Online Appendix for "Automation and New Tasks: How Technology Displaces and Reinstates Labor"

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This Appendix contains four parts. Section 1 presents our theoretical framework formally and derives expressions for the change in labor demand. Section 2 provides details of our empirical exercise. Section 3 presents additional findings, decompositions, and robustness checks. Section 4 describes the sources of data used.

A1 Theory

This subsection outlines our model in detail. This material complements our discussion in the text.

Full Model Description

Denote the level of production of the sector by Y. Production takes place by combining a set of tasks, with measure normalized to 1, using the following production function

$$Y = \left(\int_{N-1}^{N} Y(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}, \tag{A1}$$

where $Y(z)$ denotes the output of task z for $z \in [N-1, N]$ and $\sigma \geq 0$ is the elasticity of substitution between tasks.

Tasks can be produced using capital or labor according to the production function

$$Y(z) = \begin{cases} A^L \gamma^L(z) l(z) + A^K \gamma^K(z) k(z) & \text{if } z \in [N-1, I] \\ A^L \gamma^L(z) l(z) & \text{if } z \in (I, N]. \end{cases}$$

We denote total employment and capital used in the sector (economy) by

$$L = \int_{N-1}^{N} l(z)dz \qquad \text{and} \qquad K = \int_{N-1}^{N} k(z)dz,$$

and take them as given for now.

As mentioned in the text, we assume that it is cost-minimizing to use capital in all automated tasks (see next subsection).

Following the same steps outlined in Acemoglu and Restrepo (2018a), we can write the equilibrium output in the economy as

(A2)

$$Y(L,K;\theta) = \left(\left(\int_{N-1}^{I} \gamma^K(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}} (A^K K)^{\frac{\sigma-1}{\sigma}} + \left(\int_{I}^{N} \gamma^L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}} (A^L L)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}.$$

Therefore, the expression for the task content of production, defined in the text, is

$$\Gamma(I,N) = \frac{\int_I^N \gamma^L(z)^{\sigma-1}}{\int_{N-1}^I \gamma^K(z)^{\sigma-1}dz + \int_I^N \gamma^L(z)^{\sigma-1}}. \tag{A3}$$

The TFP term is then

$$\Pi(I,N) = \left(\int_{N-1}^{I} \gamma^K(z)^{\sigma-1}dz + \int_{I}^{N} \gamma^L(z)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}.$$

The labor share follows directly from the expression in equation (A2). Because of the CES structure, the labor share is simply

$$s^L = \frac{1}{1 + \frac{1-\Gamma(I,N)}{\Gamma(I,N)}\left(\frac{A^L}{W}\frac{R}{A^K}\right)^{1-\sigma}}. \tag{A4}$$

The labor share can also be expressed as a function of labor, capital and factor-augmenting technologies as well as the task content of production:

$$s^L(L,K;\theta) = \frac{1}{1 + \left(\frac{1-\Gamma(I,N)}{\Gamma(I,N)}\right)^{\frac{1}{\sigma}}\left(\frac{A^K K}{A^L L}\right)^{\frac{\sigma-1}{\sigma}}}. \tag{A5}$$

Restriction that Ensures I Binds

As mentioned in the text, we assume that it is cost-minimizing to use capital in all automated tasks. The formal assumption that ensures this is the case is given by

$$\text{(A6)} \qquad \frac{1-\Gamma(I,N)}{\Gamma(I,N)}\left(\frac{A^L}{A^K}\frac{\gamma^L(I)}{\gamma^K(I)}\right)^{\sigma} < \frac{K}{L} < \frac{1-\Gamma(I,N)}{\Gamma(I,N)}\left(\frac{A^L}{A^K}\frac{\gamma^L(N)}{\gamma^K(N-1)}\right)^{\sigma}.$$

When this restriction holds, we have that

$$\text{(A7)} \qquad \frac{A^L}{A^K}\frac{\gamma^L(I)}{\gamma^K(I)} < \frac{W}{R} < \frac{A^L}{A^K}\frac{\gamma^L(N)}{\gamma^K(N-1)},$$

which implies that new automation technologies (an increase in I) and new tasks (an increase in N) raise productivity and will be immediately adopted. The general case in which the above assumption does not hold is analyzed in detail in Acemoglu and Restrepo (2018a).

Technology and Labor Demand

This subsection explains how changes in automation, new tasks and factor-augmenting technologies impact labor demand in the one sector model, and thus establishes the results presented in the text. We provide all of the following derivations for the case with a fixed stock of capital and labor, K and L.

For a given level of factor utilization, L and K, labor demand from the sector can be written as

$$\text{(A8)} \qquad W^d(L,K;\theta) = \frac{Y(L,K;\theta)}{L} \times s^L(L,K;\theta).$$

Labor demand $W^d(L,K;\theta)$ is decreasing in L and increasing in K. We next analyze the effects of different types of technologies on labor demand. All of the expressions we present next can be obtained by differentiating (A8) and then using (A2) and (A5).

The effect of automation—an increase in I—on labor demand is given by

$$\begin{aligned}\frac{\partial \ln W^d(L,K;\theta)}{\partial I} =& \frac{\partial \ln Y(L,K;\theta)}{\partial I} && \text{(Productivity effect)}\\ &+\frac{1}{\sigma}\frac{1-s^L(L,K;\theta)}{1-\Gamma(I,N)}\frac{\partial \ln \Gamma(I,N)}{\partial I} && \text{(Displacement effect)}.\end{aligned}$$

Moreover, we can also use equation (A2) to compute the productivity effect as

$$\frac{\partial \ln Y(L,K;\theta)}{\partial I} = \frac{1}{\sigma-1}\left[\left(\frac{R}{A^K\gamma^K(I)}\right)^{1-\sigma} - \left(\frac{W}{A^L\gamma^L(I)}\right)^{1-\sigma}\right] > 0.$$

This expression also establishes our claim in the text that productivity effects are increasing in the wage W (holding the productivity of labor in the marginal task, $A^L\gamma^L(I)$, constant).

The effect of new tasks—an increase in N—on labor demand is given by

$$\begin{aligned}\frac{\partial \ln W^d(L,K;\theta)}{\partial N} =& \frac{\partial \ln Y(L,K;\theta)}{\partial N} && \text{(Productivity effect)}\\ &+\frac{1}{\sigma}\frac{1-s^L(L,K;\theta)}{1-\Gamma(I,N)}\frac{\partial \ln \Gamma(I,N)}{\partial N} && \text{(Reinstatement effect)}\end{aligned}$$

where the productivity effect from new tasks is given by

$$\frac{\partial \ln Y(L,K;\theta)}{\partial N} = \frac{1}{\sigma-1}\left[\left(\frac{W}{A^L\gamma^L(N)}\right)^{1-\sigma} - \left(\frac{R}{A^K\gamma^K(N-1)}\right)^{1-\sigma}\right] > 0.$$

Finally, turning to the implications of factor-augmenting technologies, we have

$$\begin{aligned}\frac{\partial W^d(L,K;\theta)}{\partial \ln A^L} =& s^L(L,K;\theta) && \text{(Productivity effect)}\\ &+\frac{\sigma-1}{\sigma}(1-s^L(L,K;\theta)) && \text{(Substitution effect)},\\ \frac{\partial W^d(L,K;\theta)}{\partial \ln A^K} =& (1-s^L(L,K;\theta)) && \text{(Productivity effect)}\\ &+\frac{1-\sigma}{\sigma}(1-s^L(L,K;\theta)) && \text{(Substitution effect)}.\end{aligned}$$

Multi-sector Economy

This section explains how technology affects aggregate labor demand in a model with multiple sectors. The decomposition for labor demand we derive here both establishes the decomposition presented in the text and provides the basis for our empirical exercise.

Index industries by i and let $\mathcal{I}$ represent the set of industries. We denote the price of the goods produced by sector i by P_i, while its factor prices are denoted by W_i and R_i—which continue to satisfy the assumption imposed in (A7). The technology available to sector i is summarized by $\theta_i = \{I_i, N_i, A_i^L, A_i^K\}$, and L_i and K_i are the quantities of labor and capital used in each sector, so that output (value added) of sector i is $Y_i = Y(L_i, K_i; \theta_i)$. In addition, the comparative advantage schedules for labor and capital, γ_i^L and γ_i^K, are also part of the industry's technology but as in the text, we hold these fixed throughout. We denote the task content of sector i by $\Gamma_i = \Gamma(N_i, I_i)$ and its labor share by s_i^L. Total value added (GDP) in the economy is $Y = \sum_{i \in \mathcal{I}} P_i Y_i$, and we define $\chi_i = \frac{P_i Y_i}{Y}$ as the share of sector i's in total value added. Finally, we denote by s^L the economy-wide labor share.

Changes in economy-wide wage bill, WL, can then be exactly decomposed as

(A9)

$$\begin{aligned}
d\ln(WL) =& d\ln Y && \text{(Productivity effect)}\\
&+ \sum_{i\in\mathcal{I}} \frac{s_i^L}{s^L} d\chi_i && \text{(Composition effect)}\\
&+ \sum_{i\in\mathcal{I}} \ell_i \frac{1-s_i^L}{1-\Gamma_i} d\ln\Gamma_i && \text{(Change task content)}\\
&+ \sum_{i\in\mathcal{I}} \ell_i (1-\sigma)(1-s_i^L)(d\ln W_i/A_i^L - d\ln R_i/A_i^K) && \text{(Substitution effect)}
\end{aligned}$$

where $\ell_i = \frac{W_i L_i}{WL}$ is the share of the wage bill generated in sector i. Note that this derivation does not require these prices to be equal across sectors, and so it can accommodate several different assumptions on factor mobility, heterogeneous types of labor and how factor payments are determined. Moreover, it applies for any changes in the environment, though our focus is on changes in technologies as summarized by the vector $\theta = \{\theta_i\}_{i \in \mathcal{I}}$.

We next provide the derivation of this decomposition. Note that the wage bill can be expressed as

$$WL = \sum_{i\in\mathcal{I}} W_i L_i = \sum_{i\in\mathcal{I}} P_i Y_i s_i^L = \sum_{i\in\mathcal{I}} Y \chi_i s_i^L.$$

Here, P_i is the price of sector i (in terms of the final good, Y) and Y_i the output of the sector.

Totally differentiating this expression, we obtain

$$dW \cdot L + W \cdot dL = \sum_{i \in \mathcal{I}} dY \cdot \chi_i s_i^L + \sum_{i \in \mathcal{I}} Y \cdot d\chi_i \cdot s_i^L + \sum_{i \in \mathcal{I}} Y \chi_i \cdot ds_i^L.$$

Dividing both sides by WL, using the definitions of χ_i ($= \frac{P_i Y_i}{Y}$) and s_i^L ($= \frac{W_i L_i}{P_i Y_i}$), and rearranging, we get

$$\frac{dW}{W} + \frac{dL}{L} = \sum_{i \in \mathcal{I}} \frac{dY}{Y} \cdot \frac{Y}{WL} \cdot \frac{P_i Y_i}{Y} \cdot \frac{W_i L_i}{P_i Y_i} + \sum_{i \in \mathcal{I}} \frac{Y}{WL} \cdot d\chi_i \cdot \frac{W_i L_i}{P_i Y_i} + \sum_{i \in \mathcal{I}} \frac{Y}{WL} \cdot \frac{P_i Y_i}{Y} \cdot ds_i^L.$$

Now canceling terms and using the definition of ℓ_i ($= \frac{W_i L_i}{WL}$), we obtain

$$\frac{dW}{W} + \frac{dL}{L} = \sum_{i \in \mathcal{I}} \frac{dY}{Y} \cdot \ell_i + \sum_{i \in \mathcal{I}} \frac{s_i^L}{s^L} \cdot d\chi_i + \sum_{i \in \mathcal{I}} \ell_i \cdot \frac{ds_i^L}{s_i^L}.$$

Next noting that $\frac{dx}{x} = d \ln x$, and that $\sum_{i \in \mathcal{I}} \ell_i = 1$, this expression can be written as

$$d \ln W + d \ln L = d \ln Y + \sum_{i \in \mathcal{I}} \frac{s_i^L}{s^L} \cdot d\chi_i + \sum_{i \in \mathcal{I}} \ell_i \cdot d \ln s_i^L.$$

Finally, differentiating (A4), we have

$$\text{(A10)} \qquad d \ln s_i^L = \frac{(1 - s_i^L)}{1 - \Gamma_i} d \ln \Gamma_i + (1 - \sigma)(1 - s_i^L)(d \ln W_i / A_i^L - d \ln R_i / A_i^K).$$

Substituting this into the previous expression, we obtain (A9).

As the derivation shows, the decomposition in equation (A9) is quite general. To derive it, we do not need to make assumptions about factor mobility across sectors, input-output linkages or the consumer demand-side (about their marginal rate of substitution across different types of goods). We can also accommodate different types of labor being employed in different industries and certain types of labor market imperfections. The only (and the critical) assumption is that firms are along their labor demand curve, so that in each industry we have $W_i L_i = P_i Y_i s_i^L$. This holds whenever the labor share equals the elasticity of output with respect to labor.

Alternative Production Function

Suppose that instead of (A1), we assume the following sectoral production function

$$Y_i = N^{\frac{1}{1-\sigma}}\left(\int_0^N Y_i(z)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}},$$

which implies that new tasks will not replace old ones but are used additionally in the production process.

Following the same steps as in Acemoglu and Restrepo (2018a), with this production function we obtain that output is again given by the equation in the text but now

$$\Gamma(I,N) = \frac{\int_I^N \gamma^L(z)^{\sigma-1}}{\int_0^I \gamma^K(z)^{\sigma-1}dz + \int_I^N \gamma^L(z)^{\sigma-1}}$$

gives the task content of production and

$$\Pi(I,N) = \left(\frac{1}{N}\int_0^I \gamma^K(z)^{\sigma-1}dz + \frac{1}{N}\int_I^N \gamma^L(z)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$$

The main difference with what we have done so far is that now, the impact of new tasks on output is given by

$$\begin{aligned}\frac{dY_i^{\frac{\sigma-1}{\sigma}}}{dN_i} =& \frac{1}{\sigma}\left(\frac{1}{N_i}\int_{I_i}^{N_i} \gamma^L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}-1}(A_i^L L_i)^{\frac{\sigma-1}{\sigma}}\frac{\gamma^L(N_i)^{\sigma-1}}{N_i} - \frac{1}{\sigma}\frac{Y_i^{\frac{\sigma-1}{\sigma}}}{N_i}\\ \frac{d\ln Y_i}{dN_i} =& \frac{1}{(\sigma-1)N_i}\left(\left[\frac{W_i}{A_i^L\gamma^L(N_i)}\right]^{1-\sigma} - 1\right)\end{aligned}$$

Provided that the effective wage in new tasks less than one, new tasks continue to increase output.

A2 Details of Empirical Exercise

In this section, we describe how we use the decomposition presented in the previous section to estimate productivity, composition and substitution effects and the changes in the task content of production.

Productivity and Composition Effects

Equation (A9) shows how small (infinitesimal) changes in the wage bill can be decomposed into productivity, composition and substitution effects and the change in the task content of production. We now explain how this theoretical result can be used for decomposing *discrete changes* in the wage bill. Throughout, as explained in the text, we normalize the economy-wide wage bill by total population in order to abstract from differential changes in population across different periods.

In this subsection, we show how a change in the wage bill can be decomposed into productivity and composition effects and a change in industry labor shares. In the next subsection, we then show how a change in industry labor share can be broken into a substitution effect and a change in the task content of production.

We index time in years with the subscript t. Let t_0 denote the starting year of our decomposition. Because the economy-wide wage bill is the sum of wage bills across industries, we have:

$$\ln\left(W_t L_t\right) = \ln\left(Y_t \sum_i \chi_{i,t} s^L_{i,t}\right)$$
$$\ln(W_{t_0} L_{t_0}) = \ln\left(Y_{t_0} \sum_i \chi_{i,t_0} s^L_{i,t_0}\right).$$

We can then express the percent change in wage bill normalized by population, N_t, between t_0 and t as

$$\text{(A11)} \qquad \ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t_0} L_{t_0}}{N_{t_0}}\right) = \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right)$$
$$+ \ln\left(\sum_i \chi_{i,t} s^L_{i,t}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right)$$
$$+ \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t_0}\right).$$

The first line in equation (A11) represents changes in GDP per capita, which directly corresponds to our productivity effect (the term $d\ln Y$ in equation (A9)). Hence, the empirical counterpart of our productivity effect is

$$\text{Productivity effect}_{t_0,t} = \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right).$$

The second line in equation (A11) captures the impact of sectoral shifts (changes in $\chi_{t,i}$ over time) on labor demand holding the labor share within each sector constant. Conceptually, this corresponds to the composition effect (the term $\sum_i \frac{s^L_{i,t}}{s^L_t} d\chi_i$ in equation (A9)). Thus, we measure the composition effect as

$$\text{Composition effect}_{t_0,t} = \ln\left(\sum_i \chi_{i,t} s^L_{i,t}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right).$$

To further illustrate the connection between our empirical measure of the composition effect and equation (A9), we use a first-order Taylor expansion of the previous expression, in particular expanding $\ln\left(\sum_i \chi_{i,t} s^L_{i,t}\right)$ around $\ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right)$, we obtain

$$\begin{aligned}\text{Composition effect}_{t_0,t} \approx& \frac{1}{\sum_i \chi_{i,t_0} s^L_{i,t}} \left(\sum_i \chi_{i,t} s^L_{i,t} - \sum_i \chi_{i,t_0} s^L_{i,t}\right)\\ =& \sum_i \frac{s^L_{i,t}}{\sum_j \chi_{j,t_0} s^L_{j,t}} (\chi_{i,t} - \chi_{i,t_0}).\end{aligned}$$

This approximation shows that, as in the second line of equation (A9), the empirical counterpart of the composition effect equals a weighted sum of changes in sectoral shares of GDP. In both cases, the weights capture how labor intensive a sector is relative to the rest.

Finally, the third line captures the role of changes in labor shares within sectors (changes in $s^L_{i,t}$ over time) on labor demand holding the sectoral shares of GDP constant at their initial value. Conceptually, this corresponds to the combined effect of substitution and changes in task content. This is because, as noted in the text, with competitive markets the labor share changes only due to the substitution effect and changes in the task content of production.

Estimating the Substitution Effects and the Task Content of Production

With another first-order Taylor expansion, in particular expanding $\ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right)$ around $\ln\left(\sum_i \chi_{i,t_0} s^L_{i,t_0}\right)$, the third term in equation (A11) can be expressed as

$$\begin{aligned}\ln\left(\sum_i \chi_{i,t_0} s^L_{i,t}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t_0}\right) \approx& \sum_i \frac{\partial \ln\left(\sum_j \chi_{j,t_0} s^L_{j,t_0}\right)}{\partial \ln s^L_{i,t_0}} \cdot \left(\ln s^L_{i,t} - \ln s^L_{i,t_0}\right)\\ =& \sum_i \frac{\chi_{i,t_0} s^L_{i,t_0}}{\sum_j \chi_{j,t_0} s^L_{j,t_0}} \cdot \left(\ln s^L_{i,t} - \ln s^L_{i,t_0}\right)\\ =& \sum_i \ell_{i,t_0} \left(\ln s^L_{i,t} - \ln s^L_{i,t_0}\right),\end{aligned}$$

where the last line uses the fact that $\chi_{i,t_0} s^L_{i,t_0} = \frac{W_{i,t_0} L_{i,t_0}}{Y_{t_0}}$, and therefore

$$\frac{\chi_{i,t_0} s^L_{i,t_0}}{\sum_j \chi_{j,t_0} s^L_{j,t_0}} = \frac{W_{i,t_0} L_{i,t_0}}{\sum_j W_{j,t_0} L_{j,t_0}} = \ell_{i,t_0}.$$

Equation (A4) shows that the labor share can be written as a function of effective factor prices and the task content of production, $s^L_{i,t} = s^L(\rho_{i,t}, \Gamma_{i,t})$, where $\rho_{i,t} = \frac{W_{i,t}}{A^L_{i,t}} \frac{A^K_{i,t}}{R_{i,t}}$ is the relative effective price of labor. To further decompose the percent change in labor share within an industry, $\ln s^L_{i,t} - \ln s^L_{i,t_0}$, we use another first-order Taylor expansion, this time $\ln s^L(\rho_{i,t}, \Gamma_{i,t})$ around $\ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})$. This yields:

$$\begin{aligned}\ln s^L_{i,t} - \ln s^L_{i,t_0} \approx & \frac{\partial \ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})}{\partial \ln \rho_{i,t_0}} \left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t} \right) \\ & + \frac{\partial \ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})}{\partial \ln \Gamma_{i,t_0}} \left(\ln \Gamma_{i,t} - \ln \Gamma_{i,t_0} \right),\end{aligned}$$

where $g_{t_0,t}$ is the growth rate of A^L_t / A^K_t between t_0 and t. From equation (A4), it follows that

$$\frac{\partial \ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})}{\partial \ln \rho_{i,t_0}} = (1-\sigma)(1-s^L_{i,t_0}), \qquad \frac{\partial \ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})}{\partial \ln \rho_{i,t_0}} = \frac{\left(1-s^L_{i,t_0}\right)}{1-\Gamma_{i,t_0}},$$

and so we obtain the approximation

$$\begin{aligned}\ln s^L_{i,t} - \ln s^L_{i,t_0} \approx & (1-\sigma)(1-s^L_{i,t_0}) \left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t} \right) \\ & + \frac{\left(1-s^L_{i,t_0}\right)}{1-\Gamma_{i,t_0}} \left(\ln \Gamma_{i,t} - \ln \Gamma_{i,t_0} \right),\end{aligned} \tag{A12}$$

The first line is the substitution effect in industry i. The second line represents changes in the task content of production, which in our model are driven by automation and the creation of new tasks in industry i.

Based on equation (A12), we compute the substitution effect in an industry between t_0 and t as

$$\text{Substitution effect}_{i,t_0,t} = (1-\sigma)(1-s^L_{i,t_0}) \left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t} \right).$$

We use data on factor prices from the BLS (described in the data section of this Appendix). We impose a baseline value for σ of 0.8 and different estimates for $g^A_{i,t_0,t}$ as described in the text.

With estimates of the industry-level substitution effect at hand, we estimate the change in task content in an industry between t_0 and t as the residual from equation (A12):

$$\text{Change task content}_{i,t_0,t} = \ln s^L_{i,t} - \ln s^L_{i,t_0} - (1-\sigma)(1-s^L_{i,t_0})\left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t}\right).$$

The economy-wide contribution of the substitution effect is given by

$$\text{Substitution effect}_{t_0,t} = \sum_{i\in\mathcal{I}} \ell_{i,t_0} \text{Substitution effect}_{i,t_0,t},$$

which maps directly to the fourth line in the theoretical decomposition in equation (A9). Finally, the economy-wide change in the task content of production is computed by aggregating across industry-level changes in task content:

$$\text{Change task content}_{t_0,t} = \sum_{i\in\mathcal{I}} \ell_{i,t_0} \text{ Change task content}_{i,t_0,t}.$$

Displacement vs. Reinstatement

We can further decompose changes in task content into displacement and reinstatement effects. To do so, we assume, as noted in the text, that over five-year windows, an industry engages in either automation or the creation of new tasks but not in both activities. This assumption implies that

$$\text{(A14)} \quad \text{Displacement}_{t-1,t} = \sum_{i\in\mathcal{I}} \ell_{i,t_0} \min\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} \text{Change task content}_{i,\tau-1,\tau}\right\}$$

$$\text{Reinstatement}_{t-1,t} = \sum_{i\in\mathcal{I}} \ell_{i,t_0} \max\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} \text{Change task content}_{i,\tau-1,\tau}\right\}.$$

We can compute the total contribution of displacement and reinstatement effects by cumulating these expressions over t_0 and t,

A3 Additional Empirical Findings

In this section, we describe additional empirical results and robustness checks.

The Role of Factor-Augmenting Technologies

Figure A1 provides our decomposition for 1947-1987 and 1987-2017 using different assumptions for the term g^{A}_{i,t,t_0}—the growth rate of labor-augmenting technologies relative to capital-augmenting ones. We see very small differences when we impose different growth rates of factor-augmenting technological change.

Even more telling about the limited role of factor-augmenting technologies in accounting for the changes in labor demand in the US economy is a complimentary exercise where we compute the changes in factor-augmenting technologies at the industry level that would be necessary to explain changes in industry labor shares *without any* change in task content of production (and without any technological regress).

Suppose that there are no changes in task content—thus no true displacement and reinstatement effects. As a result, observed changes in the labor share of an industry must be explained by factor-augmenting technological advances (that is, the $A^L_{i,t}$ and $A^K_{i,t}$ terms cannot decline and either increase or stay constant). In particular, we can back up the growth rate of factor-augmenting technologies required to explain the observed changes in labor shares as

$$\ln A^L_{i,t} - \ln A^L_{i,t_0} = \frac{1}{(\sigma-1)(1-s^L_{i,t_0})} \times \text{ Displacement}_{i,t_0,t} > 0$$

and

$$\ln A^K_{i,t} - \ln A^K_{i,t_0} = \frac{1}{(1-\sigma)(1-s^L_{i,t_0})} \times \text{ Reinstatement}_{i,t_0,t} > 0.$$

Under the additional assumption that there are no distortions, we can then use the envelope theorem to conclude that the improvements in $A^L_{i,t}$ increase TFP by

(A15)

$$\text{Contribution of } A^L \text{ to TFP}_{t,t_0} = \sum_i \chi_{i,t_0} \frac{s^L_{i,t_0}}{(\sigma-1)(1-s^L_{i,t_0})} \times \text{Displacement}_{i,t,t_0} > 0,$$

and the improvements in $A^K_{i,t}$ increase TFP by

(A16)

$$\text{Contribution of } A^K \text{ to TFP}_{t,t_0} = \sum_i \chi_{i,t_0} \frac{1-s^L_{i,t_0}}{(1-\sigma)(1-s^L_{i,t_0})} \times \text{Reinstatement}_{i,t,t_0} > 0.$$

Figure A2 provides the counterfactual TFP increases that one would have to observe if displacement were explained by increases in A_i^L and reinstatement by increases in A_i^K across all industries. The implied increases in TFP are gargantuan—several folds larger than the observed TFP increases during the last seven decades. Very large changes in factor-augmenting technologies would be necessary to explain the sizable changes in industry labor shares and especially the declines in manufacturing labor share between 1987 and 2017. This exercise underscores the need for major changes in the task content of production to account for the evolution of sectoral labor shares and aggregate labor demand.

The Decline in Manufacturing

Our main findings show that the acceleration of automation was particularly pronounced in manufacturing during 1987-2017. During this period, the wage bill in manufacturing declined in absolute terms. We can use our framework to study the sources of decline in manufacturing labor demand.

Equation (A9) must be extended to include the role of the price of manufacturing goods. Changes in total wage bill can then be decomposed as

$$
\begin{aligned}
d\ln(WL)_{manuf} =& d\ln P_{manuf} && \text{(Price effect)}\\
&+ d\ln Y_{manuf} && \text{(Productivity effect)}\\
&+ \sum_{i\in M}\left(\frac{s_i^L}{s^L}-1\right)d\chi_i && \text{(Composition effect)}\\
&+ \sum_{i\in M}\ell_i\frac{1-s_i^L}{1-\Gamma_i}d\ln\Gamma_i && \text{(Change task content)}\\
&+ \sum_{i\in M}\ell_i(1-\sigma)(1-s_i^L)(d\ln W_i/A_i^L - d\ln R_i/A_i^K) && \text{(Substitution effect)}
\end{aligned}
$$

where the sums are now computed over manufacturing industries, Y_{manuf} denotes the quantity of manufacturing output, and P_{manuf} denotes the relative price of manufacturing goods.

The price effect arises because technological improvements in manufacturing will reduce its relative price, P_{manuf}, which generates a negative effect on labor demand of the sector. This is one of the main mechanisms that explains the structural transformation of the economy (see Ngai and Pissarides, 2007).

Figure A3 presents this decomposition for manufacturing for 1947-1987 and 1987-2017. As in the text, we normalize manufacturing wage bill by population. The figure shows that, from 1947 to 2007, quantities produced by the sector grew at a steady rate of 3% per year. However, in line with theories of structural transformation, this did not translate into an equally large increase in labor demand in the sector because of a strong price effect, which has reduced the wage bill in manufacturing at a rate of 1.3% per year between the mid-1960s and 2007.

More importantly, our decomposition also shows that besides the standard price effects, changes in the task content of the manufacturing sector also played a sizable role in explaining the absolute decline in manufacturing labor demand. During the 1987-2017 period, the displacement effect from automation reduced labor demand in the sector at a rate of 1.1% per year (33% cumulatively), making displacement as important as the price effect during this period (accounting for a cumulative decline of 40%). Within manufacturing, composition effects were negative but not as important as displacement and price effects, and reduced labor demand by less than 0.3% per year during the 1987-2017 period (9% cumulatively).

Correlates of Automation and New Tasks

We complement the evidence presented in Table 1 of the text with a series of figures.

Figure A4 present the relationships between our three proxies for automation with changes in task content visually. The fourth panel of Figure A4 also shows the relationship between offshoring and our measure of change in task content of production. Though the two variables are correlated, it is clear that there is a large amount of change in task content unrelated to offshoring. Figure A5 present the relationships between our four proxies for new tasks with changes in task content visually.

Finally, Table A1 shows that the *gross* change in task content (the sum of the absolute value of the displacement and reinstatement effects in an industry) predicts an increase in industry output (columns 1 and 2) and higher TFP (columns 3 and 4).[1] Both of these correlations support our interpretation that changes in the task content of production signal an undergoing process of automation or new task creation, which raises productivity. In columns 5 and 6, we look at skill intensity of an industry, measured by the share

[1] Both of these measures are available for the 61 industries used in our analysis from the BEA KLEMS industry accounts

of college-educated workers among all employees (from the 1990 Census and 2012-2016 ACS). Industries experiencing more displacement or reinstatement are also becoming more skill-intensive. A natural interpretation of this finding is that automation technologies have mostly substituted for low-skill workers, while new tasks have benefit mostly high-skill labor (which is in line with the theoretical predictions in Acemoglu and Restrepo, 2018a).

Robustness Exercises

We also conducted a series of robustness checks.

■ Figure A6 investigates whether the order in which we decompose the wage bill in equation (A11) (composition effects first within-industry changes next) matters. The figure presents the results from reversing this order and undertaking within-industry changes first and composition effects thereafter. In this alternative decomposition, equation (A11) takes the form:

$$
\begin{aligned}
\text{(A18)} \qquad \ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t_0} L_{t_0}}{N_{t_0}}\right) = & \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right) \\
& + \ln\left(\sum_i \chi_{i,t} s^L_{i,t}\right) - \ln\left(\sum_i \chi_{i,t} s^L_{i,t_0}\right) \\
& + \ln\left(\sum_i \chi_{i,t} s^L_{i,t_0}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t_0}\right),
\end{aligned}
$$

where the second line represents the role of within-industry changes in the labor share and the last line is the composition effect in this case.

Following the same steps as before, we find that with this ordering the overall contribution of the substitution effect is

$$
\text{Substitution effect}_{t_0,t} = \sum_{i \in \mathcal{I}} \frac{\chi_{i,t} s^L_{i,t_0}}{\sum_j \chi_{j,t} s^L_{j,t_0}} \text{Substitution effect}_{i,t_0,t};
$$

the economy-wide change in the task content of production is

$$
\text{Change task content}_{t_0,t} = \sum_{i \in \mathcal{I}} \frac{\chi_{i,t} s^L_{i,t_0}}{\sum_j \chi_{j,t} s^L_{j,t_0}} \text{Change task content}_{i,t_0,t};
$$

and the composition effect is given by

$$
\text{Composition effect}_{t_0,t} = \ln\left(\sum_i \chi_{i,t} s^L_{i,t_0}\right) - \ln\left(\sum_i \chi_{i,t_0} s^L_{i,t_0}\right).
$$

We can see from Figure A6 that the results are very similar to our baseline.

■ Figure A7 presents a decomposition of the wage bill for the entire economy (inclusive self-employment income) using data from the BLS. These data are available for 60 industries. See Elsby et al. (2013) for details regarding the imputation procedure followed by the BLS. The results are similar to those reported in the text.

■ Figure A8 presents estimates of the displacement and reinstatement effect using yearly changes in the task content. For comparison, we also present the five-year moving averages used in the text. Predictably, the implied displacement and reinstatement effects are larger, but the overall patterns are similar and we find that displacement effects have become stronger and reinstatement effects weaker during the last three decades.

■ Figures A9, A10 and A11 provide our decomposition for the 1947-1987 period using different values for the elasticity of substitution σ, while Figures A12, A13 and A14 do the same for 1987-2017. The results are very similar for the different values of the elasticity of substitution.

A4 Data Sources

We now provide the sources of the various data we use in the text and in this Appendix.

Aggregate data: We use aggregate data on employment, population and the PCE (Personal Consumption Expenditure) price index for the US economy obtained from FRED.

Data for 1987-2017: We use the BEA *GDP by Industry Accounts* for 1987-2017. These data contain information on value added and worker compensation for 61 private industries (19 manufacturing industries and 42 non-manufacturing industries) defined according to the 2007 NAICS classification system.

We use price data from the BLS *Multifactor Productivity Tables*, which report for each industry measures of worker compensation and capital income, and indices of the quantity of labor used, the composition of labor used, and the quantity of capital used. The BLS then estimates a price index for labor—the wage $W_{i,t}$—as:

$$\Delta \ln W_{i,t} = \Delta \ln Y_{i,t}^{L} - \Delta \ln L_{i,t}^{qty} - \Delta \ln L_{i,t}^{comp},$$

where $Y^L_{i,t}$ denotes worker compensation in industry i, $L^{qty}_{i,t}$ denotes the index for the quantity of labor used (in full-time equivalent workers), and $L^{comp}_{i,t}$ denotes the index for the composition of labor used (adjusting for the demographic characteristics of workers).

The BLS also estimates a price index for the use of capital—the rental rate $R_{i,t}$—as:

$$\Delta \ln R_{i,t} = \Delta \ln Y^K_{i,t} - \Delta \ln K^{qty}_{i,t},$$

where $Y^K_{i,t}$ denotes capital income in industry i and $K^{qty}_{i,t}$ denotes the index for the quantity of capital used, which they construct from data on investment (deflated to quantities) using the perpetual inventory method. The BLS computes capital income as a residual by subtracting the costs of labor, energy, materials and services from gross output. Therefore, by construction, $Y^K_{i,t} + Y^L_{i,t}$ account for the entire value added of industry i.

In our decomposition exercise for 1987-2017, we use the BLS measures for $W_{i,t}$ and $R_{i,t}$. Finally, the BLS reports data for all of the NAICS industries, but pools the car manufacturing industry (NAICS code) with other transportation equipment (NAICS code). We use the pooled price indices for both of these industries in our decomposition.

Data for 1947-1987: We use the BEA *GDP by Industry Accounts* for 1947-1987. These data contain information on value added and worker compensation for 58 industries, defined according to the 1977 SIC (21 manufacturing industries and 37 non-manufacturing industries). We converted these data to constant dollars using the PCE price index.

The BLS does not report price indices for this period, so we constructed our own following their procedure. Specifically, we computed a price index for labor—the wage $W_{i,t}$—as:

$$\Delta \ln W_{i,t} = \Delta \ln Y^L_{i,t} - \Delta \ln L^{qty}_{i,t}, \tag{A19}$$

where $Y^L_{i,t}$ denotes worker compensation in industry i and $L^{qty}_{i,t}$ denotes the index for the quantity of labor used (in full-time equivalent workers). Both of these measures come from the BEA Industry Accounts. Unlike the wage index from the BLS, our wage index for 1947-1987 does not adjust for the composition of workers.

Second, we construct a price index for the use of capital—the rental rate

$R_{i,t}$—as:

$$\Delta \ln R_{i,t} = \Delta \ln(Y_{i,t} - Y^L_{i,t}) - \Delta \ln K^{qty}_{i,t}, \tag{A20}$$

where $Y_{i,t} - Y^L_{i,t}$ denotes capital income in industry i, which following the BLS we compute as value added minus labor costs. Also, $K^{qty}_{i,t}$ is an index for the quantity of capital used, which we take from NIPA *Fixed Asset Tables* by industry. These tables provide, for each industry, an index of capital net of depreciation constructed from data on investment (deflated to quantities) using the perpetual inventory method. We take the indices for total assets, but there are also indices for equipment, intellectual property and structures.

The data from NIPA are at a slightly different level of aggregation than the data from the BEA. To address this issue, we aggregated the data to 43 consolidated industries (18 manufacturing industries and 25 non-manufacturing industries) which can be tracked consistently over time with these two sources of data.

Alternative way of computing the substitution effect and changes in task content: Our baseline estimation of the substitution effect and changes in task content within an industry requires estimates of $W_{i,t}$ and $R_{i,t}$ as well as σ and the growth rate of factor augmenting technologies, g^A_{i,t,t_0}.

One can equivalently estimate the substitution effect and changes in the task content using only data on *the quantity of labor and capital* used in industry i, together with estimates for the growth rate of factor augmenting technologies, g^A_{i,t,t_0}. In particular, the substitution effect and the change in the task content of production in industry i can also be computed as:

(A21)

$$\begin{aligned}
\text{Substitution}_{i,t,t_0} =& (1-\sigma)\ln\frac{s^L_{i,t}}{s^L_{i,t_0}} - (1-\sigma)(1-s^L_{i,t_0})\left(\ln\frac{L^{qty}_{i,t}}{L^{qty}_{i,t_0}} - \ln\frac{K^{qty}_{i,t}}{K^{qty}_{i,t_0}} + g^A_{i,t,t_0}\right), \\
\text{Task content}_{i,t,t_0} =& \sigma\ln\frac{s^L_{i,t}}{s^L_{i,t_0}} + (1-\sigma)(1-s^L_{i,t_0})\left(\ln\frac{L^{qty}_{i,t}}{L^{qty}_{i,t_0}} - \ln\frac{K^{qty}_{i,t}}{K^{qty}_{i,t_0}} + g^A_{i,t,t_0}\right)
\end{aligned}$$

This equivalence shows how one can implement our methodology using factor price data or quantity indices of the capital and labor used in each industry. Both methodologies produce identical result so long as price and quantity indices by industry satisfy equations (A19) and (A20).

Detailed manufacturing data: For our exercise using the Survey of Manufacturing Technologies, we used a detailed set of four-digit industries. We obtained the data for these industries from the 1987, 1992, 1997, 2002, and 2007 BEA *Input-Output Accounts*. One challenge when using these data is that industries are reported using different classifications over the years. To address this issue, we use the crosswalks created by Christina Patterson, who mapped the detailed industries to a consistent set of four-digit manufacturing industries, classified according to the 1987 SIC.

In addition, in a few cases, value added is below the compensation of employees, and in such instances, we recoded value added as equal to the compensation of employees, ensuring that the labor share remains between 0 and 1. Finally, we converted these data to constant dollars using the PCE price index.

For these four-digit SIC industries, we compute indices for the quantity of capital and labor used from the NBER-CES *manufacturing database*. For labor, we computed an index of employment adjusting for the composition of workers (between production and non-production workers). For capital, we used the NBER-CES measure of real capital stock in each industry, which is constructed from data on investment (deflated to quantities) using the perpetual inventory method. We then computed the change in task content and substitution effect using the formulas in (A21).

Data for 1850-1910: The historical data for 1850 to 1910 referenced in our discussion of the mechanization of Agriculture come from Table 1 in Budd (1960) and is presented in Figure A15. We use Budd's adjusted estimates, which account for changes in self-employment during this period. Table A1 in Budd (1960) also provides data on total employment. We converted Budd's estimates to 1910 dollars using a historical series for the price index from the Minneapolis Federal Reserve Bank.

As noted in the text, the data on wage bill as a share of income in agriculture and industry are from Budd (1960). These numbers ignore proprietors income accruing to farmers and entrepreneurs, which are partly compensation for labor. Johnson (1948, 1954) provide estimates for the labor share of income inclusive of proprietors income in the early 1900s. The resulting labor shares in 1900-1910 are between 45% and 55% for agriculture (as opposed to an 18% wage share) and 70% for the overall economy (as opposed to a 47%

wage share). Because (owner-occupied) farming was more important in agriculture than entrepreneurship in the rest of the economy, the gap in the labor intensity of agriculture relative to the overall economy halves once one takes into account farmers and entrepreneurs income.

Even with these adjustments, it is still the case that agriculture was a relatively capital-intensive sector, with the capital to labor ratio (including land) in agriculture being twice that of manufacturing, trade, and services (Johnson, 1954). As a consequence, the reallocation of economic activity away from agriculture to manufacturing, trade and services is again estimated to have generated a positive composition effect. Although the adjustment for proprietors income affects the size of the composition effect, it does not change the conclusion that the labor share within agriculture declined during this period while the labor share in manufacturing, trade, and services increased. This is largely because, as noted in Budd (1960), during this period the percentage of proprietors income within each sector remained roughly constant.

Proxies for automation technologies: The measure of *adjusted penetration of robots* is from Acemoglu and Restrepo (2018b). It is available for 19 industries which are then mapped to the 61 industries in our analysis.

Acemoglu and Autor's (2011) share of *routine occupations* measures the share of occupations that are highly susceptible to computerization and automation. Routine occupations include sales, clerical, administrative support, production, and operative occupations. This measure is available for 243 Census industries, which we mapped to the 61 industries used in our analysis.

The measure of adoption of automation technologies from the Survey of Manufacturing Technologies (SMT) is available for 1988 and 1993 (see Doms et al., 1997). We combine both surveys and use the share of firms (weighted by employment) using automation technologies, which include automatic guided vehicles, automatic storage and retrieval systems, sensors on machinery, computer-controlled machinery, programmable controllers, and industrial robots. This measure is available for 148 four-digit SIC industries are all part of the following three-digit "technology-intensive" manufacturing industries: fabricated metal products, nonelectrical machinery, electric and electronic equipment, transportation equipment, and instruments and related products. To exploit these disaggregated data, in these models we use estimates of changes in the task content over 1987-2007 for these 148 four-digit SIC industries computed from the BEA input-output data.

Proxies for new tasks: The share of new job titles by occupation from the 1991 Dictionary of Occupational Titles comes from Lin (2011). We mapped this measure to our 61 industries using the share of employment by occupation from the 1990 Census.

The measure of emerging tasks by occupation comes from O*NET. Since 2008, O*NET has been tracking "emerging tasks", defined as those that are not currently listed for an occupation but are identified by workers as becoming increasingly important in their jobs. As with the Dictionary of Occupational Titles data, we projected this measure to industries using the employment distribution across occupations in the 1990 Census.

Finally, both measures of occupational diversity were computed using the 1990 Census and the 2012-2016 American Community Survey.

Measure of offshoring: The measure of offshoring is based on work by Feenstra and Hanson (1999), which was extended by Wright (20130). This measure is available for over 400 NAICS industries which we then mapped to the 61 industries in our analysis. For each industry, this measure captures the penetration of trade among the industries that supply it with intermediate goods between 1993 and 2007.

Appendix References

Acemoglu, Daron and David Autor (2011) "Skills, tasks and technologies: Implications for employment and earnings," *Handbook of Labor Economics*, 4: 1043–1171.

Acemoglu, Daron and Pascual Restrepo (2018a) "The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment" *American Economic Review*, 108(6): 1488–1542.

Elsby, Michael, Bart Hobijn, and Aysegul Sahin (2013) "The Decline of the U.S. Labor Share," *Brooking Papers on Economic Activity,* 2: 1–63.

Feenstra, Robert, and Gordon Hanson (1999) "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990." *The Quarterly Journal of Economics,* 114(3): 907–940.

Gale D. Johnson (1954) "Allocation of Agricultural Income," Journal of Farm Economics, 30(4):724–749.

Gale D. Johnson (1954) "The Functional Distribution of Income in the United States, 1850-1952," *The Review of Economics and Statistics*, 36(2):175–182.

Lin, Jeffrey (2011) "Technological Adaptation, Cities, and New Work" *Review of Economics and Statistics* 93(2): 554–574.

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

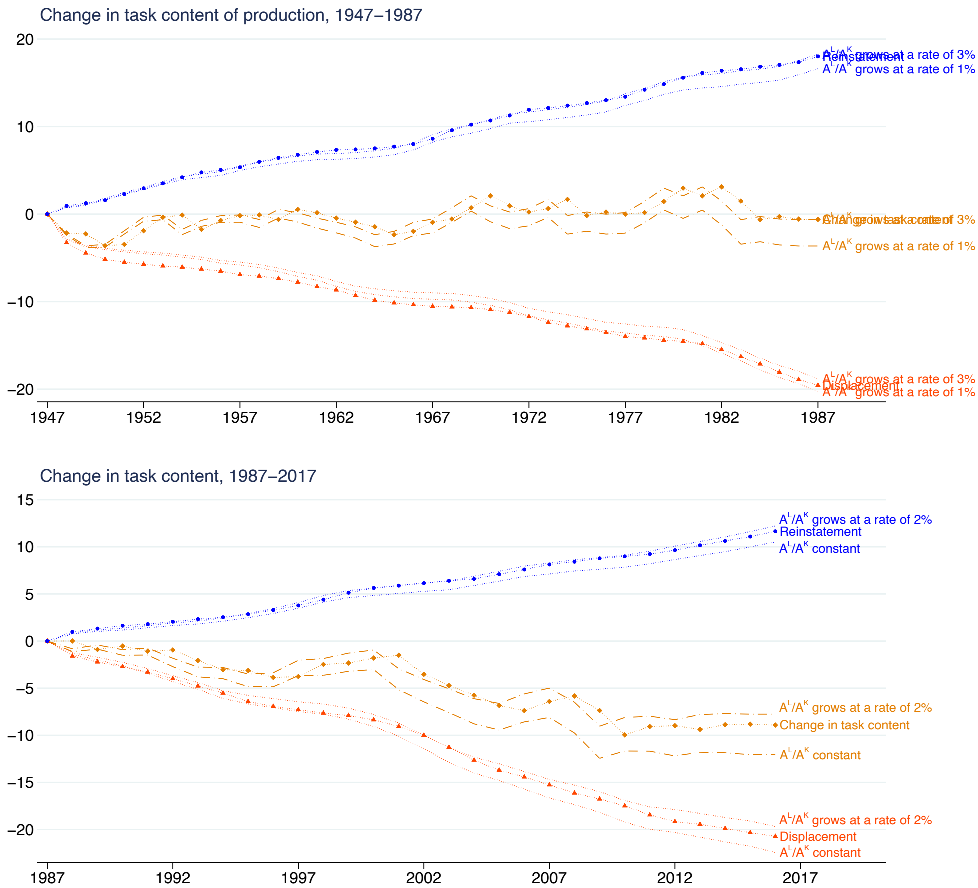


FIGURE A1: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR DIFFERENT ASSUMED GROWTH RATES FOR A_i^L/A_i^K.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A14) for different values of the growth rate of A_i^L/A_i^K. The top panel is for 1947-1987, and as the baseline, assumes a growth rate for the relative labor-augmenting technological change of 2%. The bottom panel is for 1987-2017, and as the baseline, assumes a growth rate for the relative labor-augmenting technological change of 1.5%. Results for an elasticity of substitution $\sigma = 0.8$.

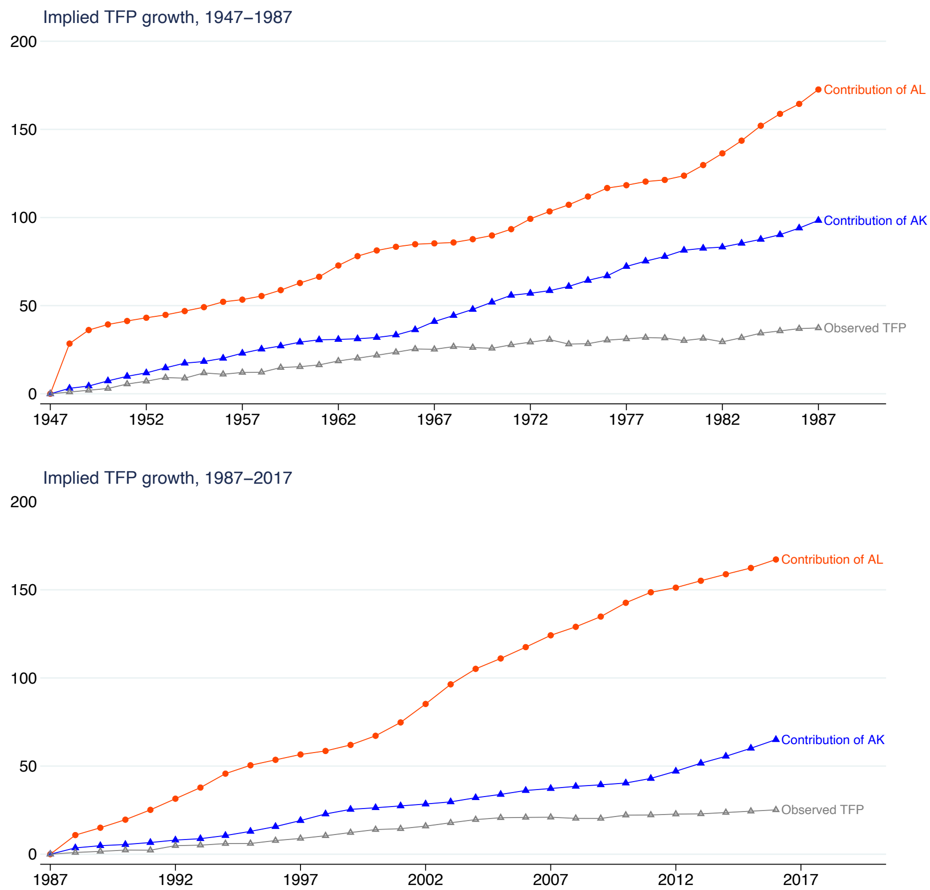
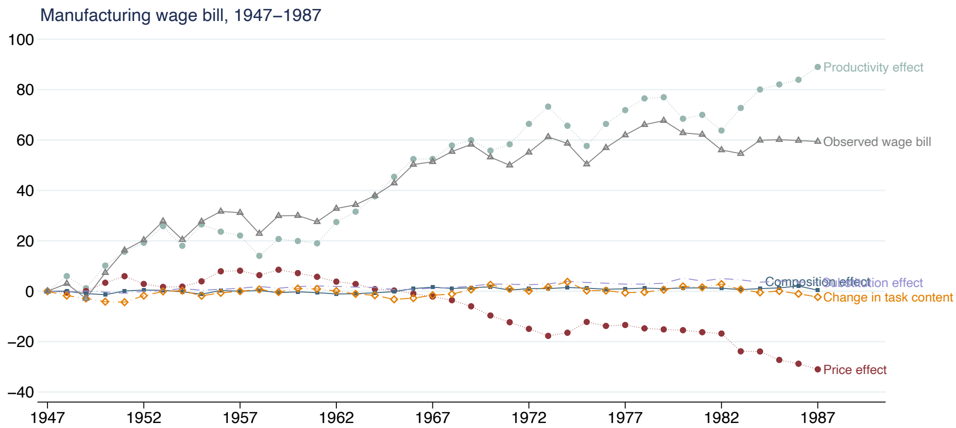


FIGURE A2: COUNTERFACTUAL TFP CHANGES.

Note: This figure presents the counterfactual TFP changes that would be implied if our estimates of the displacement and reinstatement effect in 1947-1987 and 1987-2017 were accounted for by industry-level changes in labor-augmenting and capital-augmenting technological changes alone, respectively, as derived in equations (A15) and (A16). For comparison, the figure also reports the observed increase in TFP for both periods.



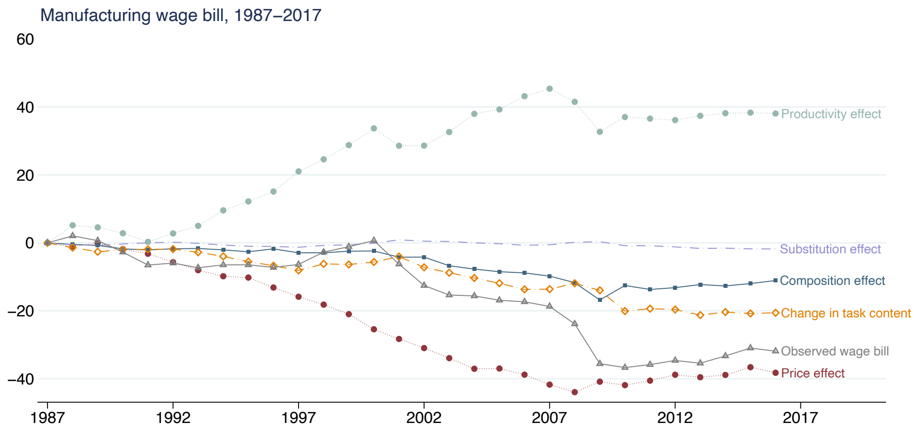


FIGURE A3: LABOR DEMAND IN MANUFACTURING.
Note: This figure presents the decomposition derived in equation (A3) for the manufacturing wage bill in 1947-1987 and 1987-2017. The top panel is for 1947-1987 and assumes a growth rate for the relative labor-augmenting technological change of 2%. The bottom panel is for 1987-2017 and assumes a growth rate for the relative labor-augmenting technological change of 1.5%. Results for an elasticity of substitution $\sigma = 0.8$.

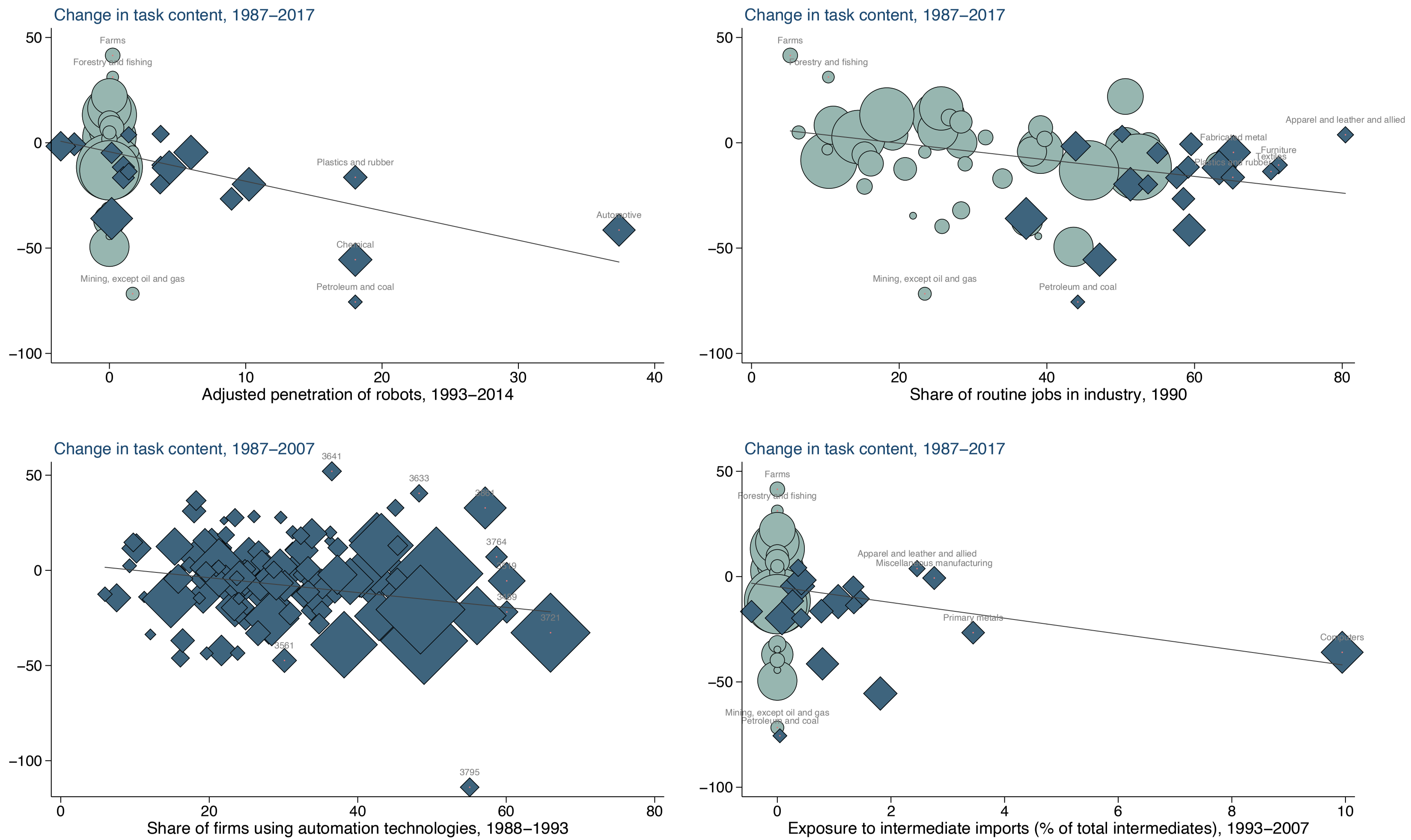


FIGURE A4: AUTOMATION TECHNOLOGIES, OFFSHORING, AND CHANGES IN THE TASK CONTENT OF PRODUCTION.
Note: Each panel presents the bivariate relationship at the industry level between change in task content and the indicated proxy for automation technologies or offshoring. Diamond markers designate manufacturing industries and circles non-manufacturing industries. The proxies are: adjusted penetration of robots, 1993-2014 (from Acemoglu and Restrepo, 2018b), share of employment in routine occupations in 1990 (Acemoglu and Autor, 2011), share of firms (weighted by employment) using automation technologies, from the 1988 and 1993 SMT, and exposure to imports of intermediate goods, from Feenstra and Hanson (1999). See text for details.

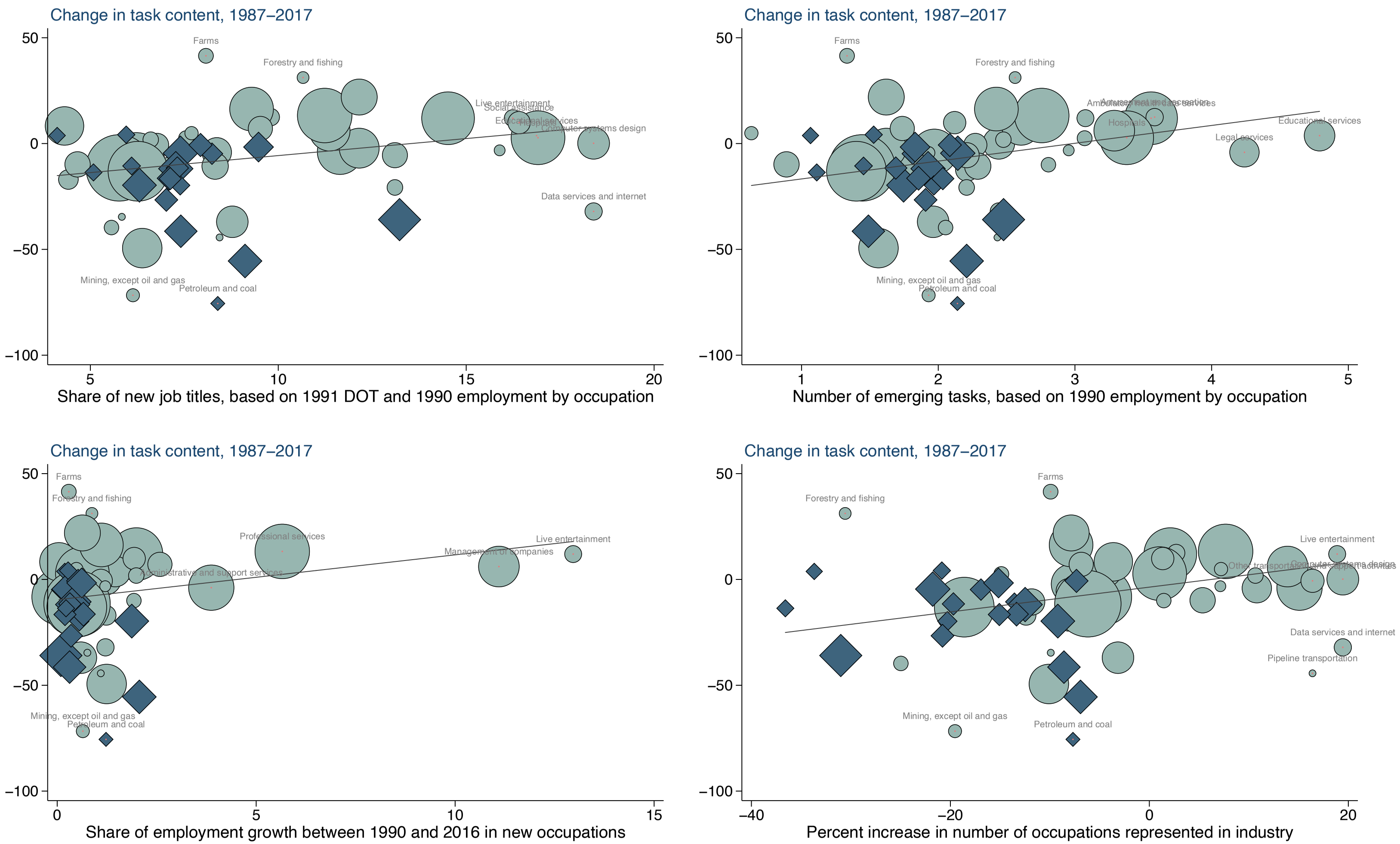


Figure A5: New tasks and change in task content of production.

Note: Each panel presents the bivariate relationship at the industry level between change in task content and the indicated proxy for new tasks. Diamond markers designate manufacturing industries and circles non-manufacturing industries. The proxies are: share of new job titles (from Linn, 2011), number of emerging tasks (from ONET), share employment growth between 1990 and 2016 in "new occupations"—those that were not present in the industry in 1990—, and the percent increase in the number of occupations present in the industry between 1990 and 2016. See text for details.

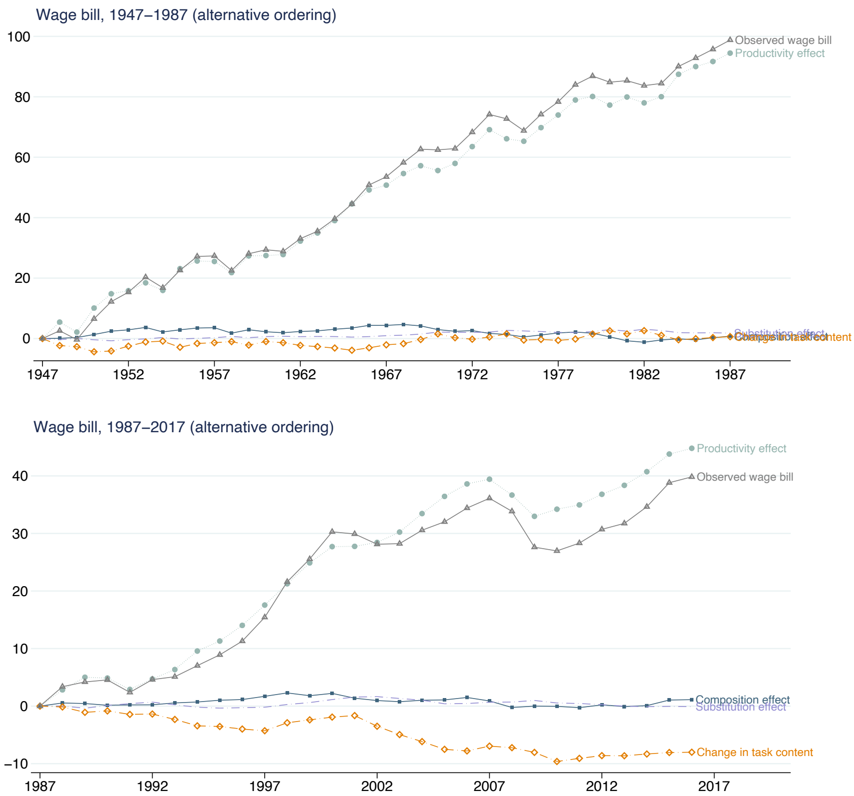


FIGURE A6: ALTERNATIVE ORDERING OF THE WAGE BILL DECOMPOSITION.
Note: The two panels present decompositions of changes in wage bill using the alternating ordering in equation (A18). The top panel presents the decomposition of labor demand (wage bill) between 1947 and 1987. The bottom panel presents the decomposition of labor demand (wage bill) between 1987 and 2017. Results for an elasticity of substitution $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 2% per year (for 1947-1987) and 1.5% a year (for 1987-2017).

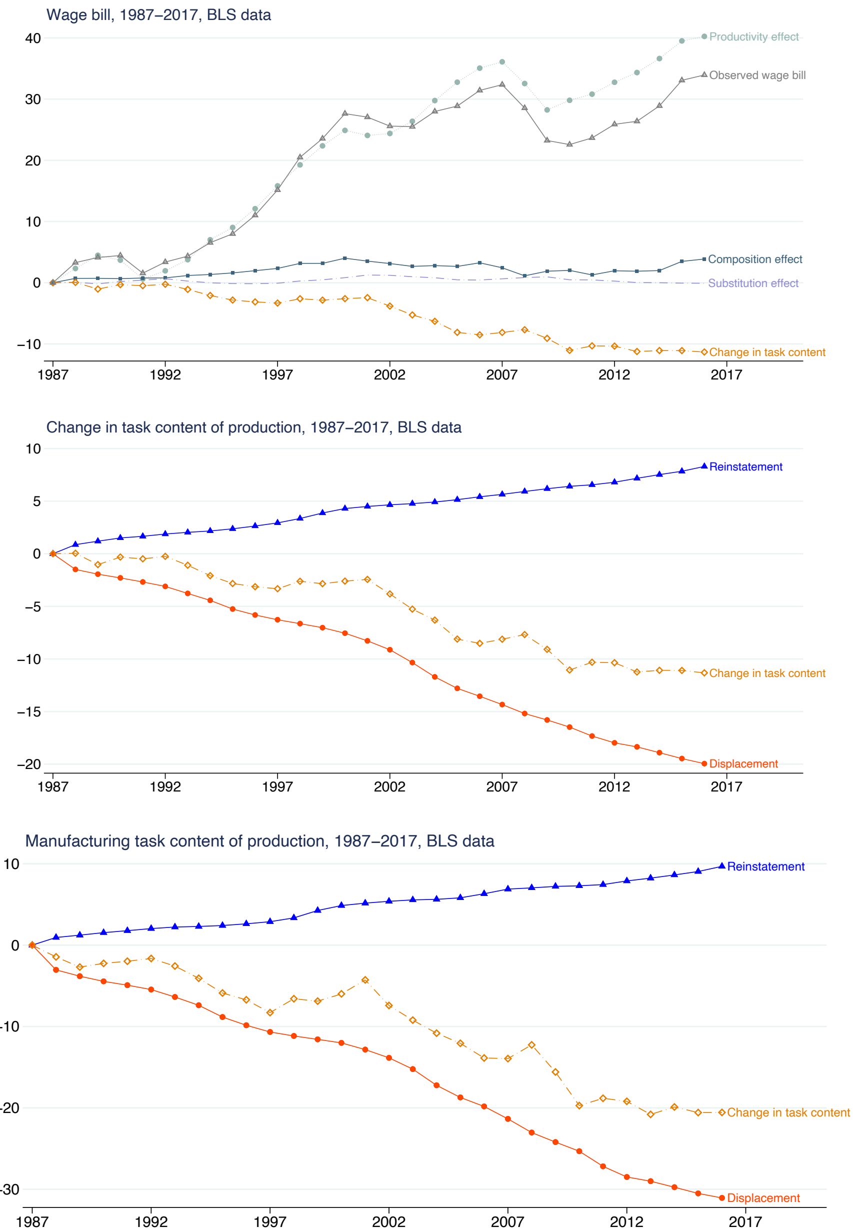


FIGURE A7: SOURCES OF CHANGES IN LABOR DEMAND, 1987-2017.

Note: The top panel presents the decomposition of labor demand (wage bill) between 1987 and 2017 using BLS data. The middle and bottom panels present our estimates of the displacement and reinstatement effects for the entire economy and the manufacturing sector, respectively. Results for an elasticity of substitution $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 1.5% a year.

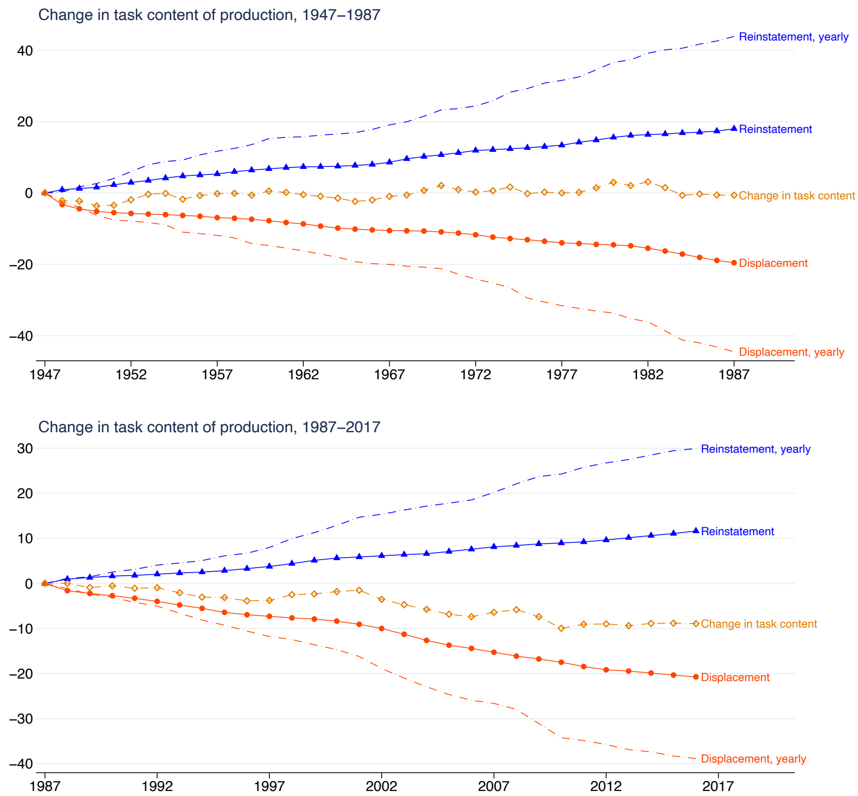


FIGURE A8: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS, YEARLY AND FIVE-YEAR CHANGES.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A14) and additional estimates using yearly changes (rather than five-year windows). The top panel is for 1947-1987 and assumes a growth rate for the relative labor-augmenting technological change of 2%. The bottom panel is for 1987-2017 and assumes a growth rate for the relative labor-augmenting technological change of 1.5%. Results for an elasticity of substitution $\sigma = 0.8$.

FIGURE A9: SOURCES OF CHANGES IN LABOR DEMAND FOR THE ENTIRE ECONOMY, 1947-1987, FOR DIFFERENT VALUES OF σ.

Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (A9) in the text. The panels present the results for the vauels of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

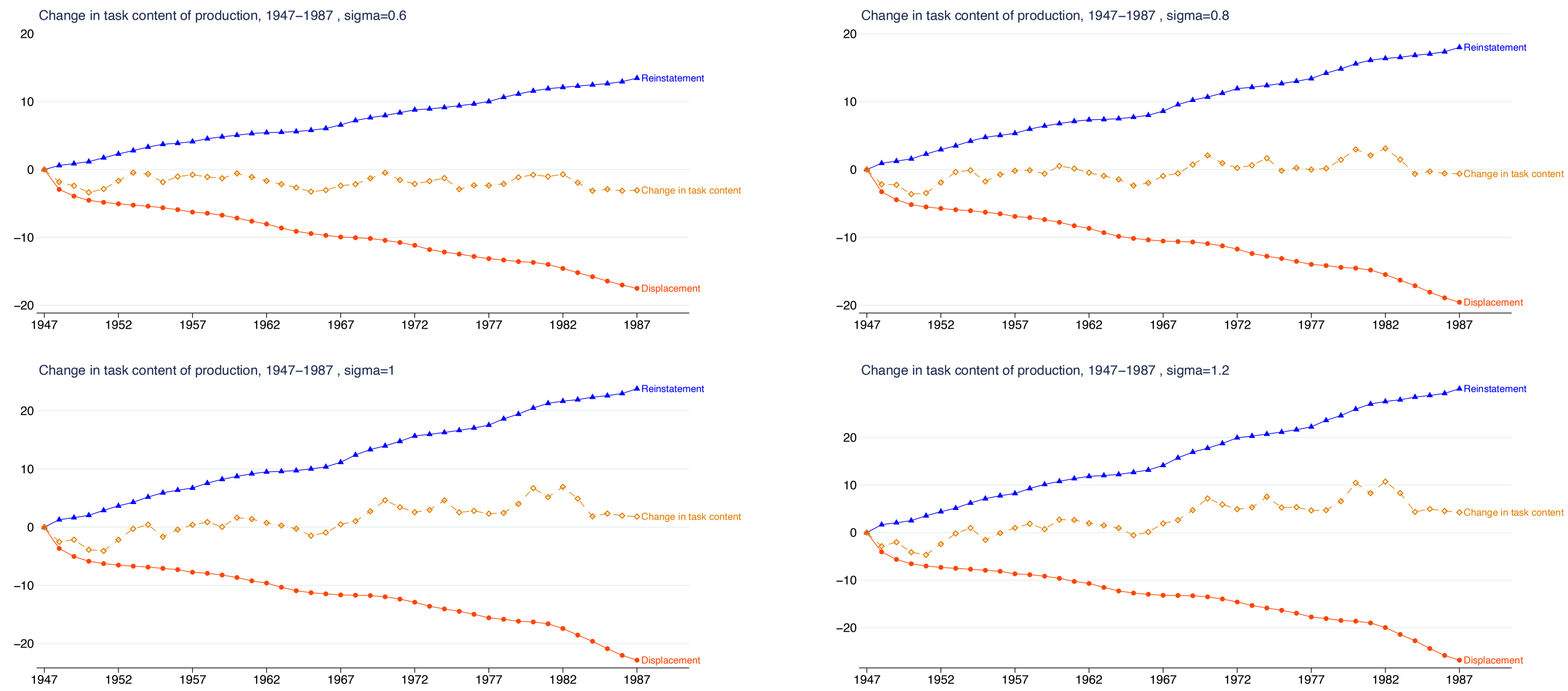


FIGURE A10: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR THE ENTIRE ECONOMY, 1947-1987, FOR DIFFERENT VALUES OF σ.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A14) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

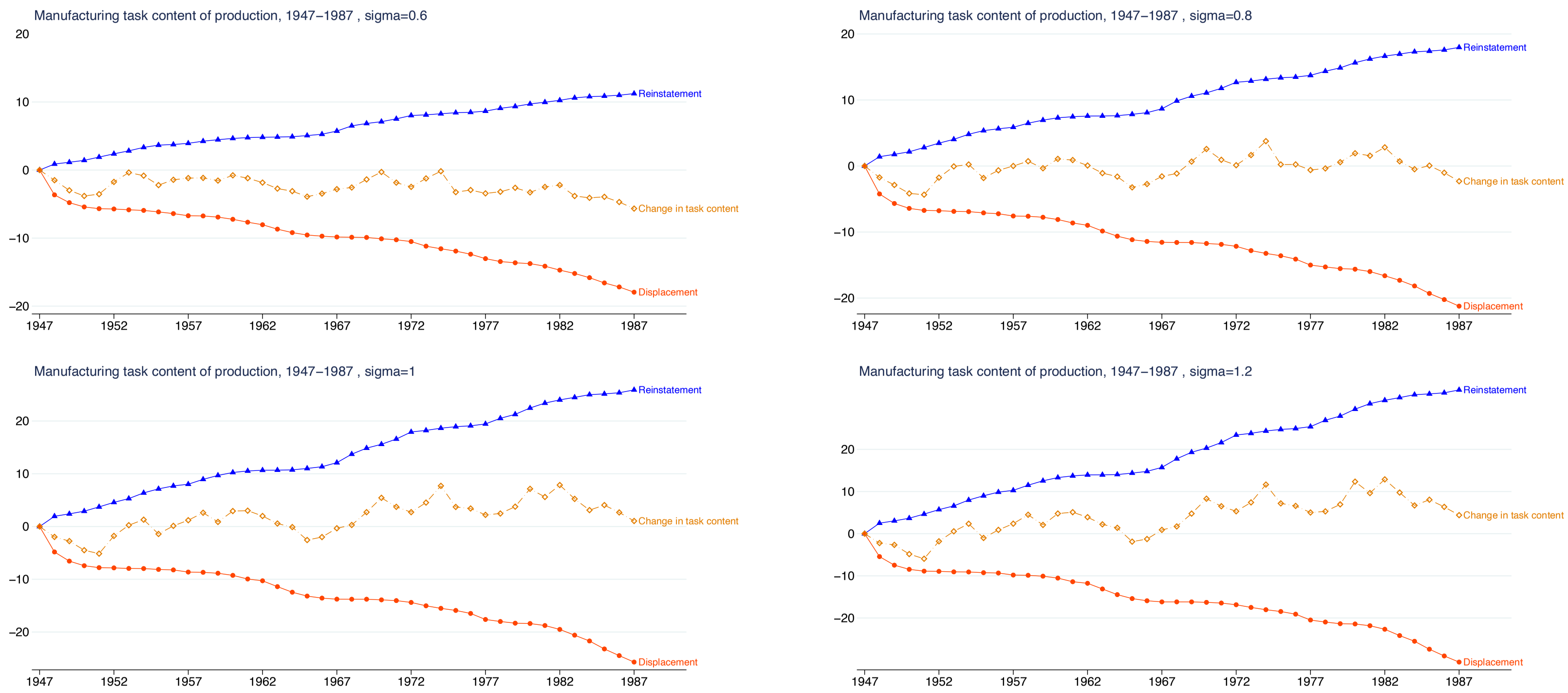


FIGURE A11: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR MANUFACTURING, 1947-1987, FOR DIFFERENT VALUES OF σ.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A14) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

FIGURE A12: SOURCES OF CHANGES IN LABOR DEMAND FOR THE ENTIRE ECONOMY, 1987-2017, FOR DIFFERENT VALUES OF σ.

Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (A9) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.

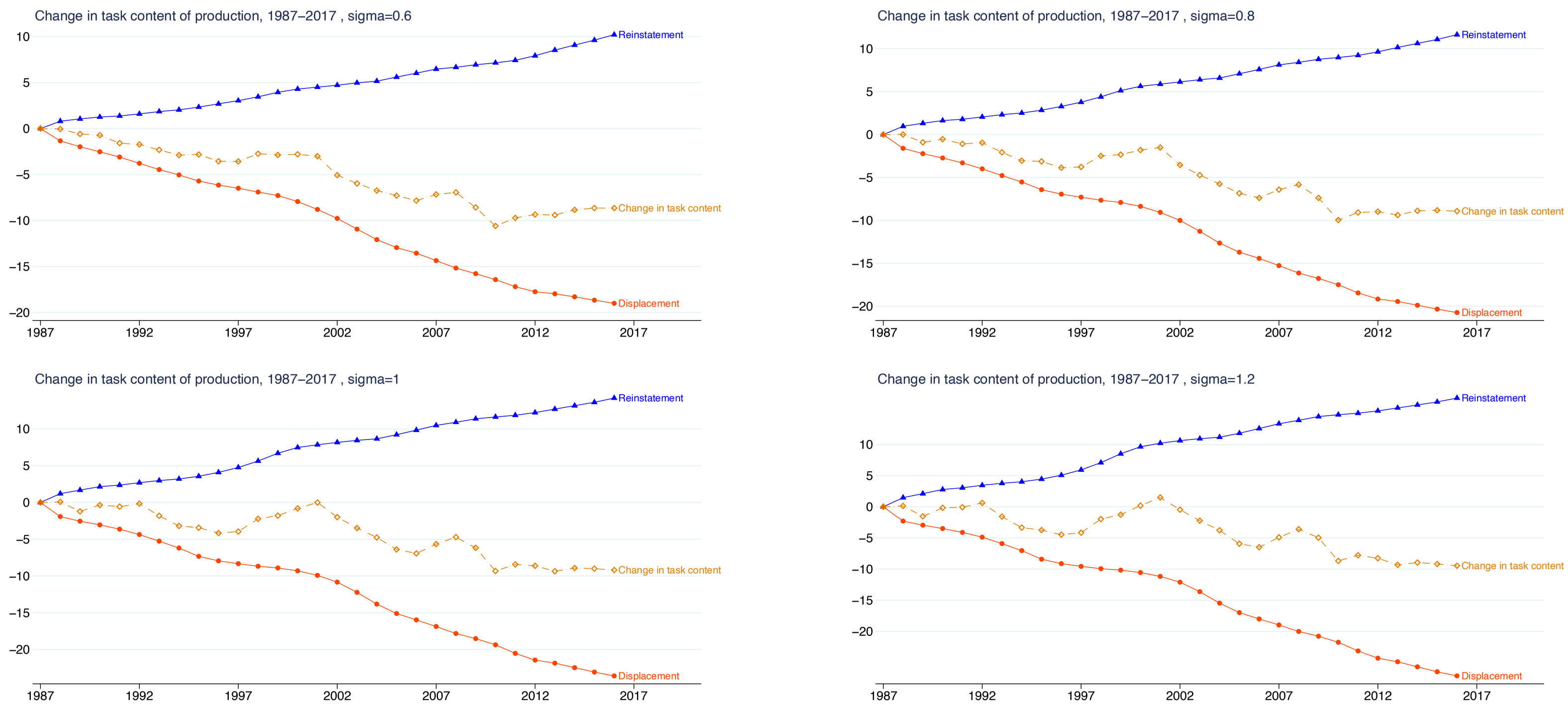


Figure A13: Estimates of the displacement and reinstatement effects for the entire economy, 1987-2017, for different values of σ.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A14) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.

FIGURE A14: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR MANUFACTURING, 1987-2017, FOR DIFFERENT VALUES OF σ.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A14) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.

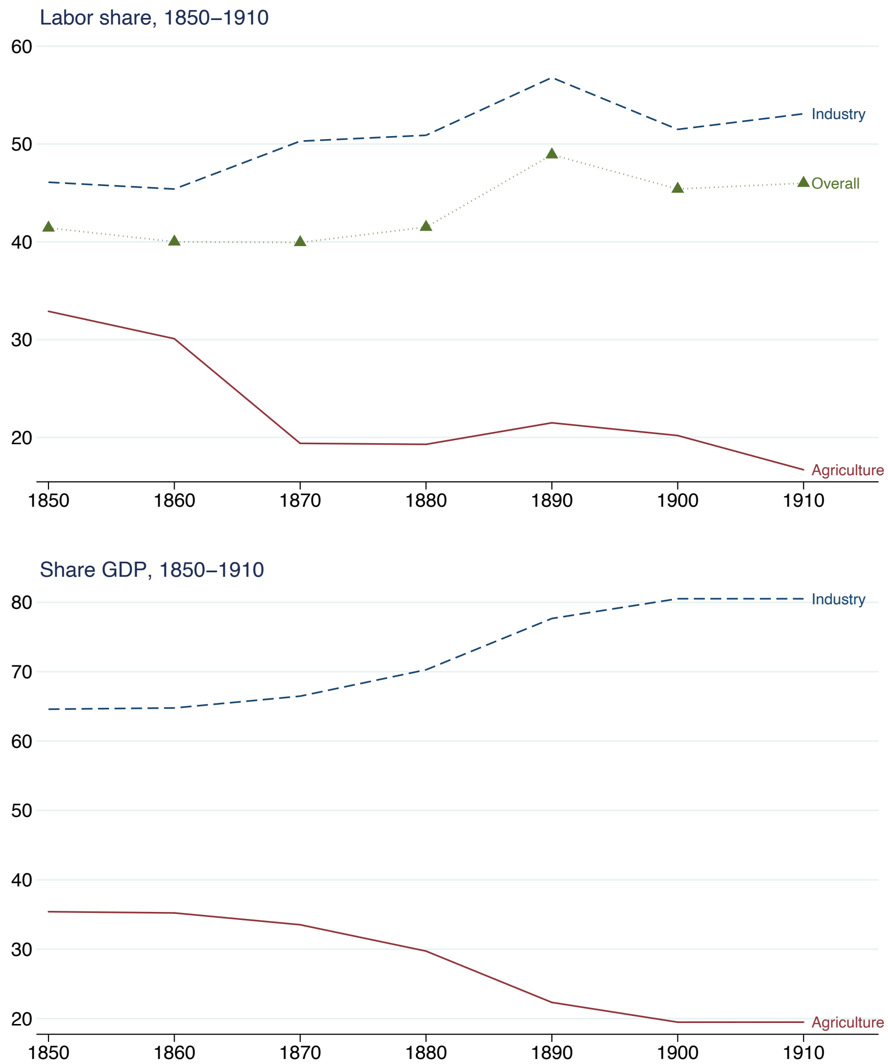


Figure A15: Labor share and sectoral evolutions during the mechanization of agriculture, 1850-1910.
Note: The top panel shows the labor share in value added in industry (services and manufacturing) and agriculture between 1850-1910, while the bottom panel shows the share of value added in these sectors relative to GDP. Data from Budd (1960).

Table A1: Relationship between gross change in task content of production, quantities produced, TFP, and skill intensity of industries.

	Log change quantity, 1987-2016		Log change TFP, 1987-2016		Change skill intensity, 1990-2016	
	(1)	(2)	(3)	(4)	(5)	(6)
Gross change in task content	0.799	0.581	0.321	0.233	0.096	0.096
	(0.262)	(0.235)	(0.152)	(0.141)	(0.037)	(0.037)
Chinese import competititon		-3.463		-0.357		0.324
		(1.541)		(0.407)		(0.149)
Offshoring of intermediates		40.957		17.930		0.593
		(2.726)		(1.219)		(0.219)
Manufacturing	-0.286	-0.884	0.161	-0.187	-0.000	-0.037
	(0.427)	(0.162)	(0.206)	(0.086)	(0.019)	(0.018)
Computer industry						
Observations	61	61	61	61	61	61
R-squared	0.08	0.61	0.12	0.60	0.16	0.23

Note: The table reports estimates between gross changes in task content of production and the change in quantities, TFP, and skill intensity of industries. The gross change in task content is defined as the sum of the absolute values of the displacement and reinstatement effects computed in equation (A14). Columns 1-2 present results for the change in quantities produced (from the BEA-KLEMS). Columns 3-4 present results for the change in TFP (from the BEA-KLEMS). Columns 5-6 present results for the change in skill requirements, measured by the share of college educated workers in each industry (from the 1990 US Census and the pooled 2012-2016 ACS). All regressions are for the 61 industries used in or analysis of the 1987-2017 period. Standard errors robust against heteroskedasticity are in parenthesis.