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IMPLICATIONS FOR WAGES, INTEREST RATES, AND GROWTH

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ABSTRACT

Digital versions of labor and capital can be reproduced much more cheaply than their traditional forms. This increases the supply and reduces the marginal cost of both labor and capital. What then, if anything, is becoming scarcer? We posit a third factor, ‘genius’, that cannot be duplicated by digital technologies. Our approach resolves several macroeconomic puzzles. Over the last several decades, both real median wages and the real interest rate have been stagnant or falling in the United States and the World. Furthermore, shares of income paid to labor and capital (properly measured) have also decreased. And despite dramatic advances in digital technologies, the growth rate of measured output has not increased. No competitive neoclassical two-factor model can reconcile these trends. We show that when increasingly digitized capital and labor are sufficiently complementary to inelastically supplied genius, innovation augmenting either of the first two factors can decrease wages and interest rates in the short and long run. Growth is increasingly constrained by the scarce input, not labor or capital. We discuss microfoundations for genius, with a focus on the increasing importance of superstar labor. We also consider consequences for government policy and scale sustainability.

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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 by a million-fold in just three decades, while digital storage and digital communications have grown at equally dizzying rates.¹ Machine learning systems can now diagnose diseases (Esteve et al., 2017), speech recognition is here (The AI Index, 2017), and driverless cars are around the corner. AI and other digital technologies, for good or ill, are increasing the effective supply of increasingly diverse types of 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.

One striking feature of these new technologies is their replicability at low or even zero cost. Any digitizable innovation can spread almost instantly worldwide. Cloud services create a digital fire-hose that gives rapidly expanding companies access to eyeballs, venture finance, connections, effective labor, computation and software.

In this increasingly digital economy, ordinary workers have seen their wages stagnate. Meanwhile, while some investors have done very well, the return on ordinary capital – as measured by real interest rates – has fallen substantially as well.

In any competitive two-factor model of aggregate production, this is impossible. Technological changes that boost the ability of capital to substitute for labor should increase interest rates, at least in the short run.² For an intuition why, consider an economy where firms unexpectedly gain the ability to replace some workers with highly

¹From 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).

²In 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.

productive robots. Firms will bid up interest rates in an attempt to take advantage of this attractive new investment opportunity.

Why then, if emerging technologies are so impressive, are interest rates so low, wage growth so slow and investment rates so flat? And why is total factor productivity growth so lukewarm? To resolve this paradox, we propose a model of aggregate production with three inputs. The third factor corresponds to a bottleneck which prevents firms from making full use of digital abundance. Bottlenecks are ubiquitous in economics. This paper is typed on a computer that is over 1000 times faster than those of the past, but our typing is still limited by our interface with the keyboard. An assembly line that doubles the output, speed or precision of 1, 2 or 99 out of 100 of processes will still be limited by that line's weakest link. In other words, no matter how much we increase the other inputs, if an inelastically supplied complement remains scarce, it will be the gating factor for growth.

Our model can explain 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 both indispensable and impossible to digitize. This puts them in a position to capture the gains from digitization.

In our digital economy technology advances rapidly, but humans and their institutions change slowly. Institutional, managerial, technological, and political constraints become bottlenecks (Brynjolfsson et al., 2017). Before a firm can make use of AI decision making, its leaders need to make costly and time-consuming investments in quantifying its business processes; before it can scale rapidly using web services it needs figure out how to codify its systems in software. Therefore, digital advances benefit neither unexceptional labor nor standard capital, at least insofar as they can be replicated digitally (Brynjolfsson et al., 2014). The invisible hand instead favors those who are a scarce complement to these factors.

The inputs in our model are traditional capital and labor and a relatively inelastic complement we dub 'genius' or G . When G is relatively abundant, the economy approximates a two-factor one. But as G 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 G , innovations in automation technology can reduce both labor's share of income and the interest rate.

This theory fits what we know about the limitations of digital technologies, in-

cluding cutting-edge AI. While general artificial intelligence might someday lead to an economic singularity, contemporary AI technologies have clear limitations, making humans indispensable for many essential tasks. Agrawal et al. (2018a) and Agrawal et al. (2018c) observe that AI is good at prediction tasks, but struggles with judgment – often a close complement. Brynjolfsson et al. (2018) create a rubric for assessing which tasks are suitable for machine learning and use it to evaluate the content of over 18,000 tasks described in O-Net. They find that while the new technology delivers super-human performance for some tasks, it is ineffective for many others. In particular, despite their many strengths, existing computer systems weak or ineffective at tasks that involve significant creativity or large-scale problem solving. Even tasks amenable to automation may require large organizational investments before business processes can be automated.

The only essential feature of G in our model is that it is inelastically supplied, because, in part, it is not subject to digitization. For concreteness, our primary interpretation for G is 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,³ or effectively manage a business. If these good ideas are owned by and accumulate within firms, they correspond to a kind of alienable genius.

Our reading of the economic landscape is that digital and communication technologies have multiplied the possibilities for innovation,⁴ but humans still play an indispensable role in identifying which potential innovations are most likely to be valuable and understanding how to effectively scale up those ideas. That being said, we do not take a normative stance on their contributions. We allow for the possibility that the innovators, investors, and entrepreneurs who benefit from this scarcity are not necessarily the most objectively virtuous. Luck and connections play an important role in determining which workers or intellectual properties end up collecting rents. More problematically, they may find ways to tighten the bottlenecks they have monopolized to extract even more value.⁵

We also consider the possibility that G is a form of intangible asset distinct from

³Although some claim that innovations in AI may eventually overcome this bottleneck by automating the idea selection process (Agrawal et al., 2018b)

⁴Because of a combinatorial explosion in attractive ideas to investigate. See Weitzman (1998).

⁵For example, in Jones et al. (2018), agents face an incentive to hoard valuable information, leading to underutilization.

superstar workers and their creations. 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.

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.

While distinct, these microfoundations are closely interrelated. Organizational capital may be hard to accumulate because it requires human geniuses to create it, nurture it, or sustain it. Similarly, huge 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 geniuses. Many have hypothesized that the comparative advantage of large digital platform companies is their special ability to recruit and motivate exceptional workers.

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, in-

creases in the productivity of unexceptional capital and labor have suppressed interest rates and median wages (Baumol, 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 .”

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 (2013). They find an approximately 5 percent decrease in labor’s share of global corporate gross value added from 1980 through 2014.

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

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

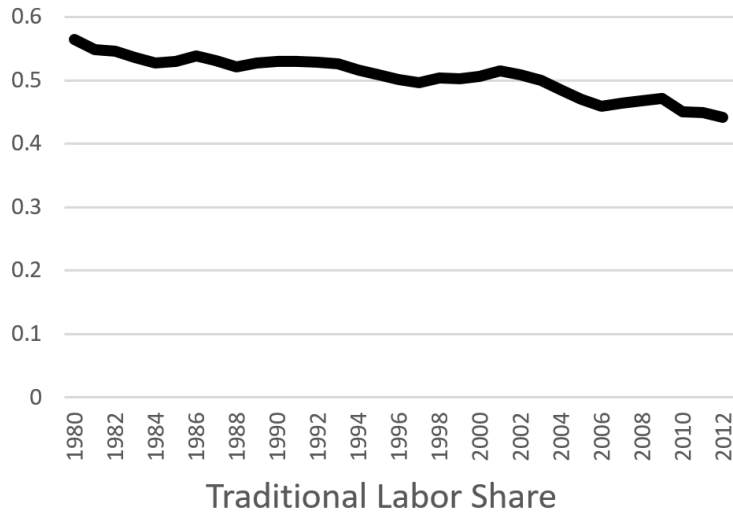


Figure 1: Traditional labor’s share of US non-financial corporation gross value added. The traditional labor income share is the bottom 97 percent share of all US labor income (equal split adults) from the World Wealth and Income Database World Wealth and Income Database (2016) multiplied by total US 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 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.⁶

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.⁷ An example of a model with automation of this form is Peretto and Seater (2013).⁸ 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.⁹ 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 are those in Autor and Dorn (2013) and Benzell et al. (2016). In Autor and Dorn (2013), traditional capital is a complement to manual,

⁶Consistent 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).

⁷Peretto and Seater (2013) show that economies will use both of the most extreme mix of α technologies available.

⁸In the full version of this model firms in monopolistic competition pay a cost to gain access to new α s. 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.

⁹A related model is Zeira (1998), in which automation corresponds to an additional, more capital intensive, *Leontief* technology becoming available.

routine and high skilled labor. Information technology capital is a substitute for 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.¹⁰ 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 capital depreciation and inflation rates constant, a decrease in real interest rates must mean a decrease in the required rate of return on capital investment. 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

¹⁰Appendix Figure 10 reports four indexed measures of the US real rate of return.

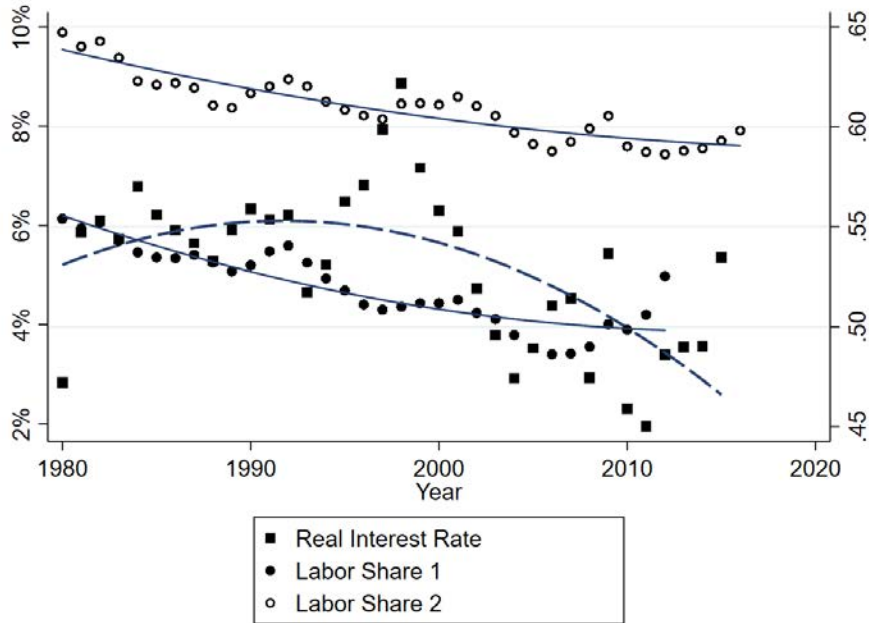


Figure 2: Average labor shares and real interest rates over time. Labor share 1 is total labor share of income as constructed in Karabarbounis and Neiman (2013); unbalanced panel of 111 countries from 1980-2012. Labor share 2 is labor’s share of income as reported by IMF-WEO; balanced panel of 24 countries 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 line of best fit is superimposed.

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

¹¹Karabarbounis 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 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

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 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, genius’ 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 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.

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

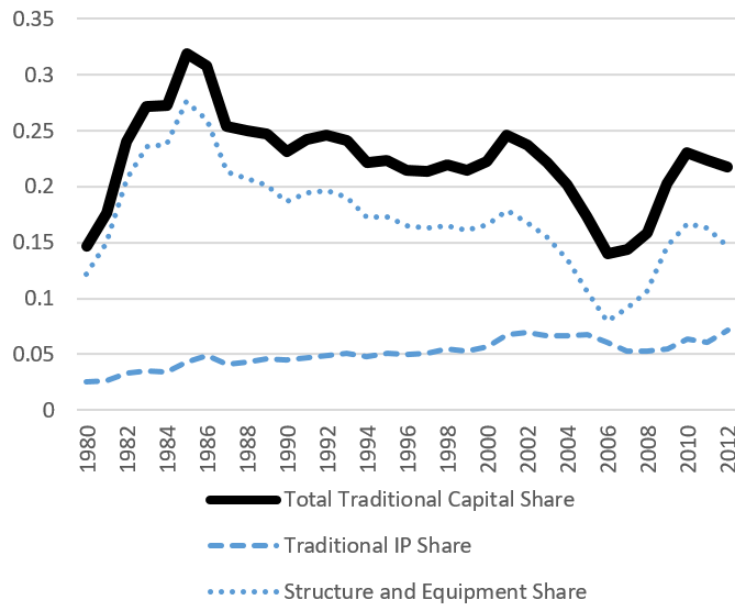


Figure 3: Traditional capital’s share of US non-financial corporation gross value added. Calculation of each form of traditional capital’s share of income follows Barkai (2016) and Barkai and Benzell (2018). Data on US non-financial gross value added from BEA table 1.14.

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 fluctuations 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 (2013) 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

¹³Lawrence (2015) makes this point as well, and concludes that recent declines in the labor

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.

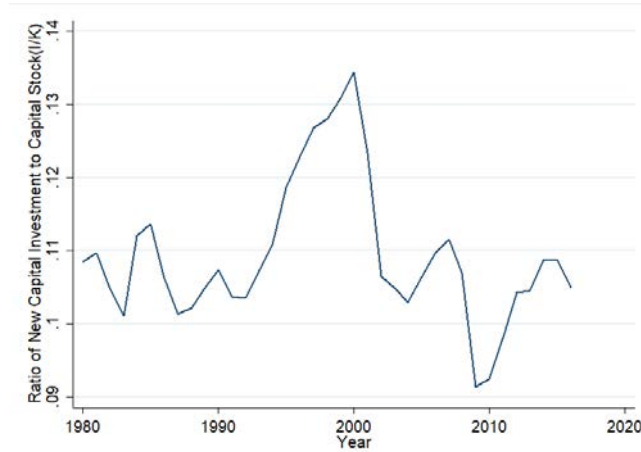


Figure 4: Capital investment rate for US non-financial corporations. The investment rate is calculated as total nominal investment divided by the total current cost capital stock. Underlying data from BEA NIPA tables.

2.3 The Rise of Genius’ Share of Income

There is evidence that innovative automation technologies have led to a 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.

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.

	(1)	(2)	(3)	(4)	(5)	(6)
	LS_1	LS_1	LS_1	LS_2	LS_2	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 Karabarounis and Neiman (2013). 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.

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 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, C corresponds to production and technology parameters. Let $\gamma(K, L, C)$, a function of K , L , and C 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

¹⁴It 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.

the prices. In other words, assuming that capital fully depreciates each period,

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

$$w = \frac{\gamma Y}{L} \quad (3)$$

In the short run, any technological improvement (i.e. a change from some C to some C' , 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 “genius” or G . 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

The first component of genius corresponds to exceptional labor income. Brynjolfsson and Saint-Jacques (2015) conceptualizes the US labor force as consisting of individuals of normal and exceptional abilities (or luck). Normal workers face a log-normal distribution of labor income which is consistent with a multiplicative model of normally-distributed abilities. But exceptional workers sort themselves into sectors with superstar-style returns, such as digital and networked industries, and draw their incomes from a Pareto distribution. This approach explains the fractal nature of top labor income percentiles. In 2008, the top 25 percent of US workers earned more than half of all labor income, the top 2.5 percent of workers earned over 20 percent of labor income, the top .25 percent of workers earned over 7 percent of total labor earnings, and so on. Using a maximum likelihood approach, Brynjolfsson and Saint-Jacques (2015) study US data and find that approximately 3 percent of workers draw from this ‘power-law economy’ while the rest draw their incomes from log-normal distribution. They also find that there has been significantly increasing skewness in this part of

¹⁵Indirect taxes on production and imports less subsidies.

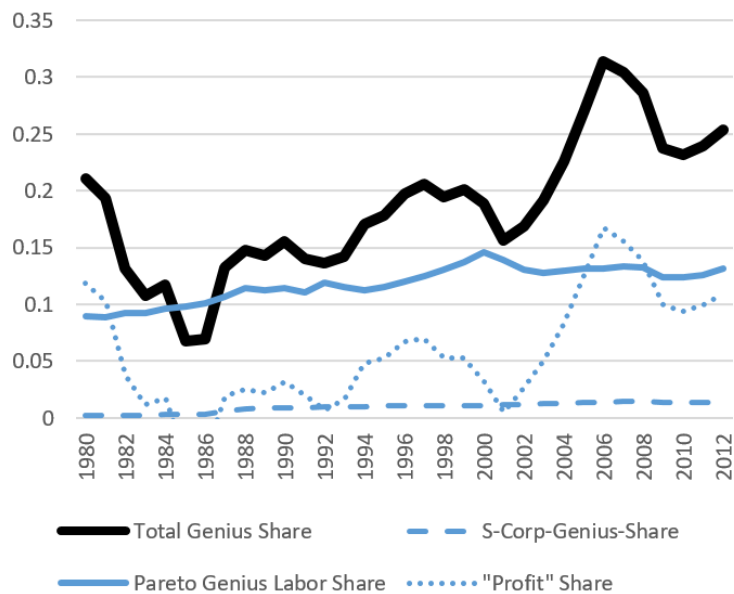


Figure 5: Genius' share of US non-financial corporation gross value added. The Genius labor income share is the top 3 percent share of all US labor income (equal split adults) from the World Wealth and Income Database World Wealth and Income Database (2016) multiplied by total US non-financial corporate 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 genius 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 genius labor income. Data on US non-financial gross value added from BEA table 1.14.

the economy, and that has further the increased share of income accruing to superstar workers. Accordingly, we use their 3 percent cutoff to motivate our distinction between traditional and 'genius' labor. To this we add the labor income of owner-operators of S-corporations which ?? finds to have been mislabeled as profits.

The final component of genius 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 slightly negative in 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.

All together, genius' share of income increases from a nadir of 6.7 percent in 1984 to a peak of 31.4 percent in 2006.¹⁶ 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 (Brynjolfsson and Saint-Jacques, 2015) .

To those in the business world, the result that non-traditional factors are increasingly scarce will come as no surprise. Many employers complain about the rarity of exceptional talent. 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."¹⁷

Despite the occasional unicorn, average rates of returns to investors in venture capital who attempt to gain a slice of G are typically unexceptional. Although there was a period of high returns in the mid-90s, 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.

While G 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.¹⁸

¹⁶The increase in profit/genius 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 3 year backward looking moving average. Barkai (2016) shows that the overall trend is robust to changes in this assumption.

¹⁷Consider also the following commonplace, traditionally attributed to Bill Gates. "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."

¹⁸Despite 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."

In the remainder of this paper, we develop the Genius Model in greater depth and show how it can better account for trends in the US non-financial corporate sector since the mid-1980s.¹⁹

3 The Genius Model

In this section of the paper we describe the key features of the Genius Model. On the production side, firms are perfectly competitive and have constant returns to scale. Production uses three inputs: capital, labor, and genius. Capital is produced from the final output good, and depreciates fully each period.

3.1 Supply Side

Firms maximize each period's profits

$$\Pi_t = Y_t(G_t, K_t, L_t) - g_t G_t - \rho_t(K_t) - w_t L_t \quad (4)$$

Where P_t are profits, Y is the production function, w , g , and ρ are the wage and rental rates of genius and capital, respectively, G is genius, L is traditional labor, and K is traditional capital, which depreciates fully every period.

We consider an economy with the following production function

$$Y_t = (\beta_1^{\frac{1}{\sigma}} (T(L_t, K_t, c_t))^{\frac{\sigma-1}{\sigma}} + \beta_2^{\frac{1}{\sigma}} (z_{G,t} G_t)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \quad (5)$$

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 genius.

¹⁹Gutiérrez 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 Philippon 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.

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.²⁰

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

$$1 + r_t = \rho_t = \frac{\partial Y_t}{\partial T_t} \frac{\partial T_t}{\partial K_t} \quad (7)$$

and the wage and rental rate of genius are

$$w_t = \frac{\partial Y_t}{\partial T_t} \frac{\partial T_t}{\partial L_t} \quad (8)$$

and

$$g_t = z_{G,t} \beta_2^{\frac{1}{\sigma}} \left(\frac{Y_t}{z_{G,t} G_t} \right)^{\frac{1}{\sigma}}. \quad (9)$$

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

$$\mathbf{t}_t = \beta_1^{\frac{1}{\sigma}} \left(\frac{Y_t}{T_t} \right)^{\frac{1}{\sigma}} \quad (10)$$

and there are no profits.

3.2 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 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 genius. Therefore, determining the price of genius 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.

$$U_t = C_t \quad (11)$$

²⁰This is a special case of the nested CES production function. When traditional output is produced using a Cobb-Douglas technology, we have,

$$T_t = A_t (z_{L,t} L_t)^{1-\alpha} (z_{K,t} K_t)^\alpha \quad (6)$$

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

Genius 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 G is treated as an ownable asset it will crowd out investment in capital.²¹ To the extent genius is ownable, households also incur a cost from “buying” genius, and receive income from “selling” genius at the end of every period. This income is in zero net supply.

$$\pi_t = w_t L_t + g_t G_t + \rho_t K_t \quad (12)$$

where π_t is household income in period t .

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

$$\pi_t = w_t L_t + (1 - \theta)g_t G_t + r_t(S_{t-1}) \quad (13)$$

Where θ is the share of genius considered owned.

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

$$S_t = s\pi_t \quad (14)$$

Savings are held in the form of capital investments. If genius is ownable, then it also consists of rights to a flow of genius. So,

$$S_t = \theta p_t G_t + K_{t+1} \quad (15)$$

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

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

$$1 + r_{t+1} = \rho_{t+1} = \frac{g_{t+1} + p_{t+1}}{p_t} \quad (16)$$

²¹In 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 genius is equal to the discounted value of its rents.

$$p_t = \sum_{s=t}^{\infty} R_{s+1,t}^{-1} g_{s+1}, \quad (17)$$

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

$$R_{s,t} = \prod_{j=t}^s (1 + r_j). \quad (18)$$

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

3.3 Market Clearing

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

$$Y_t = I_t + C_t \quad (19)$$

Where C_t is consumption and I_t is capital investment.

$$I_t = S_t - \theta p_t G_t \quad (20)$$

Capital fully depreciates every period, so

$$K_{t+1} = I_t \quad (21)$$

Assuming an initial condition for K closes the model.

4 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.

4.1 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-genius income paid to labor, and $1 - \gamma_t(K_t, L_t, C_t)$ the share paid to traditional capital. In other words

$$\gamma_t = \frac{w_t L_t}{\mathbf{t}_t T(L_t, K_t, C_t)} \quad (22)$$

Labor's share of total income can then be written

$$LS_t = \frac{w_t L_t}{Y_t} = \frac{\gamma T_t \mathbf{t}_t}{Y_t} \quad (23)$$

and the interest rate is

$$1 + r_t = \frac{(1 - \gamma) T_t \mathbf{t}_t}{K_t} \quad (24)$$

Substituting for \mathbf{t}_t yields

$$\frac{w_t L_t}{Y_t} = \gamma \beta_1^{\frac{1}{\sigma}} \left(\frac{Y}{T} \right)^{\frac{1}{\sigma} - 1} \quad (25)$$

and

$$1 + r_t = \frac{(1 - \gamma) \beta_1 Y_t^{\frac{1}{\sigma}}}{K_t} \quad (26)$$

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

$$\frac{\partial r_t}{\partial c_t} = \frac{\beta_1^{\frac{1}{\sigma}}}{K} Y_t^{\frac{1}{\sigma}} T_t^{1 - \frac{1}{\sigma}} \left(\frac{\partial T_t}{\partial c_t} (1 - \gamma_t) \left(\left(1 - \frac{1}{\sigma}\right) T_t + \frac{1}{\sigma} Y_t^{-1} \mathbf{t}_t \right) - \frac{\partial \gamma_t}{\partial c_t} \right) \quad (27)$$

The change in labor share is determined by

$$\frac{\partial LS_t}{\partial c_t} = \beta_1^{\frac{1}{\sigma}} \left(\frac{Y_t}{T_t} \right)^{\frac{1}{\sigma}-1} \left(\gamma_t \left(1 - \frac{1}{\sigma} \right) \frac{\partial T_t}{\partial c_t} T_t^{-1} \left(1 - \frac{LS_t}{\gamma_t} \right) + \frac{\partial \gamma_t}{\partial c_t} \right) \quad (28)$$

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 (27) 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 close 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 genius 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.

$$T_t = A_t (z_{L,t} L_t)^{1-\alpha} (z_{K,t} K_t)^\alpha \quad (29)$$

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

$$\frac{\partial \rho_t}{\partial z_{K,t}} = \mathbf{t}_t \alpha^2 A_t \left(\frac{z_{L,t} L_t}{z_{K,t} K_t} \right)^{1-\alpha} \left(\sigma^{-1} \left(\frac{\mathbf{t}_t T_t}{Y_t} - 1 \right) + 1 \right) \quad (30)$$

Note that the sign of $\frac{\partial \rho_t}{\partial z_{K,t}}$ is determined by the term $\sigma^{-1}(\frac{tT}{Y} - 1) + 1$ as the rest of the function must all be positive. $\frac{tT}{Y}$ has a handy interpretation as the share of final output which is devoted to compensating the traditional inputs.²²

Suppose that $\alpha = .3$ and that in the year before the z_K increase $\frac{tT}{Y} = .5$. If half of the income from renting out G 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

$$\sigma^{-1}(.5 - 1) < -1 \tag{31}$$

$$\sigma < .5 \tag{32}$$

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

Figure 6 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 G are highly complementary and the increase in z_K is large.

4.2 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 (9) by $\frac{G}{Y}$ yields an equation for G 's share of income

$$\frac{gG}{Y} = \beta_2^{\frac{1}{\sigma}} \left(\frac{Y}{z_G G} \right)^{\frac{1}{\sigma} - 1} \tag{33}$$

Assuming that $z_G G$ is constant, we can choose a value of β_2 and σ that fits the trend in genius's share since 1985 from figure 5. Figure 7 displays the empirical trend in the genius share, as well as our prediction of geniuses' share using (33):

The above relationship holds true no matter the level of capital accumulation.

²²A very similar result holds for increases in technology A :

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

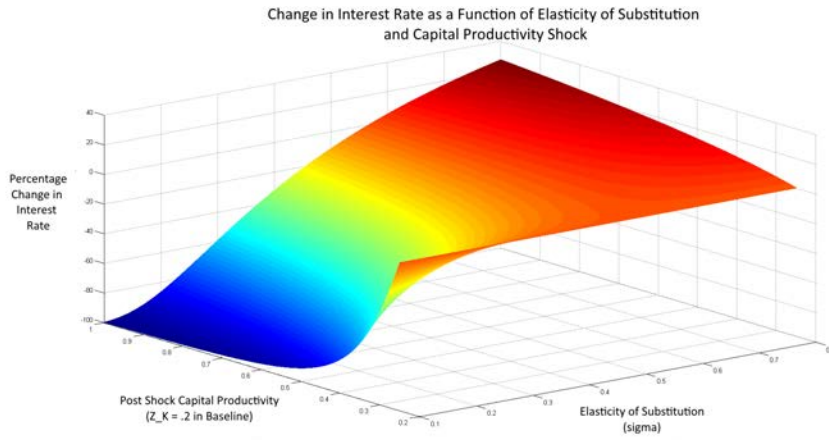


Figure 6: Immediate percent change in interest rates as a function of elasticity of substitution and the size of the z_K increase. Cobb Douglas traditional production technology. Initial parameters are: $K = 1$, $L = 1$, $G = .5$, $\alpha = .5$, $\beta_1 = \beta_2 = z_L = 1$, $z_K = .2$. σ for both periods on the x axis, z_K after the increase is on the Y axis.

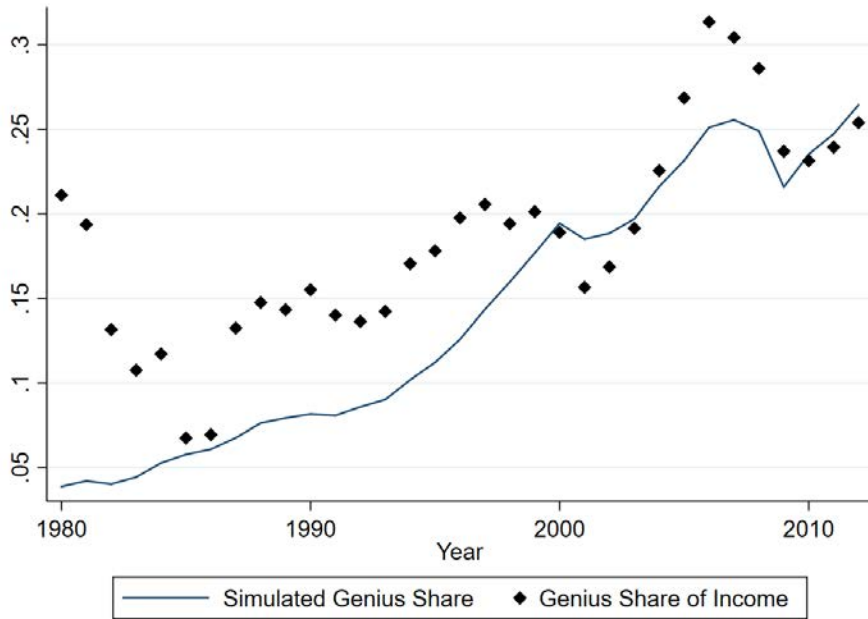


Figure 7: Observed and calibrated values of genius' share of non-financial corporate gross value added. Observed measure of geniuses' share replicates Barkai (2016)'s calculation of profit share plus top percentile labor income. Calibrated value takes $\sigma = .33$, $z_G G = 1$ and $\beta_1 = 1$ in all periods, simulated G share in 1985 = .0578

However, the long term effect of an 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

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

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 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 G rather than vice versa.

Figure 8 shows the long term response of prices and output after a increase

in z_K . A Cobb Douglas traditional technology and no crowding out from genius is assumed. Additionally, if G income accrues to only a small subset of the population, inequality will increase.

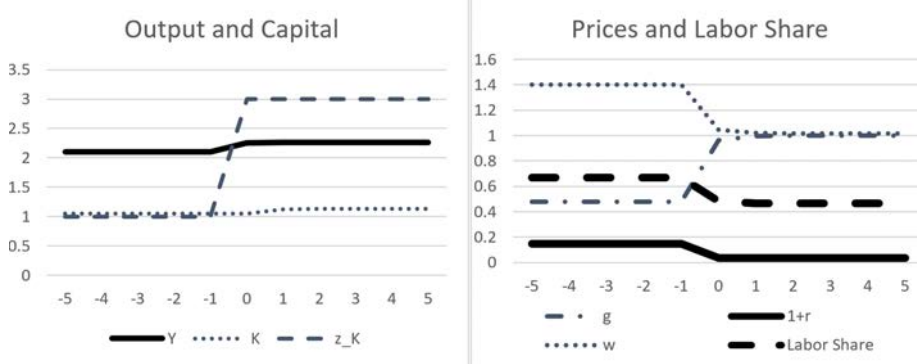


Figure 8: Simulated changes in prices, capital and output after an increase in z_K . Cobb Douglas traditional production technology. Parameters are $\beta_1 = \beta_2 = s = .5$, $L = z_L = z_G = G = 1$, $\alpha = \sigma = .1$. z_K increases from 1.13 to 3 in period 0. The capital stock begins in its steady state level for initial parameters.

In the case $\theta > 0$, some of genius is owned. In this case, increases in traditional output technology (such as greater digitization of production production) may increase the price of genius. That is because if genius' share increases, but the quantity of genius is fixed, the rental price of genius g must increase. The price of owning genius 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 G that is owned by, or associated with,²³ 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 G 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 9 displays the observed stock of intangibles in the US non-financial

²³We say associated with, because for privately held firms, extra normal rates of return on capital investment due to a founder's flow of genius 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).

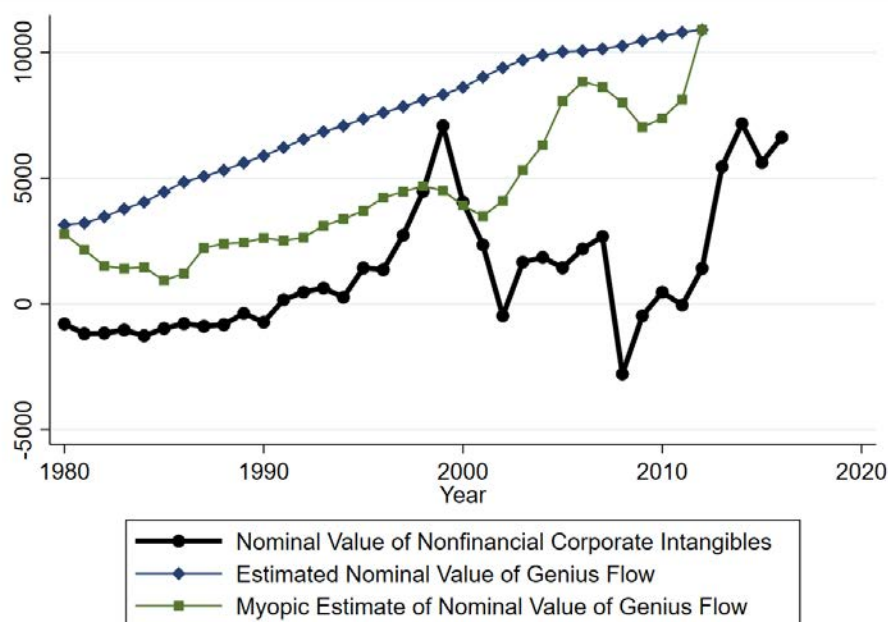


Figure 9: Observed and estimated stock of intangible assets in the US non-financial corporate sector in nominal billions. US Corporate intangible assets are calculated as US corporate equity and liabilities less financial assets from Federal Reserve series Z.1 and less fixed capital from BEA table 4.1.

corporate sector corporate sector.²⁴ However, it displays a clear upward trend. The figure also displays estimates of the nominal value of the G flow. The ‘myopic’ estimate of the value of the G flow takes V as $g_t G_t = V_t r_t$ where r is the Moody’s AAA bond portfolio rate. The primary estimate values the G flow as $V_t = \frac{V_{t+1} + g_{t+1} G_{t+1}}{1+r_t}$, with $g_{2012} G_{2012} = V_{2012} r_{2012}$. In other words, the myopic estimate is of the value of the period’s G assuming no appreciation or G stock changes, while the first is an estimate of the value of all future G payment flows (assuming no appreciation or stock changes after 2012). This figure suggests that approximately half of the increased value of genius 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.

²⁴This measure is often negative, perhaps due to an overestimate of the stock of capital in the economy, see Wright (2004)

5 Microfoundations of Genius

Our primary interpretation of G 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.

Alternatively G 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 genius may lie in the system itself, not in any single individual.

In the limit, the supply of these bottlenecks 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 genius 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, so at least about a third) not be counted as labor income in conventional statistics. Otherwise, as G gets a higher share of income, labor’s share of income will increase.

5.1 Increasing Returns to Superstars

A natural way to think about genius 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 shown in Brynjolfsson and Saint-Jacques (2015). Smith et al. (2017) provides complementary evidence that some of this increase in returns might be mistakenly counted as profits rather than labor income. That paper uses administrative data to show that owner deaths at small and medium sized privately held companies since 2000 have led to large output decreases. Profits attributable to the skill of manager-owners can explain much of the increase in top percentile inequality over this interval.

Treating genius 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,

$$Y_{i,t} = (\beta_1^{\frac{1}{\sigma}} (T_{i,t})^{\frac{\sigma-1}{\sigma}} + \beta_2^{\frac{1}{\sigma}} (z_{G,i,t} (\max_{i,t} (\mathbb{1}(G_{p,i,t} = 1)) \theta_p))^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \quad (35)$$

$$Y_t = \sum_{i=0}^I Y_{i,t} \quad (36)$$

Where $\mathbb{1}(G_{p,i,t} = 1) = 1$ 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

$$L = \bar{L} \left(1 - \frac{\sum_p \sum_i \mathbb{1}(G_{p,i,t} = 1)}{P} \right) = \bar{L} \left(1 - \frac{I}{P} \right) \quad (37)$$

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

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

Suppose that P is extremely large relative to the total number of firms I . Then, assuming the market for G is competitive (i.e. superstars are paid their marginal products), this will reduce to the aggregate production function above with $\bar{L} = L$ and $G_t = \sum_i \sum_p \theta_p \mathbb{1}(G_{p,i,t} = 1)$. The G 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 genius of the 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 one percent inequality.

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

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

income.

5.2 Alternative Microfoundation – Intangible Assets

We can also think of G 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, genius 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 genius is destroyed and replaced with a lump-sum rebate of genius to all members of society.

$$p_t = \theta_t \sum_{s=t}^{\infty} R_{s+1,t}^{-1} g_{s+1}, \quad (38)$$

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

$$R_{s,t} = \prod_{j=t}^s (1 + r_j). \quad (39)$$

The remaining genius $(1 - \theta)$ is transferred to the population as in equation 13.

Note that the representation of θ here is slightly different than in the main model. There the price of genius guarantees the right's indefinite flow, but only a portion of genius is owned. Here, all of genius 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 G was exogenous. It is the inelasticity of aggregate supply of G 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 genius be Γ_t . Any individual investment is risky, but assume that total new genius created is a function of total Γ_t invested and the current genius stock:

$$G_{t+1} = \Omega(\Gamma_t, G_t) + G_t \quad (40)$$

Where Ω_t is the total new supply of genius created at the end of the period, a weakly increasing function of Γ_t .

While investment in new genius 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 genius must be the same as the return to buying already created genius. Individuals will invest in trying to make more genius so long as the price of genius is less than or equal to the average return (in units of genius) from the investment

$$p_t \leq \frac{\Gamma_t}{\Omega(\Gamma_t, G_t)} \quad (41)$$

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

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

then, so long as (41) binds there will be a fixed ratio between the marginal products of capital and labor. This is because

$$p_t = \theta_t \sum_{s=t}^{\infty} R_{s+1,t}^{-1} g_{s+1} = \frac{\Gamma_t}{\Omega(\Gamma_t, G_t)} = \frac{1}{z_\Gamma} \quad (42)$$

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

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

The cost of genius 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 genius. 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 genius (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 genius creation to increase over time would be 'fishing out'. This is simply the idea that as the easiest sources of new genius 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 genius creation may have decreased is due to an increase in wasteful replication or attempts at "genius 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' genius, this would reduce the return to owning legacy genius, effectively increasing $1 - \theta$.

6 Policy Implications

Countries face tough macroeconomic challenges in the age of digital abundance and scarce genius. 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.

One proposed policy is education reform. Some suggest that wages for me-

dian and low-skill workers can be increased through upskilling. This is possible in two scenarios. First, to the extent that an economy is a small taker of global prices, 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 genius labor will boost traditional wages and reduce inequality. Consider the consequences of increasing by one percentage point the share of workers providing genius labor (to 4 percent).²⁵ 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 G providers by 53.1 percent.

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 G increases output by 2.4 percent, increases traditional wages by 4.9 percent, and reduces G rental prices by 13.6 percent.

²⁵In 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 G inputs are assumed to be labor, and all workers within a genius or traditional labor category provide the same amount of effective labor.

There are potential downsides to focusing on increasing G. 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 G, increasing its price. Counterintuitively, countries will know that their policies to increase the effective supply of G 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 genius 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 G 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 G-first economic strategy.²⁶

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

²⁶As 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 G supply.

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.

7 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 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 decrease in the traditional capital and labor share of income is increased profits. 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 con-

fusion 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.

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 genius’ share. Whether or not it does, we expect these desideratum to be connected well into the future.

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A Additional Figures

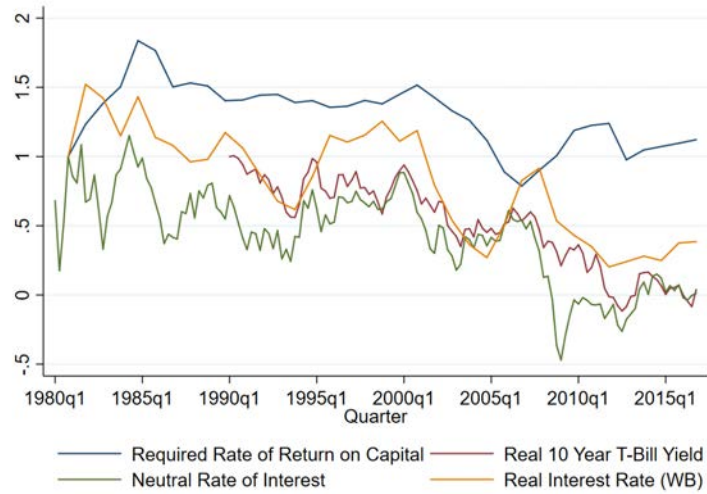


Figure 10: Four indexed measures of the US real rate of return. The required rate of return on capital is an annual measure constructed following Barkai (2016). The US real interest rate is an annual measure from The World Bank (2017). The US neutral rate of interest and real 10 year T-Bill yield are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