Automation and New Tasks: The Implications of the Task Content of Technology for Labor Demand*

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Abstract

We present a framework for understanding the effects of automation and other types of technological changes on labor demand, and use it for interpreting changes in US employment over the recent past. Automation enables capital to replace labor in tasks it was previously engaged in. Because of the *displacement effect* it generates, automation is qualitatively different from factor-augmenting technological changes; it always reduces the labor share in value added (of an industry or economy) and may also reduce employment and wages even as it raises productivity. The effects of automation are counterbalanced by the creation of new tasks in which labor has a comparative advantage, which generates a *reinstatement effect* raising the labor share and labor demand by expanding the set of tasks allocated to labor. We show how the role of changes in the task content of production—due to automation and new tasks—can be inferred from industry-level data. Our empirical exercise suggests that the slower growth of employment over the last three decades is accounted for by an acceleration in the displacement effect, especially in manufacturing, a weaker reinstatement effect, and slower growth of productivity than in previous decades.

Keywords: automation, displacement effect, labor demand, inequality, productivity, reinstatement effect, tasks, technology, wages.

JEL classification: J23, J24.

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1 Introduction

The implications of automations for employment and wages are still imperfectly understood. While some see the ongoing process of automation, as exemplified by computer numerical control machinery, industrial robots and artificial intelligence (AI), as the harbinger of widespread joblessness, others reason that, like other waves of new technologies, automation will ultimately increase labor demand, wages and employment.

In this paper, we develop a task-based framework that explains why automation technologies have qualitatively different labor market effects than other types of technologies, but also why they do not necessarily spell the end of human work. Our framework starts from and extends our previous work in Acemoglu and Restrepo (2018a, 2018b), which in turn builds on Acemoglu and Autor (2011), Autor, Levy and Murnane (2003) and Zeira (1998). Automation corresponds to new technologies that enable capital to be substituted for labor in certain tasks. The distinctive feature of automation is that it generates a powerful *displacement effect*—because it replaces labor in tasks it was previously performing.

The displacement effect is in evidence in previous episodes of automation. Many of the early innovations of the British Industrial Revolution specifically aimed to automate tasks previously performed by skilled artisans in spinning and weaving (Mantoux, 1928). As they succeeded in doing so, they created widespread displacement (and accompanying discontent as evidenced by the Luddite riots; see Mokyr, 1990). The process of mechanization of agriculture, which started in the first half of the 19th century with the cotton gin and continued with horse-powered reapers, harvesters and plows later in the century and with tractors and combine harvesters in the 20th century, similarly displaced agricultural workers in large numbers (Rasmussen, 1982, Olmstead and Rhode, 2001). Today too we are witnessing a period of rapid automation, driven by industrial robots and various other dedicated automated machinery, replacing production workers (Graetz and Michaels, 2018, Acemoglu and Restrepo, 2018b).

The displacement effect makes automation technologies qualitatively different from other types of new technologies, most notably from factor-augmenting technological changes. Although all technological progress increases productivity and via this channel the demand for labor—which we call the*productivity effect*—automation always reduces the labor share in value added (of a sector or of the entire economy). It may also reduce wages and employment—especially if it is accompanied with only limited gains in productivity. In contrast, factor-augmenting technological improvements lead to greater labor demand, employment and wages (unless there is an extremely and implausibly low elasticity of substitution between capital and labor; see Acemoglu and Restrepo, 2018c).

A notable implication of the displacement effect is this: if the history of technology were one of continuous automation, human labor would be confined to a shrinking set of tasks and jobs, with steadily declining share of labor in national income. That is not what we see because, we argue, automation is counterbalanced by the creation of new tasks in which labor has a comparative advantage. New tasks generate not only the same type of productivity effect as automation technologies, but also a *reinstatement effect*—they reinstate labor into a broader range of tasks. The reinstatement effect is the polar opposite of the displacement effect and directly increases the labor share as well as employment and wages.

History is also replete with examples of the creation of new tasks and the reinstatement effect that this engenders. In the 19th century, as automation was ongoing, other new technologies generated employment opportunities in new occupations. These included jobs for line workers, engineers, machinists, repairmen, conductors, back-office and clerical workers, managers and financiers (Chandler, 1977, Mokyr, 1990). New occupations and jobs in new industries also played a pivotal role in generating labor demand during the decades of rapid mechanization of agriculture in the US economy, including in clerical occupations and in manufacturing (Kuznets, 1966, Olmsted and Rhode, 2001, Rasmussen, 1982). New tasks have been important sources of employment growth during the last three decades as well (Acemoglu and Restrepo, 2018a).

One important conceptual lesson from this framework, illustrated by these historical examples, is that it is wrong to expect automation technologies to seamlessly create balanced growth and robust wage increases for all workers. Rather, balanced growth and in particular wage growth commensurate with productivity growth are a consequence of other technological changes balancing the effects of automation.

In the second part of the paper, we develop a methodology for decomposing changes in labor demand into various components related to productivity, factor-augmenting technological changes, sectoral composition of economic activity, substitution effects and crucially changes in the task content of production—driven by the displacement and reinstatement effects.

This decomposition can be implemented using industry-level data on factor prices, value added and the labor share, which we proceed to do for different subperiods of recent US economic history. Using this methodology, we show that the evolution of labor demand during the last century and a half, and especially over the last 30 years, cannot be understood by focusing on factor-augmenting technologies or sectoral reallocation of resources. Instead, changes in the task content of technology appear to play a defining role. This empirical exercise also highlights that what sets this recent period apart from previous episodes is partly slower than usual productivity growth, but even more importantly, it is adverse changes in the task content of production—driven by more rapid displacement and slower reinstatement effects.

Finally, we bolster our interpretation of the role of the task content of new technologies by verifying that our inferred measures of task content are negatively correlated with various measures of automation technologies (which reduce the set of tasks allocated to labor) and positively correlated with proxies of new tasks (which in contrast tend to increase the set of tasks allocated to labor).

The rest of the paper is organized as follows. Section 2 introduces our conceptual framework. Section 3 explains how this framework can be used for inferring changes in the task content of production and its role in changes in labor demand during different subperiods of recent US economic history. Section 4 concludes, while an Online Appendix contains proofs, additional empirical results and details on the construction of our data.

2 Conceptual Framework

At the center of our conceptual framework are tasks that need to be performed for production, and they can be performed using either labor or capital. Automation corresponds to an expansion of the set of tasks that can be produced by capital. We also allow the introduction of new tasks in which labor has a comparative advantage relative to capital. We start with a model for a single sector. We then embed this structure in a multi–sector setup. Finally, we show how the task content of new technologies can be inferred from data.

2.1 Tasks and Production in a Single Sector

We start with a model for a single sector, or alternatively for an economy consisting of a single sector. Denote the level of production of the sector by Y (we do not include industry subscript in order to simplify notation in this subsection). Production takes place by combining a set of tasks, with measure normalized to 1, using the following production function

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

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.[1]

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

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

Critically, technology determines whether a task can be produced with capital. Tasks $z \leq I$ are (technologically) *automated* and can be produced with capital, while those $z > I$ are not automated and can only be produced with labor. In addition, $l(z)$ and $k(z)$ denote the total labor and capital allocated to producing task z. The productivity of the two factors in different tasks are determined by factor-augmenting technology terms, A^L and A^K, which increase the productivity of these factors in all tasks, and by task-specific terms $\gamma^L(z)$ and $\gamma^K(z)$. We assume throughout that $\gamma^L(z)/\gamma^K(z)$ is increasing in z, so that labor has a *comparative advantage* in higher-indexed tasks, and that $\gamma^L(z)$ increasing in z, so that labor is more productive in new tasks than in old ones. Finally, an increase in N corresponds, as we discuss below, to the creation

[1]The assumption that the range of tasks is always of measure 1 and lies between $N-1$ and N is adopted to simplify the exposition, and the general results are similar if we instead assume $Y = N^{\frac{1}{1-\sigma}} \left(\int_0^{N_i} Y(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}$ as we show in the Appendix.

of new tasks replacing older versions.

This specification implies that the state of technology of the sector/economy is captured by I (automation), N (creation of new tasks), A^L (labor-augmenting technology) and A^K (capital–augmenting technology) as well as the comparative advantage schedules $\gamma^L(z)$ and $\gamma^K(z)$. In what follows, we summarize technology by the vector $\theta = \{I, N, A^K, A^L\}$.

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.

Throughout, we also simplify the exposition by imposing the following condition on the wage rate W and the rental rate of capital R,

$$\frac{A^L}{A^K}\frac{\gamma^L(I)}{\gamma^K(I)} < \frac{W}{R} < \frac{A^L}{A^K}\frac{\gamma^L(N)}{\gamma^K(N-1)}. \tag{2}$$

This inequality ensures that new automation technologies (an increase in I) and new tasks (an increase in N) raise productivity and will be immediately adopted.[2] Under this assumption, tasks in $[N-1, I]$ will be produced with capital, and tasks in $[I, N]$ will be produced with labor, creating a simple mapping between the component of technology summarized by I and N and the allocation of tasks to factors.

Following the same steps as in Acemoglu and Restrepo (2018a), output (of the sector or the economy) can be written as

$$Y(L,K;\theta) = \left(\left(\int_{N-1}^{I}\gamma^K(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}(A^K K)^{\frac{\sigma-1}{\sigma}} + \left(\int_{I}^{N}\gamma^L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}(A^L L)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

and the labor share (in value added) can be computed as

$$s^L(W,R;\theta) = \frac{WL}{Y} = \frac{\Gamma(N,I)(W/A^L)^{1-\sigma}}{(1-\Gamma(N,I))(R/A^K)^{1-\sigma} + \Gamma(N,I)(W/A^L)^{1-\sigma}}. \tag{4}$$

where

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

is the labor task content or simply the *task content of production*.[3]

Equation (3) shows that output is given by a standard constant elasticity of substitution

[2] This assumption is indirectly on the amount of capital and labor used in the sector, K and L, as we show in the Appendix. See further details as well as the analysis of the case in which this assumption does not hold in Acemoglu and Restrepo (2018a).

[3] Expressed in terms of capital and labor utilization, the labor share would again be a function of the task content of production: $s^L(L,K;\theta) = \frac{\Gamma(N,I)^{\frac{1}{\sigma}}(A^L L)^{\frac{\sigma-1}{\sigma}}}{(1-\Gamma(N,I))^{\frac{1}{\sigma}}(A^K K)^{\frac{\sigma-1}{\sigma}} + \Gamma(N,I)^{\frac{1}{\sigma}}(A^L L)^{\frac{\sigma-1}{\sigma}}}$.

(CES) production function. The labor share depends on the task content of production, $\Gamma(N,I)$, which is a summary measure of the importance of tasks performed by labor relative to those performed by capital. Clearly, $\Gamma(N,I)$, and thus the labor share, is decreasing in I, which automates tasks previously performed by labor, and is increasing in N, which expands the range of tasks performed by labor. In the special case where $\gamma^L(z) = \gamma^K(z) = 1$, $\Gamma(N,I) = N - I$.

Effective factor prices, W/A^L and R/A^K, do *not* impact the allocation of tasks to factors but still affect the labor share because they influence the substitution of tasks produced by labor for those produced by capital (except when $\sigma \to 1$ so that we have Cobb-Douglas technology).[4]

2.2 Technology and Labor Demand

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

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

Naturally, 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.[5]

We start with automation—an expansion in I.

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

This formula shows that automation has two distinct effects on labor demand. First, there is a *productivity effect*, as automation increases productivity—that is $\frac{\partial \ln Y(L,K;\theta)}{\partial I} > 0$—and raises the demand for labor in non-automated tasks. If nothing else happened, this increase in productivity would directly, and by the same amount, increase labor demand. However, there is a powerful force reducing the labor demand—the *displacement effect*. This reflects the fact that automation displaces labor from certain tasks and squeezes it into fewer non-automated ones. Automation raises labor demand when the productivity effect dominates displacement, but reduces it otherwise.

[4] Factor prices would affect the allocation of tasks to factors when either the assumption in (2) does not hold (see Zeira, 1998; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a) or when the development of technology is endogenous (Acemoglu and Restrepo, 2018a). The separation of the roles of (effective) factor prices and technology as summarized by I and N is convenient both for conceptual clarity and for our empirical decomposition in the next section.

[5] Once the effects of technology on labor demand are determined, how this translates into employment and wage changes is partly regulated by labor supply and partly by labor market imperfections, neither of which we model explicitly in this paper (see Acemoglu and Restrepo, 2018a, 2018b). It suffices to note that with an upward-sloping (quasi-)labor supply schedule, lower labor demand will translate into both lower employment and lower wages.

We can also use equation (3) 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 is intuitive. The productivity gains from automation depend on the difference in the cost of producing the automated tasks with labor, $\frac{W}{A^L\gamma^L(I)}$, and the cost of producing them with capital, $\frac{R}{A^K\gamma^K(I)}$. The productivity effect will be stronger when automation significantly increases productivity (because capital is more productive than labor in these tasks).[6] This last point, though simple, is important. Not only does it show that when the effective wage is similar to the effective rental rate, the productivity effect will be small and thus automation will reduce labor demand. It also implies that, contrary to a common presumption in popular debates, it is not "brilliant" automation technologies but those that are "so so", generating only small productivity improvements, that will tend to worsen the prospects of labor. The fact that the productivity effects of different types of technologies can have potentially very different magnitudes is the reason why we cannot generally presume that one set of automation technologies will impact labor demand in exactly the same way as another set—that will depend on their respective productivity effects.

The effects of creation of new tasks in which labor has a competitive advantage—an expansion in N—can be determined similarly.

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

where the productivity effect is now given by

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

The new item here is the *reinstatement effect*, which reinstates labor into additional tasks and via this channel, increases labor demand and the labor share.

[6] In addition to the productivity effect, automation may generate additional countervailing forces raising labor demand. First, automation is likely to induce additional usage of capital in the sector or additional capital accumulation, which can increase labor demand (Acemoglu and Restrepo, 2018a). Second, there could be deepening of automation, meaning increases in the productivity of capital and tasks already automated, which also increases labor demand (Acemoglu and Restrepo, 2018d). Even factoring in these changes, automation always reduces the labor share (Acemoglu and Restrepo, 2018d).

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

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

Critically, there is no displacement or reinstatement effect here, because there is no reallocation of tasks to factors, highlighting the qualitatively different nature of factor-augmenting technological changes (relative to automation and creation of new tasks).[7] The new items are the *quality substitution effects*, which capture the change in the pattern of capital-labor substitution resulting from changes in technology. This is because factor-augmenting technological change impacts the "quality" (effective productivity) of the factors, inducing a substitution between capital-intensive and labor-intensive tasks and production when $\sigma \neq 1$—but crucially *without* a change in the allocation of tasks to factors. Whether this substitution increases or reduces labor demand (and the labor share) depends on whether the elasticity of substitution σ is greater than or less than 1.

2.3 The Multi-sector Economy

We now embed the model for a single sector developed into an economy with multiple sectors. Though in general this would require us to specify consumer preferences over goods produced in different sectors as well as any input-output linkages that may exist, for our purposes here we can remain agnostic on these issues. In particular, we have general preferences over sectors and also allow factor prices to differ across sectors, because they may employ different types of labor or feature different degrees of labor market imperfections.

We index sectors by subscript 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 (2). The technology available to sector i is represented by $\theta_i = \{I_i, N_i, A_i^K, A_i^L\}$, and K_i and L_i are the quantities of capital and labor used in each sector, so that output (value added) of sector i is $Y_i = Y(L_i, K_i; \theta_i)$. 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.

[7] See Acemoglu and Restrepo (2018c) for further details of the qualitative differences between automation and factor-augmenting technological changes.

Denoting the average wage by W and aggregate employment by L, total labor demand is

$$WL = \sum_{i\in\mathcal{I}} W_i L_i = \sum_{i\in\mathcal{I}} Y \times \chi_i \times s^L(W_i, R_i; \theta_i).$$

The effects of a change—of any type—in technology can then be summarized as follows:

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

where $\ell_i = \frac{W_i L_i}{WL}$ is the share of the wage bill generated in sector i. This decomposition is formally derived in the Appendix and showcases the several distinct impacts of technology on labor demand. First, there is the multi-sector equivalent of the *productivity effect*: technology raises productivity, which tends to increase aggregate value added, Y, raising the demand for labor.[8] Second, there is a *composition effect* resulting from sectoral reallocation in response to changes in technology (and this reallocation in turn depends on consumer preferences among other things). The composition effect increases labor demand when economic activity is reallocated towards labor-intensive sectors (those with $s_i^L > s^L$) and has the opposite effect when the reallocation is towards capital-intensive sectors (those with $s_i^L < s^L$). Third, we come to the main notable feature of our framework: the *change in task content* resulting from changes in the allocation of tasks to factors (which is a multi-sector generalization of the displacement and reinstatement effects introduced in the previous subsection). Finally, there are changes resulting from variations in capital-labor substitution; these are themselves a consequence of the same *quality substitution effect* emphasized in the previous subsection as well as a multi-sector generalization of this effect, the *price substitution effect*, which results from changes in wage to rental rate ratio at the sectoral level. The direction of the impact of these last two effects on labor demand depends on the elasticity of substitution across tasks, σ.

This general decomposition can be applied to study the impact of specific technologies on labor demand. For illustration purposes, consider the introduction of a new automation technology in sector j, that is, an increase in I_j. This will first generate a displacement effect in the same sector, given by

$$\frac{1-s_j^L}{1-\Gamma_j} \frac{\partial \ln \Gamma(N_j, I_j)}{\partial I_j} < 0.$$

[8] More generally, $d\ln Y = d\ln TFP + s^L d\ln L + \sum_i \frac{R_i K_i}{Y} d\ln K_i$. In our setup, technological improvements increase TFP but their overall impact on GDP depends on the adjustment of labor and capital as well.

This displacement effect reduces labor demand. In addition, the substitution of (effectively) cheaper capital for labor increases TFP by

$$d\ln TFP = \frac{\chi_j}{\sigma - 1}\left[\left(\frac{R_j}{A_j^K \gamma^K(I_j)}\right)^{1-\sigma} - \left(\frac{W_j}{A_j^L \gamma^L(I_j)}\right)^{1-\sigma}\right] dI_j > 0.$$

This change in TFP generates the productivity effect partially restoring labor demand, and typically also generates a series of sectoral reallocations. First, consumers will change their demands as a result of changes in relative prices and their real income (e.g., the increase in productivity resulting from mechanization of agriculture leading to greater demand for non-agricultural products). Second, differential factor intensities of sectors may induce additional reallocation (Acemoglu and Guerrieri, 2008).

The implications of different types of technologies can be analyzed similarly. The creation of new tasks in a sector continues to generate the reinstatement effect, increasing the task content of production (i.e., $\frac{1-s_j^L}{1-\Gamma_j}\frac{\partial \ln \Gamma(N_j, I_j)}{\partial N_j} > 0$) and thus labor demand; it also generates similar productivity and reallocation effects. Factor-augmenting technological changes generate productivity and relocation effects as well, but do not impact the task content of production.

In summary, the implications of *any* technological change will work through, and can be decomposed into, a productivity effect, composition effects, price and quality substitution effects, and changes in the task content of production. We next proceed to implement this decomposition.

3 Empirical Analysis

In this section, we use the conceptual framework developed in the previous section to interpret the sources of the growth and then deceleration of labor demand in recent US economic history. In the next subsection we describe how we adapt this framework for empirical analysis and present our results in subsequent subsections. We discuss different empirical approaches in Section 4.

3.1 Inferring the Task Content of Production

Our point of departure is equation (5). We use a discrete approximation to this equation using yearly changes, that is, we approximate dX by $\Delta X_t = X_{t+1} - X_t$. On the basis of this, we construct

$$\begin{aligned}
\text{Observed change in wage bill}_t =& \Delta \ln(W_t L_t / Pop_t) \\
\text{Productivity effect}_t =& \Delta \ln(Y_t / Pop_t) \\
\text{Composition effect}_t =& \sum_{i \in \mathcal{I}} \left(\frac{s_{i,t}^L}{s_t^L} - 1 \right) \Delta \chi_{i,t} \\
\text{Price substitution effect}_t =& (1-\sigma) \sum_{i \in \mathcal{I}} \ell_{i,t} (1 - s_{i,t}^L) \Delta \ln(W_{i,t}/R_{i,t}),
\end{aligned}$$

where Pop_t denotes US population in year t, Y_t is GDP, and $W_t L_t$ is total wage bill, which is an inclusive measure of overall labor demand and thus our main object of interest. Relative to (5), we are normalizing the wage bill and GDP by population to account for population growth during our sample period. Note also that we are using sector-specific measures of wages and returns to capital from the BLS (see the Appendix).

We take a baseline value for σ of 0.8 (which is in line with the estimates in Oberfield and Raval, 2014).[9] We show in the Appendix that the overall qualitative and even quantitative implications of our approach are very similar for different values of σ. Throughout, we impose "no technological regress" meaning that no component of θ_i will get worse over time. Furthermore, in the text we start with the assumption that $A_{i,t}^L / A_{i,t}^K$ in all sectors improves at the rate of GDP per worker—e.g., by 1.5% a year between 1987 and 2017—so that without any changes in the task content and capital-augmenting technologies, labor-augmenting technological change can account for the entire growth of productivity. We can then compute the quality substitution effect as

$$\begin{aligned}
\text{Quality substitution effect}_t &= (1-\sigma) \sum_{i \in \mathcal{I}} \ell_{i,t} (1 - s_{i,t}^L) \Delta \ln(A_{i,t}^L / A_{i,t}^K) \\
&= 0.015(1-\sigma) \sum_{i \in \mathcal{I}} \ell_{i,t} (1 - s_{i,t}^L).
\end{aligned}$$

Under these assumptions, we can compute an estimate for the change in task content at the industry level, $(1 - s_{i,t}^L) \Delta \widehat{\ln(\Gamma_{i,t}}/(1-\Gamma_{i,t}))$, as

$$\begin{aligned}
\text{Change in task content}_{i,t} &= (1 - s_{i,t}^L) \Delta \widehat{\ln(\Gamma_{i,t}}/(1-\Gamma_{i,t})) \\
&= \Delta \ln s_{i,t}^L - (1-\sigma)(1 - s_{i,t}^L)[(\Delta \ln(W_{i,t}/R_{i,t}) - (\Delta \ln(A_{i,t}^L / A_{i,t}^K)].
\end{aligned}$$

[9] The relevant σ in our model is the elasticity of substitution between capital and labor at the industry level. This tends to be greater than the firm-level elasticity, estimated to be between 0.4 and 0.7 (e.g., Raval, 2018; Chirinko et al., 2011), because of output substitution between firms. Note also that our framework, in particular the central role of changes in the task content of production, makes it clear that the elasticity of substitution cannot be estimated from aggregate data.

The change in the task content of the entire economy is then given by

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

Using this approach, we can decompose observed changes in labor demand (wage bill) during any sample period into a productivity effect, a composition effect, a change in task content, a price substitution effect and a quality substitution effect. We now proceed to apply this decomposition to various sample periods.

We further note that our estimates should be interpreted as upper bounds for the quality substitution effect (since in general growth in GDP per worker will be driven not just by labor-augmenting technological changes) and thus for changes in the task content of production (meaning that when our estimates are negative, the actual changes may be even larger). Nevertheless, reasonable variations on the magnitude of relative labor-augmenting technological change have very small impacts on our decomposition results as we discuss below.

3.2 Changes in the Task Content of Production: 1987-2017

The main focus of our analysis is the recent thirty-year period, 1987-2017, where we have the most detailed data at the sectoral level (and where we will also be able to relate changes in the task content of production to measures of automation and creation of new tasks). For this period we use data from the Bureau of Economic Analysis (BEA) for 61 NAICS industries. Details and summary statistics for these data are provided in the Appendix. We start in the top panel of Figure 1 by presenting the evolution of the labor share at the level of (roughly) one-digit sectors—for construction, services, transportation, manufacturing, agriculture and mining. We see a sharp decline in the labor share for manufacturing and mining, with much less change for the other industry groupings. The bottom panel of the figure shows the evolution of the share of value added of these sectors, highlighting the reallocation of economic activity away from manufacturing.

The top panel of Figure 2 reports the implied decomposition for the entire economy. Several points are worth noting. First, comparing this figure to Figure 7 below for the period 1947-1987, we see that overall labor demand grows much more slowly during the more recent 30 years—its annual growth rate is 1.33% compared to 2.44% between 1947 and 1987. Second, labor demand follows productivity fairly closely until the late 1990s, so the slow growth of labor demand in the first half of the sample is accounted for by the slow growth of productivity. Third, after the late 1990s, the gap between labor demand and productivity opens up sharply. Fourth, our estimates of composition and price substitution effects are quite small (and so are the quantity substitution effects implied by factor-augmenting technological changes, which are not shown in the figure). The small magnitude of the composition effect is particularly noteworthy because several popular mechanisms work entirely through sectoral reallocation captured by this composition effect.[10] Finally and most importantly, we see a sizable decline in the task content of production—reflecting the fact that production is becoming less labor-intensive. The figure makes it clear that it is this change in task content that accounts for the decoupling of labor demand and productivity after 2000.[11]

The large decline in labor share in manufacturing depicted in Figure 1 suggests that changes in the task content of production in manufacturing may be playing a particularly important role. To investigate these changes, the bottom panel of the figure applies the same decomposition to just manufacturing industries. The resulting pattern is similar but even more pronounced. Notably, during this period, labor demand in manufacturing exhibits an absolute decline—which is in stark contrast to what we see in the previous 40 years in Figure 7 below. Our decomposition shows that this is accounted for by sizable negative changes in the task content of manufacturing production—with again a very limited role for composition, price substitution and quality substitution effects. In addition, the productivity effect in manufacturing is particularly weak during this period, reflecting the fact that manufacturing output has grown at roughly the same rate as the rest of the economy while the relative prices of manufacturing goods have declined sharply.[12]

In the Appendix, we show that the pattern of within manufacturing changes is similar when we focus on 452 four-digit industries, for which we estimate our decomposition using data from the BEA input-output tables for 1977-2007.

3.3 Estimating Displacement and Reinstatement Effects

Under the assumption of no technological regress, negative changes in the task content of production of an industry indicate that there is faster automation than creation of new tasks, and likewise positive changes are evidence of faster creation of new tasks than automation. We can thus estimate the extent of displacement (automation) and reinstatement (new task) effects at the industry level under the additional assumption that when there is faster automation, there will be no creation of new tasks in that industry during that same time period, and vice versa. To reduce the influence of measurement error, here we compute estimates for displacement and

[10] These include any effects from international trade in final goods, mechanisms emphasizing the "Baumol effect" (Aghion, Jones, and Jones, 2017), and any non-homotheticities in preferences and structural transformation (Hubmer, 2018).

[11] These results are consistent with Elsby et al. (2016) who document the central role of within-industry changes that are uncorrelated with factor prices in accounting for the aggregate behavior of the labor share. They are also consistent with the findings of Autor and Salomons (2018) who similarly emphasize the negative impact of automation on the labor share and the positive effect of productivity on employment, but do not distinguish automation technologies from new tasks and from factor-augmenting technological change.

[12] As pointed out in the previous section, in our framework rapid automation can go hand-in-hand with slow productivity growth if new automation technologies are "so-so", or in the tasks it is being replaced the effective wage of labor is not much higher than the effective cost of capital.

reinstatement effects for five-year time windows using the equations

$$\text{(6)} \qquad \text{Displacement}_t = \sum_{i \in \mathcal{I}} \ell_{i,t} \min \left\{ 0, \frac{1}{5} \sum_{\tau=t-2}^{t+2} \text{Change in task content}_{i,\tau} \right\} \text{ and}$$

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

The resulting estimates are depicted in Figure 3. In the top panel, we see that both the displacement and reinstatement effects are sizable, so both automation and new tasks appear to be ongoing at the industry level at all times. Nevertheless, the displacement effect is significantly larger, explaining the net negative change in the task content of production. In the bottom panel, we show the same decomposition for just manufacturing industries. Now the displacement effect is considerably larger, plausibly reflecting the greater extent of automation within manufacturing.

These estimates should be interpreted as "lower bounds" since within a five-year time window there is likely to be both automation and new tasks created in some industries, and this procedure only considers the difference between these two. Indeed, when we analogously estimate displacement and reinstatement effects at the yearly frequency in the Appendix, these are larger than the five-year averaged estimates presented in Figure 3.

3.4 Robustness and the Role of Factor-Augmenting Technologies

The patterns reported in the previous two subsections are robust and fairly insensitive to the assumptions on the elasticity of substitution and the rate of factor-augmenting technological change we have imposed. In the Appendix, we verify that the results are very similar for different values of the elasticity of substitution (in particular, with $\sigma = 0.6$, $\sigma = 1$ and $\sigma = 1.2$). They are also very similar when we assume different rates of factor-augmenting technological changes.

Even more telling is a complementary exercise on the importance of factor-augmenting technologies we report in the Appendix; we compute the extent of factor-augmenting technological change at the industry level that would be necessary to account for the changes in the labor share we observe without any change in the task content of technology. We find that this would require gargantuan changes in technology, several folds larger than observed TFP growth over the same time period; this again underscores the need for major changes in the task content of production to account for the evolution of labor demand during recent decades.

There is a simple reason why the exact rate of factor-augmenting technological change does not affect the labor share by much (while at the same time the magnitudes of changes necessary to account for observed task contents is huge). The formula for the quality substitution effect in equation (5) implies that a 1% increase in labor-augmenting technologies reduces the labor share by $(1-\sigma)(1-s_i^L)$ percent. This implies a very small elasticity—between -0.08 and 0.08—given plausible values for the elasticity of substitution between capital and labor (between 0.8 and 1.2) and the observed labor share in most industries (around 60%).

3.5 What Does the Change in Task Content Capture?

Since we are computing the change in task content as a residual, a natural concern is that it corresponds to something completely different than the displacement and reinstatement effects. In this subsection, we provide suggestive evidence to support our interpretation. We show that our measure of change in task content at the industry level is correlated negatively with several measures of the introduction of automation technologies and positively with some proxies of new tasks.

The results are presented in Figures 4 and 5 and Table 1.[13] Figure 4 provides the bivariate cross-industry associations between change in task content 1987-2017 and four proxies for industry-level automation technologies. The first one is the adjusted penetration of robots measure from Acemoglu and Restrepo (2018b) for our 61 industries (matched to 19 industries as classified by the International Federation of Robotics). A strong negative correlation is visible in the top left panel, and Table 1 verifies this relationship. The coefficient estimate is -1.23 (s.e. = 0.34) and this variable accounts for 17% of cross-industry variation in change in task content. The second column of the table confirms that this relationship is not driven by the contrast of manufacturing to non-manufacturing sectors; the coefficient estimate is similar, -0.82 (s.e. = 0.30), when we control for a manufacturing dummy. The third column further controls for import competition from China (Autor, Dorn and Hanson, 2013; Acemoglu et al., 2015) and for the extent of offshoring (Feenstra and Hanson, 1999; Wright, 2004), with very similar results.[14] Since industrial robots are a clear and important exemplar of automation technologies, this negative association is reassuring for our interpretation.

The top right panel uses a broader measure of the potential for automation technologies, Graetz and Michaels's (2018) measure of share of replaceable tasks in an occupation, mapped to our 61 industries using their distribution of employment across occupations in 1990. There is a similar negative relationship, but Table 1 shows that this is driven by the contrast of manufacturing to the rest of the aggregate of industries.

The bottom left panel uses measures of other automation technologies from the Survey of Manufacturing Technologies for 1988 and 1993 (specifically the share of firms using automation technologies). These technologies include automatic guided vehicles, automatic storage and retrieval systems, sensors on machinery, computer-controlled machinery, programmable controllers, and industrial robots (see Doms et al., 1997, Acemoglu et al., 2014). Since these technology measures are available only the "technology-intensive" manufacturing industries, this panel

[13] Further details on all of the variables discussed in this subsection are provided in the Appendix.

[14] This reflects the fact that, as we show in the Appendix, neither import competition from China nor offshoring predict changes in the task content of production, which is noteworthy in and of itself. Instead, imports from China impact aggregate labor demand via the composition and productivity effects.

uses estimates of changes in task content for 1987-2007 for 148 more detailed, four-digit SIC industries (which are all part of the two-digit manufacturing industries fabricated metal products, industrial machinery, electronics, transportation equipment, and controlling instruments). There is once again a strong negative association, which is confirmed in Table 1. Finally, the bottom right panel also uses the same data but now focuses on all advanced technologies, which include sensors used on products, computed aided design, networks and computers used on the factory floor, flexible manufacturing cells, and material working lasers. The relationship is again similar.

Figure 5 turns to proxies for new tasks. The top left panel uses the share of new job titles from the 1991 Dictionary of Occupational Titles as compiled by Lin (2011), which we then project to our 61 industries again using their employment distribution across occupations in 1990. As expected there is a positive correlation between this measure of new tasks and change in task content, and the relevant coefficient estimate is 1.60 (s.e. = 0.52). Table 1 shows that this relationship is essentially unchanged when we control for manufacturing, imports from China and offshoring. The top right panel uses a related proxy based on "emerging tasks" as classified by O*NET projected to industries. The results are similar and equally strong. The two bottom panels use two measures of increased occupational diversity with very similar results. The first is the share of employment growth in an industry accounted for by "new occupations" defined as four-digit occupations appearing for the first time in that industry in 2016, while the second is the percent increase in the number of occupations in an industry between 1990 and 2016.

As an additional exercise, the Appendix also shows a strong positive correlation between change in task content and employment growth across industries.

These patterns bolster our confidence that our measure contains valuable information about to changes in task content of production and also support the interpretation that the rapid displacement effect of the last three decades is related to the introduction of modern automation technologies such as industrial robots and computer numerical control.

3.6 Changes in the Task Content of Production: 1947-1987 and 1850-1910

We next turn to the four decades following World War II, 1947-1987. For this period we have data for 60 SIC industries. Figure 6 shows changes in the labor share and value added distribution for the same six sectors as in Figure 1. Particularly noteworthy is that there are no significant changes in the labor share for any of these industries. Figure 7 depicts the observed changes in labor demand together with our decomposition.[15] During this period, labor demand grew more rapidly than in the last 30 years (notice that the vertical scale here is different than in Figure 2). Our decomposition shows that there is a more robust productivity effect and a tighter relationship between labor demand and productivity during this time period. This more pronounced productivity effect underscores our conceptual conclusion that rapid productivity

[15] We now assume that $A^L_{i,t}/A^K_{i,t}$ grows at 2% a year to match the growth of GDP per worker during the sample period. The results are similar if we continue to assume a 1.5% annual growth.

growth is an important contributor to growth in labor demand, even if it comes from automation technologies. Also noteworthy is the steady growth of labor demand in manufacturing, at least until the 1980s, which contrasts with its sharp contraction after the late 1990s in Figure 2. Furthermore, consistent with the stable patterns of the labor share during this period, the change in the task content is small both for the entire economy and for manufacturing. Figure 8 confirms that this is because the displacement effect is more limited (compare this figure to Figure 3), and the reinstatement effect is more sizable during this period than in the last 30 years.

The Appendix again demonstrates that these results are similar for different values of the elasticity of substitution and different assumed rates of factor-augmenting technological changes.

Finally, we turn to the period 1850-1910, which witnessed rapid automation of a range of manual tasks in the context of the mechanization of agriculture. Figure 9 reports results from an analogous exercise during this period, but using only variation between agriculture and industry from data reported in Budd (1960). Because we do not have information on factor prices at the industry level for this period, in this figure we are forced to impose $\sigma = 1$, thus setting the quality and price substitution effects equal to zero. During this critical period of mechanization of agriculture, we see a decline in the labor share of agriculture—a telltale sign of automation in that sector—but a corresponding increase in the labor share in industry. As a result, the change in the task content of production of the overall economy, though negative, is not very large. Our decomposition suggests that this in turn reflects the fact that the displacement effect in agriculture is being counterbalanced by a powerful reinstatement effect in manufacturing. In addition, in this case we estimate a composition effect that is somewhat larger, and this plausibly captures the sizable reallocation of labor away from agriculture towards the more labor-intensive (manufacturing) industry.

The patterns reported in this subsection thus contrast with those of the last three decades and highlight that the major difference setting the recent period apart from other epochs is not just the more anemic productivity effect but a sizable displacement effect driven by automation and the absence of a powerful, countervailing reinstatement effect.

4 Conclusion, Discussion and Implications

In this paper we developed a task-based model based on Acemoglu and Restrepo (2018a, 2018b) to study the effects of different types of technologies on labor demand. At the center of our framework is the task content of production—measuring the fraction of tasks allocated to labor. Automation, by creating a displacement effect, reduces the task content of production, while the introduction of new tasks in which labor has a competitive advantage, by generating a reinstatement effect, increases the task content of production. These types of technological changes are qualitatively different from factor-augmenting ones which do not impact the task content of production. For example, automation always reduces the labor share and may reduce employment and wages, and new tasks always increase the labor share. We then showed how a multi-sector model incorporating different types of technological changes and the resulting reallocations of labor and value added across sectors can be used to interpret the sources of changes in labor demand over the last century and a half. The main implication of this empirical exercise is that the recent sluggish behavior of labor demand is explained by the relative weakness of the reinstatement effect (creation of new tasks) and the comparatively anemic growth of productivity.

A number of issues are worth discussing in conclusion.

First, there are several interesting theoretical and conceptual issues with which our framework can be easily enriched. Particularly important is to incorporate workers with different types of skills and study the implications of new technologies for the employment and wages of different groups of workers. Both automation and new tasks may generate forces towards greater inequality (Acemoglu and Restrepo, 2018a), but the next stage of automation technologies might also start displacing more skilled workers with different implications (Acemoglu and Restrepo, 2018f). Furthermore, the relative supplies of skills might impact how productively new technologies may be deployed as well (Acemoglu and Restrepo, 2018d). Also interesting is to recognize the possibility of excessive automation (and perhaps insufficient creation of new tasks) because of labor market imperfections that make labor more expensive to employers than its social opportunity cost (Acemoglu and Restrepo, 2018a, 2018d) and because of distortions in the tax code or peculiarities of corporate strategies. Both shortages of skills and excessive automation may also account for part of the slowdown of productivity growth in the midst of rapid automation. The endogenous incentives for the development of different types of technologies are also important to study. These can generate forces that keep automation and creation of new tasks at least partially balanced (Acemoglu and Restrepo, 2018a) and also account for why the United States, which is aging less rapidly than countries such as Germany, Japan and South Korea, is a laggard in the development and adoption of various industrial automation technologies (Acemoglu and Restrepo, 2018e). It is important as well to study other types of technologies with differential implications for labor demand (e.g., Hemous and Olsen, 2018). Finally, another major area for investigation is the relationship between new automation technologies and changes in market structure, which may impact the demand for labor both directly and indirectly.

Second, our empirical exercise was an illustrative one, showing how changes in the task-content of production can be inferred from data and appears to be potentially important. More systematic studies have obtained results consistent with the approach here: Graetz and Michaels (2018), Acemoglu and Restrepo (2018e) and Autor and Salomons (2018) document the negative impact of robots on the labor share using the cross-country, cross-industry design, while Acemoglu and Restrepo (2018b) shows the same thing for US industries. A complementary empirical strategy, more often used in the literature, is to study the effects of different types of technologies at the level of local labor markets (e.g., Beaudry, Doms and Lewis, 2006, Autor and Dorn, 2013, Gregory, Salomons and Zierahn, 2016, Acemoglu and Restrepo, 2018b) or countries (Goos, Manning and Salomons, 2009, Michaels, Natraj and Van Reenen, 2014). Obvious next stages for empirical work include firm-level studies of automation as well as approaches combining local and industry-level analyses.

Finally, this paper also generates some simple implications for the future of work. Our framework and empirical results clearly depart both from arguments foreseeing the imminent end of human work and from those that directly link the prospects of labor to productivity growth. Rather, our approach suggests that if the origin of productivity growth in the future continues to be automation, the relative standing of labor, together with the task content of production, will decline. The creation of new tasks and other technologies raising the labor intensity of production and the labor share are vital for continued wage growth commensurate with productivity growth. Whether such technologies will be forthcoming may depend not just on our innovation capabilities but also on the supply of different types of skills, demographic changes, various aspects of labor market institutions, corporate strategies and market competition, and tax and R&D policies of governments.

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, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price (2014) "Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing," *American Economic Review: Papers & Proceedings* 104(5):394–99.

Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price (2015) "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics* 34:S141–S198.

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.

Acemoglu, Daron and Pascual Restrepo (2018b) "Robots and Jobs: Evidence from US Labor Markets" NBER WP No. 23285.

Acemoglu, Daron and Pascual Restrepo (2018c) "Modeling Automation" NBER WP No. 24321.

Acemoglu, Daron and Pascual Restrepo (2018d) "Artificial Intelligence, Automation and Work" NBER Working Paper No. 24196.

Acemoglu, Daron and Pascual Restrepo (2018e) "Demographics and Automation" NBER WP No. 24421.

Acemoglu, Daron and Pascual Restrepo (2018f) "Low-Skill and High-Skill Automation," Journal of Human Capital, vol 12(2): 204–232.

Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones (2017) "Artificial Intelligence and Economic Growth," NBER Working Paper No. 23928.

Autor, David H., Frank Levy and Richard J. Murnane (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics,* 118(4): 1279–1333.

Autor, David H., David Dorn, and Gordon H. Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103(6): 2121–68

Autor, David H. and David Dorn (2013) "The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review,* 103(5): 1553–97.

Autor, David and Anna Salomons (2018) "Is Automation labor Displacing? Productivity Growth, Employment, and the Labor Share," *Brooking papers on Economic Activity.*

Beaudry, Paul , Mark Doms, and Ethan Lewis (2006) "Endogenous Skill Bias in Technology Adoption: City-Level Evidence from the IT Revolution," NBER WP No. 12521.

Chandler, Alfred D. (1977) *The Visible Hand: The Managerial Revolution in American Business,* Harvard University Press: Cambridge, MA.

Chirinko, Robert S., Fazzari, Steven M., and Andrew P. Meyer (2011) "A New Approach to Estimating Production Function Parameters: The Elusive Capital- Labor Substitution Elasticity," *Journal of Business and Economic Statistics,* 29:587-?594.

Doms, Mark, Timothy Dunne and Kenneth R. Troske (1997) "Workers, Wages, and Technology," *The Quarterly Journal of Economics*, 112(1): 253-?290.

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

Goos, Maarten, Alan Manning, and Anna Salomons (2009) "Job Polarization in Europe," *American Economic Review*, 99(2): 58–63.

Graetz, Georg and Guy Michaels (2018) "Robots at Work," *Review of Economics and Statistics,* forthcoming.

Gregory, Terry, Anna Salomons, and Ulrich Zierahn (2016) "Racing With or Against the Machine? Evidence from Europe," ZEW - Centre for European Economic Research Discussion Paper No. 16-053

Hemous, David and Morten Olsen (2018) "The Rise of the Machines: Automation, Horizontal Innovation and Income Inequality," MIMEO, University of Zurich.

Hubmer, Joachim (2018) "The Race Between Preferences and Technology," MIMEO, Yale University.

Kuznets, Simon (1966) *Modern Economic Growth.* New Haven: Yale University Press.

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

Mantoux, Paul (1928) *The Industrial Revolution in the Eighteenth Century: An Outline of the Beginnings of the Modern Factory System in England.* New York: Harcourt.

Michaels, Guy, Ashwini Natraj and John Van Reenen (2014) "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years," *Review of Economics and Statistics,* 96(1): 60–77.

Mokyr, Joel (1990) *The Lever of Riches: Technological Creativity and Economic Progress,* Oxford University Press: New York.

Oberfield, Ezra and Devesh Raval (2014) "Micro Data and Macro Technology," NBER WP No. 20452

Olmstead, Alan L. and Paul W. Rhode (2001) "Reshaping the Landscape: The Impact and Diffusion of the Tractor in American Agriculture, 1910-1960," *The Journal of Economic History* 61(3): 663–98.

Raval, Devesh (2018) "The Micro Elasticity of Substitution and Non Neutral Technology," *RAND Journal of Economics* (forthcoming).

Rasmussen, Wayne D. (1982) "The Mechanization of Agriculture," *Scientific American,* 247(3): 76–89.

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

Zeira, Joseph (1998) "Workers, Machines, and Economic Growth," *Quarterly Journal of Economics,* 113(4): 1091–1117.

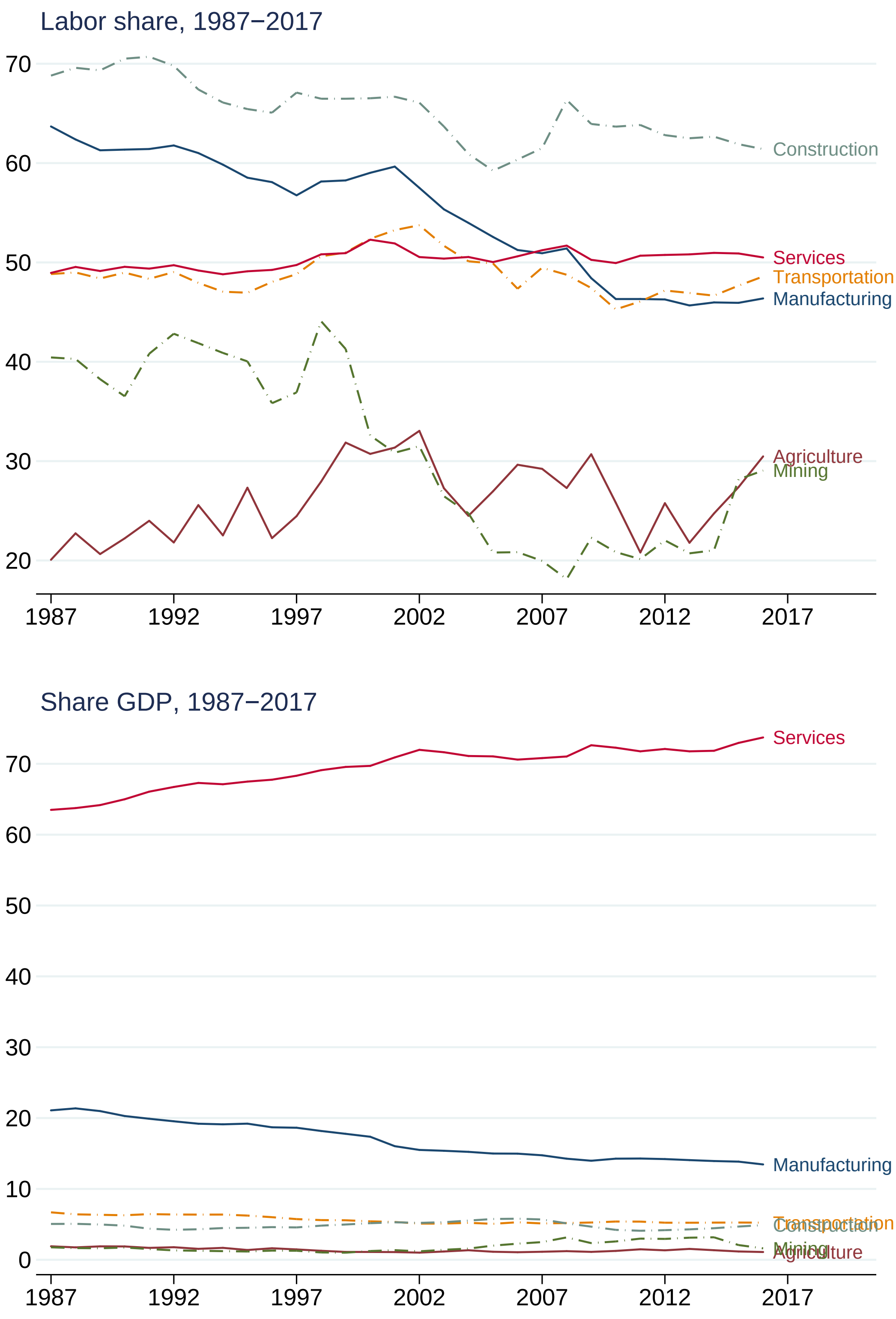

FIGURE 1: THE LABOR SHARE AND SECTORAL EVOLUTIONS, 1987-2017.
Note: The top panel shows the labor share in value added in services, manufacturing, construction, transportation, mining and agriculture between 1987 and 2017, while the bottom panel shows the share of value added in the sectors relative to GDP.

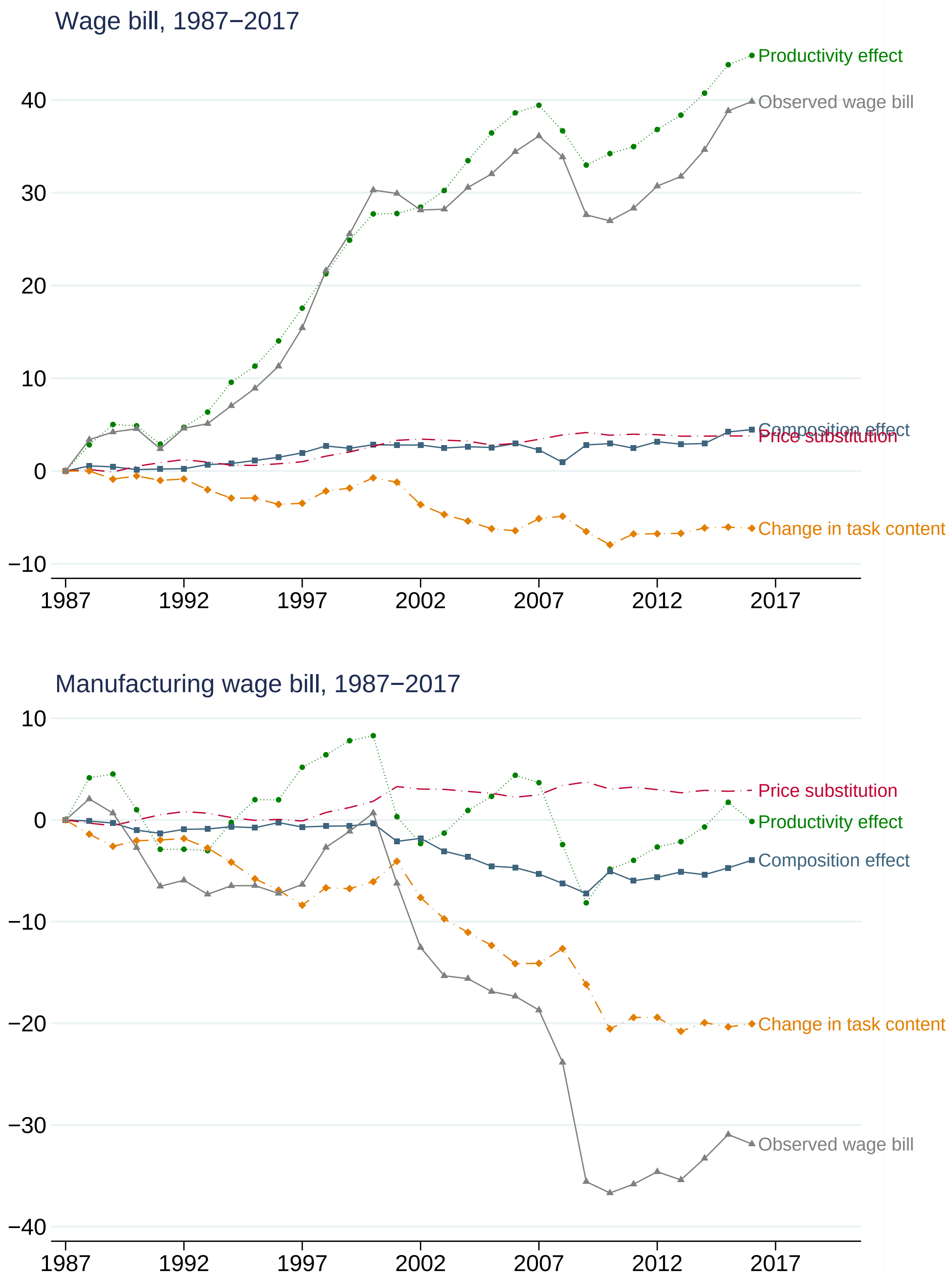

FIGURE 2: SOURCES OF CHANGES IN LABOR DEMAND, 1987-2017.

Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (5) in the text. The top panel is for the entire economy and the bottom panel is for the manufacturing sector. In both panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 1.5% a year.

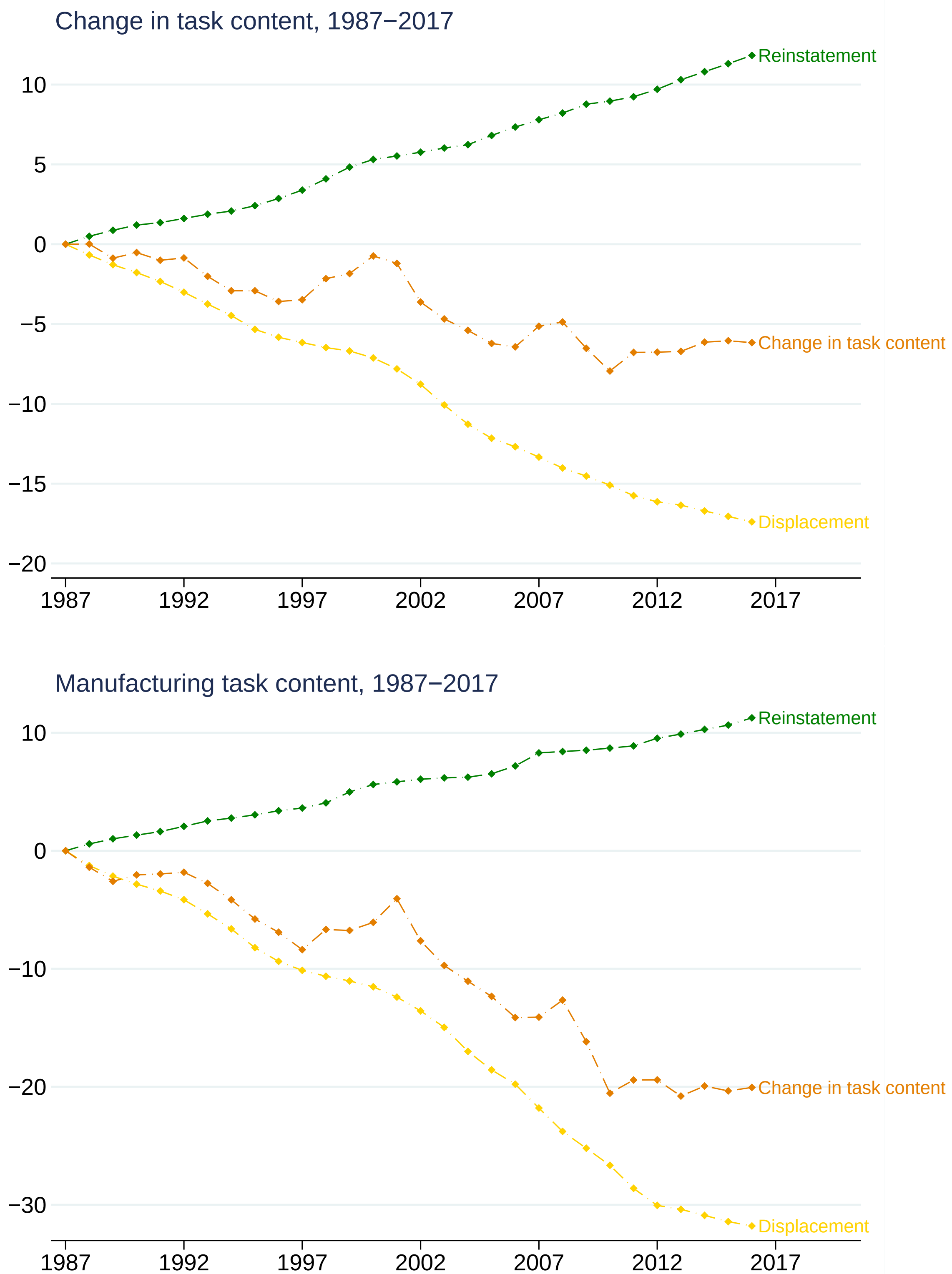

FIGURE 3: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS, 1987-2017.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) in the text. The top panel is for the entire economy and the bottom panel is for the manufacturing sector. In both panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 1.5% a year.

Figure 4: Automation technologies and change in the task content of production.

Note: Each panel presents the bivariate relationship between change in task content and the indicated proxy for automation technologies at the industry level. Orange designates manufacturing industries and blue non-manufacturing industries. The proxies are: adjusted penetration of robots, 1993-2014 (from Acemoglu and Restrepo, 2018b), share of employment in replaceable occupations, 1990 (Graetz and Michaels, 2018), share of firms using automation technologies, 1988-1993 SMT and share of firms using advanced technologies, 1988-1993 SMT. See text for details.

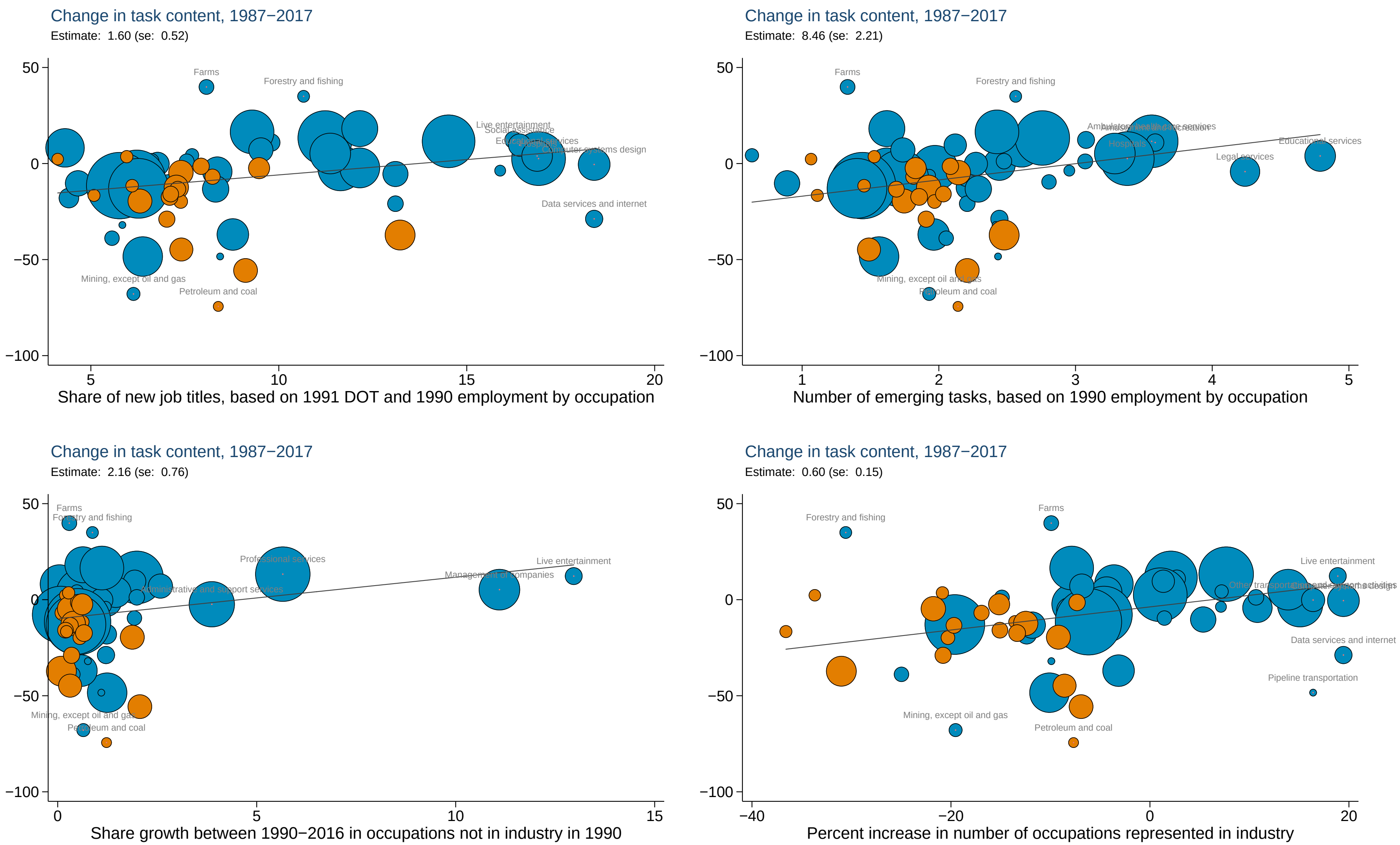

FIGURE 5: NEW TASKS AND CHANGE IN TASK CONTENT OF PRODUCTION.

Note: Each panel presents the bivariate relationship between change in task content and the indicated proxy for new tasks at the industry level. Orange designates manufacturing industries and blue non-manufacturing industries. The proxies are: share of new job titles (from Linn, 2011), number of emerging tasks (from ONET), share growth between 1990-2016 in occupations 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.

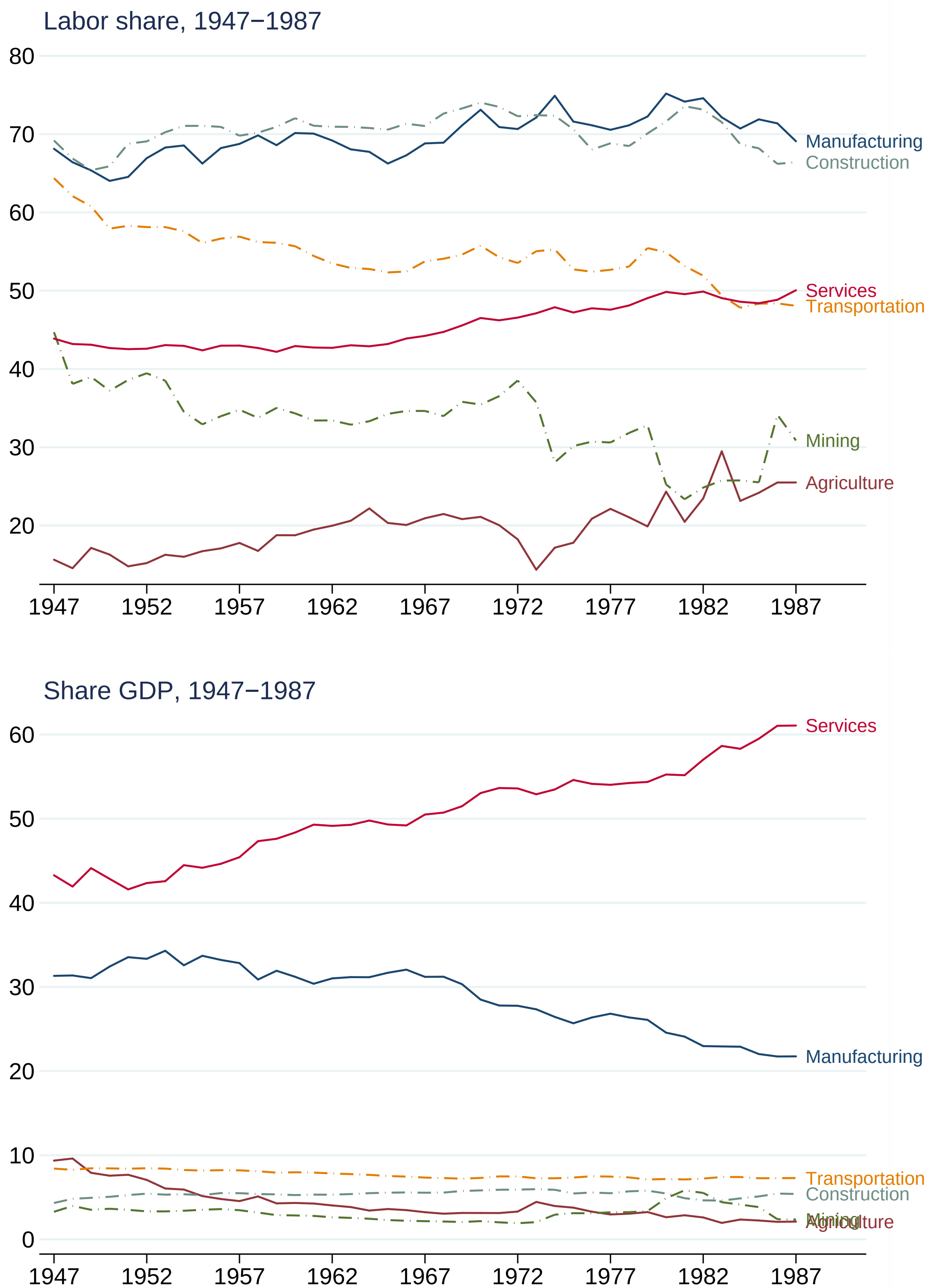

FIGURE 6: THE LABOR SHARE AND SECTORAL EVOLUTIONS, 1947-1987.

Note: The top panel shows the labor share in value added in services, manufacturing, construction, transportation, mining and agriculture between 1947 and 1987, while the bottom panel shows the share of value added in the sectors relative to GDP.

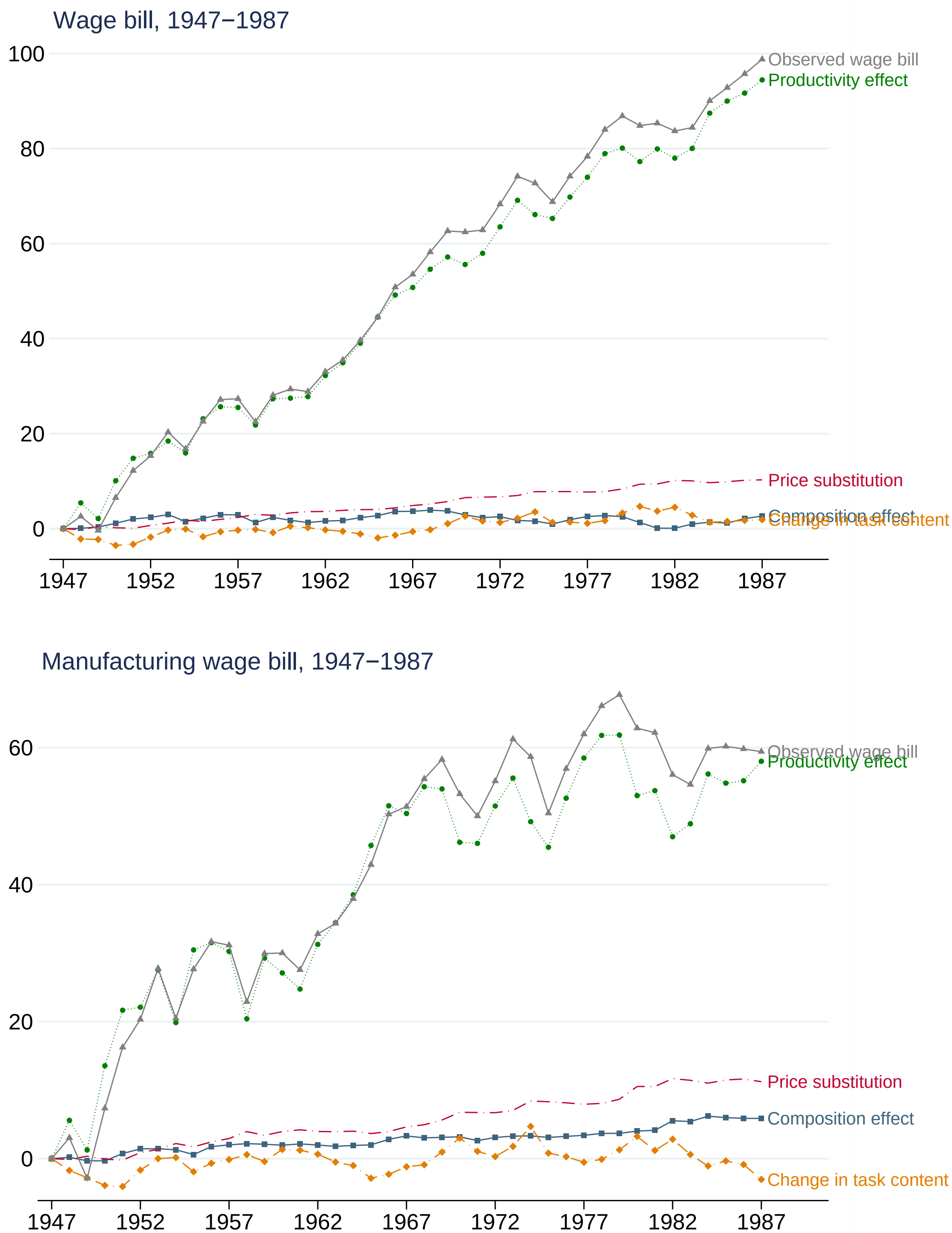

Figure 7: Sources of changes in labor demand, 1947-1987.

Note: This figure presents the decomposition of labor demand (wage bill) between 1947 and 1987 based on equation (5) in the text. The top panel is for the entire economy and the bottom panel is for the manufacturing sector. In both panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 2% a year.

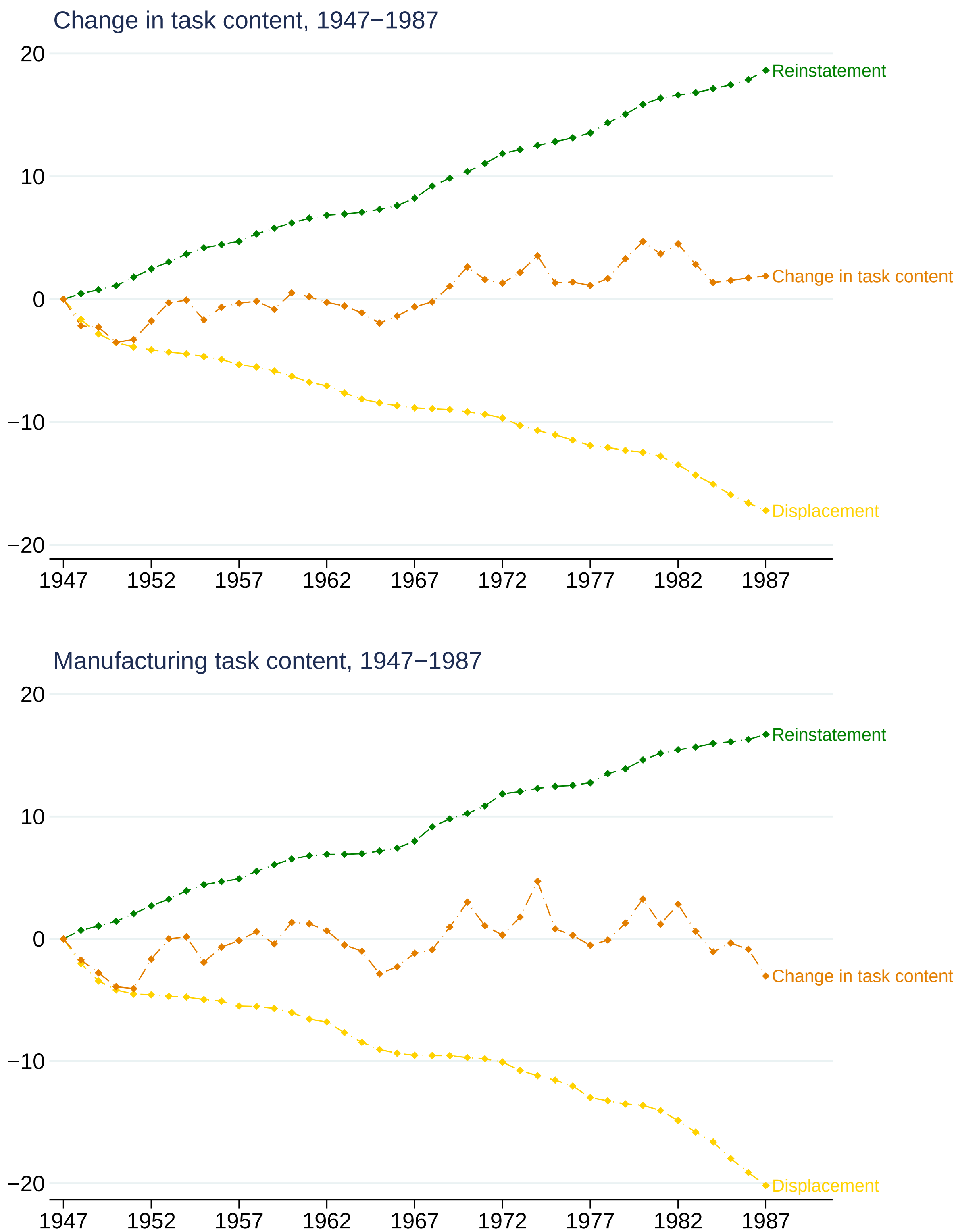

Figure 8: Estimates of the displacement and reinstatement effects, 1947-1987.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) in the text. The top panel is for the entire economy and the bottom panel is for the manufacturing sector. In both panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 2% a year.

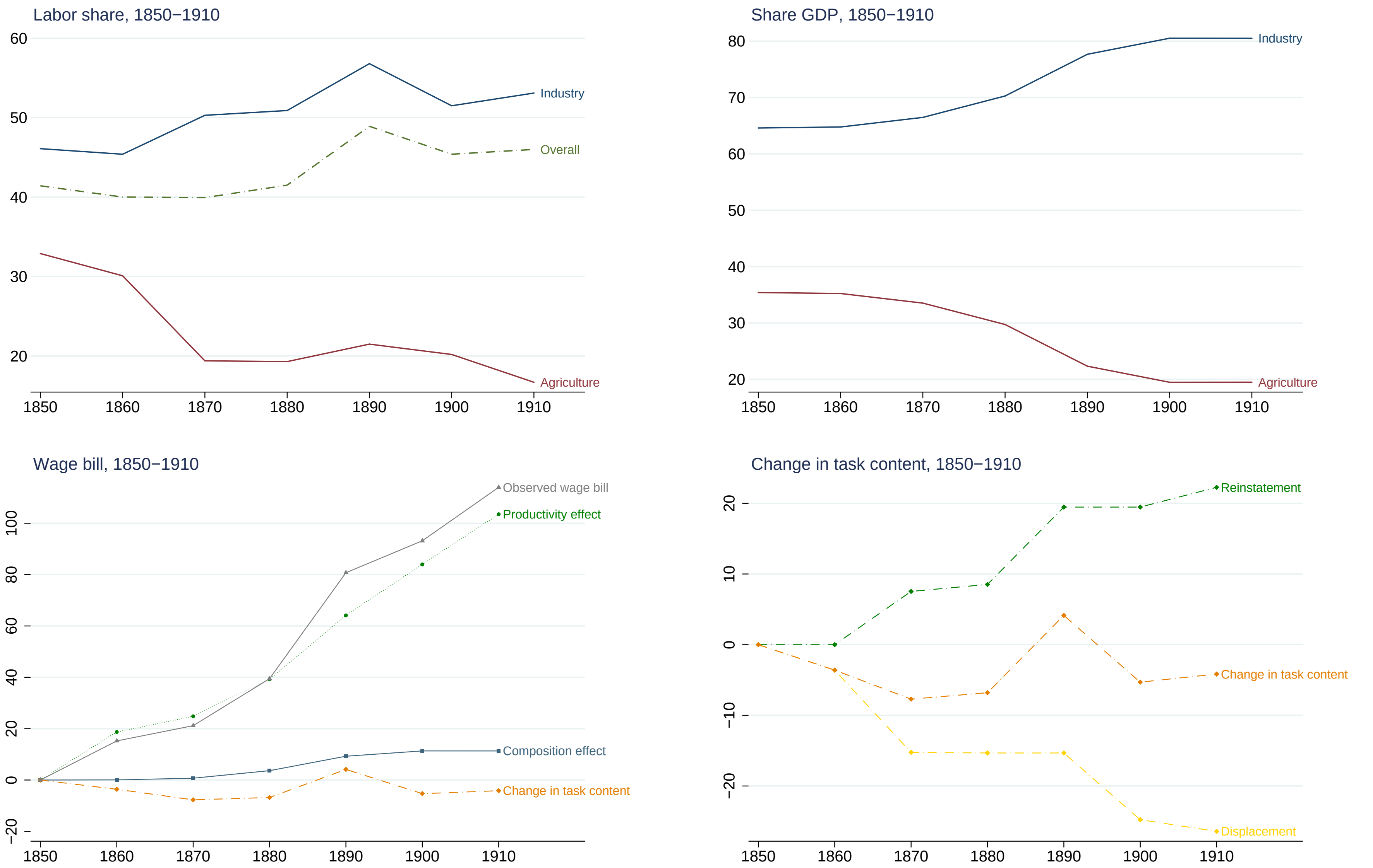

FIGURE 9: THE LABOR SHARE, SECTORAL EVOLUTIONS, AND THE SOURCES OF LABOR DEMAND, 1850-1910.
Note: The top-left panel shows the labor share in value added in industry (services and manufacturing) and agriculture between 1850-1910, while the top-right panel shows the share of value added in these sectors relative to GDP. The bottom-left panel presents the decomposition of labor demand (wage bill) for this period based on equation (5) in the text. The bottom-right panel presents our baseline estimates of the displacement and reinstatement effects based on equation (6) in the text. In the bottom panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 1$.

Table 1: Relationship between change in task content of production and proxies of automation and new tasks.

	Raw data	Controlling for manufacturing	Controlling for Chinese import and offshoring
	(1)	(2)	(3)
Proxies of automation technologies:			
Adjusted penetration of robots, 1993-2014	-1.227	-0.817	-0.949
	(0.341)	(0.297)	(0.239)
Observations	61	61	61
R-squared	0.17	0.23	0.23
Share employment in replaceable occupations, 1990	-0.560	-0.171	-0.126
	(0.181)	(0.318)	(0.347)
Observations	61	61	61
R-squared	0.14	0.18	0.18
Detailed manufacturing industries (from SMT):			
Share firms using broad automation technologies, 1988-1993	-0.395		-0.471
	(0.165)		(0.150)
Observations	148		139
R-squared	0.08		0.14
Share firms using advanced technologies, 1988-1993	-0.399		-0.483
	(0.152)		(0.137)
Observations	148		139
R-squared	0.09		0.16
Proxies of new tasks:			
Share of new job titles, based on 1991 DOT and	1.597	1.308	1.299
1990 employment by occupation	(0.517)	(0.519)	(0.524)
Observations	61	61	61
R-squared	0.12	0.25	0.25
Number of emerging tasks, based on	8.460	7.071	7.063
1990 employment by occupation	(2.215)	(2.289)	(2.340)
Observations	61	61	61
R-squared	0.15	0.27	0.28
Share growth between 1990-2016 in occupations not in industry in 1990	2.159	1.653	1.686
	(0.758)	(0.690)	(0.706)
Observations	61	61	61
R-squared	0.08	0.22	0.23
Percent increase in number of occupations represented in industry	0.602	0.375	0.414
	(0.153)	(0.195)	(0.199)
Observations	61	61	61
R-squared	0.15	0.21	0.23

Note: The table reports estimates of the relationship between the change in task content from 1987-2017 and proxies of technology. Column 1 reports estimates of the bivariate relationship between change in task content and the indicated proxy at the industry level. Column 2 includes a dummy for manufacturing industries as a control. Column 3 controls for the increase in Chinese imports (defined as the increase in imports relative to US consumption between 1991 and 2011, as in Acemoglu et al. 2016) and the increase in offshoring from China (defined as the increase in the share of intermediates imported from China, as in Wright, 2014). Except for the panels using the Survey of Manufacturing Technologies (SMT), all regressions are for the 61 industries used in or analysis of the 1987-2017 period. When using the SMT, the regressions are for 148 detailed manufacturing industries in column 1 and 139 industries in column 3, where we miss 9 industries due to lack of offshoring data. Standard errors robust against heteroskedasticity are in parenthesis.

Online Appendix

We now present proofs of some of the results in the text, details on the construction of our dataset, and additional robustness checks.

Additional Theoretical Results and Proofs

Primitive Conditions for Assumption (2)

In the text, we imposed Assumption (2) directly on factor prices. It is equivalent to the following condition on the relative utilization of capital to labor:

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

Proof of Equation (5)

The wage bill can be expressed as

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

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 $(=\frac{P_iY_i}{Y})$ and s_i^L $(=\frac{W_iL_i}{P_iY_i})$, and rearranging, we get

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

Now canceling terms and using the definition of ℓ_i $(=\frac{W_iL_i}{WL})$, 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 $\frac{dx}{x} = d\ln x$, that $\sum_{i\in\mathcal{I}} \ell_i = 1$, and that $\sum_{i\in\mathcal{I}} \frac{s_i^L}{s^L} \cdot d\chi_i = \sum_{i\in\mathcal{I}} \left(\frac{s_i^L}{s^L} - 1\right) \cdot d\chi_i$ (because $\sum_{i\in\mathcal{I}} d\chi_i = 0$), this expression can be written as

$$d\ln W + d\ln L = d\ln Y + \sum_{i\in\mathcal{I}} \left(\frac{s_i^L}{s^L} - 1\right) \cdot d\chi_i + \sum_{i\in\mathcal{I}} \ell_i \cdot d\ln s_i^L.$$

Finally, differentiating (4), we have

$$d\ln s_i^L = \left(1 - s_i^L\right) \left[\frac{1}{1-\Gamma_i} d\ln\Gamma_i + (1-\sigma) d\ln(\frac{W_i}{R_i}) - (1-\sigma) d\ln(\frac{A_i^L}{A_i^K})\right].$$

Substituting this into the previous expression, we obtain (5).

Alternative Production Function

Suppose that instead of (1), we assume the following sectoral production function

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

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

$$Y_i = \left(\left(\frac{1}{N_i} \int_0^{I_i} \gamma^K(z)^{\sigma-1} dz\right)^{\frac{1}{\sigma}} (A_i^K K_i)^{\frac{\sigma-1}{\sigma}} + \left(\frac{1}{N_i} \int_{I_i}^{N_i} \gamma^L(z)^{\sigma-1} dz\right)^{\frac{1}{\sigma}} (A_i^L L_i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

and

$$s_i^L = \frac{\Gamma(N_i, I_i)(W/A_i^L)^{1-\sigma}}{(1-\Gamma(N_i, I_i))(R_i/A_i^K)^{1-\sigma} + \Gamma(N_i, I_i)(W/A_i^L)^{1-\sigma}},$$

where

$$\Gamma(N_i, I_i) = \frac{\int_{I_i}^{N_i} \gamma^L(z)^{\sigma-1} dz}{\int_0^{I_i} \gamma^K(z)^{\sigma-1} dz + \int_{I_i}^{N_i} \gamma^L(z)^{\sigma-1} dz}.$$

Finally, the impact of new tasks on output is given by

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

This implies that provided that the effective wage is less than one, new tasks continue to increase output.

Counterfactual TFP implications

We now show that if the observed changes in industry labor shares were explained by factor-augmenting technological changes, this would necessitate huge increases in TFP.

Suppose that there are no true changes in task content—thus no true displacement and reinstatement effects. Under the assumption of no technological regress, this implies that our estimates of the displacement and reinstatement effects completely reflect changes in labor-augmenting and capital-augmenting technologies. Denoting our estimates by Displacement_t and Reinstatement_t, we have

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

and

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

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

$$\text{(A1)} \qquad \text{Contribution of } A^L \text{ to TFP}_t = \sum_i \chi_{i,t} \frac{s^L_{i,t}}{(\sigma - 1)(1 - s^L_{i,t})} \times \text{Displacement}_t > 0,$$

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

$$\text{(A2)} \qquad \text{Contribution of } A^K \text{ to TFP}_t = \sum_i \chi_{i,t} \frac{1 - s^L_{i,t}}{(1 - \sigma)(1 - s^L_{i,t})} \times \text{Reinstatement}_t > 0.$$

These estimates are plotted in Figure A8.

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:

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

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 in industry i.

In our decomposition exercise in Section 3.2, 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:

$$\Delta \ln W_{i,t} = \Delta \ln Y^L_{i,t} - \Delta \ln L^{qty}_{i,t}, \tag{A3}$$

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:

$$\Delta \ln R_{i,t} = \Delta \ln (Y_{i,t} - Y^L_{i,t}) - \Delta \ln K^{qty}_{i,t}, \tag{A4}$$

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.

Detailed data for 1977-2007: For 1977, 1982, 1987, 1992, 1997, 2002, and 2007 we have detailed data on value added and employee compensation from the 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 factor prices as described above in equations (A3) and (A4) using data from the NBER-CES *manufacturing database*. For wages, we computed a wage index 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.

Data for 1850-1910: The historical data for 1850 to 1910 come from Table 1 in Budd (1960). 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.

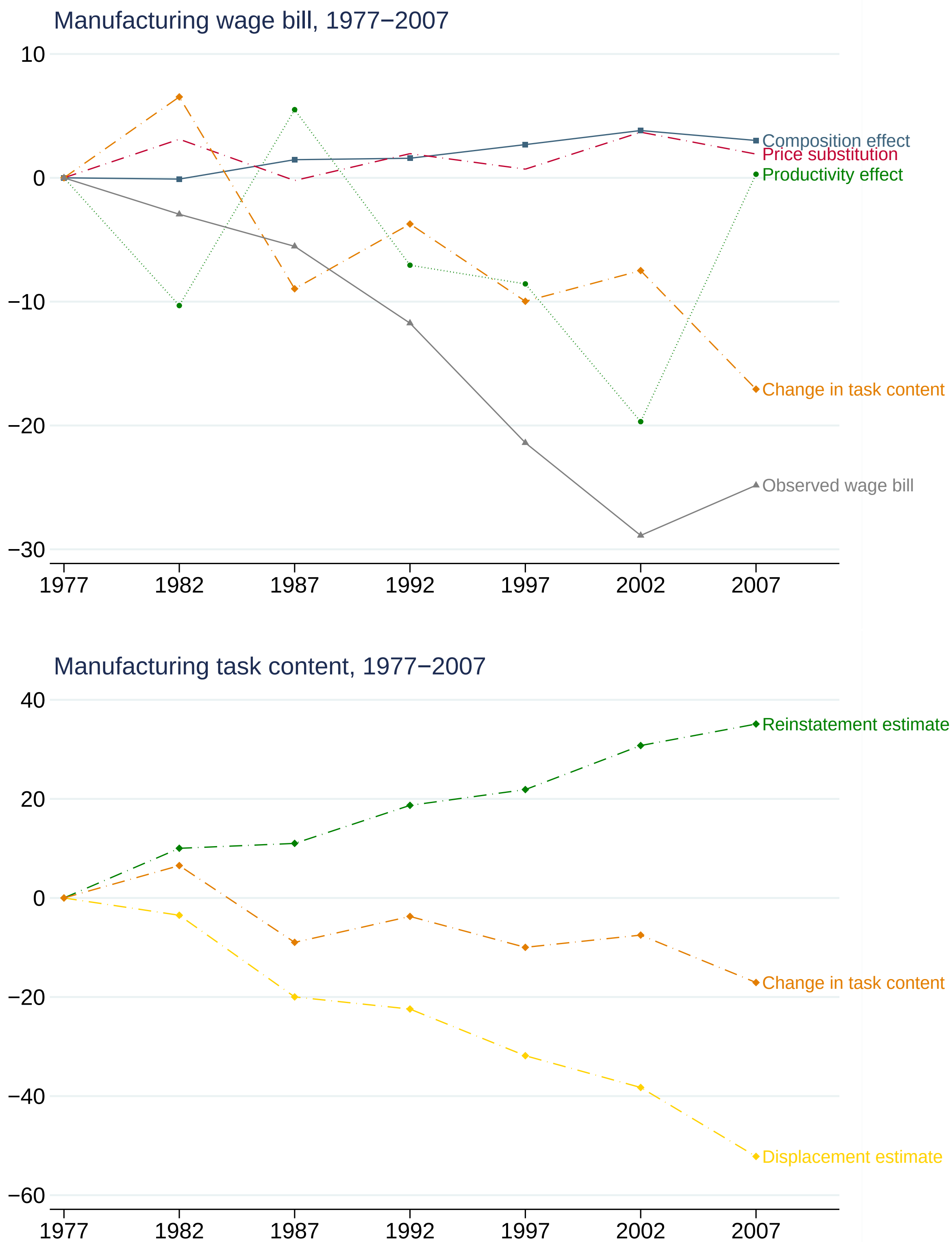

FIGURE A1: SOURCES OF CHANGES IN LABOR DEMAND FOR DETAILED INDUSTRIES, 1977-2007.

Note: This figure presents the decomposition of labor demand (wage bill) between 1977 and 2007 based on equation (5) in the text and the estimates for the displacement and reinstatement effect based on equation (6). Both panels are for the manufacturing sector and assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 1.5% a year.

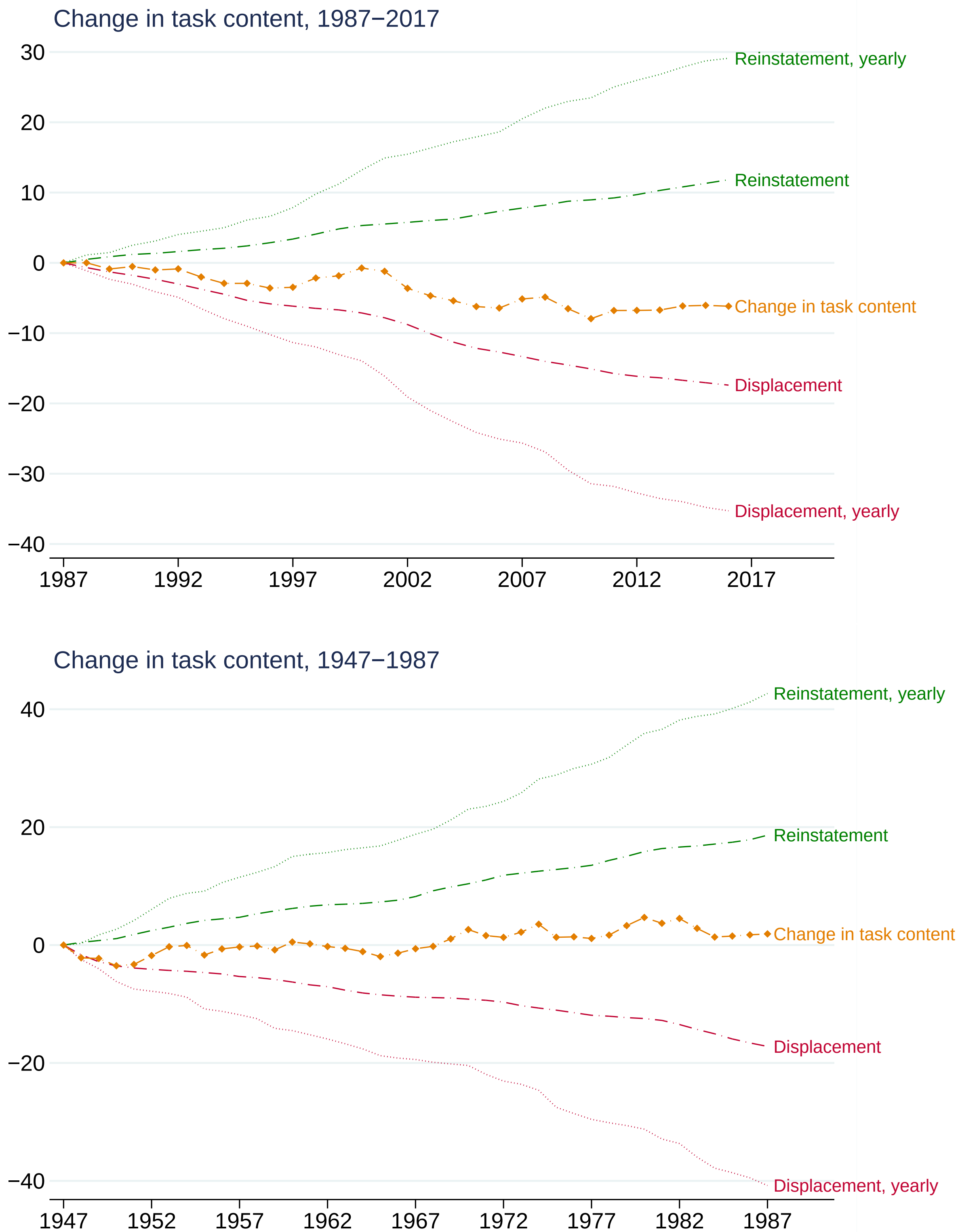

Figure A2: Estimates of the displacement and reinstatement effects, yearly and five-year changes. Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) and using yearly changes. The top panel is for 1987-2017 and assumes a growth rate for the relative labor-augmenting technological change of 1.5%. The bottom panel is for 1947-1987 and assumes a growth rate for the relative labor-augmenting technological change of 2%. In both panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$.

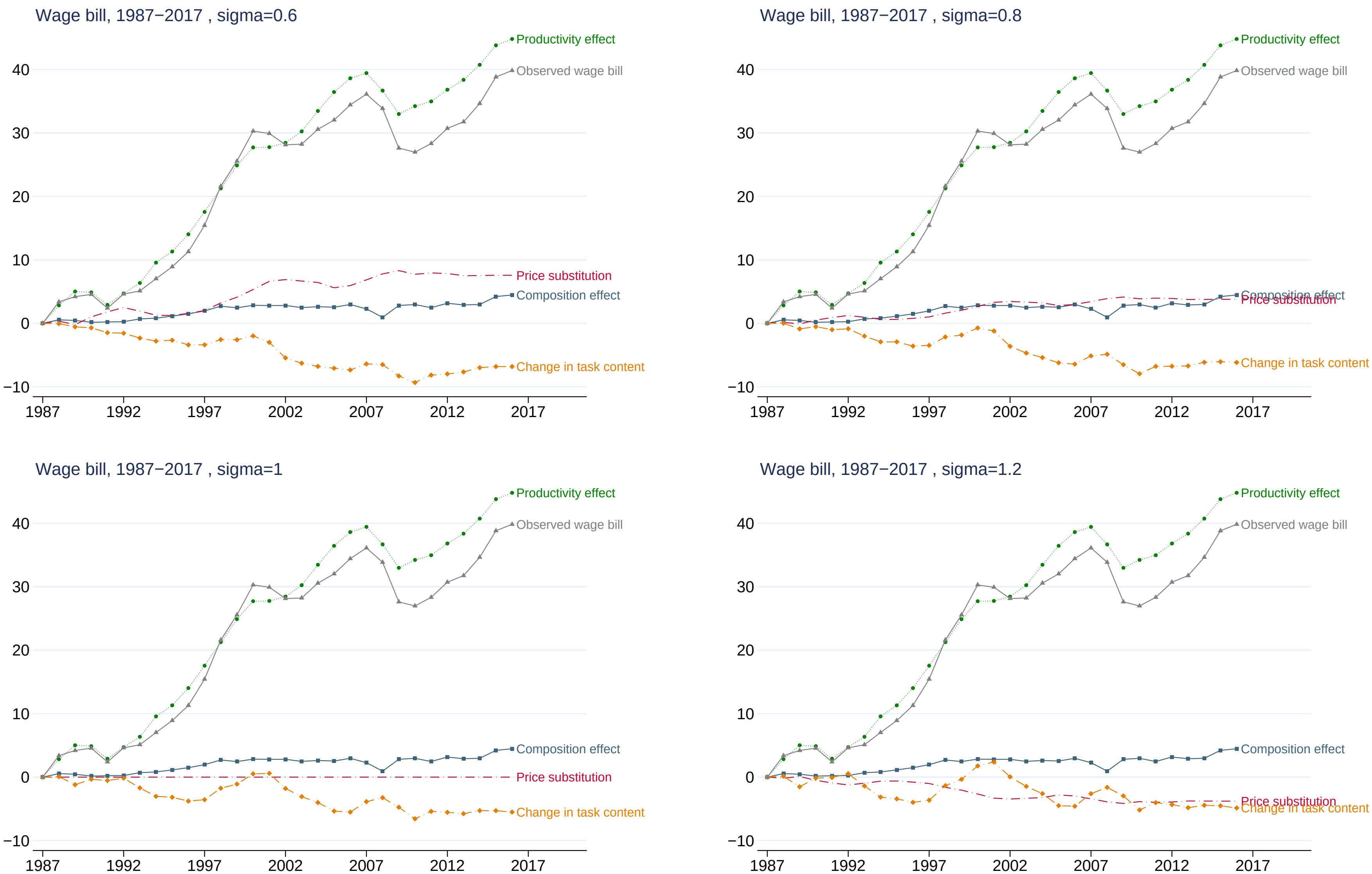

Figure A3: Sources of changes in labor demand for the entire economy, 1987-2017, for different assumed values of σ..
Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (5) in the text. The panels present the results for the vauels of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.

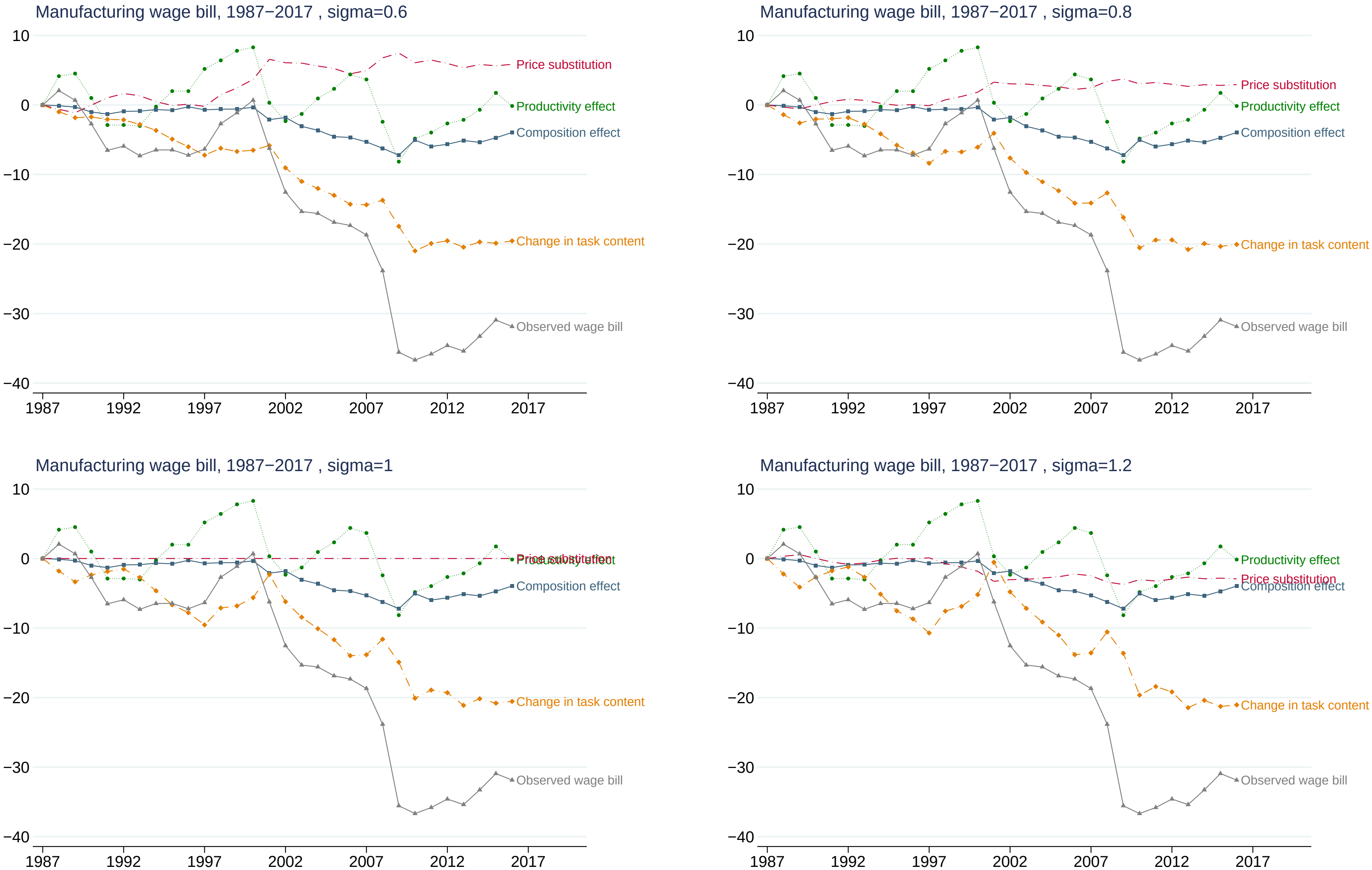

Figure A4: Sources of changes in labor demand for manufacturing, 1987-2017, for different assumed values of σ..
Note: This figure presents the decomposition of labor demand for manufacturing (wage bill) between 1987 and 2017 based on equation (5) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.

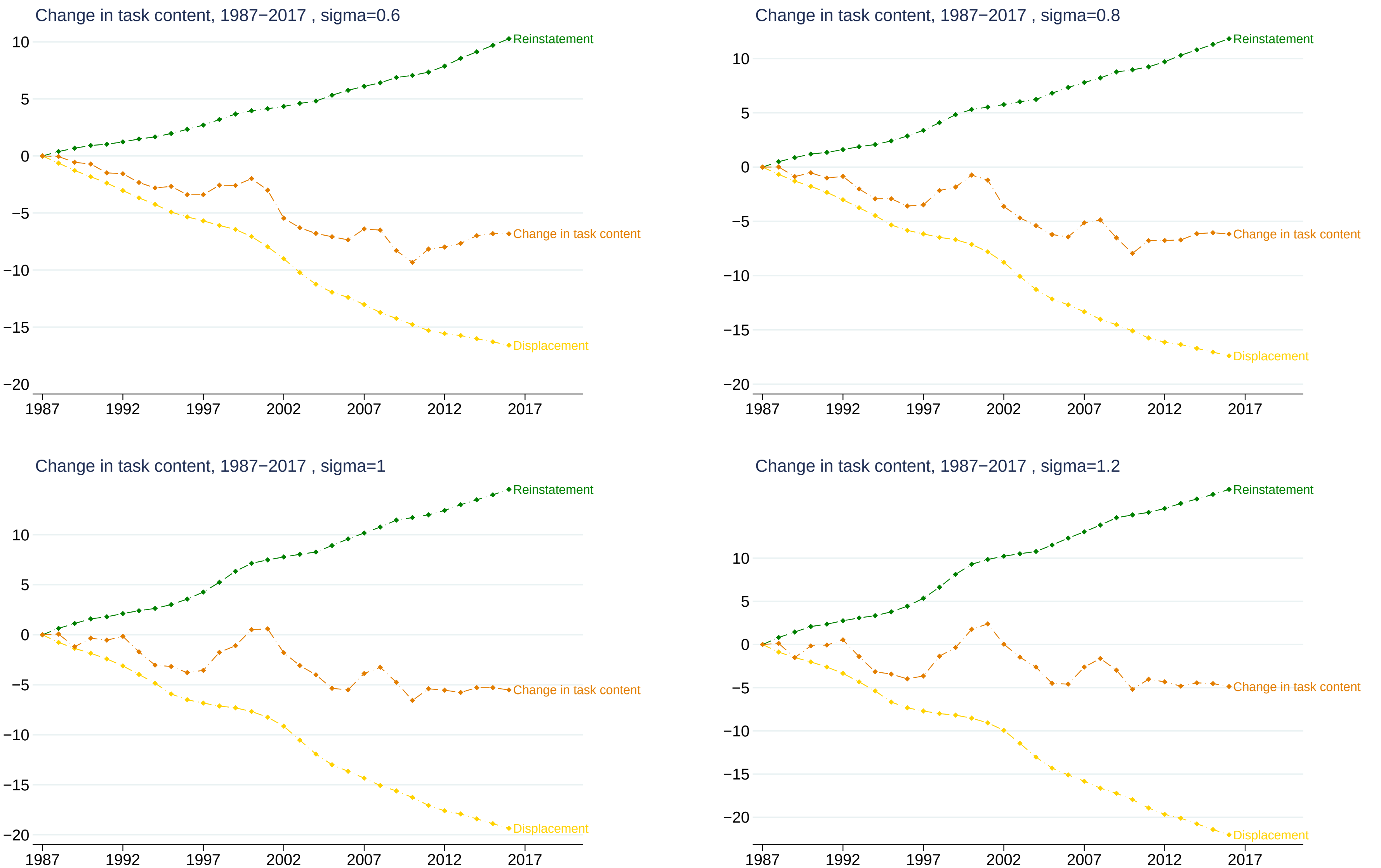

Figure A5: Estimates of the displacement and reinstatement effects for the entire economy, 1987-2017, for different assumed values of σ.
Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) in the text. The panels present the results for 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.

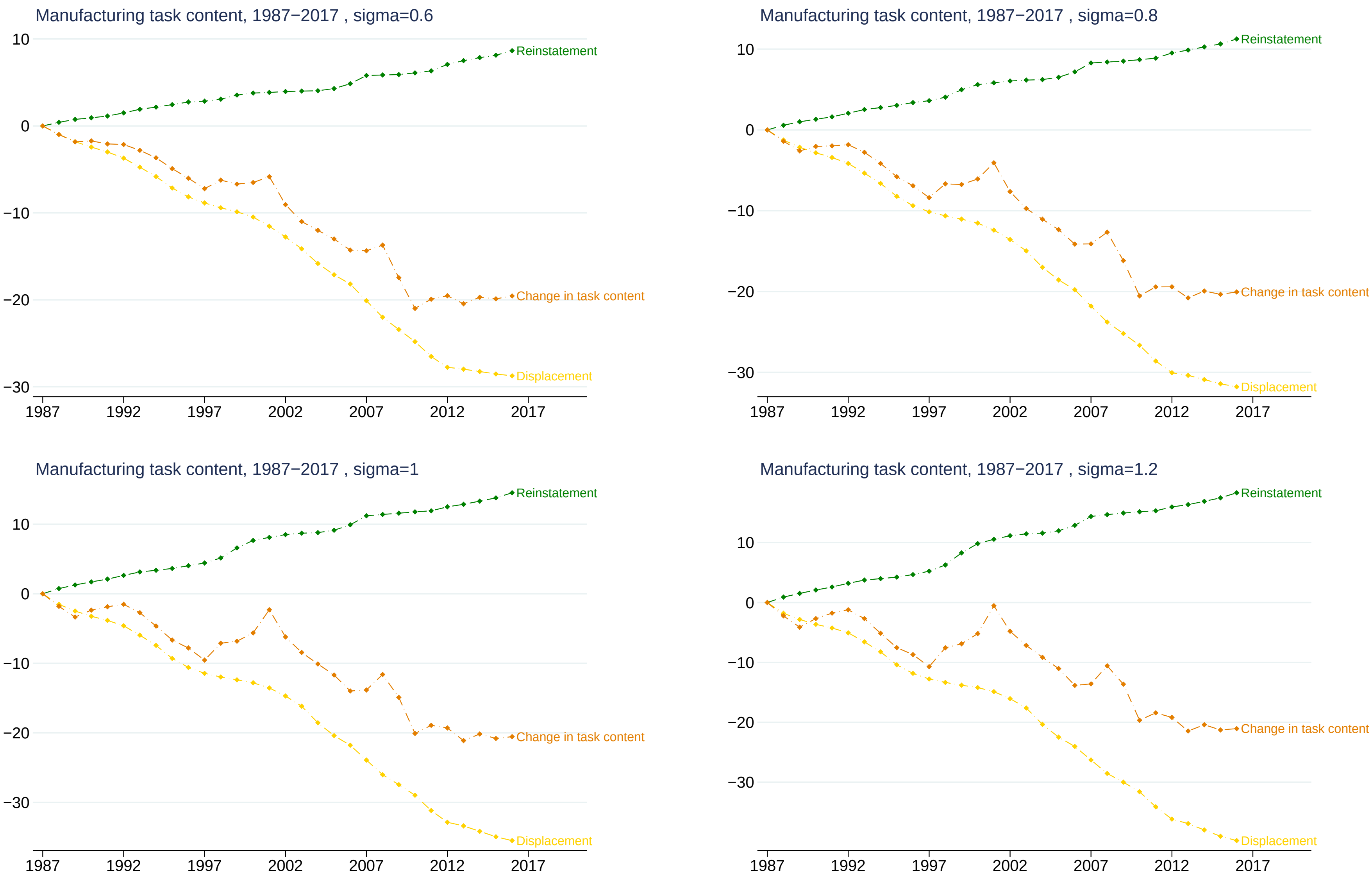

Figure A6: Estimates of the displacement and reinstatement effects for manufacturing, 1987-2017, for different assumed values of σ. Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) in the text. The panels present the results for the 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.

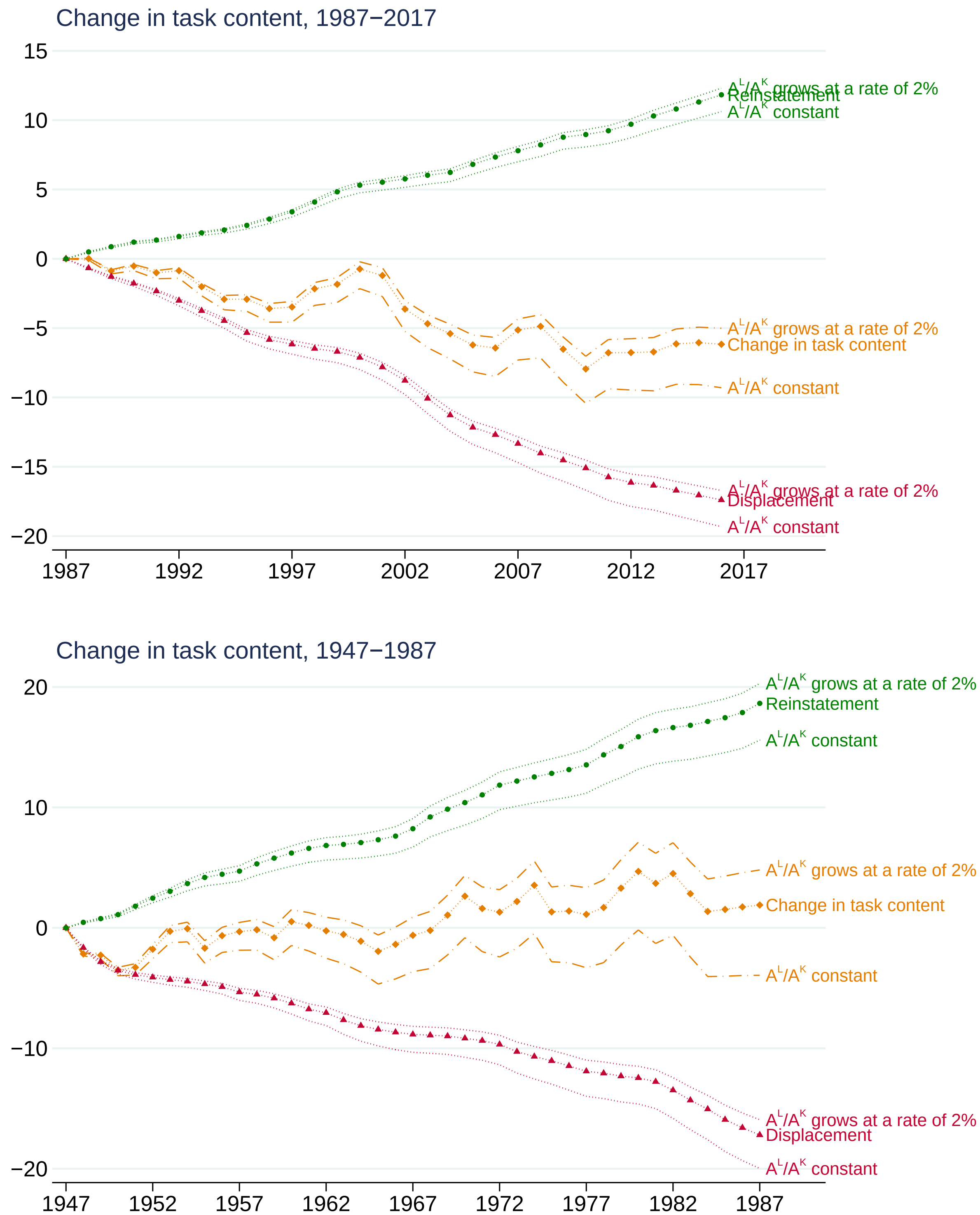

Figure A7: Estimates of the displacement and reinstatement effects for different assumed changes in A_i^L/A_i^K. Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) for different values of the growth rate of A_i^L/A_i^K. The top panel is for 1987-2017, and as the baseline, assumes a growth rate for the relative labor-augmenting technological change of 1.5%. The bottom panel is for 1947-1987, and as the baseline, assumes a growth rate for the relative labor-augmenting technological change of 2%. In both panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$.

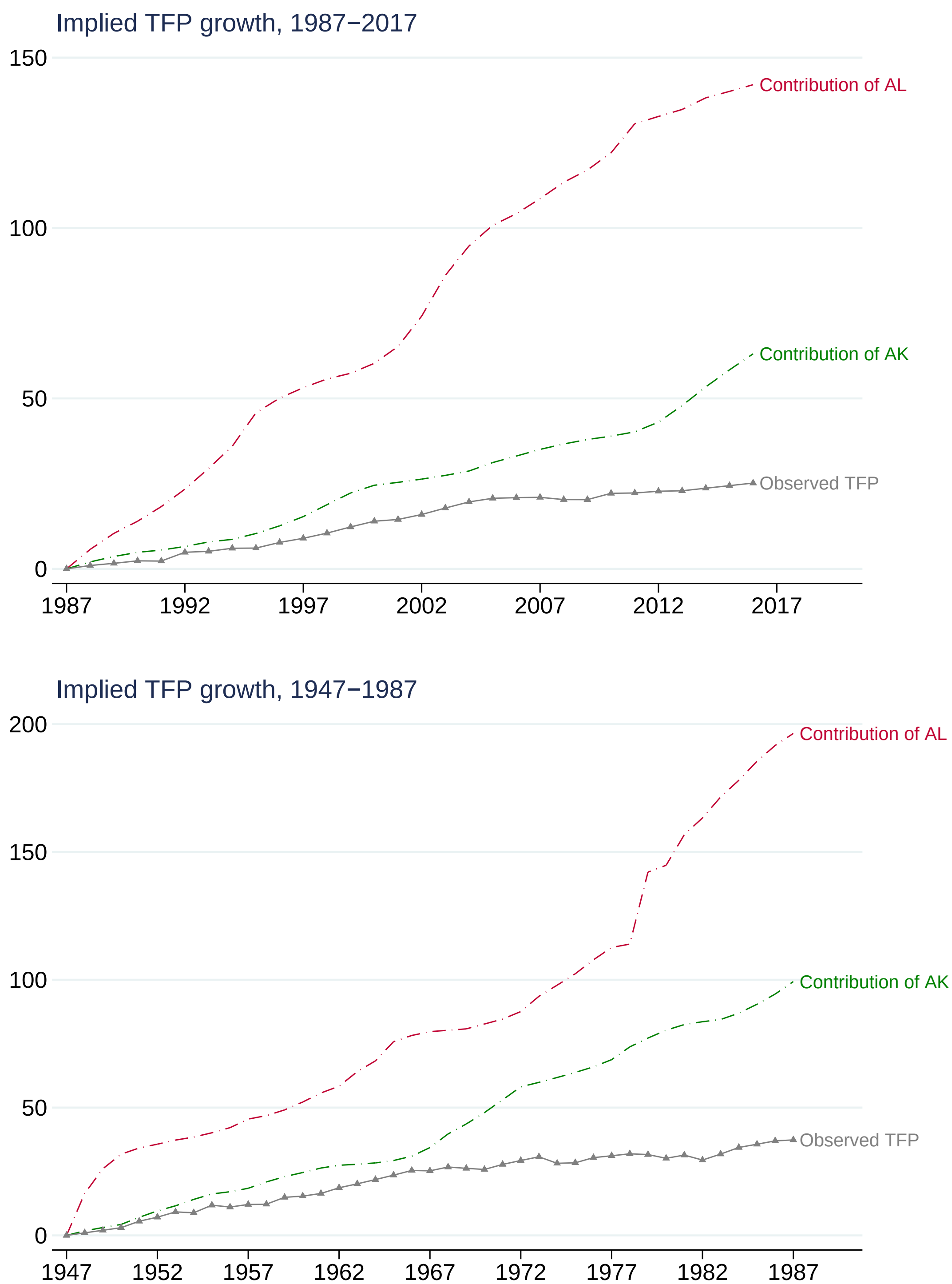

Figure A8: Counterfactual TFP changes.

Note: This figure presents the counterfactual TFP changes that would be implied if our estimates of the displacement and reinstatement effect in Figures 3 and 8 were accounted for by industry-level changes in labor-augmenting and capital-augmenting technological changes alone, respectively, as derived in equations (A1) and (A2). For comparison, the figure also reports the observed increase in TFP for both periods. These numbers are computed assuming a value of $\sigma = 0.8$.

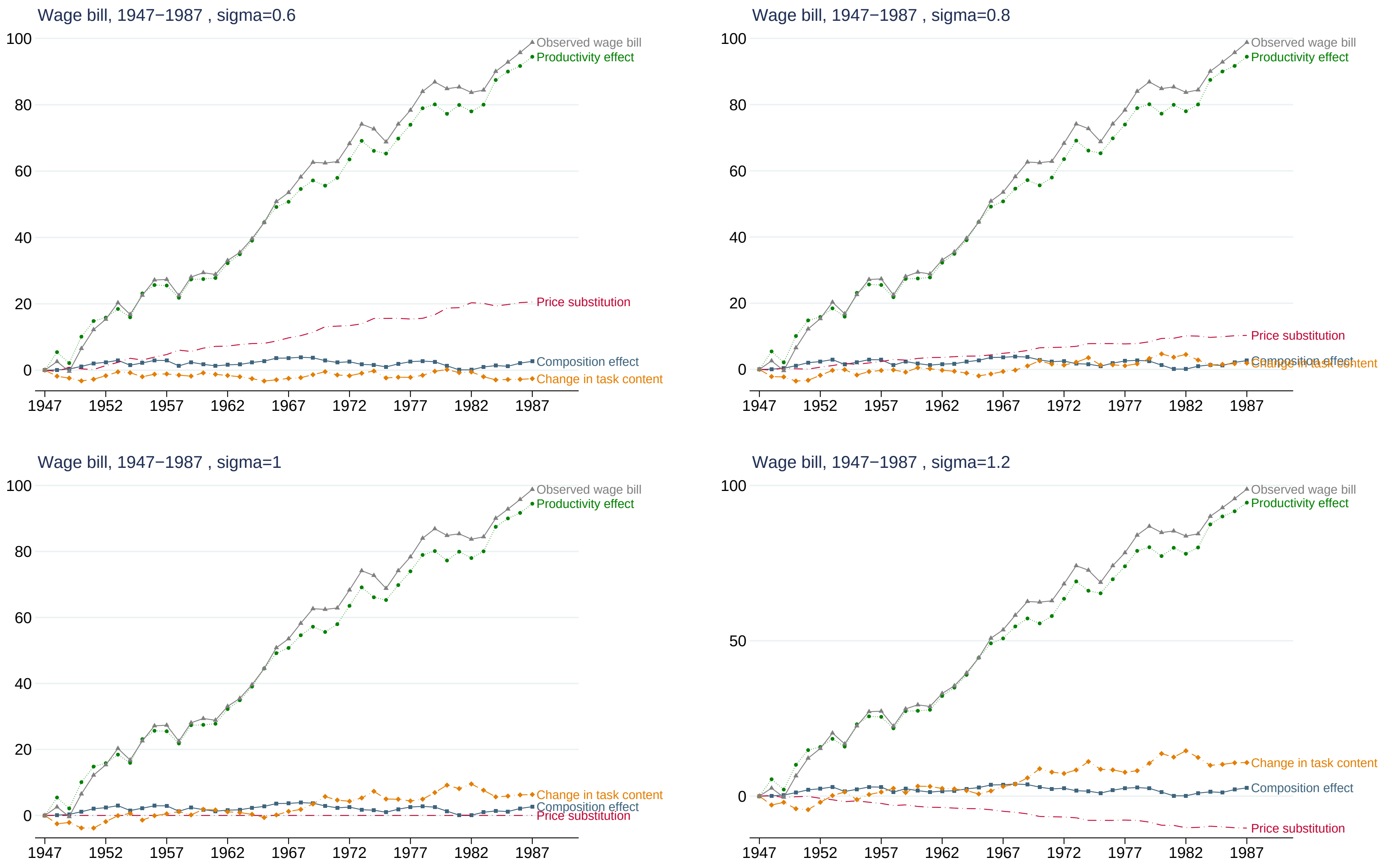

Figure A9: Sources of changes in labor demand for the entire economy, 1947-1987, for different assumed values of σ..
Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (5) in the text. The panels present the results for the vauels of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

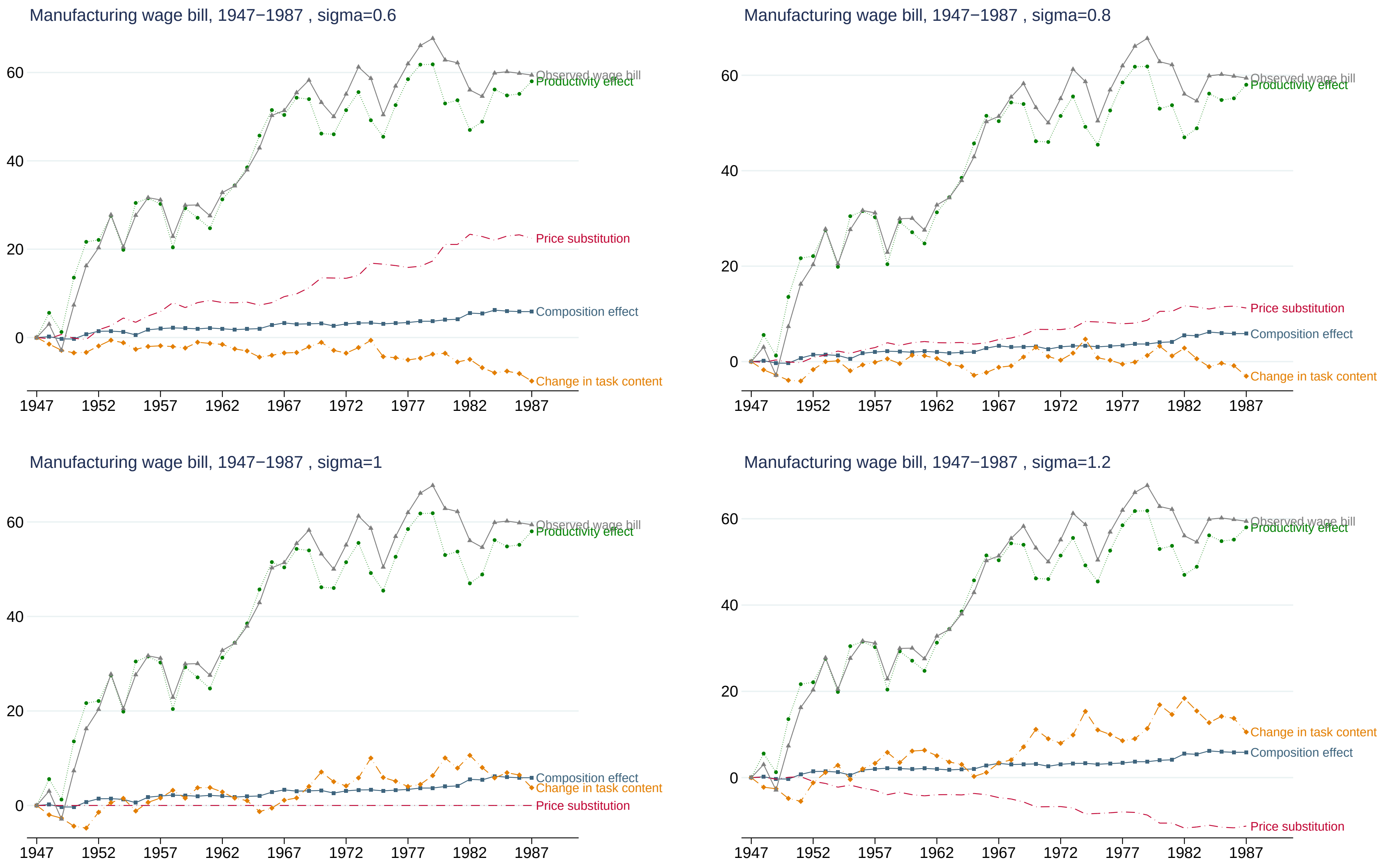

FIGURE A10: SOURCES OF CHANGES IN LABOR DEMAND FOR MANUFACTURING, 1947-1987, FOR DIFFERENT ASSUMED VALUES OF σ..
Note: This figure presents the decomposition of labor demand for manufacturing (wage bill) between 1987 and 2017 based on equation (5) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

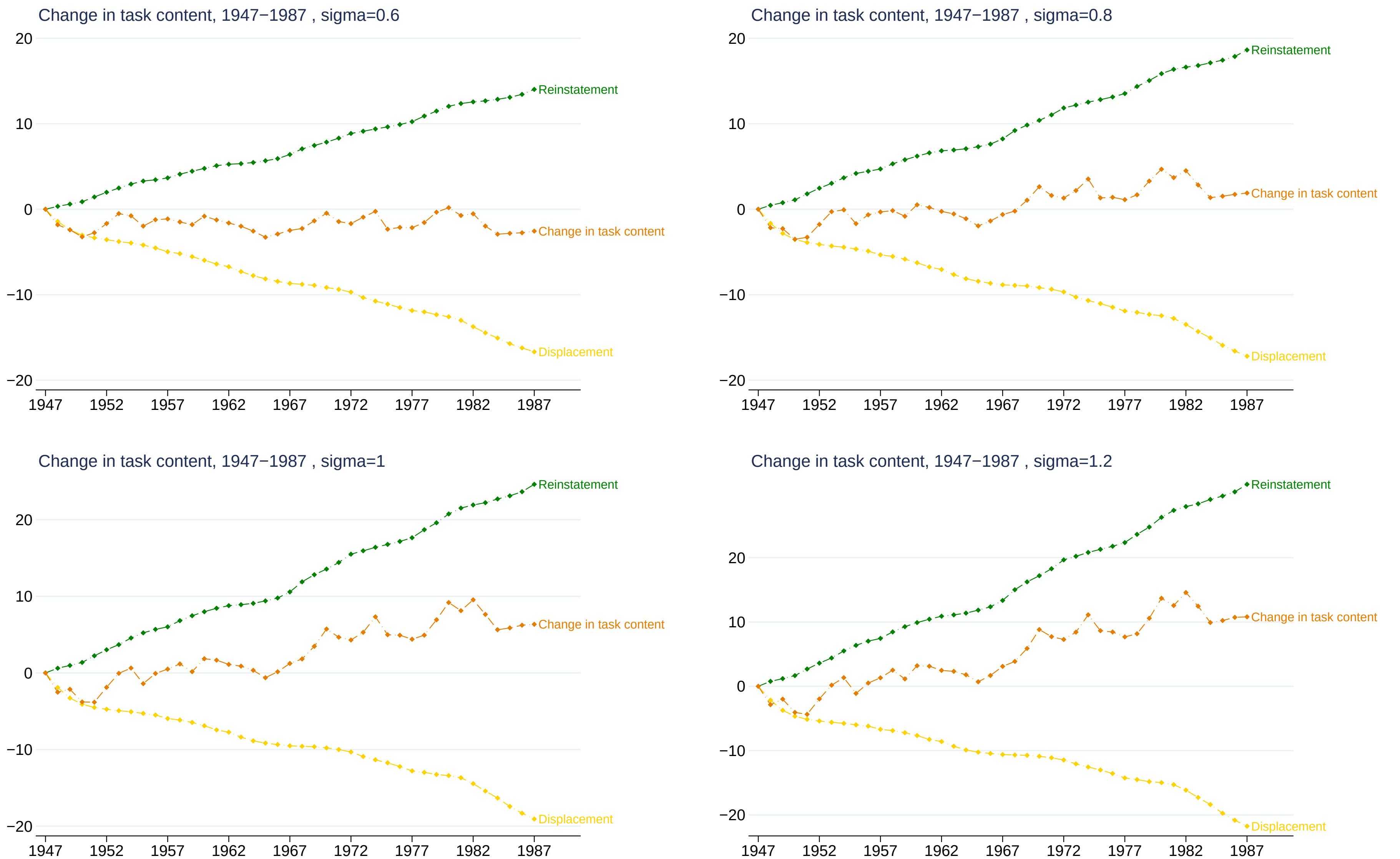

Figure A11: Estimates of the displacement and reinstatement effects for the entire economy, 1947-1987, for different assumed values of σ.
Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) in the text. The panels present the results for 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.

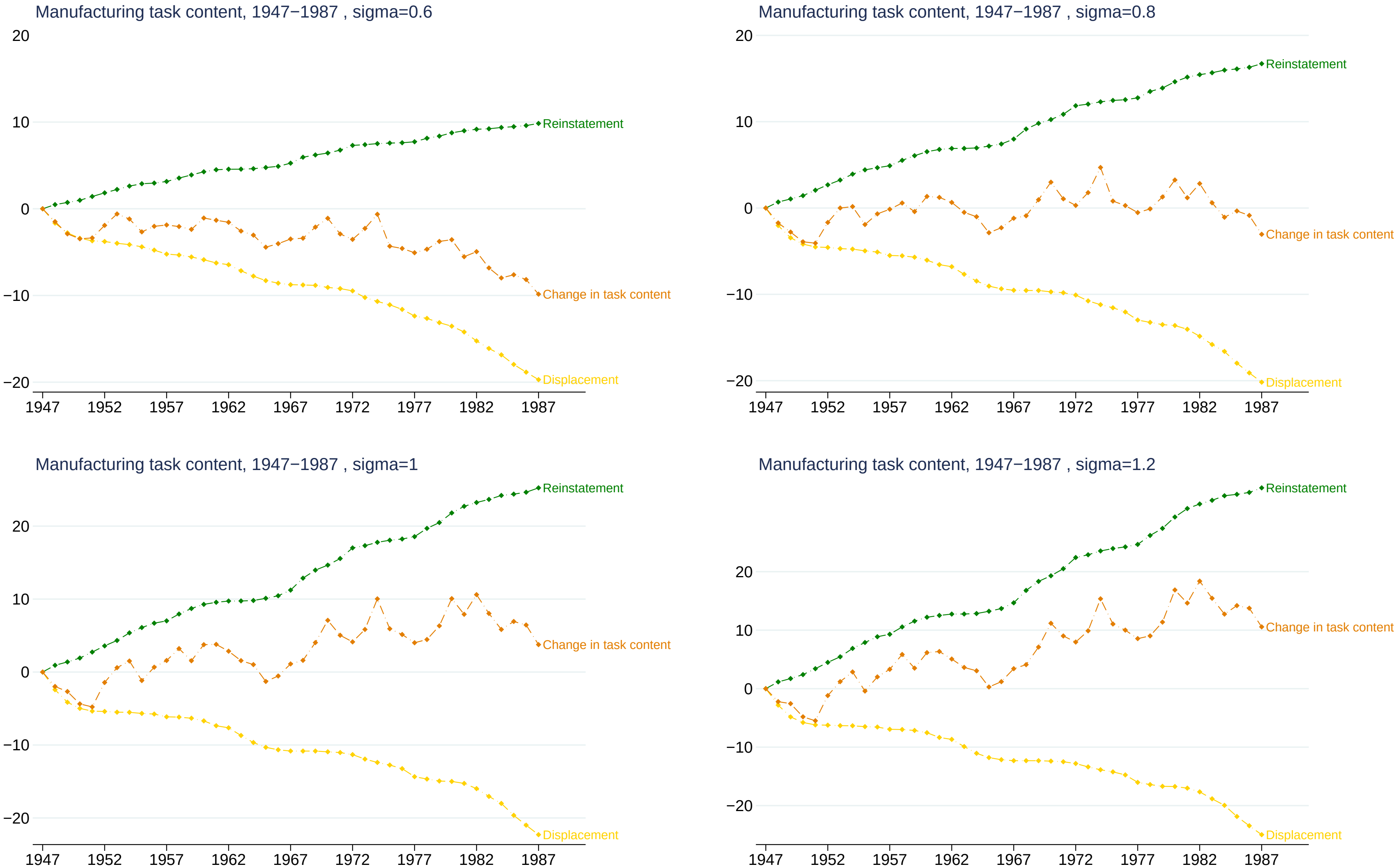

FIGURE A12: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR MANUFACTURING, 1947-1987, FOR DIFFERENT ASSUMED VALUES OF σ. Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (6) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

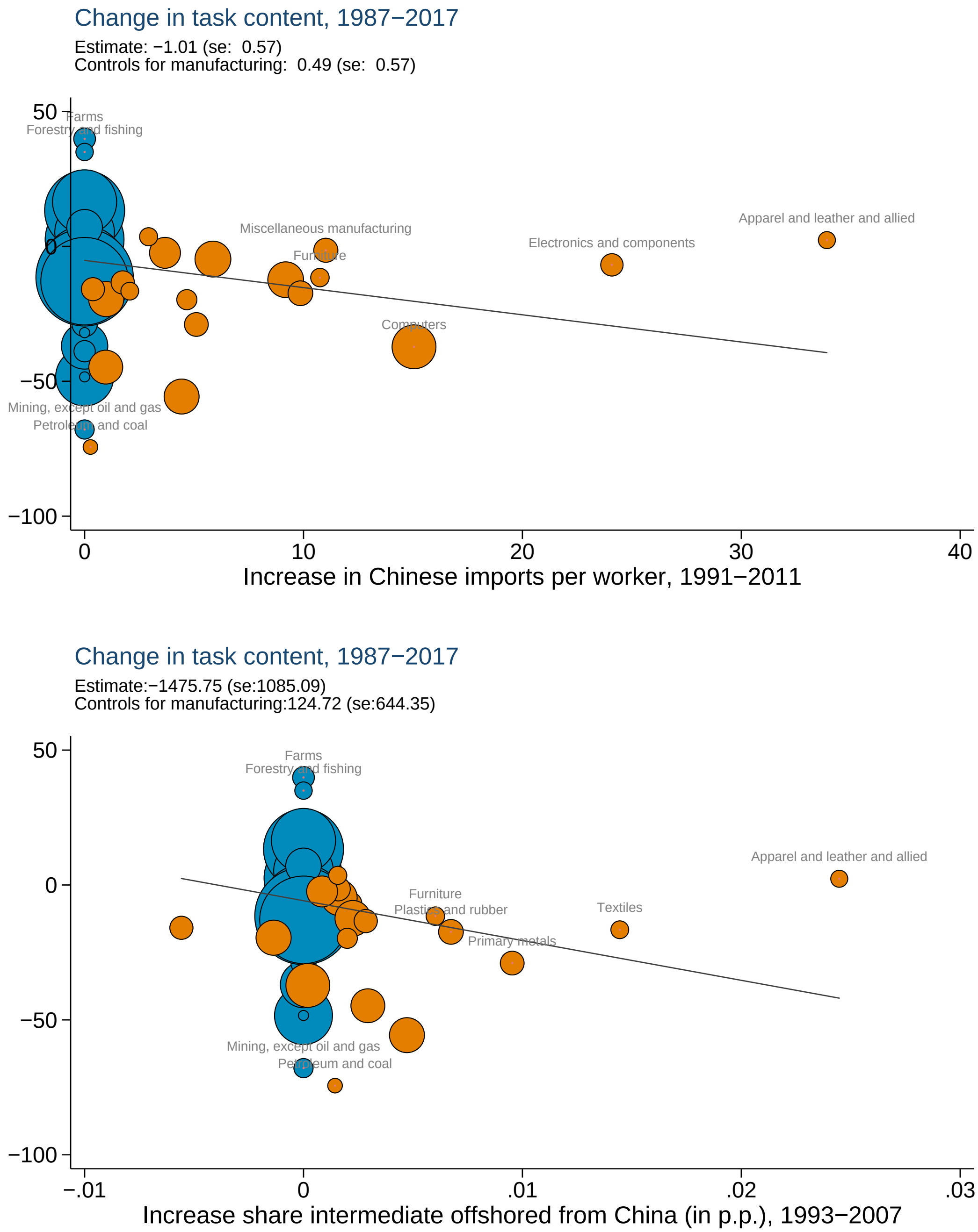

FIGURE A13: TRADE AND THE TASK CONTENT OF PRODUCTION.

Note: The top panel presents the bivariate relationship between change in task content and the growth in imports from China per worker from 1991 and 2011 (from Acemoglu et al. 2015). The bottom panel presents the bivariate relationship between change in task content and the growth in the share of intermediates offshored from China from 1993 to 2007 (from Wright 2014). Orange designates manufacturing industries and blue non-manufacturing industries. See text for details.

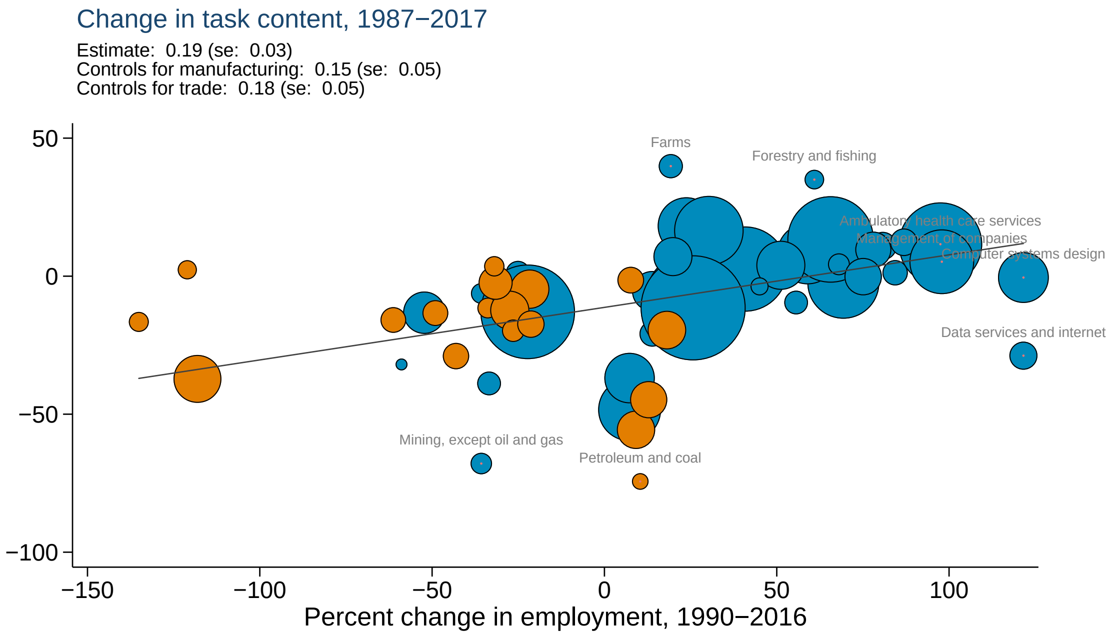

FIGURE A14: EMPLOYMENT GROWTH AND CHANGE IN TASK CONTENT OF PRODUCTION.
Note: The figure presents the bivariate relationship between change in task content and the growth of employment by industry between 1990 and 2016. Orange designates manufacturing industries and blue non-manufacturing industries. See text for details.