Automation and New Tasks: How Technology Displaces and Reinstates Labor*

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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 allocation of tasks to capital and labor—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 and may 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.

Introduction

The implications of technological change for employment and wages are a source of controversy. Some see the ongoing process of automation, as exemplified by computer numerical control machinery, industrial robots and artificial intelligence, as the harbinger of widespread joblessness. Others reason that current automation, like previous waves of technologies, will ultimately increase labor demand, and thus employment and wages.

This paper presents a task-based framework, building on Acemoglu and Restrepo (2018a, 2018b) as well as Acemoglu and Autor (2011), Autor, Levy and Murnane (2003) and Zeira (1998), for thinking through the implications of technology for labor demand and productivity. Production requires tasks which are allocated to capital or labor. New technologies not only increase the productivity of capital and labor at tasks they currently perform, but also impact the allocation of tasks to these factors of production—what we call the *task content of production*. Shifts in the task content of production can have major effects for how labor demand changes as well as for productivity.

Automation corresponds to the development and adoption of new technologies that enable capital to be substituted for labor in a range of tasks. Automation changes the task content of production adversely for labor because of a *displacement effect*—as capital takes over tasks previously performed by labor. The displacement effect implies that automation reduces the labor share of value added. Historical examples of automation are aplenty. Many early innovations of the Industrial Revolution automated tasks performed by artisans in spinning and weaving (Mantoux 1928), which led to widespread displacement, triggering the Luddite riots (Mokyr 1990). The mechanization of agriculture, which picked up speed with horse-powered reapers, harvesters and plows in the second half of the 19th 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. The jobs of production workers are being disrupted with the rise of industrial robots and other automated machinery (Graetz and Michaels 2018; Acemoglu and Restrepo 2018b), while white-collar workers in accounting, sales, logistics, trading and some managerial occupations are seeing some of the tasks they used to perform being replaced by specialized software and artificial intelligence.

By allowing a more flexible allocation of tasks to factors, automation technology also increases productivity, and via this channel, which we call the *productivity effect*, it contributes to the demand for labor in non-automated tasks. The net impact of automation on labor demand thus depends on how the displacement and productivity effects weigh against each other.

The history of technology is not only about the displacement of human labor by au-

tomation technologies. If it were, we would be confined to a shrinking set of old tasks and jobs, with a steadily declining labor share in national income. Instead, the displacement effect of automation has been counterbalanced by technologies that create new tasks in which labor has a comparative advantage. Such new tasks generate not only a positive productivity effect, 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.[1] 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. In the 19th century, as automation of some tasks was ongoing, other technological developments 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 agricultural mechanization in the United Staes, 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 replaced labor in some white-collar tasks, they have simultaneously created several new tasks. These include tasks related to programming, design and maintenance of high tech equipment, such as software and app development, database design and analysis, and computer security related tasks, as well as tasks related to more specialized functions in existing occupations, including administrative assistants, analysts for loan applications and medical equipment technicians (see Lin, 2011). Using data from Lin (2011), Acemoglu and Restrepo (2018a) show that about half of employment growth over 1980-2015 took place in occupations where job titles or tasks performed by workers changed.

Our conceptual framework offers several lessons. First, the presumption that *all* technologies increase (aggregate) labor demand simply because they raise productivity is wrong. Some automation technologies may in fact reduce labor demand because they bring sizable displacement effects but modest productivity gains (especially when substituted workers were cheap to begin with and the automated technology is only marginally better than them). Second, because of the displacement effect, we should not expect automation to create wage increases commensurate with productivity growth. In fact, as we noted already, automation by itself always reduces the labor share in industry value added and tends to reduce the overall labor share in the economy (meaning that it leads to slower wage growth than productivity growth). The reason why we have had rapid

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[1]There are also new tasks in which capital has a comparative advantage (e.g., automated detection). Throughout our focus is on "labor-intensive" new tasks, and for brevity, we will simply refer to these as "new tasks".

wage growth and stable labor shares in the past is a consequence of other technological changes that generated new tasks for labor and counterbalanced the effects of automation on the task content of production. Some technologies displaced labor from automated tasks while others reinstated labor into new ones. On net, labor retained a key role in production. By the same token, our framework suggests that the future of work depends on the mixture of new technologies and how these change the task content of production.

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 and explain how industry data can be used to infer the behavior of the task content of production and the displacement and reinstatement effects. We start by showing that there has been a slowdown in the growth of labor demand over the last three decades and an almost complete stagnation over the last two. We establish this by studying the evolution of the economy-wide wage bill, which combines information on average wages and total employment and is thus informative about changes in overall labor demand. We then use industry data to decompose changes in the economy-wide wage bill into productivity, composition and substitution effects, and 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 between labor- and capital-intensive tasks within an industry in response to a change in task prices (for instance, caused by factor-augmenting technologies making labor or capital more productive at tasks they currently perform). We estimate changes in the task content of production from residual changes in industry-level labor shares (beyond what can be explained by substitution effects). We further decompose changes in the task content of production into displacement effects caused by automation and reinstatement effects driven by new tasks. We provide external support for this decomposition by relating estimated changes in the task content of production to a battery of measures of automation and introduction of new tasks across sectors.

Our decomposition suggests that the evolution of the US wage bill, especially over the last 20 years, cannot be understood without factoring in changes in the task content of production. In particular, we find that the sharp slowdown of US wage bill growth over the last three decades is a consequence of weaker-than usual-productivity growth and significant shifts in the task content of production against labor. By decomposing the change in the task content of production, we estimate stronger displacement effects and considerably weaker reinstatement effects during the last 30 years than the decades before. These patterns hint at an acceleration of automation and a deceleration in the creation of new tasks. They also raise the question of why productivity growth has been so anemic while automation has accelerated during recent years. We finally use our framework to

shed light on this critical question.

An online Appendix available with this paper at http://jep.org contains a more detailed exposition of our framework, proofs, additional empirical results, and details on the construction of our data.

Conceptual Framework

Production requires the completion of 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, including accounting, marketing, transportation, and sales. Each one of these tasks can be performed by human labor or by capital (including both machines and software). The allocation of tasks to factors determines the task content of production.

Automation enables some of the tasks previously performed by labor to be produced by capital. As a recent example, 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 performed manually (Ayres and Miller 1983; Groover et al. 1986; 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 as well as productivity. In textiles, examples of new labor-intensive tasks include computerized designs, new methods of market research and various managerial activities for better targeting of demand and cost-saving. By changing the allocation of tasks to factors, both automation and the introduction of new tasks impact the task content of production.

Tasks are thus the fundamental unit of production, and the factors of production contribute to output by performing these tasks. In contrast, the canonical approach in economics bypasses tasks and directly posits a production function of the form $Y = F(A^K K, A^L L)$, which additionally imposes that all technological change takes a factor-augmenting form. There are three related reasons we prefer our conceptual framework. First, the canonical approach lacks descriptive realism. Advances in robotics, for example, do not make capital or labor more productive, but expand the set of tasks that can be produced by capital. Second, capital-augmenting technological change (an increase in A^K) or labor-augmenting technological change (an increase in A^L) corresponds to the relevant factor becoming *uniformly more productive in all tasks* which, we will show, ignores potentially important changes in the task content of production. Third and most importantly, we will also see that the quantitative and qualitative implications of factor-augmenting technological advances are different from those of technologies that change

the task content of production. Focusing just on factor-augmenting technologies can force us into misleading conclusions.

Tasks and Production

We present our task-based framework by first describing the production process in a single-sector economy.[2] Suppose that production combines the output of a range of tasks, normalized to lie between $N-1$ and N.[3] Tasks can be produced using capital or labor, as illustrated in Figure 1. Tasks with $z > I$ are not automated, and can only be produced with labor, which has a wage rate W. Tasks $z \leq I$ are automated and can be produced with capital, which has a rental rate R, as well as labor. We assume that labor has both a comparative and an absolute advantage in higher indexed tasks. An increase in I therefore represents the introduction of an automation technology, or *automation* for short. An increase in N, on the other hand, 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 sector depends on A^L (labor-augmenting technology) and A^K (capital-augmenting technology), which increase the productivities of these factors in all tasks.

Let us assume that it is cost-minimizing for firms to use capital in all tasks that are automated (all $z \leq I$) and to adopt all new tasks immediately. This implies an allocation of tasks to factors as summarized in Figure 1, which also shows how automation and new tasks 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,

$$(1) \qquad Y = \Pi(I,N) \left(\Gamma(I,N)^{\frac{1}{\sigma}} (A^L L)^{\frac{\sigma-1}{\sigma}} + (1 - \Gamma(I,N))^{\frac{1}{\sigma}} (A^K K)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

As in the canonical model, we have production as a function of the quantities of labor and capital, L and K. The labor-augmenting technology term A^L and capital augmenting term A^K increase the productivity of labor and capital in all tasks they currently produce. The elasticity of substitution between tasks, σ, determines how easy it is to substitute one task for another, and is also the (derived) elasticity of substitution between capital and labor.

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[2] This also describes the production process in a sector situated in a multi-sector economy, with the only difference that in that case changes in technology impact relative prices and induce reallocation of capital and labor across sectors. We discuss these relative price and reallocation effects below.

[3] Namely, the production function takes the form $Y = \left(\int_{N-1}^{N} Y(z)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$, 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. The online Appendix presents more detail on underlying assumptions and on derivations of results that follow throughout the discussion. As one example, nothing major changes if we instead allow tasks to lie on the interval between 0 and N.

The crucial difference from the canonical model is that the share parameters of this CES depend on automation and new tasks. The share parameter for labor, $\Gamma(I, N)$, is the (labor) task content of production, which represents the share of tasks performed by labor relative to capital (adjusted for differences in labor and capital productivity across these tasks). Conversely, $1 - \Gamma(I, N)$ is the (capital) task content of production. Hence, an increase in $\Gamma(I, N)$ shifts the task content of production in favor of labor and against capital. In the special case where $\sigma = 1$, $\Gamma(I, N) = N - I$. More generally, $\Gamma(I, N)$ is always increasing in N and decreasing in I. This, in particular, implies that automation (greater I) shifts the task content of production against labor because it entails capital taking over tasks previously performed by labor. In contrast, new (labor-intensive) tasks shift the task content of production in favor of labor.[4] Finally, automation and new tasks not only change the task content of production but also generate productivity gains by allowing the allocation of (some) tasks to cheaper factors. The term $\Pi(I, N)$, which shows up as TFP, represents these productivity gains.

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

$$(2) \qquad s^L = \frac{1}{1 + \dfrac{1 - \Gamma(I, N)}{\Gamma(I, N)} \left(\dfrac{A^L}{W} \dfrac{R}{A^K} \right)^{1-\sigma}}.$$

This expression, which will be used extensively in the rest of the paper, clarifies the two distinct forces shaping the labor share (in an industry or the entire economy). As it is standard, the labor share depends on the ratio of effective factor prices, $\frac{W}{A^L}$ and $\frac{R}{A^K}$. Intuitively, as effective wages rise relative to effective rental rates of capital, the price of tasks produced by labor increases relative to the price of tasks produced by capital, and this generates a *substitution effect* across tasks. This is the only force influencing the labor share in the canonical model. Its magnitude and size depends on whether σ is greater than or less than 1. For example, when tasks are complements ($\sigma < 1$), an increase in the effective wage raises the cost share of tasks produced by labor. The opposite happens when $\sigma > 1$. When $\sigma = 1$, we obtain a Cobb Douglas production function and the substitution effect vanishes, because the share of each task in value added is fixed.

More novel are the effects of the task content of production, $\Gamma(I, N)$, on the labor share.

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[4]Our exposition assumes that the task content of production does not depend on factor-augmenting technologies or the supply of capital or labor. This will be the case when it is cost-minimizing for firms in this sector to use capital in all tasks that are automated (all $z \leq I$) and use all new tasks immediately. The Appendix presents the assumption on technology and 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 with factor supplies and factor-augmenting technologies. Even in this case, the impact of factor-augmenting technologies on the task content will be small relative to the productivity gains from these technologies.

Intuitively, as more tasks are allocated to capital instead of labor, the task content shifts against labor and the labor share will decline unambiguously. Our model thus predicts that, independently from the elasticity of substitution σ, automation (which changes the task content of production against labor) will reduce the labor share in the industry, while new tasks (which alter the task content of production in favor of labor) will increase it.

Technology and Labor Demand

We now investigate how technology changes labor demand. We focus on the behavior of the wage bill, WL, which captures the total amount employers pay for labor. Recall that

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

Changes is the wage bill will translate into some combination of changes in employment and wages, and the exact division will be affected by the elasticity of labor supply and labor market imperfections, neither of which we model explicitly in this paper (for discussion, see Acemoglu and Restrepo, 2018a, 2018b).

We use this relationship to think about how three classes of technologies impact labor demand: automation, new tasks and factor-augmenting advances. Consider the introduction of new automation technologies (an increase in I in Figure 1). The impact on labor demand can be represented as

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

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 of the industry would increase at the same rate as value added, and the labor share would remain constant. However, automation also generates a *displacement effect*— it displaces labor from the tasks previously allocated to it—which shifts the task content of production against labor and always reduces the labor share. Automation therefore increases the size of the pie, but labor gets a smaller slice. There is no guarantee that the productivity effect is greater than the displacement effect; some automation technologies can reduce labor demand even as they raise productivity.[5]

Hence, contrary to a common presumption in popular debates, it is not the "brilliant" automation technologies that threaten employment and wages, but *"so-so technologies"*

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[5]Indeed, in Acemoglu and Restrepo (2018b) we show that industrial robots, a leading example of automation technology, 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. This result is consistent with a powerful displacement effect that has dominated the productivity effect from this class of automation technologies.

that generate small productivity improvements. 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 and 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 relative to its wage and the smaller is the productivity of capital in these tasks relative to the rental rate of capital, the more limited the productivity gains from automation will be. Examples of so-so technologies include automated customer service, which has displaced human service representatives but is generally deemed to be low-quality and thus unlikely to have generated large productivity gains. They may also include several of the applications of artificial intelligence technology to tasks that are currently challenging for machines.

Different technologies are accompanied by productivity effects of varying magnitudes, and hence, we cannot presume that one set of automation technologies will impact labor demand in the same way as others. Likewise, because the productivity gains of automation depend on the wage, the net impact of automation on labor demand will depend on the broader labor market context. When wages are high and labor is scarce, automation will generate a strong productivity effect and will tend to raise labor demand. When wages are low and labor is abundant, automation will bring modest productivity benefits and could end up reducing labor demand. This observation might explain why automation technologies adopted in response to the scarcity of (middle-aged) production workers in countries where the labor force is aging rapidly, such as Germany, Japan and South Korea, appear to have more positive effects than in the United States (on cross-country patterns, see Acemoglu and Restrepo 2018e; on the effect of robots in the US, see Acemoglu and Restrepo, 2018b, and in Germany, see Dauth et al. 2018). It also suggests a reinterpretation of the famous Habakkuk hypothesis that the faster growth of the 19th-century US economy compared to Britain was due to its relative scarcity of labor (Habakkuk, 1962; see also Allen, 2009, for a similar argument in the context of the British Industrial Revolution). Labor scarcity encourages automation and the high wages it causes help explain why this automation process led to rapid productivity and further wage growth.

Consider next the effect of the introduction of new tasks on the wage bill, 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

Effect of new tasks on labor demand = Productivity effect + Reinstatement effect.

The *reinstatement effect* captures the change in the task content of production, 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 new tasks exploit labor's comparative advantage. The resulting productivity improvement, together with the change in task content, ensures that labor demand always increases following the introduction of new tasks.

Finally, as we claimed previously, 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,

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

With factor-augmenting technological improvements, either labor or capital becomes more productive in all tasks, making the productivity effect proportional to their share in value added.

Factor-augmenting technologies also impact labor demand via the *substitution effect* introduced above, which changes the labor share but does not alter the task content of production. Available estimates of σ place this parameter to be less than but close to 1, which implies that the substitution effects of factor-augmenting technologies are small relative to their productivity effects.

In summary, in contrast to automation and new tasks that can generate significant displacement and reinstatement effects, factor-augmenting technologies affect labor demand mostly via the productivity effect and have a relatively small impact on the labor share. As a result, they are unlikely to generate a lower labor demand from technological advances: capital-augmenting technologies always increase labor demand, and labor-augmenting technologies do the same for plausible parameter values, in particular, so long as $\sigma > 1 - s^L$ (see Acemoglu and Restrepo, 2018c).[6]

Tasks, Production and Aggregate Labor Demand

We now embed the model of tasks and production in an economy with multiple industries and investigate how technology changes aggregate labor demand by characterizing the

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[6]Many other technologies share the feature that they do not impact the task content of production. For example, improvements in the quality or productivity of equipment in any subset of already-automated tasks in $(N-1, I)$ (what Acemoglu and Restrepo, 2018d, call a "deepening of automation") will have an impact on labor demand identical to capital-augmenting technologies. These technologies do not change the allocation of tasks to factors (as a new piece of equipment is replacing an older one), and so they affect labor demand mostly through the productivity effect.

behavior of the (economy-wide) wage bill. In our multi-sector economy we have

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

The multi-sector perspective offers an additional margin for adjustment in response to automation, which we refer to as the *composition effect*. Following automation in sector i (an increase in I for that sector) we have

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

The first two effects are the same as above—the productivity effect represents the impact of automation in sector i on GDP, while the displacement effect represents the change in the task content of production sector i (which affects the labor share within this sector). These effects are scaled by the size of sector i, since larger sectors will have larger aggregate effects.

The composition effect, which was absent when we were focusing on the effect of automation in a one-sector economy, captures the implications of sectoral reallocations (changes in the share of value added across sectors). For example, automation in sector i may reallocate economic activity towards sector j (depending on demand elasticities and input-output linkages). This reallocation contributes positively to aggregate labor demand when sector j has higher labor share than the contracting sector i, and negatively when the opposite holds.

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

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

where the new feature is again the composition effect.

The mechanization of agriculture in the US illustrates how these forces jointly determine the behavior of aggregate labor demand. Data from Budd (1960) shows that between 1850 and 1910, the replacement of manual labor by horse-powered reapers and harvesters in agriculture coincided with a sharp decline in the labor share of value added in this sector from 33 percent to 17 percent—a telltale sign of the displacement effect created by mechanization. Despite rapid mechanization of agriculture, at the time making up one-third of the US economy, two forces combined to generate an increase in aggregate labor demand. First, and in part as a consequence of mechanization, value added and employment were reallocated from agriculture to the industrial sector. This created a

powerful composition effect, as industry was (and still continues to be) much more labor intensive than agriculture. In addition, the labor share within the industrial sector rose further during this process, from 47 percent in 1850 to 55 percent by 1890. This change in industry labor share signals the presence of a powerful reinstatement effect created by the introduction of 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 subsequently, clerical occupations in trade and manufacturing industries (Goldin and Katz, 2007; Michaels, 2007).

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

Sources of Labor Demand Growth in the US

We now use our framework to shed light on the factors that have shaped the evolution of US labor demand since World War II. To do this, we develop a decomposition of observed changes in the total wage bill in the economy. Our decomposition requires data on industry value added, factor payments and labor shares.

We show in the online Appendix that the change in aggregate wage bill between two periods can be decomposed as

$$\text{Change in aggregate wage bill} = \text{Productivity effect} + \text{Composition effect}$$
$$+ \text{Substitution effect} + \text{Change in task content.}$$

The productivity effect is the sum of the contributions from various sources of technology to value added and thus GDP. Correspondingly, in our empirical exercise we measure this effect using changes in (log) GDP per capita.

The composition effect captures changes in labor demand resulting from reallocation of value added across sectors. As discussed in the previous section, this is related to the gap between the labor share of contracting and expanding sectors. In our empirical exercise, we measure it as the sum of the change in the value added share of an industry weighted by its labor share (if all sectors had the same labor share, this term would be equal to zero). The composition effect includes not only the sectoral reallocation brought by new technologies but also compositional changes resulting from structural transformations and sectoral reallocation due to preferences (for example, Herrendorf, Rogerson, and Valentinyi 2013; Hubmer 2018; Aghion, Jones, and Jones 2017), differences in factor intensities (for

example, Acemoglu and Guerrieri 2008), differential sectoral productivity growth (for example, Ngai and Pissarides, 2007) or international trade in final goods (for example, Autor, Dorn, and Hanson 2013).

The substitution effect is an employment-weighted sum of the substitution effects of industries, and thus depends on industry-level changes in effective factor prices and the elasticity of substitution σ (as shown in equation (2)). To estimate the substitution effect in an industry, we choose as our baseline Oberfield and Raval's (2014) estimate of the elasticity of substitution between capital and labor, $\sigma = 0.8$.[7] In addition, we utilize information on sectoral factor prices from the Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS) and National Income and Product Accounts (NIPA). To convert observed factor prices into effective ones, we start with a benchmark where A_i^L/A_i^K grows at a common rate equal to average labor productivity, which we take to be 2 percent a year between 1947 and 1987 and 1.46 percent a year between 1987 and 2017. The motivation for this choice is that, if all technological progress were labor-augmenting, this would be the rate of growth in A_i^L required to match the behavior of labor productivity.[8]

The change in task content is given by an employment-weighted sum of the changes in task content of production of industries. We estimate industry-level change in task content as the residual change in labor share (observed directly in the data) which cannot be explained by the substitution effect. Namely,

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

Intuitively, with competitive factor and product markets, the change in task content of production and the substitution effect are the only forces impacting the labor share of an industry. Hence, changes in task content can be inferred once we have estimates of the substitution effect.

Under additional assumptions, we can also separate the change in task content into its two components: the displacement and reinstatement effects. Assume that an industry will not simultaneously undertake automation and introduce new tasks (this is implied,

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

[8]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 in reducing the task content of production. Nevertheless, reasonable variations on the growth rate of A_i^L/A_i^K have small impacts on our decomposition results as we show in the online Appendix.

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). Then, when the labor share of an industry declines beyond what one would expect based on factor prices, we estimate a positive displacement effect resulting from automation in that industry. Conversely, when the labor share in an industry rises beyond what one would expect based on factor prices, we estimate a positive reinstatement effect, attributed in our model to the introduction of new tasks. Motivated by this reasoning, we 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 effect as the five-year moving average of the change in task content for industries with a positive change. The five-year time window is chosen to minimize the influence of measurement error in industry labor shares. To the extent that there are simultaneous introduction of new automation technologies and new tasks in a given industry within a five-year period, our estimates will be lower bounds both for the displacement and reinstatement effects.

Sources of Labor Demand: 1947-1987

We first apply this decomposition to data from the four decades following World War II, from 1947 to 1987. For this period, we have data from the BEA for 58 industries on value added and labor shares.[9] We combine these with data from the NIPA on quantities of capital and labor in each industry to obtain measures of factor prices. We consolidate the data into 43 industries that covered the private sector and can be tracked consistently over time and across sources.

Figure 2 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 percent of GDP—there are no significant declines in labor shares in these broad sectors. In fact, the labor share in manufacturing and services increased modestly 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 3 presents our decomposition using the 43 industries in our sample. We have divided the wage bill by population, so that changes in population do not confound the effects we are focusing on. The top panel in Figure 3 shows that wage bill per capita grew at 2.5% per year during this period. The rapid and steady growth of the wage bill

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[9]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 apportioning self-employment income between labor and capital income. Elsby et al. (2013) explore this issue in detail and conclude that labor income from self-employment has either declined or remained constant as a share of total labor income over this period. This implies that labor share inclusive of self-employment income likely declined by even more, and thus, if anything, focusing on the labor share in the private sector understates the overall decline in labor demand.

during this period is largely explained by the productivity effect (2.4% per year). The substitution and composition effects are small, and during this period changes in the task content of production are small as well.

The middle panel of Figure 3 shows that, even though the overall change in the task content of production during this period is small, there is considerable displacement and reinstatement. Between 1947 and 1987, the displacement effect reduced labor demand at about 0.48% per year, but simultaneously, there was an equally strong reinstatement effect, equivalent to an increase in labor demand of 0.47% per year. The bottom panel of Figure 3 depicts a similar pattern in manufacturing, where the overall change in task content was also small, while displacement and reinstatement effects were substantial.

In sum, our findings suggest that during the four decades following World War II there was plenty of automation, 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 counterbalanced the adverse labor demand consequences of automation.

Sources of Labor Demand: 1987-2017

For the 1987-2017 period, we use data from the BEA for 61 industries covering the private sector and complement them with data from the BLS on factor prices.

The top panel of Figure 4 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 in 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 5 shows a striking slowdown in the growth of labor demand between 1987 and 2017. Wage bill per capita grew at a modest 1.33% per year during the entire period and essentially stagnated since 2000. The first factor accounting for the deceleration of labor demand during this period is the slowdown of productivity growth (1.54% per year compared to 2.4% in 1947-1987). The second factor contributing to slower wage bill growth, especially after the late 1990s, is a significant negative shift in the task content of production against labor (of 0.35% per year), which caused labor demand to decouple from productivity. Cumulatively, changes in the task content of production reduced labor demand by 10% during this period.

The middle and bottom panels of Figure 5 show that, relative to the earlier period, the change in task content is driven by a deceleration in the introduction of technologies reinstating labor (reinstatement increased labor demand only by 0.35% per year compared to 0.47% in 1947-1987) and an acceleration of displacement (displacement reduced labor

demand by 0.7% per year compared to 0.48% in 1947-1987). This pattern is particularly pronounced in manufacturing where the displacement effect reduced labor demand at about 1.1% per year or about 30% cumulatively. These results are consistent with Elsby et al. (2013) who document the important role of within-industry changes that are uncorrelated with factor prices in accounting for the aggregate behavior of the labor share. The change in the balance between displacement and reinstatement also corroborates the findings of Autor and Salomons (2018) who find that technological improvements after 1980 have been associated with declines in the labor share, while those in the previous decades have not been.

Finally, the top panel also shows that the composition and substitution effects had a very limited impact on the wage bill. Although there is a sizable shift away from manufacturing, which is itself not unrelated to automation in this sector as well as to import competition, the resulting composition effects are small because the labor share in manufacturing is similar to that in the expanding service industries (see the top panel of Figure 4). These findings highlight that unlike the 19th-century mechanization of agriculture, there are no powerful composition effects contributing to labor demand. Even more importantly, there appears to be no equivalent of the powerful reinstatement effects that accompanied the mechanization of agriculture.

In summary, the deceleration of labor demand growth over the last 30 years is due to a combination of anemic productivity growth and adverse shifts in the task contents of production owing to rapid automation that is not being counterbalanced by the creation of new tasks.[10]

What Does the Change in Task Content Capture?

A natural concern is that our estimates of the change in task content capture something different than displacement effects from automaton technologies and reinstatement effects of new tasks. Here, we provide additional evidence that our estimates are informative about changes in the task content of production. We focus on the 1987-2017 period where we have measures of automation and can compute proxies for new tasks at the industry level, and then document the correlation between these measures and our estimates of the change in the task content of production.

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[10]In the Appendix, we verify that this pattern is robust to different values of the elasticity of substitution and to reasonable variations in the rates of factor-augmenting technological changes. Furthermore, we computed the changes in factor-augmenting technologies at the industry level that would be necessary to explain changes in industry labor shares without any change in task content of production. We found that this would require gargantuan changes in factor-augmenting technologies and productivity increases—several folds larger than the observed increases in total factor productivity during the last seven decades. This exercise underscores the need for major changes in the task content of production to account for the evolution of sectoral labor shares and the wage bill.

We also demonstrate in the Appendix that the order in which the decomposition is carried out (composition effects first and within-industry changes next) does not matter for the results.

We have three measures of industry-level automation technologies. The proxies are: (1) the adjusted penetration of robots measure from Acemoglu and Restrepo (2018b) for 19 industries, which are then mapped to our 61 industries; (2) the share of routine jobs in an industry in 1990, where we define routine jobs in an occupation as in Acemoglu and Autor (2011) and then project these across industries according to the share of the relevant occupation in the employment of the industry in 1990 (see also vom Lehn, 2018); (3) the share of firms (weighted by employment) across 148 detailed manufacturing industries using automation technologies, which include automatic guided vehicles, automatic storage and retrieval systems, sensors on machinery, computer-controlled machinery, programmable controllers, and industrial robots.[11]

Table 1 shows that with all these proxies there is the expected negative relationship between higher levels of automation and our measure of changes in the task content of production in favor of labor (see also visual representations of these relationships in the online Appendix). These negative relationships remain very similar when we add various control variables, including a dummy for the manufacturing sector as well as imports from China (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). Consistent with our conceptual framework, changes in task content are unrelated to imports of final goods from China, but are correlated with offshoring, which often involves the offshoring of labor-intensive tasks (see Elsby et al. 2013). Controlling for offshoring does not change the relationship we report in Table 1 because offshoring is affecting a different set of industries than our measures of automation (see the Appendix).

We also looked at a series of proxies for the introduction of new tasks across industries, and how they are correlated with our measure of the change in task content for 1987-2017. Our four proxies for new tasks are: (1) the 1990 share of employment in occupations with a large fraction of new job titles, according to the 1991 Dictionary of Occupational Titles compiled by Lin (2011); (2) the 1990 share of employment in occupations with a large number of "emerging tasks" according to O*NET, which correspond to new tasks that workers identify as becoming increasingly important in their jobs; (3) the share of employment growth in an industry accounted for by "new occupations," defined as occupations that were not present in that industry in 1990 but are present in 2016; and (4) the percent increase in the number of occupations in an industry between 1990 and 2016.

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[11]These data are from the Survey of Manufacturing Technologies (SMT), and are available in 1988 and 1993 for 148 four-digit SIC industries which are all part of three three-digit manufacturing sectors: fabricated metal products, nonelectrical machinery, electric and electronic equipment, transportation equipment, and instruments and related products (see Doms et al., 1997). For this exercise, we computed measures for the change in task content of these manufacturing industries using detailed data from the BEA input-output tables for 1987 to 2007.

The first two measures are projected onto industries using the share of these occupations in industry employment in 1990. All four of these measures are meant to capture major changes in the types of activities performed in occupations (then mapped to industries) or the introduction of certain new activities into an industry. We thus expect the correlations between these proxies for new tasks and our measure of changes in task content in favor of labor to be positive and significant, and they are. These results hold regardless of whether or not we include additional controls in Table 1.

These correlations bolster the interpretation that our estimates of changes in task content of production contain valuable information on displacement from automation technologies and reinstatement from the introduction of new tasks.

Confounding Factors

Our approach has been predicated on competitive markets and has also abstracted from various other changes potentially affecting labor markets in the US. We now briefly discuss these issues.

First, as we have already noted, trade in final goods should have no impact on our estimates of the change in the task content of production (because they will affect prices and sales, which are captured by our productivity effect, and they induce sectoral reallocations, which are part of our composition effects). This is confirmed by our results in Table 1. Offshoring, on the other hand, will directly change the task content of production because it involves the replacement of some labor-intensive tasks by services from abroad (Grossman and Rossi-Hansberg, 2008). Our estimates in Table 1 confirm this, but show that offshoring does not change the quantitative or qualitative relationship between various measures of automation and our estimates of the change in the task content of production.

Second, as also noted above, sectoral reallocations resulting from structural transformation do not affect the task content of production either and are part of our composition effects. The fact that these composition effects are small suggests that these sectoral reallocations have not been a major factor in the slowdown in labor demand and changes in labor share in national income.

Third, we have abstracted from the presence of workers with different skills, and one question is whether changes in the skill composition of the workforce would affect our estimates of the change in the task content of production. The answer is no provided that industry-level factor payments are well measured. Hence, as long as the increase in the wage bill caused by skill upgrading in a sector is factored in, this compositional change does not cause a shift in the task content of production. An implication is that secular changes such as population aging and increased female labor force participation, though

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they will impact the composition of the workforce and factor prices, should not confound our estimates of changes in task content of production.

Third, changes in factor supplies should also have no impact provided that our estimates of the substitution effect (which form the basis of our estimates of the change in the task content of production) remain accurate.

In contrast to these factors, deviations from competitive labor or product markets would potentially confound our estimates of task content. Particularly worth noting are deviations from competitive labor markets. If the supply side of the market is determined by bargaining or other rent-sharing arrangements, then our approach still remains valid provided that firms are on their labor demand curve (for overall labor or for different types of labor in the presence of heterogeneity). This is because our analysis only uses information from the labor demand side, so whether workers are along a well-defined labor supply curve is not important. On the other hand, changes in the extent of monopsony and bilateral bargaining and holdup problems forcing firms of their labor demand curve would potentially confound our estimates. A similar confounding would result if there are changing product market markups. Though these issues are important, they are beyond the scope of the current paper and are some of the issues we are investigating in ongoing work.

What Explains the Changing Nature of Technology and Slow Productivity Growth Since 1987?

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 accounts for the sluggish growth of labor demand over the last three decades and especially since 2000. Why has the balance between automation and new tasks changed recently? Why has productivity growth been so disappointing despite the acceleration in automation technologies? Though we do not have complete answers to these questions, our conceptual framework points to a number of ideas worth considering.

There are two basic reasons why the balance between automation and new tasks may have changed. First, the innovation possibilities frontier linking these two types of technological change may have shifted, facilitating further automation and making the creation of new tasks more difficult (see Acemoglu and Restrepo, 2018a, for a formal analysis). For example, new general-purpose technologies based on advances in hardware and software may have made further automation cheaper or we may have run out of ideas for generating new high-productivity (labor-intensive) tasks. Though these are all logically possible, we find the second reason for a change in this balance more plausible: we may have moved along a given innovation possibilities frontier because incentives for automation have in-

creased and those for creating new tasks have declined. There are several factors that may push in this direction. To start with, the US tax code aggressively subsidizes the use of equipment (e.g., via various tax credits and accelerated amortization) and taxes the employment of labor (e.g., via payroll taxes). The tendency towards further (and potentially excessive) automation may have been reinforced by the growing focus on automation and use of artificial intelligence for removing the human element from most of the production process. This focus has recently been boosted both by the central role that large tech companies have come to play in innovation with their business model based on automation and small workforces, and by the vision of many of the luminaries of the tech world (think of the efforts of Tesla to automate everything, which turned out to be very costly). Finally, the declining government support for innovation may have also contributed by discouraging research with longer horizon, which likely further disadvantaged the creation of new tasks (which bear fruit more slowly) relative to automation.

The factors discussed in the previous paragraph may contribute not just to the changing balance between automation and new tasks but also to the slowdown in productivity growth. First, since new tasks contribute to productivity, slower reinstatement will be associated with slower productivity growth. Therefore, factors tilting the balance against new tasks likely translate into lost opportunities for improved productivity. In addition, the lower wage growth resulting from a weak reinstatement effect indirectly makes automation less productive—because productivity gains from automation are increasing in the effective wage in tasks being replaced, and lower wages thus reduce these productivity gains.

Second, if innovations in both automation and new tasks are subject to diminishing returns (within a given period of time or over time), a significant change in the balance between these two types of new technologies will push us towards more marginal developments and cause slower productivity growth.

Third, as we already emphasized, productivity gains from automation could be quite small for so-so technologies—when automation substitutes for tasks in which labor was already productive and capital is not yet very effective. In this light, further automation, especially when it is induced by tax distortions or excessive enthusiasm about automating everything, would take the form of such so-so technologies and would not bring much productivity gains.

Finally, Acemoglu and Restrepo (2018d) suggest there may be a mismatch between the available skills of the workforce and the needs for new technologies. This 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 tasks can be utilized.

If the balance between automation and new tasks has shifted inefficiently and this is contributing to rapid automation, the absence of powerful restatement effects and the slow-down of productivity growth, then there may be room for policy interventions, which could improve both job creation and productivity growth. These might include removing incentives for excessive automation (such as the preferential treatment of capital equipment) and policies designed to rebalance the direction of technological change (see Acemoglu and Restrepo, 2019, for a more detailed discussion in the context of artificial intelligence).

Concluding Remarks

This paper develops a task-based model to study the effects of different technologies on labor demand. At the center of our framework is the task content of production—measuring the allocation of tasks to factors of production. Automation, by creating a displacement effect, shifts the task content of production against labor, while the introduction of new tasks in which labor has a comparative advantage improves it via the reinstatement effect. 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 show how changes in the task content of production and other contributors to labor demand can be inferred from data on labor shares, value added and factor prices at the industry level. The main implication of our empirical exercise using this methodology is that the recent stagnation of labor demand is explained by an acceleration of automation, particularly in manufacturing, and a deceleration in the creation of new tasks. In addition, and perhaps reflecting this shift in the composition of technological advances, the economy also experienced a marked slowdown in productivity growth, contributing to sluggish labor demand.

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, it 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. We have also pointed out a number of reasons why the balance between automation and new tasks may

have become inefficiently tilted in favor of the former, with potentially adverse implications for jobs and productivity and some directions for policy interventions to redress this imbalance.

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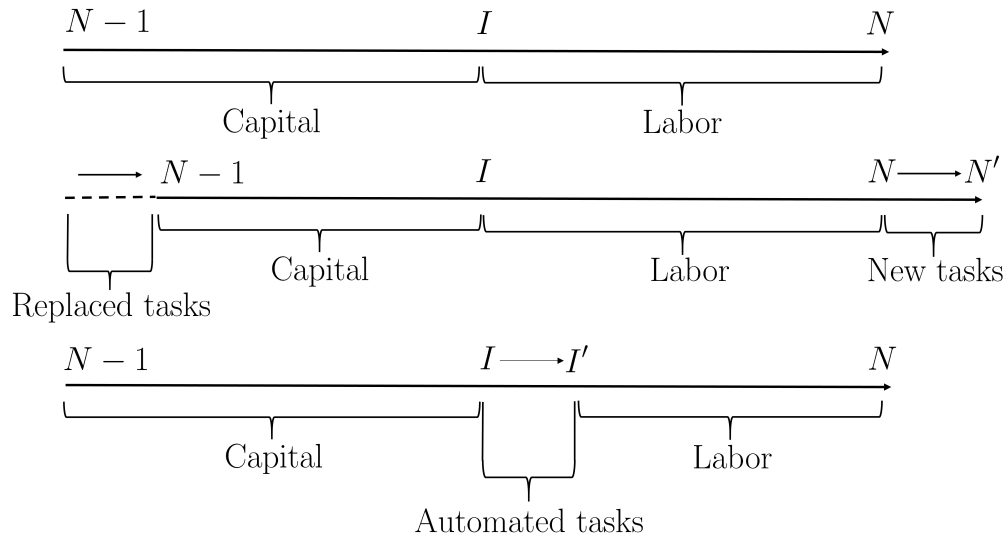
FIGURE 1: THE ALLOCATION OF CAPITAL AND LABOR TO THE PRODUCTION OF TASKS AND THE IMPACT OF AUTOMATION AND THE CREATION OF NEW TASKS.
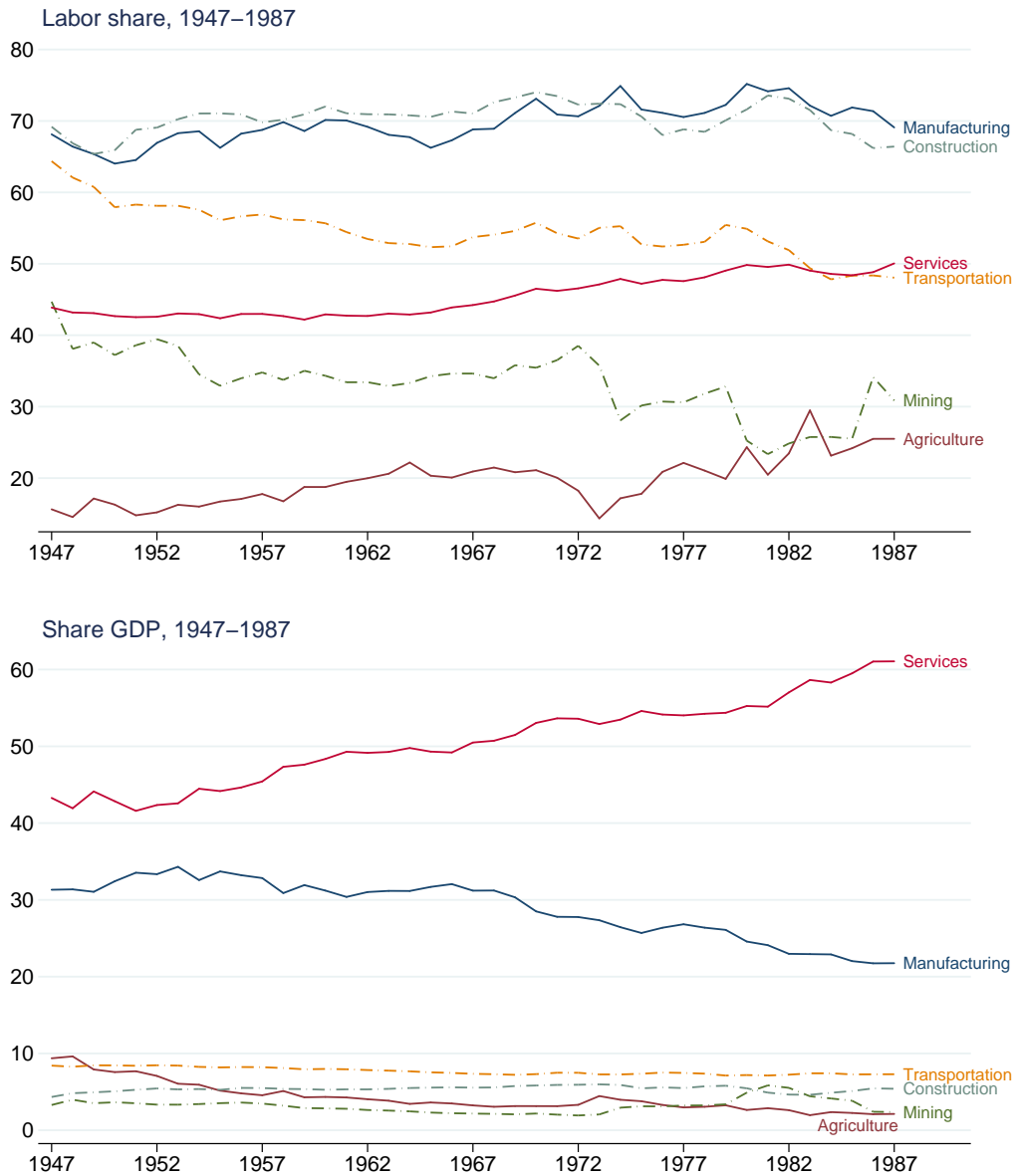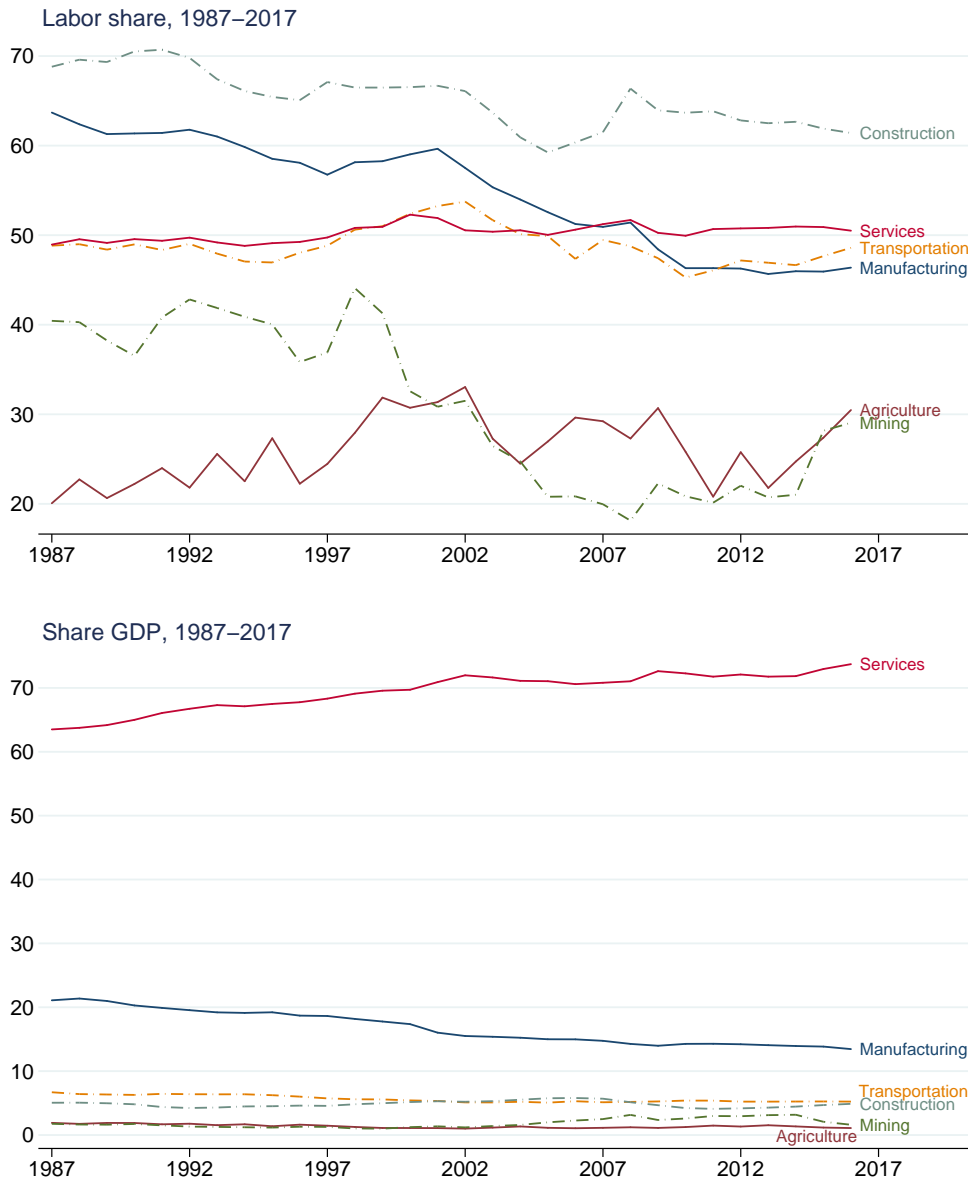
FIGURE 2: THE LABOR SHARE AND SECTORAL EVOLUTIONS, 1947-1987.
Note: The top panel shows the labor share in value added in services, manufacturing, construction, transportation, mining and agriculture between 1947 and 1987, while the bottom panel shows the share of value added in these sectors relative to GDP. Data from the BEA industry accounts.
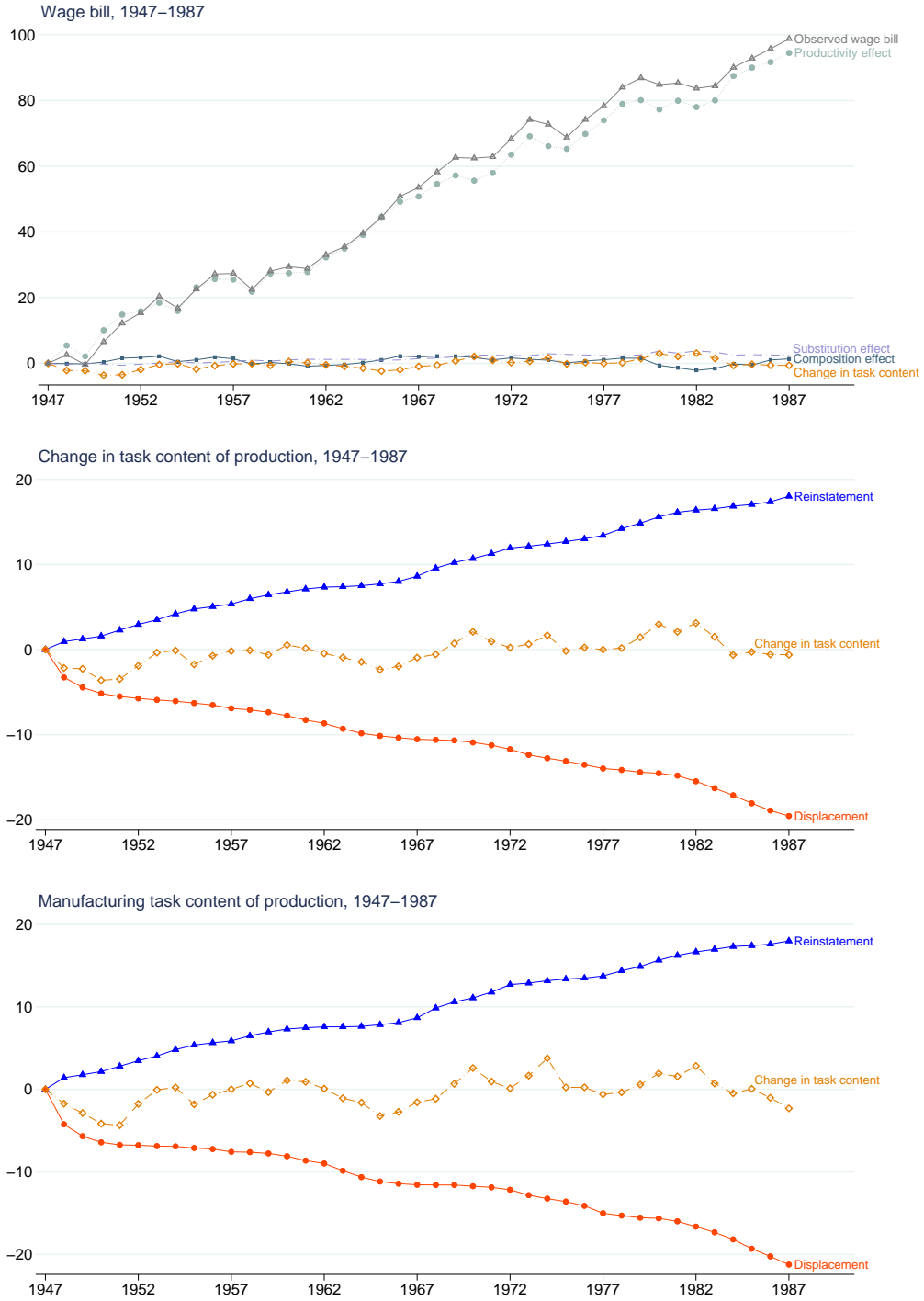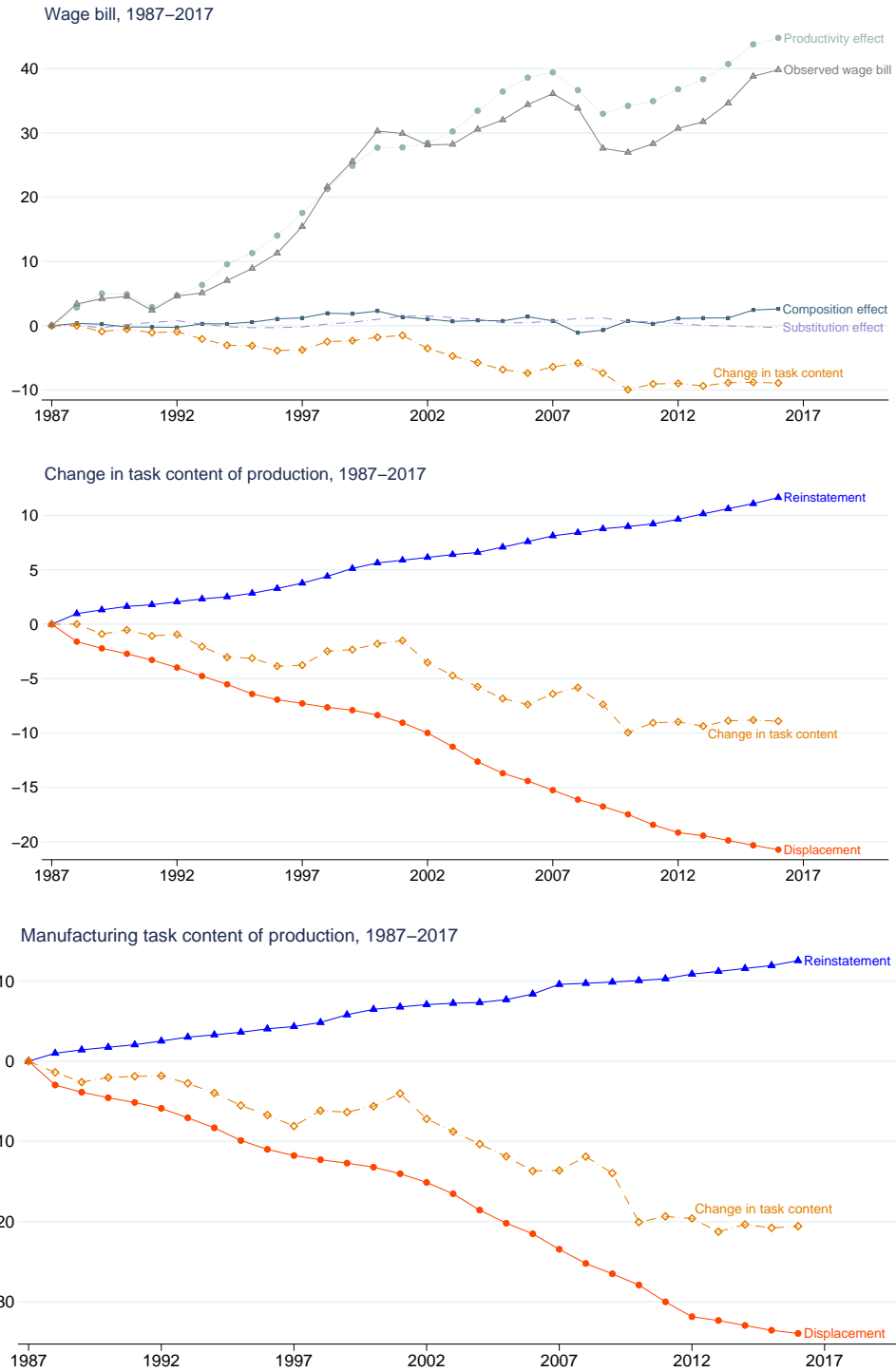
FIGURE 3: SOURCES OF CHANGES IN LABOR DEMAND, 1947-1987.

Note: The top panel presents the decomposition of wage bill divided by population 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. See text for the details of the estimation of the changes in task content and displacement and reinstatement effects.

FIGURE 4: 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 these sectors relative to GDP. Data from the BEA industry accounts.

Figure 5: Sources of changes in labor demand, 1987-2017.
Note: The top panel presents the decomposition of wage bill divided by population 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. See text for the details of the estimation of the changes in task content and displacement and reinstatement effects.

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

	RAW DATA (1)	CONTROLLING FOR MANUFACTURING (2)	CONTROLLING FOR CHINESE IMPORT AND OFFSHORING (3)
Proxies for automation technologies:			
Adjusted penetration of robots, 1993-2014	-1.404	-0.985	-1.129
	(0.377)	(0.369)	(0.362)
Observations	61	61	61
R-squared	0.18	0.21	0.27
Share of routine jobs in industry, 1990	-0.394	-0.241	-0.321
	(0.122)	(0.159)	(0.164)
Observations	61	61	61
R-squared	0.14	0.19	0.27
Detailed manufacturing industries (SMT):			
Share of firms using automation technologies, 1988-1993	-0.390		-0.397
	(0.165)		(0.166)
Observations	148		148
R-squared	0.08		0.09
Proxies for new tasks:			
Share of new job titles, based on 1991 DOT and 1990 employment by occupation	1.609	1.336	1.602
	(0.523)	(0.530)	(0.541)
Observations	61	61	61
R-squared	0.12	0.23	0.32
Number of emerging tasks, based on 1990 employment by occupation	8.423	7.108	7.728
	(2.261)	(2.366)	(2.418)
Observations	61	61	61
R-squared	0.14	0.25	0.33
Share of growth between 1990-2016 in occupations not in industry in 1990	2.121	1.638	1.646
	(0.723)	(0.669)	(0.679)
Observations	61	61	61
R-squared	0.08	0.20	0.26
Percent increase in number of occupations represented in industry	0.585	0.368	0.351
	(0.156)	(0.207)	(0.215)
Observations	61	61	61
R-squared	0.14	0.19	0.25

Note: The table reports estimates of the relationship between the change in task content of production between 1987-2017 and proxies for automation technologies and new tasks. Column 1 reports estimates of the bivariate relationship between change in task content of production and the indicated proxy at the industry level. Column 2 includes a dummy for manufacturing industries as a control. In addition, 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). 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. Standard errors robust against heteroskedasticity are in parenthesis. When using the measure of robot penetration, we cluster standard errors at the 19 industries for which this measure is available.

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

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

A1   Theory

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

Full Model Description

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

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

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

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

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

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

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

and take them as given for now.

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

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

(A 2)

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

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

$$(A\ 3) \qquad \Gamma(I, N) = \frac{\int_I^N \gamma^L(z)^{\sigma-1}}{\int_{N-1}^I \gamma^K(z)^{\sigma-1} dz + \int_I^N \gamma^L(z)^{\sigma-1}}.$$

The TFP term is then

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

The labor share follows directly from the expression in equation (A 2). Because of the CES structure, the labor share is given by equation (2). The labor share can also be expressed as a function of labor, capital and factor-augmenting technologies as well as the task content of production:

$$(A\ 4) \qquad s^L(L, K; \theta) = \frac{1}{1 + \left(\dfrac{1 - \Gamma(I, N)}{\Gamma(I, N)} \right)^{\frac{1}{\sigma}} \left(\dfrac{A^K K}{A^L L} \right)^{\frac{\sigma-1}{\sigma}}}.$$

Restriction that Ensures I Binds

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

$$(A\ 5) \qquad \frac{1 - \Gamma(I, N)}{\Gamma(I, N)} \left(\frac{A^L}{A^K} \frac{\gamma^L(I)}{\gamma^K(I)} \right)^{\sigma} < \frac{K}{L} < \frac{1 - \Gamma(I, N)}{\Gamma(I, N)} \left(\frac{A^L}{A^K} \frac{\gamma^L(N)}{\gamma^K(N-1)} \right)^{\sigma}.$$

When this restriction holds, we have that

$$(A\ 6) \qquad \frac{A^L}{A^K} \frac{\gamma^L(I)}{\gamma^K(I)} < \frac{W}{R} < \frac{A^L}{A^K} \frac{\gamma^L(N)}{\gamma^K(N-1)},$$

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

Technology and Labor Demand

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

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

written as

$$(A\,7) \qquad W^d(L,K;\theta) = \frac{Y(L,K;\theta)}{L} \times s^L(L,K;\theta).$$

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 (A 7) and then using (A 2) and (A 4).

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

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

Moreover, we can also use equation (A 2) to compute the productivity effect as

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

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

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

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

where the productivity effect from new tasks is given by

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

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

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

Multi-sector Economy

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

Index industries by i and let $\mathcal{I}$ represent the set of industries. We denote the price of the goods produced by sector i by P_i, while its factor prices are denoted by W_i and R_i—which continue to satisfy the assumption imposed in (A 6). The technology available to sector i is summarized by $\theta_i = \{I_i, N_i, A_i^L, A_i^K\}$, and L_i and K_i are the quantities of labor and capital used in each sector, so that output (value added) of sector i is $Y_i = Y(L_i, K_i; \theta_i)$. In addition, the comparative advantage schedules for labor and capital, γ_i^L and γ_i^K, are also part of the industry's technology but as in the text, we hold these fixed throughout. We denote the task content of sector i by $\Gamma_i = \Gamma(N_i, I_i)$ and its labor share by s_i^L. Total value added (GDP) in the economy is $Y = \sum_{i \in \mathcal{I}} P_i Y_i$, and we define $\chi_i = \frac{P_i Y_i}{Y}$ as the share of sector i's in total value added. Finally, we denote by s^L the economy-wide labor share.

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

(A 8)

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

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

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

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

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

Totally differentiating this expression, we obtain

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

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

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

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

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

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

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

Finally, differentiating (2), we have

$$(\text{A 9}) \qquad d\ln s_i^L = \frac{\left(1 - s_i^L\right)}{1 - \Gamma_i} d\ln \Gamma_i + (1 - \sigma)(1 - s_i^L)(d\ln W_i/A_i^L - d\ln R_i/A_i^K).$$

Substituting this into the previous expression, we obtain (A 8).

As the derivation shows, the decomposition in equation (A 8) is quite general. To derive it, we do not need to make assumptions about factor mobility across sectors, input-output linkages or the consumer demand-side (about their marginal rate of substitution across different types of goods). We can also accommodate different types of labor being employed in different industries and certain types of labor market imperfections. The only (and the critical) assumption is that firms are along their labor demand curve, so that in each industry we have $W_i L_i = P_i Y_i s_i^L$. This holds whenever the labor share equals the elasticity of output with respect to labor.

Alternative Production Function

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

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

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

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

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

gives the task content of production and

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

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

$$\frac{dY_i^{\frac{\sigma-1}{\sigma}}}{dN_i} = \frac{1}{\sigma}\left(\frac{1}{N_i}\int_{I_i}^{N_i}\gamma^L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}-1}(A_i^L L_i)^{\frac{\sigma-1}{\sigma}}\frac{\gamma^L(N_i)^{\sigma-1}}{N_i} - \frac{1}{\sigma}\frac{Y_i^{\frac{\sigma-1}{\sigma}}}{N_i}$$

$$\frac{d\ln Y_i}{dN_i} = \frac{1}{(\sigma-1)N_i}\left(\left[\frac{W_i}{A_i^L\gamma^L(N_i)}\right]^{1-\sigma} - 1\right)$$

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

A2 Details of Empirical Exercise

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

Productivity and Composition Effects

Equation (A 8) shows how small (infinitesimal) changes in the wage bill can be decomposed into productivity, composition and substitution effects and the change in the task content of production. We now explain how this theoretical result can be used for decomposing *discrete changes* in the wage bill. Throughout, as explained in the text, we normalize the economy-wide wage bill by total population in order to abstract from differential changes in population across different periods.

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

substitution effect and a change in the task content of production.

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

$$\ln\left(W_t L_t\right) = \ln\left(Y_t \sum_i \chi_{i,t} s_{i,t}^L\right)$$

$$\ln(W_{t_0} L_{t_0}) = \ln\left(Y_{t_0} \sum_i \chi_{i,t_0} s_{i,t_0}^L\right).$$

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

(A 10) $$\ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t_0} L_{t_0}}{N_{t_0}}\right) = \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right)$$
$$+ \ln\left(\sum_i \chi_{i,t} s_{i,t}^L\right) - \ln\left(\sum_i \chi_{i,t_0} s_{i,t}^L\right)$$
$$+ \ln\left(\sum_i \chi_{i,t_0} s_{i,t}^L\right) - \ln\left(\sum_i \chi_{i,t_0} s_{i,t_0}^L\right).$$

The first line in equation (A 10) represents changes in GDP per capita, which directly corresponds to our productivity effect (the term $d\ln Y$ in equation (A 8)). Hence, the empirical counterpart of our productivity effect is

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

The second line in equation (A 10) captures the impact of sectoral shifts (changes in $\chi_{t,i}$ over time) on labor demand holding the labor share within each sector constant. Conceptually, this corresponds to the composition effect (the term $\sum_i \frac{s_{i,t}^L}{s_t^L} d\chi_i$ in equation (A 8)). Thus, we measure the composition effect as

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

To further illustrate the connection between our empirical measure of the composition effect and equation (A 8), we use a first-order Taylor expansion of the previous expression,

in particular expanding $\ln\left(\sum_i \chi_{i,t} s_{i,t}^L\right)$ around $\ln\left(\sum_i \chi_{i,t_0} s_{i,t}^L\right)$, we obtain

$$\text{Composition effect}_{t_0,t} \approx \frac{1}{\sum_i \chi_{i,t_0} s_{i,t}^L}\left(\sum_i \chi_{i,t} s_{i,t}^L - \sum_i \chi_{i,t_0} s_{i,t}^L\right)$$

$$= \sum_i \frac{s_{i,t}^L}{\sum_j \chi_{j,t_0} s_{j,t}^L}(\chi_{i,t} - \chi_{i,t_0}).$$

This approximation shows that, as in the second line of equation (A 8), the empirical counterpart of the composition effect equals a weighted sum of changes in sectoral shares of GDP. In both cases, the weights capture how labor intensive a sector is relative to the rest.

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

Estimating the Substitution Effects and the Task Content of Production

With another first-order Taylor expansion, in particular expanding $\ln\left(\sum_i \chi_{i,t_0} s_{i,t}^L\right)$ around $\ln\left(\sum_i \chi_{i,t_0} s_{i,t_0}^L\right)$, the third term in equation (A 10) can be expressed as

$$\ln\left(\sum_i \chi_{i,t_0} s_{i,t}^L\right) - \ln\left(\sum_i \chi_{i,t_0} s_{i,t_0}^L\right) \approx \sum_i \frac{\partial \ln\left(\sum_j \chi_{j,t_0} s_{j,t_0}^L\right)}{\partial \ln s_{i,t_0}^L} \cdot \left(\ln s_{i,t}^L - \ln s_{i,t_0}^L\right)$$

$$= \sum_i \frac{\chi_{i,t_0} s_{i,t_0}^L}{\sum_j \chi_{j,t_0} s_{j,t_0}^L} \cdot \left(\ln s_{i,t}^L - \ln s_{i,t_0}^L\right)$$

$$= \sum_i \ell_{i,t_0} \left(\ln s_{i,t}^L - \ln s_{i,t_0}^L\right),$$

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

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

Equation (2) shows that the labor share can be written as a function of effective factor prices and the task content of production, $s_{i,t}^L = s^L(\rho_{i,t}, \Gamma_{i,t})$, where $\rho_{i,t} = \frac{W_{i,t}}{A_{i,t}^L}\frac{A_{i,t}^K}{R_{i,t}}$ is the relative effective price of labor. To further decompose the percent change in labor share within an industry, $\ln s_{i,t}^L - \ln s_{i,t_0}^L$, we use another first-order Taylor expansion, this time

$\ln s^L(\rho_{i,t}, \Gamma_{i,t})$ around $\ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})$. This yields:

$$\ln s_{i,t}^L - \ln s_{i,t_0}^L \approx \frac{\partial \ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})}{\partial \ln \rho_{i,t_0}} \left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g_{i,t_0,t}^A \right)$$
$$+ \frac{\partial \ln s^L(\rho_{i,t_0}, \Gamma_{i,t_0})}{\partial \ln \Gamma_{i,t_0}} \left(\ln \Gamma_{i,t} - \ln \Gamma_{i,t_0} \right),$$

where $g_{t_0,t}$ is the growth rate of A_t^L/A_t^K between t_0 and t. From equation (2), it follows that

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

and so we obtain the approximation

(A 11)
$$\ln s_{i,t}^L - \ln s_{i,t_0}^L \approx (1-\sigma)(1 - s_{i,t_0}^L) \left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g_{i,t_0,t}^A \right)$$
$$+ \frac{\left(1 - s_{i,t_0}^L\right)}{1 - \Gamma_{i,t_0}} \left(\ln \Gamma_{i,t} - \ln \Gamma_{i,t_0} \right),$$

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

Based on equation (A 11), we compute the substitution effect in an industry between t_0 and t as

$$\text{Substitution effect}_{i,t_0,t} = (1-\sigma)(1 - s_{i,t_0}^L) \left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g_{i,t_0,t}^A \right).$$

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

With estimates of the industry-level substitution effect at hand, we estimate the change in task content in an industry between t_0 and t as the residual from equation (A 11):

$$\text{Change task content}_{i,t_0,t} = \ln s_{i,t}^L - \ln s_{i,t_0}^L - (1-\sigma)(1 - s_{i,t_0}^L) \left(\ln \frac{W_{i,t}}{W_{i,t_0}} - \ln \frac{R_{i,t}}{R_{i,t_0}} - g_{i,t_0,t}^A \right).$$

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

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

which maps directly to the fourth line in the theoretical decomposition in equation (A 8).

Finally, the economy-wide change in the task content of production is computed by aggregating across industry-level changes in task content:

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

Displacement vs. Reinstatement

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

(A 13)
$$\text{Displacement}_{t-1,t} = \sum_{i \in \mathcal{I}} \ell_{i,t_0} \min \left\{ 0, \frac{1}{5} \sum_{\tau=t-2}^{t+2} \text{Change task content}_{i,\tau-1,\tau} \right\}$$
$$\text{Reinstatement}_{t-1,t} = \sum_{i \in \mathcal{I}} \ell_{i,t_0} \max \left\{ 0, \frac{1}{5} \sum_{\tau=t-2}^{t+2} \text{Change task content}_{i,\tau-1,\tau} \right\}.$$

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

A3 Additional Empirical Findings

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

The Role of Factor-Augmenting Technologies

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

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

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

changes in labor shares as

$$\ln A_{i,t}^L - \ln A_{i,t_0}^L = \frac{1}{(\sigma - 1)(1 - s_{i,t_0}^L)} \times \text{Displacement}_{i,t_0,t} > 0$$

and

$$\ln A_{i,t}^K - \ln A_{i,t_0}^K = \frac{1}{(1 - \sigma)(1 - s_{i,t_0}^L)} \times \text{Reinstatement}_{i,t_0,t} > 0.$$

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

$$(\text{A } 14) \quad \text{Contribution of } A^L \text{ to TFP}_{t,t_0} = \sum_i \chi_{i,t_0} \frac{s_{i,t_0}^L}{(\sigma - 1)(1 - s_{i,t_0}^L)} \times \text{Displacement}_{i,t,t_0} > 0,$$

and the improvements in $A_{i,t}^K$ increase TFP by

$$(\text{A } 15) \quad \text{Contribution of } A^K \text{ to TFP}_{t,t_0} = \sum_i \chi_{i,t_0} \frac{1 - s_{i,t_0}^L}{(1 - \sigma)(1 - s_{i,t_0}^L)} \times \text{Reinstatement}_{i,t,t_0} > 0.$$

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

The Decline in Manufacturing

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

Equation (A 8) must be extended to include the role of the price of manufacturing

goods. Changes in total wage bill in manufacturing can then be decomposed as

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

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

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

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

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

Correlates of Automation and New Tasks

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

Figure A4 present the relationships between our three proxies for automation with

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

Finally, Table A 1 shows that the *gross* change in task content (the sum of the absolute value of the displacement and reinstatement effects in an industry) predicts an increase in industry output (columns 1 and 2) and higher TFP (columns 3 and 4).[12] Both of these correlations support our interpretation that changes in the task content of production signal an undergoing process of automation or new task creation, which raises productivity. In columns 5 and 6, we look at skill intensity of an industry, measured by the share of college-educated workers among all employees (from the 1990 Census and 2012-2016 ACS). Industries experiencing more displacement or reinstatement are also becoming more skill-intensive. A natural interpretation of this finding is that automation technologies have mostly substituted for low-skill workers, while new tasks have benefit mostly high-skill labor (which is in line with the theoretical predictions in Acemoglu and Restrepo, 2018a).

Robustness Exercises

We also conducted a series of robustness checks.

■ Figure A6 investigates whether the order in which we decompose the wage bill in equation (A 10) (composition effects first within-industry changes next) matters. The figure presents the results from reversing this order and undertaking within-industry changes first and composition effects thereafter. In this alternative decomposition, equation (A 10) takes the form:

$$(A\ 17) \qquad \ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t_0} L_{t_0}}{N_{t_0}}\right) = \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right)$$
$$+ \ln\left(\sum_i \chi_{i,t} s_{i,t}^L\right) - \ln\left(\sum_i \chi_{i,t} s_{i,t_0}^L\right)$$
$$+ \ln\left(\sum_i \chi_{i,t} s_{i,t_0}^L\right) - \ln\left(\sum_i \chi_{i,t_0} s_{i,t_0}^L\right),$$

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

Following the same steps as before, we find that with this ordering the overall contri-

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

bution of the substitution effect is

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

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

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

and the composition effect is given by

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

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

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

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

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

A4   Data Sources

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

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

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

We use price data from the BLS *Multifactor Productivity Tables*, which report for each

industry measures of worker compensation and capital income, and indices of the quantity of labor used, the composition of labor used, and the quantity of capital used. The BLS then estimates a price index for labor—the wage $W_{i,t}$—as:

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

where $Y_{i,t}^L$ 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 $L_{i,t}^{comp}$ 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:

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

where $Y_{i,t}^K$ denotes capital income in industry i and $K_{i,t}^{qty}$ 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, $Y_{i,t}^K + Y_{i,t}^L$ account for the entire value added of industry i.

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

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

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

$$(A\ 18) \qquad \Delta \ln W_{i,t} = \Delta \ln Y_{i,t}^L - \Delta \ln L_{i,t}^{qty},$$

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

$$(A\ 19) \qquad \Delta \ln R_{i,t} = \Delta \ln(Y_{i,t} - Y_{i,t}^L) - \Delta \ln K_{i,t}^{qty},$$

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

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

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

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

$$(A\ 20)\quad \text{Substitution}_{i,t,t_0} = (1-\sigma)\ln\frac{s_{i,t}^L}{s_{i,t_0}^L} - (1-\sigma)(1-s_{i,t_0}^L)\left(\ln\frac{L_{i,t}^{qty}}{L_{i,t_0}^{qty}} - \ln\frac{K_{i,t}^{qty}}{K_{i,t_0}^{qty}} + g_{i,t,t_0}^A\right),$$

$$\text{Task content}_{i,t,t_0} = \sigma\ln\frac{s_{i,t}^L}{s_{i,t_0}^L} + (1-\sigma)(1-s_{i,t_0}^L)\left(\ln\frac{L_{i,t}^{qty}}{L_{i,t_0}^{qty}} - \ln\frac{K_{i,t}^{qty}}{K_{i,t_0}^{qty}} + g_{i,t,t_0}^A\right)$$

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 (A 18) and (A 19).

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

In addition, in a few cases, value added is below the compensation of employees, and in such instances, we recoded value added as equal to the compensation of employees,

ensuring that the labor share remains between 0 and 1. Finally, we converted these data to constant dollars using the PCE price index.

For these four-digit SIC industries, we compute indices for the quantity of capital and labor used from the NBER-CES *manufacturing database.* For labor, we computed an index of employment adjusting for the composition of workers (between production and non-production workers). For capital, we used the NBER-CES measure of real capital stock in each industry, which is constructed from data on investment (deflated to quantities) using the perpetual inventory method. We then computed the change in task content and substitution effect using the formulas in (A 20).

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

As noted in the text, the data on wage bill as a share of income in agriculture and industry are from Budd (1960). These numbers ignore proprietors income accruing to farmers and entrepreneurs, which are partly compensation for labor. Johnson (1948, 1954) provide estimates for the labor share of income inclusive of proprietors income in the early 1900s. The resulting labor shares in 1900-1910 are between 45% and 55% for agriculture (as opposed to an 18% wage share) and 70% for the overall economy (as opposed to a 47% wage share). Because (owner-occupied) farming was more important in agriculture than entrepreneurship in the rest of the economy, the gap in the labor intensity of agriculture relative to the overall economy halves once one takes into account farmers and entrepreneurs income.

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

Proxies for automation technologies: The measure of *adjusted penetration of robots* is from Acemoglu and Restrepo (2018b). It is available for 19 industries which are

then mapped to the 61 industries in our analysis.

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

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

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

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

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

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

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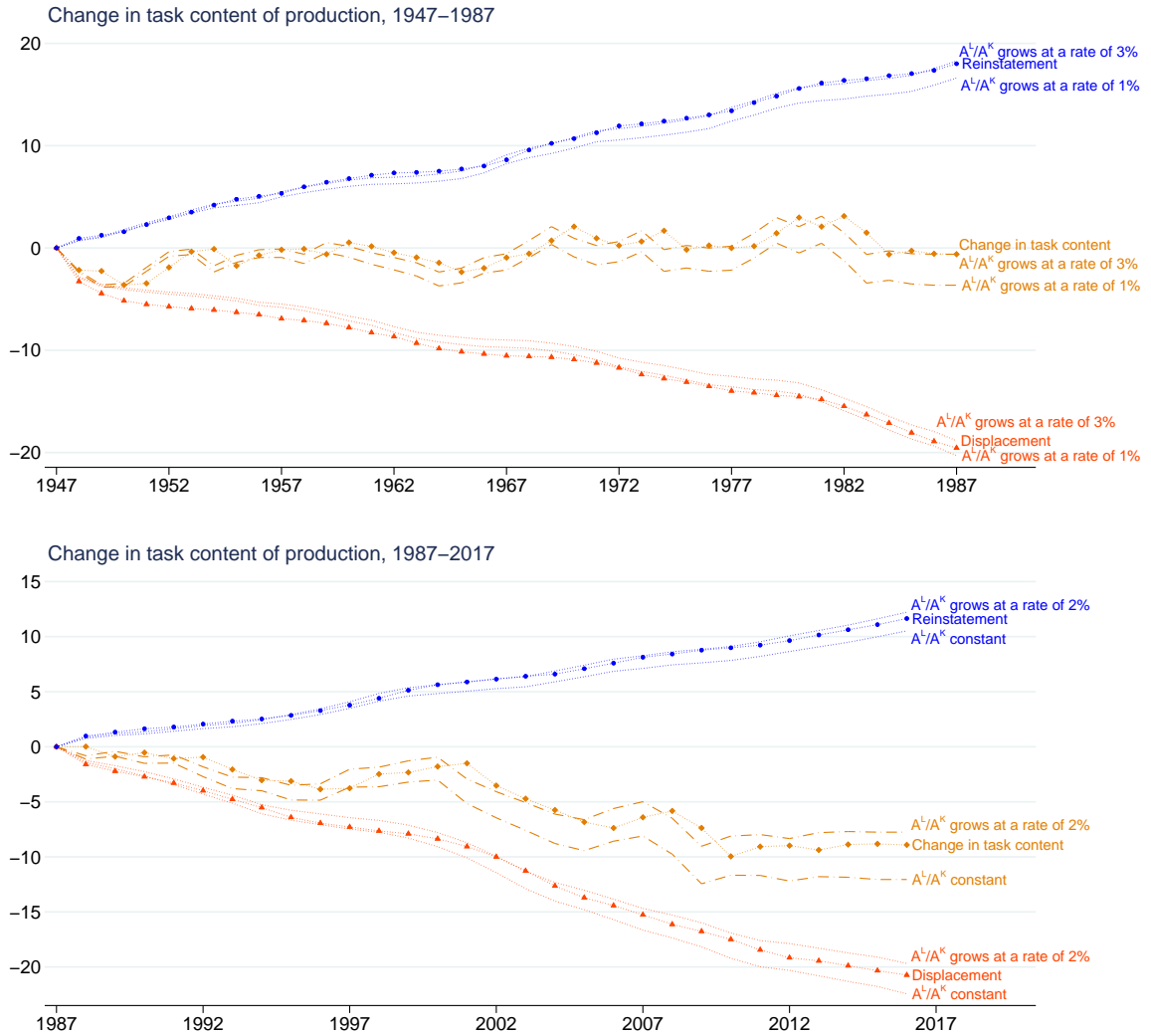
FIGURE A1: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR DIFFERENT ASSUMED GROWTH RATES FOR A_i^L/A_i^K.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A 13) for different values of the growth rate of A_i^L/A_i^K. The top panel is for 1947-1987, and as the baseline, assumes a growth rate for the relative labor-augmenting technological change of 2%. The bottom panel is for 1987-2017, and as the baseline, assumes a growth rate for the relative labor-augmenting technological change of 1.5%. Results for an elasticity of substitution $\sigma = 0.8$.
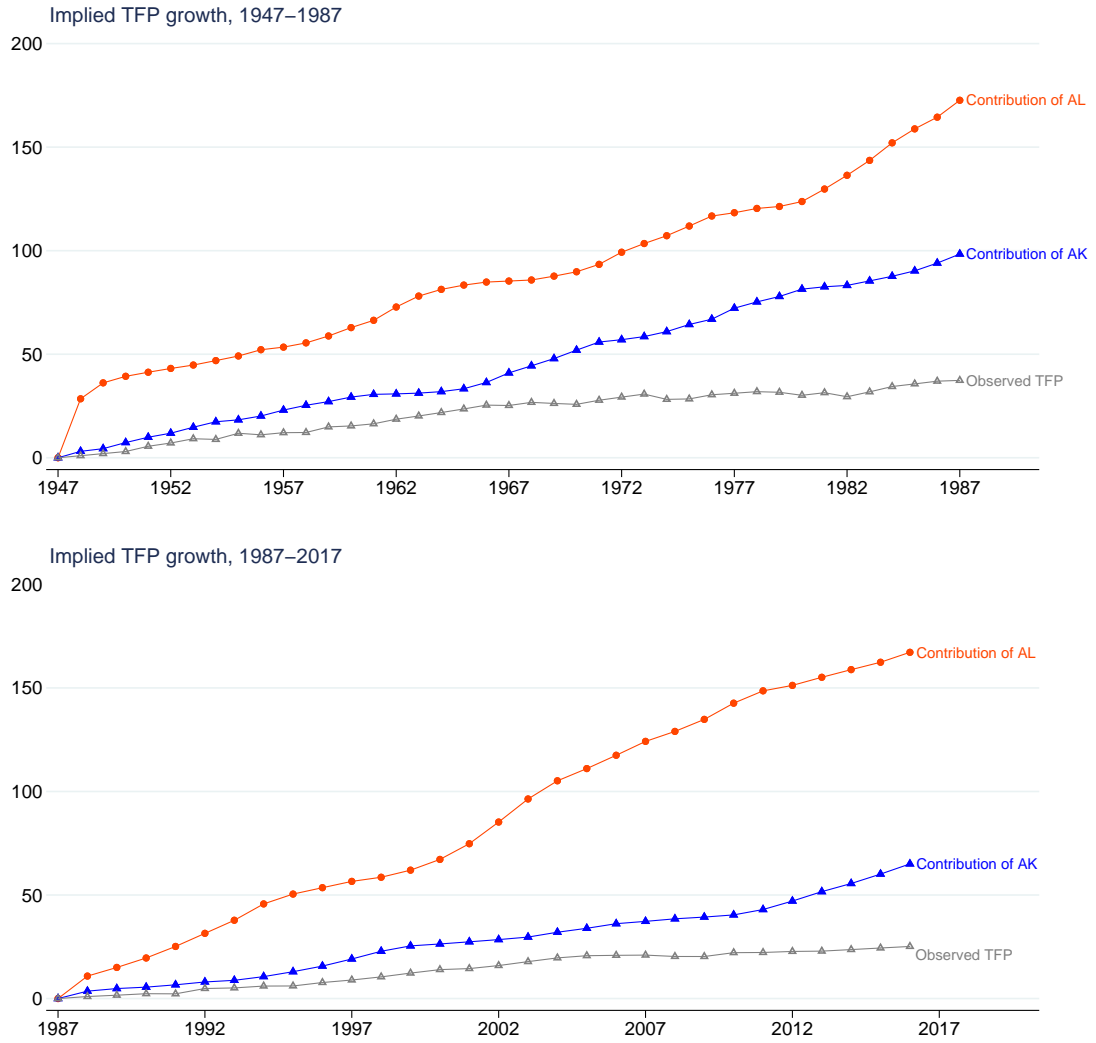
FIGURE A2: COUNTERFACTUAL TFP CHANGES.

Note: This figure presents the counterfactual TFP changes that would be implied if our estimates of the displacement and reinstatement effect in 1947-1987 and 1987-2017 were accounted for by industry-level changes in labor-augmenting and capital-augmenting technological changes alone, respectively, as derived in equations (A 14) and (A 15). For comparison, the figure also reports the observed increase in TFP for both periods.
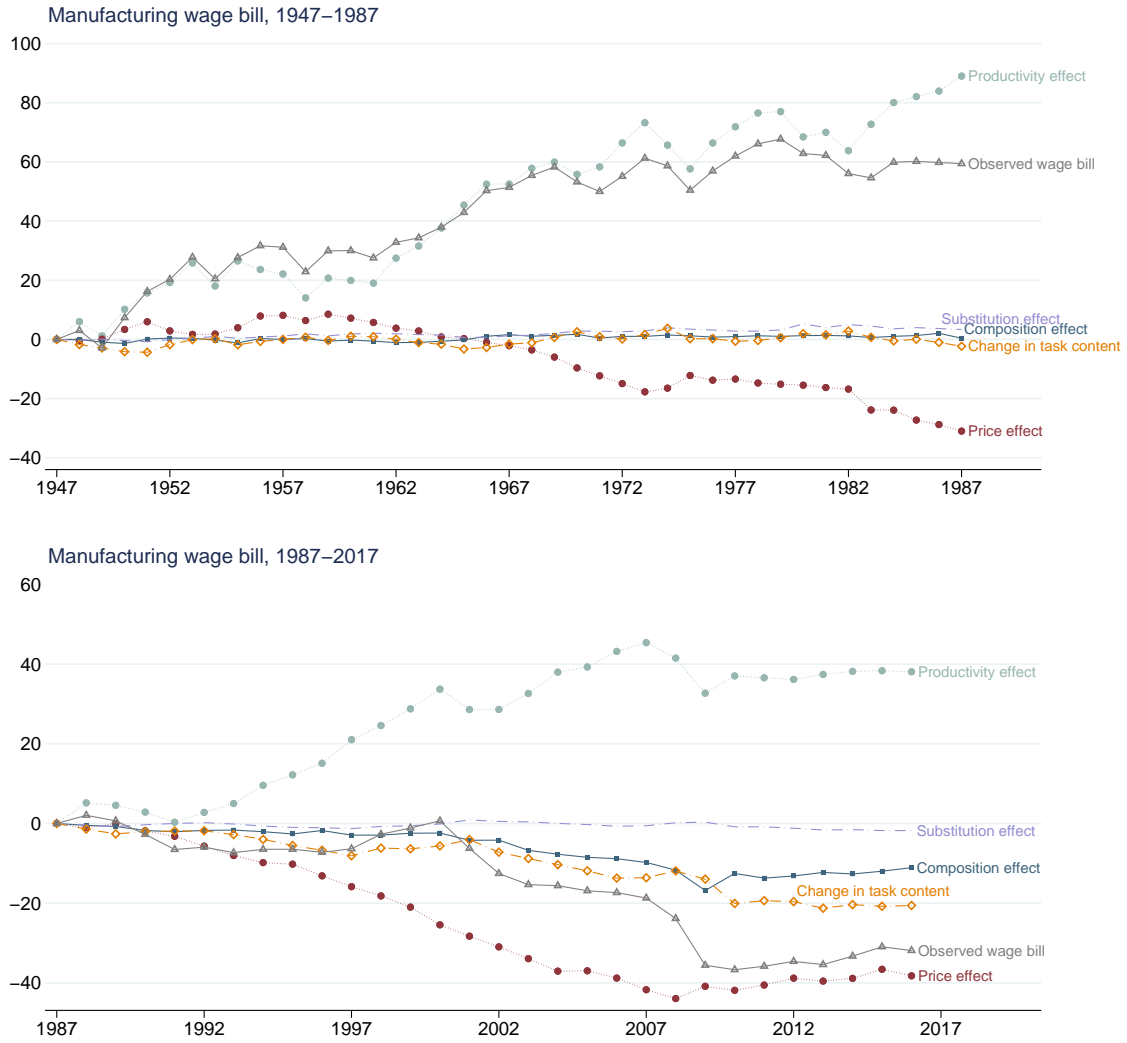
FIGURE A3: LABOR DEMAND IN MANUFACTURING.
Note: This figure presents the decomposition derived in equation (A3) for the manufacturing wage bill in 1947-1987 and 1987-2017. The top panel is for 1947-1987 and assumes a growth rate for the relative labor-augmenting technological change of 2%. The bottom panel is for 1987-2017 and assumes a growth rate for the relative labor-augmenting technological change of 1.5%. Results for an elasticity of substitution $\sigma = 0.8$.
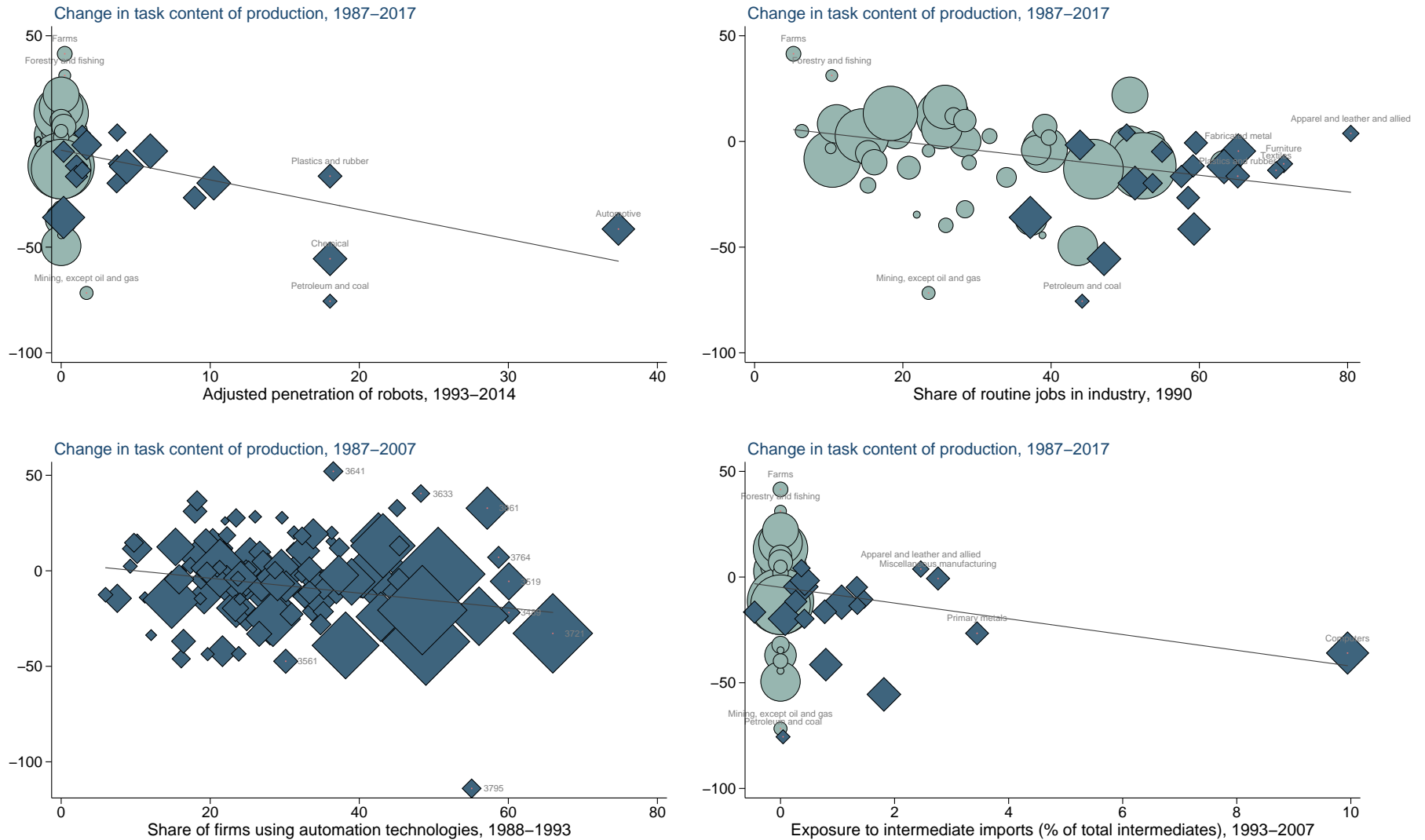
FIGURE A4: Automation technologies, offshoring, and changes in the task content of production.
Note: Each panel presents the bivariate relationship at the industry level between change in task content and the indicated proxy for automation technologies or offshoring. Diamond markers designate manufacturing industries and circles non-manufacturing industries. The proxies are: adjusted penetration of robots, 1993-2014 (from Acemoglu and Restrepo, 2018b), share of employment in routine occupations in 1990 (Acemoglu and Autor, 2011), share of firms (weighted by employment) using automation technologies, from the 1988 and 1993 SMT, and exposure to imports of intermediate goods, from Feenstra and Hanson (1999). See text for details.
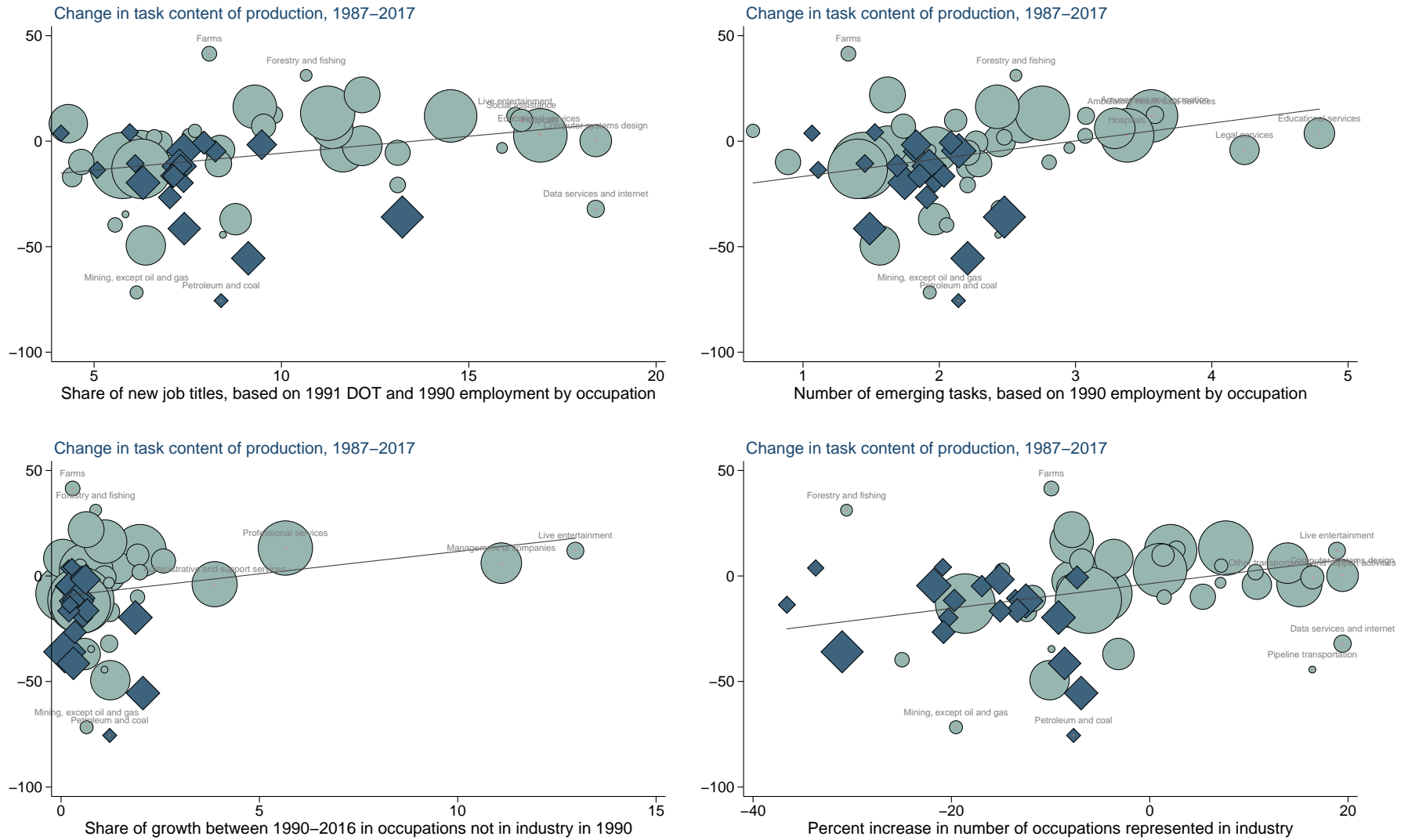
FIGURE A5: NEW TASKS AND CHANGE IN TASK CONTENT OF PRODUCTION.
Note: Each panel presents the bivariate relationship at the industry level between change in task content and the indicated proxy for new tasks. Diamond markers designate manufacturing industries and circles non-manufacturing industries. The proxies are: share of new job titles (from Linn, 2011), number of emerging tasks (from ONET), share employment growth between 1990 and 2016 in "new occupations"—those that were not present in the industry in 1990—, and the percent increase in the number of occupations present in the industry between 1990 and 2016. See text for details.
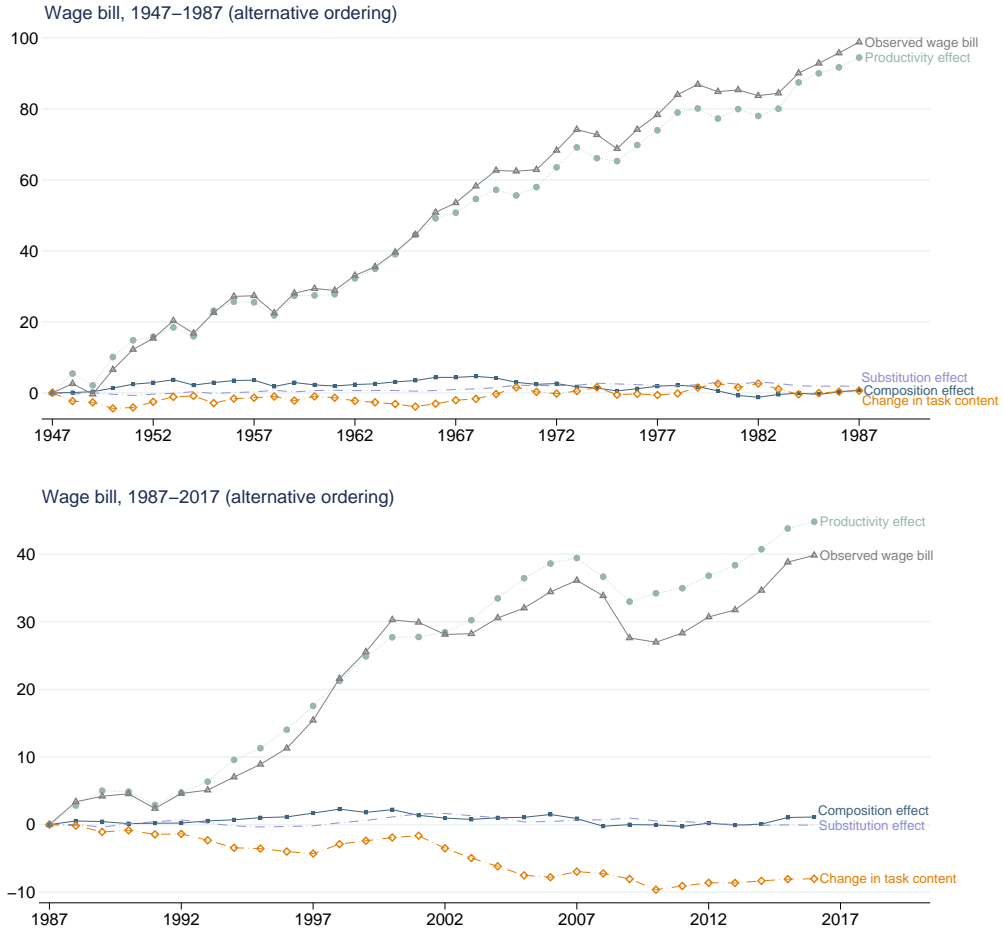
FIGURE A6: ALTERNATIVE ORDERING OF THE WAGE BILL DECOMPOSITION.

Note: The two panels present decompositions of changes in wage bill using the alternating ordering in equation (A 17). The top panel presents the decomposition of labor demand (wage bill) between 1947 and 1987. The bottom panel presents the decomposition of labor demand (wage bill) between 1987 and 2017. Results for an elasticity of substitution $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 2% per year (for 1947-1987) and 1.5% a year (for 1987-2017).
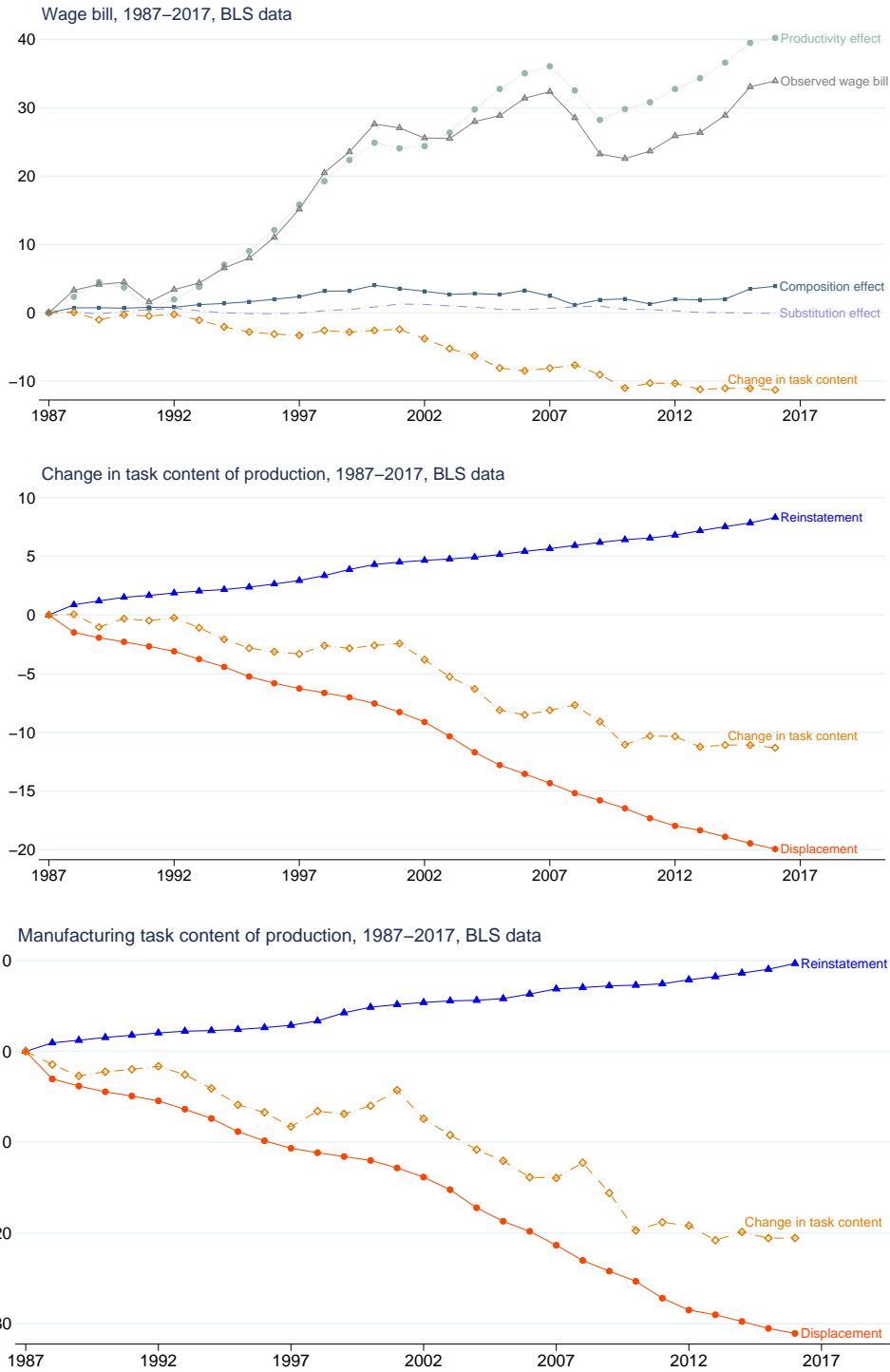
FIGURE A7: SOURCES OF CHANGES IN LABOR DEMAND, 1987-2017.

Note: The top panel presents the decomposition of labor demand (wage bill) between 1987 and 2017 using BLS data. The middle and bottom panels present our estimates of the displacement and reinstatement effects for the entire economy and the manufacturing sector, respectively. Results for an elasticity of substitution $\sigma = 0.8$ and relative labor-augmenting technological change at the rate of 1.5% a year.
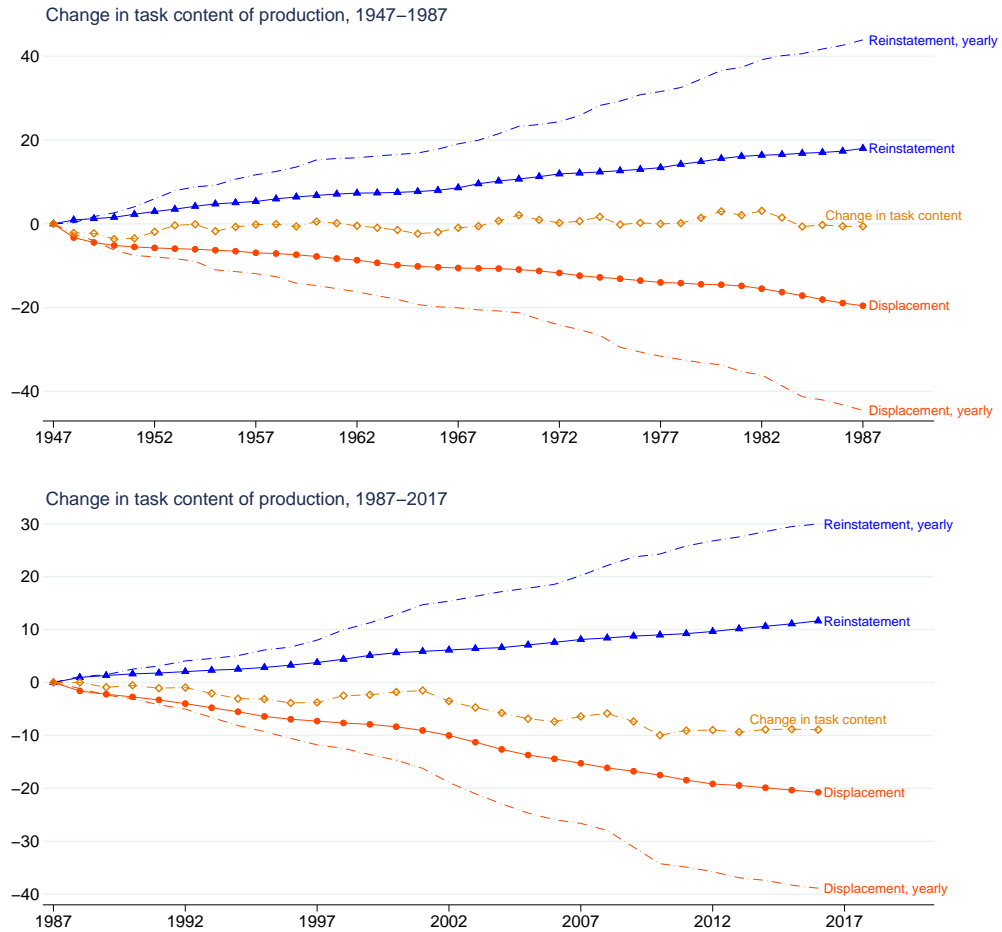
FIGURE A8: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS, YEARLY AND FIVE-YEAR CHANGES.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A 13) and additional estimates using yearly changes (rather than five-year windows). The top panel is for 1947-1987 and assumes a growth rate for the relative labor-augmenting technological change of 2%. The bottom panel is for 1987-2017 and assumes a growth rate for the relative labor-augmenting technological change of 1.5%. Results for an elasticity of substitution $\sigma = 0.8$.
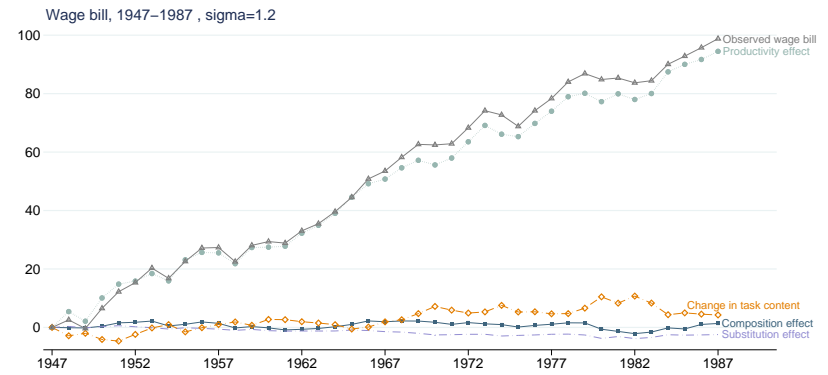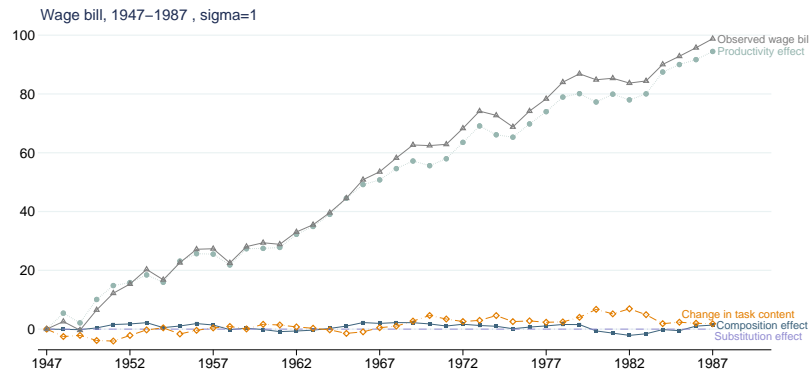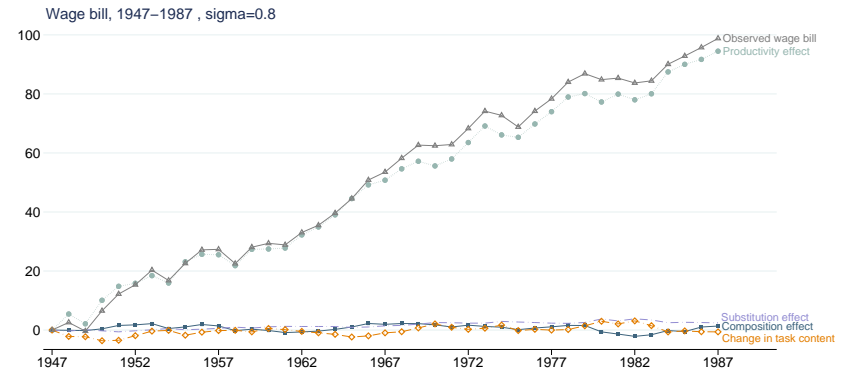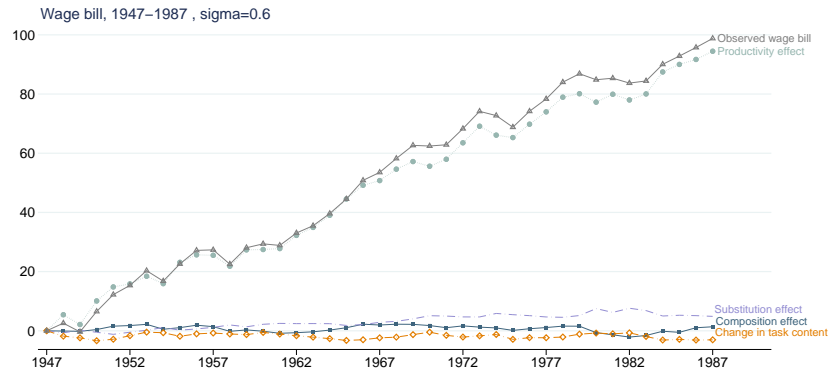
FIGURE A9: SOURCES OF CHANGES IN LABOR DEMAND FOR THE ENTIRE ECONOMY, 1947-1987, FOR DIFFERENT VALUES OF σ.
Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (A 8) in the text. The panels present the results for the vauels of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.
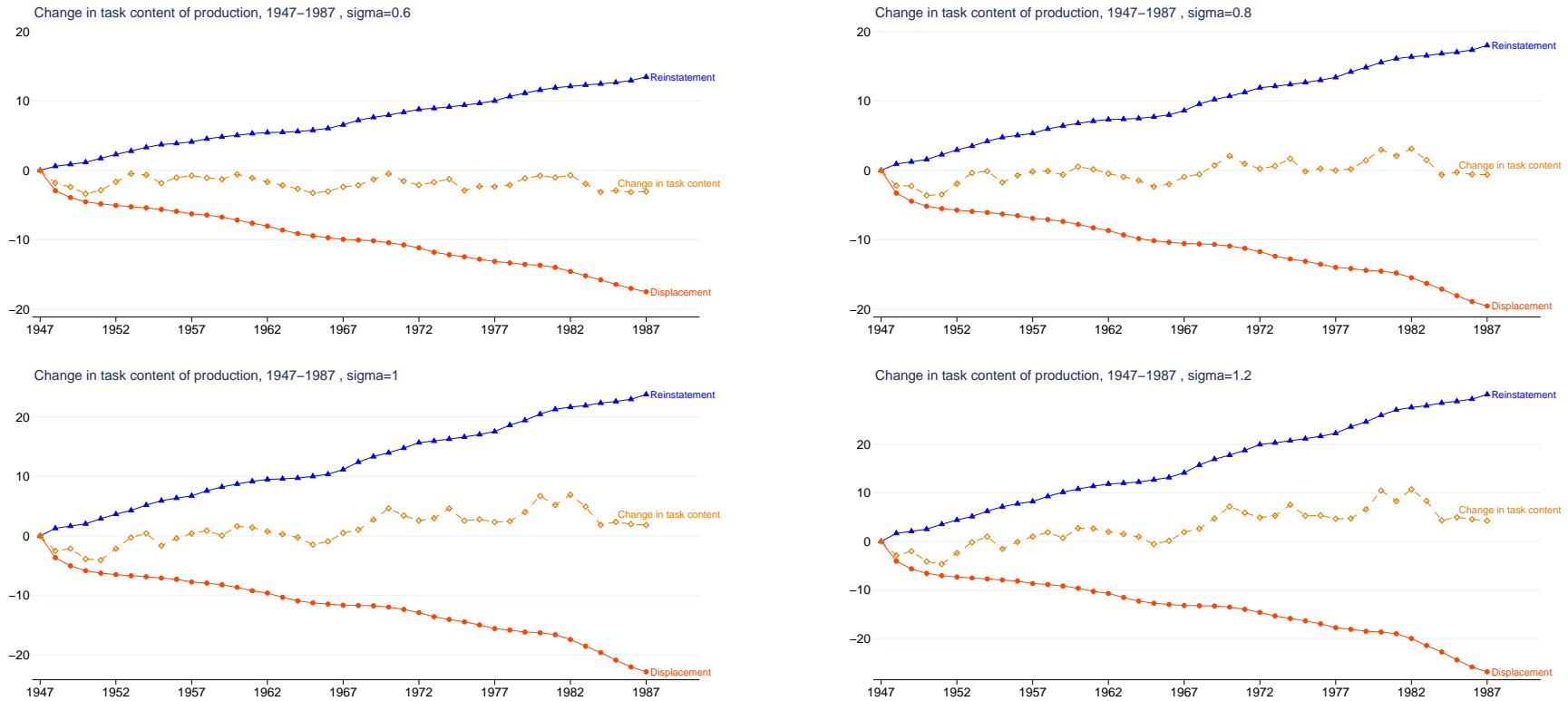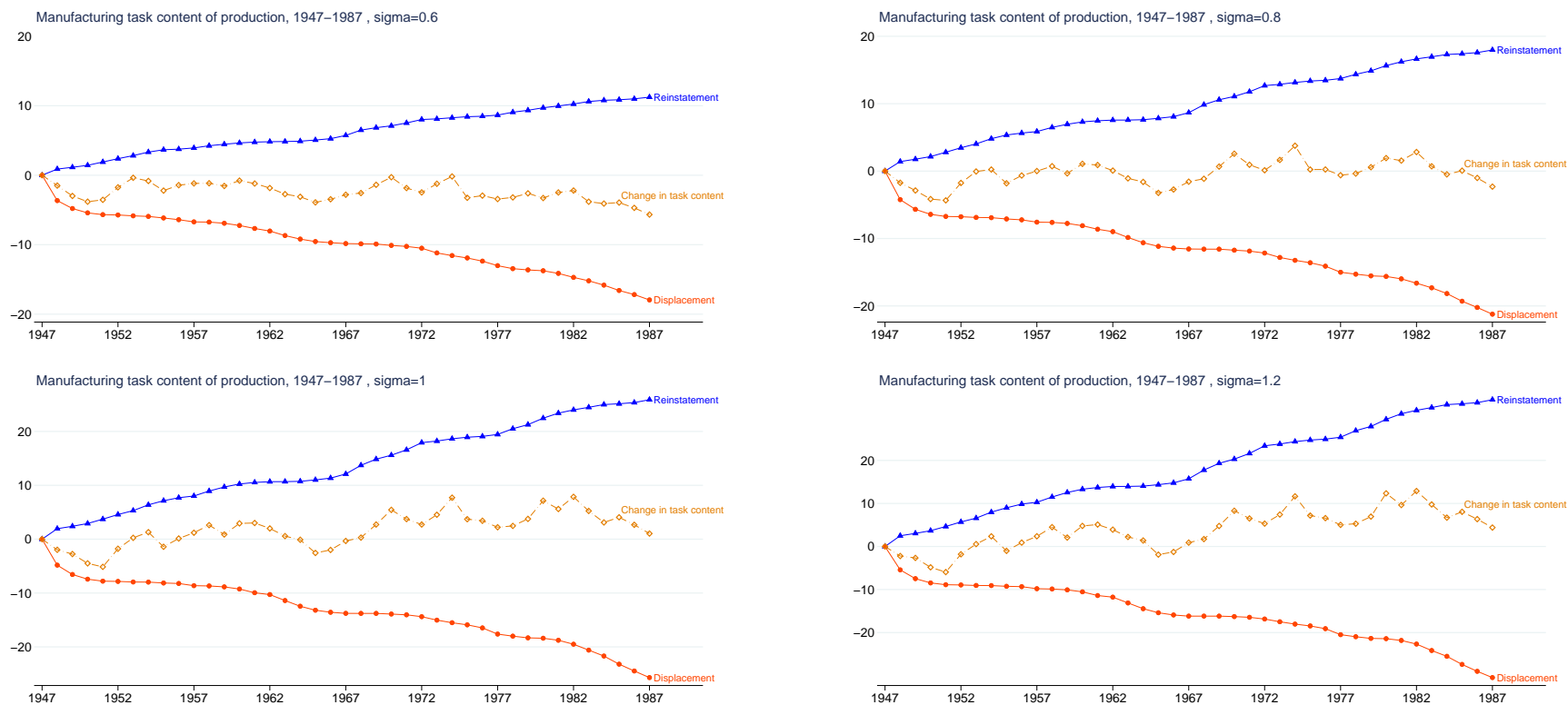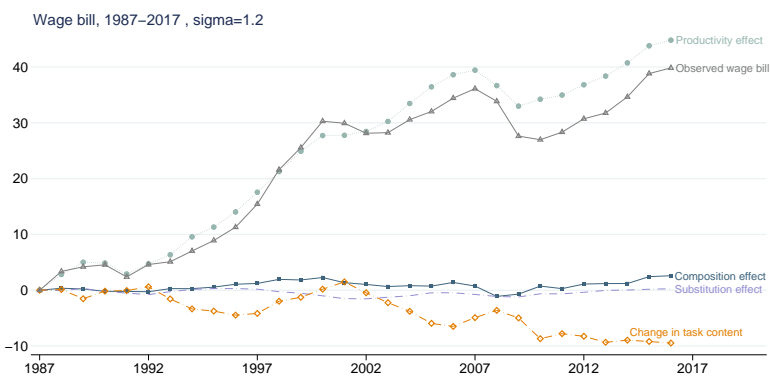
FIGURE A10: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR THE ENTIRE ECONOMY, 1947-1987, FOR DIFFERENT VALUES OF σ.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A 13) 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.

Manufacturing task content of production, 1947–1987 , sigma=0.6

Manufacturing task content of production, 1947–1987 , sigma=0.8

Manufacturing task content of production, 1947–1987 , sigma=1

Manufacturing task content of production, 1947–1987 , sigma=1.2

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

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A 13) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 2% a year.
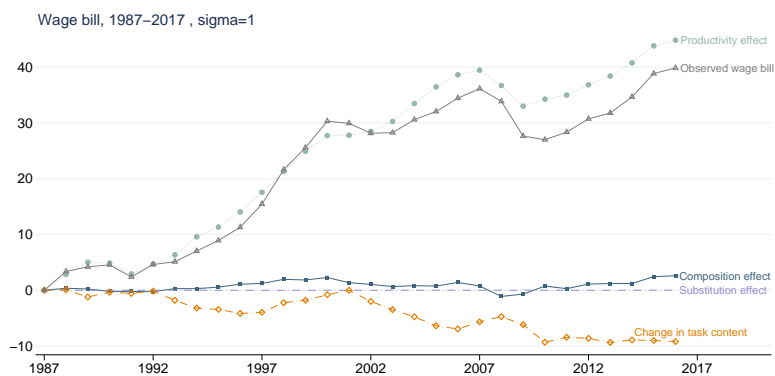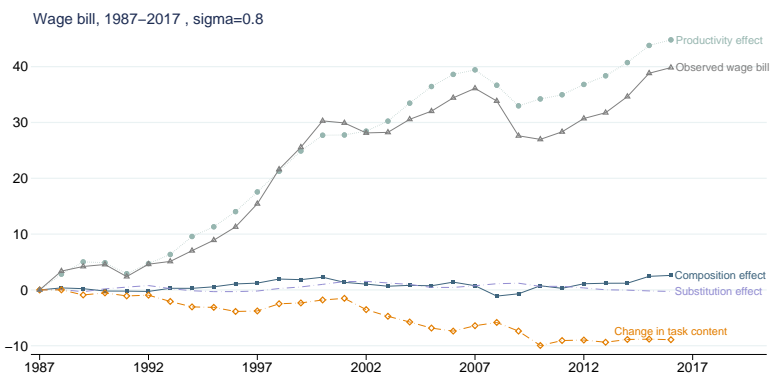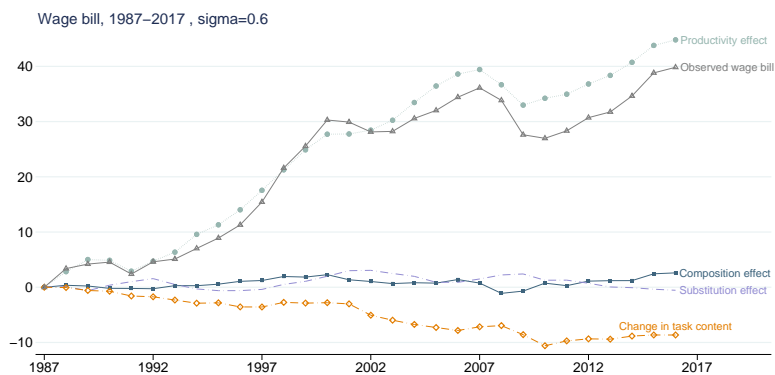
FIGURE A12: SOURCES OF CHANGES IN LABOR DEMAND FOR THE ENTIRE ECONOMY, 1987-2017, FOR DIFFERENT VALUES OF σ.
Note: This figure presents the decomposition of labor demand (wage bill) between 1987 and 2017 based on equation (A 8) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.
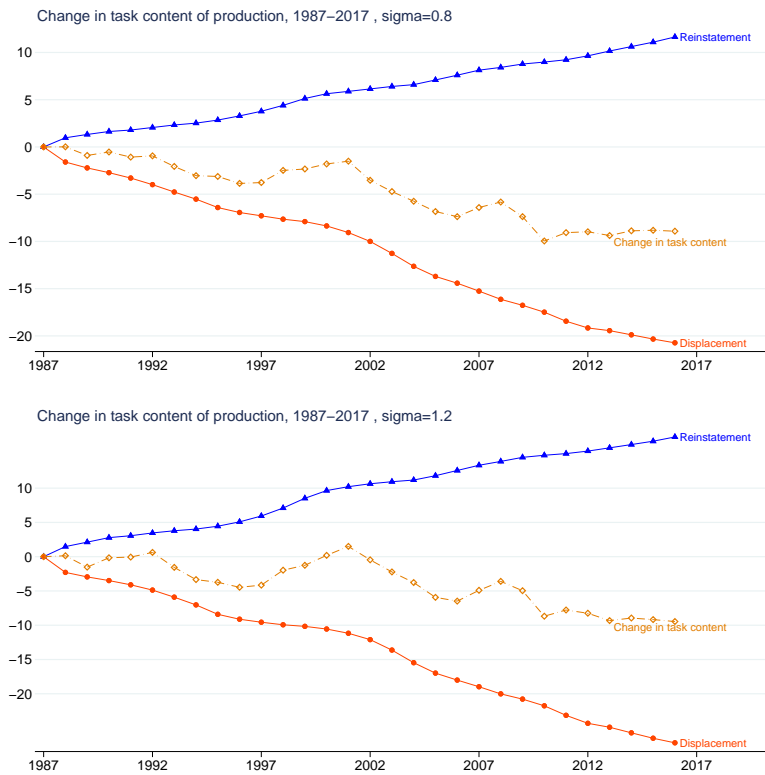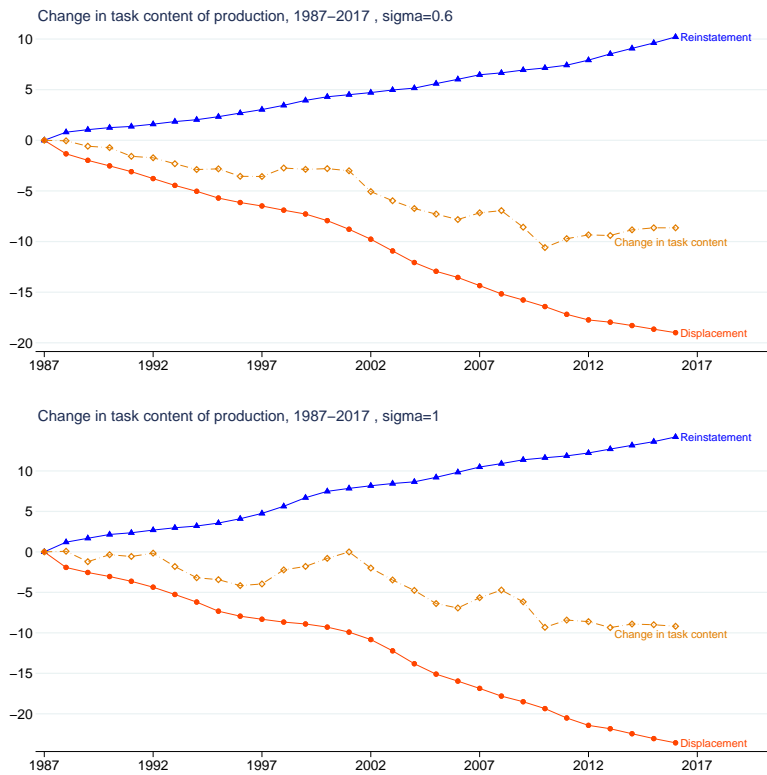
FIGURE A13: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR THE ENTIRE ECONOMY, 1987-2017, FOR DIFFERENT VALUES OF σ.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A 13) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.
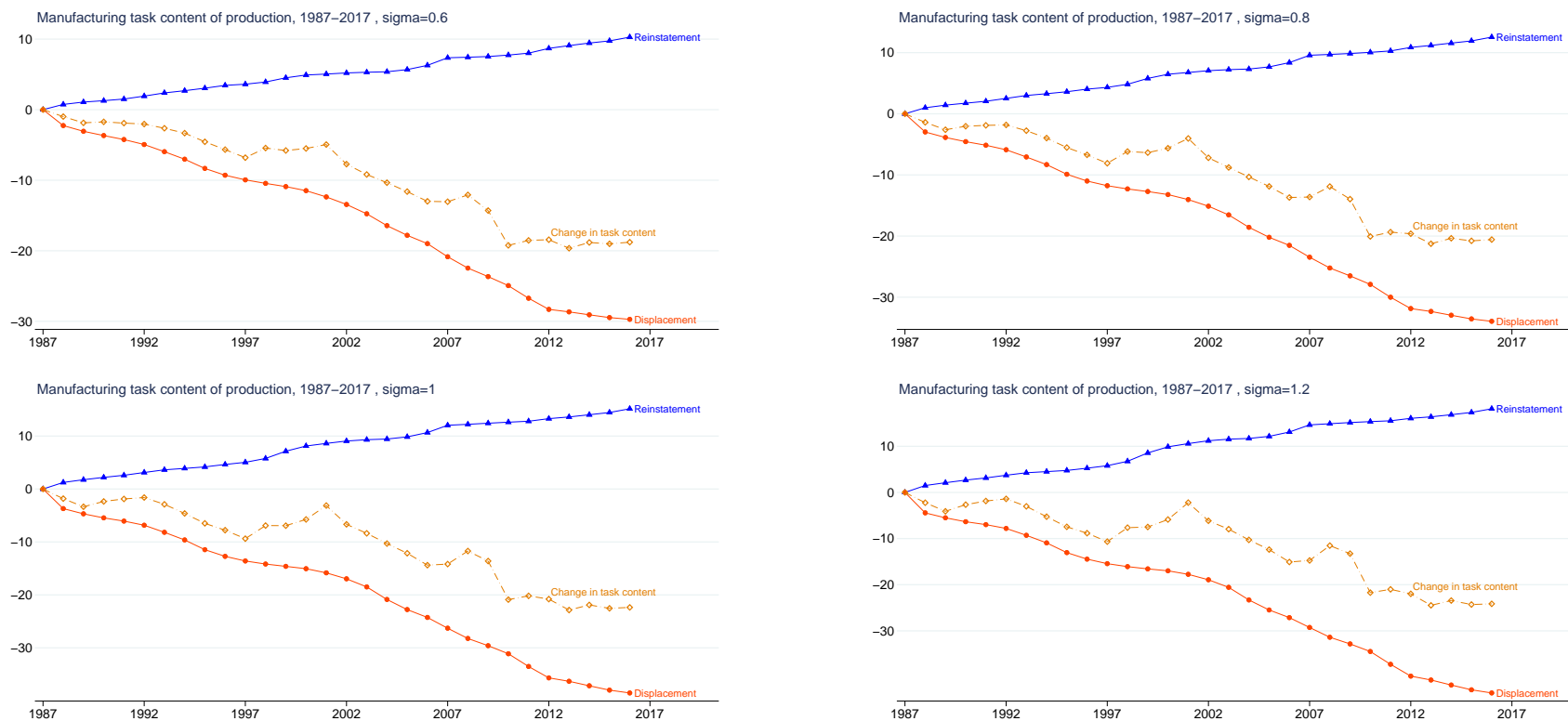
FIGURE A14: ESTIMATES OF THE DISPLACEMENT AND REINSTATEMENT EFFECTS FOR MANUFACTURING, 1987-2017, FOR DIFFERENT VALUES OF σ.

Note: This figure presents our baseline estimates of the displacement and reinstatement effects based on equation (A 13) in the text. The panels present the results for the values of σ indicated in their headers. In all panels, we assume relative labor-augmenting technological change at the rate of 1.5% a year.
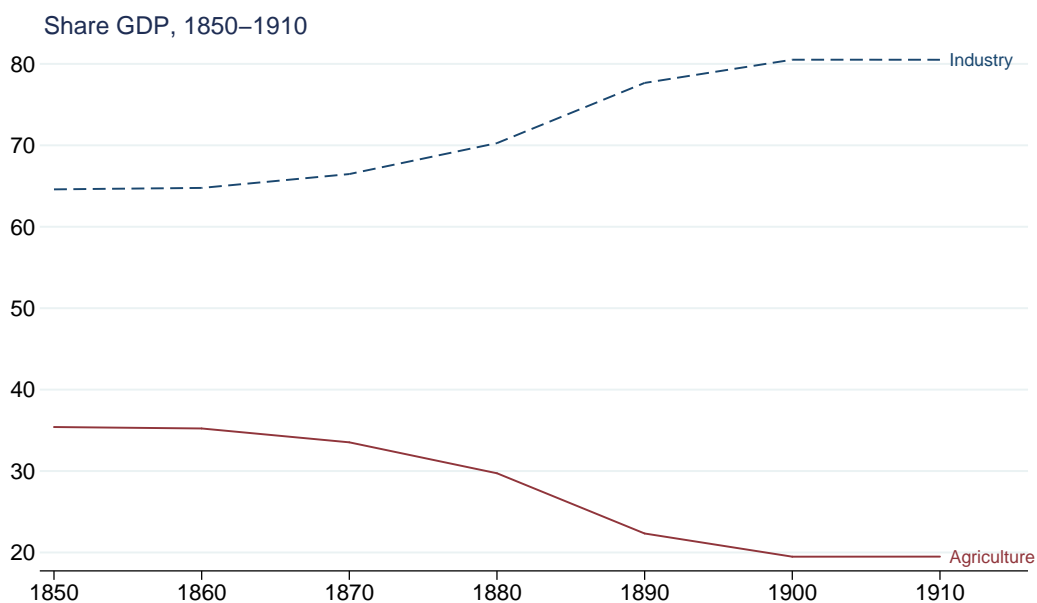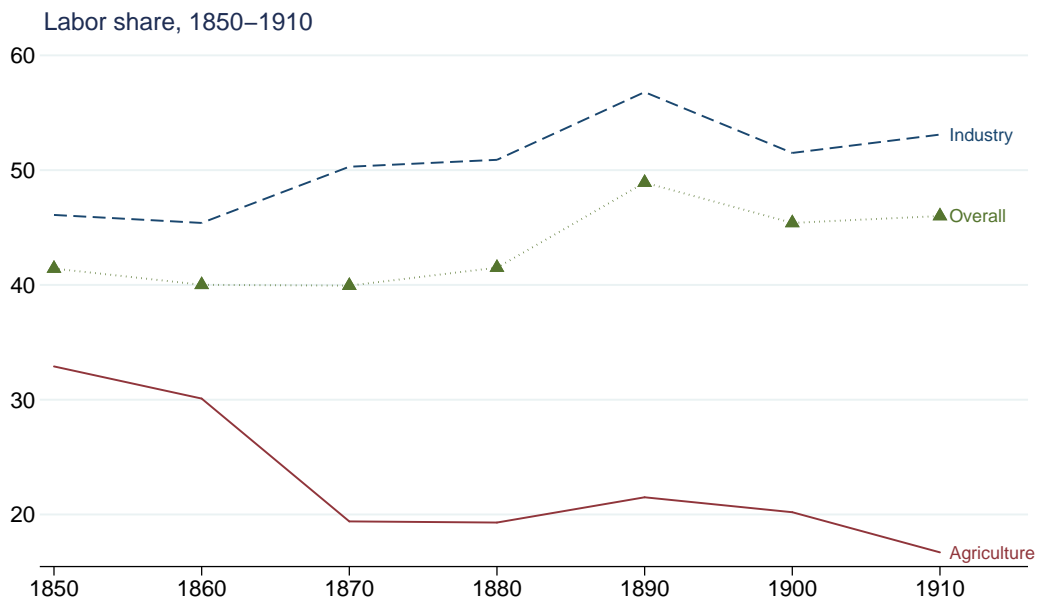
FIGURE A15: LABOR SHARE AND SECTORAL EVOLUTIONS DURING THE MECHANIZATION
OF AGRICULTURE, 1850-1910.
Note: The top panel shows the labor share in value added in industry (services and
manufacturing) and agriculture between 1850-1910, while the bottom panel shows the
share of value added in these sectors relative to GDP. Data from Budd (1960).

TABLE A 1: Relationship between gross change in task content of production, quantities produced, TFP, and skill intensity of industries.

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

Note: The table reports estimates between gross changes in task content of production and the change in quantities, TFP, and skill intensity of industries. The gross change in task content is defined as the sum of the absolute values of the displacement and reinstatement effects computed in equation (A 13). Columns 1-2 present results for the change in quantities produced (from the BEA-KLEMS). Columns 3-4 present results for the change in TFP (from the BEA-KLEMS). Columns 5-6 present results for the change in skill requirements, measured by the share of college educated workers in each industry (from the 1990 US Census and the pooled 2012-2016 ACS). All regressions are for the 61 industries used in or analysis of the 1987-2017 period. Standard errors robust against heteroskedasticity are in parenthesis.