Digital Abundance Meets Bottlenecks: Implications for Wages, Interest Rates, and Growth

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Abstract

Digital technologies are creating dramatically cheaper and more abundant substitutes for many types of ordinary labor and capital. If these inputs are are becoming more abundant, what is constraining growth? We posit that most growth requires a third factor, a scarce 'bottleneck' input, that cannot be duplicated by digital technologies. Our approach parsimoniously resolves several macroeconomic puzzles involving automation, inequality, and secular stagnation. We show that when capital and labor are sufficiently complementary to the bottleneck input, augmentation of either will lower their price and income shares in the short and long run. We consider three distinct microfoundations for bottlenecks as well as implications for government policy.

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1 Introduction

"Seek to be a scarce complement to increasingly abundant inputs"

Hal Varian, Google Chief Economist

Signs of rapid technological change abound. Computer processing power has increased a million-fold in just three decades, and digital storage and communication capacity have grown at dizzying rates as well.[1] Machine learning systems can now diagnose diseases (Esteva et al., 2017), recognize images and understand speech (The AI Index, 2021).

AI and other digital technologies can perform an increasingly diverse array of tasks previously done only by human labor: over 294,000 robots were purchased for factories in 2016 while software "bots" conduct over half of all trades on Wall Street (International Federation of Robotics, 2017). Technology has increased the effective supply of capital as well. AI routing algorithms allow firms to optimize the effective capacity of delivery trucks, enterprise resource planning systems boost the effective output of factories, and systems from peer-to-peer ride sharing to property rental services multiply the utilization rates of many other types of existing capital.

Despite this digital abundance, economic performance over the last 40 years has been lackluster. Ordinary workers have seen their wages stagnate. The return on capital – as measured by real interest rates – has fallen substantially as well. Overall productivity growth has been averaged only 1.3 percent since 2006, less than half the rate of the preceding decade.

Why, if emerging technologies are so impressive, is productivity growth not increasing? And wny are interest rates so low, wage growth so slow and investment rates so flat?

At the same time, while the income paid to ordinary capital or ordinary labor has fallen, some groups have enjoyed tremendous increases in income. To understand what's driving these changes, we look to those who have done the best in recent years – a small number of fortunate investors and highly skilled individuals who have seen their shares of national income skyrocket. We propose a model of aggregate production with three inputs: capital, labor, and a distinct third factor. This third factor corresponds to a 'bottleneck', inelastically supplied by some top workers and capitalists, which allows firms to make full use of digital abundance.

We introduce this third factor because reconciling the above trends in a traditional competitive two-factor model of aggregate production is impossible. If capital and labor are imperfect substitutes, technological changes that boost the productivity of capital should raise the wages of workers. Technological changes that increase the ability of capital to substitute for labor should increase interest rates, at least in the

[1] From 1986 through 2007, global general-purpose computing capacity, bidirectional telecommunication capacity, and stored information grew at annual rates of 58%, 28% and 23% respectively (Hilbert and López, 2011).

short run.[2] For an intuition why, consider an economy where firms unexpectedly gain the ability to replace some workers with highly productive robots. Firms will bid up interest rates in an attempt to take advantage of this attractive new investment opportunity.

The inputs in our model are traditional capital and labor and a relatively inelastic complement. For concreteness, we dub the third factor B for which we discuss several interpretations. When B is not the scarce factor, the economy approximates a two-factor one. But as B becomes relatively scarce, it becomes a bottleneck for output and captures an increasing share of national income. We show that when traditional inputs are sufficiently complementary to B, innovations in automation technology can reduce both labor's share of income and the interest rate.

Our model parsimoniously explains why ordinary labor and ordinary capital haven't captured the gains from digitization, while a few superstars have earned immense fortunes. Their contributions, whether due to genius or luck, are indispensable to making use of digital technologies.

Conceptually, the essential feature of B in our model is that it is inelastically supplied complement to increasingly abundant digital inputs. Our primary interpretation of B is as the labor of superstar individuals. They may be exceptionally gifted with the ability to come up with an exciting new idea, sort through bad ideas for a diamond in the rough, or effectively manage a business. These are the individuals that find new ways to make use of abundant and cheap capital and labor resources.

Measuring B is challenging. It is not obvious which types of labor or capital income should be included. In a set of exploratory cross-firm and cross-country regressions, we proxy for bottleneck-labor income using CEO compensation and top 1 percentile incomes. In these regressions, we provide suggestive evidence that IT capital investment and low capital costs are related to increases in CEO compensation and the top percentile's share of national income respectively.

We derive our main estimates of B's share as the sum of measured 'B-labor income' and a residual – incomes which aren't being paid to ordinary workers or capital. To identify B-labor income, we harness a key insight from the theoretical literature on superstars. While theory and evidence suggests that the earnings of normal workers are log-normally distributed, top labor incomes are better described as following a power law or Pareto distribution. These distributions naturally arise from superstar markets through processes such as preferential attachment. Using data from the IRS Tax Model Files, we document that the US wage distribution is well described as a mixture of a log-normal distribution for lower incomes and a Pareto distribution for higher incomes. Using maximum likelihood estimates for the parameters of this mixture, we find that the portion of US workers in the 'superstar economy' has stayed relatively stable at about 3 percent since 1980. However, this group's share of national income has almost doubled from 1980 to 2016, as the upper tail grows longer.

In addition to the wages of B-labor, we add the 'factorless' income[3] which is being

[2] In the long run, the relationship between technological change and interest rates is mediated by the impact on aggregate saving and investment. This is explored later.

[3] To borrow a coinage from (Karabarbounis and Neiman, 2018).

paid to neither ordinary labor or capital. We do so for several reasons. One reason is that this factorless income may actually be mislabled labor income (e.g. because it is tax advantaged to report owner-operator income as profits rather than labor income, or because executive compensation in the form of stock options are not counted as labor income). Another reason is that super-normal capital income is potentially earned because of extraordinary investing talent or lucky access to opportunities.

A third reason to consider the profit share part as part of B income is that some of the product of B-workers may be owned and accumulated by firms in the form of intangible assets. Research has pointed to super-normal returns to companies that make investments in information technology. These returns are best explained by only a subset of firms possessing the intangible assets that make these investments possible. We show that this interpretation is consistent with decreasing interest rates if organizational capital faces large adjustment costs in its accumulation.[4]

While distinct, the organizational microfoundation is closely related to the interpretation of B as superstar workers. Organizational capital may be hard to accumulate because it requires exceptional workers to create it, nurture it, or sustain it. Similarly, large profits gained by titans of digital industries may be attributed to their discovery of some new patch of virtual real estate. In a sense then, virtual real estate and organizational capital can be thought of as a type of crystallized human genius, perhaps reflecting the collective, if not necessarily consciously-coordinated, efforts of many individuals. Conversely, the scarce asset owned by firms may include their attractiveness as a workplace for exceptional workers. Many have hypothesized that the comparative advantage of large digital platform companies is their special ability to recruit and motivate exceptional workers.

2 Data and Literature

2.1 Decreasing Labor Shares

Over the last thirty years, many developed economies have experienced a decrease in labor's share of income. This decrease is present in both the corporate sector and in the overall economy. The decrease was comprehensively documented in Karabarbounis and Neiman (2014). They find an approximately 5 percentage point decrease in labor's share of global corporate gross value added since 1980.

The decrease in labor's share of income is even more extreme if we exclude the top

[4]The limit case of intangible assets, where the adjustment cost is infinite or nearly so, can be thought of as 'virtual real estate'. Intellectual property, including monopolies created by patents, copyrights, or trade secrets, is one category of virtual real estate. It can also reflect an exclusive opportunity to profit from strong network effects (including two-sided networks and platforms), control of an indispensable standard, or privileged access to exceptional supply-side economies of scale. All three are common in digital goods, which typically have high fixed costs and low or zero marginal costs. The owners of the social network that consumers have coordinated on may therefore be thought of as collecting rents on virtual real estate. This is still true if there were, *ex-ante*, many distinct and equally good networks for a particular application. Only one can become the *ex-post* focal network after some combination of ingenuity, effort, and random events makes it pre-eminent.

percentiles of workers. In figure 1 we present the decline in the share of income paid to the lowest paid 97 percent of workers in US non-financial corporations.

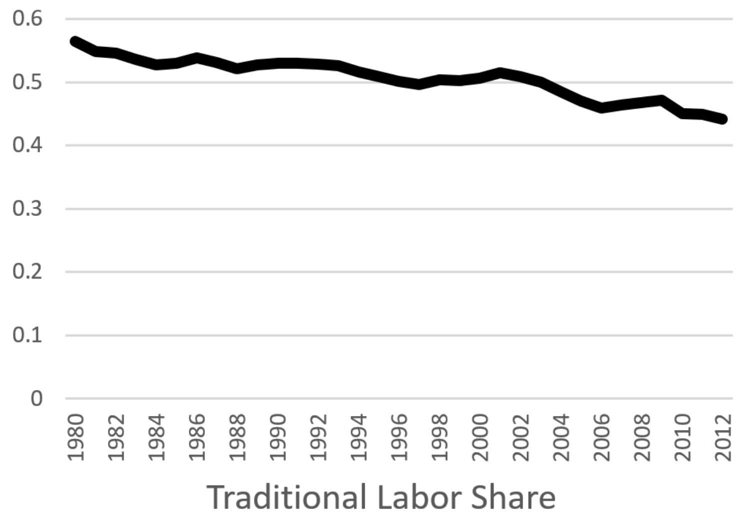

Figure 1: Traditional labor's share of US non-financial corporation gross value added. The traditional labor income share is the bottom 97 percent share of all US labor income (equal split adults) from the World Wealth and Income Database World Wealth and Income Database (2016) multiplied by total US non-financial corporate labor income (we assume that the top 3 percent share of labor income is the same in the corporate sector as for the economy as a whole). Data on US non-financial gross value added from BEA table 1.14.

The most common explanation for a decrease in labor's share of income is the adoption of new automation technologies. This theory finds both theoretical and empirical support. For example, Acemoglu and Restrepo (2017) find that adding one more robot for every thousand workers reduces wages by .25 - .5 percent and employment rates by .18 to .34 percent.

There is a large class of growth and directed technical change models exploring the consequences of enhanced automation. One example of such a model is Acemoglu and Restrepo (2018). In that model, final output is made of several tasks. Scientists decide whether to invent new tasks or to automate old ones. New tasks are relatively labor intensive. Automating old tasks means they can be performed with capital alone. In the context of their model, stagnant wage growth and a decline in the labor share is explained by an increase in the rate of automation relative to new task creation. An important corollary of this result is that a boost in automation technology will increase interest rates in the short run. In an accounting sense, this is because the technology increases total output by more than it increases wages. In a general equilibrium sense, this increase is due to increased investment demand, which raises interest rates until savings catch up.

In Acemoglu and Restrepo (2018) the long-run interest rate is not impacted by automation, as it is pinned down by the discount rate of the representative agent.

In the meantime, saving and investment rates rise so that capital accumulates to its new steady state level. Alternatively, if households are modeled as constituted of overlapping generations, as in the automation model of Benzell et al. (2016), then long-run interest rates can increase as well. In overlapping generations models, savings are modeled as being made by young workers to pay for their retirements. Therefore, labor income is saved at a higher rate than capital income. A sufficiently large decrease in labor's share of income will *decrease* saving and investment. A decrease in investment raises the marginal product of capital, increasing interest rates.[5]

Other models of automation also generate a decrease in labor's share of income. One way of modeling automation is to directly model a broadening of choices of Cobb-Douglas production functions in terms of α, i.e. capital intensity.[6] An example of a model with automation of this form is Peretto and Seater (2013).[7] Automation corresponds to an expansion in the upper range of capital intensities available. This leads to a rise capital's share and lower wages in the short run. It also leads to an increase in interest rates. These effects are caused by capital moving into more capital-intensive production technology, and, therefore, capital being used in a lower ratio in combination with labor in the labor-intensive technology.[8] While some parameterizations of Acemoglu and Restrepo (2018) lead to a balanced growth path with a constant labor share of income, these other models generally see continual decreases in labor's share of income a necessary condition of long term growth. Labor per person is fixed while capital per labor can be increased. In models where labor's innate productivity is capped, long-term growth requires increasing reliance on reproducible factors.

Another approach to modeling automation is allowing for output to be created, with constant returns to scale, by capital alone. Such a model is explored in Sachs et al. (2015). In these models, firms have a choice between producing using a traditional technology and a robotic technology. The interest rate is pinned down by the productivity of robotic capital. Therefore an increase in the productivity of this technology causes interest rates to increase. Wages decrease because capital in the form of labor complementing machines is reinvested into non-human complementary robots. If the saving rule is such that capital stocks accumulate, the interest rate will remain unchanged, but the capital share of income will continue to increase.

A related family of models is exemplified by Autor and Dorn (2013) and Benzell et al. (2016). In Autor and Dorn (2013), traditional capital is a complement to manual, routine and high skilled labor. Information technology capital is a substitute for

[5]Consistent with this mechanism, US personal saving as a share of disposable income decreased from 12 percent in 1982 to a nadir of 3.2 percent in 2005. It measures 6.7 percent in 2017, lower than any annual rate between 1950 and 1999 (FRED, 2018).

[6]Peretto and Seater (2013) show that economies will use both of the most extreme mix of α technologies available.

[7]In the full version of this model firms in monopolistic competition pay a cost to gain access to new αs. Their model reduces to the one discussed here when all firms produce perfect substitutes and technological change is exogenous. This model is discussed and developed in a series of blogposts by Avent (2017) and Krugman (2017). Zuleta (2008) also features a similar form of technological change.

[8]A related model is Zeira (1998), in which automation corresponds to an additional, more capital intensive, *Leontief* technology becoming available.

routine labor. An increase in the effective quantity of information technology capital will lower routine wages. Labor's share of income will decrease. Interest rates increase as well. Similarly, in Benzell et al. (2016) when a new form of software substitute for some workers becomes available for investment, labor's share must decrease in the long run. Interest rates increase in the short and long run. Investment in the new form of capital crowds out investment in capital types that complement workers.

2.2 Decreasing Real Interest Rates

Thus, models of automation correctly predict a decrease in labor's share of income. However, they also predict *increases* in interest rates and capital's share of income. Some additionally predict increases in the rate of investment. In representative agent models, this increase in interest rates is temporary, and is offset over time by increased investment.

None of these predictions comport with the recent experience of the US or the developed world. Since the mid-1980's, nominal and real interest rates have steadily *declined* in the US.[9] A decade after the Great Recession, world interest rates remain low and are expected to remain low for a long time. In fact, Belgium recently issued a 100-year bond at a nominal interest rate just above the ECB inflation target of 2 percent (Moore, 2016). Figure 2 displays how as world labor shares have decreased, so too have real interest rates.

Holding all else constant, a decrease in real interest rates must mean a decrease in the required rate of return on capital investment.[10] By multiplying the required rate of return by the stock of capital in the economy, one can arrive at a measure of the share of income paid to capital analogous to the labor share. Barkai (2016) and Barkai and Benzell (2018) do exactly this. They measure the traditional capital share of income by using the static maximization condition that the marginal product of investment, less depreciation, must be equal to the nominal interest rate less expected inflation (the Jorgensonian interest rate). Assuming $r^* = F'(K) = r_{nominal} - E[\pi] + \delta$ for each form of capital, they attribute r^*K to be that form of capital's share of national income. δ and K are available from the BEA, $E[\pi]$ is assumed to be a moving average of realized inflation (again from the BEA) and $r_{nominal}$ is taken from Moody's AAA bond rate. From the firm's profit maximization condition, r^* is the marginal revenue product of capital net of adjustment costs. $\frac{r^*K}{Y}$ is therefore a measure of the capital share analogous to labor's share of income. Subtracting r^*K and wL from a firm's total post-tax income leaves a measure of firms' infra-marginal profits and/or return on unmeasured intangible assets.[11]

[9] Appendix Figure 14 reports four indexed measures of the US real rate of return, with all in steady decline.

[10] Gomme et al. (2011) estimate a relatively constant return on capital from 1954 to 2003 primarily because they attribute all non-labor income to capital. In other words, they combine capital and profit income, a distinction we emphasize.

[11] Karabarbounis and Neiman (2018) carefully evaluate this approach to measuring capital's share. They consider three possible causes for what they call the rise in 'factorless income' not obviously attributable to labor or capital. The first two possibilities they evaluate are that it corresponds to an increase in intangible assets' or profits' share of income. They however

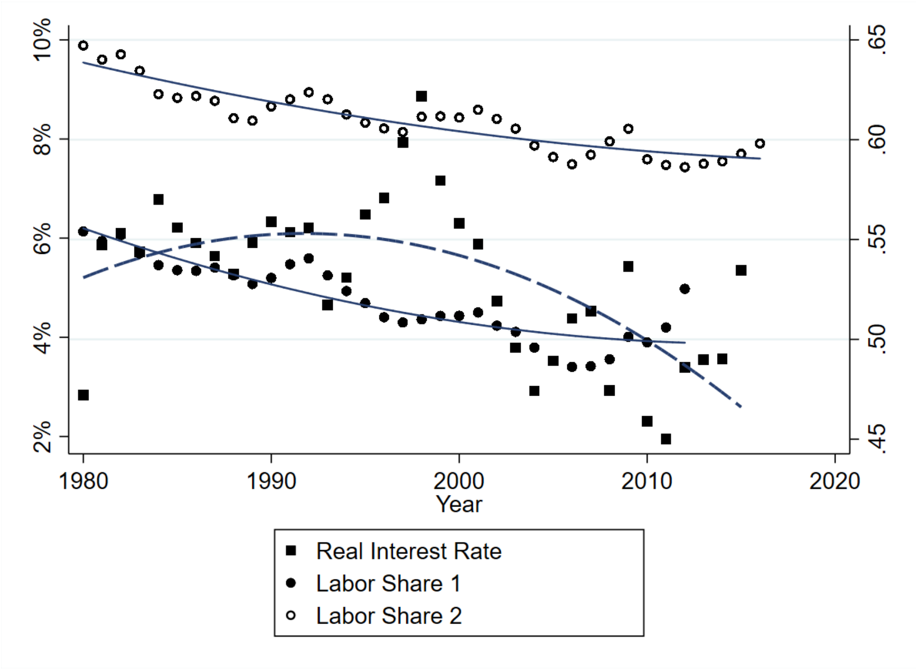

Figure 2: Average labor shares and real interest rates over time. *Labor share 1* is total labor share of income as constructed in Karabarbounis and Neiman (2014); unbalanced panel of 111 countries from 1980-2012. *Labor share 2* is labor's share of income as reported by IMF-WEO; balanced panel of 24 countries from 1980-2016. Real interest rates as reported by the World Bank Development Indicators. The World Bank (2017); unbalanced panel of 168 countries from 1980-2016. For each series, a quadratic best fit is superimposed.

emphasize a third possibility – that the Jorgensonian interest rate is not a good measure of the rental rate of capital. They prefer this interpretation because the first two are inconsistent with relatively stable capital and labor shares or capital and labor substitutability.

We disagree with this interpretation of the facts. First, we think there is clear evidence in favor of the first two interpretations, especially for the post-1980 period. Using Compustat data on the elasticity of output to variable costs, De Loecker and Eeckhout (2017) and Traina (2018) find that markups have been increasing since the mid 1980's. The increase in the share of firm assets not explained by physical capital is also *prima facie* evidence of an increase in intangible assets or expected profits. Barkai and Benzell (2018) present the profit or intangible share of income measured three additional ways (accounting profits, markups, and assuming a constant real interest rate), untied to the Jorgensonian interest rate and find increases since the 1980s across each.

Second, concern that this measure produces an implausibly volatile series for factor shares and productivity growth is circular. Under our theory, B's share does fluctuate independently of the labor share because of technological developments. A related version of this critique focuses on the fact that fluctuations in the 'factorless' share of income are more strongly anti-correlated with capitals' share than the relatively steady labor share. This is potentially surprising because the simplest model of monopolistic competition would imply that an increase in markups would reduce labor and physical capitals' shares by the same percentage. Barkai and Benzell (2018) suggests another possible explanation, following Blanchard and Giavazzi (2003), in positing that the surprisingly low volatility in labor's share is due to labor negotiating power leading to profit sharing. In the post-1984 period labor's share become strongly anti-correlated with profit share as well, consistent with a decline in union power and

Figure 3 reports capital's share of income for the US non-financial corporate sector using this measure. In the US, the decrease in the share of income paid to capital begins in the mid-1980s. Capital's share has declined from a peak of 29.5 percent in 1984 to 17.1 percent in 2012. Excluding the share paid to measured intellectual property products, which has increased 2.5 percentage points over the same interval, the decrease is even more dramatic.[12]

A literature almost entirely separate from, and implicitly at odds with, the literature on automation has emerged to explain these low interest rates. This is the literature on secular stagnation (e.g. Summers (2014)). Eichengreen (2015) defines secular stagnation as "a downward tendency of the real interest rate, reflecting an excess of desired saving over desired investment, and resulting in a persistent output gap and/or slow rate of economic growth." Fundamentally, this mismatch must be caused by either a decrease in investment demand or an increase in investment supply.

There is significant evidence from the financial system for reduced investment demand as a cause of low interest rates. In the last decade, US banks have dramatically increased their holdings of federal reserve deposits. The level of excess reserves held by banks increased from approximately one billion dollars in the mid-2000s to over 2 trillion in 2016. Banks make money by paying low interest on deposits and gleaning higher interest rates on loans. So why are they investing so much in an asset with a near-zero return? In a model with a strongly micro-founded financial system, Bianchi and Bigio (2014) reject changing capital requirements, interest on reserves, increased volatility, or lending frictions as the main driver of this phenomenon. They find that the evidence is most consistent with reduced loan demand. Similarly, Ennis (2018) develops a macroeconomic model in which low inflation, low interest rates, and large excess reserves are most compatible with weak investment demand.

Summers (2014) and others believe that decreased investment demand could be due, in part, to decreased aggregate consumption demand. Certainly, cyclical fluctu-

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labor market deregulation in this latter period.

Finally, the hypothesis that a wedge between apparent costs of borrowing and the marginal product of capital for marginal firms has expanded widely since the 1980s – an era of increasing globalization and financial liberalization– seems implausible and backed by little evidence.

Caballero et al. (2017) provides a useful taxaonomy of possibilities for why the real safe rate of return has decreased by more than the average rate of return on assets. The first is through an increase in the capital risk premium. This increases the spread between the safe rate and the rate of return to holding capital. The second is the markups. When markups are positive, this drives a wedge between the marginal product of capital (i.e. the required rate of return) and the rate of return to holding capital. Finally, if capital is expected to depreciate (or deflate) at a faster rate, this can decrease the average rate of return on assets for a constant safe rate of return.

Our measure of the required rate of return explicitly takes into account capital depreciation and inflation. A claim that the risk premium has dramatically increased is implausible. The final possibility, that average markups have increased, is close to the hypothesis of our model. As we pointed out, payments to an unobserved factor (either B-labor or intangible assets) will look the same as a markup. Additionally, for there to be a wedge between the average rate of return on capital and the average rate of return on all assets, there must be some factor preventing marginal asset prices from holding a portfolio of both. This is also consistent with B either being inalienable labor or a type of intangible asset with very restricted ownership

[12]Intellectual property measured by the BEA constitute depreciated expenditures on R+D, the creation of artistic originals, mineral exploration, and some forms of software

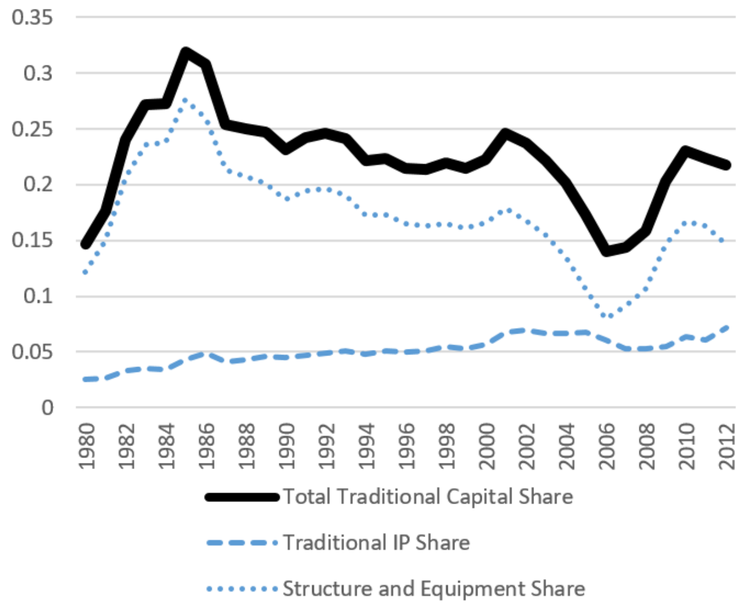

Figure 3: Traditional capital's share of US non-financial corporation gross value added. Calculation of each form of traditional capital's share of income follows Barkai (2016) and Barkai and Benzell (2018). Data on US non-financial gross value added from BEA table 1.14.

ations in aggregate demand, such as due to a financial crisis, can temporarily depress demand for consumption and thereby investment. This contributed to low investment demand during the Great Recession. But, in 2017 interest rates remained low despite unemployment rates of less than 5%. Even if, like Summers (2014), one believes that the US could still benefit from fiscal or monetary stimulus, the secular trend in interest rates and capital's share of income pre-dates the Great Recession. Judging by the current yield curve, low real interest rates are expected to persist well into the future as well.

In the long-run, Says Law asserts that supply creates its own demand. This suggests that a plausible source of a long-term decline in investment demand is low or negative technological growth. Gordon (2016) notes that observed US productivity growth has declined following the 1970s. Complementary evidence comes from Bloom et al. (2017), which observes that research productivity has declined dramatically in many areas, perhaps because of fishing out.

Of course, the idea that technological growth has been slowing is a contentious one. To the contrary, Brynjolfsson and McAfee (2014), Brynjolfsson and McAfee (2011) and Cowen (2013) argue that we are experiencing dramatic technological changes, citing numerous specific examples, as well as concerns about growing output mismeasurement.

The other possible cause of low interest rates is increased saving supply. Eichengreen (2015) notes that China and other rapidly developing nations have high saving rates. As the citizens of these nations capture a larger share of world income, the world saving rate will naturally increase, all else being equal. Summers (2014) notes that changes in inequality may have increased the rate of saving, noting that high income individuals save at a higher rate than the poor. Exacerbating the saving glut, the quality-adjusted price of investment has gone down by almost half in the two decades following 1983 (Eichengreen, 2015). Both an increase in the saving rate or a decrease in the price of investment are supply side shifters of the rental rate of capital. These shifts will increase the capital to labor ratio, driving down the marginal product of capital until it equals the rental rate. Eggertsson et al. (2017) splits the difference in an OLG New-Keynesian model. They attribute the largest portion of the decrease in interest rates to demographically driven changes in saving, and the second largest to a productivity growth slowdown.

In a two-factor neoclassical model, an increase in the capital-labor ratio is only consistent with a decrease in labor's share of income if capital and labor are gross substitutes. Using data on the price of investment and labor's share of income, Karabarbounis and Neiman (2014) calibrate just such a model. They find that an elasticity of substitution of 1.25 is most consistent with the observed trends in these variables.

This estimate is not the end of the story for four reasons. First, empirical evidence on the elasticity of substitution between capital and labor tends to find that the inputs are gross *complements*, not substitutes. An elasticity of .6 or .7 is best supported by this data (Knoblach et al., 2016).[13] Second, whether complements or substitutes, a large increase in the capital-labor ratio should increase wages as well. Third, the US non-financial corporate investment rate is flat or decreasing over this interval (figure 4). A glut of saving would lead to low interest rates through an 'investment glut', and there is no evidence of this. Finally, the saving glut hypothesis fails to account for the increasing share of output not captured by either traditional capital or labor.

3 The Rise of Bottlenecks' Share of Income

There is evidence that innovative automation technologies have led to an decrease in capital's share of income. There is also evidence that decreased investment demand has contributed to a decrease in interest rates. As figure 2 showed, these trends are occurring simultaneously.

This aggregate relationship is not due to a Simpson's paradox. Rather, as table 1 shows, within countries a positive relationship exists between labor's share and interest rates. What's more, this relationship is present whether or not one controls for country and year fixed effects.

[13]Lawrence (2015) makes this point as well, and concludes that recent declines in the labor share are better explained by large gains in labor productivity and labor and capital being gross complements. However, large increases in labor productivity would tend to generate large increases in interest rates.

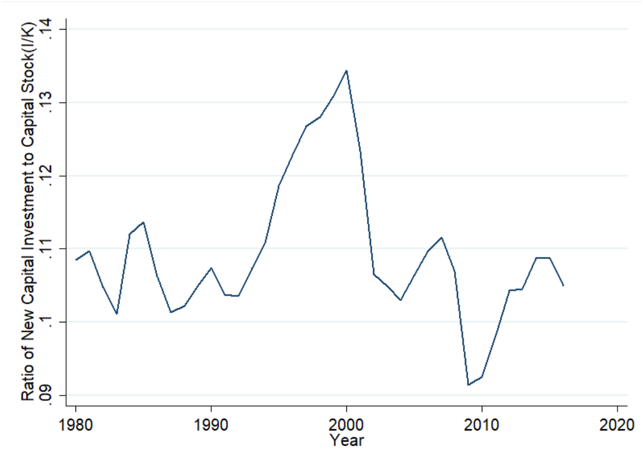

Figure 4: Capital investment rate for US non-financial corporations. The investment rate is calculated as total nominal investment divided by the total current cost capital stock. Underlying data from BEA NIPA tables.

	(1) LS_1	(2) LS_1	(3) LS_1	(4) LS_2	(5) LS_2	(6) LS_2
Real Interest	0.0562^{*}	0.0566^{*}	0.0496^{*}	0.239^{*}	0.238^{*}	0.241^{**}
	(2.32)	(2.33)	(2.00)	(2.43)	(2.41)	(2.90)
Constant	38.78^{***}	41.82^{***}	44.11^{***}	53.36^{***}	53.26^{***}	57.30^{***}
	(29.38)	(261.53)	(42.35)	(18.46)	(119.57)	(73.65)
Country FEs?		X	X		X	X
Year FEs?			X			X
N	1337	1337	1337	606	606	606

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Country level panel regression of labor share on real interest rates. Labor share 1 is total labor share of income as constructed in Karabarbounis and Neiman (2014). Labor share 2 is labor's share of income as reported by IMF-WEO. Real interest rates as reported by the World Bank Development Indicators The World Bank (2017). Standard errors clustered at the country level. Data from 1980 through 2016.

As suggested above, some simple accounting indicates that these two phenomena should not coexist in a two-factor model of technological growth.[14] Consider an economy where a range of firms suddenly gain the ability to replace some workers with

[14]It is easy to reconcile the trends with productivity growth slowing, because if total output decreases then both wages and interest rates can decrease. Grossman et al. (2017) examines a variation of this approach. They show that in a model with endogenous education, a productivity growth slowdown can lead to a decrease in labor's share. The mechanism is that when growth slows the real interest rate falls, inducing more education. This raises the effective labor to capital ratio, leading to a decrease in labor's share when the two are gross complements. Assuming a rate of inter-temporal substitution of less than one, the decrease in interest rates also leads to an increase in saving and investment.

highly productive robots. Firms should bid up interest rates in response. To see this, consider the two-factor aggregate production function

$$Y = F(K, L, C) \tag{1}$$

Where K is stock of capital, L is the input of labor, and C corresponds to a vector of production and technology parameters. Let $\gamma(K, L, C)$, a function of K, L, and Z correspond to the share of income paid to labor and $1-\gamma$ be the share paid to capital. Assume there are no profits.

Assuming factors are fungible, γ pinning down the factor shares also pins down the prices. In other words, assuming that capital fully depreciates each period,

$$1 + r = \frac{(1-\gamma)Y}{K} \tag{2}$$

$$w = \frac{\gamma Y}{L} \tag{3}$$

In the short run, any technological improvement (i.e. a change from some Z to some Z', holding K and L constant) by definition increases output Y. If γ is held constant, both the wage and interest rate must increase. If γ decreases, labor's share decreases and interest rates increase even further. The interest rate will increase in the long run so long K increases slower than $(1-\gamma)Y$. In the case of a representative agent, K accumulation will hold the interest rate constant in the long run. If households are modeled as overlapping generations with logarithmic preferences, then long-term K will grow or shrink in proportion to the long-term wage.

This accounting necessity ceases to hold if a third factor of production is available to accrue the income from productivity gains. Indeed, by our measure, this is exactly what has happened. We call this third factor "bottlenecks" or B. Figure 5 presents the share of US non-financial corporate gross value added that is not paid to traditional labor, traditional capital, or to the government.[15] This residual is what we measure as B.

3.1 Measuring Bottlenecks Through Top Labor Incomes

The first component of what we measure as B is top labor incomes. Despite the overall decrease in labor's share, the share of national income paid to top workers has only increased.

As figure 6 shows, top percentile inequality in the US has increased dramatically over the last forty years. The ratio of the average top percentile wage to the average wage of those in the bottom 90 percentiles doubled from about 10 in 1980 to about 20 in 2008. Total income inequality, which includes capital income, has increased even further.

There is theoretical and empirical evidence of technology playing a role in the rise of top workers' share of income. The increase in top income shares has impacted top

[15] Indirect taxes on production and imports less subsidies. This stays stable at between 8.1 and 9.1 percent of GDP over the period under consideration.

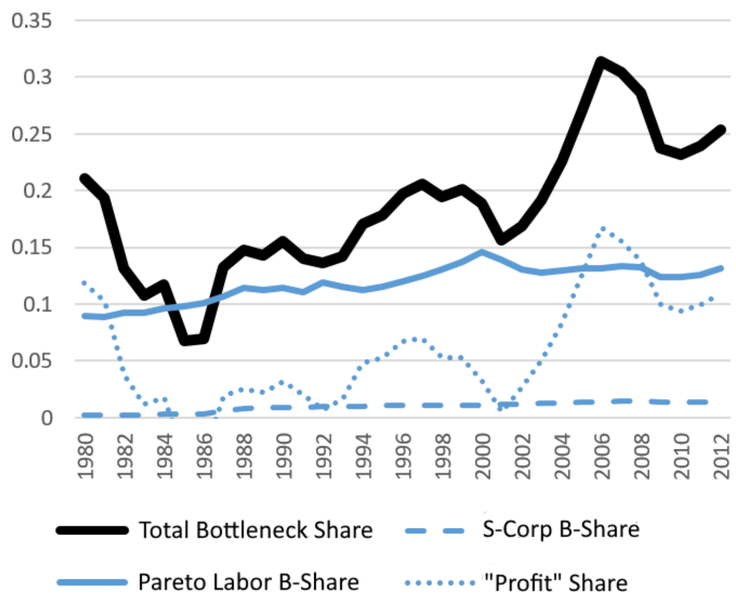

Figure 5: B's share of US non-financial corporation gross value added. The B-labor income share is the top 3 percent share of all US labor income (equal split adults) from the World Wealth and Income Database World Wealth and Income Database (2016) multiplied by total US non-financial corporate labor income (we assume that the top 3 percent share of labor income is the same in the corporate sector as for the economy as a whole). S-Corporation B-labor share is entrepreneur income misclassified as corporate profits from Smith et al. (2017) (we assume none of these corporations are financial). "Profit" share is total non-financial corporate gross value added less all the above, the traditional labor share, the traditional capital share, and taxes on production and imports less subsidies. This corresponds to Barkai (2016)'s estimate of non-financial corporate profits less S-Corporation B-labor income. Data on US non-financial gross value added from BEA table 1.14.

earners in all industries (Kaplan and Rauh, 2013). Rosen (1981) presciently forecasted that economies of scale enabled by new technologies would increase inequality. He hypothesized that innovations in telecommunications had, and would increasingly lead tasks to become winner-take-all.

To those in the business world, the result that top employees are increasingly the scarce input will come as no surprise. Many employers complain about the rarity of exceptional talent. In the words of Bill Gates[16] "A great lathe operator commands several times the wage of an average lathe operator, but a great writer of software code is worth 10,000 average coders."[17] Indeed evidence shows that start-ups are particularly starved for very high skilled labor by harnessing exogenous variation in firms' H-1B visa win rates. Dimmock et al. (2019) find that a one standard deviation

[16] This quote is traditionally attributed to Mr. Gates, but we cannot find a firm reference.

[17] Or, similarly, in the words of Elbert Hubbard, "One machine can do the work of fifty ordinary men. No machine can do the work of one extraordinary man."

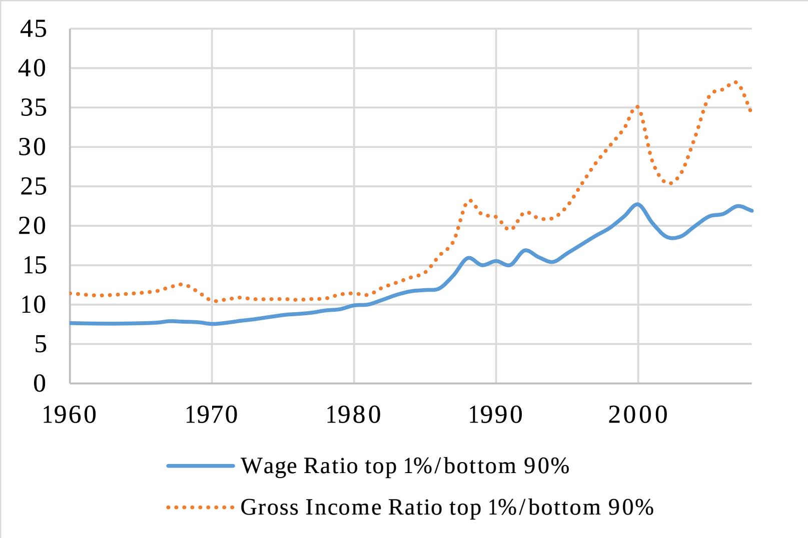

Figure 6: Average US income reported by the top 1% (either wage income or total gross income) divided by the same for the bottom 90%. Estimates based on the IRS Tax Model Files.

in the win rate causes a 23% increase in the probability of a successful IPO within five years in addition to higher rates patenting and raising funding.[18]

A conceptual link between increases in managerial productivity and information technology can be established using the concept of effective size (Kim and Brynjolfsson, 2009). As companies become more IT-intensive, managers can monitor and control larger and larger spans of activity. With increased influence, a good manager can create more value, and a bad manager can destroy more of it.

As additional evidence that digital technologies have increased the marginal productivity of top workers, we examine the impact of IT on the apex position: CEO. Table 2 displays the results of linear regressions of various measures of IT usage on the log of a CEO's compensation. Our BEA derived measures of IT intensity apply at the whole economy or industry-year level. BEA IT intensity is defined as IT capital stock divided by the sum of Structure, Equipment and Intellectual property.[19] We use two BEA derived measures: one is the IT intensity in the whole economy each year, and the other is the IT intensity of each industry each year. Both of these variables are computed in real terms, taking into account the steep decline in the cost of storage and computing power. Our results using industry level data come from a panel of 3413 firms over 23 years (1990-2014).

[18] The average firm in the data applies for 2.5 H-1B visas, and a standard deviation in win rate is about 44%, meaning this is approximately the effect of a single additional high skilled immigrant worker; the baseline IPO rate is 6.6%.

[19] The capital stock data for IT, Structures, Plant, and Intellectual Property are available from the Bureau of Economic Analysis's (BEA) "Fixed Assets Table" for 63 industry sectors at approximately three-digit NAICS level from 1947 to 2014. The list of asset types defined as IT is available in appendix 2.

We also include specifications testing the relationship between firm-level IT usage and CEO pay. Our firm-level IT data is based on LinkedIn resume data, and is only available for the year 2015. we start with a list of jobs (about 300) which we classify manually as a primary IT or non-IT job. For each job, we then collect all the employee skills associated with these jobs in a resume database from a large professional social network. This leaves us with over 40,000 different skills. For each skill, we then compute their relative frequency of appearance in IT job profiles (normalized by their total number of appearances). If a skill appears relatively more in IT jobs than in other jobs (relative frequency is over 50%), we classify it as an IT skill. Otherwise, it is a "non-IT skill".

For example, "Hadoop" would be considered a skill with high IT intensity, because it appears many times on IT job profiles, but relatively seldom on other profiles. "Microsoft Word", even though it is a computer program, would not be considered an IT skill, because it appears in many types of job profiles, not only the IT ones. For each company in our profile, we then compute the proportion of IT skills present at the company, which becomes our labor-based measure of IT intensity.

Our results indicate that CEO pay is significantly and robustly associated with IT usage at the economy, industry, and firm level. Further details for this analysis can be found in appendix B, including regressions that tie industry-level IT investment to an increase in the variance of CEO pay.

	(1) CEO Log Wage	(2) CEO Log Wage	(3) CEO Log Wage	(4) CEO Log Wage
log(Firm MV)	0.367*** (0.026)	0.369*** (0.026)	0.345*** (0.010)	0.373*** (0.0008)
log(MV of 250th Firm)	0.357*** (0.077)			
BEA Whole Economy IT Intensity	2.643* (1.454)			
BEA Industry-Year IT Intensity	0.255** (0.110)	0.252** (0.110)		
Firm-Level IT Skill Intensity			0.147*** (0.047)	0.271*** (0.0838)
Industry FE				X
Year FE		X		
N	36,531	36,531	1,366	1,327
Adjusted R2	.411	.416	.485	.647
Notes			2015 Data Only	2015 Data Only

*p≤.1; **p≤.05; ***p≤.1. Errors clustered by industry.

Table 2: CEO Compensation and IT Investment

While CEOs have clearly benefited from the new technological environment, it is not clear exactly where to draw the line between the percentile of workers we would expect to benefit from the winner take all economy. To do so, we look deeper into the wage distribution.

Figures 7 to 9 display the share of wage income paid to individuals at different percentiles of the wage distribution from 1960 to 2008.[20]

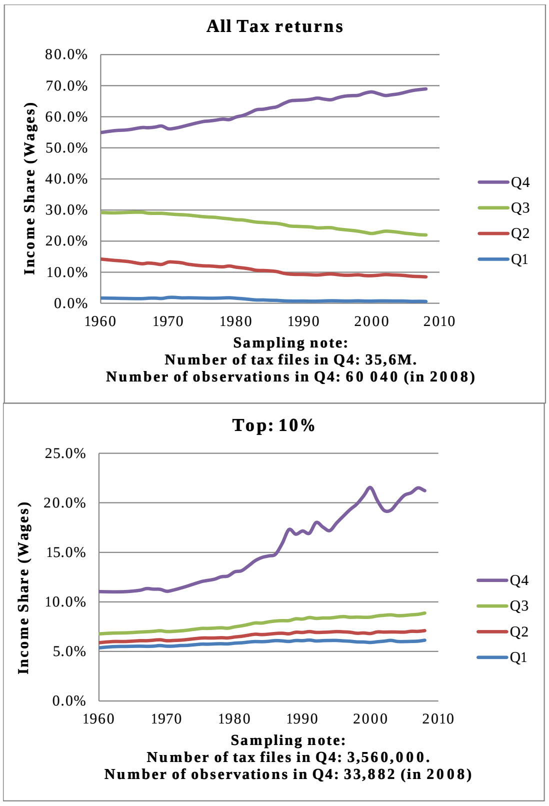

Figure 7: Share of total labor income by labor income percentile. Estimates based on the IRS Tax Model Files. Data from 1960 to 2008. In 2008, the top 10% starts at an annual wage of $96,000. The top 1% starts at $260,000. The top 0.1% starts at $860,000. The top 0.01% starts at $3.7M. Finally the top 0.001% starts at $15.4M.

Traditionally, labor incomes had been thought of as following a log normal distribution (Gibrat (1931); Mincer (1958)). Lognormal distributions are typically generated as the product of a large number of random variables. For example, assume that the productivity of a car mechanic is the product of a number of her individual abilities, such as attention to detail, information gathering ability, skill in operating vehicles,

[20] All estimates and analysis of the wage distribution are based on the IRS Tax Model Files, which are samples of US Federal Individual Income Tax returns between 1960 and 2008 (except for 1961, 1963 and 1965). All technical details for this analysis are identical to Saint-Jacques and Brynjolfsson (2015)

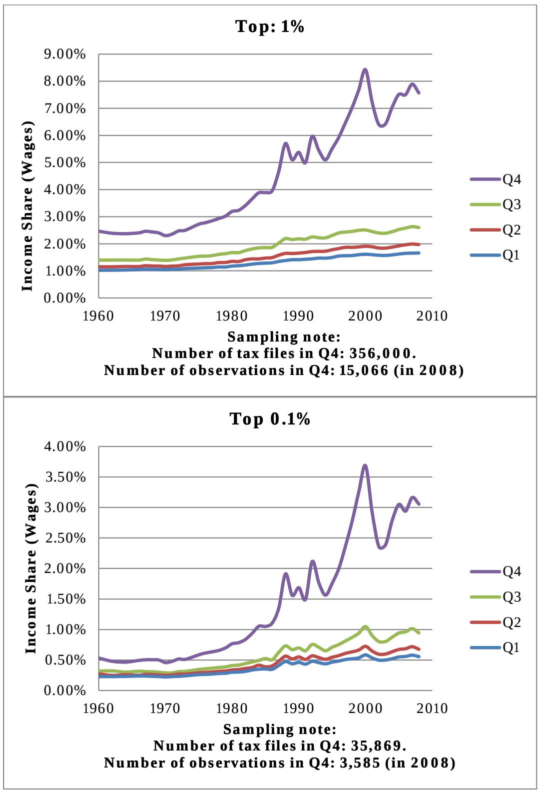

Figure 8: Share of total labor income by labor income percentile. Data from 1960 to 2008. Estimates based on the IRS Tax Model Files. In 2008, the top 10% starts at an annual wage of $96,000. The top 1% starts at $260,000. The top 0.1% starts at $860,000. The top 0.01% starts at $3.7M. Finally the top 0.001% starts at $15.4M.

decision making skill, ability to establish and maintain relationships, strength, fine motor skills, and so on. The higher the number of relevant characteristics, the more then distribution of productivity in the population will resemble a lognormal. Two main implications follow: first, if a car mechanic becomes 25% stronger, his productivity will increase by 25%. But if he becomes both 25% stronger and has a 25% increase in fine motor skills, one can expect his productivity to increase by over 56%. In other words, there are complementarities between individual abilities, so that the overall productivity effect of having high abilities is higher than the sum of marginal productivity effects of these abilities taken individually. If compensation is proportional to marginal productivity, then this process will create a log-normal distribution of income.

Indeed, much of the US wage distribution does seem to be log-normal. But as can be seen, incomes at the very top of the wage distribution have a fractal pattern. This pattern means that the underlying distribution is likely Pareto.

To determine which share of workers are drawing their wage from the ‘power law

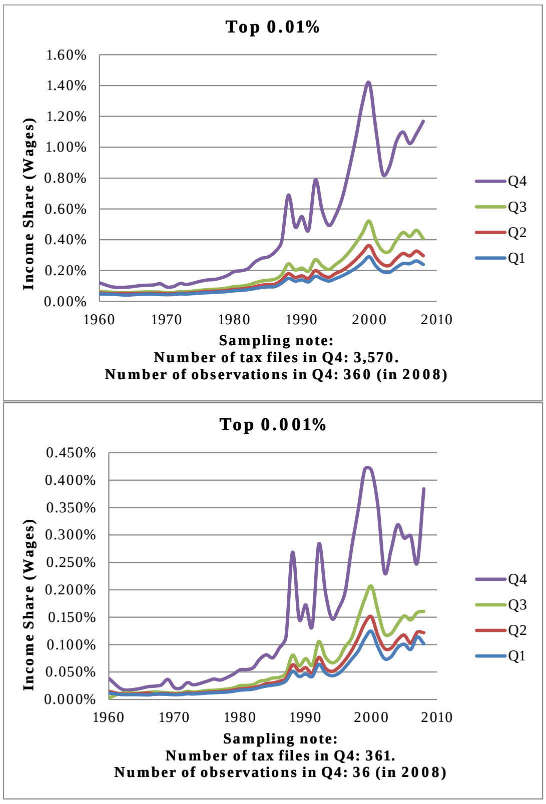

Figure 9: Share of total labor income by labor income percentile. Estimates based on the IRS Tax Model Files. Data from 1960 to 2008. In 2008, the top 10% starts at an annual wage of $96,000. The top 1% starts at $260,000. The top 0.1% starts at $860,000. The top 0.01% starts at $3.7M. Finally the top 0.001% starts at $15.4M.

economy', we conceptualize workers as deciding between choosing to work providing 'B-labor' or to supply traditional labor. We think of them as drawing a potential wage from both distributions, and then choosing the labor market that maximizes their wage. We observe only the maximum of these two draws. In other words,

$$W_L \sim LogNormal(\mu, \sigma) \tag{4}$$

$$W_B \sim Pareto(c, \alpha) \tag{5}$$

$$W = Max(W_L, W_B) \tag{6}$$

For each year from 1960 through 2008, we estimate the underlying parameters of each distribution using maximum likelihood estimation.[21] The resulting probability

[21]Note that the tax data contains many individuals (roughly around 15%) who report an income of zero, as well as many individuals with a very low income. We therefore fit a censored lognormal distribution. For simplicity, we give the Pareto and the Lognormal distribution the same support by fixing c at the 25th percentile and then truncating the lognormal distribution at the same value of c. While this model embodies a number of simplifications, our results

density function of this model is:

$$\frac{e^{\frac{(\mu-\log(x))^2}{2\sigma^2}}\left(1-\left(\frac{x}{c}\right)^{-\alpha}\right)}{\sqrt{2\pi}x\sqrt{\sigma^2}}+\frac{\left(\frac{x}{c}\right)^{-1-\alpha}\alpha\left(1-\frac{1}{2}\Psi\left(-\frac{\mu-\log(x)}{\sqrt{2}\sqrt{\sigma^2}}\right)\right)}{c} \tag{7}$$

where Ψ is the canonical complementary error function. Our maximum likelihood estimates are obtained using numerical optimization.

Using bootstrapping, we derive standard errors for our estimates of each distribution parameter (μ, σ, α), the share of workers who choose to supply B-labor instead of traditional labor (Q), as well as the likelihood maximizing parameters of a single lognormal distribution. Our results are reported in figure 3.

We find strong evidence of three important facts. First, the wage distribution is much better described as a mixture of lognormal and Pareto distributions, rather than the first alone. Second, the share of workers employed in a Pareto distribution occupation has increased from 1960 to 1980, but has remained relatively constant at around 3% since. Finally, we find that the average outcome for workers drawing wages from the Pareto distribution has increased substantially (i.e. α has decreased substantially). For these reasons, the first share of national income we include in our measure of bottleneck income is the wages of those in the top 3% of labor income.

Some researchers have already investigated the idea that increases in wage inequality may be tied to decreases in the cost of capital. These papers on 'capital-skill complementarity' often focus on explaining high school and college education wage premiums.

The paper in that literature most methodologically similar to ours is Krusell et al. (2000). That paper calibrates a neoclassical aggregate production function where capital and high skill labor are more complementary than capital and low skill labor. This framework is successful in explaining growth in the college/high school wage premium from 1962-1992. However, wage changes since the 1980s have not primarily favored college educated workers, but rather top percentile workers. In the capital-skill complementarity framework, deceleration in the growth of relative demand for college workers and physical capital in recent decades is a riddle (Autor et al., 2008). Our paper seeks not to explain the evolution of the college wage premium, but rather top percentile inequality.

What we distinguish as B and the microfoundations we give for bottlenecks' importance distinguish our concept from merely educated workers. Further, our paper measures capital payments using the Jorgensonian required rate of return rather than using ex-post rates of return. This allows us to distinguish between payments to ordinary capital and the super-normal returns due to superstar firms. These changes, in addition to the different time period under consideration, lead us to find that capital and B are much more complementary than Krussel et. al. estimate capital and college educated labor are (elasticity of substitution of .33 versus .67).

Another related paper on capital-skill complementarity is (Eisfeldt et al., 2018).

are not sensitive to different specifications or to the use of a different goodness-of-fit measure than maximum likelihood. See Saint-Jacques and Brynjolfsson (2015) for more details.

	Max(P,LN) model				Lognormal Only		
year	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\alpha}$	$\hat{Q}$	$\hat{\mu}$	$\hat{\sigma}$	ΔBIC
1960	8.42	0.63 (0.005)	13.28 (1.28)	1.79% (0.48%)	8.4	0.65	2028***
1962	8.48	0.65 (0.005)	13.74 (1.5)	1.8% (0.51%)	8.46	0.67	2285***
1964	8.57	0.67 (0.003)	15.29 (1)	1.62% (0.27%)	8.55	0.68	2583***
1966	8.64	0.7 (0.004)	11.15 (0.69)	1.92% (0.44%)	8.62	0.72	2190***
1967	8.7	0.69 (0.004)	11.75 (0.72)	2% (0.43%)	8.68	0.71	2451***
1968	8.76	0.7 (0.005)	10.77 (0.64)	2.25% (0.46%)	8.74	0.72	2247***
1969	8.82	0.71 (0.005)	10.82 (0.74)	2.14% (0.51%)	8.8	0.73	2368***
1970	8.93	0.67 (0.005)	10.1 (0.83)	2.32% (0.47%)	8.91	0.69	1735***
1971	8.99	0.67 (0.006)	9.77 (0.88)	2.34% (0.55%)	8.96	0.69	1610***
1972	9.04	0.68 (0.006)	11.17 (1.42)	2.01% (0.56%)	9.01	0.7	1553***
1973	9.08	0.71 (0.008)	12.74 (1.74)	2.37% (0.77%)	9.05	0.73	2445***
1975	9.2	0.73 (0.004)	8.9 (0.45)	2.95% (0.41%)	9.16	0.75	1773***
1976	9.27	0.73 (0.003)	9.43 (0.34)	3.03% (0.28%)	9.23	0.76	1915***
1977	9.33	0.74 (0.003)	8.85 (0.35)	3.1% (0.32%)	9.29	0.77	1796***
1978	9.41	0.74 (0.003)	9.27 (0.49)	3.46% (0.34%)	9.36	0.78	1881***
1979	9.5	0.73 (0.006)	8.01 (0.71)	3.68% (0.62%)	9.46	0.76	1305***
1980	9.57	0.75 (0.002)	8.25 (0.28)	3.5% (0.23%)	9.52	0.78	1470***
1981	9.64	0.77 (0.004)	7.63 (0.43)	3.58% (0.44%)	9.6	0.8	1364***
1983	9.71	0.81 (0.003)	7.74 (0.3)	3.15% (0.31%)	9.66	0.84	1449***
1984	9.76	0.81 (0.003)	7.84 (0.36)	3.27% (0.35%)	9.72	0.85	1464***
1985	9.8	0.82 (0.003)	7.35 (0.3)	3.1% (0.29%)	9.76	0.85	1218***
1986	9.83	0.84 (0.005)	6.92 (0.44)	3.22% (0.47%)	9.79	0.86	1212***
1987	9.83	0.87 (0.003)	7.22 (0.23)	2.73% (0.26%)	9.79	0.89	1337***
1988	9.86	0.88 (0.003)	7.48 (0.3)	2.65% (0.32%)	9.82	0.91	1402***
1989	9.89	0.89 (0.005)	7.27 (0.49)	2.72% (0.49%)	9.85	0.92	1415***
1990	9.93	0.89 (0.004)	7.34 (0.36)	2.71% (0.36%)	9.89	0.92	1345***
1991	9.95	0.9 (0.005)	7.04 (0.52)	2.8% (0.51%)	9.91	0.93	1272***
1992	9.99	0.9 (0.004)	6.83 (0.32)	3.02% (0.38%)	9.95	0.93	1237***
1993	10.03	0.88 (0.004)	6.24 (0.36)	3.23% (0.43%)	9.98	0.91	959***
1994	10.07	0.88 (0.003)	6.56 (0.31)	3.32% (0.32%)	10.02	0.91	1047***
1995	10.09	0.89 (0.004)	6.54 (0.35)	3.36% (0.42%)	10.04	0.93	1073***
1996	10.11	0.9 (0.004)	6.63 (0.29)	3.07% (0.37%)	10.07	0.93	1064***
1997	10.16	0.9 (0.003)	6.34 (0.26)	3.45% (0.35%)	10.11	0.93	986***
1998	10.21	0.89 (0.004)	6.51 (0.38)	3.47% (0.4%)	10.16	0.92	893***
1999	10.24	0.9 (0.004)	6.6 (0.34)	3.3% (0.38%)	10.19	0.94	905***
2000	10.28	0.9 (0.006)	6.59 (0.59)	3.46% (0.61%)	10.23	0.94	888***
2001	10.32	0.9 (0.003)	6.07 (0.23)	3.59% (0.3%)	10.27	0.93	764***
2002	10.34	0.89 (0.003)	6.28 (0.24)	3.5% (0.29%)	10.29	0.92	838***
2003	10.35	0.89 (0.003)	6.78 (0.28)	3.33% (0.3%)	10.3	0.93	982***
2004	10.38	0.9 (0.003)	6.01 (0.22)	3.58% (0.3%)	10.33	0.93	729***
2005	10.4	0.9 (0.005)	6.27 (0.46)	3.52% (0.52%)	10.35	0.94	791***
2006	10.42	0.92 (0.004)	6.5 (0.37)	3.17% (0.44%)	10.37	0.96	861***
2007	10.44	0.92 (0.003)	5.84 (0.24)	3.56% (0.29%)	10.39	0.96	663***
2008	10.46	0.93 (0.003)	6.03 (0.23)	3.55% (0.31%)	10.41	0.97	768***

Table 3: Maximum likelihood estimates of parameters underlying the US wage distribution by year, assuming both a mix of Pareto and lognormal distributions (left) and only a lognormal distribution (right). Standard errors are derived from bootstrapping 500 estimates.

That paper finds that decreases in labor's share of income has been overstated, because traditional measures omit some forms of corporate equity compensation due to the high skilled. It then introduces a model where high skill labor is a complement to capital, which are jointly substitutes for low-skill labor. Unlike our model, theirs does not not generate declines in growth or low-skill labor (or interest rates, which are constant and exogenous in their calibration).[22]

3.2 Measuring Bottlenecks through Firm 'Profits'

The second component that we add to our measure of bottleneck income is what is measured as profits: i.e. income earned by firms surpassing what they implicitly pay to labor, owner-operators, traditional capital, and the government. This share was near zero the mid-1980s, but was 10.8 percent of corporate gross value added in 2012. While some of this share may correspond to 'true' profits, we argue in the micro-foundations section that the majority of this share is better interpreted as payments to extremely talented individuals or returns to inelastically supplied intangible assets.

We add the residual income not paid to ordinary labor or capital (i.e. the 'profit share') to our measure of B's share for four main reasons. First, a growing literature suggests that an increasing share of profit income may be misclassified labor income. Extra normal rates of return on capital investment for an innovative company due to a founder's flow of a scarce input may look like profits or returns to an intangible asset (Smith et al., 2017)[23], and some forms of executive compensation in the form of stock options are not captured in labor income (Eisfeldt et al., 2018). In figure 5 break out separately the labor income of owner-operators of S-corporations which (Smith et al., 2017) finds to have been mislabeled as profits.

Also, in reshaping an existing businesses to take advantage of digital abundance, B-workers likely develop firm-specific human capital. In this circumstance, bargaining between the superstar and the corporation will alienate some of the bottleneck labor supplier's marginal product as profit. Third, there is significant evidence of increasing heterogeneity in rates of return are investment, with those who are already successful getting higher returns. This may be because their genius consists in part in the ability to identify early stage projects that are likely to have high rates of return.[24] The

[22]Other broadly related papers on capital skill complementarity include (Lewis, 2011) and (Violante, 2002)

[23]Smith et al. (2017) uses administrative data to show that owner deaths at small and medium sized privately held companies since 2000 have led to large output decreases. They use this result to impute a share of owner-operator labor income that has been relabeled as profits due to changes in the tax treatment of labor and capital income.

[24]While B is very valuable to those who can possess it, it is hard to identify and benefit financially from *ex-ante*. Investors cannot get large returns simply by piling additional funding into projects already known to be exceptional. Executives of mature businesses, startups and R&D departments with promising projects may wisely refuse even low interest rate loans or additional low cost labor. Despite this, investors are insatiable for growth. "They are basically force-feeding capital into these companies," observed Sramana Mitra, founder and CEO of startup accelerator One Million by One Million, in the wake of the 2017 collapse of the tech unicorn Jawbone (Somerville, 2017)."I expect there will be a lot more deaths by overfunding."

Despite the occasional unicorn, average rates of returns to investors in venture capital who portfolios of the wealthy are balanced more towards high-return and harder to value private equity and real estate, and less towards easier to value and lower return public equity and bonds (Smith et al., 2019). Some moments of the wealth distribution are impossible to match without the highest earning and wealthiest agents earning a higher rate of return on investment than others (Benhabib et al. (2011) and Benhabib et al. (2019)). Finally, it may well be the case that some supernormal returns are not due to the direct product of labor but rather to organizational capital, intangible assets, and other forms of 'crystallized' B.

All together, B's share of income increases from a nadir of 6.7 percent in 1984 to a peak of 31.4 percent in 2006.[25] Roughly half of this increase is due to an increase in corporate intangible income and half from an increase in genius labor income. These trends are robust to variations in the calculation of capital's share of income (Barkai (2016) and (Barkai and Benzell, 2018)) or the precise labor income percentiles considered exceptional (Saint-Jacques and Brynjolfsson, 2015) .

In the remainder of this paper, we develop the Bottleneck Model in greater depth and show how it can better account for trends in the US non-financial corporate sector since the mid-1980s.[26]

4 The B Model

In this section of the paper we describe the key features of the Model. On the production side, firms are perfectly competitive and have constant returns to scale. Production uses three inputs: capital, labor, and bottleneck-inputs. Capital is produced

attempt to gain a slice of B are typically unexceptional. Although there was a period of high returns in the mid-1990s, Kaplan and Lerner (2010) shows average VC returns net of fees have been competitive with the return from public markets. While exceptional entrepreneurs and top venture capitalists may earn significant incomes, an ordinary investor putting money in a VC fund does not seem to share in this bounty. This reflects the relative scarcity of the former relative to the later, and the simple economics of arbitrage.

[25]The increase in profit income share in 2004-2006 is driven by appreciation in the value of capital- structures in particular- during the housing boom. The value of business structures appreciates by 11 percent in 2005. This is equivalent to a negative cost for investing in structure assets, so it is subtracted from the required rate of return. The exact timing of when this appreciation shows up in the capital income series depends on how one assumes inflation expectations are formed. In the results displayed, they are calculated as a three year backward looking moving average. Barkai (2016) shows that the overall trend is robust to changes in this assumption.

[26]Gutiérrez and Philippon (2016) also attempt to determine why the US rate of investment has been so low over the last two decades. Because interest rates are in large part a function of investment demand, this question is tightly linked to our own. Gutierrez and Philipon begin by documenting important facts about this trend. The first is that net investment rates are low despite high profitability. Second, net investment rates are low despite a high Tobin's Q. Third, the decrease in net investment is not explained by increases in investment costs or depreciation rates. Having documented relatively high Q, they rule out explanations for the lack of investment that would lead to lower measures of Q, such as a shock to risk aversion or expected economic growth. They then present evidence that increased short-termism by firms, decreased competition, and increased investment in intangible assets (alongside an increase in the cost of intangible assets) are the most important factors. Döttling and Perotti (2015) point out that if new technologies lead to forms of assets that are harder to borrow against, this may also lead to more lending being directed towards property purchases and higher land prices.

from the final output good, and depreciates fully each period.

4.1 Supply Side

Firms maximize each period's profits

$$\Pi_t = Y_t(B_t, K_t, L_t) - b_t B_t - \rho_t(K_t) - w_t L_t \tag{8}$$

Where Pi_t are profits, Y is the production function, w, b, and ρ are the wage and rental rates of B and capital, respectively, B is the quantity of bottleneck-inputs, L is traditional labor, and K is traditional capital, which depreciates fully every period.

We consider an economy with the following production function

$$Y_t = (\beta_1^{\frac{1}{\sigma}}(T(L_t, K_t, C_t))^{\frac{\sigma-1}{\sigma}} + \beta_2^{\frac{1}{\sigma}}(z_{B,t}B_t)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{9}$$

Where T is some production function over L_t and K_t. C_t is a vector of technological terms, and σ is the elasticity of substitution between traditional production and bottleneck-inputs. Note that this is the normal constant elasticity of substitution production function in two inputs, except that one of the inputs is itself an aggregate of capital and labor. [27]

The economy is perfectly competitive, so all factors are paid their marginal products. Thus, the interest rate, and marginal product of capital, are

$$1 + r_t = \rho_t = \frac{\partial Y_t}{\partial T_t}\frac{\partial T_t}{\partial K_t} \tag{11}$$

and the wage and rental rate of B are

$$w_t = \frac{\partial Y_t}{\partial T_t}\frac{\partial T_t}{\partial L_t} \tag{12}$$

and

$$b_t = z_{B,t}\beta_2^{\frac{1}{\sigma}}\left(\frac{Y_t}{z_{B,t}B_t}\right)^{\frac{1}{\sigma}}. \tag{13}$$

There is also an implicit price $\mathbf{t}_t$ for the capital labor aggregate T_t

$$\mathbf{t}_t = \beta_1^{\frac{1}{\sigma}}\left(\frac{Y_t}{T_t}\right)^{\frac{1}{\sigma}} \tag{14}$$

and there are no profits.

4.2 Households

The focus of this model is on dynamics in prices and output, so the household sector is kept extremely simple. That being said, saving behavior does have to be modeled. This

[27] This is a special case of the nested CES production function. When traditional output is produced using a Cobb-Douglas technology, we have,

$$T_t = A_t(z_{L,t}L_t)^{1-\alpha}(z_{K,t}K_t)^{\alpha} \tag{10}$$

is because the long-term impact of technological change on interest rates in particular will be mediated by saving behavior, which depend in part on the returns to owning bottleneck assets or supplying bottleneck labor. Therefore, determining the price of B is essential.

To capture this effect in a reduced form way, we focus on the following model of households. Within period utility is equal to consumption.

$$U_t = \kappa_t \tag{15}$$

Households receive income in the form of rents on B and capital, and a wage for labor. L and B are supplied fully inelastically at no cost.

B income is divided into two components. There is a component θ which is treated as asset income, and a component $(1-\theta)$ treated as labor income. The distinction is useful, because when a share of B is treated as an ownable asset it will crowd out investment in capital. [28] To the extent bottleneck inputs are ownable, households also incur a cost from "buying" B, and receive income from "selling" B at the end of every period. This income is in zero net supply.

$$\pi_t = w_t L_t + b_t B_t + \rho_t K_t \tag{16}$$

where π_t is household income in period t.

Equivalently, households can be viewed as receiving income from their wages, rent on B which is *not* treated as owned, as well as rent on their portfolio of savings.

$$\pi_t = w_t L_t + (1-\theta) b_t B_t + r_t(S_{t-1}) \tag{17}$$

Where θ is the share of B considered owned.

For simplicity, in the spirit of Solow (1956), households are assumed to save a constant fraction of their income s.

$$S_t = s\pi_t \tag{18}$$

Savings are held in the form of capital investments. If bottleneck inputs are ownable, then it also consists of rights to a flow of B rents. So,

$$S_t = \theta p_t B_t + K_{t+1} \tag{19}$$

where p_t is the price of the right to a flow of B and θ is the share of B_t which is considered owned.

Households must be indifferent between holding the bottleneck asset and holding capital. This arbitrage entails that,

$$1 + r_{t+1} = \rho_{t+1} = \frac{b_{t+1} + p_{t+1}}{p_t} \tag{20}$$

[28] In our microfoundations section, we point out that if the ownership of virtual real estate is unreliable then it will be less likely to crowd out capital investment.

No Ponzi schemes are allowed, so this is equivalent to stating that the price of a flow of B is equal to the discounted value of its rents.

$$p_t = \sum_{s=t}^{\infty} R_{s+1,t}^{-1} b_{s+1}, \tag{21}$$

where $R_{s,t}$ is the compound interest factor between t and s, i.e.,

$$R_{s,t} = \prod_{j=t}^{s} (1 + r_j). \tag{22}$$

If B is owned, then it captures an increasing share of income not because it has a higher rate of return. Rather, B's high productivity leads to an increase in price, making it a larger share of the households' asset portfolio.

4.3 Market Clearing

Market clearing entails that consumption is output net of capital investment.

$$Y_t = I_t + \kappa_t \tag{23}$$

Where κ_t is consumption and I_t is capital investment.

$$I_t = S_t - \theta p_t B_t \tag{24}$$

Capital fully depreciates every period, so

$$K_{t+1} = I_t \tag{25}$$

Assuming an initial condition for K closes the model.

5 Model Analysis

This model can generate decreases in both labor share of income and interest rates in the short and long run after an increase in technology.

5.1 Short Run

A short run decrease in both labor's share and interest rates can be caused by a technological advance in T or one of its inputs. We consider the short run to be the interval when, in response to the technological change, the level of inputs has not changed (i.e. $K_t = K_{t-1}$; labor supply is exogenous.)

Let $\gamma_t(K_t, L_t, C_t)$ be the share of non-B income paid to labor, and $1-\gamma_t(K_t, L_t, C_t)$ the share paid to traditional capital. In other words

$$\gamma_t = \frac{w_t L_t}{\mathbf{t}_t T(L_t, K_t, C_t)} \tag{26}$$

Labor's share of total income can then be written

$$LS_t = \frac{w_t L_t}{Y_t} = \frac{\gamma T_t \mathbf{t}_t}{Y_t} \tag{27}$$

and the interest rate is

$$1 + r_t = \frac{(1-\gamma) T_t \mathbf{t}_t}{K_t} \tag{28}$$

Substituting for $\mathbf{t}_t$ yields

$$\frac{w_t L_t}{Y_t} = \gamma \beta_1^{\frac{1}{\sigma}} (\frac{Y}{T})^{\frac{1}{\sigma}-1} \tag{29}$$

and

$$1 + r_t = \frac{(1-\gamma)\beta_1 Y_t^{\frac{1}{\sigma}}}{K_t} \tag{30}$$

A change in some traditional technology parameter c_t may lower interest rates and labor's share. Consider an economy that begins in the long-run steady state for a certain set of parameters. Suppose that some c_t changes, boosting output without impacting K_t. This would occur if the increase in c_t is unanticipated, or if $\theta = 0$. A technological change under these assumptions leaves $K_t = K_{t-1}$.

The immediate change in interest rates as a function of the change in technology c_t is

$$\frac{\partial r_t}{\partial c_t} = \frac{\beta_1^{\frac{1}{\sigma}}}{K} Y_t^{\frac{1}{\sigma}} T_t^{1-\frac{1}{\sigma}} \left(\frac{\partial T_t}{\partial c_t}(1-\gamma_t)((1-\frac{1}{\sigma})T_t + \frac{1}{\sigma} Y_t^{-1} \mathbf{t}_t) - \frac{\partial \gamma_t}{\partial c_t} \right) \tag{31}$$

The change in labor share is determined by

$$\frac{\partial LS_t}{\partial c_t} = \beta_1^{\frac{1}{\sigma}} \left(\frac{Y_t}{T_t} \right)^{\frac{1}{\sigma}-1} \left(\gamma_t (1-\frac{1}{\sigma}) \frac{\partial T_t}{\partial c_t} T_t^{-1} (1 - \frac{LS_t}{\gamma_t}) + \frac{\partial \gamma_t}{\partial c_t} \right) \tag{32}$$

We are interested in digital technologies. As forms of automation, these technologies tend to increase output of T and decrease or keep constant labor's share of traditional output. So we restrict attention to situations with $\frac{\partial \gamma_t}{\partial c_t} \leq 0$ and $\frac{\partial T_t}{\partial c_t} \geq 0$.

The only term in (31) which is potentially negative is $1 - \frac{1}{\sigma}$. Therefore the only way that interest rates can decrease as a result of an increase in digital technology is if $\sigma < 1$. In a perfectly competitive model, for digitization to decrease interest rates, it must be that some non-automatable factor is a complement to the digitizable ones. The interest rate is also more likely to decrease when the marginal product of traditional inputs $\mathbf{t}_t$ is already small.

There is a larger range of parameters for which an increase in digital technologies lowers the labor share. $\frac{LS}{\gamma}$ must be less than 1 because the share of labor income in total output must be less than the share in the traditional share. Therefore, so long as $\sigma < 1$, greater digitization will reduce labor's share of income.

To get a sense of how complementary B and traditional output must be to get this result, consider the special case where labor's share of traditional income does not change as a result of the technology change (i.e. $\frac{\partial \gamma_t}{\partial c_t} = 0$). This corresponds to a Cobb-Douglas traditional production function, i.e.

$$T_t = A_t(z_{L,t}L_t)^{1-\alpha}(z_{K,t}K_t)^{\alpha} \tag{33}$$

where $\gamma_t = (1-\alpha)$.

Consider the consequences of an increase in z_K. This is a technological change that raises capital productivity. In the Cobb-Douglas case, this is effectively equivalent to an increase in A. In other words, an increase of TFP in the creation of the traditional intermediate. Either of these increases in the usefulness of the capital can lower wages and interest rates.

The impact of a marginal increase in $z_{K,t}$ on interest rates is in this case determined by

$$\frac{\partial \rho_t}{\partial z_{K,t}} = \mathbf{t}_t \alpha^2 A_t \left(\frac{z_{L,t}L_t}{z_{K,t}K_t}\right)^{1-\alpha} (\sigma^{-1}(\frac{\mathbf{t}_t T_t}{Y_t} - 1) + 1) \tag{34}$$

Note that the sign of $\frac{\partial \rho_t}{\partial z_{K,t}}$ is determined by the term $\sigma^{-1}(\frac{\mathbf{t}T}{Y} - 1) + 1$ as the rest of the function must all be positive. $\frac{\mathbf{t}T}{Y}$ has a handy interpretation as the share of final output which is devoted to compensating the traditional inputs.[29]

Suppose that $\alpha = .3$ and that in the year before the z_K increase $\frac{\mathbf{t}T}{Y} = .5$. If half of the income from renting out B is counted as capital income, and half as labor income, then this would correspond to a case where labor share is measured as 60 percent. In this situation, an increase in z_K would decrease interest rates so long as

$$\sigma^{-1}(.5-1) < -1 \tag{35}$$

$$\sigma < .5 \tag{36}$$

Recall that in our production function σ corresponds to the elasticity of substitution between traditional inputs and B. An increase in the productivity of traditional capital will therefore decrease interest rates when B and T are sufficiently complementary.

Figure 10 shows visually how interest rates change with an increase in capital productivity as a function of σ. The decrease in interest rates is the largest when T and B are highly complementary and the increase in z_K is large.

5.2 Long Run

We can evaluate what values of σ could generate the recent decreases in capital and labor's share of income in a simple calibration. Dropping time subscripts for clarity, and multiplying equation (13) by $\frac{B}{Y}$ yields an equation for B's share of income

$$\frac{bB}{Y} = \beta_2^{\frac{1}{\sigma}} \left(\frac{Y}{z_B B}\right)^{\frac{1}{\sigma}-1} \tag{37}$$

[29] A very similar result holds for increases in technology A:

$$\frac{\partial \rho_t}{\partial A_t} = \mathbf{t}_t \alpha z_{K,t} \left(\frac{z_{L,t}L_t}{z_{K,t}K_t}\right)^{1-\alpha} (\sigma^{-1}(\frac{\mathbf{t}_t T_t}{Y} - 1) + 1)$$

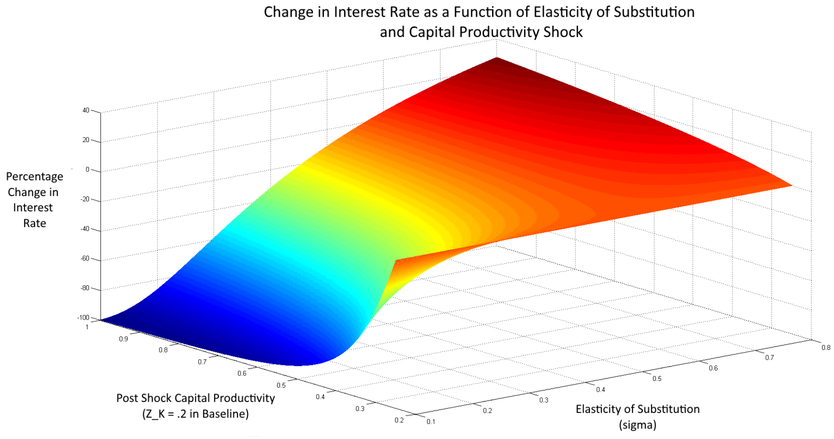

Figure 10: Immediate percent change in interest rates as a function of elasticity of substitution and the size of the z_K increase. Cobb Douglas traditional production technology. Initial parameters are: $K = 1$, $L = 1$, $B = .5$, $\alpha = .5$, $\beta_1 = \beta_2 = z_L = 1$, $z_K = .2$. σ for both periods on the x axis, z_K after the increase is on the Y axis.

Taking Y as given, and assuming that $z_B B$ is constant, we can choose values of β_2 and σ that fit the trend in bottlenecks' share since 1985 from figure 5. Figure 11 displays the empirical trend in the B share, as well as our prediction of bottlenecks' share using (37).

Figure 12 further explores calibrating the B model. The version of the model used assumes that production of the traditional good is Cobb-Douglas, that a constant share of output is saved, that the economy is closed, and that no B is owned. This calibration takes $\sigma = .33$, $\phi = .5$ and the actual path of US hours worked as given. Calibrated parameters take the values: $\beta_1 = .7$, $\beta_2 = .3$, $A = 1$, $z_B B = 1$, $z_L = 1$, $\alpha = .35$. Capital productivity z_K starts at 1, and then grows 3.5 percent per year starting in 1985.[30]

As can be seen, the Bottleneck model easily generates economic transition paths similar to the real world paths in factor shares, net investment, real GDP growth, and the required rate of return. In particular, we do a very good job fitting the magnitude of the declines in both labor and capital's share.[31] The simulations do less well in fitting the exact level of net investment.[32] This is likely because of our simplifying assumptions of a closed economy with constant saving rate and full depreciation.

[30]Precisely, we assume that the economy has a steady state level of capital in 1980 assuming 1980s level of labor supply and capital productivity. Then we allow labor supply to increase (following the real world hours worked path) starting in 1980, and allow capital productivity to begin increasing in 1985.

[31]This is a difficult feat for profit-based models of the decline in labor's share, because counting top-percentile incomes alongside ordinary labor leads labor's share to decline by much less than capital's share.

[32]We calculate real net-investment in our simulations, so the increase in capital productivity is counted in this accumulation, analogous to the real world measure

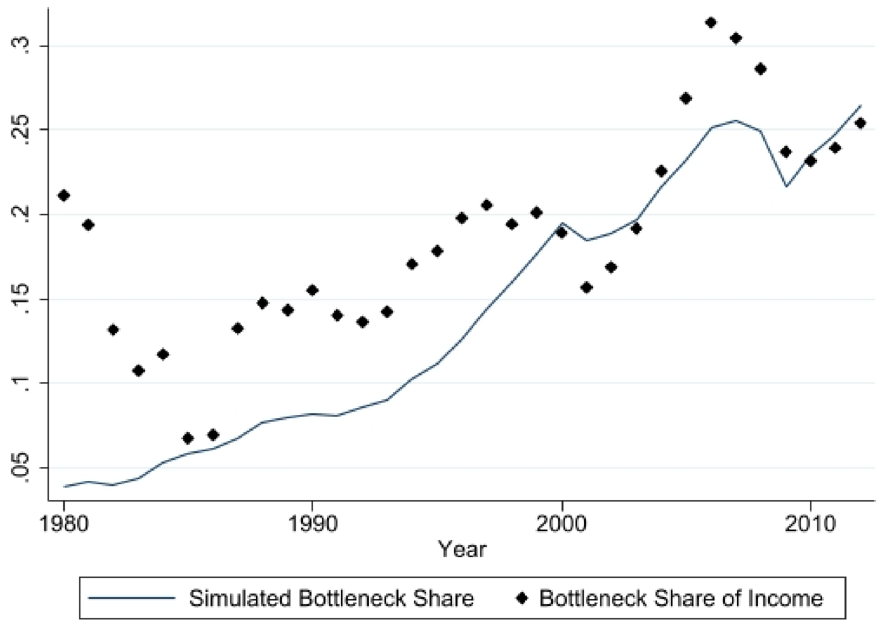

Figure 11: Observed and calibrated values of bottlenecks' share of non-financial corporate gross value added. Observed measure of bottlenecks' share replicates Barkai (2016)'s calculation of profit share plus top percentile labor income. Calibrated value takes $\sigma = .33$, $z_B B = 1$ and $\beta_1 = 1$ in all periods, simulated B share in 1985 = .0578. Real GDP is taken as given, and B's simulated share is evaluated using equation (37).

The above simulation assumes continuously increasing digital abundance (i.e. capital productivity). However, the long term effect of one time increase in digital technology on interest rates is a combination of its short term impact and its impact on capital accumulation. In the Cobb-Douglas traditional technology case, the impact of accumulation of capital on output is determined by

$$\frac{\partial \rho_t}{\partial K_t} = \frac{\mathbf{t}_t}{\sigma T_t}\left(\frac{\mathbf{t}_t T_t}{Y_t} - 1\right)\left(\alpha A_t \left(\frac{z_{K,t} L_t}{z_{K,t} K_t}\right)^{1-\alpha} z_{K,t}\right)^2 + \mathbf{t}_t \alpha(\alpha - 1) A_t z_{K,t}^2 (z_{L,t} L_t)^{1-\alpha} (z_{K,t} K_t)^{\alpha-2} \tag{38}$$

Note that each half of this is equation is negative (because $\frac{\mathbf{t}T}{Y}$ must be less than 1, $(\alpha - 1)$ must be negative, and all other terms are positive). So, further capital accumulation lowers interest rates. For interest rates to increase after an initial decrease in this setting, capital investment rates must decrease.

Keeping inputs fixed, an increase in any technology must increase total output. Furthermore, savings as a share of income in the model are constant. Thus, output must increase in the long run as well. In the case of $\theta = 0$ and a constant saving rate, an increase in technology must increase the capital stock in future

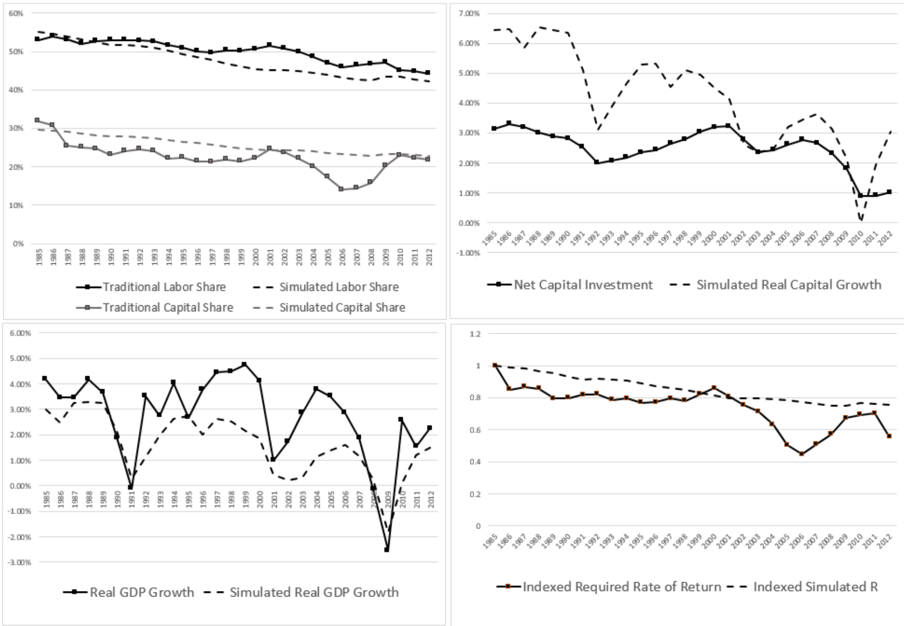

Figure 12: Simulated and actual traditional labor share, traditional capital share, real GDP growth, net investment, and indexed required rates of return in the presence of a constant z_K growth rate. Cobb Douglas traditional production technology. This calibration takes $\sigma = .33$, $\phi = .5$ and the actual path of US hours worked as given. Calibrated parameters take the values: $\beta_1 = .7$, $\beta_2 = .3$, $A = 1$, $z_B B = 1$, $z_L = 1$, $\alpha = .35$. Capital productivity z_K starts at 1, and then grows 3.5 percent per year starting in 1985. The capital stock begins in its steady state level for initial parameters.

periods. This is because savings increase, and the only way to invest savings is in the traditional output. Therefore, in this case, if technological growth lowers interest rates in the short run, rates will decrease further in the long run.

If the saving rate is not constant, the long term impact of digital abundance on interest rates is mediated by how aggregate savings evolve. In a representative agent model, the decrease in interest rates will lead to a decumulation of the capital stock to the point that the interest rate again equals the discount factor. In an overlapping generations model, where wage income is saved at a higher rate than capital income, a decrease in labor's share of income can lead to capital decumulation as well. This too will tend to increase long term interest rates. Alternatively, due to large scale and hard to measure changes in demographics and saving preferences, the interest rate may be thought of being set exogenously (as in an open economy model). In this case, the low interest rate may be thought of as causing the high value of B rather than vice versa.

In the case $\theta > 0$, some of B is owned. In this case, increases in traditional output technology (such as greater digitization of production) may increase the price of B. That is because if B's share increases, but the quantity of B is fixed, the rental price of bottleneck-inputs, b, must increase. The price of owning B will go up as well, because the price of a flow of rents is increasing in the size of the flow and decreasing in the interest rate.

The value of B that is owned by, or associated with,[33] firms in the economy should show up as an intangible asset. By measuring the stock of intangible assets in the economy, we can get another sense of what share of B corresponds to special labor versus intangible assets as well as get a sense of how big an issue 'crowding out' should be in leading to an increase in interest rates.

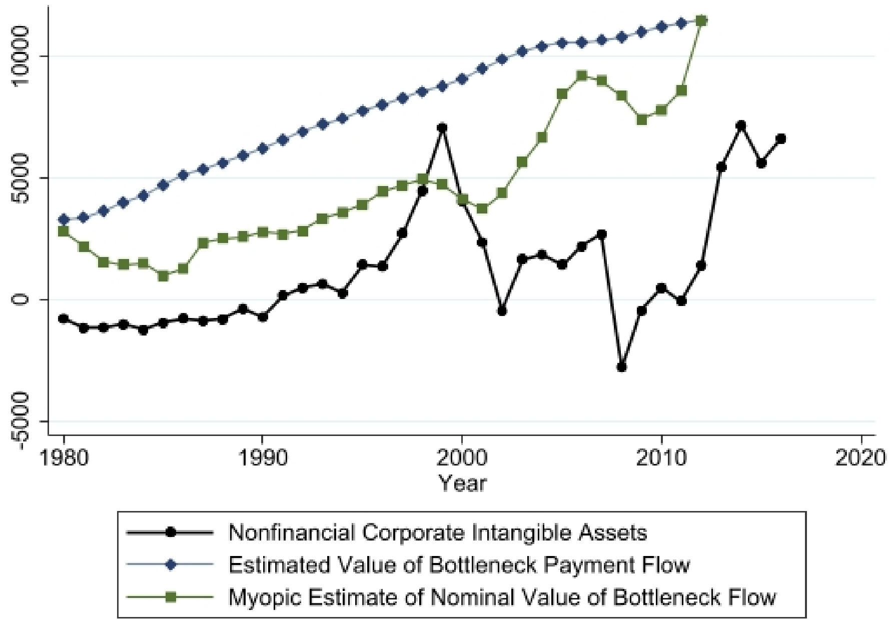

Figure 13: Observed and estimated stock of intangible assets in the US non-financial corporate sector in nominal billions. US Corporate intangible assets are calculated as US corporate equity and liabilities less financial assets from Federal Reserve series Z.1 and less fixed capital from BEA table 4.1.

Figure 13 displays the observed stock of intangibles in the US non-financial corporate sector corporate sector.[34] However, it displays a clear upward trend.

[33]We say associated with, because for privately held firms, extra normal rates of return on capital investment due to a founder's flow of B may look like profits or returns to an intangible asset, although the founder's labor is not literally owned by the firm. If firm specific organizational capital is held in the minds of employees, who gains from its supply will be determined by bargaining between the firm and its employees (Eisfeldt and Papanikolaou, 2014).

[34]This measure is often negative, perhaps due to an overestimate of the stock of capital in the economy, see Wright (2004)

The figure also displays estimates of the nominal value of the B flow. The 'myopic' estimate of the value of the B flow takes V as $b_t B_t = V_t r_t$ where r is the Moody's AAA bond portfolio rate. The primary estimate values the B flow as $V_t = \frac{V_{t+1}+b_{t+1}B_{t+1}}{1+r_t}$, with $b_{2012}B_{2012} = V_{2012}r_{2012}$. In other words, the myopic estimate is of the value of the period's B assuming no appreciation or B stock changes, while the first is an estimate of the value of all future B payment flows (assuming no appreciation or stock changes after 2012). This figure suggests that approximately half of the increased value of B flows since 1985 are owned and accounted for in the value of firms. In terms of crowding out, the size of this asset is very large but not overwhelming at 5 to 10 trillion dollars. Total US assets are approximately seven to eight times GDP.

Our model can also partly explain recent slowdowns in economic growth. Suppose that the productivity of capital (z_K) or the traditional aggregate (A) increases exogenously at a constant rate. Then, for low levels of A or z_K there will be rapid economic growth but, as bottleneck inputs become relatively scarce, economic growth will slow.

To see this, consider the special case of our model with a constant depreciation rate and full capital depreciation. The derivative of steady-state output with respect to A is

$$\frac{\partial Y}{\partial A} = A^{-\frac{1}{\sigma}} Y^{\frac{\alpha(\sigma-1)+1}{\sigma}} C \tag{39}$$

where C is a positive constant.[35] As expected, steady state output increases with A. The second derivative of steady state output with respect to A is

$$\frac{\partial^2 Y}{\partial A^2} = -\Big(\frac{1}{\sigma}\Big)\frac{\alpha(\sigma-1)+1}{\sigma} A^{\frac{\sigma-1}{\sigma}} Y^{\frac{\alpha(\sigma-1)+1}{\sigma}} \tag{40}$$

which is always negative, as the elasticity of substitution σ must be greater than zero. Economic growth due to a constant rate of innovation in non-bottleneck factors faces decreasing returns, and slows over time.

6 Microfoundations of Bottlenecks

Our primary interpretation of B supply is as certain types of exceptional talent, a.k.a. geniuses. As digital technologies improve, certain tasks previously performed by labor are easier to provide. The laborers who benefit from these changes are not the ones whose skills are substituted by robots. Instead, they are relatively rare individuals who know how to leverage the new technology to create new goods, services, or enterprises. If these individuals are inelastically supplied, then the situation described above can emerge.

[35] $C = \beta_1^{frac1\sigma} L^{\frac{(\sigma-1)(1-\alpha}{\sigma}} s^{\frac{\alpha\sigma-\alpha}{\sigma}}$, where s is the saving rate.

Alternatively B can be interpreted as a marginally costly intangible asset. If making full use of AI requires firms to make large, time-consuming, hard-to-accelerate investments in digitizing their business processes, then firms that have already bypassed this bottleneck will make large operating profits. From this perspective, the B may lie in the system itself, not in any single individual.

In the limit, the supply of these bottlenecking inputs may be fixed, corresponding to exogenous opportunities for the application of capital and labor. For example, the Internet may only be able to support one dominant social network. The individuals who control this network must use some traditional inputs to actually operate the website, but output is inelastic to traditional investments beyond a certain level. Output in an economy like this would be increasingly constrained by a lack of 'virtual real estate' in which to set up camp. And the owners of that territory would command an increasing share of national output. In John Locke's words, land is not a constraint "at least where there is enough, and as good, left for others."

Whether B is best thought of as extraordinary talent, organizational capital, or a reward to the lucky few who staked a claim on valuable virtual real estate, it is important that a portion of it (less than the overall labor share of the economy) not be counted as labor income in conventional statistics. Otherwise, as B gets a higher share of income, labor's share of income will increase.

6.1 Increasing Returns to Superstars

A natural way to think about B-income is as an increasing return to the talent of certain types of people. Rosen (1981) is the seminal paper suggesting that new technologies, especially media and communication technologies, would lead to increased economic returns to workers who are the best in their field. Kaplan and Rauh (2013) confirm that most of the increase in top percentile inequality over the last few decades seems due to increased wages for very highly skilled professionals, executives, performers, and athletes. This is reflected in the growing importance of the "power law" portion of the income distribution, as discussed above.

Power law distributions in the wages of top workers might arise in several ways. One is preferential attachment. Assume that one's ability to provide B-labor is a function of the worker's number of skills or connections. Plausibly, the frequency with which an individual masters a new skill or forms a new connection is a linearly increasing function of the number of skills or connections the worker already has. It has been shown that 'rich get richer' processes of this sort produce Pareto distributions (see for example Barabási and Albert (1999)). Another way Pareto distributions for top workers can arise is through a noisy search and matching process (Moscarini, 2005).

Treating B as increased returns to the highly talented is easy to integrate with our main model. Suppose that in the US economy there are a fixed number of superstar positions. Only the very best at these tasks will fill these positions. Let there be a large number of firms i each of which produce perfect substitutes. Let each of these firms be able to employ one superstar p. So,

$$Y_{i,t} = (\beta_1^{\frac{1}{\sigma}}(T_{i,t})^{\frac{\sigma-1}{\sigma}} + \beta_2^{\frac{1}{\sigma}}(z_{B,i,t}(\max_{i,t}(\mathbb{1}(B_{p,i,t}=1))\theta_p))^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{41}$$

$$Y_t = \sum_{i=0}^{I} Y_{i,t} \tag{42}$$

Where $\mathbb{1}(B_{p,i,t}=1)) = 1$ indicates individual p works at firm i, and θ_p is the p productivity of individual i.

Every individual p can choose between trying for superstardom and working as a traditional laborer. If every individual has the same productivity as a laborer, we have

$$L = \overline{L}\left(1 - \frac{\sum_p \sum_i \mathbb{1}(B_{p,i,t}=1)}{P}\right) = \overline{L}\left(1 - \frac{I}{P}\right) \tag{43}$$

Every individual chooses the job that gives them the highest payout with perfect foresight, so

$$\mathbb{1}(B_{p,i,t}=1) \text{ if } b_{p,i,t}\theta_p > w_t \text{ and } b_{p,i,t}\theta_p > b_{p,j,t}\ \forall j \neq i$$

Suppose that P is extremely large relative to the total number of firms I. Then, assuming the market for B is competitive (i.e. superstars are paid their marginal products), this will reduce to the aggregate production function above with $\overline{L} = L$ and $B_t = \sum_i \sum_p \theta_p \mathbb{1}(B_{p,i,t}=1)$. The B supply curve can have any properties desired by taking a stand on the distribution of θ_p in a given year.

A firm's size (i.e. the amount of traditional aggregates that is combined with a leader's input) will be in a fixed proportion (across firms, within a period) to the B-inputs supplied by the firm's leader.

One of the additional predictions of this model is that low interest rates may be associated with high inequality. The reason is that as the market becomes more saturated with the traditional aggregate, interest rates will decrease, but the share of income due to superstars will increase. If there is, on average, one superstar position for every hundred workers, this should be realized as increasing top-percentile inequality.

	(1) top1share	(2) top1share	(3) top1share	(4) top1shareunit	(5) top1shareunit	(6) top1shareunit
Real Interest	-0.0930	-0.101	-0.0126	-0.0783*	-0.0764	-0.0690
	(-1.93)	(-2.10)	(-0.30)	(-2.09)	(-2.03)	(-1.61)
_cons	11.73***	10.71***	8.549***	9.590***	8.099***	5.783***
	(13.24)	(41.28)	(21.65)	(8.18)	(41.75)	(10.17)
Country FEs?		X	X		X	X
Year FEs?			X			X
N	353	353	353	201	201	201

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Country level panel regression of top percentile inequality on real interest rates. top1share share is the share of national income earned by the top percentile of individuals and top1shareunit is the share of national income earned by the top percentile of tax units. Inequality data from World Income and Wealth Database World Wealth and Income Database (2016). Real interest rates as reported by the World Bank Development Indicators The World Bank (2017). Standard errors clustered at the country level. Data from 1980-2016.

Table 2 presents a cross country panel regression of the relationship between real interest rates and top percentile income shares. While the relationship is not significantly negative in most specifications, the fact that there is not a significant positive relationship should be surprising. Wealth inequality is much higher than income inequality in most countries, intuitively suggesting that higher interest rates should lead to a higher top percentile share of national income.

6.2 Alternative Microfoundation – Intangible Assets

We can also think of B as a special type of asset owned by firms. These intangible assets may correspond to formal intellectual property, organizational capital commanded by the firm, the flow of benefits that comes from operating a digital platform people have coordinated on, or even a reputation for creating fashionable products. The constitution of intangible assets matters insofar as it determines how their stock can be adjusted and people's property rights in it. We show that for this microfoundation to be driving the decrease in interest rates, it is necessary for these assets to face large adjustment costs in their accumulation.

Virtual Real Estate

One way to think of intangible assets is as virtual real estate. The analogy between intangible assets as being like land in a city is illuminating along several dimensions. Land in a city is roughly fixed in supply. It can produce a large amount of output, but only if complemented with sufficient capital and labor. And, as anyone who has lived in a hot real estate market knows, rents can skyrocket as a city gets more congested. Commercial platforms, from the iPhone to Uber, make money by convincing large amounts of people to use their platform for transactions, and taking a slice of the surpluses created. This business model is a highly lucrative one, but available for only a handful of firms in each niche (Van Alstyne et al., 2016).

Also like real estate, B platform investment may come with a certain amount of risk. What at one point in time is a booming business borough may one day become a beaten down backwater. This could be due to shifts in regional productivity or fashion. Land previously deemed to be worthless may reveal itself as resting upon an important natural resource. A person in the position of owning virtual real estate is in a similar position. There is always the risk of a fickle user base suddenly switching from Myspace to Facebook.

To represent this risk in our model, we say that there is a $(1-\theta_t)$ chance that at the end of a period t a unit of investment in B is destroyed and replaced with a lump-sum rebate of B to all members of society.

$$p_t = \theta_t \sum_{s=t}^{\infty} R_{s+1,t}^{-1} b_{s+1}, \tag{44}$$

where $R_{s,t}$ is the compound interest factor between t and s, i.e.,

$$R_{s,t} = \prod_{j=t}^{s} (1+r_j). \tag{45}$$

The remaining B-inputs $(1-\theta)$ are transferred to the population as in equation 17.

Note that the representation of θ here is slightly different than in the main model. There the price of B guarantees the right's indefinite flow, but only a portion of B is owned. Here, all of B is owned, but at the end of the period a percentage is transferred to people with no previous ownership interest.

Organizational Capital

A third, but closely related, microfoundation is based on the role of organizational capital. In the analysis above we assumed the total asset stock B was exogenous. It is the inelasticity of aggregate supply of B that grounds the analogy to real estate. However, it may be possible to create more of some forms of intangible assets. These intangible assets include hard-earned knowledge from previous experiences, organizational capital acquired from hiring a consultant, brand loyalty from an advertising campaign, or data from a large amount of customer interactions. It may also include the implementation of managerial best practices (Bloom et al., 2016).These sorts of intangible assets are important to making full use of new information technologies (Brynjolfsson et al., 2002). It is also the case that new platform concepts arise occasionally. However, the low ratio of unicorns to VC investments confirms their creation is a very uncertain process.

Let the total amount invested in new B be Γ_t. Any individual investment is risky, but assume that total new B created is a function Ω of total Γ_t invested and the current B stock:

$$B_{t+1} = \Omega(\Gamma_t, B_t) + B_t \tag{46}$$

While investment in new B may be a risky proposition, venture capitalists and ordinary investors can hold a portfolio of firms. Assuming that every investor can hold a portfolio eliminating their idiosyncratic risk, the return to investing in new B must be the same as the return to buying already created B. Individuals will invest in trying to make more B so long as the price of B is less than or equal to the average return (in units of B) from the investment

$$p_t \leq \frac{\Gamma_t}{\Omega(\Gamma_t, B_t)} \tag{47}$$

Throughout this paper we have made the claim that bottleneck-inputs must be inelastically supplied for changes in automation technology to decrease interest rates. In this framework it is easy to see why. Suppose that B was not inelastically supplied. For example, suppose it was supplied linearly i.e.

$$\Omega(\Gamma_t, B_t) = \Gamma_t z_\Gamma$$

then, so long as (47) binds there will be a fixed ratio between the marginal products of capital and labor. This is because

$$p_t = \theta_t \sum_{s=t}^{\infty} R^{-1}_{s+1,t} b_{s+1} = \frac{\Gamma_t}{\Omega(\Gamma_t, B_t)} = \frac{1}{z_\Gamma} \tag{48}$$

and this can only be the case if $\frac{b_t}{r_t - 1} = \frac{1}{z_\Gamma}\ \forall\ t$.

Further, a technological change that lowers labor's share of income and boosts output as a function of the B and capital stock must increase the amount of income paid to B and capital per unit. If the ratio of the rental rate on B to the price of capital is fixed, this means that both must increase. In other words, if the cost of creating a new unit of B is fixed (and there is no corner solution where new B is not invested in) then interest rates must increase as a result of greater automation.

The cost of bottleneck-input creation could be increasing for two types of reasons. The first reason could be adjustment costs as firms rapidly attempt to increase their stock of B. In our model this would correspond to the second derivative of Ω with respect to Γ being less than zero. This adjustment cost could be due to heterogeneity in the productivity of projects for creating new B (with the most productive opportunities being exploited first). Quadratic adjustment costs in intangible investment is featured in Hall (2000). He finds a 4.5 trillion dollar stock of e-capital is consistent with the price of the U.S. stock market in 1999. Likewise Brynjolfsson et al. (2002) measure the contributions of organizational capital and find that it tends to be highly complementary to new technologies, both in market value regressions and production functions.

More recent papers that have attempted to explain the rise in Tobin's Q in the US have also pointed towards intangible assets. Peters and Taylor (2017) show that adding a perpetual inventory measure of a firm's intangible assets (from R&D and SG&A spending) to its physical assets explains much better the value of companies. They find this intangible asset stock constitutes 30 to 40 percent of US firms' assets. Corrado et al. (2009) extend the standard growth accounting framework to include intangibles. They find that there were three trillion dollars in unmeasured intangible assets in 2003.

A second reason for the cost of bottleneck-input creation to increase over time would be 'fishing out'. This is simply the idea that as the easiest sources of new B supply are exploited, remaining opportunities become more marginal. Bloom et al. (2017) provides a wealth of evidence suggesting that good ideas have gotten harder to find and develop over time.

A final reason that the aggregate return to investment in bottleneck-input creation may have decreased is due to an increase in wasteful replication or attempts at "B stealing." While there may only be room for one social network, that did not stop Facebook from wresting that valuable real estate from Myspace. If a technological or regulatory change were to make it easier to steal other firms' B, this would reduce the return to owning legacy B, effectively increasing $1-\theta$.

7 Policy Implications

Countries face tough macroeconomic challenges in the age of digital abundance and binding bottlenecks. The increase in inequality and decrease in growth suggest opposite solutions when viewed through the paradigm of Okun's tradeoff. On the other hand, new technologies give governments novel policy options. Low interest rates give governments the fiscal space to consider deficit funded interventions.

Bloom et al. (2019) suggests several mechanisms for boosting innovation and growth. One of their proposed policies is education reform. They suggest that growth can be increased and inequality reduced through promoting STEM degrees and upskilling low-wage workers. There are two ways this could be consistent with our model. First, to the extent that an economy is a small, open price taker, a 10 percent increase in traditional labor productivity will lead to a 10 percent increase in traditional wages. Alternatively, whether the economy is closed or not, reforms which transform the labor of traditional workers into B-labor will boost traditional wages and reduce inequality. Consider the consequences of increasing by one percentage point the share of workers providing B-labor (to 4 percent).[36] This variety of upskilling would increase output 5.8 percent, increase wages for the remaining traditional laborers by 14.6 percent, and slash the wages of B providers by 53.1 percent. This is also consistent with Bloom et al. (2019)'s suggestion that increasing high skilled immigration would increase innovation and reduce inequality.

Under alternative assumptions, our model is more pessimistic about the consequences of education reform. Consider the case of a closed economy where education augments the productivity of workers performing traditional labor. We find that a 10 percent increase in the productivity of traditional workers, keeping all other inputs constant, would immediately raise output by 3.6 percent, but also lower traditional wages by 2.7 percent. The reason for this is simple. Further increasing the productivity of traditional laborers makes their input even more disposable. Focusing on increasing the productivity of these workers increases inequality.

On its face, our model argues for the opposite approach. Rather than upskilling median workers, governments should focus on increasing the number and productivity of top-percentile workers. This could be done by encouraging high-skill immigration, encouraging creative skills in education or widening access to top universities. Policies that help firms acquire intangible and organizational capital would be similarly beneficial. A 10 percent boost to the effective amount of B increases output by 2.4 percent, increases traditional wages by 4.9 percent, and reduces B rental prices by 13.6 percent.

Why don't those with the capacity simply increase their B themselves? One potential reason is that developing one's ability to supply B takes a large amount of time and effort, and many of the young and talented are illiquid or impatient. Bell et al. (2018) argue that many potential 'Ensteins' are lost due to inadequate

[36] In the closed economy case, keeping all other inputs fixed. Model calibrated, for the rest of this section, as in figure 7. 2012 is used as the baseline year for considering shocks. Traditional output is Cobb-Douglas with $\alpha = .3$. In this first scenario, all B inputs are assumed to be labor, and all workers within a labor category provide the same amount of effective labor.

local resources.

There are potential downsides to focusing on increasing B. Some of these are due to factors not explicitly modeled. First, such policies might be hard to target. If workers who are merely very good at providing inputs which are substitutes for traditional labor (either directly, or through the programming of digital substitutes for L) see their productivity increase, inequality will increase as well. Relatedly, there is the concern that geniuses may capture these programs to their own benefit. They may argue for reforms that effectively restrict the supply of B, increasing its price. Counterintuitively, countries will know that their policies to increase the effective supply of B are working because its share of income is decreasing.

Our model also has consequences for fiscal sustainability of government policies. Governments around the world have seen their fiscal gaps expand in the wake of the Great Recession. Their ability to continue borrowing relies on low interest rates. Our model makes predictions about how technological changes will impact the difference between the interest rate and growth rate. Increases in the effective supply of different inputs can have starkly different implications for fiscal sustainability.

In addition to boosting growth, a 10 percent increase in the supply of B will also increase the interest rate – by 4.9 percent in the short-run. In other words, the immediate impact of an increase in the supply of will be to increase the interest rate by more than output is increased. This fiscal pressure is potentially offset by a reduction in the need to provide transfers to workers. However, it is one more reason for nations to be cautious about adopting a B-first economic strategy.[37]

Fiscal sustainability can also be harmed by increases in automation technology. Consider a technological change such that total output increases by 3.6 percent but α increases to .4. Such a change would immediately increase the interest rate by 13.5 percent. In contrast, if α does not change, the interest rate decreases by 2.7 percent. While our model has shown that increases in digital abundance can decrease the interest rate, changes that sufficiently favor traditional capital over traditional labor can still increase it.

8 Conclusion

An increasing share of income is being paid to neither traditional capital nor traditional labor. At the same time interest rates, investment rates, and total

[37] As noted above, the long-term effect on growth and interest rates are mediated by the impact on saving and investment. In a model with a representative agent and no population growth, the long-term interest rate and growth rate are both unchanged by an increase in the B supply.

factor productivity growth are low. Informed by the economics of digitization, we provide a simple macroeconomic model that generates these relationships. The good news is that when inputs can be digitized, perfect copies can be made at virtually zero cost. The bad news is that not all types of inputs can be digitized. Digital abundance leads to bottlenecks whenever an input which cannot be digitized is an essential complement. Digitization can create substitutes for many types of ordinary labor and capital, driving down their compensation. At the same time, others earn extraordinary returns because their contributions, whether due to genius or luck, cannot be easily digitized.

The most popular alternative explanation of the simultaneous decrease in the traditional capital and labor share of income is increased markups.[38] This could either be due to a decrease in oligopolistic competition or from the most profitable firms lowering their markups (slightly) while capturing a larger share of the market (Barkai (2016), De Loecker and Eeckhout (2017), Autor et al. (2017)). We see Autor et al. (2017) as a model of increasing returns to intangible assets, and therefore complementary to our paper. When industries become more competitive, there is an increased return to firms with a good productivity draw. The difference between profits and returns to unmeasured intangible assets may be a semantic one.

Many have the sense that intangible assets and superstar workers are more abundant than ever. Perhaps the most surprising thing then about our result is that these factors are increasingly scarce. We contend that this is due to confusion between the *value and importance* of these inputs, which are increasing, and their *relative abundance*, which is decreasing.

We suggest several microfoundations of this aggregate relationship and explore implications. Our 'microfoundations' are not mutually exclusive and may ultimately be revealed as a simplified representation of a complex underlying trend. But the relationship between high non-capital and labor shares, inequality, low interest rates, digital abundance and low TFP growth is a real one, and one parsimoniously captured in our framework.

Idealists had imagined that digital abundance would be an inexorably egalitarian force. Reductions in the cost of information and communication capital, improvements in automation technologies, and the diffusion of AI were hoped to decentralize information and power, to the benefit of all. In contrast, our paper makes the case that this digital abundance can actually have highly non-egalitarian effects. In a process analogous to Baumol's cost disease or immiserating growth at the country level, increases in the productivity of unexceptional capital and labor have suppressed interest rates and median wages (Baumol,

[38]See, for example, Caballero et al. (2017) which attributes low safe rates and a decreasing labor share to, in part, increased markups and capital risk premia.

1967). Output has increased somewhat as a result of this abundance, but not anywhere near in proportion to the increased ubiquity of digital goods, services and processes. Furthermore, an increasing share of output has accumulated to a scarce complement, owned or provided by a lucky few. As in Aghion et al. (2017), the impact of AI on growth is determined not only by what it is good at, but rather what we are bad at. Science fiction author William Gibson is quoted as saying "The future is already here — it's just not very evenly distributed." It might be more accurate to say "the future is already here – but its rewards are not very evenly distributed ."

Perhaps, over time, Le Chatelier's principle will win out, and the bottlenecks in innovation will be overcome, simultaneously raising wages, interest rates, productivity growth and lowering inequality and bottlenecks' share. Whether or not it does, we expect these desideratum to be connected well into the future.

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A Additional Figures

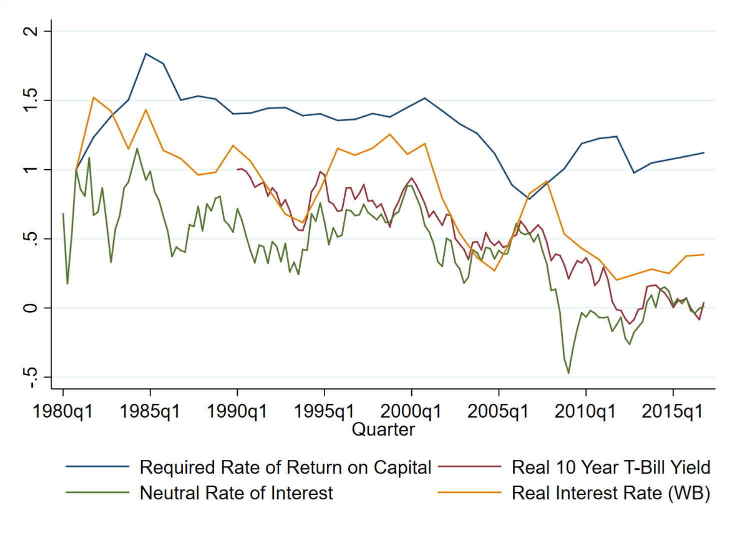

Figure 14: Four indexed measures of the US real rate of return. The required rate of return on capital is an annual measure constructed following Barkai (2016). The US real interest rate is an annual measure from The World Bank (2017). The US neutral rate of interest and real 10 year T-Bill yield are quarterly measures from Roberts (2018).

B Details for CEO Pay Analysis

B.1 4. Data Sources and Variables

B.1.1 IT intensity at industry level

We follow a method similar to one described in a previous study Brynjolfsson et al. (2007) to estimate IT intensity at the industry level. In summary, IT intensity is defined as IT capital stock divided by the sum of Structure, Equipment and Intellectual property. The capital stock data for IT, Structures, Plant, and Intellectual Property are available from the Bureau of Economic Analysis's (BEA) "Fixed Assets Table" for 63 industry sectors at approximately three-digit NAICS level from 1947 to 2014. A precise list of asset types used to define "IT" is available below. We use two variables for IT intensity: one is the IT intensity in the whole economy each year, and the other is the IT intensity of each industry each year. Both of these variables are computed in real terms, taking into account the steep decline in the cost of storage and computing power. For example, the BEA price index for mainframes has declined by a factor of 60 between 1992 and 2014.[39]

B.1.2 Executive compensation and firm-level company data

We use two Compustat databases, *Industrial* and *Executives*, for the period from 1992 to 2014. Compustat provides commercially available databases for public companies. The *Industrial* database provides firm characteristics such as physical assets, employee numbers, common stock, and sales. The *Executives* database provides data on compensation for up to thirteen of the top executives from each company. It is compiled from proxy statements filed by the companies in compliance with Securities and Exchange Commission (SEC) regulations and covers S&P 1500 companies starting in 1992.

Executive compensation is taken from Execucomp variable *tdc1*. *tdc1* and includes salary, bonus, other annual, restricted stock grants, LITP payouts, all other, and present value of option grants. We select companies with at least three executives included in the database. We restrict our attention to full-year CEOs [CEOANN='CEO'] in Execucomp, with pay > $200,000 (in 2000 dollars). We then merge the Execucomp dataset with the Compustat Fundamentals database, downloaded in 2015. Compustat offers various levels of aggregations. We use **C**, the highest available level of aggregation. Compustat and Execucomp are merged using the GVKEY variable. All nominal quantities are converted into 2000 dollars using the GDP deflator from the BEA.

We measure firm size through market value. It is computed using the same equation as in Gabaix and Landier (2008), who also use it to measure firm size. The equation is

data199 x abs(data25) + data6 − data60 − data74, where *data199* is the share price of closing at fiscal year, *data25* is Common Shares Outstanding, *data6* is Total Assets, *data60* is Total Common Equity, and *data74* is Deferred Taxes. Note that using 2015 Compustat variable names, this equation becomes:

csho x abs(prcc_f) + at - ceq- txdb

Capital stock values are deflated using BEA price indices for each asset type. All other nominal quantities (such as market values) are converted into year 2000 dollars using the GDP deflator from the BEA.

Excluding the observations with missing variables, we examine panel data from 3413 publicly traded firms from 61 industries over 23 years.

[39] Our results are, however, robust to using "constant-dollar" IT figures, i.e., simply deflated by GDP growth or by the CPI.

B.1.3 Firm Level IT Intensity

Table 2 also includes as an explanatory variable labor-based measure of IT intensity, which is computed at the firm level. For year 2015, we construct two new measures: IT-Intensity of workforce skills and Workforce skill variety.

These measures are constructed as follows: we start with a list of jobs (about 300) which we classify manually as a primary IT or non-IT job. For each job, we then collect all the employee skills associated with these jobs in a resume database from a large professional social network. This leaves us with over 40,000 different skills. For each skill, we then compute their relative frequency of appearance in IT job profiles (normalized by their total number of appearances). If a skill appears relatively more in IT jobs than in other jobs (relative frequency is over 50%), we classify it as an IT skill. Otherwise, it is a "non-IT skill".

For example, "Hadoop" would be considered a skill with high IT intensity, because it appears many times on IT job profiles, but relatively seldom on other profiles. "Microsoft Word", even though it is a computer program, would not be considered an IT skill, because it appears in many types of job profiles, not only the IT ones.

For each company in our profile, we then compute the proportion of IT skills present at the company, which becomes our labor-based measure of IT intensity. For each company, also construct a histogram counting how many different workers at the company are associated with each skill. The variance of these skill frequencies gives us our measure of skill variety at the company level. Tables **??** and 5 present additional specifications of regressions explaining CEO pay using these regressors. A main advantage of using firm-level data is that it becomes possible to add an industry-level fixed effect, controlling for industry-level unobserved heterogeneity. As shown in Table 5, the effect of IT intensity on executive is still significant (column 3).

We conduct a number of robustness checks to examine whether our results are driven by a small subset of industries, particularities of CEOs versus other C-level executives, by the IT price deflator provided by the BEA, or by simultaneity or reverse causality problems. All of the tables and charts presented in this paper analyzing the combinations of the conditions described below are available from the authors.

Excluding IT producing industries. One might be worried that the results may be influenced by a small subset of highly IT intensive industries, such as the IT producing ones. We therefore also run the analysis excluding the four main IT producing industries[40]. The results remain broadly the same: the

[40] These have the following BEA industry codes: 5140 - Information and data processing services; 5415 - Computer systems design and related services; 3340 - Computer and electronic products, 5110 - Publishing industries (including software).

Table 4: Firm-level, labor-based IT intensity regressions, no industry fixed effects

	(1) CEO Log Wage	(2) CEO Log Wage	(3) CEO Log Wage	(4) CEO Log Wage	(5) CEO Log Wage	(6) CEO Log Wage
Log market value	0.343***	0.348***	0.345***	0.328***	0.329***	0.287***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
BEA IT intensity		0.147***				
		(0.047)				
Skills-based IT intensity			0.342***	0.281***	0.351***	0.202**
			(0.096)	(0.096)	(0.106)	(0.095)
Skills variety				-1.131***		-6.440***
				(0.223)		(0.906)
High skill variety dummy					-0.122*	-0.490***
					(0.072)	(0.078)
IT x Variety interaction					-0.317	
					(0.246)	
Variety x High Variety						6.272***
						(0.955)
Constant	5.374***	5.295***	5.267***	5.503***	5.443***	6.115***
	(0.084)	(0.088)	(0.089)	(0.100)	(0.097)	(0.133)
Observations	1,366	1,366	1,366	1,366	1,366	1,366
R2	0.481	0.484	0.485	0.495	0.494	0.512
Adjusted R2	0.480	0.484	0.485	0.494	0.493	0.510
Residual Std. Error	0.585	0.583	0.583	0.577	0.578	0.568
Note:	*, **, and *** indicate p<0.1; p<0.05; p<0.01 respectively					

Table 5: Firm-level, labor-based IT intensity regressions, with industry fixed effects

	(1) CEO Log Wage	(2) CEO Log Wage	(3) CEO Log Wage	(4) CEO Log Wage	(5) CEO Log Wage	(6) CEO Log Wage
Log market value	0.375***	0.375***	0.373***	0.364***	0.363***	0.333***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.011)
BEA IT intensity						
Skills-based IT intensity			0.271**	0.257**	0.322***	0.234**
			(0.112)	(0.111)	(0.121)	(0.111)
Skills variety				-0.509***		-3.522***
				(0.185)		(0.820)
High skill variety dummy					-0.021	-0.286***
					(0.063)	(0.071)
IT x Variety interaction					-0.314	
					(0.218)	
Variety x High Variety						3.483***
						(0.861)
Observations	1,327	1,327	1,327	1,327	1,327	1,327
R2	0.655	0.655	0.656	0.658	0.659	0.663
Adjusted R2	0.639	0.639	0.641	0.642	0.643	0.647
Residual Std. Error	0.443	0.443	0.443	0.441	0.441	0.439
Note:	*, **, and *** indicate p<0.1; p<0.05; p<0.01 respectively					

coefficient associated with industry level IT loses significance for regressions run on CEOs only, but remains significant if all C-level executives are included.

Including all C-level executives. Including all C-level executives (between 3 and 5 executives per firm in our dataset), and regressing IT on the firm-average of their pay does not affect our results.

Using constant-dollar IT instead of the "Moore's Law" deflator. Instead of using the strong deflator provided by the BEA that seeks to adjust for the tremendous decline in prices of computing power over the years we studied, it is also possible to simply use nominal values or constant-dollar values. Neither of these options change our results.

Causality concerns: using lagged IT values. IT data as it is currently available from the BEA does not lend itself well to instrumental variable analysis, which is why we cannot formally exclude all possible sources of reverse causation. Accordingly, our analysis focuses on motivated empirical correlations. Analyzing the impact of lagged values of IT intensity on pay and mobility can partially alleviate concerns about reverse causation. Here as well, our results do not seem affected by the use of IT intensity values lagged by a year.

B.1.4 Merging Compustat/Execucomp data with BEA Data

The final industry classification used in this paper is made of 63 "BEA" industries, whereas Compustat data contains NAICS codes. NAICS codes are therefore converted to BEA industries using the below table:

INDUSTRY TITLE	BEA CODE	1997 NAICS Codes	2002 NAICS Codes	2007 NAICS Codes
Agriculture, forestry, fishing, and hunting	**--------**	**11**	**11**	**11**
Farms	110C	111,112	111,112	111,112
Forestry, fishing, and related activities	113F	113,114,115	113,114,115	113,114,115
Mining	**--------**	**21**	**21**	**21**
Oil and gas extraction	2110	211	211	211
Mining, except oil and gas	2120	212	212	212
Support activities for mining	2130	213	213	213
Utilities	**2200**	**22**	**22**	**22**
Construction	**2300**	**23**	**23**	**23**
Manufacturing	**--------**	**31-33**	**31-33**	**31-33**
Durable goods	--------	--------	--------	--------
Wood products	3210	321	321	321
Nonmetallic mineral products	3270	327	327	327
Primary metals	3310	331	331	331
Fabricated metal products	3320	332	332	332
Machinery	3330	333	333	333
Computer and electronic products	3340	334	334	334
Electrical equipment, appliances, and components	3350	335	335	335
Motor vehicles, bodies and trailers, and parts	336M	3361-3	3361-3	3361-3
Other transportation equipment	336O	3364-9	3364-9	3364-9
Furniture and related products	3370	337	337	337
Miscellaneous manufacturing	338A	339	339	339
Nondurable goods	--------	--------	--------	--------
Food, beverage, and tobacco products	311A	311,312	311,312	311,312

INDUSTRY TITLE	**BEA CODE**	**1997 NAICS Codes**	**2002 NAICS Codes**	**2007 NAICS Codes**
Textile mills and textile product mills	313T	313,314	313,314	313, 314
Apparel and leather and allied products	315A	315,316	315,316	315, 316
Paper products	3220	322	322	322
Printing and related support activities	3230	323	323	323
Petroleum and coal products	3240	324	324	324
Chemical products	3250	325	325	325
Plastics and rubber products	3260	326	326	326
Wholesale trade	**4200**	**42**	**42**	**42**
Retail trade	**44RT**	**44-45**	**44-45**	**44-45**
Transportation and warehousing	**--------**	**48-49**	**48-49**	**48-49**
Air transportation	4810	481	481	481
Railroad transportation	4820	482	482	482
Water transportation	4830	483	483	483
Truck transportation	4840	484	484	484
Transit and ground passenger transportation	4850	485	485	485
Pipeline transportation	4860	486	486	486
Other transportation and support activities	487S	487,488,492	487,488,492	487,488,492
Warehousing and storage	4930	493	493	493
Information	**--------**	**51**	**51**	**51**
Publishing industries (including software)	5110	511	511, 516 (pt.)	511
Motion picture and sound recording industries	5120	512	512	512
Broadcasting and telecommunications	5130	513	515, 517	515, 517
Information and data processing services	5140	514	516 (pt.), 518, 519	518, 519
Finance and insurance	**--------**	**52**	**52**	**52**
Federal Reserve banks	5210	521	521	521
Credit intermediation and related activities	5220	522	522	522
Securities, commodity contracts, and investments	5230	523	523	523

INDUSTRY TITLE	BEA CODE	1997 NAICS Codes	2002 NAICS Codes	2007 NAICS Codes
Insurance carriers and related activities	5240	524	524	524
Funds, trusts, and other financial vehicles	5250	525	525	525
Real estate and rental and leasing	**--------**	**53**	**53**	**53**
Real estate	5310	531	531	531
Rental and leasing services and lessors of intangible assets	5320	532,533	532,533	532,533
Professional, scientific, and technical services	**--------**	**54**	**54**	**54**
Legal services	5411	5411	5411	5411
Computer systems design and related services	5415	5415	5415	5415
Miscellaneous professional, scientific, and technical services	5412	541 ex. 5411,5415	541 ex. 5411,5415	541 ex. 5411,5415
Management of companies and enterprises	**5500**	**55**	**55**	**55**
Administrative and waste management services	**--------**			
Administrative and support services	5610	561	561	561
Waste management and remediation services	5620	562	562	562
Educational services	**6100**	**61**	**61**	**61**
Health care and social assistance	**--------**	**62**	**62**	**62**
Ambulatory health care services	6210	621	621	621
Hospitals	622H	622	622	622
Nursing and residential care facilities	6230	623	623	623
Social assistance	6240	624	624	624
Arts, entertainment, and recreation	**--------**	**71**	**71**	**71**

INDUSTRY TITLE	BEA CODE	1997 NAICS Codes	2002 NAICS Codes	2007 NAICS Codes
Performing arts, spectator sports, museums, and related activities	711A	711,712	711,712	711,712
Amusements, gambling, and recreation industries	7130	713	713	713
Accommodation and food services	**--------**	**72**	**72**	**72**
Accommodation	7210	721	721	721
Food services and drinking places	7220	722	722	722
Other services, except government	**8100**	**81**	**81**	**81**

Note: to make this process easier, the authors have built an R package (NAICStoBEA), which supports most variants of NAICS, available upon request.

B.1.5 Building Industry-Level IT measures

As of 2015, the BEA reports the following asset classes in its survey of tangible wealth. For each class, we report whether it is included in measure of IT spending. The denominator used to convert IT capital into IT intensity is the sum of the equipment and structures categories below. HW indicates the asset code is included in "hardware only" variables, and SW indicates it is included in "software only" variables. The general "IT" variable in our paper includes both hardware and software.

Asset Codes	NIPA Asset Types	Included in IT variable
EQUIPMENT	**TOTAL EQUIPMENT**	
EP1A	**Mainframes**	**Yes-HW**
EP1B	**PCs**	**Yes-HW**
EP1C	**DASDs**	**Yes-HW**
EP1D	**Printers**	**Yes-HW**
EP1E	**Terminals**	**Yes-HW**
EP1F	**Tape drives**	**Yes-HW**
EP1G	**Storage devices**	**Yes-HW**
EP1H	**System integrators**	**Yes-HW**

Asset Codes	NIPA Asset Types	Included in IT variable
EP20	**Communications**	**Yes-HW**
EP34	**Nonelectro medical instruments**	
EP35	**Electro medical instruments**	
EP36	**Nonmedical instruments**	
EP31	**Photocopy and related equipment**	
EP12	**Office and accounting equipment**	
EI11	**Nuclear fuel**	
EI12	**Other fabricated metals**	
EI21	**Steam engines**	
EI22	**Internal combustion engines**	
EI30	**Metalworking machinery**	
EI40	**Special industrial machinery**	
EI50	**General industrial equipment**	
EI60	**Electric transmission and distribution**	
ET11	**Light trucks (including utility vehicles)**	
ET12	**Other trucks, buses and truck trailers**	
ET20	**Autos**	
ET30	**Aircraft**	
ET40	**Ships and boats**	
ET50	**Railroad equipment**	
EO11	**Household furniture**	
EO12	**Other furniture**	
EO30	**Other agricultural machinery**	
EO21	**Farm tractors**	
EO40	**Other construction machinery**	
EO22	**Construction tractors**	
EO50	**Mining and oilfield machinery**	
EO60	**Service industry machinery**	
EO71	**Household appliances**	
EO72	**Other electrical**	
EO80	**Other**	
STRUCTURES	**TOTAL STRUCTURES**	
SOO1	**Office**	
SB31	**Hospitals**	
SB32	**Special care**	
SOO2	**Medical buildings**	
SC03	**Multimerchandise shopping**	

Asset Codes	NIPA Asset Types	Included in IT variable
SC04	**Food and beverage establishments**	
SC01	**Warehouses**	
SOMO	**Mobile structures**	
SC02	**Other commercial**	
SI00	**Manufacturing**	
SU30	**Electric**	
SU60	**Wind and solar**	
SU40	**Gas**	
SU50	**Petroleum pipelines**	
SU20	**Communication**	
SM01	**Petroleum and natural gas**	
SM02	**Mining**	
SB10	**Religious**	
SB20	**Educational and vocational**	
SB41	**Lodging**	
SB42	**Amusement and recreation**	
SB43	**Air transportation**	
SB45	**Other transportation**	
SU11	**Other railroad**	
SU12	**Track replacement**	
SB44	**Local transit structures**	
SB46	**Other land transportation**	
SN00	**Farm**	
SO01	**Water supply**	
SO02	**Sewage and waste disposal**	
SO03	**Public safety**	
SO04	**Highway and conservation and development**	
IPP	**TOTAL INTELLECTUAL PROPERTY PRODUCTS**	
ENS1	**Prepackaged software**	**Yes-SW**
ENS2	**Custom software**	**Yes-SW**
ENS3	**Own account software**	**Yes-SW**
RD11	**Pharmaceutical and medicine manufacturing**	
RD12	**Chemical manufacturing, ex. pharma and med**	

Asset Codes	NIPA Asset Types	Included in IT variable
RD23	**Semiconductor and other component manufacturing**	**Yes-HW**
RD21	**Computers and peripheral equipment manufacturing**	**Yes-HW**
RD22	**Communications equipment manufacturing**	**Yes-HW**
RD24	**Navigational and other instruments manufacturing**	
RD25	**Other computer and electronic manufacturing, n.e.c.**	**Yes-HW**
RD31	**Motor vehicles and parts manufacturing**	
RD32	**Aerospace products and parts manufacturing**	
RDOM	**Other manufacturing**	
RD70	**Scientific research and development services**	
RD40	**Software publishers**	**Yes-SW**
RD50	**Financial and real estate services**	
RD60	**Computer systems design and related services**	**Yes-SW**
RD80	**All other nonmanufacturing, n.e.c.**	
RD91	**Private universities and colleges**	
RD92	**Other nonprofit institutions**	
AE10	**Theatrical movies**	
AE20	**Long-lived television programs**	
AE30	**Books**	
AE40	**Music**	
AE50	**Other entertainment originals**	

These IT, Software, and Hardware measures are built at the industry level for each year, and at the level of the whole economy for each year.