Unpacking Skill Bias: Automation and New Tasks

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Tinbergen's (1974) approach to inequality, based on the race between technological change increasing the demand for skills and the rise in the supply of skills due to education, has been a mainstay of labor economics. Its canonical formalization in the SBTC (skill-biased technological change) model of, inter alia, Katz and Murphy (1992) and Goldin and Katz (2008) has transformed the study of inequality and skills. In this model, technological change takes a factor-augmenting form and increases the productivity of skilled workers more than those of less skilled workers. In its most common version, changes in the demand for skills can be expressed as

$$d\ln\left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma}d\ln\frac{H}{L} + \frac{\sigma-1}{\sigma}d\ln\frac{A_H}{A_L}.$$

where w_H/w_L is the skill premium, H/L is the relative supply of skills, σ is the elasticity of substitution between skilled and unskilled workers and A_L and A_H are factor-augmenting technologies for unskilled and skilled workers respectively. In Katz and Murphy's seminal paper, σ is estimated to be around 1.4, and, combined with a steady growth path for A_H/A_L, this model accounts for the time-series of the college premium in the US fairly successfully.

As argued in Acemoglu and Autor (2011), however, this framework is restrictive in some crucial respects. It does not help us understand the occupational trends in the labor market of most advanced economies, whereby, rather than general skill upgrading, we see the disappearance of middle-skill occupations, such as production and clerical jobs. More importantly, as pointed out in Acemoglu and Restrepo (2019), the economic mechanism in the canonical model is the substitution of the tasks and goods produced by skilled workers who are becoming more productive for those produced by less skilled workers (and is thus mediated by the elasticity of substitution σ). This implies that the canonical SBTC model cannot account for major changes in the US labor market without technological regress. First, without technological regress, real wages of unskilled workers should be rising, whereas, in the US over the last four decades, they have declined notably. Second, even if A_L were constant, this model could only generate the rise in the US college premium between 1963 and 1987 with a growth of 11.3% per annum in A_H. But this would translate into at least a 1.9% increase in TFP, whereas the US TFP over this time period grew only by 1.2% per annum (the same applies for the more recent 1992-2008 period; see the Appendix).

Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2019) propose a task-based model that redresses some of these problems and extends the types of technological changes that impact the demand for skills. At the center of the framework are (1) the allocation of tasks to different factors of production (skilled labor, unskilled labor and capital); and (2) new technologies that affect the productivity of factors in specific tasks and, as with automation, change the task content of production. In this framework, the effect of technology on the demand for skills and wages is not mediated via the elasticity of substitution; the impacts of technology on productivity and wages are decoupled; and new technologies can easily reduce wages for some or all workers. In this paper, we develop a flexible version of this conceptual framework, study the impact of different types of technologies on productivity and wages, and provide evidence on the link between automation and inequality.[1]

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[1] Our companion paper, Acemoglu and Restrepo (2020b), develops a multi-sector model with multiple skill types and estimates the contribution of factor-augmenting technological changes and changes in the task content of production to the evolution of US wage structure. It finds that the bulk of the changes are due to the task content of production.

I. A Model of Tasks, Output and Inequality

We start with a single-industry model. The unique final good is produced from a mass M of tasks $x \in \mathcal{T}$ combined via a CES aggregator:

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

where $\lambda \geq 0$ is the elasticity of substitution across tasks. Tasks are performed by unskilled labor, $\ell(x)$, skilled labor $h(x)$, or capital $k(x)$:

$$y(x) = \psi_L(x)\ell(x) + \psi_H(x)h(x) + \psi_K(x)k(x),$$

where $\psi_j(x) \equiv A_j \cdot \gamma_j(x)$ for $j \in \{L, H, K\}$ denotes the productivity of factor j at task x.

We assume $k(x)$ is produced using $q(x)$ units of the final good, while skilled and unskilled labor is supplied inelastically, with market-clearing conditions $L = \int_{\mathcal{T}} \ell(x)dx$ and $H = \int_{\mathcal{T}} h(x)dx$. We denote by $\mathcal{T}_L$, $\mathcal{T}_H$ and $\mathcal{T}_K$ the set of tasks performed by each factor. A competitive equilibrium is represented by an allocation of tasks to factors and a production of capital goods that maximizes net output $Y - \int_x q(x)k(x)dx$. The Appendix shows that net output is given by

$$NY = \left(\Gamma_L^{\frac{1}{\lambda}}(A_L L)^{\frac{\lambda-1}{\lambda}} + \Gamma_H^{\frac{1}{\lambda}}(A_H H)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda-1}{\lambda}},$$

where the share parameters, Γ_L and Γ_H, are endogenously determined and represent the range of tasks performed by the two types of labor:

$$\Gamma_j = \frac{\frac{1}{M}\int_{\mathcal{T}_j} \gamma_j(x)^{\lambda-1}dx}{1 - \frac{1}{M}\int_{\mathcal{T}_K}\left(\frac{\psi_K(x)}{q(x)}\right)^{\lambda-1} dx} \text{ for } j \in \{L, H\}.$$

Analogously to equation (1) in the canonical model, the effects of various technologies on the skill premium can be expressed as

(1)
$$d\ln\left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma} d\ln\frac{H}{L} + \frac{\sigma-1}{\sigma} d\ln\frac{A_H}{A_L} + \frac{1}{\lambda}\, d\ln\frac{\Gamma_H}{\Gamma_L}\bigg|_{\frac{A_H H}{A_L L}},$$

where the last term—the main difference from (1)—is evaluated at the initial ratio of effective skilled to unskilled labor, $\frac{A_H H}{A_L L}$, and captures the effect of changes in the allocation of tasks to factors on the skill premium. Moreover, $\sigma = \lambda \Big/ \left(1 - \frac{\partial \ln \Gamma_H/\Gamma_L}{\partial \ln A_H H/A_L L}\right) \geq \lambda$ is the *derived* elasticity of substitution between skilled and unskilled labor. This elasticity reflects two types of substitution: between tasks, represented by λ (with more productive skilled labor, there is greater production of skill-intensive tasks), and substitution at the extensive margin whereby some tasks are reallocated from unskilled labor and capital to skilled labor. It is because of this second type of substitution that $\sigma \geq \lambda$.

In addition to factor-augmenting changes—the A_L, A_H and A_K terms—that increase the productivity of a factor in all tasks, this framework enables us to analyze the impact of technologies that affect the productivity of a factor in some tasks. Particularly relevant is *automation*—changes that enable capital to be used in tasks that were previously performed by labor (or equivalently increase the productivity of capital in such tasks). For example, robots can become more productive in welding, a task that was previously performed by human welders. The effects of automation and other technological changes impacting the allocation of tasks to factors work through the last term in (1).

Formally, consider an increase in $\gamma_K(x)$ for a set of tasks currently not in $\mathcal{T}_K$. This type of advances in automation technology will lead to an expansion in the set of tasks allocated to capital, $\mathcal{T}_K$. Automation can displace skilled or unskilled labor. In the context of industrial robotics technology, the evidence presented in Acemoglu and Restrepo (2020a) suggests that most of the automated tasks used to be performed by less skilled workers, and we start with this case. We also simplify the analysis by assuming that $\gamma_K(x) = 0$ for all $x \notin \mathcal{T}_K$ and that if a task *can be* automated and produced by capital it *will be* produced by capital in equilibrium (see the Appendix for primitive conditions that ensure this).

PROPOSITION 1: *Consider an improvement in automation technologies such that the productivity of capital in a set of tasks in $\mathcal{A} \subset \mathcal{T}_L$ increases to $\psi_K(x) > 0$. Then*

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\frac{\int_{\mathcal{A}} \gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1}dx}.$$

Moreover, w_H increases, while w_L may increase *or decrease.*

Several points are worth noting. First, the effect of automation technologies on the skill premium is completely driven by the set of tasks (weighted by their effective productivity) unskilled labor loses relative to the entire set of tasks previously performed by these workers (and is not mediated by the elasticity of substitution, and σ does not need to be greater than one). This close connection between the set of task reallocations and factor price changes is the main conceptual insight of this class of models. Second, advances in automation technologies increase TFP, but these effects, coming from cost savings due to automation, may be small (see the Appendix). Third, the magnitude of the change in the skill premium is decoupled from productivity increases.[2] Fourth, the unskilled wage may decline precisely when the increase in TFP is small (Acemoglu and Restrepo, 2018), but the skilled wage always increases because tasks produced by other factors, which are q-complements to those produced by skill workers, are becoming cheaper.[3]

This framework also allows us to study the implications of new labor-intensive tasks. The role of new tasks was emphasized in Acemoglu and Restrepo (2018, 2019) in both maintaining a stable labor share in GDP in the face of steady automation and as a source of productivity growth. For example, design tasks, most manufacturing engineering tasks, most back-office activities and all programming occupations are new relative to the first half of the 20th century and have been major drivers of the growth of labor demand. Suppose, in particular, that a set of new tasks is introduced. Then:

PROPOSITION 2: *Suppose a small set of new tasks that expand M is introduced. If skilled workers have comparative advantage at these tasks—that is, $w_H/\psi_H(x) < w_L/\psi_L(x)$ at current wages—then the skill premium increases by*

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\frac{\int_{\mathcal{N}} \gamma_H^{\lambda-1} dx}{\int_{\mathcal{T}_H} \gamma_H^{\lambda-1} dx}.$$

If, on the other hand, unskilled workers have comparative advantage at these tasks—that is, $w_L/\psi_L(x) < w_H/\psi_H(x)$ at current wages—then the skill premium will decline by

$$d\ln\left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma}\frac{\int_{\mathcal{N}} \gamma_L^{\lambda-1} dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1} dx}.$$

The interpretation of this proposition is similar to that of Proposition 1. In particular, the effect on the skill premium is again a function of the set of tasks reallocated across factors. Analogously, these changes always increase TFP, but small changes in TFP can go hand-in-hand with sizable changes in the skill premium. Also notable is that new tasks may increase or reduce the skill premium, depending on whether they are allocated to skilled or unskilled labor.[4]

Two other types of technological changes can be studied in this framework. The first is "standardization", which involves the simplification of previously complex tasks performed by skilled labor so that they can now be more cheaply performed by unskilled workers (see Acemoglu and Restrepo, 2018), and the second is "skill upgrading", which involves the transformation of unskilled tasks so that they can be more productively performed by skilled workers. We derive the implications of these two types of technological changes in the Appendix.

II. Empirical Evidence from US industries

We next suppose that the model outlined in the previous section describes production at the

[2] Specifically, in the canonical model, we have $\left.\frac{d\ln TFP}{d\ln(w_H/w_H)}\right|_{A_L} = s_H \cdot \sigma/(\sigma-1)$, where s_H is the share of skilled labor in value added. Thus, to get the demand for skilled labor to increase by 1%, one needs a 0.83% increase in productivity. Instead, in our model, in response to automation, $\frac{d\ln TFP}{d\ln w_H/w_L} = \sigma \cdot s_L \cdot \pi$, where $\pi > 0$ is the average proportional cost reduction in automated tasks. This expression shows that, when $\pi \to 0$, our model generates large swings in the skill premium from very small changes in TFP. Because of this difference, our framework generates sizable changes in the skill premium for reasonable changes in TFP. For example, if automation reduces the cost of producing a task by $\pi = 30\%$, as in the case of industrial robots, then the increase in the college premium between 1963 and 1987 can be explained with as little as 0.6% per annum growth in TFP.

[3] Some of the automated tasks in $\mathcal{A}$ may be previously performed by skilled workers: AI may replace tasks currently employing skilled workers, and many of the iconic innovations of the Industrial Revolution automated spinning, weaving and knitting tasks previously performed by skilled artisans. If so, automation may have the opposite effect on the skill premium.

[4] This is in contrast to the extension considered in Acemoglu and Restrepo (2018), where we assumed that new tasks were always performed by skilled workers.

industry level and then use industry-level data from the US to investigate whether automation and new tasks are associated with changes in the demand for skills. We follow Acemoglu and Restrepo (2019), who show how changes in the task content of production in a multi-sectors setting can be estimated. We use data from the BEA, BLS, and NIPA on factor shares, factor prices, and capital stocks for 1947-1987 and 1987-2016 at 3-digit level, and exclude industries heavily dependent on commodity prices, in particular, oil and gas, mining, and agriculture, which exhibit large temporary fluctuations in factor shares. This leaves us with 44 industries. We combine these with data on wage bill and hours of work by college and high school workers from the US Censuses and the ACS.[5]

We then repeat the empirical exercise in Acemoglu and Restrepo (2019) to obtain estimates of displacement and reinstatement effects (corresponding to automation and the creation of new tasks) at the industry level for our two subperiods. Displacement [resp., reinstatement] effects correspond to declines [resp., increases] in the labor share of value added in industry not explained by changes in factor prices in a five-year period. In the Appendix, we provide details on data sources and the construction of these variables, present descriptive statistics, and document how they covary across industries. Both measures are expressed in percent changes, so that a 0.1 displacement corresponds to a 10% decline in the labor share.

Using these measures, we estimate the following model separately for the two periods:

$$\Delta \mathrm{SBTC}_i = \beta_d \mathrm{displacement}_i + \beta_r \mathrm{reinstatement}_i + \varepsilon_i, \tag{2}$$

where $\Delta \mathrm{SBTC}_i$ is our measure of industry-level increase in the demand for skills—the change in the log of the college wage bill relative to the high school wage bill in each industry during the relevant period. All regressions are weighted by the average share of the aggregate wage bill accounted by the industry during the period. These regression results are presented in the Appendix. Here we depict them visually.

Figure 1 shows a strong association between industry-level demand for skills and our measures of displacement (due to automation) and reinstatement (due to new tasks). During both subperiods, displacement is associated with increases in the demand for skills of the industry, though displacement changes are larger and the relationship becomes steeper in 1987-2016, shown in Panel b. A 10% increase in displacement during 1987-2016 is associated with a 8% increase in the relative demand for college workers (s.e.=0.015). This estimate implies that displacement alone explains about 30% of the variation in the demand for skills across industries during this period.[6] Panels c and d depict the relationship between new tasks and the demand for skills. Greater reinstatement is associated with lower demand for skills during 1947-1987, presumably because unskilled labor had a comparative advantage in many of the new tasks introduced during this period. In contrast, reinstatement goes hand-in-hand with greater demand for skills in 1987-2016, which we interpret as new tasks being allocated to skilled workers during the last three decades. Our estimates suggest that during this latter period, a 10% increase in reinstatement is associated with a 7% increase in the relative demand for college workers (s.e.=0.035).[7]

III. Conclusion

Automation and new tasks can have sizable effects on the demand for skills and factor prices (including declines in the wages for some or all types of labor), while leading only to small changes in TFP. These effects are not mediated by the elasticity of substitution between factors and work instead via the changes in the allocation of factors to tasks (the task content of pro-

[5] We follow Acemoglu and Autor (2011) and define college workers as those with a college degree and half of those with some college. High school workers are therefore those with a high school degree or less and half of the workers with some college.

[6] The 0.55% increase in displacement per annum at the aggregate level during this period could account for as much as a 0.44% increase in the demand for college skills (out of an estimated shift in the relative demand of 2.4% per annum—see Acemoglu and Autor, 2011). Assuming that $\pi = 30\%$, this substantial increase in the relative demand for college skills is consistent with new technologies increasing TFP by as little as 0.16% per annum between 1987 and 2016.

[7] The Appendix provides several robustness checks, using different measures of the demand for skills and different constructions of the displacement and reinstatement effects, and also present estimates from several regression models. These results confirm the patterns summarized in the text.

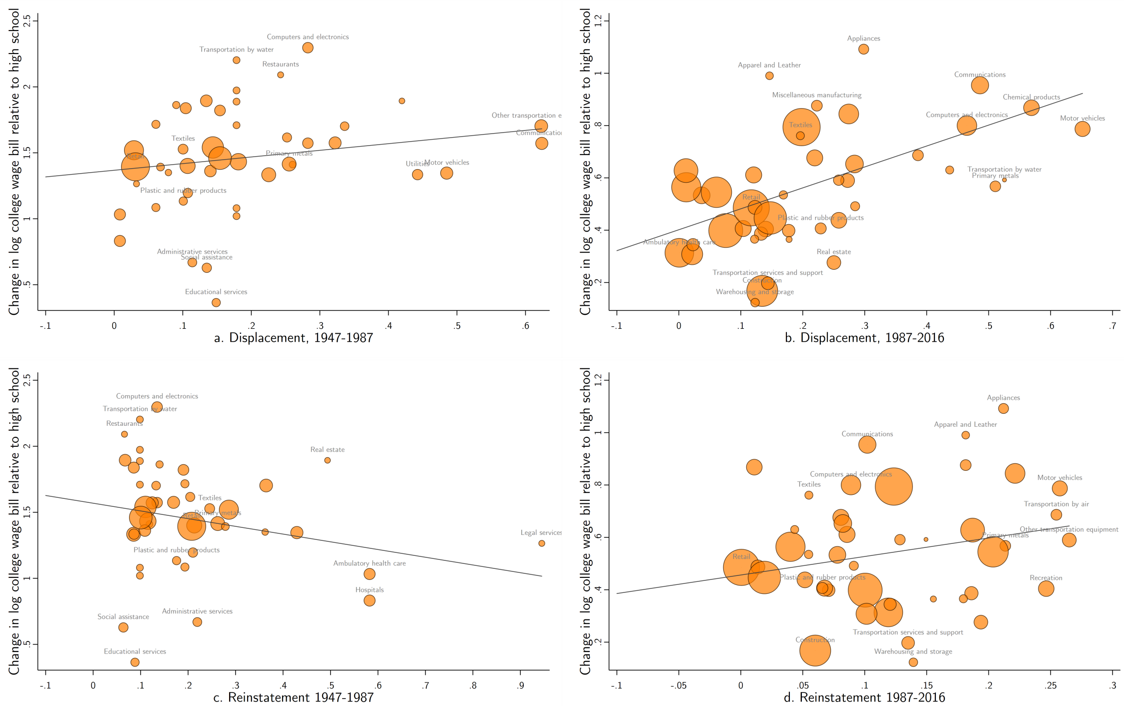

FIGURE 1. RELATIVE DEMAND FOR SKILLS 1947-1987 AND 1987-2016 VERSUS DISPLACEMENT AND REINSTATEMENT. CHANGE IN RELATIVE DEMAND FOR SKILLS MEASURED AS CHANGE IN THE COLLEGE WAGE BILL RELATIVE TO THE HIGH SCHOOL WAGE BILL. SEE THE APPENDIX FOR DETAILS AND DERIVATION OF THE ESTIMATES FOR DISPLACEMENT AND REINSTATEMENT.

duction). This contrasts with factor-augmenting technological changes, which are assumed to raise the productivity of factors in *all* tasks and therefore always cause large TFP increases.

We have argued that the canonical model of the demand for skills can be significantly enriched by incorporating this task-level perspective and technologies that change the allocation of tasks to factors. We also document that proxies for automation and the introduction of new tasks are robustly associated with demand for skills at the industry level. This perspective further suggests that a primary reason for the increase in the skill premium (and the decline in the real wages of less skilled workers) has been rapid automation that has replaced tasks previously performed by less skilled workers.

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Online Appendix for "Automation, New Tasks, and Inequality."

Appendix A. Model, Additional Results, and Proofs

This section of the Appendix provides the derivation of equation (1) and the proofs of generalized versions of Propositions 1 and 2. We also present additional results on the effects of standardization and skill upgrading on wages, inequality and productivity.

CHARACTERIZATION OF EQUILIBRIUM

We first provide a full characterization of the equilibrium for the model presented in the main text.

To simplify the notation and without loss of any generality, we assume that when indifferent between producing with labor or capital, firms produce with capital. Also, when indifferent between producing with skilled and unskilled labor, firms produce with skilled labor. Cost minimization then implies that

$$\mathcal{T}_L = \left\{ x : \frac{w_L}{\psi_L(x)} < \frac{w_H}{\psi_H(x)}, \frac{w_L}{\psi_L(x)} < \frac{q(x)}{\psi_K(x)} \right\}$$
$$\mathcal{T}_H = \left\{ x : \frac{w_H}{\psi_H(x)} \leq \frac{w_L}{\psi_L(x)}, \frac{w_H}{\psi_H(x)} < \frac{q(x)}{\psi_K(x)} \right\},$$
$$\mathcal{T}_K = \left\{ x : \frac{q(x)}{\psi_K(x)} \leq \frac{w_L}{\psi_L(x)}, \frac{q(x)}{\psi_K(x)} \leq \frac{w_H}{\psi_H(x)} \right\}.$$

It also follows that the price of task x is given by

$$p(x) = \begin{cases} \frac{w_L}{\psi_L(x)} & \text{if } x \in \mathcal{T}_L \\ \frac{w_H}{\psi_H(x)} & \text{if } x \in \mathcal{T}_H \\ \frac{q(x)}{\psi_K(x)} & \text{if } x \in \mathcal{T}_K \end{cases}$$

Because the price of the final good is normalized to 1, we have that task prices satisfy the price-index condition

$$1 = \frac{1}{M} \int_x p(x)^{1-\lambda} dx,$$

which can be written in terms of factor prices and the cost of producing capital as follows:

$$1 = \frac{1}{M} \int_{\mathcal{T}_L} \left(\frac{w_L}{\psi_L(x)} \right)^{1-\lambda} dx + \frac{1}{M} \int_{\mathcal{T}_H} \left(\frac{w_H}{\psi_H(x)} \right)^{1-\lambda} dx + \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{q(x)}{\psi_K(x)} \right)^{1-\lambda} dx. \quad \text{(A.1)}$$

The demand for task x is given by $y(x) = \frac{1}{M} \cdot Y \cdot p(x)^{-\lambda}$. Thus, the demand for unskilled labor from tasks in $\mathcal{T}_L$ satisfies

$$L^d = \int_{\mathcal{T}_L} \frac{y(x)}{\psi_L(x)} dx = \int_{\mathcal{T}_L} \frac{\frac{1}{M} Y \cdot p(x)^{-\lambda}}{\psi_L(x)} dx = Y \cdot w_L^{-\lambda} \cdot \frac{1}{M} \int_{\mathcal{T}_L} \psi_L(x)^{\lambda-1} dx,$$

and the demand for skilled labor from tasks in $\mathcal{T}_H$ satisfies

$$H^d = \int_{\mathcal{T}_H} \frac{y(x)}{\psi_H(x)} dx = \int_{\mathcal{T}_H} \frac{\frac{1}{M} Y \cdot p(x)^{-\lambda}}{\psi_H(x)} dx = Y \cdot w_H^{-\lambda} \cdot \frac{1}{M} \int_{\mathcal{T}_H} \psi_H(x)^{\lambda-1} dx.$$

Let $K = \int_x q(x)k(x)$ denote the total amount of capital used in the economy. The demand for capital from tasks in $\mathcal{T}_K$ is

$$K^d = \int_{\mathcal{T}_K} q(x) \cdot \frac{y(x)}{\psi_K(x)} dx = \int_{\mathcal{T}_K} \frac{\frac{1}{M} q(x) \cdot Y \cdot p(x)^{-\lambda}}{\psi_K(x)} dx = Y \cdot \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{\psi_K(x)}{q(x)} \right)^{\lambda - 1} dx.$$

Market clearing implies that $L^d = L$, $H^d = H$ and $K^d = K$. Using the expressions for factor demands above, we can express equilibrium wages as

$$w_L = \left(\frac{Y}{L} \right)^{\frac{1}{\lambda}} \cdot \left(\frac{1}{M} \int_{\mathcal{T}_L} \psi_L(x)^{\lambda - 1} dx \right)^{\frac{1}{\lambda}}$$
$$w_H = \left(\frac{Y}{H} \right)^{\frac{1}{\lambda}} \cdot \left(\frac{1}{M} \int_{\mathcal{T}_H} \psi_H(x)^{\lambda - 1} dx \right)^{\frac{1}{\lambda}}.$$

Substituting these expressions into (A.1) and solving for Y we obtain

$$Y = \left(\frac{\left(\frac{1}{M} \int_{\mathcal{T}_L} \psi_L(x)^{\lambda-1} dx \right)^{\frac{1}{\lambda}}}{1 - \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{q(x)}{\psi_K(x)} \right)^{1-\lambda} dx} \cdot L^{\frac{\lambda-1}{\lambda}} + \frac{\left(\frac{1}{M} \int_{\mathcal{T}_H} \psi_H(x)^{\lambda-1} dx \right)^{\frac{1}{\lambda}}}{1 - \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{q(x)}{\psi_K(x)} \right)^{1-\lambda} dx} \cdot H^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}.$$

Combining this expression with the market cleaning condition for capital, we can write the equilibrium net output as

$$\begin{aligned} Y - K =& Y \cdot \left(1 - \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{\psi_K(x)}{q(x)} \right)^{\lambda-1} dx. \right) \\ =& \left(\left(\frac{\frac{1}{M} \int_{\mathcal{T}_L} \psi_L(x)^{\lambda-1} dx}{1 - \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{q(x)}{\psi_K(x)} \right)^{1-\lambda} dx} \right)^{\frac{1}{\lambda}} \cdot L^{\frac{\lambda-1}{\lambda}} + \left(\frac{\frac{1}{M} \int_{\mathcal{T}_H} \psi_H(x)^{\lambda-1} dx}{1 - \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{q(x)}{\psi_K(x)} \right)^{1-\lambda} dx} \right)^{\frac{1}{\lambda}} \cdot H^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}, \end{aligned}$$

which coincides with the expression for net output in the main text.

Finally, the capital share in output is given by K/Y. Using the market-clearing condition for capital we obtain

$$s_K = \frac{K}{Y} = \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{\psi_K(x)}{q(x)} \right)^{\lambda-1} dx,$$

and the labor share is given by

$$s = 1 - \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{\psi_K(x)}{q(x)} \right)^{\lambda-1} dx.$$

The labor share can be decomposed into the share of unskilled labor in production

$$s_L = \frac{1}{M} \int_{\mathcal{T}_L} \left(\frac{w_L}{\psi_L(x)} \right)^{1-\lambda} dx,$$

and the share of skilled labor in production

$$s_H = \frac{1}{M} \int_{\mathcal{T}_H} \left(\frac{w_H}{\psi_H(x)} \right)^{1-\lambda} dx,$$

where $s = s_L + s_H$.

DERIVATION OF EQUATION (1)

A proportional increase in $A_H H$ and $A_L L$ does not alter the allocation of tasks to factors. We can therefore write:

$$\ln\left(\frac{\Gamma_H}{\Gamma_L}\right) = \Gamma\left(\frac{A_H H}{A_L L}, \theta\right),$$

where θ is a vector denoting the state of technology. We can then decompose changes in $\ln\left(\frac{\Gamma_H}{\Gamma_L}\right)$ as

$$d\ln\frac{\Gamma_H}{\Gamma_L} = \frac{\partial \ln \Gamma_H/\Gamma_L}{\partial \ln A_H H/A_L L} \cdot d\ln\frac{A_H H}{A_L L} + d\ln\frac{\Gamma_H}{\Gamma_L}\bigg|_{\frac{A_H H}{A_L L}},$$

where $d\ln\frac{\Gamma_H}{\Gamma_L}\Big|_{\frac{A_H H}{A_L L}}$ denotes changes in Γ_H and Γ_L due to technology holding $\frac{A_H H}{A_L L}$ constant.

From the expression for net output given in the main text it follows that the skill premium is

$$\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\lambda}\ln\left(\frac{\Gamma_H}{\Gamma_L}\right) + \frac{\lambda-1}{\lambda}\ln\frac{A_H}{A_L} - \frac{1}{\lambda}\ln\frac{H}{L}.$$

Taking a total differential of this equation, we obtain

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\lambda}\left(\frac{\partial \ln \Gamma_H/\Gamma_L}{\partial \ln A_H H/A_L L} \cdot d\ln\frac{A_H H}{A_L L} + d\ln\frac{\Gamma_H}{\Gamma_L}\bigg|_{\frac{A_H H}{A_L L}}\right) + \frac{\lambda-1}{\lambda}d\ln\frac{A_H}{A_L} - \frac{1}{\lambda}d\ln\frac{H}{L}.$$

Regrouping terms, we obtain

$$\begin{aligned} d\ln\left(\frac{w_H}{w_L}\right) = & -\left(\frac{1}{\lambda} - \frac{1}{\lambda}\frac{\partial \ln \Gamma_H/\Gamma_L}{\partial \ln A_H H/A_L L}\right)d\ln\frac{H}{L} + \left(1 - \frac{1}{\lambda} + \frac{1}{\lambda}\frac{\partial \ln \Gamma_H/\Gamma_L}{\partial \ln A_H H/A_L L}\right)d\ln\frac{A_H}{A_L} \\ & + \frac{1}{\lambda}d\ln\frac{\Gamma_H}{\Gamma_L}\bigg|_{\frac{A_H H}{A_L L}}, \end{aligned}$$

which coincides with equation (1) in the main text with $\sigma = \lambda \Big/ \left(1 - \frac{\partial \ln \Gamma_H/\Gamma_L}{\partial \ln A_H H/A_L L}\right)$.

ADDITIONAL RESULTS AND PROOFS

This section of the Appendix provides general statements and proofs for the propositions in the main text. We first present a lemma that provides sufficient conditions for all tasks that *can be* produced by capital *to be* produced by capital in equilibrium. We then state and prove an additional lemma that will be used for computing the productivity gains from different types of technology. Finally, we present five propositions characterizing the effects of different types of technologies on wages, skill premium and productivity. The first three of those are generalizations of Propositions 1 and 2 in the text. The next two study the implications of skill upgrading (technologies that allow skilled workers to perform more efficiently/cheaply some of the tasks that were previously allocated to unskilled labor) and standardization (technologies that simplify tasks and increase the relative productivity of unskilled labor in tasks reviously performed by skilled workers).

LEMMA A.1: *Suppose that $\gamma_K(x)$ is bounded away from zero in the set of tasks for which $\gamma_K(x) > 0$ and that $\gamma_L(x)$ and $\gamma_H(x)$ are bounded above. Then there exists a threshold $\underline{q}$ such that, if $q(x) < \underline{q}$ for all tasks, then all tasks for which $\gamma_K(x) > 0$ are produced by capital.*

PROOF:

Consider an allocation in which

$$\mathcal{T}_L = \left\{ x : \frac{w_L}{\psi_L(x)} < \frac{w_H}{\psi_H(x)}, \gamma_k(x) = 0 \right\}$$
$$\mathcal{T}_H = \left\{ x : \frac{w_H}{\psi_H(x)} \leq \frac{w_L}{\psi_L(x)}, \gamma_K(x) = 0 \right\},$$
$$\mathcal{T}_K = \{x : \gamma_K(x) > 0\}.$$

We prove that there exists a $\underline{q}$ such that, if $q(x) < \underline{q}$ for all tasks, this allocation is the equilibrium allocation. This is equivalent to showing that

$$w_j = \Gamma_L^{\frac{1}{\lambda}} A_L^{\frac{\lambda-1}{\lambda}} \left(\frac{NY}{L}\right)^{\frac{1}{\lambda}} > \frac{A_j}{A_K} \cdot q(x) \cdot \frac{\gamma_j(x)}{\gamma_K(x)} \text{ for } j \in \{L, H\} \text{ and } x \in \mathcal{T}_k.$$

A sufficient condition for this inequality to hold is that

$$\text{(A.2)} \qquad w_j = \Gamma_L^{\frac{1}{\lambda}} A_L^{\frac{\lambda-1}{\lambda}} \left(\frac{NY}{L}\right)^{\frac{1}{\lambda}} > \frac{A_j}{A_K} \cdot \underline{q} \cdot \frac{\overline{\gamma}_j}{\underline{\gamma}_K} \text{ for } j \in \{L, H\},$$

where $\overline{\gamma}_j$ is an upper bound for $\gamma_j(x)$ and $\underline{\gamma}_K$ is a lower bound for $\gamma_K(x)$ in $\mathcal{T}_K$.

As $\underline{q}$ declines, the left-hand side of this equation (weakly) increases. To see this, note that we can rewrite the left-hand side as

$$w_j = \left(1 - \frac{1}{M} \int_{\mathcal{T}_K} \left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda}\right)^{\frac{1}{1-\lambda}}$$
$$\cdot \left(\left(\frac{1}{M} \int_{\mathcal{T}_L} \psi_L(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}} \cdot L^{\frac{\lambda-1}{\lambda}} + \left(\frac{1}{M} \int_{\mathcal{T}_H} \psi_H(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}} \cdot H^{\frac{\lambda-1}{\lambda}} \right)^{\frac{1}{\lambda-1}} \cdot \frac{A_L^{\frac{\lambda-1}{\lambda}}}{L^{\frac{1}{\lambda}}},$$

which increases as $q(x)$ falls.

Instead, as $\underline{q}$ declines towards zero, the right-hand side of equation (A.2) converges to zero. It follows that, for some $\underline{q} > 0$, the sufficient condition in equation (A.2) holds, as claimed. □

We now provide an additional lemma that we use repeatedly in the proof of the main propositions.

LEMMA A.2: *Consider any improvement in technology increasing TFP by* $d \ln TFP > 0$. *Then*

$$d \ln TFP = s_L d \ln w_L + s_H d \ln w_H.$$

PROOF:

Because of constant returns to scale and the fact that we have competitive markets,

$$Y = w_L \cdot L + w_H \cdot H + K.$$

Following an improvement in technology, both sides of this equation change by

$$\frac{\partial \ln Y}{\partial \ln K} d \ln K + d \ln TFP = s_L \cdot d \ln w_L + s_H \cdot d \ln w_H + s_K d \ln K,$$

where $d \ln TFP = d \ln Y|_{L,H,K}$ denotes the expansion in output holding inputs constant. The lemma follows from the fact that in a competitive equilibrium $\frac{\partial \ln Y}{\partial \ln K} = s_K$. □

We now turn to general statements of Propositions 1 and 2 and their corresponding proofs.

PROPOSITION A.1: *Suppose that $q(x) < \underline{q}$, with $\underline{q}$ as defined in Lemma A.1. Consider an improvement in automation technologies such that the productivity of capital in a small set of tasks in $\mathcal{A} \subset \mathcal{T}_L$ increases to $\psi_K(x) > 0$. Then:*

- *the skill premium changes by*

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\frac{\int_{\mathcal{A}} \gamma_L^{\lambda-1} dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1} dx}; \tag{A.3}$$

- *TFP increases by*

$$d\ln TFP_{\mathcal{A}} = \frac{1}{M}\int_{\mathcal{A}} \frac{\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} - \left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda}}{1-\lambda} dx > 0; \tag{A.4}$$

- *the labor share declines by*

$$ds = -\frac{1}{M}\int_{\mathcal{A}} \left(\frac{\psi_K(x)}{q(x)}\right)^{\lambda-1} dx$$

- *w_H increases while the effect on w_L is ambiguous.*

PROOF:

Define the function

$$\tilde{\Gamma}(w_H/w_L;\theta) = \frac{\displaystyle\int_{w_H/\psi_H(x)\le w_L/\psi_L(x), \gamma_K(x)=0} \psi_H(x)^{\lambda-1} dx}{\displaystyle\int_{w_H/\psi_H(x)> w_L/\psi_L(x), \gamma_K(x)=0} \psi_L(x)^{\lambda-1} dx}.$$

Because $q(x) < \underline{q}$, we have that in equilibrium $\tilde{\Gamma}(w_H/w_L;\theta) = \Gamma(A_H H/A_L L;\theta)$. Thus, the skill premium satisfies the implicit equation

$$\frac{w_H}{w_L} = \tilde{\Gamma}(w_H/w_L;\theta)^{\frac{1}{\lambda}} \cdot \left(\frac{A_H}{A_L}\right)^{\frac{\lambda-1}{\lambda}} \left(\frac{H}{L}\right)^{-\frac{1}{\lambda}}. \tag{A.5}$$

The definition of the derived elasticity of substitution implies that a change in $\ln H/L$ reduces the skill premium by

$$\frac{\partial \ln w_H/w_L}{\partial \ln H/L} = -\frac{1}{\sigma}.$$

Using equation (A.5), we can expand this expression as

$$\frac{\partial \ln w_H/w_L}{\partial \ln H/L} = \frac{1}{\lambda}\frac{\partial \ln \tilde{\Gamma}}{\partial \ln w_H/w_L}\frac{\partial \ln w_H/w_L}{\partial \ln H/L} - \frac{1}{\lambda} \Rightarrow \frac{\partial \ln w_H/w_L}{\partial \ln H/L} = -\frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\partial \ln \tilde{\Gamma}}{\partial \ln w_H/w_L}}.$$

Therefore, the function $\tilde{\Gamma}$ satisfies the equation

$$\frac{1}{\sigma} = \frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\partial \ln \tilde{\Gamma}}{\partial \ln w_H/w_L}}. \tag{A.6}$$

To obtain the effect of automation on the skill premium, we can take a log differential of (A.5):

$$d\ln\left(\frac{w_H}{w_L}\right)=\frac{1}{\lambda}\frac{\partial\ln\tilde{\Gamma}}{\partial\ln w_H/w_L}d\ln\ln\left(\frac{w_H}{w_L}\right)+\frac{1}{\lambda}\frac{\int_{\mathcal{A}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx}.$$

Solving for $d\ln\ln\left(\frac{w_H}{w_L}\right)$ yields

$$d\ln\ln\left(\frac{w_H}{w_L}\right)=\frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\partial\ln\tilde{\Gamma}}{\partial\ln w_H/w_L}}\frac{\int_{\mathcal{A}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx}=\frac{1}{\sigma}\frac{\int_{\mathcal{A}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx},$$

where the last step follows by substituting σ from (A.6).

To derive the expression for the change in TFP, we start by taking a differential of equation (A.1):

$$0=s_L\cdot(1-\lambda)\cdot d\ln w_L+s_H\cdot(1-\lambda)\cdot d\ln w_H+\frac{1}{M}\int_{\mathcal{A}}\left[\left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda}-\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}\right]dx.$$

Note that, because the cost of producing a task with different factors is equated at marginal tasks, additional changes in the allocation of tasks to factors are second order and do not contribute to this expression. Hence, we can rewrite this equation as

$$s_L\cdot d\ln w_L+s_H\cdot d\ln w_H=\frac{1}{M}\int_{\mathcal{A}}\frac{\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}-\left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda}}{1-\lambda}dx.$$

Lemma A.2 then implies that the left-hand side of the above equation equals $d\ln TFP_{\mathcal{A}}$, as claimed. Furthermore, because $q(x)<\underline{q}$, we have that $w_L/\psi_L(x)>q(x)/\psi_K(x)$ for tasks in $\mathcal{A}$, and therefore the right-hand side of the above equation is positive, as stated in the proposition.

The expression for the decline in the labor share follows from differentiating equation (III).

Finally, the fact that w_H increases follows from the fact that the skill premium increases and Lemma A.2 implies that $s_L\cdot d\ln w_L+s_H\cdot d\ln w_H=d\ln TFP_{\mathcal{A}}>0$. The fact that the effect on w_L is ambiguous follows from the fact that

$$w_L=\Gamma_L^{\frac{1}{\lambda}}\cdot A_L^{\frac{\lambda-1}{\lambda}}\left(\frac{NY}{L}\right)^{\frac{1}{\lambda}}.$$

On the one hand, an improvement in automation reduces Γ_L (in particular, equation (A.1) implies $A_L^{\lambda-1}\Gamma_L+A_H^{\lambda-1}\Gamma_H=1$, and $\Gamma_H/\Gamma_L=\tilde{\Gamma}$ increases with automation, which implies that Γ_L must decrease and Γ_H must increase). On the other hand, NY increases by $d\ln TFP_{\mathcal{A}}/(1-s_K)$. Consequently, automation reduces unskilled wages when the productivity gains from this technology are small, but increases unskilled wages when the productivity gains from automation are large. □

PROPOSITION A.2: *Suppose that $q(x)<\underline{q}$, with $\underline{q}$ as defined in Lemma A.1. Consider the introduction of a small set of tasks $\mathcal{N}$ that expand $\overline{M}$ such that: i. $w_H/\psi_H(x)<w_L/\psi_L(x)$, ii. $w_H/\psi_H(x)<1$, and iii. $\gamma_K(x)=0$ for all tasks in $\mathcal{N}$. These new tasks will be produced by skilled labor, and:*

- *the skill premium changes by*

$$d\ln\left(\frac{w_H}{w_L}\right)=\frac{1}{\sigma}\frac{\int_{\mathcal{N}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx};$$

- *TFP increases by*

$$d \ln TFP_{\mathcal{N}} = \frac{1}{M} \int_{\mathcal{N}} \frac{1 - \left(\frac{w_h}{\psi_h(x)}\right)^{1-\lambda}}{1-\lambda} dx > 0;$$

- *and the labor share increases by*

$$ds = \frac{|\mathcal{A}|}{M^2} \int_{\mathcal{T}_K} \left(\frac{\psi_K(x)}{q(x)}\right)^{\lambda-1} dx.$$

PROOF:

By assumption, the most cost effective way of producing the new tasks is with skilled labor. Thus, new tasks expand the set $\mathcal{T}_H$ and the mass of tasks M increases to $M + |\mathcal{N}|$.

To obtain the effect of new tasks on the skill premium, we can take a log differential of (A.5):

$$d \ln \ln \left(\frac{w_H}{w_L}\right) = \frac{1}{\lambda} \frac{\partial \ln \tilde{\Gamma}}{\partial \ln w_H/w_L} d \ln \ln \left(\frac{w_H}{w_L}\right) + \frac{1}{\lambda} \frac{\int_{\mathcal{N}} \gamma_H^{\lambda-1} dx}{\int_{\mathcal{T}_L} \gamma_H^{\lambda-1} dx}.$$

Solving for $d \ln \ln \left(\frac{w_H}{w_L}\right) L$ yields

$$d \ln \ln \left(\frac{w_H}{w_L}\right) = \frac{\frac{1}{\lambda}}{1 - \frac{1}{\lambda} \frac{\partial \ln \tilde{\Gamma}}{\partial \ln w_H/w_L}} \frac{\int_{\mathcal{N}} \gamma_H^{\lambda-1} dx}{\int_{\mathcal{T}_L} \gamma_H^{\lambda-1} dx} = \frac{1}{\sigma} \frac{\int_{\mathcal{N}} \gamma_H^{\lambda-1} dx}{\int_{\mathcal{T}_L} \gamma_H^{\lambda-1} dx},$$

where the last step follows by substituting σ from (A.6).

To derive the expression for the change in TFP, we start by taking a differential of equation (A.1):

$$0 = s_L \cdot (1-\lambda) \cdot d \ln w_L + s_H \cdot (1-\lambda) \cdot d \ln w_H + \frac{1}{M} \int_{\mathcal{N}} \left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda} dx - \frac{|\mathcal{N}|}{M}$$

We can rewrite this equation as

$$s_L \cdot d \ln w_L + s_H \cdot d \ln w_H = \frac{1}{M} \int_{\mathcal{A}} \frac{1 - \left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda}}{1-\lambda} dx.$$

Lemma A.2 then implies that the left-hand side of the above equation equals $d \ln TFP_{\mathcal{N}}$. Moreover, the assumptions made in the proposition ensure that $w_H/\psi_H(x) < 1$ for tasks in $\mathcal{N}$, and therefore the right-hand side of the above equation is positive, as stated in the proposition.

The expression for the increase in the labor share follows from differentiating equation (III). □

PROPOSITION A.3: *Suppose that $q(x) < \underline{q}$, with $\underline{q}$ as defined in Lemma A.1. Consider the introduction of a small set of tasks $\mathcal{N}$ that expand M such that: i. $w_L/\psi_L(x) < w_H/\psi_H(x)$, ii. $w_L/\psi_L(x) < 1$, and iii. $\gamma_K(x) = 0$ for all tasks in $\mathcal{N}$. These new tasks will be produced by unskilled labor, and:*

- *the skill premium falls by*

$$d \ln \left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma} \frac{\int_{\mathcal{N}} \gamma_L^{\lambda-1} dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1} dx};$$

- *TFP increases by*

$$d\ln TFP_{\mathcal{N}} = \frac{1}{M}\int_{\mathcal{N}} \frac{1-\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}}{1-\lambda}dx > 0;$$

- *and the labor share increases by*

$$ds = \frac{|\mathcal{A}|}{M^2}\int_{\mathcal{T}_K}\left(\frac{\psi_K(x)}{q(x)}\right)^{\lambda-1}dx.$$

PROOF:
The proof is analogous to that of Proposition A.2 and is omitted. □

Propositions 1 and 2 in the main text follow as a corollary from Propositions A.1-A.3. We now provide two additional propositions characterizing the effect of skill upgrading and standardization.

PROPOSITION A.4: *Suppose that $q(x) < \underline{q}$, with $\underline{q}$ as defined in Lemma A.1. Suppose that the productivity of skilled labor rises in a small set of tasks $\mathcal{U} \subset \mathcal{T}_L$ in such a way that $w_H/\psi_H(x) < w_L/\psi_L(x)$ for all $x \in \mathcal{U}$ at the new productivity levels. Then:*

- *the skill premium changes by*

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\frac{\int_{\mathcal{U}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx} + \frac{1}{\sigma}\frac{\int_{\mathcal{U}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx} > 0;$$

- *TFP increases by*

$$d\ln TFP_{\mathcal{U}} = \frac{1}{M}\int_{\mathcal{A}} \frac{\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}-\left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda}}{1-\lambda}dx > 0;$$

- *the labor share remains unchanged;*
- *w_H increases while the effect on w_L is ambiguous.*

PROOF:
To obtain the effect of skill upgrading on the skill premium, we can take a log differential of (A.5), which yields

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\lambda}\frac{\partial\ln\tilde{\Gamma}}{\partial\ln w_H/w_L}d\ln\left(\frac{w_H}{w_L}\right) + \frac{1}{\lambda}\frac{\int_{\mathcal{U}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx} + \frac{1}{\lambda}\frac{\int_{\mathcal{U}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx}.$$

Solving for $d\ln\left(\frac{w_H}{w_L}\right)$ yields

$$\begin{aligned} d\ln\left(\frac{w_H}{w_L}\right) &= \frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\partial\ln\tilde{\Gamma}}{\partial\ln w_H/w_L}}\left(\frac{\int_{\mathcal{U}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx} + \frac{\int_{\mathcal{U}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx}\right) \\ &= \frac{1}{\sigma}\frac{\int_{\mathcal{U}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx} + \frac{1}{\sigma}\frac{\int_{\mathcal{U}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx} > 0, \end{aligned}$$

where the second equation follows by substituting σ from (A.6), and the overall expression is positive because both terms are positive.

To derive the expression for the change in TFP, we start by taking a differential of equation (A.1):

$$0 = s_L \cdot (1-\lambda) \cdot d\ln w_L + s_H \cdot (1-\lambda) \cdot d\ln w_H + \frac{1}{M}\int_{\mathcal{U}} \left[\left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda} - \left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}\right] dx.$$

We can rewrite this equation as

$$s_L \cdot d\ln w_L + s_H \cdot d\ln w_H = \frac{1}{M}\int_{\mathcal{U}} \frac{\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} - \left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda}}{1-\lambda} dx.$$

Lemma A.2 then implies that the left-hand side of the above equation equals $d\ln TFP_{\mathcal{U}}$. Also, note that because $w_H/\psi_H(x) < w_L/\psi_L(x)$ for all tasks in $\mathcal{U}$, we have that the right-hand side of the above equation is positive, as stated in the Proposition.

The fact that the labor share remains unchanged follows from equation (III).

Finally, the fact that w_H increases follows from the fact that the skill premium increases and Lemma A.2 implies that $s_L \cdot d\ln w_L + s_H \cdot d\ln w_H = d\ln TFP_{\mathcal{U}} > 0$. The fact that the effect on w_L is ambiguous follows from the fact that

$$w_L = \Gamma_L^{\frac{1}{\lambda}} \cdot A_L^{\frac{\lambda-1}{\lambda}} \left(\frac{NY}{L}\right)^{\frac{1}{\lambda}}.$$

On the one hand, skill upgrading reduces Γ_L. On the other hand, NY increases by $d\ln TFP_{\mathcal{U}}/(1-s_K)$. Consequently, skill upgrading reduces unskilled wages when the productivity gains from this technology are small, but increases unskilled wages when the productivity gains are large. □

One interesting implication of this proposition is that skill upgrading, though it increases inequality between skilled and unskilled labor, leaves the labor share unchanged. This highlights that recent developments in the US labor market, which involves both greater inequality between skilled and unskilled labor and lower labor share (at least in manufacturing, see Acemoglu and Restrepo, 2019), cannot just be explained by skill upgrading and likely involve some reallocation of tasks previously performed by workers to capital.

Finally, we turn to the implications of standardization.

PROPOSITION A.5: *Suppose that $q(x) < \underline{q}$, with $\underline{q}$ as defined in Lemma A.1. Suppose that the productivity of unskilled labor rises in a small set of tasks $\mathcal{S} \subset \mathcal{T}_H$ in such a way that $w_L/\psi_L(x) < w_H/\psi_H(x)$ for all $x \in \mathcal{S}$ at the new productivity levels. Then:*

- *the skill premium falls by*

$$d\ln\left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma}\frac{\int_{\mathcal{S}} \gamma_H^{\lambda-1} dx}{\int_{\mathcal{T}_H} \gamma_H^{\lambda-1} dx} - \frac{1}{\sigma}\frac{\int_{\mathcal{S}} \gamma_L^{\lambda-1} dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1} dx};$$

- *TFP increases by*

$$d\ln TFP_{\mathcal{S}} = \frac{1}{M}\int_{\mathcal{A}} \frac{\left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda} - \left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}}{1-\lambda} dx > 0;$$

- *the labor share remains unchanged;*
- *w_L increases while the effect on w_H is ambiguous.*

PROOF:

To obtain the effect of automation on the skill premium, we can take a log differential of (A.5):

$$d\ln\left(\frac{w_H}{w_L}\right)=\frac{1}{\lambda}\frac{\partial\ln\tilde{\Gamma}}{\partial\ln w_H/w_L}d\ln\left(\frac{w_H}{w_L}\right)-\frac{1}{\lambda}\frac{\int_{\mathcal{S}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx}-\frac{1}{\lambda}\frac{\int_{\mathcal{S}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx}.$$

Solving for $d\ln\left(\frac{w_H}{w_L}\right)$ yields

$$d\ln\left(\frac{w_H}{w_L}\right)=-\frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\partial\ln\tilde{\Gamma}}{\partial\ln w_H/w_L}}\left(\frac{\int_{\mathcal{S}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx}+\frac{\int_{\mathcal{S}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx}\right)=-\frac{1}{\sigma}\frac{\int_{\mathcal{S}}\gamma_H^{\lambda-1}dx}{\int_{\mathcal{T}_H}\gamma_H^{\lambda-1}dx}+\frac{1}{\sigma}\frac{\int_{\mathcal{S}}\gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L}\gamma_L^{\lambda-1}dx},$$

where the last step follows by substituting σ from (A.6).

To derive the expression for the change in TFP, we start by taking a differential of equation (A.1):

$$0=s_L\cdot(1-\lambda)\cdot d\ln w_L+s_H\cdot(1-\lambda)\cdot d\ln w_H+\frac{1}{M}\int_{\mathcal{S}}\left[\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}-\left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda}\right]dx.$$

We can rewrite this equation as

$$s_L\cdot d\ln w_L+s_H\cdot d\ln w_H=\frac{1}{M}\int_{\mathcal{S}}\frac{\left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda}-\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda}}{1-\lambda}dx.$$

Lemma A.2 then implies that the left-hand side of the above equation equals $d\ln TFP_{\mathcal{S}}$. Also, note that because $w_L/\psi_L(x)<w_H/\psi_H(x)$ for all tasks in $\mathcal{S}$, we have that the right-hand side of the above equation is positive, as stated in the Proposition.

The fact that the labor change remains unchanged follows from equation (III).

Finally, the fact that w_L increases follows from the fact that the skill premium decreases and Lemma A.2 implies that $s_L\cdot d\ln w_L+s_H\cdot d\ln w_H=d\ln TFP_{\mathcal{S}}$. The fact that the effect on w_H is ambiguous follows from the fact that

$$w_H=\Gamma_H^{\frac{1}{\lambda}}\cdot A_H^{\frac{\lambda-1}{\lambda}}\left(\frac{NY}{L}\right)^{\frac{1}{\lambda}}.$$

Following a standardization of tasks, Γ_H decreases. On the other hand, NY increases by $d\ln TFP_{\mathcal{S}}/(1-s_K)$. □

Appendix B. Productivity Calculations

This section provides the details behind the productivity calculations provided in the introduction and in footnote 2. Throughout, we approximate changes over time using first-order expansions.

Productivity Implications of Skill-Biased Technological Change in the Canonical Model

We provide two complementary exercises to illustrate the implications for productivity of the canonical model. First, we use the estimates for the growth rate in A_H/A_L from Katz and Murphy (1992) and Acemoglu and Autor (2011) and compute the productivity gains that would result from such changes. We then estimate the growth in A_H that one would need to explain the observed shift in the relative demand for college workers, and also compute how real wages would respond to such changes.

Regarding the fist exercise, the resulting productivity gains from improvements in factor-augmenting technologies are approximately

$$\Delta \ln TFP_{SBTC} = s_H \Delta \ln A_H + s_L \Delta \ln A_L.$$

If there is no technological regress, then $\Delta \ln A_L \geq 0$, and thus

$$\Delta \ln TFP_{SBTC} \geq s_H \Delta \ln A_H / A_L. \tag{A.7}$$

Katz and Murphy (1992) estimate $\sigma = 1.41$ and a yearly growth rate for $\ln A_H/A_L$ of 11.34% during the 1963-1987 period. In addition, $s_H = 17\%$ at the beginning of their sample (skilled workers accounted for 25% of wages, and the labor share was roughly of 2/3, which gives $s_H = 25\% \cdot 2/3 = 17\%$). Using equation (A.7), their estimates imply a yearly increase in TFP of at least 1.9% per annum. If we used the average value of s_H between 19663 and 1987, we obtain an increase in TFP of at least 2.76% per annum.

Acemoglu and Autor (2011) estimate $\sigma = 1.63$ and a yearly growth rate for $\ln A_H/A_L$ of 7.22% during the 1963-1992 period and of 4.64% during the 1992-2008 period. In addition, $s_H = 17\%$ at the beginning of their sample, $s_H = 32\%$ around 1992 and $s_H = 38\%$ around 2008. Using equation (A.7), their estimates imply an annual increase in TFP of at least 1.2% per annum for 1963-1992 (1.76% if we use the midpoint of s_H during this period). Finally, their estimates imply a yearly increase in TFP of at least 1.48% per annum for 1992-2008 (1.62% if we use the midpoint of s_H during this period).

Table A.1 provides the estimates and calculations for different time periods. For comparison, Fernald's (2012) estimates of TFP are provided in the last column of the table. In particular, these estimates imply a 1.2% per annum increase in TFP for 1963-1987; 1.1% per annum for 1963-1992; and 1% per annum for 1992-2008, which are much smaller than the lower bounds implied by the canonical model.

TABLE A.1—PRODUCTIVITY IMPLICATIONS OF THE CANONICAL MODEL

	Period	σ	Growth rate of A_H/A_L	Share of college labor in GDP (start of period)	Share of college labor in GDP (end of period)	TFP growth using beginning of period estimate for s_H	TFP growth using midpoint estimate for s_H	Observed TFP growth (Fernald, 2012)
Katz and Murphy	63-87	1.41	11.3%	16.7%	32.0%	1.89%	2.76%	1.18%
Acemoglu and Autor	63-92	1.63	7.2%	16.7%	32.0%	1.20%	1.76%	1.11%
Acemoglu and Autor	92-08	1.63	4.6%	32.0%	37.8%	1.48%	1.62%	0.98%

Turning to the second exercise, note that the total shift in the relative demand for college workers is given by

$$\Delta \ln \left(\frac{w_H}{w_L} \right) + \frac{1}{\sigma} \Delta \frac{H}{L}.$$

Using the numbers from Acemoglu and Autor (2011), it follows that the relative demand for college workers increased by 3.3% per annum from 1963 to 1992 (1.3% from wages and 2% from the 90% increase in the relative supply of skills during this period), and then by 2.4% per annum from 1992 to 2008.

Equation (A.7) implies that, if shifts in the relative demand for college workers were driven by factor augmenting technologies, then:

$$\frac{\Delta \ln TFP_{SBTC}}{\Delta \ln w_H/w_L} = s_H \cdot \frac{\sigma}{\sigma - 1}.$$

The estimates from Katz and Murphy in Table A.1 then imply that, if the only source of technological change were improvements in A_H, a 1% increase in the relative demand for college workers would be associated with an increase in TFP of 0.83% for 1963-1987 (using the midpoint estimate for s_H). Likewise, The estimates from Acemoglu and Autor in Table A.1 imply that a 1% increase in the relative demand for college workers would be associated with an increase in TFP of 0.63% for 1963-1992 and 0.9% for 1992-2008 (using the midpoint estimate for s_H). Thus, the changes in A_H required to explain the total shift in the relative demand for college workers would generate productivity increases of at least 2% per annum for 1963-1992 (= 0.63 × 3.3) and 2.16% per annum for 1992-2008 (= 0.9 × 2.4).

Moreover, the implied change in unskilled wages can be written as

$$\Delta \ln w_L = \Delta \ln TFP_{SBTC} - s_H \Delta \ln \left(\frac{w_H}{w_L}\right) = s_H \cdot \frac{1}{\sigma - 1} \Delta \ln \left(\frac{w_H}{w_L}\right)$$

Thus, if all changes in inequality were driven by factor-augmenting technologies we would expect an increase in unskilled wages of at least 1.2% per annum for 1963-1992 and of 1.3% per annum for 1992-2008. In contrast, as noted in the text, real wages for unskilled workers have declined over these time periods.

Productivity Implications of Automation

To illustrate the differences between the task framework and the canonical model, we now estimate the amount of automation that one would need to explain the observed shift in the relative demand for college workers, and also compute how real wages would respond to such technological changes.

Suppose instead that technological changes are driven by automation. Then, the increases in TFP would be given by equation (A.4). Using a first-order Taylor expansion, these productivity gains can be approximated as

$$d \ln TFP_{\mathcal{A}} \approx \int_{\mathcal{A}} \left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} \cdot \left(\ln \left(\frac{w_L}{\psi_L(x)}\right) - \ln \left(\frac{q(x)}{\psi_K(x)}\right)\right) dx.$$

This expression shows that the productivity gains from automating a task are given by its initial share in value added (the term $(w_L/\psi_L(x))^{1-\lambda}$), and the percent reduction in the unit cost of producing the task (the term $\ln (w_L/\psi_L(x)) - \ln (q(x)/\psi_K(x))$). We can also express the productivity gains from automation as

$$d \ln TFP_{\mathcal{A}} \approx \pi \cdot \int_{\mathcal{A}} \left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} dx, \tag{A.8}$$

where $\pi > 0$ is the (weighted) average reduction in the cost of producing tasks due to automation and $\int_{\mathcal{A}} \left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} dx$ gives the share of automated tasks in value added.

Using equations (A.3) and (A.8), it follows that if shifts in the relative demand for college workers were driven by automation, then:

$$\frac{\Delta \ln TFP_{\mathcal{A}}}{\Delta \ln w_H/w_L} = \sigma \cdot s_L \cdot \pi.$$

This equation shows that automation technologies that generate modest reductions in costs (in the extreme, $\pi \to 0$) can generate sizable changes in inequality accompanied by modest increases in TFP.

In particular, suppose $\pi = 30\%$, which is in line with estimates for industrial automation surveyed in Acemoglu and Restrepo (2020a). Using a value for σ of 1.63 and a midpoint estimate for s_L, we obtain that, if the only source of technological change were automation, a 1% increase in the relative demand for college workers would be associated with an increase in TFP of 0.21% for 1963-1992 and 0.14% for 1992-2008. Using a value for σ of 1.41 (as in Katz and Murphy, 1992) and a midpoint estimate for s_L, we obtain that a 1% increase in the relative demand for college workers would be associated with an increase in TFP of 0.18% for 1963-1987.

Thus, the changes in automation technology required to explain the total shift in the relative demand for skill labor would generate productivity increases of as little as 0.6% per annum for 1963-1987 (using Katz and Murphy's estimates of 0.18 × 3.3); 0.7% per annum for 1963-1992 (= 0.21 × 3.3); and 0.34% per annum for 1992-2008 (= 0.14 × 2.4).

Moreover, automation technologies would change unskilled wages by

$$\Delta \ln w_L = \Delta \ln TFP_{\mathcal{A}} - s_H \Delta \ln \left(\frac{w_H}{w_L}\right) = (\sigma \cdot s_L \cdot \pi - s_H) \cdot \Delta \ln \left(\frac{w_H}{w_L}\right)$$

Thus, if all changes in inequality were driven by automation, we would expect a reduction of unskilled wages by 0.1% per annum for 1963-1992 and of 0.34% per annum for 1992-2008.

Appendix C. Data Description and Additional Empirical Exercises

This part of the Appendix describes the data and provides additional empirical exercises.

Set of Industries Used in the Analysis

We use a set of 44 industries that we could track across different sources, including the Census, the BEA industry accounts, and NIPA. The crosswalks used are part of the replication package for this paper (see http://economics.mit.edu/faculty/acemoglu/data). Our sample excludes industries that are heavily dependent on commodity prices, including oil and gas, mining, agriculture, and petroleum derivatives.

Measures of Demand for Skills

Using the US Census and the American Community Survey (ACS), we compiled data on the college and high school wage bill and hours of work by industry for 1950, 1990, and 2016. We follow Acemoglu and Autor (2011) and define college workers as those with a college degree and half of those with some college. We then define high school workers as those with a high school degree or less and half of the workers with some college.

For the 44 industries in our sample, we study two separate periods. First, for the period from 1987-2016 we use the 1990 Census and 2016 ACS to construct measures of changes in the relative demand for skills across industries during this period. Second, for the period from 1947-1987, we use the 1950 and 1990 Censuses to construct measures of changes in the relative demand for skills across industries during this period.

Measures of Displacement and Reinstatement

The construction of these measures follows Acemoglu and Restrepo (2019). First, suppose that the model in the main text describes the production process of an industry, i. The labor share in that industry is given by

$$s = \frac{\int_{\mathcal{T}_L} \left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} dx + \int_{\mathcal{T}_H} \left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda} dx}{\int_{\mathcal{T}_L} \left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} dx + \int_{\mathcal{T}_H} \left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda} dx + \int_{\mathcal{T}_K} \left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda} dx}.$$

We can decompose changes in the labor share in two components. On the one hand, we have changes driven by factor prices and by technologies that do not change the allocation of tasks between capital and labor (including improvements in factor-augmenting technologies). On the other hand, we have the effect of technologies, like automation and new tasks, which directly change the allocation of tasks between capital and labor. As in Acemoglu and Restrepo (2019) we refer to these as *changes in the task content of production*. Specifically, we decompose changes in the labor share of an industry as follows (suppressing industry indices to simplify notation):

$$d \ln s = d\text{task content} + (1-\lambda)\cdot(1-s)\cdot(d\ln w - d\ln r + g), \tag{A.9}$$

where $d\ln w = (s_L/(s_L+s_H))\cdot d\ln w_L + (s_H/(s_L+s_H))\cdot d\ln w_H$ denotes the change in the average wage paid in the industry, $d\ln r = \frac{1}{s_K}\int_{\mathcal{T}_K}\left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda} d\ln q(x)dx$ denotes the change in the average rental rate of capital used in the industry, and

$$\begin{aligned} g =& \frac{1}{s_L+s_H}\left(\int_{\mathcal{T}_L}\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} d\ln\psi_L(x)dx + \int_{\mathcal{T}_H}\left(\frac{w_H}{\psi_H(x)}\right)^{1-\lambda} d\ln\psi_H(x)dx\right) \\ &- \frac{1}{s_K}\int_{\mathcal{T}_K}\left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda} d\ln\psi_K(x)dx \end{aligned}$$

denotes the increase in the productivity of labor relative to capital in the tasks that are currently allocated to labor. Note that g also incorporates the effect of changes in A_L, A_H and A_K through the ψ terms. Because $q(x) < \underline{q}$, these improvements in factor-augmenting technologies do not alter the allocation of tasks between capital and labor and for the same reason λ coincides with the elasticity of substitution between capital and labor.

Building on equation (A.9), for each of the 44 industries in our sample, we compute its yearly changes in the task content of production as

$$\Delta\text{task content}_{it} = \Delta\ln s_{it} - (1-\sigma_K)\cdot(1-s_{it})\cdot(\Delta\ln w_{it} - \Delta\ln r_{it} - g_{it}).$$

We measure s_{it} using the industry payroll share, which we obtained from the BEA industry accounts (in some of our robustness checks, we also used a measure from the BEA and BLS KLEMS that adjusts the payroll share by imputing self-employment). In addition, σ_K denotes the elasticity of substitution between capital and labor, which we set to 0.8 following Oberfield and Raval (2014). We obtained the industry-specific wage and capital rental rate indices, w_{it} and r_{it}, from the BLS KLEMS accounts for 1987-2016. For the earlier period, we constructed these indices using data on the quantity of labor and capital used in each industry from NIPA. Finally, we follow Acemoglu and Restrepo (2019) and set g_{it}—improvements in labor productivity relative to capital productivity—to 2% per annum for 1947-1987 and 1.46% per annum for 1987-2016.

Increases in the (labor) task content of an industry are indicative of the reinstatement effect brought by new tasks; whereas reductions in the (labor) task content are indicative of the displacement effect brought by automation. To separate these two effects, we assume that over a five-year period, each industry either introduces new automation technologies or new tasks but not both. This assumption implies that we can compute the extent of displacement and reinstatement in a given year and industry

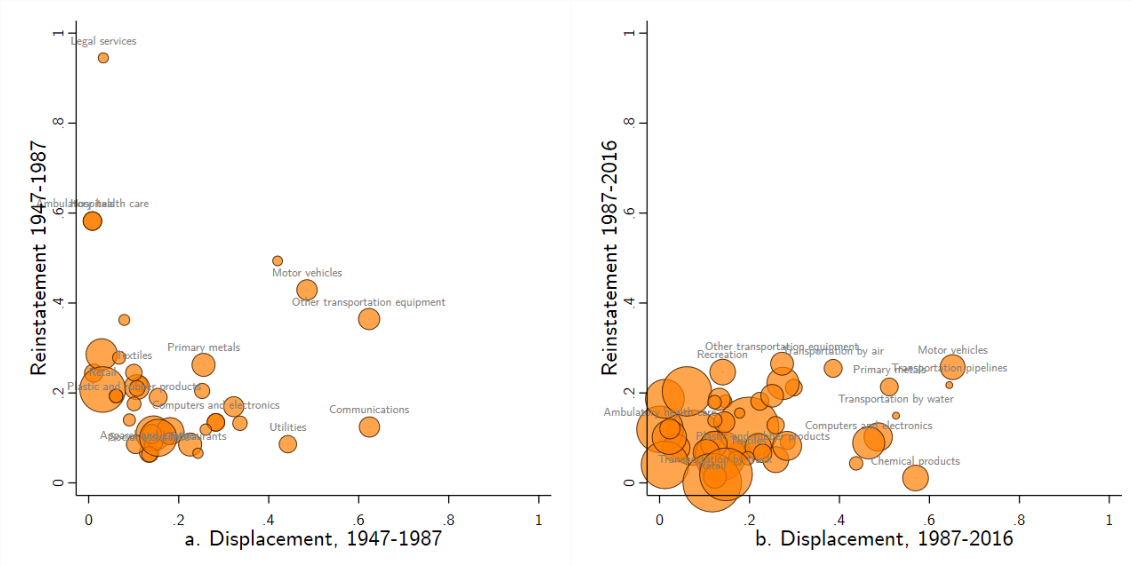

FIGURE A.1. MEASURES OF DISPLACEMENT AND REINSTATEMENT, 1947-1987 AND 1987-2016.

as

$$\text{displacement}_{it} = \max\left\{0, -\frac{1}{5}\sum_{\tau=t-2}^{t+2} \Delta\text{task content}_{i\tau}\right\}$$

$$\text{reinstatement}_{it} = \max\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} \Delta\text{task content}_{i\tau}\right\}.$$

(If there are new automation technologies and new tasks within five-year periods in our data, then our estimates will be lower bounds on the extent of displacement and reinstatement).

Finally, in our regressions we use the cumulative extent of displacement and reinstatement during our period of analysis. These measures are given in percent changes over the entire period, so that a 0.1 displacement corresponds to a 10% decline in the labor share that is unexplained by changes in factor prices.

Figure A.1 shows the total displacement and reinstatement in each industry for 1947-1987 and 1987-2016. For 1947-1987, the average reinstatement across industries was of 19.6% (0.49% per annum) and the average displacement was of 17% (0.425% per annum). For 1987-2016, the average reinstatement was of 10% (0.345% per annum) and the average displacement was of 16% (0.55% per annum).

REGRESSION RESULTS

Tables A.2, A.3 and A.4 provide various estimates of equation (2).

Table A.2 provides our main estimates. Panels A-C provide estimates for 1947-1987 and Panels D-F provide estimates for 1987-2016. In Panels A and D we use the wage bill of college workers relative to high school workers as our measure for the demand for skills in an industry. In Panels B and E we use the hours worked by college workers relative to high school workers as our measure for the demand for skills in an industry. In Panels C and F we use the number of college workers relative to high school workers as our measure for the demand for skills in an industry. Columns 1-3 present estimates of (2) for all workers, and columns 4-7 present estimates separately for men, women, and workers in different age groups.

Tables A.3 and A.4 provide estimates using alternative measures of changes in the task content of industries and the resulting measures of displacement and reinstatement. For this exercise, we use relative wage bill (columns 1-3) and relative hours (columns 4-6) as our measures of skill demand. Table A.3 focuses on the 1947-1987 period. Panel A provides results obtained by setting $\sigma_{KL} = 1$ in our computation of the displacement and reinstatement effects. Panel B reverts to $\sigma_{KL} = 0.8$ but we now use a 10-year moving average, rather than a 5-year moving average in our calculation of the displacement and reinstatement effects. Finally, in Panel C we implement both changes simultaneously.

Table A.4 focuses on the 1987-2016 period. Panel A provides results obtained by setting $\sigma_{KL} = 1$ in our computation of the displacement and reinstatement effects. Panel B reverts to $\sigma_{KL} = 0.8$ but we now use a 10-year moving average, rather than a five-year moving average in our calculation of the displacement and reinstatement effects. In Panel C we implement both changes simultaneously. In Panel D-F we repeat these exercises but now we use data from the BEA KLEMS accounts for 1987-2016. These data provide the labor share for each industry inclusive of self employment.

Overall, the results in Tables A.2, A.3 and A.4 confirm our summary in the text. Automation is associated with significant declines in the demand for skills in both periods, regardless of the specification or measure we use (and for different subgroups such as men, women and younger workers). Reinstatement between 1947 and 1987 is associated with lower demand for skills, whereas between 1987 and 2016, it is associated with higher demand for skills. This pattern is robust as well. One additional finding is worth noting: even between 1947 and 1987, reinstatement does not appear to increase the demand for unskilled men by much, likely reflecting the fact that less skilled women may have been the ones with comparative advantage in new tasks introduced during this period.

Additional References

Fernald, J.G. (2012) "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity." FRBSF Working Paper 2012-19 (data accessed on 12/25/2019).

Oberfield, E. and Raval, D. (2014) "Micro Data and Macro Technology," MIMEO, Princeton University.

TABLE A.2—CHANGES IN TASK CONTENT AND RELATIVE DEMAND FOR SKILLED LABOR, 1947-1987 AND 1987-2016.

	All employees			Men	Women	Ages 25-34	Ages 35-64
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. College wage bill relative to high school wage bill—1947-1987							
Automation	0.504		0.470	0.108	0.384	0.764	0.293
	(0.193)		(0.184)	(0.352)	(0.423)	(0.225)	(0.273)
Reinstatement		-0.585	-0.546	0.023	-0.639	-0.594	-0.544
		(0.306)	(0.278)	(0.482)	(0.501)	(0.430)	(0.261)
Observations	44	44	44	44	44	44	44
R-squared	0.06	0.06	0.12	0.00	0.05	0.08	0.07
Panel B. College hours relative to high school hours—1947-1987							
Automation	0.686		0.644	0.315	0.458	0.738	0.608
	(0.219)		(0.165)	(0.301)	(0.401)	(0.252)	(0.194)
Reinstatement		-0.723	-0.670	-0.361	-0.630	-0.707	-0.633
		(0.343)	(0.304)	(0.431)	(0.434)	(0.463)	(0.234)
Observations	44	44	44	44	44	44	44
R-squared	0.09	0.08	0.16	0.04	0.07	0.11	0.15
Panel C. College employees relative to high school employees—1947-1987							
Automation	0.873		0.834	0.587	0.536	0.941	0.769
	(0.204)		(0.158)	(0.323)	(0.337)	(0.224)	(0.206)
Reinstatement		-0.697	-0.629	-0.368	-0.575	-0.596	-0.644
		(0.352)	(0.292)	(0.363)	(0.415)	(0.422)	(0.256)
Observations	44	44	44	44	44	44	44
R-squared	0.15	0.07	0.21	0.09	0.07	0.15	0.17
Panel D. College wage bill relative to high school wage bill—1987-2016							
Automation	0.800		0.764	1.053	1.061	0.353	0.947
	(0.152)		(0.159)	(0.288)	(0.247)	(0.209)	(0.186)
Reinstatement		0.707	0.483	0.299	0.299	0.850	0.390
		(0.348)	(0.340)	(0.401)	(0.506)	(0.391)	(0.384)
Observations	44	44	44	44	44	44	44
R-squared	0.31	0.06	0.34	0.34	0.40	0.16	0.37
Panel E. College hours relative to high school hours—1987-2016							
Automation	0.558		0.520	0.754	0.778	0.185	0.697
	(0.137)		(0.141)	(0.220)	(0.227)	(0.179)	(0.169)
Reinstatement		0.658	0.506	0.196	0.404	0.768	0.431
		(0.310)	(0.317)	(0.329)	(0.431)	(0.349)	(0.371)
Observations	44	44	44	44	44	44	44
R-squared	0.19	0.07	0.22	0.29	0.33	0.12	0.25
Panel F. College employees relative to high school employees—1987-2016							
Automation	0.546		0.514	0.696	0.793	0.257	0.657
	(0.134)		(0.135)	(0.195)	(0.214)	(0.154)	(0.166)
Reinstatement		0.582	0.431	0.100	0.345	0.540	0.450
		(0.326)	(0.325)	(0.335)	(0.409)	(0.323)	(0.376)
Observations	44	44	44	44	44	44	44
R-squared	0.19	0.05	0.22	0.29	0.34	0.11	0.24

Notes: the table provides regression estimates of changes in the relative demand for college workers relative to high school workers across industries on measures of displacement and reinstatement. The Appendix provides a description of the construction of these explanatory variables. Panels A-C provide estimates for 1947-1987. Panels D-F provide estimates for 1987-2016. Each panel uses a different measure of changes in the relative demand for skills across industries. Panels A and D use the change in the log of the college wage bill relative to the high school wage bill in each industry as outcome. Panels B and E use the change in the log of college hours relative to high school hours in each industry as outcome. Panels C and F use the change in the log of the number of college employees relative to high school employees in each industry as outcome. In columns 1-3, the measures of changes in relative skill demand are computed for all employed in an industry; in column 4 only for men; in column 5 only for women; in column 6 for employees aged 25-34 years; and in column 7 for employees aged 35-64 years. Standard errors robust against heteroskedasticity are in parentheses.

TABLE A.3—ROBUSTNESS TO MEASURES OF TASK CONTENT, 1947-1987

	College wage bill relative to highschool wage bill			College hours relative to highschool hours		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. BEA data with $\sigma_{KL} = 1$ and 5-year moving averages					
Automation	0.447		0.446	0.647		0.646
	(0.207)		(0.161)	(0.249)		(0.165)
Reinstatement		-0.484	-0.483		-0.580	-0.578
		(0.226)	(0.205)		(0.256)	(0.228)
Observations	44	44	44	44	44	44
R-squared	0.06	0.07	0.13	0.10	0.08	0.18
	Panel B. BEA data with $\sigma_{KL} = 0.8$ and 10-year moving averages					
Automation	0.536		0.410	0.774		0.624
	(0.224)		(0.219)	(0.220)		(0.183)
Reinstatement		-0.660	-0.595		-0.806	-0.708
		(0.265)	(0.262)		(0.303)	(0.294)
Observations	44	44	44	44	44	44
R-squared	0.04	0.09	0.11	0.07	0.11	0.16
	Panel C. BEA data with $\sigma_{KL} = 1$ and 10-year moving averages					
Automation	0.488		0.352	0.759		0.601
	(0.235)		(0.204)	(0.245)		(0.190)
Reinstatement		-0.577	-0.529		-0.698	-0.618
		(0.203)	(0.200)		(0.230)	(0.224)
Observations	44	44	44	44	44	44
R-squared	0.04	0.10	0.12	0.08	0.12	0.17

Notes: the table provides regression estimates of changes from 1947 to 1987 in the relative demand for college workers relative to high school workers across industries on measures of displacement and reinstatement. The Appendix provides a description of the construction of these explanatory variables. Columns 1-3 use the change in the log of the college wage bill relative to the high school wage bill in each industry as outcome. Columns 4-6 use the change in the log of college hours relative to high school hours in each industry as outcome. Each panel presents results for a different construction of the displacement and reinstatement measures, as explained in the Appendix. Standard errors robust against heteroskedasticity are in parentheses.

TABLE A.4—ROBUSTNESS TO MEASURES OF TASK CONTENT, 1987-2016

	College wage bill relative to highschool wage bill			College hours relative to highschool hours		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. BEA data with $\sigma_{KL} = 1$ and 5-year moving averages					
Automation	0.620		0.535	0.412		0.335
	(0.138)		(0.154)	(0.120)		(0.136)
Reinstatement		0.931	0.606		0.755	0.551
		(0.333)	(0.350)		(0.301)	(0.329)
Observations	44	44	44	44	44	44
R-squared	0.23	0.12	0.27	0.12	0.10	0.17
	Panel B. BEA data with $\sigma_{KL} = 0.8$ and 10-year moving averages					
Automation	0.773		0.928	0.500		0.645
	(0.153)		(0.210)	(0.131)		(0.188)
Reinstatement		0.122	0.873		0.296	0.818
		(0.516)	(0.522)		(0.424)	(0.466)
Observations	44	44	44	44	44	44
R-squared	0.22	0.00	0.27	0.11	0.01	0.17
	Panel C. BEA data with $\sigma_{KL} = 1$ and 10-year moving averages					
Automation	0.630		0.807	0.385		0.537
	(0.149)		(0.195)	(0.130)		(0.169)
Reinstatement		0.593	1.195		0.627	1.028
		(0.557)	(0.563)		(0.486)	(0.512)
Observations	44	44	44	44	44	44
R-squared	0.16	0.03	0.27	0.07	0.04	0.17
	Panel D. KLEMS data with $\sigma_{KL} = 0.8$ and 5-year moving averages					
Automation	0.520		0.550	0.366		0.379
	(0.143)		(0.140)	(0.117)		(0.118)
Reinstatement		0.024	0.321		-0.072	0.132
		(0.368)	(0.333)		(0.355)	(0.344)
Observations	44	44	44	44	44	44
R-squared	0.24	0.00	0.26	0.15	0.00	0.15
	Panel E. KLEMS data with $\sigma_{KL} = 1$ and 5-year moving averages					
Automation	0.521		0.404	0.331		0.251
	(0.167)		(0.199)	(0.142)		(0.182)
Reinstatement		0.957	0.666		0.632	0.451
		(0.351)	(0.382)		(0.299)	(0.362)
Observations	44	44	44	44	44	44
R-squared	0.14	0.11	0.19	0.07	0.06	0.10
	Panel F. KLEMS data with $\sigma_{KL} = 1$ and 10-year moving averages					
Automation	0.444		0.558	0.243		0.322
	(0.200)		(0.199)	(0.170)		(0.165)
Reinstatement		1.196	1.535		0.865	1.060
		(0.716)	(0.719)		(0.670)	(0.673)
Observations	44	44	44	44	44	44
R-squared	0.08	0.07	0.18	0.03	0.04	0.09

Notes: the table provides regression estimates of changes from 1987 to 2016 in the relative demand for college workers relative to high school workers across industries on measures of displacement and reinstatement. The Appendix provides a description of the construction of these explanatory variables. Columns 1-3 use the change in the log of the college wage bill relative to the high school wage bill in each industry as outcome. Columns 4-6 use the change in the log of college hours relative to high school hours in each industry as outcome. Each panel presents results for a different construction of the displacement and reinstatement measures, as explained in the Appendix. Standard errors robust against heteroskedasticity are in parentheses.