Computerizing Industries and Routinizing Jobs: Explaining Trends in Aggregate Productivity

Sangmin Aum* Sang Yoon (Tim) Lee† Yongseok Shin‡

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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, whose employment did *not* shrink despite complementarity. At the same time, computer 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.

*Washington University in St. Louis: s.aum@wustl.edu.

†Toulouse School of Economics and CEPR: sylee.tim@tse-fr.eu.

‡Washington University in St. Louis, Federal Reserve Bank of St. Louis and NBER: yshin@wustl.edu.

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 have 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

[1] Throughout the text, we will use "sector" and "industry" interchangeably, as well as "occupations," "tasks" and "jobs."

across jobs, and substitutability between computer capital and labor, using detailed 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

[2] Or consumption, which we do not model.

industry, aggregate TFP growth during the 1990s would have been 0.5 percent per year, 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 if productivity growth in the computer sector had been completely absent, aggregate productivity growth would have declined monotonically since 1980.

In the data, sectors with higher productivity growth saw their employment shares decline, *except* for the computer sector. Our model explains this by letting all sectors requiring computer capital in production. Then, because the computer sector's productivity growth reduces the price of computer capital, leading to an 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 have 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.

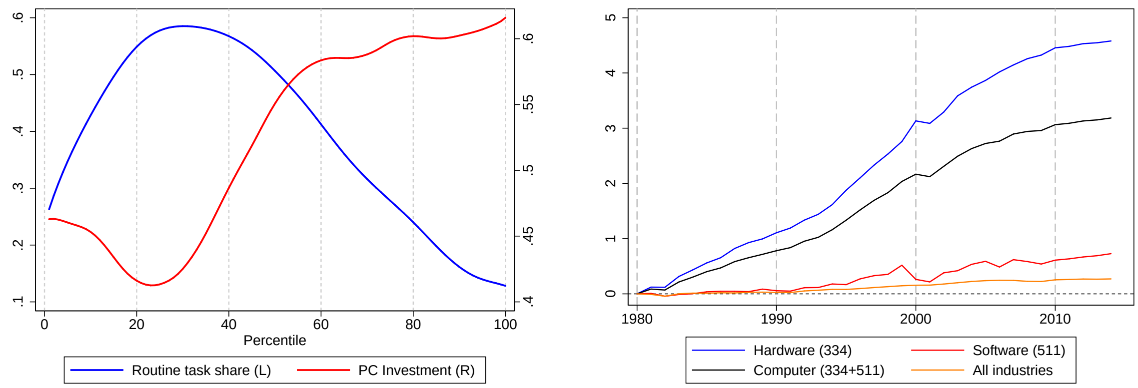
Related literature In our model, employment shifts across sectors—or "structural change"—occur due to differential sector- and occupation-specific productivity growth as in Lee and Shin (2017). Most studies in the structural change literature that consider sector-specific productivity growth, e.g., Ngai 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 has 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



(a) Routinization and computerization

(b) log-TFP of computer industry

Fig. 1: PC use by occupation and PC industry TFP

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 begin by establishing that routinization and computerization are two distinct phenomena. For the empirical analysis, occupational data is from the decennial censuses and industrial data from the BEA industry accounts. We consider industries at the 2-digit level, resulting in 60 industries.

In Figure 1(a), the horizontal axis is occupational employment shares (percentile), in increasing order of each occupation's 1980 average wage.[3] The figure shows that the routine index of occupations is high for middle-wage occupations, as is well known in the routinization/polarization literature, but that high-wage occupations tend to use computers more.[4] So at the occupational level, an increase in the use of comput-

[3]The ordering of occupational mean wages barely change from 1980 to 2010.

[4]Wages and employment by occupation are obtained from the decennial censuses. The routine index is the one constructed by and used in Autor and Dorn (2013). Computer investment is approximated from the BEA and O*NET. From the BEA, we know the total amount of investment for four categories of computer-related equipment. In O*NET, each category is broken further down into detailed subcategories, and we

ers (computerization) should be separately understood from routinization, typically understood as faster productivity growth among middle-wage or routine-intense tasks.

Computerization in our model is a consequence of the fast productivity growth of the computer industry. We first employ conventional accounting to compute each industry's TFP growth as the growth rate of real value-added, net of the growth of factor inputs weighted by the income share of each factor. Specifically, industry i's TFP growth between time s and t is

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

where Y is real value-added, L is employment, K is the net real stock of non-residential fixed capital, and α is the labor share (compensation of employees divided by value-added).[5]

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.

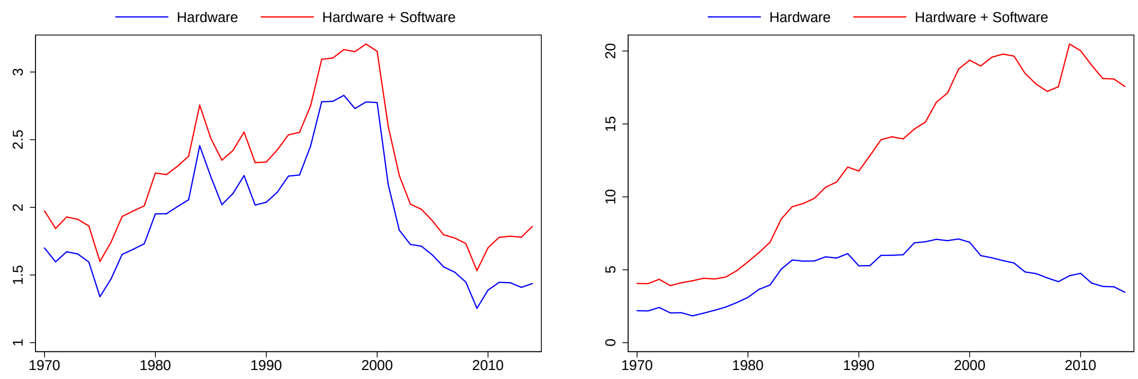
Reflecting the fast growth of the computer industry's productivity, the use of computer and software also rose substantially until the late 1990s. Figure 2(a) shows the computer and software share of total intermediates over time. Figure 2(b) plots the share of computers and software in total non-residential 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.[6]

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,

know how many of these subcategories are used in each occupation, which we assume is proportionate to the amount of computer investment into that occupation. While this is a crude measure, it is highly correlated with data from the CPS, which reports computer usage by occupation.

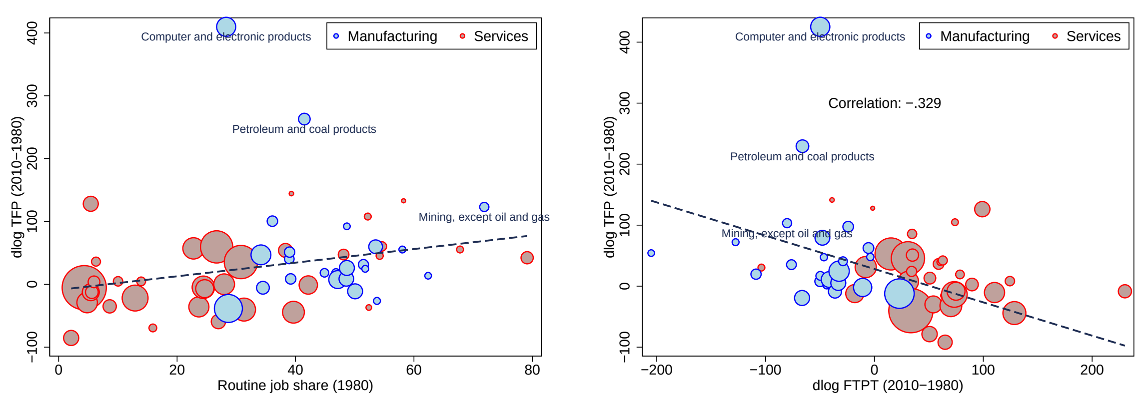
[5]Later when we separately consider computer capital, TFP computed as here becomes misspecified.

[6]Data behind Figures 2(a) and (b) come from BEA's Input-Output Tables and Fixed Assets Tables, respectively.



(a) Computer share of intermediates (%) (b) Computer share of non-residential investment (%)

Fig. 2: Computer use in production over time



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

Fig. 3: Routinization and industry TFP and employment

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).[7] Here, routine occupations are defined as occupations that are above the 66 percentile in terms of the routine task index following Autor and Dorn (2013).

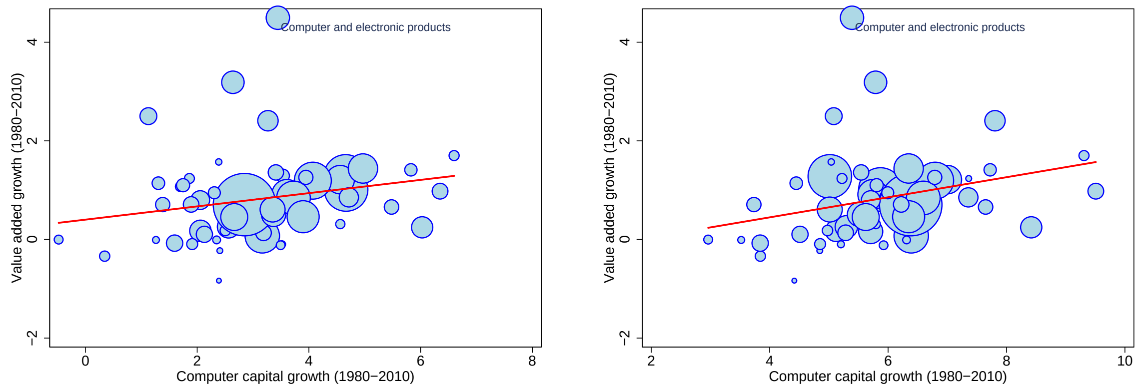
However, note that the computer industry is a conspicuous outlier. In Figure 3(a), despite having a routine job share around the median, not only is the computer industry's productivity growth 10 times larger than other industries at similar levels of routineness, it is in fact 2 to 4 times larger than the next two industries with the highest levels of productivity growth overall. Despite this, as shown in Figure 3(b), its employment barely fell, which cannot be explained by complementarity across jobs or industries alone.

This suggests that other industries depend heavily on the computer industry, so that even as its productivity grows the size of this sector would not shrink as long as other industries rely on it enough. And then, 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.

[7] Employment in this figure is full-time plus part-time workers (FTPT). Full-time equivalent (FTE) employment shows similar patterns, but is only available by industry from 1997 onward: for this period, there are level differences between the two measures, but dynamic patterns are similar for both.



(a) Hardware (b) Software

Fig. 4: Value added growth and computer capital growth

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 A representative household maximizes its discounted sum of utility

$$\sum_{t=0}^{\infty} \beta^t u(C_t)$$

subject to the sequence of budget constraints,

$$C_t + I_t + p_{I,t} F_t \leq Y_t,$$

where I is investment in traditional capital (machinery and equipment excluding computer hardware and software), F investment in computer capital, and p_I the price of computers. The final good is the numeraire, which can be used for consumption and traditional capital investment. The law of motion for each type of capital satisfies

$$K_{t+1} = I_t + (1 - \delta_K) K_t, \quad S_{t+1} = F_t + (1 - \delta_S) S_t,$$

where (K, S) are traditional and computer capital, respectively, and (δ_K, δ_S) their depreciation rates. In what follows, we drop the time subscript unless necessary, and simply denote next period variables with a prime.

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

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

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 and Z_i a labor component that combines computer capital S_i, and a task composite X_i:

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

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 ω_i and ν_{ij} are CES weights that differ by sector, as well as ρ_i, the elasticity of substitution between computers and labor in sector i. However, we assume that the elasticity of substitution across tasks, σ, is identical across sectors.

From the sectoral production technology, we see that each industry can use all types of tasks but at different intensities given by ν_{ij}. Hence any changes in M_j would have differential effects on sectoral production through X_i.

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 $S = \sum_{i=1}^{I} S_i$ and F is the total 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.

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

$$\max \left\{ Y - \sum_{i=1}^{I} p_i Y_i \right\}. \tag{1}$$

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

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

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

$$\gamma_i Y/Y_i = p_i^{\epsilon} \quad \text{for } i \in \{1, \ldots, I\}. \tag{3}$$

Since we normalized the final good price to 1,

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

is the ideal price index.

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

$$R_K K_i = \alpha_i p_i Y_i, \tag{4a}$$

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

$$w = (1-\alpha_i)\cdot(p_i Y_i/Z_i)\cdot[(1-\omega_i)Z_i/X_i]^{\frac{1}{\rho_i}}\cdot\left[\nu_{ij}\tilde{M}_j X_i/L_{ij}\right]^{\frac{1}{\sigma}}. \tag{4c}$$

where $\tilde{M} \equiv M^{\sigma-1}$.

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

$$\frac{u'(C)}{\beta u'(C')} = 1 + r = R'_K + (1-\delta_K) = \left[R'_S + (1-\delta_S)p'_I\right]/p_I, \tag{5}$$

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

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

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

$$\Rightarrow \quad \frac{A_i}{A_I} = \left(\frac{\alpha_I}{\alpha_i}\right)^{\frac{\epsilon}{\epsilon-1}}\cdot\frac{k_i^{\frac{\epsilon}{\epsilon-1}-\alpha_i}}{k_I^{\frac{\epsilon}{\epsilon-1}-\alpha_I}}\cdot\frac{z_I^{1-\alpha_I}}{z_i^{1-\alpha_i}}\cdot\left(\frac{\gamma_I L_i}{\gamma_i L_I}\right)^{\frac{1}{\epsilon-1}} \tag{6}$$

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

$$L_{ij}/L_{i1} = \nu_{ij}\tilde{M}_j/\nu_{i1}\tilde{M}_1, \quad \text{so} \quad L_i = \tilde{V}_i^{\sigma-1} \cdot L_{i1}/\nu_{i1}\tilde{M}_1 \quad \text{and } X_i = \tilde{V}_i L_i, \tag{7}$$

where L_i is the total amount of labor used in sector i and $\tilde{V}_i \equiv \left(\sum_{j=1}^{J} \nu_{ij}\tilde{M}_j\right)^{\frac{1}{\sigma-1}}$, so we can express the equilibrium allocations of L_{ij}, Z_i as

$$L_{ij}/L_i = \nu_{ij}\tilde{M}_j\tilde{V}_i^{1-\sigma}, \quad \text{and} \tag{8}$$

$$Z_i = \left[\omega_i^{\frac{1}{\rho_i}} S_i^{\frac{\rho_i-1}{\rho_i}} + V_i^{\frac{1}{\rho_i}} L_i^{\frac{\rho_i-1}{\rho_i}}\right]^{\frac{\rho_i}{\rho_i-1}} \quad \Rightarrow \quad z_i \equiv Z_i/L_i = \left[\omega_i^{\frac{1}{\rho_i}} s_i^{\frac{\rho_i-1}{\rho_i}} + V_i^{\frac{1}{\rho_i}}\right]^{\frac{\rho_i}{\rho_i-1}}$$

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

$$R_S = (1-\alpha_i) \cdot (p_i y_i/z_i) \cdot (\omega_i z_i/s_i)^{\frac{1}{\rho_i}}, \tag{9}$$

$$w = (1-\alpha_i) \cdot (p_i y_i/z_i) \cdot (V_i z_i)^{\frac{1}{\rho_i}} \tag{10}$$

$$\Rightarrow \quad \frac{(1-\alpha_i)\alpha_I}{(1-\alpha_I)\alpha_i} \cdot \frac{k_i}{k_I} = \frac{z_i^{\frac{\rho_i-1}{\rho_i}}}{z_I^{\frac{\rho_I-1}{\rho_I}}} \cdot \left(\frac{s_i}{\omega_i}\right)^{\frac{1}{\rho_i}} \cdot \left(\frac{\omega_I}{s_I}\right)^{\frac{1}{\rho_I}} = \frac{z_i^{\frac{\rho_i-1}{\rho_i}}}{z_I^{\frac{\rho_I-1}{\rho_I}}} \cdot \frac{V_I^{\frac{1}{\rho_I}}}{V_i^{\frac{1}{\rho_i}}}. \tag{11}$$

The second equality implies

$$(V_i/\omega_i) \cdot s_i = [(V_I/\omega_I) \cdot s_I]^{\frac{\rho_i}{\rho_I}} \tag{12}$$

$$z_i = V_i^{\frac{1}{\rho_i-1}} \left[1 + (\omega_i/V_i)\left[(V_I/\omega_I) \cdot s_I\right]^{\frac{\rho_i-1}{\rho_I}}\right]^{\frac{\rho_i}{\rho_i-1}}. \tag{13}$$

We can find the equilibrium from equation (6), (11), and (12) 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 the measured productivity of a sector in an accounting sense. As the task-specific productivities affect sectoral productivity through $V_i := (1-\omega_i)(\sum_j \nu_{ij}\tilde{M}_j)^{\frac{\rho_i-1}{\sigma-1}}$, sectoral productivity depends on M_j's as well as A_i. Specifically, sectoral productivity is obtained by decomposing output into factors:

$$\hat{y}_i = \underbrace{\left[\hat{A}_i + (1-\alpha_i)\frac{1}{\rho_i-1}\frac{V_i^{\frac{1}{\rho_i}}}{z_i^{\frac{\rho_i-1}{\rho_i}}}\hat{V}_i\right]}_{\text{Sectoral (measured) TFP}} + \underbrace{\alpha_i}_{K\text{ share}}\hat{k}_i + \underbrace{(1-\alpha_i)\frac{\omega_i^{\frac{1}{\rho_i}} s_i^{\frac{\rho_i-1}{\rho_i}}}{z_i^{\frac{\rho_i-1}{\rho_i}}}}_{S\text{ share}}\hat{s}_i, \tag{14}$$

where $\hat{x} := d\log x$.

In the quantitative analysis, we refer to sectoral productivity instead as "measured productivity," as it corresponds to the usual multi-factor productivity one would compute directly from the data.[8] If M_j, the productivity of task j, increases, sectoral productivity also goes up through changes in V_i. In this case, the TFP's of all sectors would move in the same direction (either up or down), but their rates of growth will be different depending on their task-sector specific weights ν_{ij}, the share of labor employed by each sector.

Since the production technology is homogeneous of degree one (HD1), aggregate productivity is a sectoral production-weighted average of the measured productivities. Hence changes in the exogenous productivities A_i or M_j affect aggregate productivity both directly through changes in measured productivity by sector, but also indirectly by altering sectoral shares of production.

Last but not least, changes in A_I, the computer industry's productivity, has further repercussions on aggregate output. As other industries, changes in A_I alter aggregate productivity both directly (through measured sectoral productivity) and indirectly (by altering the output share of the computer industry). But in addition, computerization also lowers the rental rates of computers (R_S), leading to a rise in the use of computers by all industries if the elasticity of substitution between computers and labor is larger than one. Consequently, not only because it raises aggregate productivity, but also because it increases the use of computers in all sectors, a rise in A_I will contribute more to an increase in aggregate output than any other sector.

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. In Table 2, we classify occupations into ten groups which broadly correspond to one-digit occupation groups in the census.

[8] This still differs from the conventional ways of measuring sector-level TFP using only capital and labor, because we are taking out computer capital as a distinct type of capital with its own income share.

Table 1: Industry classification

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

Table 2: Occupation classification

Occupation	Occupation code
High skill	
Management	4 - 37
Professionals	43 - 199
Middle skill	
Mechnics & Construction	503 - 599
Miners & Precision workers	614 - 699
Technicians	203 - 235
Sales	243 - 283
Transportation	803 - 889
Machine operators	703 - 799
Administrative support	303 - 389
Low skill services	405 - 498

Consistent occupation code (`occ1990dd`) constructed following Autor and Dorn (2013).

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 γ_i and complementarity parameter ϵ from

$$\log(p_i Y_i / p_I Y_I) = \frac{1}{\epsilon}(\gamma_i/\gamma_I) + \frac{\epsilon - 1}{\epsilon}\log(Y_i/Y_I), \text{ for } i = 1, \cdots, I-1. \tag{15}$$

The system of equations (15) is estimated by iterated feasible generalized nonlinear least squares method. To reflect constraints on the parameters ($\gamma_i > 0$ and $0 < \epsilon < 1$), we estimate the unconstrained coefficents 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 ϵ and γ_i are presented in Table 3.

Parameters calibrated without simulation In the calibration, we fix the traditional capital share of *only* the computer industry (α_I) from the data. Though computing the total capital share is straightforward (i.e., 1 minus labor share), computing the traditional capital share according to our model is not. To obtain this number for the computer industry, we follow Koh et al. (2016), which we briefly describe below.

We begin by specifying an empirical no-arbitrage condition for rental prices. The return on both types of capital must be equal to the interest rate $1 + r'$, so

$$[R'_K + (1 - \delta'_K)p'_K]/p_K = [R'_S + (1 - \delta'_S)p'_I]/p_I$$

where p_K is the price of traditional capital and p_I the price of computers. Note that this is different from the model's no-arbitrage condition (5), because we have included the price of capital, which in the model we had normalized to be equal to the price of consumption. Next, since sectoral production is HD1 in all factor inputs (traditional and computer capital, and labor), for the computer industry we have

$$1 - \text{labor share}_i = \frac{R_K K_I}{p_I Y_I} + \frac{R_S S_I}{p_I Y_I}.$$

Table 3: Estimation results

Parameters	Estimates
ϵ	0.765^{***} (0.002)
γ_1	0.084^{***} (0.001)
γ_2	0.159^{***} (0.002)
γ_3	0.099^{***} (0.003)
γ_4	0.124^{***} (0.002)
γ_5	0.142^{***} (0.001)
γ_6	0.087^{***} (0.002)
γ_7	0.057^{***} (0.002)
γ_8	0.094^{***} (0.003)
γ_9	0.117^{***} (0.002)
AIC	-1001.432

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We solve for R_K and R_S from these two equations assuming a steady state ($R'_K = R_K, R'_S = R_S$), plugging in for all other variables using data on labor shares, prices and depreciation rates of each type of capital which are obtained from the National Income and Product Accounts (NIPA) and Fixed Asset Table (FAT).[9]

Although the above procedure can be used for all industries, in our calibration we only use the computer industry's traditional capital share computed as such. All other industries' traditional capital shares are calibrated directly from the model as explained below. Figure 8 compares the traditional capital shares obtained using the above procedure against those predicted by the calibration, which confirms that they are generally consistent.

The value for the complementarity parameter across jobs, σ is fixed from Lee and Shin (2017).

Method of Moments The rest of parameters are recovered from simulating model moments to match corresponding data moments. Whenever possible, we plug the data

[9] We take the weighted average across industries 334 and 511 (software and hardware) to obtain this value for the computer industry, which in our quantitative model comprises both.

Table 4: Parameters

Parameters	Value	Obtained from
σ	0.700	Lee and Shin (2017)
$r+\delta_S$	0.300	Average depreciation rate of computer capital from FAT

directly into the equilibrium equations. The detailed procedure is as follows.

1. Fix α_I as above, and guess $A_{I,1980}$ and ρ_i's.
2. For 1980: obtain $(\nu_{ij},\omega_i,\alpha_i,A_{i,1980})$ given guess.
   (a) Set $M_j=1$ for all j. Then the industry-specific occupational weights (ν_{ij}'s) are recovered from (8) using data on 1980 employment shares. Then we can also compute $\tilde{V}_i$ in (7).
   (b) From (9) of industry I, ω_I must solve
   $$R_S=(1-\alpha_I)\cdot A_I k_I^{\alpha_I}\cdot\left[\omega_I^{\frac{1}{\rho_I}}s_I^{\frac{\rho_I-1}{\rho_I}}+(1-\omega_I)^{\frac{1}{\rho_I}}\tilde{V}_I^{\frac{\rho_I-1}{\rho_I}}\right]^{\frac{1-\rho_I\alpha_I}{\rho_I-1}}\cdot(\omega_I/s_I)^{\frac{1}{\rho_I}},$$
   given data on k_I and s_I in 1980. The solution $\omega_I\in(0,1)$ if $1<(1-\alpha_I)A_I(k_I/s_I)^{\alpha_I}$.
   (c) Given ω_I, obtain α_i's from (11)-(13) using data on (k_i,s_i) for all $i\neq I$, which also yields the ω_i's.
   (d) Exogenous sectoral TFP's $A_{i,1980}$'s are recovered from (6) and $A_{I,1980}$.
3. For 2010: obtain $M_{j,2010}$ and updated guesses for the substitutability between computers and workers, ρ_i^{new}.
   (a) Choose the M_j's that yields the best fit of (8) across all i given 2010 employment shares:
   $$\frac{M_j}{M_1}=\sum_i\left[\frac{L_{ij}}{L_{i1}}\cdot\frac{\nu_{i1}}{\nu_{ij}}\right]\Big/I,$$
   where I is the number of industries. Using this we can compute $\tilde{V}_i$ for 2010 using (7).
   (b) From (11), we set ρ_I^{new} to get the best fit of
   $$\rho_I^{new}=\sum_i\left\{\frac{\log(\omega_I\tilde{V}_I)-\log((1-\omega_I)s_I)}{\log\left[\left(1-\frac{\alpha_I(1-\alpha_i)k_i}{\alpha_i(1-\alpha_I)k_I}\right)\tilde{V}_I\right]-\log\left(\frac{s_I\alpha_I(1-\alpha_i)k_i}{\alpha_i(1-\alpha_I)k_I}-s_i\right)}\right\}\Big/I$$

given data on (k_i, s_i) in 2010.

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 ρ_I^{new} 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 ρ_I^{new}.

(c) Compute the implied ρ_i^{new}'s that are consistent with the 2010 s_i's, i.e.,

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

4. Iterate over ρ_i's till $\rho_i \approx \rho_i^{new}$.

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

Once we have recovered all the parameters,

1. Get $A_{i,2010}$'s to match measured TFP by industry in (14) to the 2010 data.

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

$$M_{j,t} = M_{j,1980}(M_{j,2010}/M_{j,1980})^{(t-1980)/30},$$

$$A_{i,t} = A_{i,1980}(A_{i,2010}/A_{i,1980})^{(t-1980)/30}.$$

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

Results The calibration results are summarized in Tables 5 to 7. Since changes in M_j affect occupational employment across all industries, we can identify task-specific productivities separately from the measured TFP's by industry. In other words, occupational employment data alone gives enough information to identify the M_j's. In turn, the M_j's, together with the measured sectoral TFP's from the data, provide enough information to identify the sector-specific A_i's. The calibrated values for M_j's show that routine intensive occupations, such as machine operators or mechanics, indeed experienced much faster growth in their task-specific productivities. And as expected, the sector-specific productivity of the computer industry (A_I) grew exceptionally fast especially during the 1990s.

It is also noteworthy that the ρ_i's are identified from how computer capital per worker (s_i) and traditional capital per worker (k_i) evolve differently across industries.

Table 5: Industry specific parameters

Param/Target		Const	FIRE	Health	High serv.	Low serv.	Dur	Mine	Non-durable	Trade	Computer
γ	estimated	0.084	0.159	0.099	0.124	0.142	0.087	0.057	0.094	0.117	0.037
ρ	$s_{i,2010}$	1.655	1.228	1.446	1.515	1.429	1.517	1.450	1.241	1.456	1.857
ω	$s_{i,1980}$	0.001	0.093	0.003	0.023	0.006	0.010	0.020	0.029	0.008	0.019
α	$k_{i,1980}$	0.167	0.374	0.301	0.454	0.475	0.402	0.793	0.333	0.186	0.322

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 ρ tends to be greater than one (Equation 11). 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. All calibrated ρ_i's are indeed greater than one, implying that computerization leads to a decline in the labor share.

Table 6: Industry-occupation specific weights on labor (ν_{ij})

Target: employment share by industry and occupation in 1980

	L serv.	Admin.	Mach	Sales	Trans	Tech	Mech	Mine.	Prof.	Mngm
Const	0.008	0.055	0.028	0.011	0.203	0.018	0.564	0.016	0.024	0.074
FIRE	0.040	0.410	0.004	0.243	0.012	0.014	0.013	0.004	0.022	0.236
Health	0.298	0.164	0.005	0.004	0.005	0.121	0.010	0.012	0.322	0.059
H serv.	0.085	0.209	0.010	0.020	0.018	0.046	0.046	0.008	0.424	0.134
L serv.	0.295	0.148	0.027	0.036	0.150	0.014	0.095	0.028	0.075	0.132
Durable	0.026	0.115	0.363	0.040	0.130	0.024	0.056	0.113	0.038	0.094
Mining	0.016	0.092	0.046	0.012	0.193	0.047	0.122	0.321	0.066	0.085
Non-dur	0.020	0.110	0.355	0.022	0.097	0.028	0.083	0.145	0.052	0.087
Trade	0.020	0.142	0.022	0.390	0.136	0.006	0.076	0.048	0.023	0.138
Computer	0.015	0.156	0.298	0.047	0.040	0.065	0.044	0.077	0.131	0.128

Table 7: **Industry and occupation specific productivity**

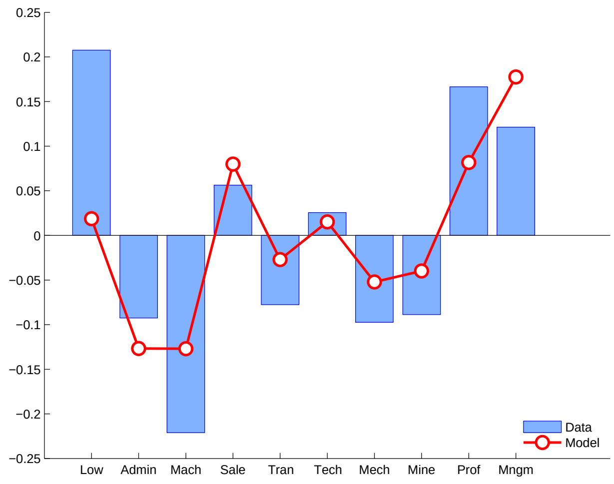
Target: emp. share by ind. and occ. in 2010					Target: measured TFP in 1980 and 2010				
M_j	1980	1990	2000	2010	A_i	1980	1990	2000	2010
Low serv.	1.000	1.000	1.000	1.000	Const	14.124	10.775	8.219	6.270
Admin.	1.000	1.325	1.755	2.324	FIRE	17.940	16.393	14.978	13.686
Machine	1.000	1.815	3.293	5.976	Health	6.156	6.001	5.850	5.703
Sales	1.000	0.732	0.536	0.393	High serv.	1.386	1.513	1.651	1.803
Trans	1.000	1.193	1.424	1.699	Low serv.	0.050	0.052	0.054	0.056
Tech	1.000	0.849	0.722	0.613	Durable	0.504	0.525	0.546	0.569
Mechanics	1.000	1.466	2.150	3.152	Mining	3.048	3.090	3.132	3.175
Mine.	1.000	1.420	2.016	2.863	Non-durable	0.274	0.273	0.272	0.271
Prof.	1.000	0.729	0.532	0.388	Trade	0.270	0.341	0.431	0.545
Mngm	1.000	0.658	0.434	0.286	Computer	1.946	3.651	13.368	25.501

4.2 Model Fit

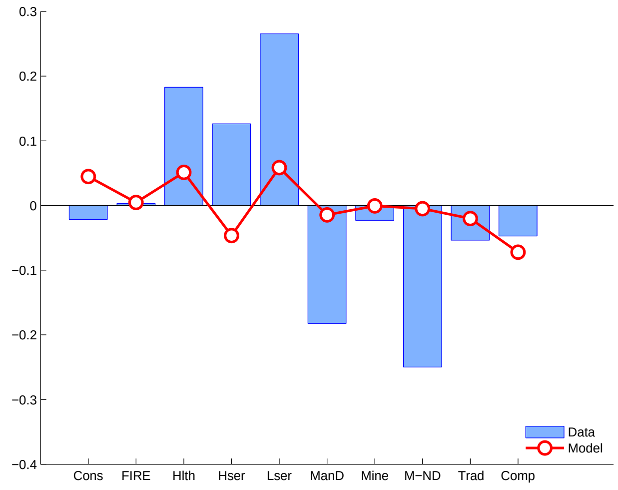
The model-implied employment share changes fit the data better by occupation than by industry (Figure 5). This is because the M_j's directly affect occupational employment through (8), whereas once we match measured TFP by industry, employment by industry is pinned down by (6). Nonetheless, employment 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 6).

The model fits generally well even for variables not directly targeted in the calibration. Most importantly for our purposes, the model generates a slowdown in aggregate output and productivity growth starting in 2000, similarly as in the data (Figure 7). 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—and do not target aggregate variables in 2010.

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 (Figure 9), despite not being targeted at all at the sectoral nor aggregate levels. Recall that our production technology assumes that traditional capital's income share is constant by construction. Thus, our results suggest that computer hardware and software, which is a subset of total capital that accounts for 14 percent of all investment, can be respon-

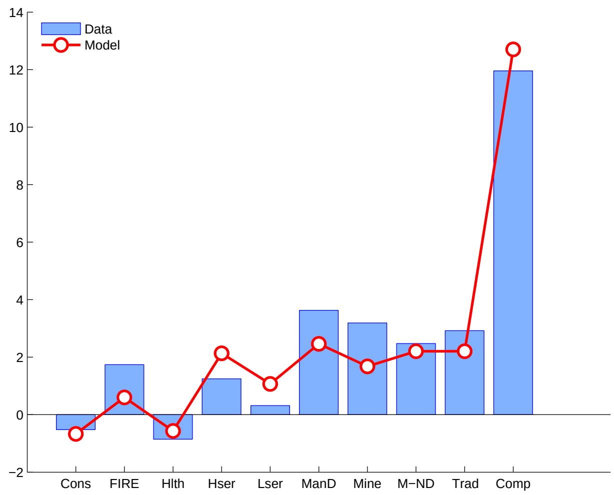


(a) By occupation

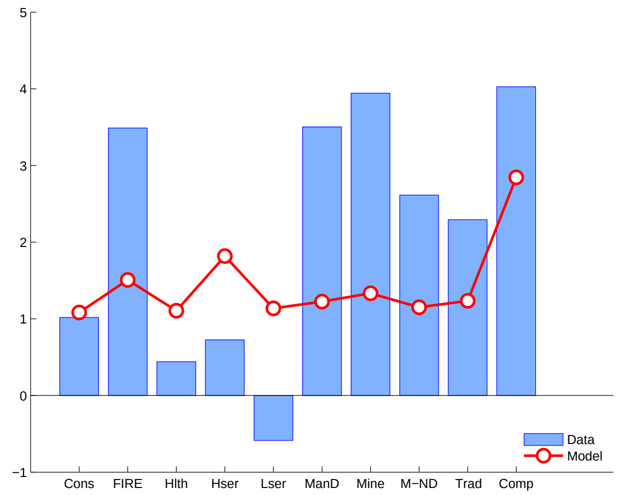


(b) By industry

Fig. 5: Changes in employment shares between 1980 and 2010

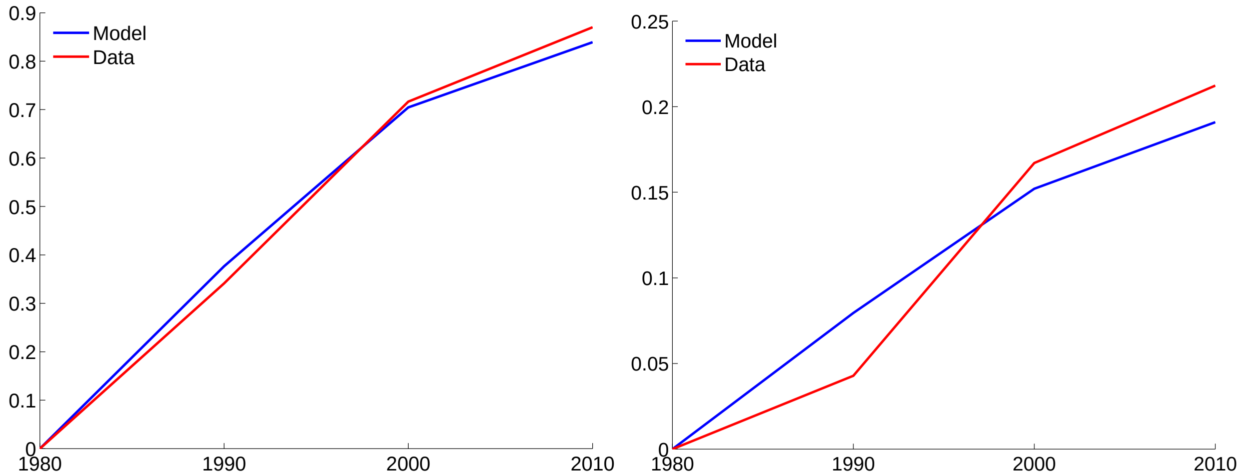


(a) Output per worker



(b) Capital per worker

Fig. 6: Log changes of y and k between 1980 and 2010



(a) Output

(b) Productivity

Fig. 7: Aggregate production

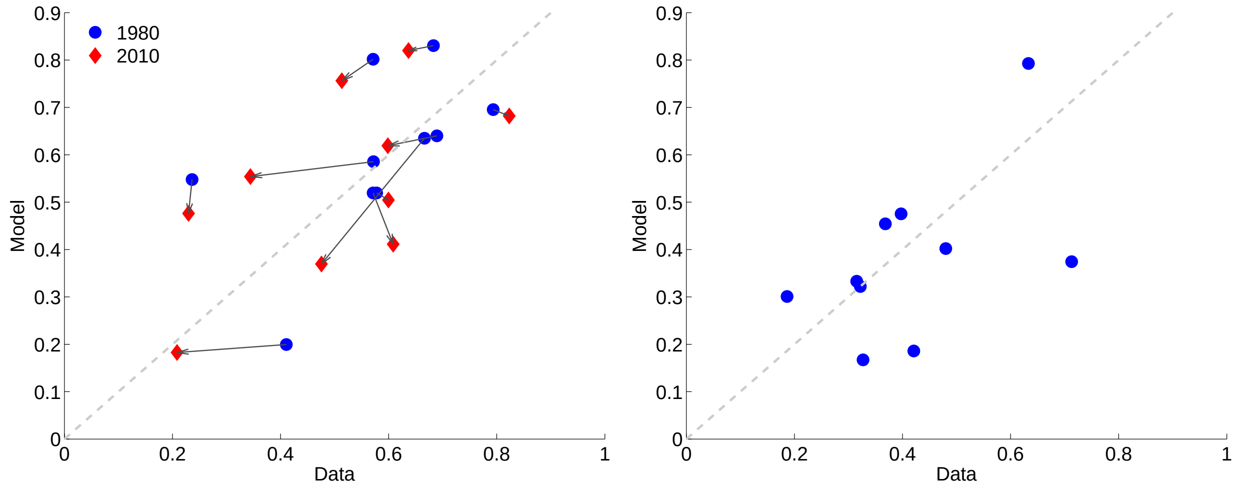
sible for the vast majority of the fall in the labor share (4 out of 5 percentage points) since 1980.

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 captured by 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.

In our model equilibrium, this propagation happens by shifting the price of computer capital. When A_I is high, the computer sector shrinks in employment because of complementarity, but also lowers the relative price of computers. This, in turn, leads to a drop in the rental rate of computer capital, which induces all sectors to use more computers. This prevents the computer sector from shrinking as much as it would in the absence of computer capital.

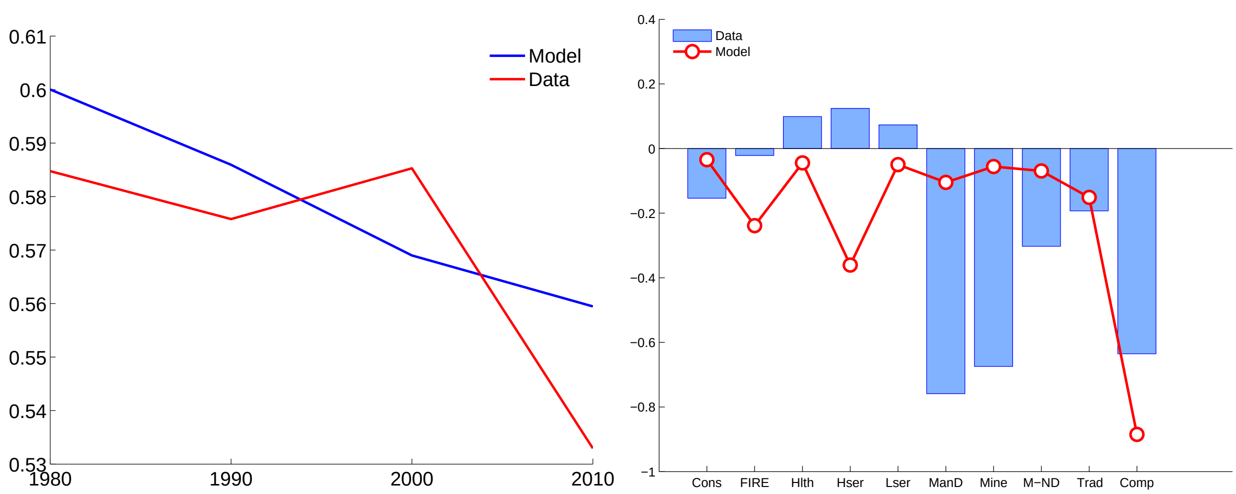
Aggregate productivity Note that the growth rates of task- and sector-specific productivities (M_j and A_i) were assumed to be constant for the entire sample period except for the computer sector (A_I). Nonetheless, in the benchmark calibration, aggregate TFP increases almost linearly from 1980 to 2000, slowing down in the last decade



(a) Labor share

(b) Capital share

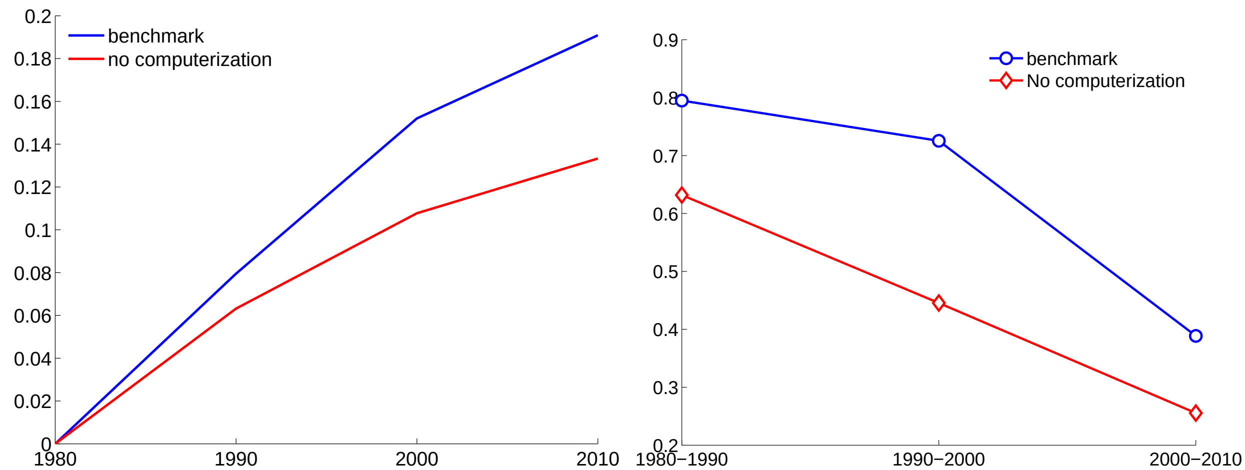
Fig. 8: Factor income shares by industry: model vs. data



(a) Aggregate

(b) By industry

Fig. 9: Changes in labor share: model vs. data



(a) Log level

(b) Growth rate

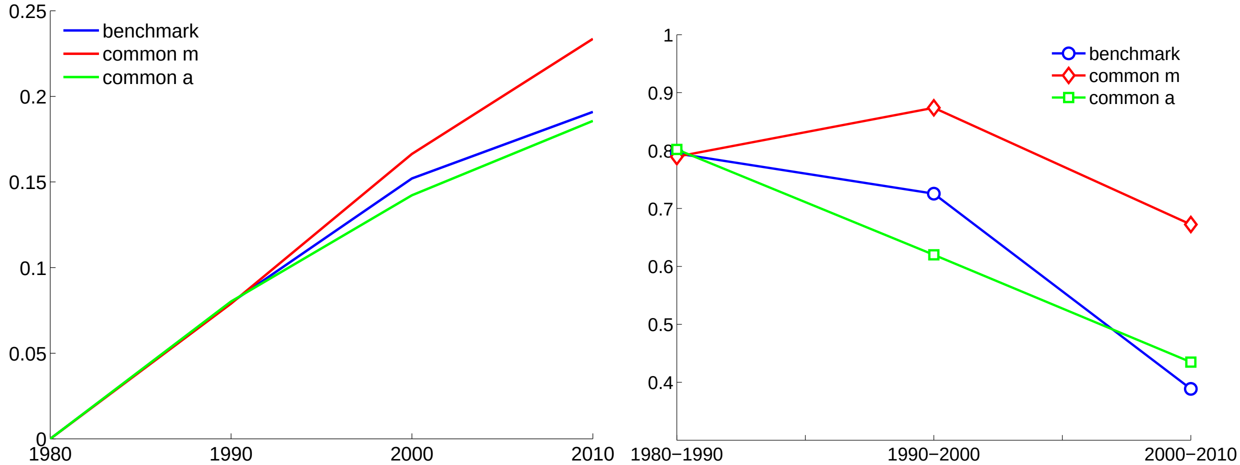
Fig. 10: Aggregate productivitiy

(Figure 10).[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, aggregate productivity would have grown by only 13 percent from 1980 to 2010, one-third lower than the benchmark growth rate of 20 percent over the same period. This magnitude is surprising considering the fact that the computer industry share of aggregate output is only 3 percent.

When all task- and sector-specific productivities grow at constant rates over time, complementarity across jobs and sectors leads to faster growing tasks and sectors to shrink in relative size, reducing their weights in the computation of aggregate productivity. Hence, as long as task- and sector-specific productivities grow at different rates, aggregate productivity growth must slow down over time. 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 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 leaving the growth rates of A_i's to be different from one another as in the benchmark. Second, we force all A_i's to grow at a common rate a while

[10] Aggregate productivity growth is measured as $d\log(y)$ − (traditional capital share) $\cdot$ $d\log(k)$ − computer share $\cdot\, d\log(s)$.



(a) Log level

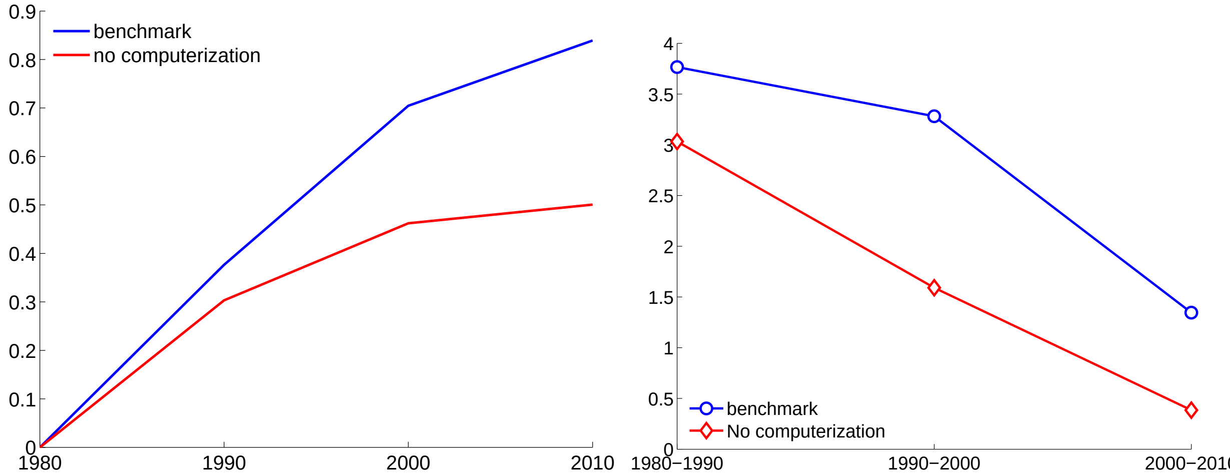
(b) Growth rate

Fig. 11: Aggregate productivity

leaving the growth rates of M_j's heterogeneous as in the benchmark. 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. In contrast, even when all sector-specific productivities grow at a common rate, aggregate productivity growth falls almost as much as in the benchmark. Of course for the latter exercise, we are also ruling out the faster growth of the computer sector, which partially 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. Furthermore, 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.

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 computer-



(a) Log level

(b) Growth rate

Fig. 12: Aggregate output

ization. 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 (ρ_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. Among all these exercises, the only two that affect labor shares are when we eliminate computerization either explicitly (in red) or by assuming common growth rates across all industries (in sky-blue). So we can conclude that the growth in A_I is the only important driving force behind the decline of the labor share.

Summary of quantitative analysis There are two main findings from our quantitative analysis. First, constant task- and sector-specific technological progress 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

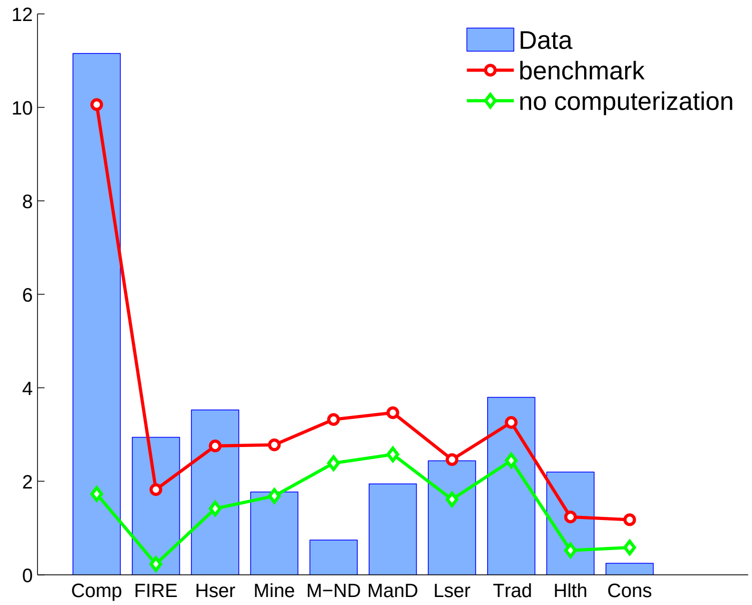


Fig. 13: Output growth by industry

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 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. More-

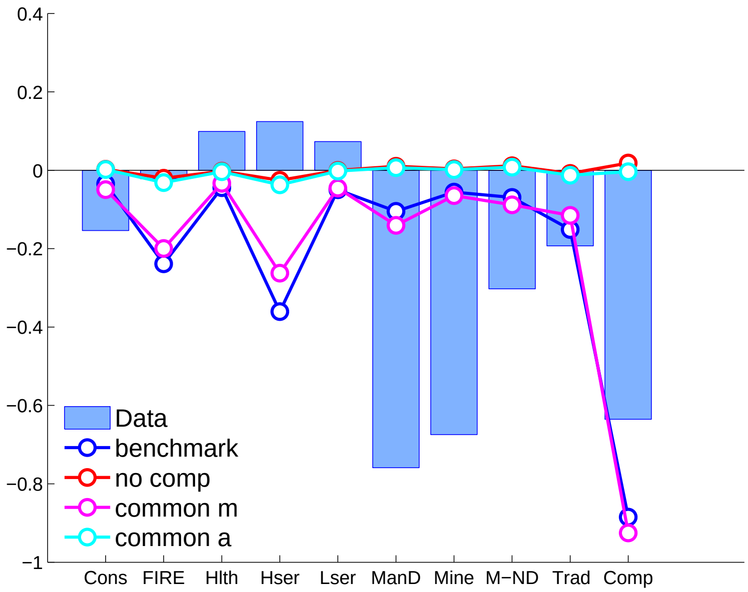


Fig. 14: Changes in labor share

over, 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; Carvalho, 2014; Atalay, 2017) 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.

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