Computerizing Industries and Routinizing Jobs: Explaining Trends in Aggregate Productivity

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Abstract

Aggregate productivity growth in the U.S. has slowed down since the 2000s. We relate this to differential productivity growth across multiple jobs (routinization) and industries since the 1980s. In our model, complementarity across jobs and industries in production leads to aggregate productivity slowdowns, as the relative size of those jobs and industries that experienced high productivity growth shrinks, reducing their contributions toward aggregate productivity. We find that this effect was countervailed by extraordinarily high productivity growth in the computer industry (computerization) during the 1980s and 1990s, of which output became an increasingly more important input in production across all industries. It was only as the productivity growth in the computer industry slowed down in the 2000s that the negative effect of differential productivity growth across jobs became apparent for aggregate productivity. Our quantitative results show that the decline in the labor share can also be explained by computerization, which substitutes labor across all industries.

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1 Introduction

Amid the sluggish recovery following the Great Recession, much attention has been given to the slowdown in productivity growth in the United States economy (sometimes referred to as “secular stagnation”). We dissect this trend in aggregate productivity by developing a model in which technological progress is both sector- and occupation-specific,¹ to better understand which sectors and occupations contribute most to the changes in aggregate productivity. In particular, we pay special attention to the computer sector (hardware and software), which has enjoyed an impressive rise in its productivity even as the rest of the economy lagged behind. Moreover, computer and software has become an important factor of production for all other sectors since the 1990s (which we call “computerization”), so we separate computer and software from other machinery equipment as a distinct type of capital. Using the model, we quantify the importance of the computer sector (which is a specific industry) and compare it against “routinization” (i.e., faster technological progress specific to occupations that involve routine or repetitive tasks), which has been found to be an important driver of aggregate employment shifts, in explaining trends in aggregate productivity.

In our model, individuals inelastically supply labor to differentiated jobs. Each sector uses all these jobs, but with different intensities. Sectors are complementary across one another for the production of the final good. Within each sector, jobs are also complementary to one another, and labor is combined with capital for sectoral production. Most important, we divide capital into computer capital (including software) and the rest (i.e., all capital not produced from the computer sector), and assume that the substitutability between labor and computer capital may differ across sectors. We model computer and software as capital used by all other sectors rather than an intermediate input, because the computer share of all investment is substantially larger than its share of all intermediates (14 vs. 2 percent, averaged between 1980 and 2010).

We note that computerization and routinization are empirically distinct phenomena. Computer and software usage increased the most for high-skill or cognitive occupations, not middle-skill or routine occupations (Aum, 2017), justifying our choice to model productivity growth in both dimensions. We then estimate the degree of complementarity across sectors, and calibrate the productivity growth rates, complementarity across jobs, and substitutability between computer capital and labor, using detailed

¹Throughout the text, we will use “sector” and “industry” interchangeably, as well as “occupations,” “tasks” and “jobs.”
data on employment shares and computer capital by industry and by occupation. We verify that as long as productivity growths are positive, (i) sectors are complementary to one another for final good production;\(^2\) (ii) jobs are complementary to one another within sectors; and most importantly, (iii) computer capital is in fact substitutable with labor in all sectors.

Given the structure of our model and estimated/calibrated parameters, when the productivity of sectors or jobs grow at constant but different rates, aggregate productivity growth declines over time due to the two types of complementarity (across jobs within sectors, and across sectors in final good production). As productivity growth slows down, so does output growth.

The mechanics of our model is consistent with our empirical findings: Since the 1980s, sectors that rely heavily on routine jobs experienced the highest growth in their productivities, as measured by conventional growth accounting. In our model, this is a result of routinization or the relatively faster productivity growth specific to routine-intensive jobs, rather than sector-specific technological progress. These occupations, and the sectors that rely relatively more on them, saw their employment shares decrease. In our model, this is a result of the complementarity across sectors and occupations: Constant growth of occupation- and sector-specific productivity implies that these jobs and sectors shrink in terms of employment and value added, which results in aggregate productivity slowdowns.

Next we compare the quantitative contributions of sectoral and occupational productivity growth to this aggregate productivity slowdown in our model. We find that the fall in aggregate TFP growth in the longer run is more due to the differential growth across occupations (i.e., routinization) rather than differential growth across sectors. In fact, if all occupation-specific productivities had grown at a common rate from 1980, holding all else equal, aggregate productivity growth rates would have stayed nearly constant through 2010.

The natural question is then why the downward trend in aggregate productivity growth did not manifest itself until the 2000s. In our model, the slowdown in aggregate productivity growth can be temporarily arrested and even reversed if certain sectors or jobs experience faster-than-usual technological progress. We find that this is exactly what happened during the 1990s, when the computer sector recorded an impressive productivity growth. Without the technological progress specific to the computer industry, aggregate TFP growth during the 1990s would have been 0.5 percent per year.

\(^2\)Or consumption, which we do not model.
instead of 0.8 percent. It is only after the subsequent slowdown in the computer sector’s productivity growth in the 2000s that the longer-run downward trend in aggregate productivity became apparent. Our analysis confirms that absent productivity growth in the computer sector, aggregate productivity growth would have declined monotonically since 1980.

Furthermore, because the computer sector’s productivity growth reduces the price of computer capital and thereby increase its usage by all sectors, it contributes to output growth in addition to its contribution to aggregate TFP growth. Indeed, if there had been no productivity growth in the computer sector and hence no computerization, output per worker growth would have been 1.5 percent per year during the 1990s, rather than the 3.5 percent as observed in the data. In other words, the sluggish growth of aggregate productivity and output in the 2000s was not abnormal. It was the faster-than-trend growth during the 1990s driven by the outburst of the computer sector’s productivity that was extraordinary.

Treating computer capital as a separate production factor as we do also has implications for the measurement of aggregate TFP. We find that the conventional way of computing aggregate TFP by summing up all capital into one category overstates the actual TFP growth by 0.4 percentage point per year on average between 1980 and 2010.

Lastly, we relate computerization to the decline in the labor income share. In our model, the labor share decline is caused by the substitutability between labor and computer capital, as the computer sector becomes more productive. We find that computerization during the 1990s accounts for most of the decline in the labor share between 1980 and 2010 (4 out of 5 percentage points). This implies that computer capital alone is more important than all other machinery and equipment in explaining the decline in the labor share.

**Related literature** In our model, employment shifts across sectors—or “structural change”—occur due to differential sector- and occupation-specific productivity growth as in Lee and Shin (2017). Most studies in the structural change literature that consider sector-specific productivity growth, e.g., Ngai and Pissarides (2007), have paid little attention to its implications for changes in aggregate productivity. In fact, most were interested in obtaining balanced growth. However, since as far back as Baumol (1967), it was well known that complementarity between industries can lead to an increase in the employment share of the low productivity growth sector, consequently leading to
a slowdown in aggregate productivity (also known as “Baumol’s disease”). We add to this literature by investigating how useful our model of structural change can be toward quantitatively explaining trends in aggregate productivity.

A recent study by Duernecker et al. (2017) is a notable exception. They explicitly consider Baumol’s disease in a model with structural change, and evaluates its quantitative importance for explaining the aggregate productivity slowdown. In our analysis, we model differential progress in occupational-specific technologies in addition to heterogeneous sectoral productivity growth rates, and find evidence that heterogeneity across occupation-level productivities have been more important for the aggregate productivity slowdown in the United States.

Our work also relates to studies on the importance of information technology (IT) in explaining the evolution of productivity (e.g., Byrne et al., 2016; Gordon, 2016; Syverson, 2017). In particular, Acemoglu et al. (2014) investigates the relationship between multi-factor productivity growth and the use of IT by industry. They conclude that IT usage has little impact on productivity. While we emphasize the role of computerization, our analysis does not contradict theirs. While computerization is important for shaping aggregate productivity shifts in our analysis, there is no direct effect of computerization on the multi-factor productivity of other industries. Instead, computerization affects industry level output and value added through an increase in the use of computer capital.

In many empirical analyses related to routinization, the price of information and communication technology (ICT) capital is often used as a proxy for routine-biased technological change (e.g., Goos et al., 2014; Cortes et al., 2017). However, when we break down computer usage by occupation, we find that computerization and routinization are two different phenomena, with different implications for the macroeconomy. Aum (2017) analyzes increasing investment in software in a model that also features routinization. While Aum (2017) focuses on its impact on changes in occupational employment, we focus on its implications for aggregate productivity.

Karabarbounis and Neiman (2014) suggests that the decline in the labor share could be due to a decline in the price of capital. Since the decline in the price of capital is mostly driven by the price of computer-related equipment, and it mirrors the productivity increase in the computer industry, our analysis appears to concur with their explanation on the cause of the fall of the labor share. Further, our results show that a specific component of capital—computer hardware and software—can be more important than all other types of capital. This is in line with Koh et al. (2016),
which emphasizes the importance of intellectual property products capital (including software) in explaining the decline of the labor share.

2 Empirical Evidence

We first show that routinization and computerization are two distinct phenomena at the occupation level in Figure 1(a). The horizontal axis is occupational employment shares (percentile), after sorting all occupations by their 1980 average wage. The figure shows that the routine index of occupations is high for middle-skill occupations, as is well known in the routinization/polarization literature, but that high-skill occupations tend to use computers more. Therefore, an increase in the use of computer by firms (computerization) should be separately understood from routinization, typically understood as faster productivity growth among middle-skill or routine-intense tasks.

The computerization in our model is a consequence of the fast productivity growth of the computer industry. We first use the conventional TFP accounting and calculate each industry’s TFP growth as the growth rate of real value-added, net of the growth of inputs weighted by the income share of each factor. Specifically, industry $i$’s TFP growth between time $s$ and $t$ is

$$ \log \frac{TFP_{it}}{TFP_{is}} = \frac{\alpha_{is} + \alpha_{it}}{2} \log \frac{L_{it}}{L_{is}} - \frac{1 - \alpha_{is} - \alpha_{it}}{2} \log \frac{K_{it}}{K_{is}}, $$

where $Y$ is real value-added, $L$ is employment, $K$ is the real net stock of non-residential fixed capital, and $\alpha$ is the labor share (compensation of employees divided by value-added).

Figure 1(b) depicts the log-TFP of computer-related industries (BEA industry code 334 for hardware and 511 for software) and the average of the log-TFP of all industries excluding agriculture and government (weighted according to the Törnqvist index). The TFP of hardware shows an average annual growth rate of 16 percent, far higher than the average. Software also features higher TFP growth compared to the average. The TFP of the “computer industry”—the value-added weighted average of hardware and software—shows that the hardware industry mostly determines the TFP of the computer industry. Note that the exceptionally fast growth of the computer industry’s TFP slowed down since around the early 2000s.

Reflecting the fast growth of the computer industry’s productivity, the use of computer and software also rose substantially until the late 1990s. Figure 2(a) shows the

\[3\] In light of the model we will present, this is a misspecified TFP calculation.
computer and software share of total intermediates over time. Figure 2(b) plots the share of computers and software in total non-residential investment. In both figures, it is clear that there was a steep rise in the importance of computers in the 1980s to 1990s, which stagnated starting in the 2000s.

We now turn to disaggregated evidence at the industry level, which will support our hypotheses of heterogeneous growth rates and complementarity across jobs and industries. Because job or occupation-level productivity is not directly measurable, we first establish two new empirical patterns, utilizing the fact that industries differ in the composition of their workers’ occupations. Figure 3(a) shows that the routine job share of an industry is positively correlated with its TFP growth between 1980
and 2010 (consistent with routinization), and Figure 3(b) shows that its TFP growth is negatively correlated with its employment growth (consistent with complementarity across jobs and industries). Here, routine occupations are defined as occupations that are above the 66 percentile in terms of the routine task index constructed following Autor and Dorn (2013).

![Figure 3](image-url)

(a) Routine occupation share and TFP growth  (b) TFP and employment growth across industries

**Fig. 3: Routinization and industry TFP and employment**

But if other industries depend heavily on the computer industry, the large rate of technological progress specific to the computer industry may be able to offset the fall in aggregate output and productivity growth incurred by routinization. If so, those industries with faster growth in computer capital should grow faster than those that use computers less intensively. Figure 4 confirms the positive relationship between the growth of computer capital (hardware and software) for an industry and its value-added growth between 1980 and 2010.

### 3 Model

The model for our quantitative analysis builds on those in Goos et al. (2014) and Lee and Shin (2017), both of which simultaneously analyze an economy’s occupational and industrial structure. In particular, the latter explicitly models how workers of heterogeneous skill sort into different occupations, and also industries that differ in the intensity with which they combine workers of different occupations for production. Here we ignore selection on skill, but instead expand previous models by letting all industries use output from the computer sector as a capital good in production, an
important channel through which the productivity gains of the computer industry affects aggregate production.

**Environment** There is a unit mass of identical individuals who supply labor inelastically to one of $J$ tasks, indexed by $j \in \{1, \ldots, J\}$. A final good is produced by combining products from $I$ sectors, which we index by $i \in \{1, \ldots, I\}$. To be specific, the final good production combines industrial output using a CES aggregator with the elasticity of substitution $\epsilon$:

$$Y = \left[ \sum_{i=1}^{I} \frac{1}{\gamma_i} Y_i^{\epsilon-1} \right]^{\frac{1}{\epsilon-1}}.$$

In each sector, a representative firm organizes the $J$ tasks to produce sectoral output $Y_i$ according to

$$Y_i = A_i K_i^{\alpha_i} Z_i^{1-\alpha_i},$$

where $A_i$ is sector $i$’s exogenous sector-specific TFP, $K_i$ is traditional capital (machinery and equipment excluding computer hardware and software), and $Z_i$ is a labor component that combines computer capital $S_i$, and a task composite $X_i$:

$$Z_i = \left[ \frac{1}{\omega_i} S_i^{\frac{1}{\sigma}} + (1 - \omega_i) X_i^{\frac{1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad X_i = \left[ \sum_{j=1}^{J} (\nu_{ij} M_j) \frac{1}{\sigma} L_{ij}^{\frac{1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

Each $L_{ij}$ is the amount of task $j$ labor (i.e., workers) used in sector $i$, and $M_j$ is the (exogenous) productivity of task $j$ that differs across tasks but not sectors. The
parameters $\omega_i$ and $\nu_{ij}$ are CES weights that differ by sector, as well as $\rho_i$, the elasticity of substitution between computers and labor in sector $i$. However, we assume that the elasticity of substitution across tasks, $\sigma$, is identical across sectors.

From sectoral production technology, we see that each industry uses all types of tasks but with different weights given by $\nu_{ij}$. Hence any changes in $M_j$ would have differential effects on sectoral production through $X_i$. One thing to note is that an increase in $\bar{M}_j = M_j^{\frac{1}{\sigma-1}}$, not $M_j$ itself, would represent a rise in the productivity of task $j$.

Computer capital $S_i$ is also an input used in all sectors, and we let the computer industry be industry $i = I$. So the total amount of computer capital in the economy is $S = \sum_{i=1}^{I} S_i$, while $F = \sum_{i=1}^{I-1} F_i$ is the amount of newly produced computers. The model essentially is assuming that computer capital is used for the production of all industrial goods, but there is no other input-output linkage among the rest. Each industry rents traditional capital and computer capital at rates $R_K$ and $R_S$.

The rest of the economy is standard. The representative consumer, who owns both types of capital, maximizes discounted sum of utility $u(C)$ subject to the sequence of budget constraints,

$$C + I_K + p_t F \leq Y,$$

where $I_K$ is investment in non-computer capital and $p_t$ is the price of computer. The final good is the numeraire, which can be used for consumption and non-computer capital investment. The law of motion for each type of capital satisfies

$$K' = I_K + (1 - \delta_K)K, \quad S' = F + (1 - \delta_S)S.$$

**Equilibrium**  The final good firm takes prices $p_i$ as given and solves

$$\max \left\{ Y - \sum_{i=1}^{I} p_i Y_i \right\}.$$  \hspace{1cm} (1)

Each sector $i$ firm takes all prices as given and chooses capital, computer capital and labor to solve

$$\max \left\{ p_i Y_i - R_K K_i - R_S S_i - w \sum_{j=1}^{J} L_{ij} \right\},$$  \hspace{1cm} (2)

where $p_i$ is the price of the sector $i$ good, $R_K$ the rental rate of traditional capital, $R_S$ the rental rate of computer capital, and $w$ the wage rate (which is equal across jobs since individuals do not differ in skill). In a competitive equilibrium,
1. Final good producers choose $Y_i$ to maximize profits (1), so

$$\gamma_i Y_i = p_i^c$$

for $i \in \{1, \ldots, I\}$. (3)

Since we normalized the final good price to 1,

$$\sum_{i=1}^{I} \gamma_i p_i^{1-\epsilon} = 1$$

is the ideal price index.

2. All sector $i$ firms maximize profits (2). The first-order necessary conditions are

$$R_K K_i = \alpha_i p_i Y_i,$$  \hspace{1cm} (4a)

$$R_S = (1 - \alpha_i) \cdot (p_i Y_i / Z_i) \cdot (\omega_i Z_i / S_i)^{\frac{1}{\gamma_i}},$$  \hspace{1cm} (4b)

$$w = (1 - \alpha_i) \cdot (p_i Y_i / Z_i) \cdot [(1 - \omega_i) Z_i / X_i]^{\frac{1}{\gamma_i}} \cdot [\nu_{ij} M_j X_i / L_{ij}]^{\frac{1}{\sigma}}.$$  \hspace{1cm} (4c)

3. Capital, computer and labor markets clear:

$$K = \sum_{i=1}^{I} K_i, \quad S = \sum_{i=1}^{I} S_i, \quad L = \sum_{i=1}^{I} \left[ \sum_{j=1}^{J} L_{ij} \right].$$

4. The rental rates satisfy

$$u'(C) \beta u'(C') = 1 + r = R_K' + (1 - \delta_K) = [R_S' + (1 - \delta_S) p_I']/p_I,$$

and the transversality conditions hold.

$$\lim_{t \to \infty} \beta^t u'(C_t) K_t = 0, \quad \lim_{t \to \infty} \beta^t u'(C_t) S_t = 0.$$

**Equilibrium Characterization**  From (3) and (4a), we find that

$$\alpha_i p_i Y_i / \alpha_I p_I Y_I = K_i / K_I = (\gamma_i / \gamma_I)^{\frac{1}{\epsilon}} \cdot (Y_i / Y_I)^{\frac{1-\epsilon}{\epsilon}},$$

$$\Rightarrow \alpha_i y_i / \alpha_I y_I = k_i / k_I = (\gamma_i / \gamma_I)^{\frac{1}{\epsilon}} \cdot (y_i / y_I)^{\frac{1-\epsilon}{\epsilon}} \cdot (L_i / L_I)^{-\frac{1}{\epsilon}},$$

$$\Rightarrow \frac{A_i}{A_I} = \left( \frac{\alpha_I}{\alpha_i} \right)^{\frac{1}{\epsilon}} \cdot \left( \frac{k_i^{\frac{1}{\epsilon} - \alpha_i}}{k_I^{\frac{1}{\epsilon} - \alpha_I}} \right) \cdot \left( \frac{z_i^{1-\alpha_i}}{z_I^{1-\alpha_I}} \right) \cdot \left( \frac{\gamma_I L_I}{\gamma_i L_i} \right)^{\frac{1}{\epsilon}}.$$  \hspace{1cm} (5)

where $y_i \equiv Y_i / L_i$ is output per worker and $k_i \equiv k_i / L_i$ is capital per worker. Similarly, $(z_i, s_i)$ is the labor productivity and computer per worker in sector $i$. From (4c), holding $i$ fixed we obtain

$$L_{ij} / L_{i1} = \nu_{ij} M_j / \nu_{i1} M_1, \quad \text{so} \quad L_i = \tilde{V}_i^{\sigma - 1} \cdot L_{i1} / \nu_{i1} M_1 \quad \text{and} \quad X_i = \tilde{V}_i L_i,$$
where \( L_i \) is the total amount of labor used in sector \( i \) and \( \hat{V}_i \equiv \left( \sum_{j=1}^{J} \nu_{ij} M_j \right)^{-\frac{1}{\rho_i}} \), so we can express the equilibrium allocations of \( L_{ij}, Z_i \) as

\[
L_{ij} / L_i = \nu_{ij} M_j \hat{V}_i^{1-\sigma}, \quad \text{and} \\
Z_i = \left[ \frac{1}{\omega_i^\rho_i S_i^\rho_i} + \hat{V}_i^{\frac{1}{\rho_i} \rho_i} L_i^{\frac{1}{\rho_i} \rho_i} \right]^{\frac{1}{\rho_i}} \quad \Rightarrow \quad z_i \equiv Z_i / L_i = \left[ \frac{1}{\omega_i^\rho_i s_i^\rho_i} + \frac{1}{\hat{V}_i^{\frac{1}{\rho_i} \rho_i}} \right]^{\frac{1}{\rho_i}}
\]

where \( V_i \equiv (1 - \omega_i) \hat{V}_i^{\rho_i} \). Plugging these expressions in (4) we obtain

\[
R_S = (1 - \alpha_i) \cdot (p_i y_i / z_i) \cdot (\omega_i z_i / s_i)^{\frac{1}{\rho_i}}, \quad (7) \\
w = (1 - \alpha_i) \cdot (p_i y_i / z_i) \cdot (V_i z_i)^{\frac{1}{\rho_i}}, \quad (8) \\
\Rightarrow \quad (1 - \alpha_i) \alpha_i \cdot \frac{k_i}{k_I} = \frac{z_i^{\frac{1}{\rho_i} \rho_i - 1} s_i^{\frac{1}{\rho_i}}}{V_i^{\frac{1}{\rho_i}} \cdot \frac{V_i^{\frac{1}{\rho_i}} V_I^{\frac{1}{\rho_i}}}{(V_I / \omega_I) \cdot s_I^{\frac{1}{\rho_i}}} \cdot \frac{1}{z_I^{\frac{1}{\rho_i}}}},
\]

The second equality implies

\[
(V_i / \omega_i) \cdot s_i = [(V_I / \omega_I) \cdot s_I]^{\frac{1}{\rho_i}} \cdot \frac{z_i^{\frac{1}{\rho_i} \rho_i - 1} s_i^{\frac{1}{\rho_i}}}{V_i^{\frac{1}{\rho_i}} \cdot \frac{V_i^{\frac{1}{\rho_i}} V_I^{\frac{1}{\rho_i}}}{(V_I / \omega_I) \cdot s_I^{\frac{1}{\rho_i}}} \cdot \frac{1}{z_I^{\frac{1}{\rho_i}}}},
\]

(10)

\[
z_i = V_i^{\frac{1}{\rho_i} \rho_i - 1} \left[ 1 + (\omega_i / V_i) [(V_I / \omega_I) \cdot s_I^{\frac{1}{\rho_i}}]^{\frac{1}{\rho_i} \rho_i - 1} \right]^{\frac{1}{\rho_i}}.
\]

(11)

We can find the equilibrium from equation (5), (10), and (9) subject to the market clearing conditions.

**Discussion** In our model, exogenous productivities are task-specific (\( M_j \)) or sector-specific (\( A_i \)). Though we call \( A_i \) as sector-specific productivity, it should be distinguished from “sectoral productivity” which refers to an overall productivity of each sector. As the task-specific productivities affect sectoral productivity through \( V_i := (1 - \omega_i) (\sum_j \nu_{ij} M_j)^{\frac{1}{\rho_i}} \), sectoral productivity depends on \( M_j \)’s as well as \( A_i \). Specifically, the sectoral productivity is obtained by decomposing output into factors:

\[
\hat{y}_i = \left[ \hat{A}_i + (1 - \alpha_i) \frac{1}{\rho_i} \frac{V_i^{\frac{1}{\rho_i}}}{z_i^{\frac{1}{\rho_i}}} \hat{V}_i \right] + \alpha_i \hat{k}_i + (1 - \alpha_i) \frac{\omega_i^{\rho_i}}{s_i^{\rho_i}} \frac{1}{z_i^{\frac{1}{\rho_i}} \cdot \hat{s}_i},
\]

(12)

where \( \hat{x} := d \log x \).

In the quantitative analysis, we call the sectoral productivity as measured productivity as it corresponds to usual multi-factor productivity computed in data.\textsuperscript{4} When a

\textsuperscript{4}This still differs from the conventional ways of measuring sector-level TFP, because we are taking out computer capital as a distinct type of capital with its own income share.
productivity of certain task \( j \) \((\tilde{M}_j := M_j^{\frac{1}{\sigma + 1}})\) increases, the sectoral productivity also goes up through changes in \( V_i \). The direction of changes in TFP is same for all industries, but the rate of growth will be different across sectors depending on task-sector specific weights \( \nu_{ij} \) and sectoral labor share.

Since the production technology is homogeneous of degree one, an aggregate productivity is a sectoral production-weighted average of the measured productivities. Changes in underlying productivity, either \( A_i \) or \( M_j \), affects aggregate productivity both directly through changes in sectoral productivity and indirectly through variations in industrial production share.

In addition, there is an important channel through which fast growth in \( A_I \) affects aggregate output. As other industries, changes in \( A_I \) alter aggregate productivity through the changes in both sectoral productivity and production share of the computer industry. Not only that, computerization also lowers the rental rates of computer \((R_S)\) and hence raises the use of computer when the elasticity of substitution between computer and labor is larger than one. Both the rise of aggregate productivity and the increased use of computer in all sectors will contribute to an increase in the aggregate output.

4 Quantitative Analysis

For the quantitative analysis, we classify industries into ten groups as summarized in Table 1. We exclude the agricultural sector and government. We also classify occupations into ten groups which broadly correspond to one-digit occupation groups in the census (Table 2).

4.1 Calibration

Aggregate production function The parameters of the final good production function are estimated outside of the model using real and nominal value-added data by industry. Specifically, we estimate the industry weights \( \gamma_i \) and complementarity parameter \( \epsilon \) from

\[
\log(p_iY_i/p_IY_I) = \frac{1}{\epsilon}(\gamma_i/\gamma_I) + \frac{\epsilon - 1}{\epsilon}\log(Y_i/Y_I), \text{ for } i = 1, \cdots, I - 1. \tag{13}
\]

The system of equations (13) is estimated by iterated feasible generalized nonlinear least squares method. To reflect constraints on the parameters \((\gamma_i > 0 \text{ and } 0 < \epsilon < 1)\),
Table 1: Industry classification

<table>
<thead>
<tr>
<th>Industry</th>
<th>BEA industry code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mining</td>
<td>211, 212, 213</td>
</tr>
<tr>
<td>Construction</td>
<td>23</td>
</tr>
<tr>
<td>Durable goods manufacturing</td>
<td>311FT, 313TT, 315AL, 322, 323, 324, 325, 326</td>
</tr>
<tr>
<td>Non-durable goods manufacturing</td>
<td>321, 327, 331, 332, 333, 335, 3361MV, 3364OT, 337, 339</td>
</tr>
<tr>
<td>FIRE</td>
<td>521CI, 523, 524, 531, 532RL</td>
</tr>
<tr>
<td>Health</td>
<td>621, 622HO</td>
</tr>
<tr>
<td>Other high-skill services</td>
<td>512, 513, 514, 5411, 5412OP, 5415, 55, 61</td>
</tr>
<tr>
<td>Trade (Retail &amp; Wholesale)</td>
<td>42, 44RT</td>
</tr>
<tr>
<td>Other low-skill services</td>
<td>22, 481, 482, 483, 484, 485, 486, 487OS, 493, 561, 562, 624, 711AS, 713, 721, 722, 81</td>
</tr>
<tr>
<td>Computer</td>
<td>334, 511</td>
</tr>
</tbody>
</table>

we estimate the unconstrained coefficients $b$ and $c_i$'s in

$$\log(p_{i,t}Y_{i,t}/p_{I,t}Y_{I,t}) = (1 + e^b)c_i + e^b\log(Y_{i,t}/Y_{I,t}) + \varepsilon_{i,t},$$

where $\epsilon = 1/(1 + e^b)$ and $\gamma_i = e^{c_i}/(1 + \sum e^{c_i}).$

Each industry $i$ in the model consists of several industries in the BEA data, to which we apply the Törnqvist index to obtain the price index of industry $i$. Real quantities $Y_i$ are similarly aggregated up from the detailed BEA data. The price index is normalized to 1 in 1963, the initial year in the data. The sample period for the estimation covers 1980 to 2010, which is our main interest. The point estimates for $\epsilon$ and $\gamma_i$ are presented in Table 3.

All other parameters The rest of parameters are recovered from simulating model moments to match corresponding data moments. The detailed procedure is as follows.

1. Fix $\alpha_I$ (from data), and guess $\sigma$, $A_{I,1980}$ and $\rho_j$'s.
2. For 1980:
   - Set $M_j = 1$ for all $j$. Then the industry-specific occupational weights ($\nu_{ij}$'s) are recovered from (6).
Table 2: Occupation classification

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Occupation code</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>High skill</strong></td>
<td></td>
</tr>
<tr>
<td>Management</td>
<td>4 - 37</td>
</tr>
<tr>
<td>Professionals</td>
<td>43 - 199</td>
</tr>
<tr>
<td><strong>Middle skill</strong></td>
<td></td>
</tr>
<tr>
<td>Mechanics &amp; Construction</td>
<td>503 - 599</td>
</tr>
<tr>
<td>Miners &amp; Precision workers</td>
<td>614 - 699</td>
</tr>
<tr>
<td>Technicians</td>
<td>203 - 235</td>
</tr>
<tr>
<td>Sales</td>
<td>243 - 283</td>
</tr>
<tr>
<td>Transportation</td>
<td>803 - 889</td>
</tr>
<tr>
<td>Machine operators</td>
<td>703 - 799</td>
</tr>
<tr>
<td>Administrative support</td>
<td>303 - 389</td>
</tr>
<tr>
<td><strong>Low skill services</strong></td>
<td>405 - 498</td>
</tr>
</tbody>
</table>

Note: 1) Consistent occupation code (occ1990dd) constructed following Autor and Dorn (2013).

- From (7) of industry $I$, $\omega_I$ must solve

$$r + \delta_s = (1 - \alpha_I) \cdot A_I k_I^{\alpha_I} \cdot \left[ \omega_I \frac{\rho_I-1}{s_I \rho_I} + (1 - \omega_I) \frac{\rho_I-1}{\rho_I} \frac{1 - \rho_I}{(\omega_I/s_I)^{\rho_I}} \cdot \left(\frac{\omega_I}{s_I}\right)^{\frac{1}{\rho_I}} \right],$$

which has a solution $\omega_I \in (0, 1)$ if $1 < (1 - \alpha_I) A_I (k_I/s_I)^{\alpha_I}$.

- Given $\omega_I$, obtain $\alpha_i$’s from (9), and then $\omega_i$’s from (10).

- Exogenous sectoral TFP’s $A_{i,1980}$’s are recovered from (5) and $A_{I,1980}$.

3. For 2010:

- Choose the $M_j$’s that yields the best fit of (6) across all $i$:

$$\frac{M_j}{M_1} = \sum_i \left[ \frac{L_{ij}}{L_{i1}} \cdot \frac{\nu_{i1}}{\nu_{ij}} \right] / I$$

- Compute the new $\tilde{V}_i$ for 2010. From (9), we set $\rho_I$ to get the best fit of $k_i/k_I$:

$$\rho_I = \sum_i \left\{ \frac{\log(\omega_I \tilde{V}_I) - \log((1 - \omega_I)s_I)}{\log \left( \frac{(1 - \alpha_i(1 - \alpha_I)k_i)}{\alpha_i(1 - \alpha_I)k_I} \right) \tilde{V}_I} - \log \left( \frac{s_i \alpha_i(1 - \alpha_i)k_i}{\alpha_i(1 - \alpha_i)k_I - s_i} \right) \right\} / I$$

15
Table 3: Estimation results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\epsilon$</td>
<td>0.765*** (0.002)</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.084*** (0.001)</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>0.159*** (0.002)</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>0.099*** (0.003)</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td>0.124*** (0.002)</td>
</tr>
<tr>
<td>$\gamma_5$</td>
<td>0.142*** (0.001)</td>
</tr>
<tr>
<td>$\gamma_6$</td>
<td>0.087*** (0.002)</td>
</tr>
<tr>
<td>$\gamma_7$</td>
<td>0.057*** (0.002)</td>
</tr>
<tr>
<td>$\gamma_8$</td>
<td>0.094*** (0.003)</td>
</tr>
<tr>
<td>$\gamma_9$</td>
<td>0.117*** (0.002)</td>
</tr>
</tbody>
</table>

AIC -1001.432

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note that we need $s_i/s_I < (1 - \alpha_i)\alpha_I k_i/(\alpha_i(1 - \alpha_I)k_I) < 1$ or $s_i/s_I > (1 - \alpha_i)\alpha_I k_i/(\alpha_i(1 - \alpha_I)k_I) > 1$ for $\rho_I$ to be a real number. We exclude those industries with $(k_i, s_i)$ for which this condition is not satisfied only when we compute $\rho_I$.

• Compute the implied $\rho_i$’s that are consistent with the 2010 $s_i$’s, i.e.,

$$\rho_i = \frac{\rho_I \log \left( \frac{1-\omega_i}{\omega_i s_i V_i} \right)}{\rho_I \log \left( \frac{\tilde{V}_i}{V_i} \right) + \log \left( \frac{1-\omega_I}{\omega_I s_I V_I} \right)}$$

4. Iterate over $\rho_i$’s till convergence.

5. Set $A_{I,1980}$ so that $y_I = y_I$ in data. Iterate over $A_{I,1980}$ till convergence.

6. Get $A_{I,2010}$’s to match measured TFP by industry in (12) to the 2010 data.

7. Between 1980 and 2010, we assume that the $M_{j,t}$’s and all $A_{i,t}$’s but $A_I$ grow at constant rates, so:

8. The productivity of the computer industry \((A_I)\) for other years are chosen so that the measured TFP of the computer industry is equal in the data and the model.

**Traditional capital share** In the calibration procedure described above, we fix the traditional capital share of computer industry \((\alpha_I)\) in the beginning with data. Though the computation of total capital share is straightforward (i.e., 1 minus labor share), the traditional capital share is not trivial to compute. We follow Koh et al. (2016) to calculate the traditional capital share of the computer industry in the data.

The no-arbitrage condition implies 
\[
1 + r' = \frac{[R'_K + \delta'_K(1 - \delta'_K)]}{p_K} \quad \text{and} \quad \frac{R'_K}{p_K} + \frac{R'_S}{p_S},
\]
and homogeneous of degree one production function implies 
\[
1 - \text{labour share} = \frac{R'_K K}{p_Y} + \frac{R'_S S}{p_Y}.
\]
We solve for \(R_K\) and \(R_S\) from these two equations and the data for labor share, price and depreciation rates of each type of capital, obtained from National Income and Product Accounts (NIPA) and Fixed Asset Table (FAT). Note that we apply the computed \(\alpha_i\) only for computer industry in the calibration. Later, we compare the traditional capital share by industry obtained here with those predicted by the model, and confirm that they are generally consistent (Figure 8).

**Results** The calibration results are summarized in Tables 4 to 7. Utilizing the fact that any changes in \(M_j\) affect occupational employment across all industries, we could identify the task-specific productivity separately from the measured TFP by industry. In other words, occupational employment data gives enough information for the identification of \(M_j\)’s. The \(M_j\)’s, together with measured sectoral TFP obtained from data, in turn, provide enough information to identify the sector-specific productivity \(A_i\)’s. Recovered \(M_j\)’s show that routine intensive occupations, such as machine operators or mechanics, indeed experienced much faster growth in task-specific productivity. The calibration shows that, as expected, the sector-specific productivity of the computer industry \((A_I)\) grew exceptionally fast especially during the 1990s.

It is also noteworthy that \(\rho_i\)’s are identified from inter-industry movements in computer capital \(s_i\)’s and traditional capital \(k_i\)’s. Roughly speaking, when an industry that increases computer per worker more than other industries also uses more traditional capital per worker, the elasticity of substitution \(\rho\) tends to be greater than one (Equation 9). Since traditional capital is a constant share of production in our model, the model is likely to have \(\rho > 1\) when output growth and computer growth have a roughly positive relationship as in Figure 4. Calibrated \(\rho_i\)’s indeed are greater than one, implying a decline of labor share due to computerization.
### Table 4: Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Obtained from</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma$</td>
<td>0.700</td>
<td>Lee and Shin (2017)</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>0.765</td>
<td>Estimation outside of the model</td>
</tr>
<tr>
<td>$r + \delta_s$</td>
<td>0.300</td>
<td>Average depreciation rate of computer capital from FAT</td>
</tr>
</tbody>
</table>

### Table 5: Industry specific parameters

<table>
<thead>
<tr>
<th>Targets</th>
<th>Const</th>
<th>FIRE</th>
<th>Health</th>
<th>High serv.</th>
<th>Low serv.</th>
<th>Dur</th>
<th>Mine</th>
<th>Non-durable</th>
<th>Trade</th>
<th>Computer</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>outside</td>
<td>0.084</td>
<td>0.159</td>
<td>0.099</td>
<td>0.124</td>
<td>0.142</td>
<td>0.087</td>
<td>0.057</td>
<td>0.094</td>
<td>0.117</td>
</tr>
<tr>
<td>$\rho$</td>
<td>$s_{i,2010}$</td>
<td>1.655</td>
<td>1.228</td>
<td>1.446</td>
<td>1.515</td>
<td>1.429</td>
<td>1.517</td>
<td>1.450</td>
<td>1.241</td>
<td>1.456</td>
</tr>
<tr>
<td>$\omega$</td>
<td>$s_{i,1980}$</td>
<td>0.001</td>
<td>0.093</td>
<td>0.003</td>
<td>0.023</td>
<td>0.006</td>
<td>0.010</td>
<td>0.020</td>
<td>0.029</td>
<td>0.008</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>$k_{i,1980}$</td>
<td>0.167</td>
<td>0.374</td>
<td>0.301</td>
<td>0.454</td>
<td>0.475</td>
<td>0.402</td>
<td>0.793</td>
<td>0.333</td>
<td>0.186</td>
</tr>
</tbody>
</table>

### Table 6: Industry-occupation specific weights on labor ($\nu_{ij}$)

Target: employment share by industry and occupation in 1980

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Const</td>
<td>0.008</td>
<td>0.055</td>
<td>0.028</td>
<td>0.011</td>
<td>0.203</td>
<td>0.018</td>
<td>0.564</td>
<td>0.016</td>
<td>0.024</td>
</tr>
<tr>
<td>FIRE</td>
<td>0.040</td>
<td>0.410</td>
<td>0.004</td>
<td>0.243</td>
<td>0.012</td>
<td>0.014</td>
<td>0.005</td>
<td>0.013</td>
<td>0.004</td>
</tr>
<tr>
<td>Health</td>
<td>0.298</td>
<td>0.164</td>
<td>0.005</td>
<td>0.004</td>
<td>0.005</td>
<td>0.121</td>
<td>0.010</td>
<td>0.012</td>
<td>0.322</td>
</tr>
<tr>
<td>H serv.</td>
<td>0.085</td>
<td>0.209</td>
<td>0.010</td>
<td>0.020</td>
<td>0.018</td>
<td>0.046</td>
<td>0.046</td>
<td>0.008</td>
<td>0.424</td>
</tr>
<tr>
<td>L serv.</td>
<td>0.295</td>
<td>0.148</td>
<td>0.027</td>
<td>0.036</td>
<td>0.150</td>
<td>0.014</td>
<td>0.095</td>
<td>0.028</td>
<td>0.075</td>
</tr>
<tr>
<td>Durable</td>
<td>0.026</td>
<td>0.115</td>
<td>0.363</td>
<td>0.040</td>
<td>0.130</td>
<td>0.024</td>
<td>0.056</td>
<td>0.113</td>
<td>0.038</td>
</tr>
<tr>
<td>Mining</td>
<td>0.016</td>
<td>0.092</td>
<td>0.046</td>
<td>0.012</td>
<td>0.193</td>
<td>0.047</td>
<td>0.122</td>
<td>0.321</td>
<td>0.066</td>
</tr>
<tr>
<td>Non-dur</td>
<td>0.020</td>
<td>0.110</td>
<td>0.355</td>
<td>0.022</td>
<td>0.097</td>
<td>0.028</td>
<td>0.083</td>
<td>0.145</td>
<td>0.052</td>
</tr>
<tr>
<td>Trade</td>
<td>0.020</td>
<td>0.142</td>
<td>0.022</td>
<td>0.390</td>
<td>0.136</td>
<td>0.006</td>
<td>0.076</td>
<td>0.048</td>
<td>0.023</td>
</tr>
<tr>
<td>Computer</td>
<td>0.015</td>
<td>0.156</td>
<td>0.298</td>
<td>0.047</td>
<td>0.040</td>
<td>0.065</td>
<td>0.044</td>
<td>0.077</td>
<td>0.131</td>
</tr>
</tbody>
</table>
Table 7: Industry and occupation specific productivity

<table>
<thead>
<tr>
<th>Target: emp. share by ind. and occ. in 2010</th>
<th>Target: measured TFP in 1980 and 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{M}_j$</td>
<td>$A_i$</td>
</tr>
<tr>
<td>Low serv.</td>
<td>Const</td>
</tr>
<tr>
<td>1.000 1.000 1.000 1.000</td>
<td>14.124 10.775 8.219 6.270</td>
</tr>
<tr>
<td>Admin.</td>
<td>FIRE</td>
</tr>
<tr>
<td>Machine</td>
<td>Health</td>
</tr>
<tr>
<td>1.000 1.815 3.293 5.976</td>
<td>6.156 6.001 5.850 5.703</td>
</tr>
<tr>
<td>Sales</td>
<td>High serv.</td>
</tr>
<tr>
<td>1.000 0.732 0.536 0.393</td>
<td>1.386 1.513 1.651 1.803</td>
</tr>
<tr>
<td>Trans</td>
<td>Low serv.</td>
</tr>
<tr>
<td>1.000 1.193 1.424 1.699</td>
<td>0.050 0.052 0.054 0.056</td>
</tr>
<tr>
<td>Tech</td>
<td>Durable</td>
</tr>
<tr>
<td>1.000 0.849 0.722 0.613</td>
<td>0.504 0.525 0.546 0.569</td>
</tr>
<tr>
<td>Mechanics</td>
<td>Mining</td>
</tr>
<tr>
<td>1.000 1.466 2.150 3.152</td>
<td>3.048 3.090 3.132 3.175</td>
</tr>
<tr>
<td>Mine.</td>
<td>Non-durable</td>
</tr>
<tr>
<td>1.000 1.420 2.016 2.863</td>
<td>0.274 0.273 0.272 0.271</td>
</tr>
<tr>
<td>Prof.</td>
<td>Trade</td>
</tr>
<tr>
<td>1.000 0.729 0.532 0.388</td>
<td>0.270 0.341 0.431 0.545</td>
</tr>
<tr>
<td>Mngm</td>
<td>Computer</td>
</tr>
<tr>
<td>1.000 0.658 0.434 0.286</td>
<td>1.946 3.651 13.368 25.501</td>
</tr>
</tbody>
</table>

Note: $\tilde{M}_j \equiv M_j^{1/(\sigma-1)}$

4.2 Model Fit

The model fits generally well even for variables not directly targeted in the calibration. In particular, the model generates a slowdown in aggregate production and productivity growth starting in 2000, similarly as in the data (Figure 5). The fit to aggregate productivity is especially remarkable considering that we assume constant productivity growth rates for $M_j$ and $A_i$ other than $A_I$.

As for employment shares, the employment changes by occupation in the model fit the data better than employment changes by industry (Figure 6). This is because $M_j$’s directly affect occupational employment through (6), whereas once we match measured TFP by industry, employment by industry is pinned down by (5). Nonetheless, employment share changes by industry are still generally consistent with the data. Moreover, the model prediction of output per worker by industry is remarkably close to the data (Figure 7).

Lastly, the model-implied factor income shares by industry are also generally consistent with the data (Figure 8). Partly because of this, the aggregate labor share in the model closely tracks the trend in the data, both in direction and magnitude, although it was not targeted at all (Figure 9). In our assumed production function, traditional capital income share is constant by construction. This result suggests that a subset of the total capital, computer hardware and software, which accounts for 14
Fig. 5: Aggregate production

Fig. 6: Changes in employment shares between 1980 and 2010
percent of all investment, is responsible for the vast majority of the fall in the labor share (4 out of 5 percentage points) since 1980.

4.3 Counterfactual Analysis

In this section, we investigate the underlying factors that shape aggregate output and productivity, focusing on routinization and computerization. Routinization in our model is the faster increases in certain occupations’ productivity terms, $M_j$. Computerization is driven by the computer industry-specific TFP term ($A_I$), which propagates through all industries because computer capital is used in the production of all industrial goods.

**Aggregate productivity** Note that the growth rates of task- and sector-specific productivities ($M_j$ and $A_i$) were assumed to be constant for the entire sample period except for the computer sector ($A_I$). Nonetheless, in the benchmark calibration, the aggregate TFP increased linearly from 1980 to 2000 and then slowed down (figure 10). We now show that the high growth rate of the computer sector’s productivity ($A_I$) prevented a potential slowdown in aggregate productivity that would have appeared between 1990 and 2000. Figure 10 shows that, if we assume $A_I$ were constant between 1980 and 2010, aggregate productivity growth would have slowed down since 1990. Without the growth in $A_I$, the aggregate productivity would have grown by only 13
Fig. 8: Factor income shares by industry: model vs. data

Fig. 9: Changes in labor share: model vs. data
percent from 1980 to 2010, one-third lower than the benchmark growth rate of 20 percent over the same period. This magnitude is surprising, once we consider the fact that the computer industry share of the total output is only 3 percent.

When all task- and sector-specific productivities grow at constant rates over time, because of the complementarity across jobs and sectors, faster growing tasks and sectors shrink, reducing their weights in the computation of aggregate productivity. Hence, the aggregate productivity growth must slow down over time, as long as task- and sector-specific productivities grow at different rates. So both the dispersions in the growth rates of task-specific productivities ($M_j$) and in sector-specific productivities ($A_i$’s) contribute to the aggregate productivity slowdown. To find out which dispersion is more important for the aggregate productivity slowdown, we conduct the following exercises.

In the first exercise, we force all $M_j$’s to grow at the same rate $m$ for all $j$ (i.e., no routinization) while allowing the growth rates of $A_i$’s to be different from one another. Second, we force all $A_i$’s to grow at a common rate $a$ while allowing for heterogeneous growth rates across the $M_j$’s. The common growth rates $m$ and $a$ are set so that aggregate productivity grows at the same rate as in the first decade of our benchmark calibration. The results are shown in Figure 11, which shows that routinization or the dispersion in the growth rates of $M_j$ is more important in explaining the decline in the growth rate of aggregate productivity. Without routinization, the growth rate of aggregate productivity remains near 0.8 percent per year throughout the three decades.

**Fig. 10: Aggregate productivity**
In contrast, even when all sector-specific productivities grow at a common rate, the aggregate productivity growth rate falls as much as in the benchmark. Of course, with a common $A_i$ growth, we are ruling out the faster growth of the computer sector, which explains the gap between the benchmark growth rate and this counterfactual growth rate in the 1990s.

**Output** Fast-growing computer sector-specific productivity directly boosts aggregate productivity, which leads to an acceleration of aggregate output growth. Fur-
thermore, there is an additional effect on aggregate output, through increases in the computer capital used by all industries. Figure 12 shows the total computerization effect on aggregate output. If $A_I$ were to remain constant between 1980 and 2010, aggregate output growth from 1980 to 2010 is 51 percent, or only about half of the growth rate in the benchmark. This is an even larger impact than that on aggregate productivity.

![Data benchmark no computerization](image)

**Fig. 13: Output growth by industry**

Figure 13 shows output growth by industry with and without $A_I$ growth. Due to the substitutability between computer and labor, all industries benefit from computerization. Unsurprisingly, the computer industry itself is affected the most, followed by finance and high-skilled services. The construction industry has the least to gain (in terms of output growth) from computerization.

**Labor share** Because the model calibration gives us industry-specific elasticities of substitution between labor and computer capital ($\rho_i$) that are larger than 1, computerization results in the decline of labor shares in all industries. Figure 14 shows changes in labor shares by industry for various counterfactual exercises. We can conclude that the growth in $A_I$ is the only important driving force behind the decline of labor share.

**Summary of quantitative analysis** There are two main findings from our quantitative analysis. First, constant task- and sector-specific technological progress nec-
necessarily slows down aggregate productivity growth over time, given complementarity across industries and jobs. Second, it was the dispersion in the growth rates across tasks (i.e., routinization) that was most responsible for the aggregate productivity slowdown. This negative impact of routinization on the growth rate of aggregate productivity was more or less perfectly counterbalanced by the impressive technological progress specific to the computer industry and its spillover through inter-industry linkages during the 1980s and the 1990s. The slower pace of the computer sector productivity growth in recent years—and the significant deceleration of computer usage by other industries since 2000—is finally revealing the negative impact that decades of routinization has had on the aggregate productivity growth.

5 Concluding Remarks

We presented a model in which productivities grow at heterogeneous rates across occupations (routinization), and also across industries. In particular, to understand the effect of the rise of the computer industry on aggregate productivity, we let its output be used in the production of all industries as a distinct type of capital.

We showed that when occupations and industries are complementary to one another and task- and sector-specific productivities grow at different rates, routinization
in particular causes a slowdown in aggregate productivity. But such a slowdown was averted prior to the 2000s in the U.S., thanks to the rapid rise of the computer industry’s productivity. It was only after the productivity of this sector slowed down that routinization began to reveal its negative impact on aggregate productivity growth.

The main message of our model is that multiple layers of the economy (i.e., occupations and sectors) can interact to generate interesting time trends that can help us reconcile evidence at the occupation and sector levels with aggregate trends. Moreover, we have also highlighted the importance of inter-industry linkages by showcasing that a single industry—in our case the computer industry—can have large effects on aggregate variables once such a propagation mechanism is taken into account.

In reality, all industries are interlinked, not only by providing intermediate inputs to one another as emphasized in some recent models (Acemoglu et al., 2012; Atalay, 2017; Carvalho, 2014) but also by serving different types of capital in which all industries need to invest (as we have modeled here). Modeling such additional layers of complexity is left for future research.

References


