)	
R^2	0.22	0.22	0.23	0.22	0.23	0.22
Observations	49	49	49	49	49	49
	Panel C. Rent proxy on right-hand side of (S12): job-to-job transition rates from CPS					
EE transition rate	-11.08	-10.37	-11.19	-9.98	-9.85	-10.82
	(3.50)	(3.40)	(3.54)	(3.32)	(3.39)	(4.49)
Proxy for compensating differentials		0.02	-0.01	0.06	0.08	
		(0.02)	(0.02)	(0.05)	(0.05)	
R^2	0.17	0.19	0.18	0.20	0.22	0.17
Observations	49	49	49	49	49	49
	Panel D. Rent proxy on right-hand side of (S12): Quit rates into non-employment from CPS					
Voluntary EU transition rate	-55.03	-53.74	-55.05	-52.86	-48.98	-44.66
	(25.73)	(22.98)	(26.32)	(21.87)	(23.81)	(26.71)
Proxy for compensating differentials		0.03	0.00	0.09	0.10	
		(0.02)	(0.03)	(0.05)	(0.05)	
R^2	0.08	0.12	0.08	0.14	0.15	0.10
Observations	49	49	49	49	49	49

Notes: This table presents estimates of the reduced-form relationship between our proxies for automation and rents at the industry level. The sample includes 49 industries. The dependent variable is the percent decline in an industry's labor share in 1987–2016. The proxy for rents varies across panels as indicated by the headers. The proxies for compensating differentials are: job quality index (column 2, in negative), the measure of job amenities (column 3, in negative), the measure of job meaning (column 4, in negative), and the measure of willingness to pay for job improvements (column 5). All regressions are weighted by total hours worked by industry in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

Table S13: Industry-level association between rent proxies and automation

		Control for compensating differentials				Control for manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Rent proxy on right-hand side of (S13): wage differentials from 1980 Census					
Wage differentials	0.41	0.37	0.41	0.37	0.34	0.31
	(0.10)	(0.08)	(0.10)	(0.08)	(0.07)	(0.09)
Proxy for compensating differentials		0.02	0.00	0.04	0.09	
		(0.02)	(0.02)	(0.04)	(0.04)	
R^2	0.33	0.36	0.33	0.35	0.41	0.43
Observations	49	49	49	49	49	49
	Panel B. Rent proxy on right-hand side of (S13): Displacement wage losses from CPS					
Wage decline from job loss	0.73	0.64	0.75	0.64	0.55	0.46
	(0.25)	(0.23)	(0.24)	(0.24)	(0.21)	(0.25)
Proxy for compensating differentials		0.01	-0.01	0.04	0.09	
		(0.02)	(0.02)	(0.06)	(0.05)	
R^2	0.24	0.26	0.25	0.26	0.32	0.33
Observations	49	49	49	49	49	49
	Panel C. Rent proxy on right-hand side of (S13): job-to-job transition rates from CPS					
EE transition rate	-9.21	-8.09	-9.18	-7.94	-7.47	-4.99
	(3.30)	(3.05)	(3.26)	(3.05)	(2.90)	(3.23)
Proxy for compensating differentials		0.03	0.00	0.07	0.11	
		(0.02)	(0.02)	(0.05)	(0.05)	
R^2	0.19	0.25	0.19	0.25	0.32	0.30
Observations	49	49	49	49	49	49
	Panel D. Rent proxy on right-hand side of (S13): Quit rates into non-employment from CPS					
Voluntary EU transition rate	-49.96	-48.33	-50.70	-47.72	-42.29	-23.37
	(16.39)	(14.34)	(17.03)	(14.53)	(13.24)	(14.09)
Proxy for compensating differentials		0.03	0.01	0.10	0.13	
		(0.02)	(0.02)	(0.05)	(0.05)	
R^2	0.10	0.20	0.11	0.21	0.27	0.28
Observations	49	49	49	49	49	49

Notes: This table presents estimates of the reduced-form relationship between our proxies for automation and rents at the industry level. The sample includes 49 industries. The dependent variable is the percent decline in an industry's labor share due to automation over 1987–2016. The proxy for rents varies across panels as indicated by the headers. The proxies for compensating differentials are: job quality index (column 2, in negative), the measure of job amenities (column 3, in negative), the measure of job meaning (column 4, in negative), and the measure of willingness to pay for job improvements (column 5). All regressions are weighted by total hours worked by industry in 1980. Standard errors robust to heteroscedasticity are reported in parentheses.

S4.6 Estimates of the propagation and rent impact matrices

The estimation assumes the parameterization of the task-share and rent Jacobians in Section 4.2. Setting $\varphi = \sigma - \lambda$, we can rewrite (23) and (24) as

$$\sigma \Delta \ln w_g + \delta_g = \tilde{\beta}_0 + \tilde{\beta}\, X_g + \sum_{g' \neq g} \theta_{gg'} \left(\Delta \ln w_{g'} - d \ln w_g\right) + u_g$$
$$\Delta \ln \mu_g = \beta_0^{\mu} - \rho\, \delta_g + \beta^{\mu}\, X_g^{\mu} + \sum_{g' \neq g} \theta_{gg'}^{\mu} \left(\Delta \ln w_{g'} - d \ln w_g\right) + e_g.$$

Here, $\tilde{\beta}_0 = \lambda \beta_0 + \varphi \, \sum_{g'} s_{g'}\, \Delta \ln w_g$, $\tilde{\beta} = \lambda \beta$ and the spillover terms are given by

$$\begin{aligned}
\theta_{gg'} = & \sum_n \frac{\ell_{gn}}{\ell_g}\, s_{ng'}\, \theta \\
& + \sum_n \frac{\ell_{gn}}{\ell_g}\, s_{ng'}\, \theta_{\text{job}} \text{ job similarity}_{gg'} \\
& + \sum_n \frac{\ell_{gn}}{\ell_g}\, s_{ng'}\, \theta_{\text{edu-age}} \text{ edu-age similarity}_{gg'} \\
\theta_{gg'}^{\mu} = & \sum_n \left(\frac{\bar{w}_{gn}}{\bar{w}_g} - 1\right) \frac{\ell_{gn}}{\ell_g}\, s_{ng'}\, \theta \\
& + \sum_n \left(\frac{\bar{w}_{gn}}{\bar{w}_g} - 1\right) \frac{\ell_{gn}}{\ell_g}\, s_{ng'}\, \theta_{\text{job}} \text{ job similarity}_{gg'} \\
& + \sum_n \left(\frac{\bar{w}_{gn}}{\bar{w}_g} - 1\right) \frac{\ell_{gn}}{\ell_g}\, s_{ng'}\, \theta_{\text{edu-age}} \text{ edu-age similarity}_{gg'}
\end{aligned}$$

Table S14 reports estimates of ρ, θ, θ_{simj}, and $\theta_{\text{edu-age}}$ obtained from estimating this system of equations via GMM. Columns 1–3 allow for ripple effects separately along each of the dimensions considered. Column 4 reports our baseline estimates. Column 5 report estimates imposing the restriction θ, θ_{simj}, $\theta_{\text{edu-age}} \geq 0$. In all specifications, the covariates for the wage equation are: education and gender dummies, sectoral demand shifts, and the share of employment in manufacturing in 1980. The covariates for the rent equation are: education and gender dummies, sectoral rent shifts, and the share of employment in manufacturing in 1980.

Table S14: GMM estimates of the parametric task share and rent Jacobians.

	(1)	(2)	(3)	(4)	(5)
Rent dissipation	0.409	0.422	0.394	0.355	0.405
	(0.137)	(0.140)	(0.134)	(0.119)	(0.127)
Ripples, θ	1.536			-0.476	
	(0.647)			(1.076)	
Ripples, θ_{job}		2.986		1.861	2.301
		(1.390)		(1.686)	(1.677)
Ripples, $\theta_{\text{edu-age}}$			1.967	0.714	0.684
			(0.867)	(1.039)	(0.815)
Joint significance spillovers (p-value)				0.28	0.07
Observations	500	500	500	500	500
Covariates in wage equation (23):					
Education and gender, sectoral demand shifters, manufacturing	✓	✓	✓	✓	✓
Covariates in rent equation (24):					
Education and gender, sectoral rent shifters, manufacturing	✓	✓	✓	✓	✓

Notes: This table presents GMM estimates of equations (23) and (24). The estimation assumes the parameterization of the task-share and rent Jacobians in Section 4.2. Columns 1–3 allow for ripple effects separately along each of the dimensions considered. Column 4 reports our baseline estimates. Column 5 report estimates imposing the restriction θ, θ_{simj}, $\theta_{\text{edu-age}} \geq 0$. Standard errors robust against heteroscedasticity are given in parenthesis. The table also reports a test for the joint significance of ripples.

S4.7 Measuring task displacement

This subsection derives the measure of automation's task displacement in equation (13) for a multi-sector economy under Assumption 3

Let $\mathcal{R}_{gi}$ denote the set of routine tasks in industry i assigned to group g. Define

$$\Gamma_{gi}^{\text{routine}} = \int_{\mathcal{R}_{gi}} \psi_{xg}^{\lambda-1} \, \mu_{xg}^{-\lambda} \, dx,$$

as the task share of group g in routine jobs at industry i.

Assumption 3 implies that all routine jobs in industry i are automated at the same rate, so that $\delta_{gi}^{\text{routine},d} = \chi_i^{\text{routine}}$, where $\delta_{gi}^{\text{routine},d}$ is the share of group g employment in routine jobs in $\mathscr{A}_{gi}$ as a fraction of all routine jobs employing g workers in industry i. In addition, the fact that non-routine jobs are not automated implies

$$\delta_{gi} = \left(\ell_{gi}^{\text{routine}}/\ell_{gi}\right) \chi_i^{\text{routine}}, \tag{S14}$$

where $\ell_{gi}^{\text{routine}}/\ell_{gi}$ is the share of employment of group g in industry i earned in routine jobs (out of all employment of group g in industry i).

Let's now turn to the labor share in industry i. This is given by

$$s_{\ell i} = \frac{\sum_g \Gamma_{gi} \, \mu_{gi} \, w_g^{1-\lambda}}{p_i^{1-\lambda}}. \tag{S15}$$

The direct effect of automation on the labor share $s_{\ell i}$ holding wages constant is

$$d \ln s_{\ell i}^{\mathcal{A}} = -\sum_g \frac{s_{gi}}{s_{\ell i}} \, \delta_{gi} \, \frac{\mu_{\mathscr{A}_{gi}}}{\mu_{gi}} - (1-\lambda) \, d \ln p_i.$$

Using the fact that $d \ln p_i = -\sum_g s_{gi} \, \delta_{gi} \, \frac{\mu_{\mathscr{A}_{gi}}}{\mu_{gi}} \, \pi_{gi}$ (as shown in Proposition 6 with factor prices held constant), we obtain

$$\begin{aligned} d \ln s_{\ell i}^{\mathcal{A}} &= -\sum_g \frac{s_{gi}}{s_{\ell i}} \, \delta_{gi} \, \frac{\mu_{\mathscr{A}_{gi}}}{\mu_{gi}} + (1-\lambda) \, \sum_g s_{gi} \, \delta_{gi} \, \frac{\mu_{\mathscr{A}_{gi}}}{\mu_{gi}} \, \pi_{gi} \\ &= -\sum_g \frac{s_{gi}}{s_{\ell i}} \, \delta_{gi} \, \frac{\mu_{\mathscr{A}_{gi}}}{\mu_{gi}} \, \left(1 - s_{\ell i} \, (1-\lambda) \, \pi_{gi}\right). \end{aligned}$$

Define the average cost-saving gains and average rent dissipation in industry i as

$$\pi_i = \frac{\sum_g s_{gi}\, \delta_{gi}\, \frac{\mu_{\mathscr{A}gi}}{\mu_{gi}}\, \pi_{gi}}{\sum_g s_{gi}\, \delta_{gi}\, \frac{\mu_{\mathscr{A}gi}}{\mu_{gi}}}, \qquad\qquad 1 + \rho_i = \frac{\sum_g s_{gi}\, \delta_{gi}\, \frac{\mu_{\mathscr{A}gi}}{\mu_{gi}}}{\sum_g s_{gi}\, \delta_{gi}}.$$

Using these definitions, we can write the change in labor shares as

$$d \ln s_{\ell i}^{\mathcal{A}} = -(1 + \rho_i)\ \left(1 - s_{\ell i}\,(1 - \lambda)\,\pi_i\right)\ \sum_g \frac{s_{gi}}{s_{\ell i}}\,\delta_{gi}.$$

Using equation (S14), we can rewrite the change in the labor share as

$$d \ln s_{\ell i}^{\mathcal{A}} = -(1 + \rho_i)\ \left(1 - s_{\ell i}\,(1 - \lambda)\,\pi_i\right)\ \sum_g \frac{s_{gi}}{s_{\ell i}}\,\left(\ell_{gi}^{\text{routine}}/\ell_{gi}\right)\,\chi_i^{\text{routine}}.$$

Using this equation, we can solve for the common rate of automation χ_i^{routine} as

$$\chi_i^{\text{routine}} = \frac{1}{\sum_g \frac{s_{gi}}{s_{\ell i}}\,\left(\ell_{gi}^{\text{routine}}/\ell_{gi}\right)}\ \frac{-d \ln s_{\ell i}^{d}}{1 - s_{\ell i}\,(1 - \lambda)\,\pi_i}\ \frac{1}{1 + \rho_i}.$$

A second use of equation (S14) then implies

$$\delta_{gi} = \text{RCA}_{gi}^{routine}\ \frac{-d \ln s_{\ell i}^{\mathcal{A}}}{1 - s_{\ell i}\,(1 - \lambda)\,\pi_i}\ \frac{1}{1 + \rho_i},$$

where the revealed comparative advantage measure is constructed as

$$\text{RCA}_{gi}^{routine} = \frac{\ell_{gi}^{\text{routine}}/\ell_{gi}}{\sum_{g'} \frac{s_{g'i}}{s_{\ell i}}\,\left(\ell_{g'i}^{\text{routine}}/\ell_{g'i}\right)}.$$