Automation and New Tasks: The Implications of the Task Content of Production 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 to interpret changes in US employment over the recent past. At the center of our framework is the *task content of production.* Automation, which enables capital to replace labor in tasks it was previously engaged in, shifts the task content of production against labor because of a *displacement effect.* As a result, automation always reduces the labor share in value added (of an industry or economy) and may also reduce labor demand even as it raises productivity. The effects of automation are counterbalanced by the creation of new tasks in which labor has a comparative advantage. The introduction of new tasks changes the task content of production in favor of labor because of a *reinstatement effect,* and always raises the labor share and labor demand. 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 decomposition 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. Figure 1, which presents the evolution of overall US labor demand (the real wage bill normalized by population) since 1947, does indicate that there are major secular changes during recent decades that need to be studied and understood. Labor demand grew on average by 2.4% per annum between 1947 and 1987, but then slowed down to a growth rate of 1.33% per annum from 1987 onwards, and has been essentially stagnant since the late 1990s.

This paper presents a task-based framework designed to think about the implications of technology for labor demand and then uses this framework to shed light on the patterns depicted in Figure 1. At the center of our framework is the allocation of tasks to factors, summarized by the *task content of production*.[1] While the type of technological change much of the economics literature focuses on—which is "factor-augmenting"—does not directly impact the task content of production, real-world technologies often do. Automation, which corresponds to the introduction of new technologies that enable capital to be substituted for labor in certain tasks, generates a powerful *displacement effect*—because it replaces labor in tasks it was previously performing—and changes the task content of production against labor.

The displacement effect is in evidence in previous episodes of automation. Many of the early innovations of the Industrial Revolution automated tasks performed by artisans in spinning and weaving (Mantoux, 1928). As they succeeded in doing so, they created widespread displacement and discontent, as evidenced by the Luddite riots (Mokyr, 1990). The 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, 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 other automated machinery replacing production workers (Graetz and Michaels, 2018, Acemoglu and Restrepo, 2018b). Software and more recently developments in machine learning and AI are allowing firms to computerize tasks performed by white-collar workers engaged in tasks such as accounting, sales, logistics, trading, and even aspects of managerial decision-making.

Technological advances increase productivity and via this channel contribute to the demand for labor—which we call the *productivity effect*. However, in the case of automation, the displacement effect (the adverse shift in the task content of production) reduces the labor share in value added. Although value added increases, a smaller share of it accrues to labor. As a result, automation may reduce wages and employment when the productivity improvements it brings are small.

If the history of technology were one of automation only, the resulting changes in the task

[1] 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).

content of production would confine human labor 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—and thus change the task content of production in favor of labor. The reinstatement effect is the polar opposite of the displacement effect and directly increases the labor share as well as labor demand.

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, 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, especially in factories (Rasmussen, 1982; Olmsted and Rhode, 2001) and in clerical occupations both in services and manufacturing (Goldin and Katz, 2007; Michaels, 2007). Although software and computers have been used to substitute for labor in some tasks, they have also enabled the emergence of a wide range of new jobs, such as web and app designers, network specialists and programmers, who specialize in tasks that would be unrecognizable to an observer from the past. Using data from Lin (2011), Acemoglu and Restrepo (2018a) show that about half of employment growth over 1980-2015 took place in occupations with significant changes in the job titles or tasks that workers perform.

The main conceptual lesson from this framework is that it is wrong to expect automation technologies to seamlessly create balanced growth and robust wage increases for all workers. Balanced growth and wage growth commensurate with productivity gains are a consequence of other technological changes balancing the effects of automation. Our emphasis on the displacement and reinstatement effect shows that new technologies do not necessarily spell the end of human work. The future of work depends on the types of technologies developed and how these change the task content of production—whether they displace or reinstate labor.

In the second part of the paper, we use our framework to study the evolution of labor demand in the United States since World War II depicted in Figure 1. Our methodology uses industry data to decompose changes in labor demand into productivity, composition, substitution effects and more importantly changes in the task content of production. All technologies create productivity effects that contribute to labor demand. The composition effect arises from the reallocation of activity across sectors with different labor intensities. The substitution effect captures the substitution across labor-intensive and capital-intensive tasks within an industry in response to a change in effective factor prices (for instance, caused by factor-augmenting technologies making labor or capital more productive or by supply-side factors). Changes in the task content of production, on the other hand, are a result of automation and the introduction of new tasks, which directly redefine the set of tasks being produced by capital and labor.

Applying this decomposition to the US, we conclude that the evolution of labor demand, especially over the last 30 years, cannot be understood without factoring in sizable changes in the task content of production. The slowdown in the growth of labor demand highlighted in Figure 1 is a consequence of weaker than usual productivity effects and significant changes in the task content of production against labor. By decomposing the change in the task content of production we find that this is in turn because of stronger than usual displacement and weaker than usual reinstatement effects coming from new technologies, which hint at an acceleration of automation and a deceleration in the creation of new tasks. These patterns raise the question of why productivity growth has been anemic during recent years despite the acceleration of automation. We conclude by outlining the pathways linking productivity growth to different technologies in this framework.

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 recent US economic history. Section 4 concludes. The Online Appendix contains a detailed exposition of our framework, proofs, additional empirical results and details on the construction of our data.

2 Conceptual Framework

Most production processes involve a range of tasks. The production of a shirt, for example, starts with a design, then requires the completion of a variety of production tasks, such as the extraction of fibers, spinning them to produce yarn, weaving, knitting, dyeing, and processing, as well as additional non-production tasks, such as accounting, marketing, transportation and sales. Each one of these tasks can be performed by human labor or by capital (machines and software). The allocation of tasks to factors determines the *task content of production* in this activity. Automation corresponds to the introduction of technologies that enable some of the tasks previously performed by labor to be now produced by capital. The famous spinning and weaving machines introduced during the Industrial Revolution (Mantoux, 1928, Mokyr, 1990) are examples of automation technologies. A more recent example are industrial robots. Advances in robotics technologies since the 1980s have allowed firms to automate a wide range of production tasks in manufacturing, such as machining, welding, painting, and assembling, that were previously performed manually (Ayres and Miller, 1983; Groover et al. 1986; Graetz and Michaels, 2015; Acemoglu and Restrepo, 2018b). The set of tasks involved in producing a product is not constant over time, and the introduction of new tasks can be a major source of labor demand. New design tasks for producing better, more fashionable products are examples of new labor-intensive tasks in textiles. Changes in the nature of many occupations over the last several decades represent new tasks as well. For instance, 70% of all computer software developers in 2000 held new job titles relative to previous decades, and radiology technician and management analysts were also new job titles, respectively, in the 1990s and 1980s (Lin, 2011).

By changing the allocation of tasks to factors, both automation and the introduction of new tasks, impact the task content of production. In contrast, the standard way the economics profession conceptualizes technological progress—as *factor-augmenting*—abstracts from the way in which technology shapes the task content of production. For example, when we assume that the production function takes the form $Y = F(A^K K, A^L L)$, we are imposing that technological change either increases the productivity of capital (via the capital-augmenting term A^K) or the productivity of labor (via the labor-augmenting term A^L) *uniformly in all tasks*. This way of thinking about technology not only lacks descriptive realism (spinning and weaving machines did not make capital, and certainly not labor, more productive in all tasks), but often misses the major implications of technological changes that directly alter the allocation of task to factors.

2.1 Tasks and Production

We present our task-based framework by first describing the production process in a single sector. Suppose that production in this sector combines the output of a range of tasks, normalized to lie between $N-1$ and N, with an elasticity of substitution σ.[2]

Tasks can be produced using capital or labor. Tasks with $z > I$ are *not automated*, and can only be produced with labor, which has productivity $A^L \gamma^L(z)$ in task z and a wage rate W. Tasks $z \le I$ are *automated* and can be produced with capital as well as labor. Capital produces $A^K \gamma^K(z)$ units of such a task at a rental rate R. We assume that $\gamma^L(z)/\gamma^K(z)$ is increasing, so that labor has a *comparative advantage* in high-index tasks, and that $\gamma^L(z)$ is also increasing, so that labor is more productive at high-index tasks. An increase in I thus corresponds to the introduction of an automation technology or *automation* for short. An increase in N, on the other hand, adds new high-indexed tasks and thus corresponds to the introduction of new labor-intensive tasks or *new tasks* for short. In addition to automation (I) and introduction of new tasks (N), the state of technology for this industry depends on A^L (labor-augmenting technology) and A^K (capital–augmenting technology), which increase the productivities of these factors in *all* tasks.[3]

Let us assume that it is cost-minimizing for firms in this sector to use capital in all tasks that are automated (all $z \le I$) and use all new tasks immediately (see the Appendix for conditions to ensure this). This implies an allocation of tasks to factors as summarized in Figure 2, which also shows how automation (an increase in I) and new tasks (an increase in N) impact this allocation.

Following the same steps as in Acemoglu and Restrepo (2018a), output can be represented as a constant elasticity of substitution (CES) function of capital and labor, with their usual factor-augmenting technology terms,

$$Y = \left(\Gamma_K(N,I)(A^K K)^{\frac{\sigma-1}{\sigma}} + \Gamma_L(N,I)(A^L L)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

but with the crucial difference that the share parameters of this CES are endogenous and depend

[2]Namely, the production function takes the form $Y = \left(\int_{N-1}^{N} Y(z)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}}$, where $Y(z)$ is the output of task z. The assumption that tasks lie between $N-1$ and N is adopted to simplify the exposition, and we show in the Appendix that nothing major changes when tasks lie between 0 and N.

[3]The comparative advantage schedules $\gamma^L(z)$ and $\gamma^K(z)$ are also part of the technology of the sector, but we hold these fixed throughout the paper to focus on the implications of automation and new tasks and their contrast with factor-augmenting technologies.

on automation and new tasks.[4] In particular, $\Gamma_K(N,I)$ is increasing in I and decreasing in N, while $\Gamma_L(N,I)$ is increasing in N and decreasing in I. This implies that automation increases the share parameter in front of capital (because it allocates more tasks to capital) and reduces the share parameter in front of labor (because it displaces labor from the tasks it was previously producing).

The labor share can be computed as the wage bill (WL) divided by value added (Y),

$$s^L = \frac{WL}{Y} = \frac{\Gamma(N,I)(W/A^L)^{1-\sigma}}{(1-\Gamma(N,I))(R/A^K)^{1-\sigma} + \Gamma(N,I)(W/A^L)^{1-\sigma}}, \tag{2}$$

where $\Gamma(N,I) = 1/[1+(\Gamma_K(N,I)/\Gamma_L(N,I))^{\sigma}]$ is the (labor) *task content of production*, and is itself increasing in N and decreasing in I. For example, in the special case where $\sigma = 1$, $\Gamma(N,I) = N - I$. This formalizes the claim in the Introduction that automation shifts the task content of production against labor while new tasks alter it in favor of labor. The task content of production does not depend on factor-augmenting technologies or the supply of capital or labor.[5] Instead, the effective supplies of capital and labor influence the labor share and labor demand by encouraging the output of some tasks to be substituted for others. This *substitution effect* works via changes in effective factor prices, W/A^L and R/A^K, and its magnitude and even direction depends on the elasticity of substitution between tasks (and between capital and labor), σ. A lower effective wage may increase or reduce the labor share depending on whether $\sigma \lesseqgtr 1$.

2.2 Technology and Labor Demand

We now investigate the implications of technology for labor demand, defined as total wage payments (wage bill), WL.[6] The labor demand of an industry can then be expressed as

$$\text{Labor demand} = \text{Value added} \times \text{Labor share}.$$

We next use this relationship to think about the effects of automation, new tasks and factor-augmenting technologies on labor demand.

Automation and labor demand: Consider the introduction of new automation technologies (an increase in I). Its impact on labor demand can be represented as

$$\text{Effect of automation on labor demand} = \text{Productivity effect} + \text{Displacement effect}.$$

[4] Specifically, $\Gamma_K(N,I) = \left(\int_{N-1}^{I} \gamma^K(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}$ and $\Gamma_L(N,I) = \left(\int_{I}^{N} \gamma^L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}$.

[5] This is a consequence of the fact that the allocation of tasks to factors remains as in Figure 2 even as factor supplies or factor-augmenting technologies change. The Appendix presents the assumption on factor supplies that ensures this is the case. When this assumption does not hold (for example, because of very large changes in factor-augmenting technologies or factor supplies), the allocation of tasks to factors will change and the strict independence of the task content of production from factor supplies and factor-augmenting technologies will no longer apply. Even in this case, the impact of factor augmenting technologies on the task content will tend to be small.

[6] 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.

The *productivity effect* arises from the fact that automation increases value added, and this raises the demand for labor from non-automated tasks. If nothing else happened, labor demand would increase at the same rate as value added, and the labor share would remain constant. However, automation also shifts the task content of production against labor (reduces the task content of production $\Gamma(N, I)$ defined above) because of a *displacement effect*—it displaces labor from the tasks previously allocated to it. As a result, the labor share in value added always declines. There is no guarantee that the productivity effect is greater than the displacement effect—automation can reduce labor demand even as value added increases.[7]

This analysis clarifies that automation will reduce labor demand when the productivity effect is not very large. Contrary to a common presumption in popular debates, it is not the "brilliant" automation technologies but those that are "so-so" and generate only small productivity improvements that will reduce labor demand. This is because the positive productivity effect of so-so technologies is not sufficient to offset the decline in labor demand due to displacement. To understand when this is likely to be the case, let us first consider where the productivity gains from automation are coming from. These are not a consequence of the fact that capital or labor are becoming more productive in the tasks they are performing, but follow from the ability of firms to use cheaper capital in tasks previously performed by labor. The productivity effect of automation is therefore proportional to cost-savings obtained from such substitution. The greater is the productivity of labor in tasks being automated ($A^L\gamma^L(I)$) relative to its wage (W) and the smaller is the productivity of capital in these tasks ($A^K\gamma^K(I)$) relative to the rental rate of capital (R), the more limited are the productivity gains from automat.

The fact that different technologies are accompanied by productivity effects of varying magnitudes is the reason why we cannot presume that one set of automation technologies will impact labor demand in the same way as others. This observation also implies that the effects of automation on labor demand will depend on the broader labor market context. When wages are high and labor is scarce, automation will have a strong productivity effect and will tend to raise labor demand.[8] Instead, when wages are low and labor is abundant, automation will have a modest productivity benefit and could end up reducing labor demand.

New tasks and labor demand: Consider next the introduction of new tasks, which is captured by an increase in N in our framework. This expands the set of tasks in which humans have a comparative advantage and its effect can be summarized as

$$\text{Effect of new tasks on labor demand} = \text{Productivity effect} + \text{Reinstatement effect}.$$

[7] Acemoglu and Restrepo (2018b) show that industrial robots are associated with lower labor share and labor demand at the industry level and lower labor demand in local labor markets exposed to this technology, which is consistent with a powerful displacement effect from this class of automation technologies.

[8] This may be one reason why the development and introduction of automation technologies in response to scarcity of production labor in countries where the labor force is aging rapidly (such as Germany, Japan and South Korea) may have very different effects than the introduction of automation technologies in the United States (see Acemoglu and Restrepo, 2018e, on cross-country patterns and Dauth et al. 2018, on the effects of robots in Germany).

The new force here is the *reinstatement effect*, which again captures the change in the task content of production, $\Gamma(N, I)$, but now in favor of labor as the increase in N reinstates labor into new tasks. This change in task content always increases the labor share. It also improves productivity as these new tasks exploit labor's comparative advantage. This productivity improvement, together with the change in task content, ensures that demand for labor always increases following the introduction of new (labor-intensive) tasks.

Factor-augmenting technologies and labor demand: The implications of factor-augmenting technologies are very different from those of automation and new tasks, because they do not change the task content of production. In particular, in this case we have

$$\begin{array}{l}\text{Effect of factor-augmenting} \\ \text{technologies on labor demand}\end{array} = \text{Productivity effect} + \text{Substitution effect}.$$

Factor-augmenting technologies also generate a productivity effect. A 1% increase in A^L raises productivity by s^L%, and a 1% increase in A^K raises productivity by $(1 - s^L)$%. This is because with factor-augmenting technological improvements, labor or capital becomes more productive *in all* tasks, making the productivity increase proportional to their share in value added.

Factor-augmenting technologies also impact labor demand via a *substitution effect*; they expand the output of the tasks produced by the factor that became more productive, which are then substituted for the output of tasks produced by the other factor. This substitution takes place without any change in the allocation of tasks to factors (summarized by the term $\Gamma(N, I)$ as our analysis above clarifies).[9] The sign of the *substitution effect* is ambiguous and depends on whether the elasticity of substitution σ is greater than or less than 1, because this determines whether increasing the production of a task raises its share in the value added of the industry. When $\sigma = 1$, equation (1) becomes a Cobb Douglas production function and the substitution effect vanishes, because the share of each task in value added is fixed. Available estimates of σ place this parameter to be less than 1 but still not too far from 1, implying that the substitution effects of factor-augmenting technologies are small relative to their productivity effects. This is the reason why factor-augmenting technologies affect labor demand mostly via the productivity effect and have a small impact on the labor share of an industry (compared to their impact on productivity).[10]

[9] Some other technologies share this feature and do not impact the task content of production (because they do not generate displacement or reinstatement effects). For example, improvements in the quality or productivity of equipment that has already been introduced to automate certain tasks in the past (what Acemoglu and Restrepo, 2018d, call a "deepening of automation") are equivalent to capital-augmenting technologies, since they do not affect the allocation of tasks to factors (the tasks in which the productivity of capital is now higher were already allocated to capital).

[10] See Acemoglu and Restrepo (2018c) for further details of the qualitative differences between automation and factor-augmenting technological changes. As we show there, capital-augmenting technologies always increase labor demand, and labor-augmenting technologies do the same so long as $\sigma > 1 - s^L$.

2.3 Tasks, Production and Labor Demand in a Multi-Sector Economy

We now embed the model of tasks and production for a single industry in an economy with multiple industries/sectors. For clarity, we now index industries with the subscript i and let $\mathcal{I}$ represent the set of industries. We summarize the state of technology for industry i by $\{I_i, N_i, A_i^K, A_i^L\}$.

Aggregate labor demand in this economy is represented by total wage bill,

$$\text{Labor demand} = \text{GDP} \times \sum_{i \in \mathcal{I}} \text{Labor share sector } i \times \text{Share of value added in sector } i.$$

Following automation in sector i (an increase in I_i) we have

$$\begin{array}{l}\text{Effect of automation} \\ \text{in } i \text{ on labor demand}\end{array} = \text{Productivity effect} + \text{Displacement effect} + \text{Composition effect}.$$

The first two effects are the same as what we saw above—the productivity effect represents the impact of automation on this sector's value added and thus on GDP, while the displacement effect represents the change in the task content of production in this sector. The only difference is that their impact on aggregate labor demand will depend on the size of sector i, with larger sectors having a stronger productivity and displacement effect. These impacts are supplemented by a *composition effect*, which captures the change in labor demand due to sectoral reallocations. For example, automation in sector i may reallocate economic activity towards sector j (this in general depends on demand elasticities and input-output linkages). This reallocation will contribute positively to labor demand when sector j has higher labor share than the contracting sector i, and negatively when the opposite holds (the exact equations for this decomposition and the other ones presented in this section are provided in the Appendix).

A similar decomposition applies for the creation of new tasks. Following the introduction of new tasks in sector i (an increase in N_i) we have

$$\begin{array}{l}\text{Effect of new tasks} \\ \text{in } i \text{ on labor demand}\end{array} = \text{Productivity effect} + \text{Reinstatement effect} + \text{Composition effect},$$

where the new feature is again the composition effect.

The mechanization of agriculture in the US illustrates how all of these forces jointly determine the behavior of aggregate labor demand. Using data from Budd (1960), Figure 3 shows that from 1850 onward the replacement of manual labor by horse-powered reapers, harvesters, and plows (e.g., Rasmussen, 1982) was associated with a sharp decline in the labor share in agriculture from 33% to 17%—a telltale sign of the displacement effect created by the mechanization of agriculture. The figure shows too that a sizable composition effect contributed to labor demand, as value added was reallocated from agriculture to the more labor-intensive industrial sector, and there was a significant increase in the labor share within the industrial sector as well, suggesting the presence of a powerful reinstatement effect created by new labor-intensive jobs in this sector. This interpretation is consistent with significant growth in new factory jobs in farm equipment (Olmstead and Rhode, 2001), cotton milling (Rasmussen, 1982) and in clerical occupations in new trade and manufacturing industries during this period (Goldin and Katz, 2007; Michaels, 2007). The composition and reinstatement effects explain why, despite the mechanization of a sector making up a third of of the economy, labor demand increased and the share of labor in national income remained stable during this period.

Finally, factor-augmenting technologies can be analyzed similarly. Although they also generate composition effects and may affect aggregate labor demand via this channel, they still have no impact on the task content of production. Absent powerful composition effects, factor-augmenting technologies will continue to affect labor demand mostly via their productivity effect.

3 Sources of Labor Demand Growth in the US Economy

In this section, we use our framework to decompose the sources of labor demand growth—or lack thereof since the 1990s as shown in Figure 1—in the US economy. We show in the Appendix that when firms are on their labor demand curve (and with no additional assumptions), changes in aggregate labor demand can be decomposed as

$$\begin{aligned}\text{Change in labor demand} &= \text{Productivity effect} + \text{Composition effect}\\ &\quad + \text{Change in task content} + \text{Substitution effect}.\end{aligned}$$

The productivity effect is the sum of the contributions from various sources of technology to value added and thus GDP. Correspondingly, we measure this effect using changes in (log) GDP per capita. The composition effects captures all changes in labor demand resulting from reallocation of value added across sectors. As our discussion in the previous section indicates, this is related to the gap between the labor share of contracting and expanding sectors (more precisely, it is given by the covariance between change in the value added share of an industry and its baseline labor share). The composition effect includes not only the sectoral reallocation brought by new technologies but also any compositional changes resulting from structural transformations and sectoral reallocation due to preferences (e.g., Herrendorf, Rogerson and Valentinyi, 2013; Hubmer, 2018), differences in factor intensities (e.g., Acemoglu and Guerrieri, 2008), differential sectoral productivity growth (e.g., Aghion, Jones and Jones, 2017) or international trade (e.g., Autor, Dorn and Hanson, 2013).

The change in task content is given by an employment-weighted sum of changes in $\ln \Gamma_i(N_i, I_i)$, which measures the net effect of the displacement and reinstatement effects in industry i. Likewise, the substitution effect is an employment-weighted sum of the substitution effect in each industry.

From equation (2), the change in task content and the substitution effect in an industry add up to the percent change in the labor share of that industry. This implies that the change in the task content of production in industry i can be estimated as

$$\text{Change in task content in } i = \text{Percent change in labor share in } i - \text{Substitution effect in } i.$$

We directly observe change in industry labor share and can estimate the substitution effect (see the formula in the Appendix) given an elasticity of substitution σ and estimates of sectoral factor prices and the growth rate of A_i^L/A_i^K. For this purpose, we use an estimate of $\sigma = 0.8$ from Oberfield and Raval (2014).[11] To estimate the growth rate of A_i^L/A_i^K, we assume "no technological regress,"meaning that no technology will worsen over time, and start with the benchmark where A_i^L/A_i^K grows at a common rate equal to average labor productivity (2% a year between 1947 and 1987 and 1.5% a year between 1987 and 2017) so that without any capital-augmenting technological progress and change in the task content of production, labor-augmenting technologies would account for the entire growth of productivity.[12] We then estimate the substitution effect combining this with data on factor payments at the industry level.

Finally, "no technological regress" also enables us to estimate the extent of displacement and reinstatement at the industry level under an additional assumption: that an industry will not simultaneously undertake automation and introduce new tasks (this is implied, for example, by the directed technological change reasoning in Acemoglu and Restrepo, 2018a, where depending on factor prices, an industry will engage in one type of innovation or the other). We then compute the displacement effect as the five-year moving average of the change in task content for industries with a negative change, and the reinstatement effects as the five-year moving average of the change in task content for industries with a positive change.[13]

3.1 Sources of Labor Demand: 1947-1987

We first apply this decomposition to data from the four decades following World War II, 1947-1987. For this period we have data for 58 SIC industries on value added and labor shares from the BEA, and combine these with NIPA data on quantities of capital and labor employed in each industry. to obtain measures of factor prices. We consolidated these into 43 industries covering the private sector that can be tracked consistently over time and across sources.[14]

Figure 4 presents the evolution of the labor share for six broad sectors: construction, services, transportation, manufacturing, agriculture and mining. Except for mining and transportation—two small sectors accounting for 10% of GDP—there are no significant changes in the labor shares

[11] We show in the Appendix that the results are very similar for reasonable variations in σ.

The relevant σ is the elasticity of substitution between capital and labor at the industry level. This is greater than the firm-level elasticity, estimated to be between 0.4 and 0.7 (e.g., 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 this elasticity of substitution cannot be estimated from aggregate data.

[12] Our estimates for the growth rate of A_i^L/A_i^K should be interpreted as upper bounds, since in general growth in GDP per worker will be driven not just by labor-augmenting technological changes. Because in our main exercise $\sigma < 1$, this implies that we are also understating the importance of displacement effects reducing the task content of production. Nevertheless, reasonable variations on the imposed growth rate of A_i^L/A_i^K have small impacts on our decomposition results as we discuss below.

[13] The five-year time window is chosen to smooth out and minimize the influence of transitory measurement error. To the extent that there are simultaneous introduction of new automation technologies and new tasks within a five-year period, our estimates will be lower bounds both for the displacement and reinstatement effects.

[14] Our measure of labor demand is given by the wage bill in the private sector and thus excludes self-employment income. This avoids the need for partitioning self-employment income between labor and capital income. Elsby et al. (2013) show that labor income from self-employment has remained stable as a share of national income, which justifies our focus on the wage bill to study aggregate labor demand.

within sectors. In fact, the labor share in manufacturing and services increased during this period. The bottom panel of the figure shows the evolution of the share of value added of these sectors and confirms the secular reallocation from manufacturing towards services starting in the late 1950s.

Figure 5 presents our decomposition using the 43 industries in our sample. Our measure of labor demand, the wage bill, is divided by population so that changes in population do not confound the effects we are focusing on. As Figure 1 indicated, during this period labor demand per capita grew at a rate of 2.4% per annum. The top panel in Figure 5 shows that this growth of labor demand is largely explained by the productivity effect. The substitution and composition effects are small, and during this period (net) changes in the task content of production are small as well.

The middle panel of Figure 5 shows that, even though the net change in the task content of production during this period is small, there is considerable displacement and reinstatement within industries. Between 1947 and 1987, displacement is equivalent to a 17 log point decline in labor demand per capita. If this were not counterbalanced by the reinstatement effect, it would have led to a significant shift in the task contend against labor and a sizable slowdown in labor demand. Indeed, during this period there is a stronger reinstatement effect, equivalent to an increase in labor demand by 18.5 log points. The bottom panel of Figure 5 depicts an even stronger displacement effect together with a somewhat weaker restatement effect in manufacturing. This pattern suggests that during the four decades following World War II there was plenty of automation, especially in manufacturing, but this was accompanied with the introduction of new tasks (or other changes increasing the task content of production in favor of labor) in both manufacturing and the rest of the economy that offset the adverse labor demand consequences of automation.

3.2 Sources of Labor Demand: 1987-2017

For the 1987-2017 period, we use data from the Bureau of Economic Analysis (BEA) for 61 NAICS industries covering the private sector and complement them with data from the BLS on factor prices. As before, we use the wage bill per capita in the private sector to measure labor demand.

The top panel of Figure 6 presents the evolution of the labor share for the same six broad sectors used above. In contrast to the 1947-1987 period, there is a sizable decline in the labor share within manufacturing, construction, and mining. The bottom panel of the figure shows the continued reallocation of economic activity from manufacturing to services.

The top panel of Figure 7 presents our decomposition for 1987-2017. The first factor accounting for the slower growth of labor demand during this period is the anemic growth of productivity. The second factor contributing to slower growth of labor demand, especially after the 1990s, is a significant negative change in the task content of production (of 8 log points), which caused labor demand to decouple from productivity.[15] The middle and bottom panels show that the negative change in task content is driven by a deceleration of technologies reinstating labor (reinstatement

[15] These results are consistent with Elsby et al. (2013) 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 emphasize that technological improvements after 1980 have been associated with declines in labor share, while those in the previous decades have not been.

increases labor demand only by 10 log points) and an acceleration of displacement, especially in manufacturing (displacement reduces labor demand by 17 log points in the aggregate and by 32 log points in manufacturing; these estimates are 25% and 50% larger, per annum, than their counterparts in 1947-1987).

Composition and substitution effects, also presented in the top panel of Figure 7, are uniformly very small. This suggests that theories emphasizing the substitution towards capital-intensive tasks (in response to factor prices or factor augmenting technologies) or working through sectoral shifts have a limited role in explaining the decline in labor demand observed during this period. Although there is a rapid sectoral shift away from manufacturing, presumably driven by the strong displacement effect in this sector, the resulting composition effects are small because the labor share in manufacturing is similar to that in services (as the top panel of Figure 6 indicates).

In summary, the deceleration of labor demand growth over the last 30 years cannot be accounted for by composition or substitution effects, but is due to a combination of anemic productivity growth and adverse shifts in the task contents of production. We return to what might account for these changes after discussing the robustness and reliability of our estimates.

3.3 The Role of Factor-Augmenting Technologies

The patterns reported in the previous two subsections are robust to the assumptions on the elasticity of substitution and the rate of factor-augmenting technological change assumed to measure substitution effects. In the Appendix we verify that our estimates are similar when we use different values of the elasticity of substitution (in particular, with $\sigma = 0.6$, $\sigma = 1$ and $\sigma = 1.2$) and 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 reported in the Appendix. We compute the changes in factor-augmenting technologies at the industry level (while still assuming no "technological regress") that would be necessary to explain changes in industry labor shares *without any* change in task content of production. We then plot the implied aggregate TFP changes. The Appendix shows that these are gargantuan—several folds larger than the observed TFP increases during the last seven decades—which reflects the fact that 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.

3.4 What Does the Change in Task Content Capture?

Since we computed the change in task content as a residual, a natural concern is that it corresponds to something different than the displacement and reinstatement effects of automation technologies and new tasks. In this subsection, we provide evidence to support our view that inferred changes in task content capture changes in technology. We show that across industries, inferred changes in task content are negatively correlated with measures of automation technologies and positively correlated with measures of new tasks. For this exercise we focus on the 1987-2017 period because our measures of automation technology and new tasks are only available for this period.

Figure 8 provides bivariate associations between changes in the task content across industries between 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 negative correlation is visible in the top left panel. This variable alone accounts for 17% of cross-industry variation in change in task content. The figure reports the bivariate regression coefficient (-1.23 with s.e.= 0.34) as well as estimate when we control for a manufacturing dummy and for imports from China and offshoring.[16] Since industrial robots are an important example of automation technologies, this negative association is reassuring for our interpretation.

The top right panel shows a similar, but somewhat weaker, relationship using Graetz and Michaels's (2018) share of *replaceable occupations* by industry, which measures the share of occupations that can be replaced using industrial automation technologies.

The bottom left panel uses two measures of technology adoption from the Survey of Manufacturing Technologies (SMT) for 1988 and 1993 (see Doms et al., 1997). The left panel uses 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. The right panel expands this measure to other advanced technologies such as sensors used on products, computer aided design, networks and computers used on the factory floor, flexible manufacturing cells, and material working lasers. The SMT measures are available for a detailed set of 148 four-digit SIC industries comprising the following two-digit "technology-intensive"manufacturing industries: fabricated metal products, industrial machinery, electronics, transportation equipment, and controlling instruments. To exploit these disaggregated data, in these two panels 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 (see the Appendix for a description of these data). Even within this detailed group of manufacturing industries, we see a strong negative association between the SMT measures of technology adoption and changes in task content.[17]

Figure 9 turns to proxies for the creation of new tasks across industries. The top left panel uses the share of new job titles within each occupation from the 1991 Dictionary of Occupational Titles compiled by Lin (2011). We mapped this measure to our 61 industries using the share

[16] See Table A1 in the Appendix for more details. In particular, we are controlling for the growth of final goods imports from China (as in Autor, Dorn and Hanson, 2013; Acemoglu et al., 2015) and a measure of offshoring of intermediate goods (Feenstra and Hanson, 1999; Wright, 2013). Changes in task content are unrelated to imports of final goods from China (which should, according to our framework, affect labor demand via productivity and composition effects). Task content changes are correlated with offshoring, which often involves the offshoring of labor-intensive tasks (see Elsby et al. 2013). Yet, controlling for offshoring does not change the relationship we report in Figure 8 because offshoring is affecting a different set of industries than our measures of automation.

[17] This relationship is again robust to controlling for manufacturing, imports from China and offshoring. Dinlersoz and Wolf (2018) document a similar relationship at the firm level—manufacturing firms using more advanced technologies appear to be more productive and to have lower labor shares.

of employment by occupation from the 1990 Census. As expected there is a positive correlation between this measure of new tasks and changes in task content across industries (the relationship is very similar when we include controls). The top right panel shows a similar pattern when we use a measure of emerging tasks by occupation from O*NET (which gives the number of new tasks that workers identify as becoming increasingly important in their jobs). Finally, the two bottom panels of Figure 9 show that increases in occupational diversity are associated with a positive change in task content. The bottom left panel uses the share of employment growth in an industry accounted for by "new occupations", defined as occupations that were not represented in that industry in 1990 but were present in 2016. The bottom right panel focuses on the percent increase in the number of occupations in an industry between 1990 and 2016.

Finally, Table A2 in the Appendix shows that (positive or negative) changes in task content predict growth of quantities produced and declines in prices across industries, consistent with the idea that they are being driven by changes in technology.

These patterns bolster our confidence that our estimates of changes in task content contain valuable information related to technology and support the interpretation that the rapid displacement effect of the last three decades is related to the introduction of modern automation technologies.

3.5 What Explains the Weak Productivity Effect Between 1987 and 2017?

Our results suggest that it is the combination of adverse shifts in the task content of production—driven by accelerated automation and decelerating reinstatement—and weak productivity growth that account for the sluggish growth of labor demand over the last three decades and especially since the late 1990s. Why has productivity growth been anemic despite the acceleration of automation technologies? Though this is a question for future research, a few points are worth making.

First, our decomposition suggests that a large component of technological change during this period came from automation. As already pointed out in Section 2, productivity gains from automation could be quite small in practice—the case of "so-so" technologies whereby automation is substituting for tasks in which labor was already productive and capital is not yet very effective.

Second, our estimates suggest that there has been a significant slowing down of the reinstatement effect (for example, because of the introduction of new tasks). To the extent that such new tasks were important in undergirding rapid productivity growth, slower reinstatement will be associated with slower productivity growth.[18]

Third, if both automation innovations and the creation of new tasks are subject to diminishing returns within a given period of time, a significant change in the balance between these two types of new technologies will push us towards greater diminishing returns and cause slower productivity growth. This will be especially the case when the reason for such a tilt in favor of automation is increasing enthusiasm or focus on automation, which we may be experiencing due to the emphasis in the technology world and Silicon Valley on automation and uses of AI geared towards replacing

[18] In addition, the lower wage growth resulting from a weak reinstatement effect would also indirectly make automation less productive because, as our framework has emphasized, productivity gains from automation are commensurate with the effective wage in tasks being replaced, and lower wages thus reduce these productivity gains.

(rather than complementing) humans in various activities. Relatedly, even with a given state of technological know-how, there may be factors pushing towards excessive automation, which will be associated with slower or even negative productivity growth. These factors include tax policies favoring capital expenditures over payments to labor and labor market imperfections increasing the wage rate over the opportunity cost of labor, which encourages firms to adopt automation technologies beyond the socially optimal point (Acemoglu and Restrepo, 2018a).

Finally, Acemoglu and Restrepo (2018d) suggest there may be a mismatch between the available skills of the workforce and the needs for new technologies, which could further reduce productivity gains from automation and hamper the introduction of new tasks—because the lack of requisite skills reduces the efficiency with which new technologies can be deployed.

4 Concluding Remarks

This paper developed a task-based model based on Acemoglu and Restrepo (2018a, 2018b) to study the effects of different 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 technologies 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 labor demand, 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 US postwar period. 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 anemic growth of productivity.

Even though we have provided evidence documenting the correlation between our measure of task content and automation and new tasks, several other factors may also be affecting our estimates. These include an increase in markups; growing monopsony power of firms; unmeasured offshoring of labor-intensive tasks; and reallocation of economic activity towards capital intensive firms within an industry. Understanding the full suite of factors shaping the task content of production and impacting labor demand beyond the task content and factor-augmenting changes is an exciting area for future research.

Our framework has clear implications for the future of work too. Our evidence and conceptual approach support neither the claims that the end of human work is imminent nor the presumption that technological change will always and everywhere be favorable to labor. 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 depends not just on our innovation capabilities but also on the supply of different skills, demographic changes, labor market institutions, tax and R&D policies of governments, market competition, corporate strategies and the ecosystem of innovative clusters.

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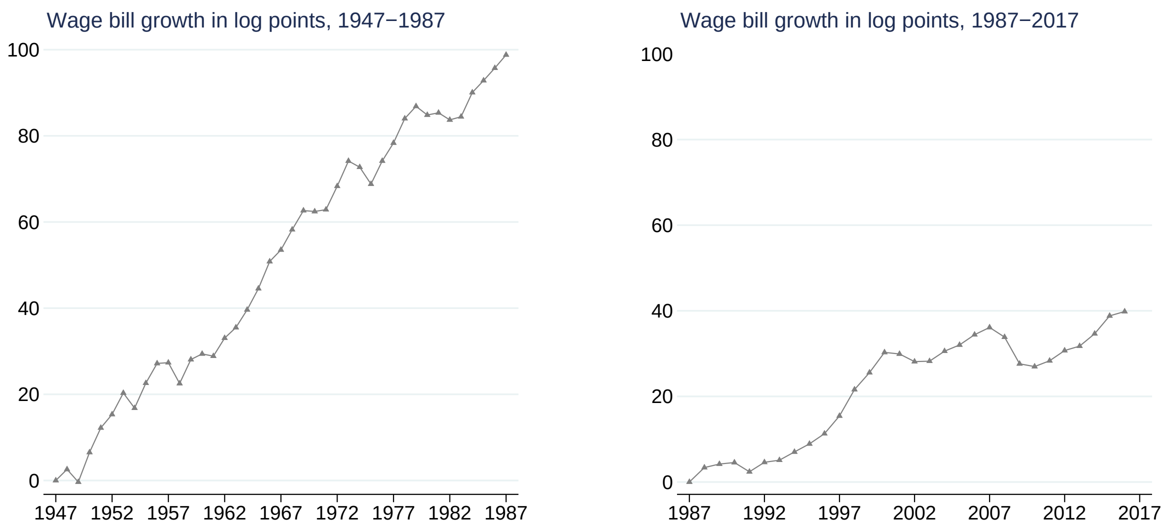


Figure 1: The evolution of labor demand for the periods 1947-1987 and 1987-2017.
Note: The figure shows the growth rate of the (real) wage bill per capita in log points. Data from the BEA industry accounts.

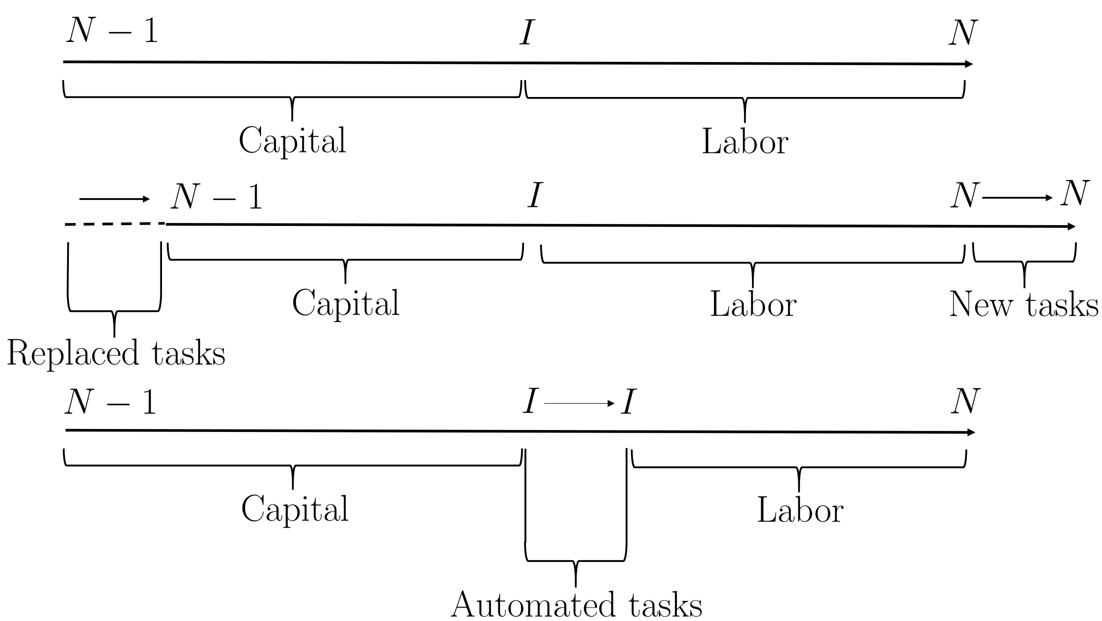


Figure 2: The allocation of capital and labor to the production of tasks and the impact of automation and the creation of new tasks.

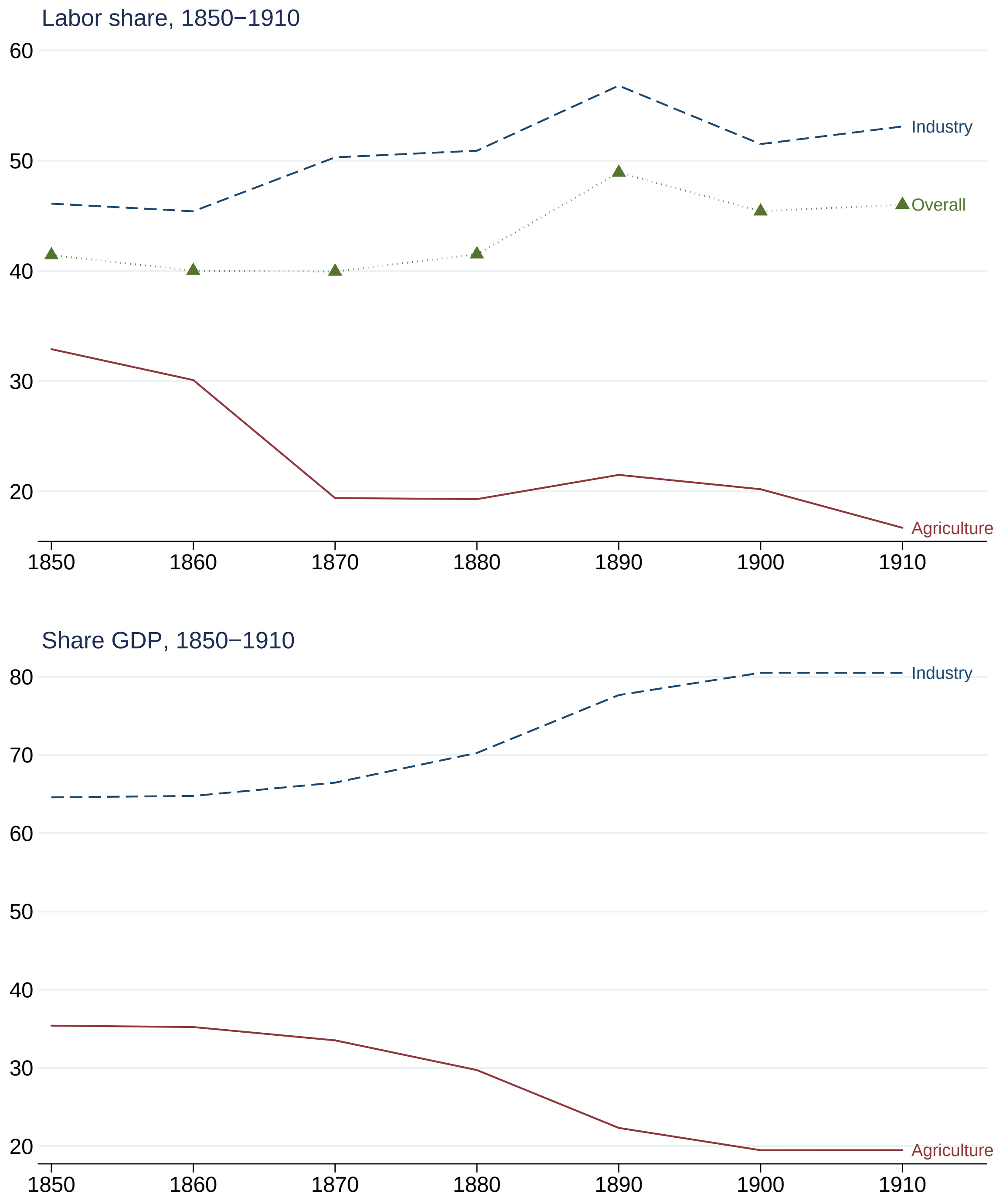


Figure 3: Labor share and sectoral evolutions during the mechanization of agriculture, 1850-1910. Note: The top panel shows the labor share in value added in industry (services and manufacturing) and agriculture between 1850-1910, while the bottom panel shows the share of value added in these sectors relative to GDP. Data from Budd (1960).

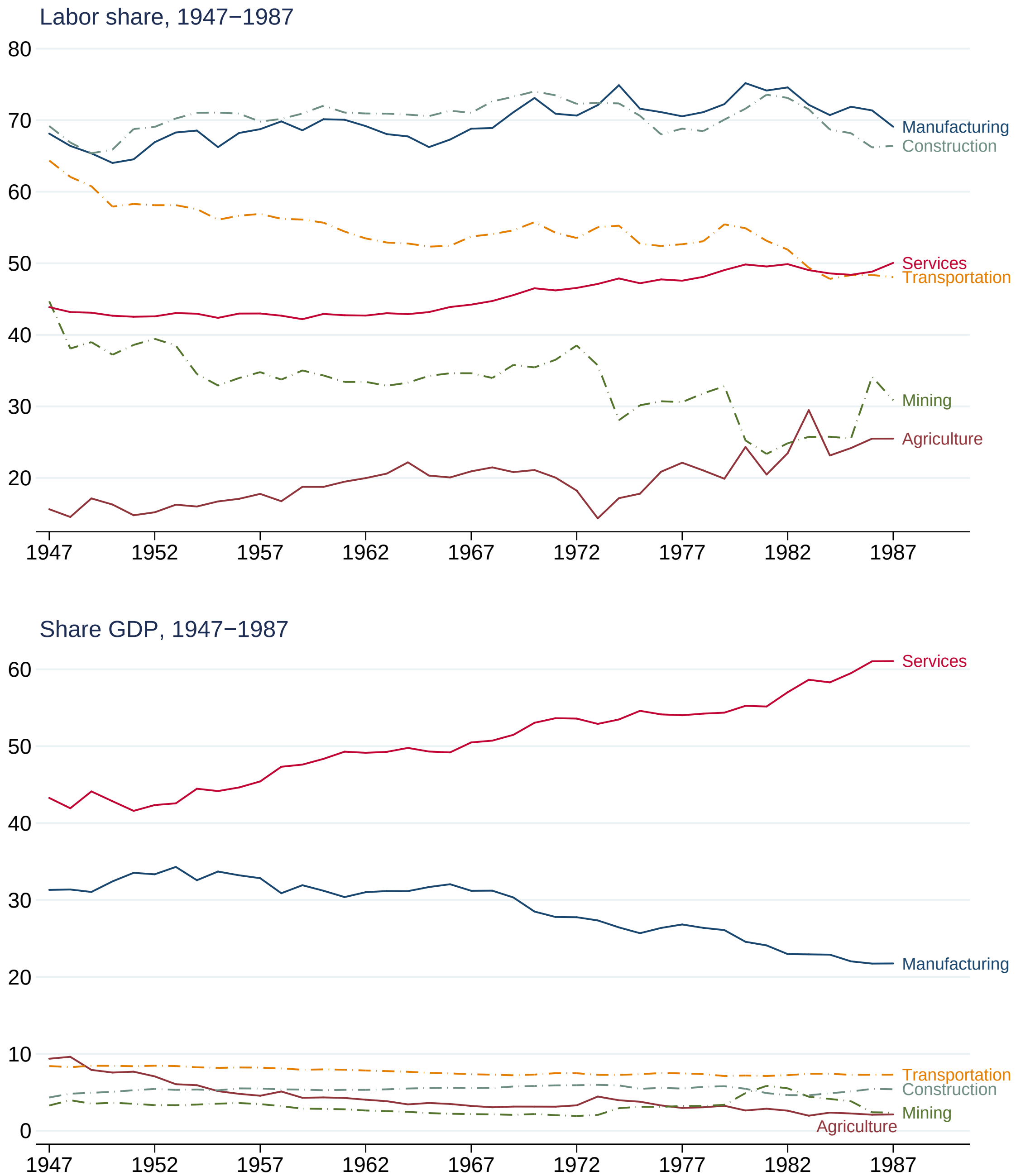


FIGURE 4: THE LABOR SHARE AND SECTORAL EVOLUTIONS, 1947-1987.

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. Data from the BEA industry accounts.

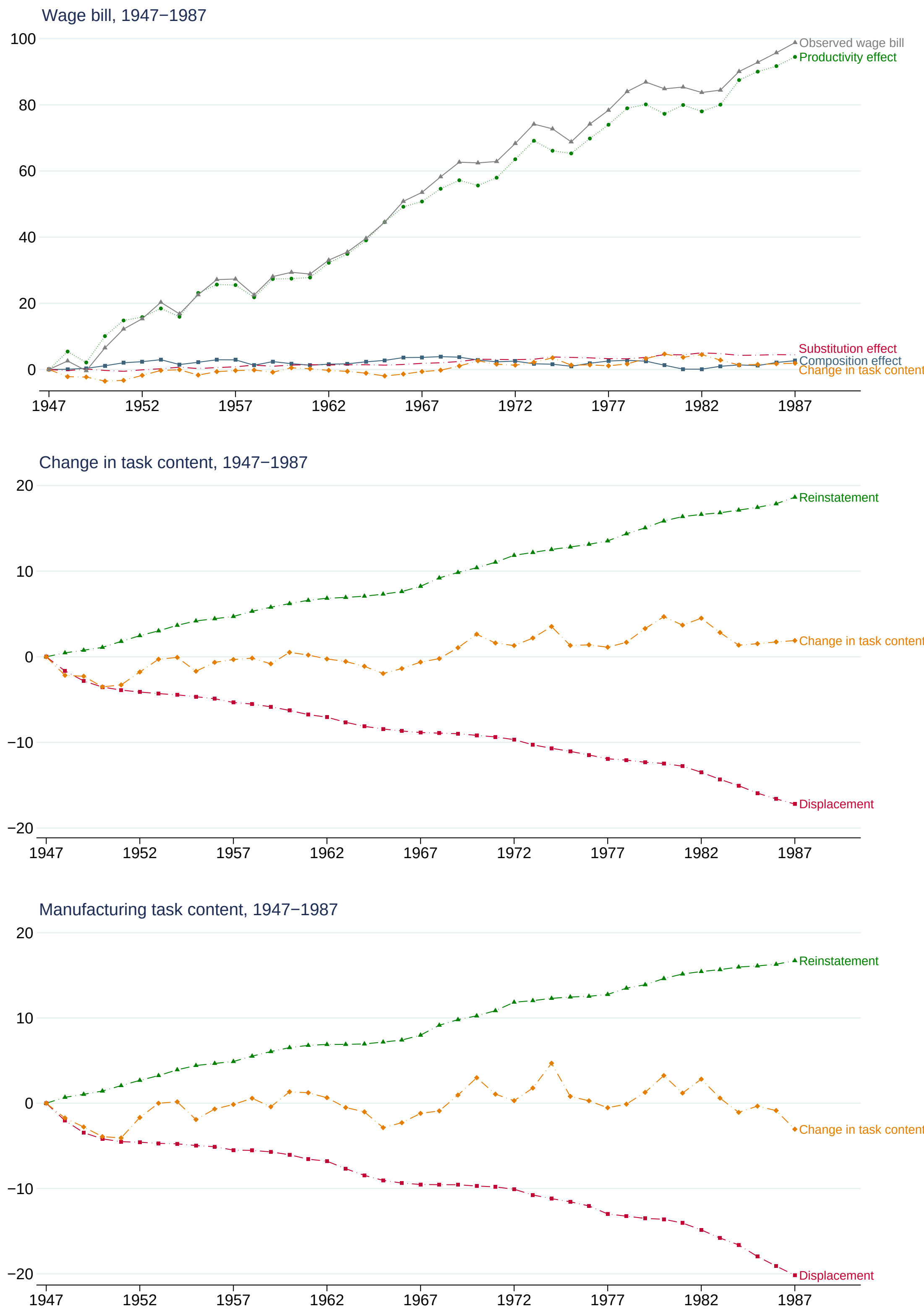


FIGURE 5: SOURCES OF CHANGES IN LABOR DEMAND, 1947-1987.

Note: The top panel presents the decomposition of labor demand (wage bill) between 1947 and 1987. The middle and bottom panels present our estimates of the displacement and reinstatement effects for the entire economy and the manufacturing sector, respectively. In all panels, we assume an 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.

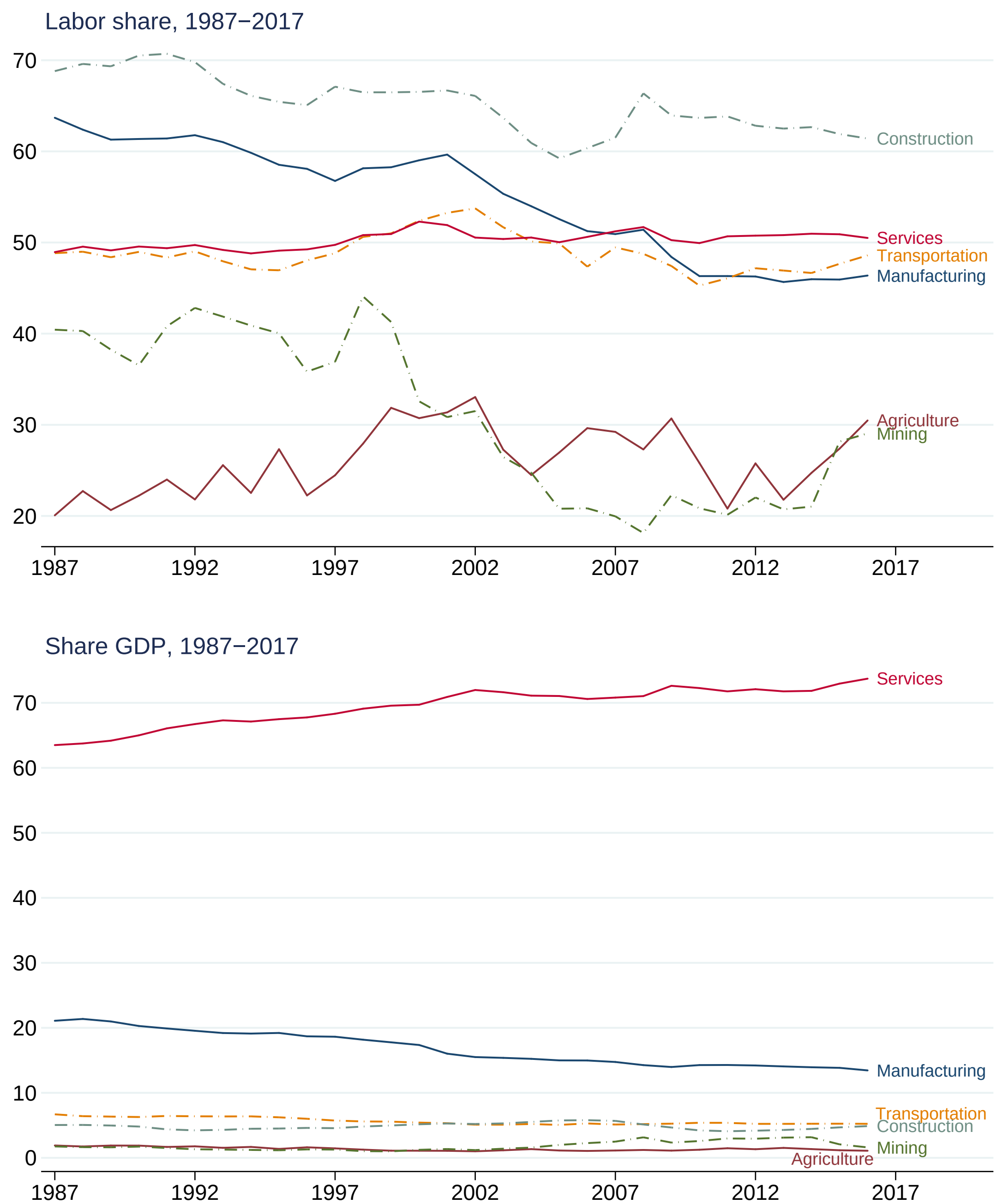


FIGURE 6: THE LABOR SHARE AND SECTORAL EVOLUTIONS, 1987-2017.
Note: The top panel shows the labor share in value added in services, manufacturing, construction, transportation, mining and agriculture between 1987 and 2017, while the bottom panel shows the share of value added in the sectors relative to GDP. Data from the BEA industry accounts.

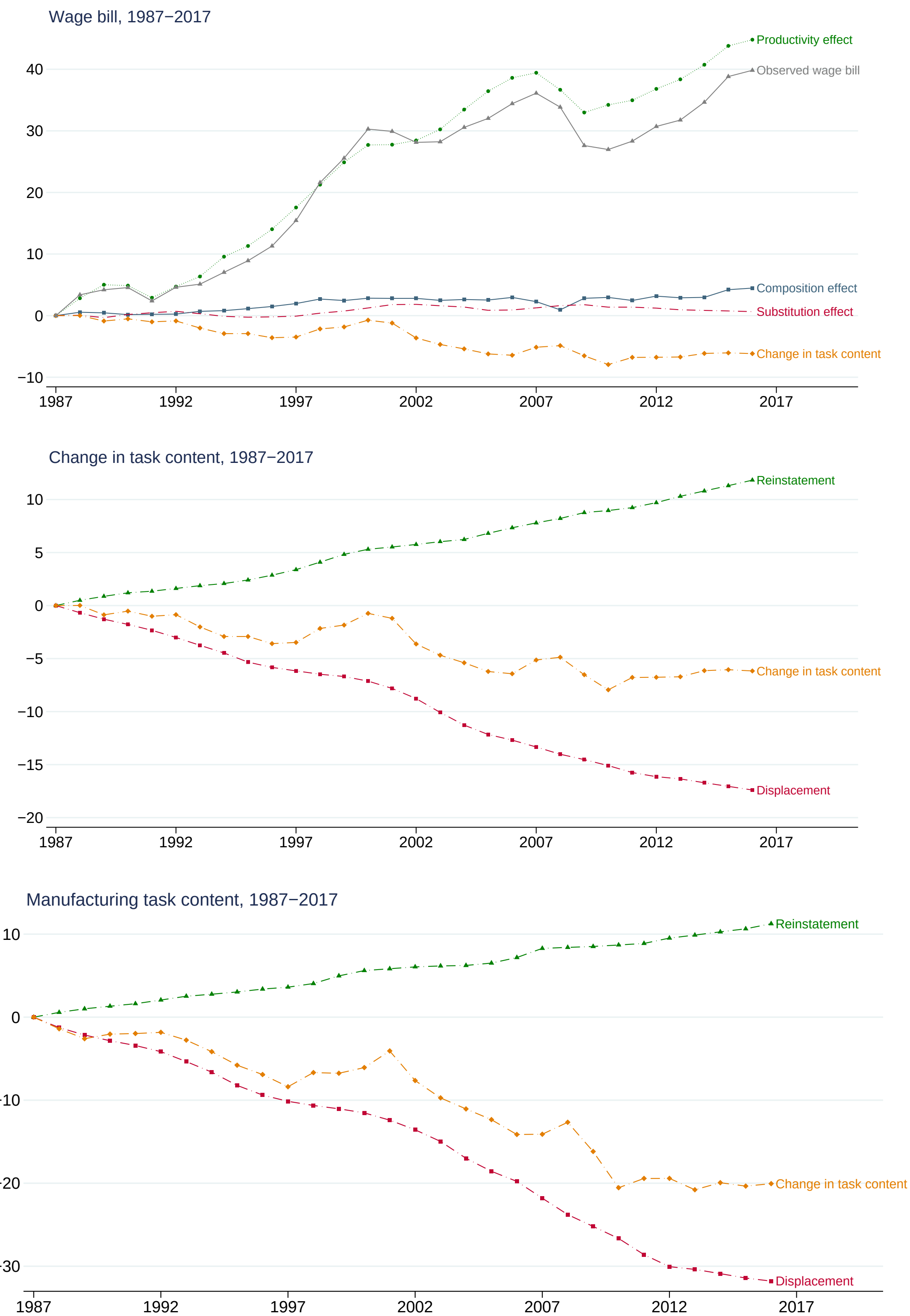


Figure 7: Sources of changes in labor demand, 1987-2017.

Note: The top panel presents the decomposition of labor demand (wage bill) between 1987 and 2017. The middle and bottom panels present our estimates of the displacement and reinstatement effects for the entire economy and the manufacturing sector, respectively. In all panels, we assume an 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.

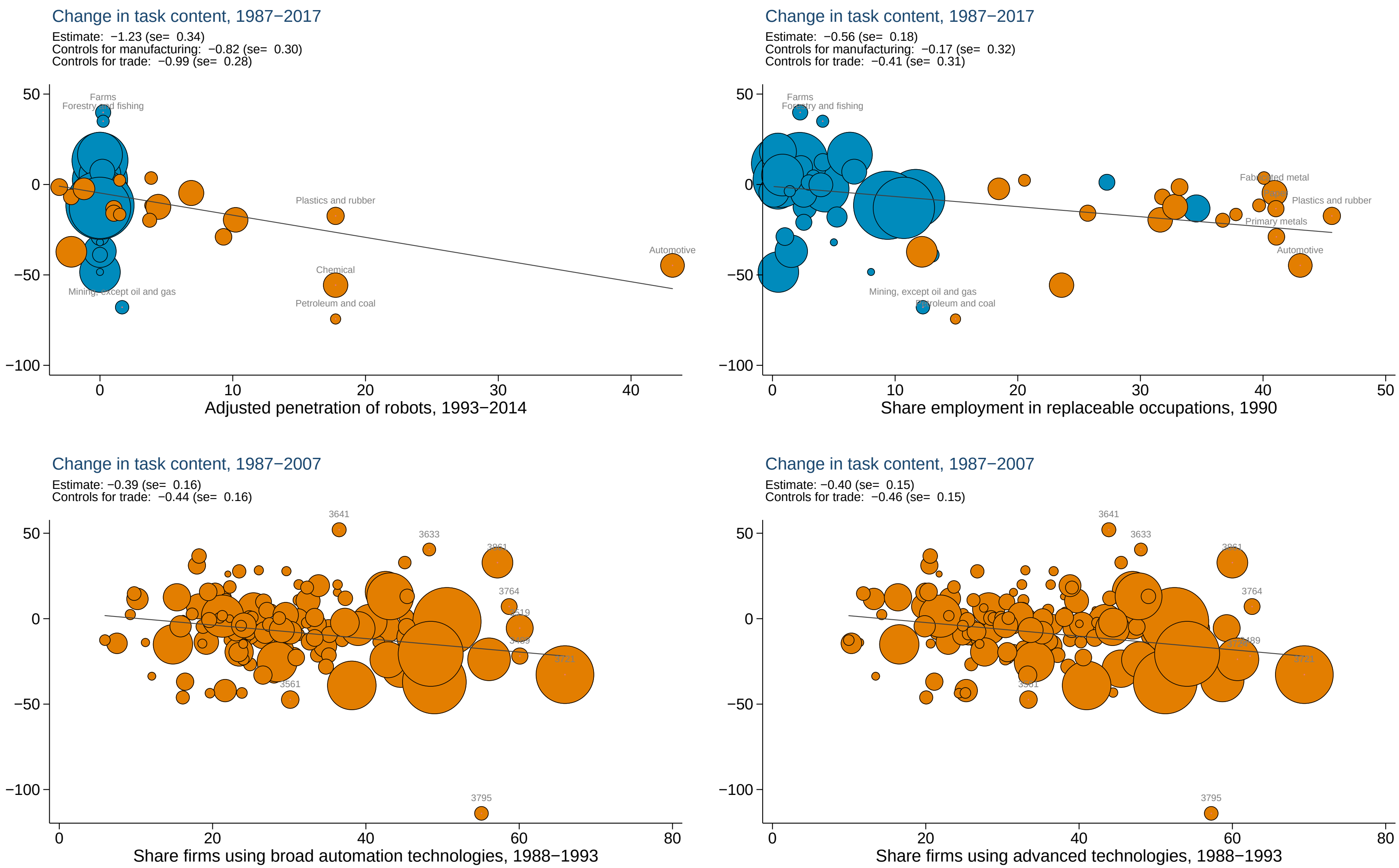


Figure 8: Automation technologies and change in the task content of production.

Note: Each panel presents the bivariate relationship at the industry level between change in task content and the indicated proxy for automation technologies. 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.

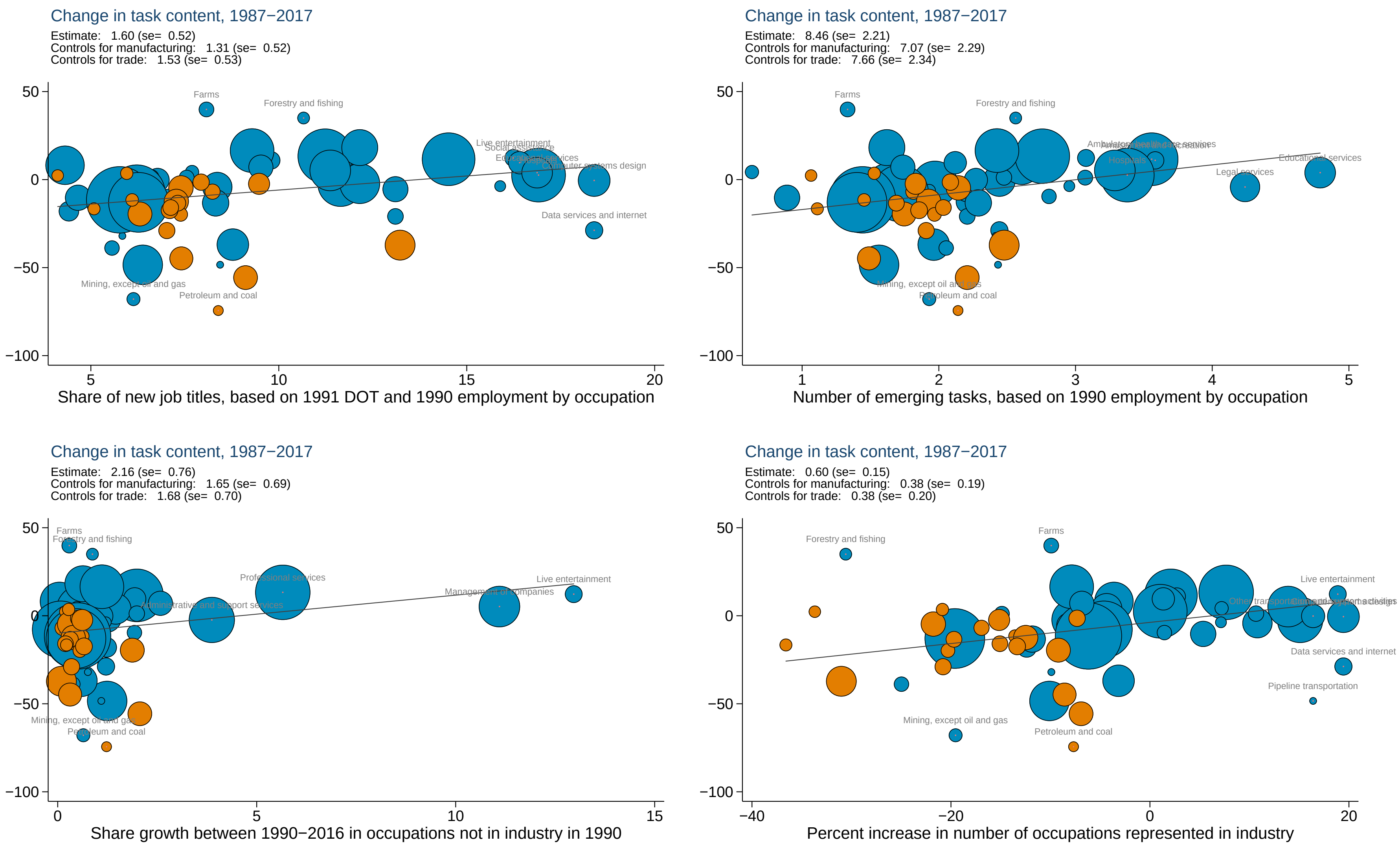


FIGURE 9: NEW TASKS AND CHANGE IN TASK CONTENT OF PRODUCTION.

Note: Each panel presents the bivariate relationship at the industry level between change in task content and the indicated proxy for new tasks. 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.

Online Appendix

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

A1 Theory

Full Model Description

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

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 main text and in footnote 5, we assume that

$$\frac{1-\Gamma(N,I)}{\Gamma(N,I)} \left(\frac{A^L}{A^K} \frac{\gamma^L(I)}{\gamma^K(I)} \right)^{\sigma} < \frac{K}{L} < \frac{1-\Gamma(N,I)}{\Gamma(N,I)} \left(\frac{A^L}{A^K} \frac{\gamma^L(N)}{\gamma^K(N-1)} \right)^{\sigma}. \tag{A2}$$

This assumption guarantees that

$$\frac{A^L}{A^K} \frac{\gamma^L(I)}{\gamma^K(I)} < \frac{W}{R} < \frac{A^L}{A^K} \frac{\gamma^L(N)}{\gamma^K(N-1)}, \tag{A3}$$

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 treated in Acemoglu and Restrepo (2018a).

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

$$\text{(A4)} \qquad Y(L,K;\theta) = \left(\left(\int_{N-1}^{I} \gamma^K(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A^K K)^{\frac{\sigma-1}{\sigma}} + \left(\int_{I}^{N} \gamma^L(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A^L L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

Equation (2) now follow directly from this expression. The labor share can also be equivalently expressed as a function of labor, capital and factor-augmenting technologies as well as the task content of production:

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

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

$$\text{(A6)} \qquad W^d(L,K;\theta) = \frac{Y(L,K;\theta)}{L} \times s^L(L,K;\theta).$$

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 (A6) and then using (A4) and (A5).

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

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

Moreover, we can also use equation (A4) to compute the productivity effect as

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

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

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

where the productivity effect is now given by

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

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

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

Decomposition of Labor Demand

This section explains how technology affects aggregate labor demand in a model with multiple sectors. This section complements our discussion in section 2.3 of the main text. The decomposition for labor demand that we derive here provides the basis for the exercise in Section 3 of the main text.

Recall that sectors are indexed by subscript i and $\mathcal{I}$ represents 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 (A3). The technology available to sector i is summarized 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 $\chi_i = \frac{P_iY_i}{Y}$ as the share of sector i's in total value added. Finally, we denote by s^L the economy-wide labor share.

Changes in total wage bill in the economy, WL, can then be decomposed as

$$\begin{aligned}
\text{(A7)}\quad d\ln(WL) =& d\ln Y && \text{(Productivity effect)}\\
&+\sum_{i\in\mathcal{I}}\left(\frac{s_i^L}{s^L}-1\right)d\chi_i && \text{(Composition effect)}\\
&+\sum_{i\in\mathcal{I}}\ell_i\frac{1-s_i^L}{1-\Gamma_i}d\ln\Gamma_i && \text{(Change in task content)}\\
&+\sum_{i\in\mathcal{I}}\ell_i(1-\sigma)(1-s_i^L)(d\ln W_i/A_i^L - d\ln R_i/A_i^K) && \text{(Substitution effect)}
\end{aligned}$$

where $\ell_i = \frac{W_iL_i}{WL}$ 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 many assumptions related to factor mobility. 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 $\frac{dx}{x} = d\ln x$, 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 (2), we have

$$\text{(A8)} \qquad d\ln s_i^L = \frac{\left(1 - s_i^L\right)}{1 - \Gamma_i} d\ln \Gamma_i + (1-\sigma)(1 - s_i^L)(d\ln W_i/A_i^L - d\ln R_i/A_i^K).$$

Substituting this into the previous expression, we obtain (A7).

As the derivation shows, the decomposition in equation (A7) is quite general. To derive it, we do not need to make assumptions about factor mobility across sectors, or about input-output linkages or preferences over different goods. The only assumption is that firms are in 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.

Inferring the Task Content of Production

This section explains how to compute all the terms in equation (A7) using our data. This is the methodology we follow to produce the figures described in Section 3 of the main text.

Our point of departure is equation (A7). 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

$$\begin{aligned}\text{Observed change in wage bill}_t =& \Delta \ln(W_t L_t / Pop_t)\\ \text{Productivity effect}_t =& \Delta \ln(Y_t/Pop_t)\\ \text{Composition effect}_t =& \sum_{i\in\mathcal{I}} \left(\frac{s^L_{i,t}}{s^L_t} - 1\right)\Delta\chi_{i,t}\end{aligned}$$

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 (A7), we are normalizing the wage bill and GDP by population to account for population growth during our sample period.

Based on equation (A7), we define the substitution effect in industry i as

$$(1-\sigma)(1-s^L_i)\left(d\ln(W_i/R_i) - d\ln(A^L_i/A^K_i)\right),$$

and the change in task content in industry i as

$$\frac{(1-s^L_i)}{1-\Gamma_i} d\ln\Gamma_i.$$

To compute the substitution effect in an industry at a yearly frequency, we use data on yearly changes in prices from the BLS (described in the data section of this Appendix) and a baseline value for σ of 0.8. Furthermore, we impose different estimates for the annual growth rate of $A^L_{i,t}/A^K_{i,t}$. Using these values, we compute the substitution effect in an industry as

$$\text{Substitution effect}_{i,t} = (1-\sigma)(1-s^L_{i,t})\left(\Delta\ln(W_{i,t}/R_{i,t}) - \Delta\ln(A^L_{i,t}/A^K_{i,t})\right),$$

and the economy-wide substitution effect as

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

To compute the change in task content in an industry, we exploit the fact that, as equation A8 shows, the substitution effect and the change in task content add up to the percent change in the labor share of the industry. We estimate the change in task content in an industry as

$$\text{Change in task content}_{i,t} = \Delta\ln s^L_{i,t} - (1-\sigma)(1-s^L_{i,t})\left(\Delta\ln(W_{i,t}/R_{i,t}) - \Delta\ln(A^L_{i,t}/A^K_{i,t})\right).$$

The economyu-wide change in the task content of production is then given by

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

Finally, under the assumption that, over five-year windows, an industry engages in either automation or the creation of new tasks but not in both activities, we have

$$\text{(A9)}\qquad \text{Displacement}_t = \sum_{i\in\mathcal{I}} \ell_{i,t} \min\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} \text{Change in task content}_{i,\tau}\right\} \text{ and}$$
$$\text{Reinstatement}_t = \sum_{i\in\mathcal{I}} \ell_{i,t} \max\left\{0, \frac{1}{5}\sum_{\tau=t-2}^{t+2} \text{Change in task content}_{i,\tau}\right\}.$$

Counterfactual TFP implications

This section describes how to derive estimates of the change in factor augmenting technologies that one would need to explain the entire change in industries labor shares. This derivation provides the basis for our discussion in Section 3.3 in the main text.

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

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

and

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

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

$$\text{(A10)}\qquad \text{Contribution of } A^L \text{ to TFP}_t = \sum_i \chi_{i,t} \frac{s^L_{i,t}}{(\sigma-1)(1-s^L_{i,t})} \times \text{Displacement}_{i,t} > 0,$$

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

$$\text{(A11)}\qquad \text{Contribution of } A^K \text{ to TFP}_t = \sum_i \chi_{i,t} \frac{1-s^L_{i,t}}{(1-\sigma)(1-s^L_{i,t})} \times \text{Reinstatement}_{i,t} > 0.$$

Alternative Production Function

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

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

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

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

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

A2 Data and Additional Empirical Results

We now describe the data and the construction of the variables used in the text, and provide additional results and robustness checks.

Data Description

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 $Y_{i,t}^L$ denotes worker compensation in industry i, $L_{i,t}^{qty}$ 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:

$$\Delta \ln W_{i,t} = \Delta \ln Y^L_{i,t} - \Delta \ln L^{qty}_{i,t}, \tag{A12}$$

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:

$$\Delta \ln R_{i,t} = \Delta \ln(Y_{i,t} - Y^L_{i,t}) - \Delta \ln K^{qty}_{i,t}, \tag{A13}$$

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: In our baseline estimates, the substitution effect and the change in the task content of production in industry i are computed as:

$$\begin{aligned}\text{Substitution}_{i,t} =& (1-\sigma)(1-s_i^L)\left(\Delta\ln(W_{i,t}/R_{i,t}) - \Delta\ln A_{i,t}^L/A_{i,t}^K\right),\\ \text{Task content}_{i,t} =& \Delta\ln s_{i,t}^L - (1-\sigma)(1-s_{i,t}^L)\left(\Delta\ln(W_{i,t}/R_{i,t}) - \Delta\ln(A_{i,t}^L/A_{i,t}^K)\right).\end{aligned}$$

This computation requires estimates of $\Delta\ln W_{i,t}$ and $\Delta\ln R_{i,t}$ as well as σ and the growth rate of factor augmenting technologies, $\Delta\ln A_{i,t}^L/A_{i,t}^K$.

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, $\Delta\ln A_{i,t}^L/A_{i,t}^K$. In particular, the substitution effect and the change in the task content of production in industry i can also be computed as:

$$\begin{aligned}\text{Substitution}_{i,t} =& (1-\sigma)\Delta\ln s_{i,t}^L - (1-\sigma)(1-s_{i,t}^L)\left(\Delta\ln(L_{i,t}^{qty}/K_{i,t}^{qty}) + \Delta\ln(A_{i,t}^L/A_{i,t}^K)\right),\\ \text{Task content}_{i,t} =& \sigma\Delta\ln s_{i,t}^L + (1-\sigma)(1-s_{i,t}^L)\left(d\ln(L_{i,t}^{qty}/K_{i,t}^{qty}) + d\ln(A_{i,t}^L/A_{i,t}^K)\right).\end{aligned} \tag{A14}$$

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 (A12) and (A12).

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. With our measures of capital and labor used by industry at hand, we computed the change in task content and substitution effect using the alternative formulas in equation (A14).

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.

As noted in the text, the numbers on wages 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 and towards 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 and new tasks: For a description of the *adjusted penetration of robots* measure see Acemoglu and Restrepo (2018b).

The top right panel of Figure 8 uses Graetz and Michaels's (2018) measure of *replaceable occupations*, which captures the occupations that can be replaced using industrial automation technologies. We mapped this measure to our 61 industries using the share of employment by occupation from the 1990 Census. We use the detailed occupational codes provided by the Census, which include more than 300 distinct occupations.

For a description of the two additional measures of technology adoption from the Survey of Manufacturing Technologies (SMT) used in Figure 8 see Doms et al. (1997) and Acemoglu et al. (2014).

The top left panel of Figure 9 uses the share of new job titles within each occupation from the 1991 Dictionary of Occupational Titles compiled by Lin (2011). As before, we mapped this measure to our 61 industries using the share of employment by occupation from the 1990 Census. We use the detailed occupational codes provided by the Census, which include more than 300 distinct occupations.

The top right panel of Figure 9 uses a related proxy based on the number of emerging tasks in an occupation, as classified by O*NET, and projected to industries using their employment distribution across occupations in the 1990 Census. 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.

The bottom panels of Figure 9 use two measures of occupational diversity. The bottom left panel uses Census data and measures occupational diversity as the share of employment growth in an industry accounted for by "new occupations," defined as occupations that were not represented in that industry in 1990 but appeared in the industry in 2016. The bottom right panel measures occupational diversity as the percent increase in the number of occupations in an industry between 1990 and 2016, computed also from Census data. Our data for 2016 comes from the pooled American Community Survey sample for 2012-2016.

Additional Empirical Results

- Figure A1 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 main text.

- Figures A2, A3 and A4 provide our decomposition for the 1947-1987 period using different values for the elasticity of substitution σ.

- Figures A5, A6 and A7 provide our decomposition for the 1987-2017 period using different values for the elasticity of substitution σ.

- Figure A8 provides our decomposition for 1947-1987 and 1987-2017 using different assumptions for the term $g^A_{i,t}$—the growth rate of labor-augmenting technologies relative to capital-augmenting ones.

- Figure A9 provides the counterfactual TFP increases that one would have to observe if displacement were explained by increases in A^L_i and reinstatement by increases in A^K_i across all industries.

- Figure A10 presents bivariate regression plots of the change in task content and import competition from China and offshoring.

- Table A1 presents the regression results already summarized in Figures 8 and 9 in the main text. Table A2 presents results for changes in quantities produced, prices and the skill intensity of industries.

Appendix References

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.

FIGURE A1: 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 (A9) 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 an elasticity of substitution between capital and labor equal to $\sigma = 0.8$.

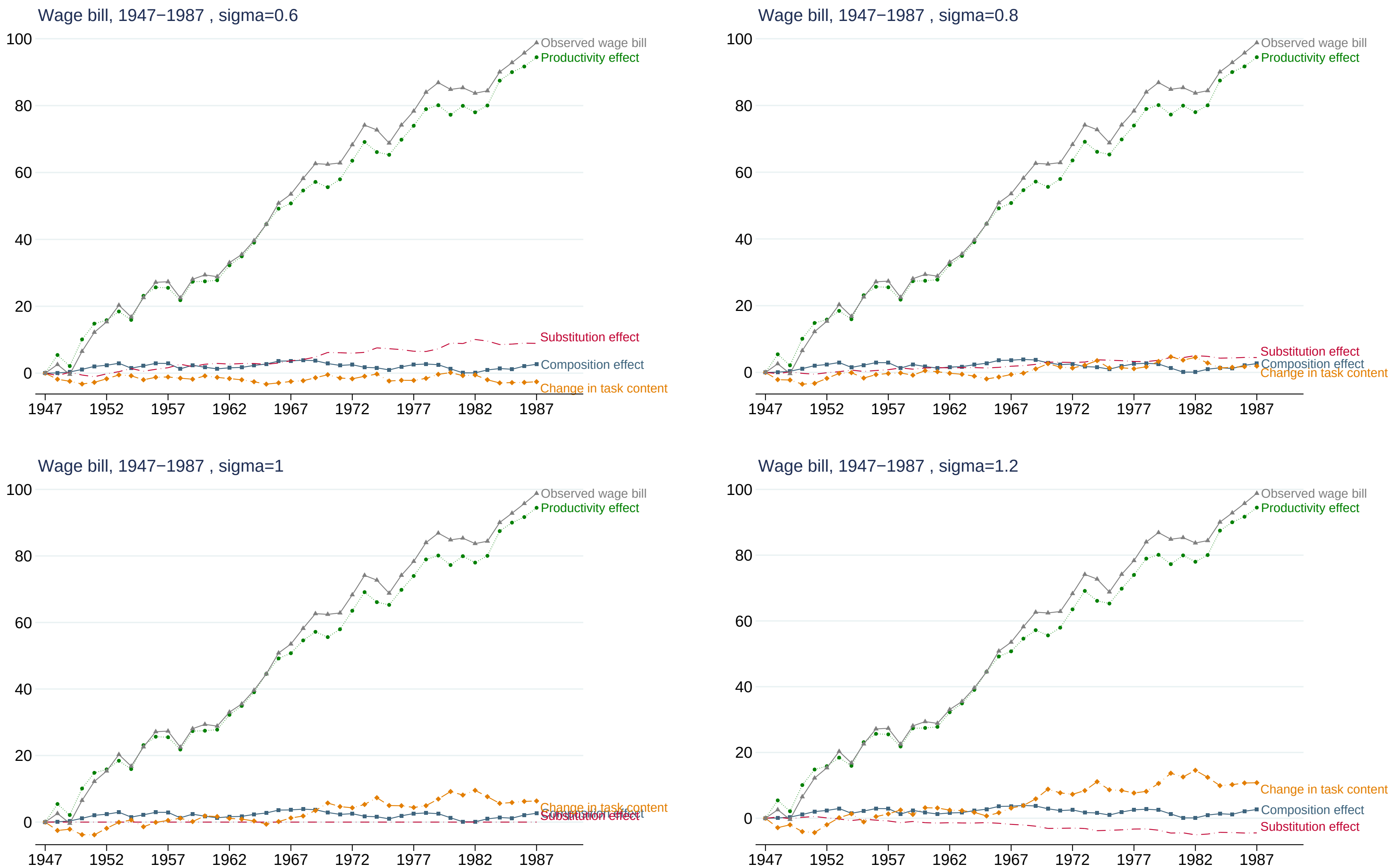


Figure A2: Sources of changes in labor demand for the entire economy, 1947-1987, for different assumed values of σ.

Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (A7) 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.

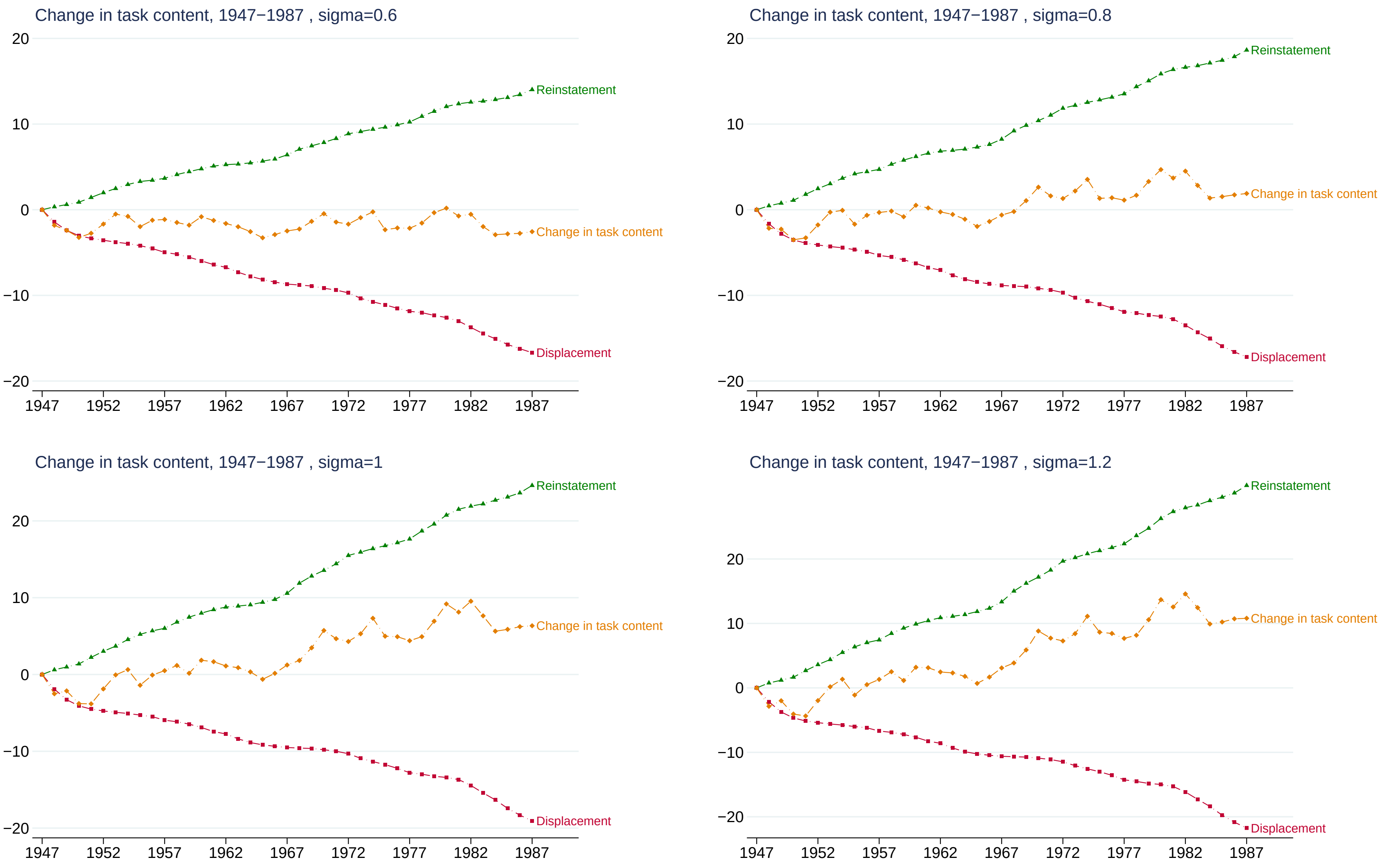


Figure A3: Estimates of the displacement and reinstatement effects for the entire economy, 1947-1987, for different assumed values of σ.
Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A9) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

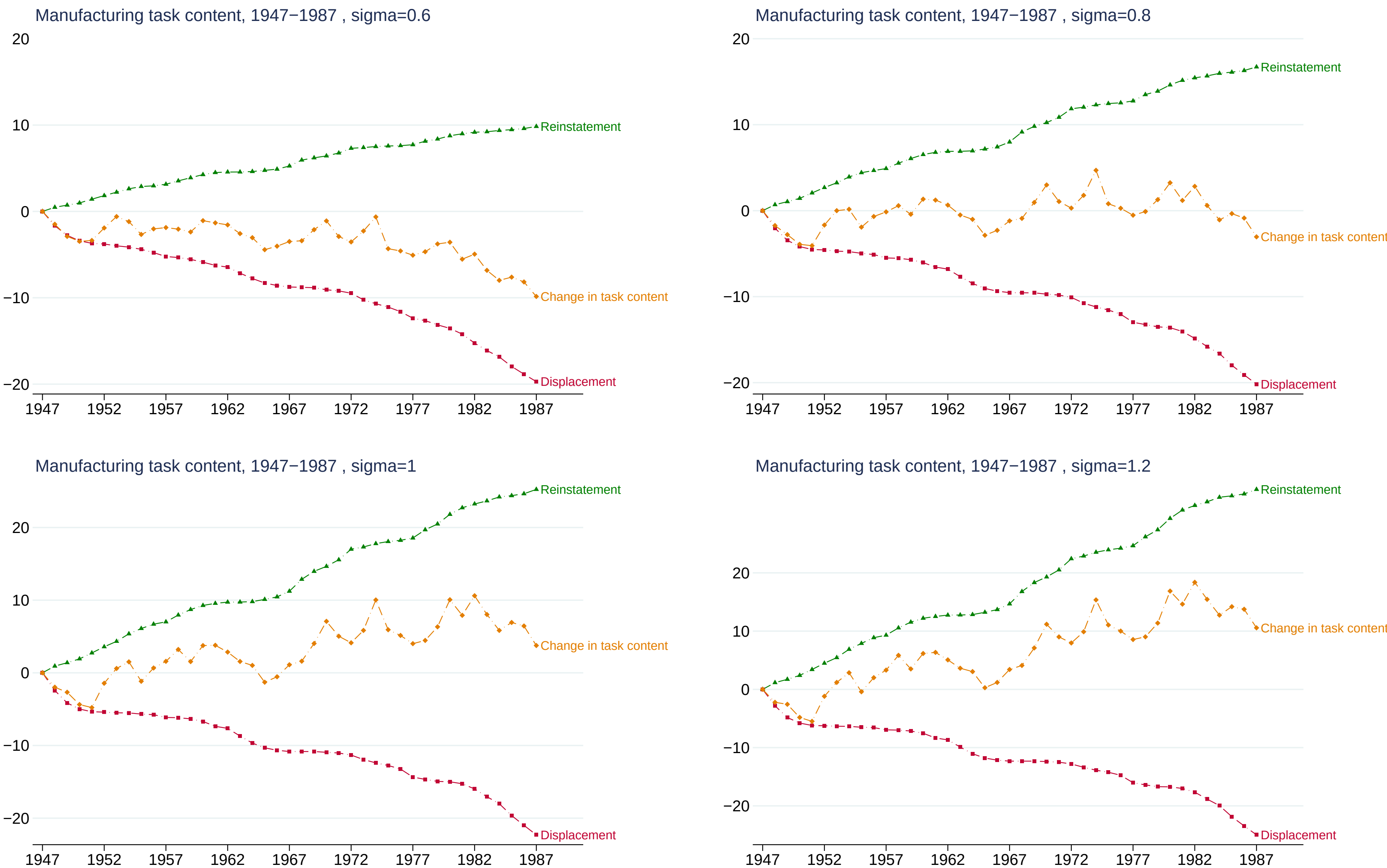


Figure A4: Estimates of the displacement and reinstatement effects for manufacturing, 1947-1987, for different assumed values of σ.
Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A9) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.

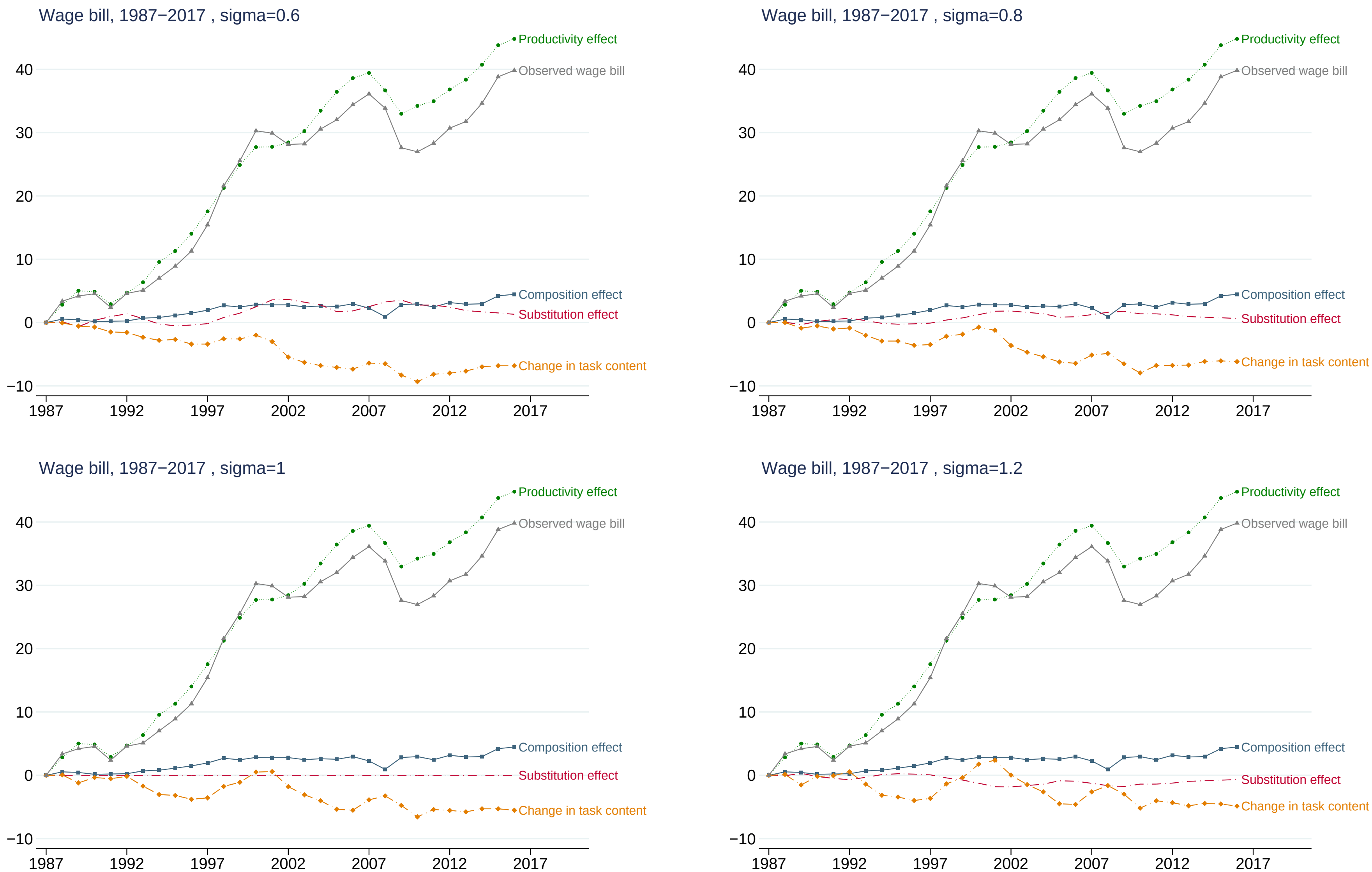


FIGURE A5: SOURCES OF CHANGES IN LABOR DEMAND FOR THE ENTIRE ECONOMY, 1987-2017, FOR DIFFERENT ASSUMED VALUES OF σ.
Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (A7) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.

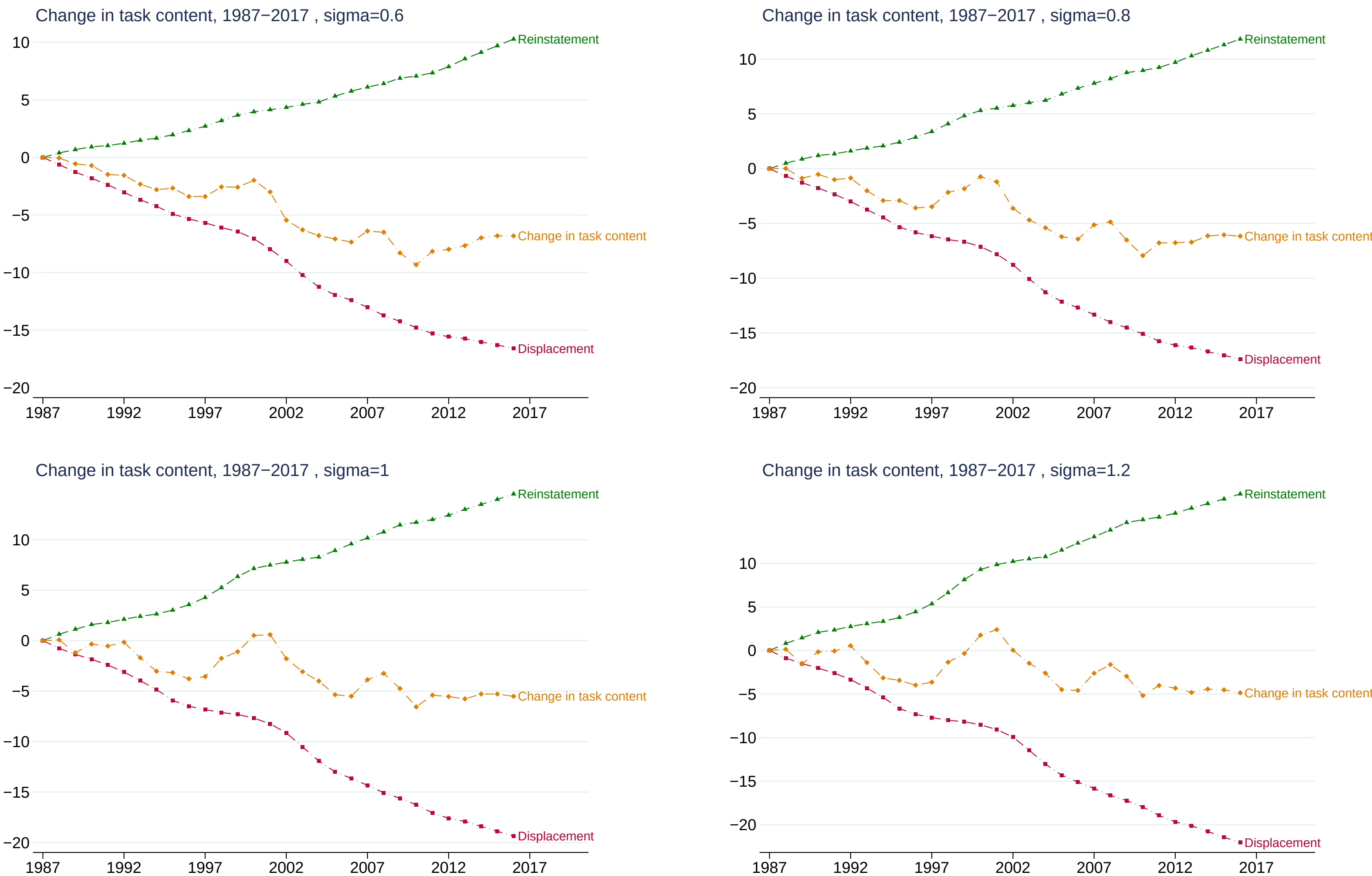


Figure A6: Estimates of the displacement and reinstatement effects for the entire economy, 1987-2017, for different assumed values of σ.
Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A9) in the text. The panels present the results for 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.

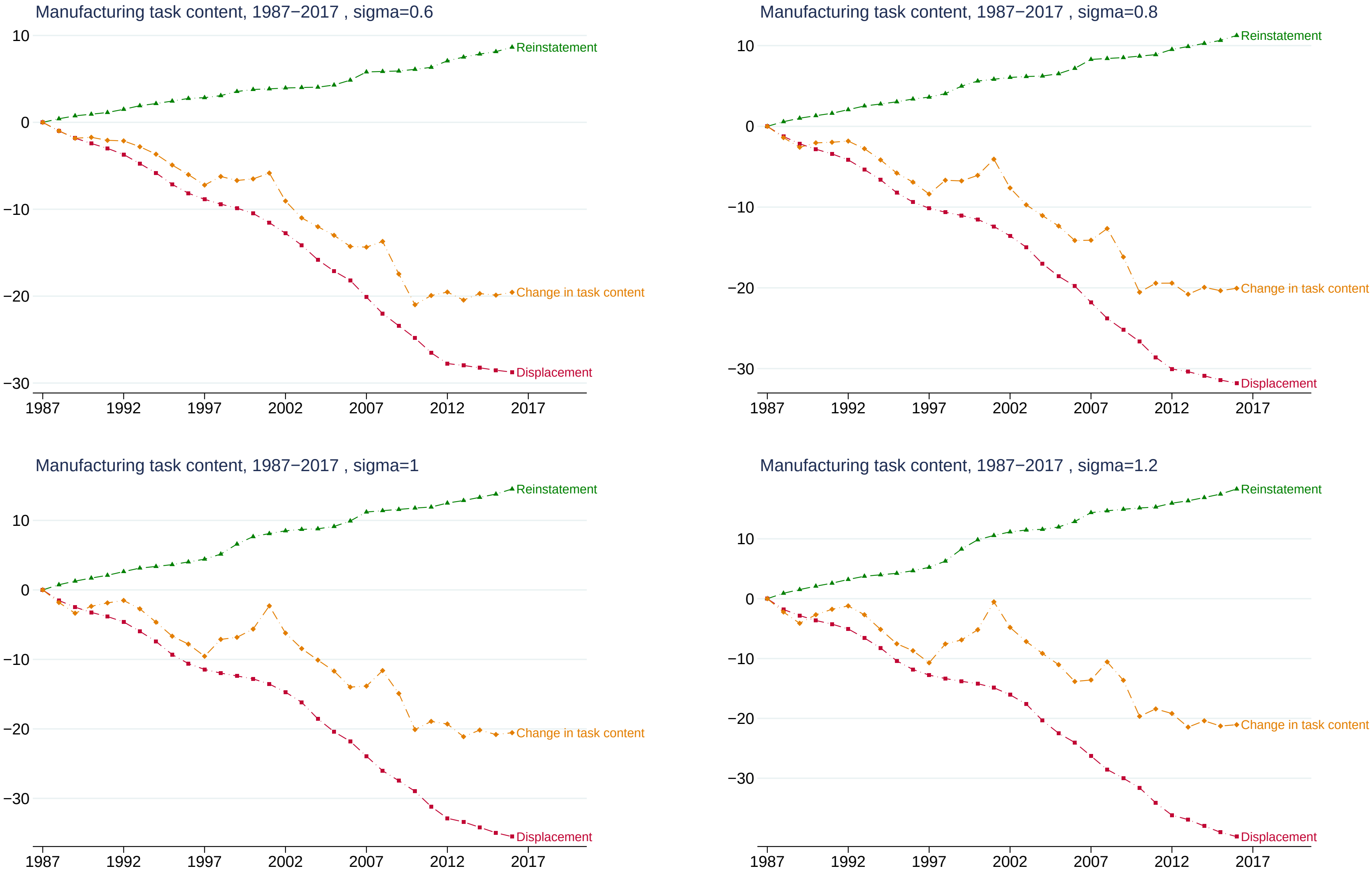


FIGURE A7: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR MANUFACTURING, 1987-2017, FOR DIFFERENT ASSUMED VALUES OF σ.
Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A9) in the text. The panels present the results for the 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.

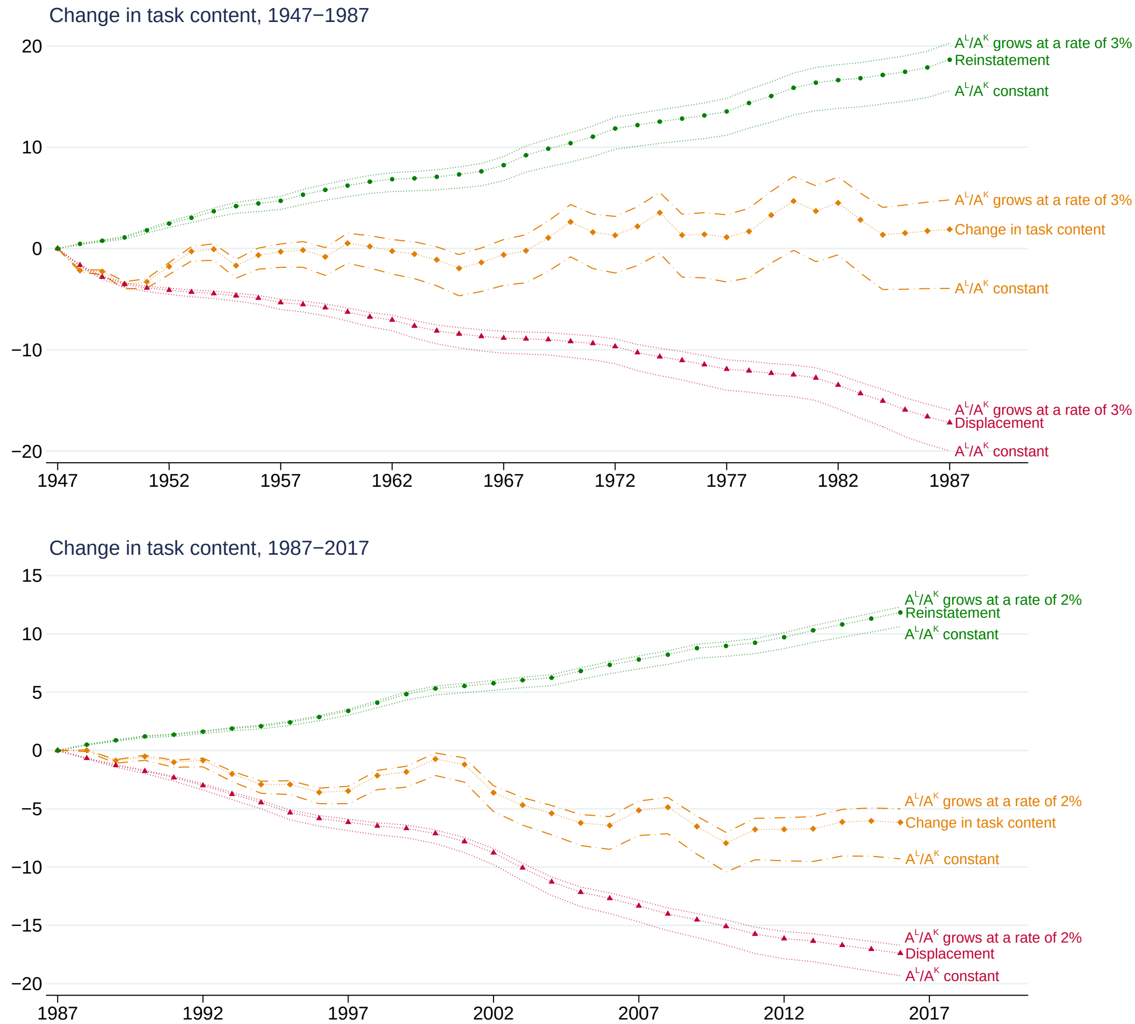
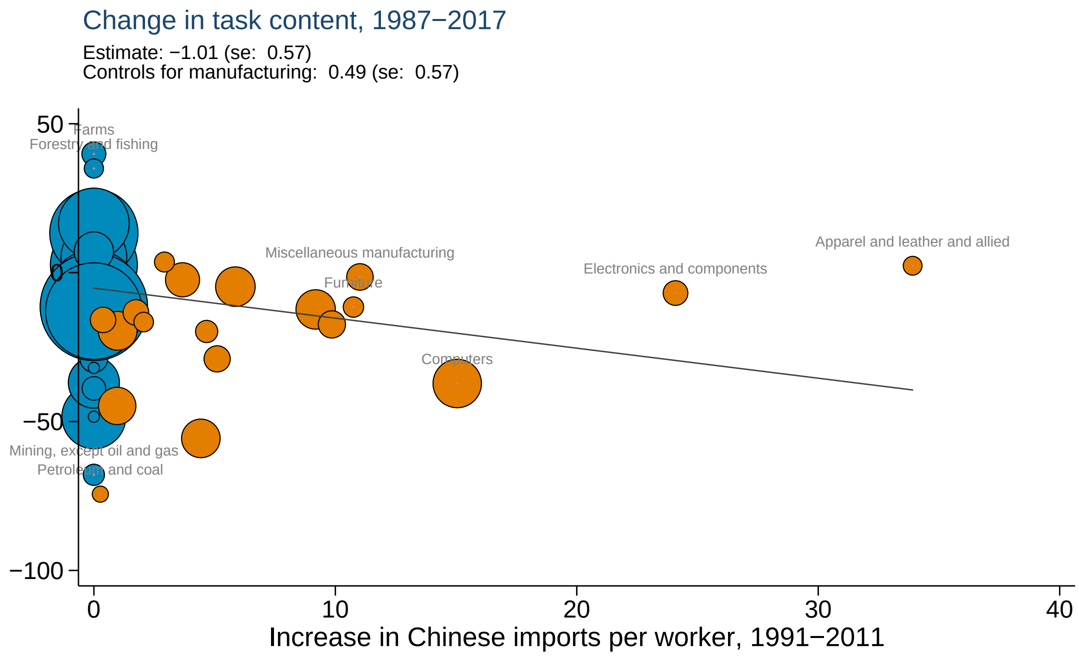


FIGURE A8: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR DIFFERENT ASSUMED CHANGES IN A_i^L/A_i^K.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A9) for different values of the growth rate of A_i^L/A_i^K. The top panel is for 1946-1987, 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%. In both panels, we assume and elasticity of substitution between capital and labor equal to $\sigma = 0.8$.

Figure A9: 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 7 and 5 were accounted for by industry-level changes in labor-augmenting and capital-augmenting technological changes alone, respectively, as derived in equations (A10) and (A11). For comparison, the figure also reports the observed increase in TFP for both periods. These numbers are computed assuming a value of $\sigma = 0.8$.



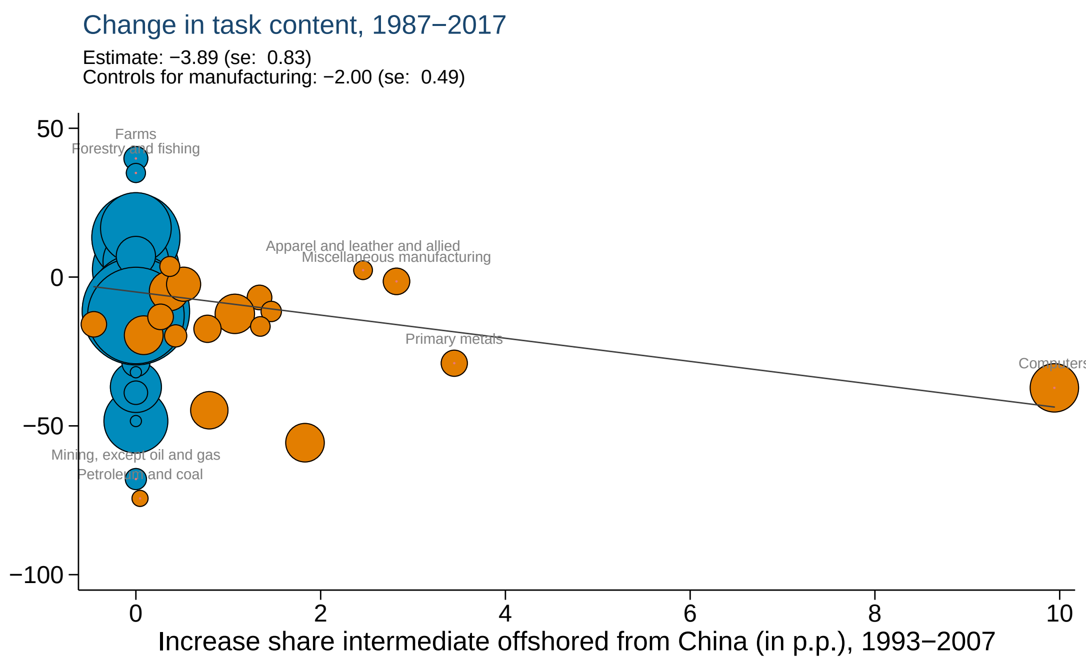


Figure A10: Trade and the task content of production.

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 between 1993 to 2007 (updated from Feenstra and Hanson, 1999). Orange designates manufacturing industries and blue non-manufacturing industries. See text for details.

Table A1: Relationship between change in task content of production and proxies of automation and new tasks.

	Raw data (1)	Controlling for manufacturing (2)	Controlling for Chinese import and offshoring (3)
Proxies of automation technologies:			
Adjusted penetration of robots, 1993-2014	-1.227 (0.341)	-0.817 (0.297)	-0.987 (0.282)
Observations	61	61	61
R-squared	0.17	0.23	0.29
Share employment in replaceable occupations, 1990	-0.558 (0.180)	-0.173 (0.317)	-0.409 (0.306)
Observations	61	61	61
R-squared	0.14	0.18	0.25
Detailed manufacturing industries (from SMT):			
Share firms using broad automation technologies, 1988-1993	-0.395 (0.165)		-0.437 (0.165)
Observations	148		145
R-squared	0.08		0.12
Share firms using advanced technologies, 1988-1993	-0.399 (0.152)		-0.462 (0.153)
Observations	148		145
R-squared	0.09		0.13
Proxies of new tasks:			
Share of new job titles, based on 1991 DOT and 1990 employment by occupation	1.597 (0.517)	1.308 (0.519)	1.531 (0.526)
Observations	61	61	61
R-squared	0.12	0.25	0.32
Number of emerging tasks, based on 1990 employment by occupation	8.460 (2.215)	7.071 (2.289)	7.663 (2.335)
Observations	61	61	61
R-squared	0.15	0.27	0.33
Share growth between 1990-2016 in occupations not in industry in 1990	2.159 (0.758)	1.653 (0.690)	1.676 (0.702)
Observations	61	61	61
R-squared	0.08	0.22	0.27
Percent increase in number of occupations represented in industry	0.602 (0.153)	0.375 (0.195)	0.382 (0.199)
Observations	61	61	61
R-squared	0.15	0.21	0.26

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 (defined as the increase in the share of imported intermediates between 1993 and 2007, as in Feenstra and Hanson, 1999, and 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.

Table A2: Relationship between gross change in task content of production and prices and quantities produced.

	log change quantity, 1987-2017		log change price, 1987-2017		Change skill intensity, 1990-2016	
	(1)	(2)	(3)	(4)	(5)	(6)
Gross change in task content	0.571	0.607	-0.432	-0.471	0.088	0.090
	(0.244)	(0.247)	(0.258)	(0.264)	(0.037)	(0.038)
Chinese import competititon	-3.409	-2.104	0.074	-1.296	0.330	0.387
	(1.580)	(1.355)	(0.875)	(1.036)	(0.162)	(0.161)
Offshoring of intermediates	41.065	13.027	-34.475	-5.053	0.505	-0.723
	(2.747)	(8.469)	(2.071)	(10.406)	(0.236)	(0.925)
Manufacturing	-0.887	-0.721	0.261	0.086	-0.040	-0.032
	(0.163)	(0.148)	(0.167)	(0.140)	(0.017)	(0.018)
Computer industry		2.562		-2.689		0.112
		(0.729)		(0.898)		(0.074)
Observations	61	61	61	61	60	60
R-squared	0.61	0.63	0.67	0.70	0.21	0.21

Note: The table reports estimates between gross changes in task content of production and the change in prices, quantities, and skill requirements 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 (A9). Columns 1-2 present results for the change in quantities produced (from the BEA). Columns 3-4 present results for the change in prices (from the BEA). 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 (except columns 5 and 6, where we could not match one industry to the Census codes). Standard errors robust against heteroskedasticity are in parenthesis.