Capital Composition and the Declining Labor Share

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Abstract: To what extent can technological advances in the production of capital account for the recent, worldwide decline in the labor income share? We pose two challenges to the automation narrative: first, estimates of the elasticity of substitution (EOS) between capital and labor tend to fall below or around one, suggesting that a decline in the price of capital should not lead to a decline in the labor income share. Second, we illustrate that, despite technological improvements, the price of capital relative to output has remained roughly constant, worldwide. This poses a challenge to the view that cheaper capital has caused the displacement of workers. We show that a more nuanced approach, which takes seriously the composition of capital, ascribes a prominent role to the automation hypothesis. Though information and communications (ICT) capital is a small fraction of the capital stock, it is highly substitutable with labor, and its user cost declined sharply over the last few decades. A framework that distinguishes between ICT and non-ICT capital is empirically plausible and suggests that automation accounts for more than one quarter of the global decline in the labor share, even if the aggregate EOS is substantially less than unity.

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1. Introduction

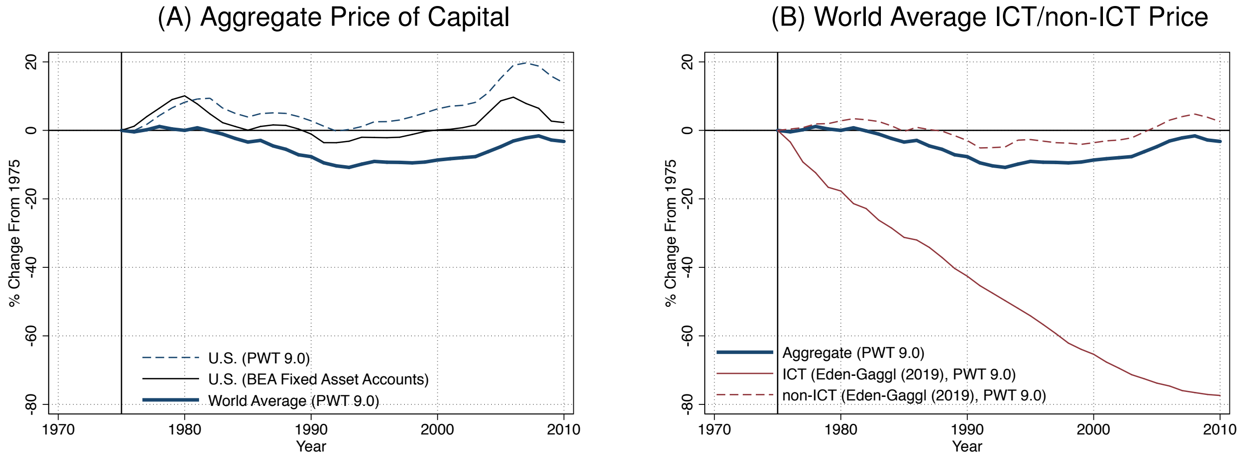
Concerns about the effects of automation have been fueled by ample evidence of machines replacing workers (Frey and Osborne, 2017; Acemoglu and Restrepo, 2017). Auto factories that were once bustling with workers are now filled with mechanical arms instead. Readily available software now cheaply performs accounting work that once required skilled labor. Especially given the rapid advances in the types of tasks that machines can perform (Brynjolfsson and Mitchell, 2017), there is understandable concern regarding the future of labor income and the distributional implications of automation. Karabarbounis and Neiman (2014, henceforth KN) show that, from a macroeconomic perspective, these concerns can be captured by an aggregate production function in which capital and labor are substitutable. In this production model, technological improvements resulting in the decline of the price of capital lead to the erosion of the labor income share.

While intuitively appealing, there are two problems with this narrative: first, it relies on a decline in the price of capital, reflecting technological improvements in its production. However, we document that the price of capital has remained relatively stable over the last few decades, both in the U.S. and worldwide (see panel A of Figure 1). Second, the narrative requires capital and labor to be substitutable, with an elasticity of substitution (EOS) greater than one. Yet, almost all existing estimates imply an EOS between capital and labor that is at most one (e.g., Oberfield and Raval, 2014; Chirinko, 2008).

Taken together, these challenges to the automation narrative make it seem unlikely. After all, alternative explanations for the decline in the labor share are abundant: some prominent examples are trade liberalization (Harrison, 2005), demographics (Glover and Short, 2018), credit conditions (Leblebicioglu and Weinberger, 2017), increasing market power of firms (De Loecker and Eeckhout, 2017; Barkai, 2017; Eggertsson, Robbins and Wold, 2018), the rise of "superstar" firms (Autor, Dorn, Katz, Patterson and Van Reenen, 2017; Kehrig and Vincent, 2018), and the rise and fall in public sector enterprises (Bridgman and Greenaway-McGrevy, 2019).

In this paper, we establish a stronger case for the automation narrative using a more nuanced framework that highlights the importance of capital composition within this context. If capital types that are relatively more substitutable with labor become disproportionately cheaper, then the labor income share will decline. Crucially, we show that this more nuanced view can accommodate an EOS between labor and *aggregate*

Figure 1: The Price of Capital Relative to GDP



Notes: The figure shows the trend in the relative price of capital relative to GDP based on the BEA fixed asset accounts as well as the Penn world Table 9.0 (PWT 9.0). Panel A shows the price of aggregate capital for the U.S. and a world average. Panel B shows the world average price trends for ICT and non-ICT capital in comparison to the price of aggregate capital. To compute the "world average" based on data for 67 countries taken from Eden and Gaggl (2019) and the PWT 9.0, we run a panel regression of the log relative price on a complete set of time fixed effects with the base year (1975) omitted. The growth series is computed as $100 \times (\exp(\hat{\beta}_t) - 1)$, where $\hat{\beta}_t$ is the estimated time effect, and the regressions is weighted with the nominal USD value of the respective capital stock (aggregate, ICT, non-ICT) in each country.

capital that is less than one. Moreover, we document that the stable price of aggregate capital masks differential trends in the prices of disaggregated types of capital. Specifically, while the prices of structures and equipment have remained mostly stable, there has been a sharp decline in the price of information and communication technology (ICT) capital, which has been shown to be more substitutable with labor (Eden and Gaggl, 2018). However, since ICT is a small share of aggregate capital, this decline only has a minor effect on the price of the aggregate capital stock (see panel B of Figure 1).

We use these empirical regularities to reinterpret the cross-country correlation between declining investment prices and declining labor shares documented by KN. We show that this correlation is driven by cross-country differences in ICT intensities, rather than differences in technological advances in capital production: countries with larger shares of ICT investment saw greater declines in their (aggregate) investment prices, *and* greater declines in their labor income shares. This correlation is therefore informative of the elasticity of substitution between ICT capital and labor, rather than the elasticity of substitution between aggregate capital and labor.

Using a sample of almost 40 high income countries, we calibrate a model with country specific produciton functions that illustrates how this correlation can be made consistent with a wide range of elasticities of substitution between labor and aggregate capital, corresponding to the range of empirical estimates in the extant literature (e.g., Oberfield and Raval, 2014; Chirinko, 2008). Our calibration suggests that, in a model with differentiated capital inputs, the global decline in the relative price of ICT capital accounts for roughly 40 percent of the decline in the labor income share in the United States and explains more than one quarter of the global decline in the labor share, regardless of the elasticity of substitution between aggregate capital and labor.

Though a number of recent papers study various disaggregations of the basic KN framework (e.g. Krusell, Ohanian, Ríos-Rull and Violante, 2000; Eden and Gaggl, 2018; vom Lehn, 2019; Orak, 2017), the goal of this paper is to clarify why the composition of capital is key for understanding the impact of technology on the distribution of income between aggregate capital and labor. Splitting labor into different groups of workers is primarily useful for the study of other relevant questions, such as the effects of automation on the composition of labor income, its relation to the rising college wage premium (Krusell et al., 2000) and job polarization (Eden and Gaggl, 2018; vom Lehn, 2019; Orak, 2017). We further recognize that disaggregating labor may also contribute to the understanding of general equilibrium effects that cannot be captured by the framework presented here.

The remainder of this paper is organized as follows. Section 2 reviews the key elements of the aggregate automation narrative in the spirit of KN. Sections 3 and 4 pose two challenges to this narrative. Section 5 documents large differences between the price trends of ICT capital goods and non-ICT capital goods. Section 6 uses this observation to question the validity of a production framework with a single capital aggregate. Section 7 proposes that differences in ICT intensities across countries may be driving cross-country variation in the decline in the labor share. Section 8 uses this insight to calibrate the effects of declining ICT prices on the global labor income share. Section 9 offers some concluding remarks.

2. The Automation Narrative

This section presents a model of the automation narrative with a single capital input, in the spirit of KN. The purpose of this model is to highlight the roles of the elasticity of substitution between capital and labor and the declining capital price.

Output is produced according to a constant returns to scale production function, $F(K, L)$, where K are capital inputs and L are labor inputs. Given a real rental rate of r and a real wage rate of w, firms maximize profits by solving

$$\max_{K,L} F(K,L) - rK - wL \tag{1}$$

yielding the standard first-order conditions that equalize marginal products with factor prices:

$$\frac{\partial F(K,L)}{\partial K} = r \text{ and } \frac{\partial F(K,L)}{\partial L} = w \tag{2}$$

The focus of the automation narrative is on how the share of labor income, $s_L \equiv wL/F(K,L)$, responds to a technological innovation that reduces the price of producing capital goods. Formally, the capital accumulation equation is given by:

$$K_{t+1} = (1-\delta)K_t + I_t \tag{3}$$

Here, K_{t+1} is the capital stock at time $t+1$; $(1-\delta)K_t$ is the depreciated capital stock at the end of time t; and I_t is investment goods.

The production of investment goods is governed by a productivity parameter, A: one unit of output is transformed into A units of investment. Assuming that investment goods are sold competitively, the relative price of investment goods is $p = 1/A$. In this model, an improvement in the production of capital goods—an increase in A—leads to an equilibrium decline in the capital price, p. Given that there is only one capital type, there is no distinction between investment prices and capital prices. As new and old capital goods are perfect substitutes, p is the market price of both.

As we will illustrate below, the labor income share is not directly affected by the relative price of capital goods, p; rather, it is a function of equilibrium rental rate, r, which is given by the standard no-arbitrage condition

$$r + p(1-\delta) = p(1+\bar{r}) \tag{4}$$

On the left hand side is the return from renting out a unit of capital, and then selling it at the end of the period (after it depreciated). On the right hand side is the return from selling the unit of capital at the beginning of the period, and lending the proceeds at the market interest rate $\bar{r}$.

This condition implies that the equilibrium rental rate is given by $r = p(\bar{r} + \delta)$, demonstrating a tight link between the relative price of capital goods, p, and the equilibrium rental rate, r. As the technological improvement leads to a reduction in p, firms face a lower rental rate and demand more capital inputs. Capital accumulation inevitably follows.

How the productivity shock affects the labor income share depends on the elasticity of substitution between capital and labor. By definition, the elasticity of substitution between capital and labor is the percent change in the capital-labor ratio generated by a percent change in the ratio of wages to rental rates:

$$EOS(K, L) = \frac{\partial \ln\left(\frac{K}{L}\right)}{\partial \ln\left(\frac{w}{r}\right)} \tag{5}$$

To understand the role of the elasticity of substitution, it is useful to rewrite the labor income share as a function of the capital-labor ratio:

$$s_L = \frac{wL}{F(K, L)} = \frac{w}{F(\frac{K}{L}, 1)} \tag{6}$$

Using the constant returns to scale assumption, the denominator can be rewritten as the sum of capital income and labor income. Substituting in the firm's optimality conditions in equation (2) yields

$$s_L = \frac{w}{w + r\frac{K}{L}} = \frac{1}{1 + \frac{K/L}{w/r}} \tag{7}$$

The labor share is therefore a decreasing function of the ratio $(K/L)/(w/r)$ and therefore directly related to $EOS(K, L)$. Using a first-order Taylor series approximation, the change in the capital-labor ratio from some initial date 0 to the current period is given by

$$\ln\left(\frac{K}{L}\right) - \ln\left(\frac{K_0}{L_0}\right) \approx EOS(K, L)\left[\ln\left(\frac{w}{r}\right) - \ln\left(\frac{w_0}{r_0}\right)\right] \tag{8}$$

which implies that

$$\frac{K/L}{K_0/L_0} \approx \left(\frac{w/r}{w_0/r_0}\right)^{EOS(K,L)} \tag{9}$$

Thus, the ratio of factor inputs and factor prices that determines the labor income share can be written as

$$\frac{K/L}{w/r} = \frac{\frac{K/L}{K_0/L_0}\,(K_0/L_0)}{\frac{w/r}{w_0/r_0}\,(w_0/r_0)} \approx \left(\frac{w/r}{w_0/r_0}\right)^{EOS(K,L)-1} \frac{K_0/L_0}{w_0/r_0} \tag{10}$$

Note that the "technology shock" at the center of the automation narrative has an unambiguously positive effect on the factor price ratio w/r due to two effects: first, the improvement in technology leads to an equilibrium decline in p which results in a steady-state decline in r; second, given that F has constant returns to scale, the marginal product of labor is increasing in capital inputs (regardless of the elasticity of substitution). The accumulation of capital in response to a lower r therefore increases w, and unambiguously increases the ratio w/r, implying $\frac{w/r}{w_0/r_0} > 1$.

What matters for the labor income share is the effect of this change on the ratio of factor inputs to factor prices, $(K/L)/(w/r)$. If $EOS(K, L) > 1$, this ratio increases, resulting in a decline in the labor income share. In contrast, if $EOS(K, L) < 1$, then the technology shock will lead to an increase in the labor share, while it will remain unchanged if $EOS(K, L) = 1$.

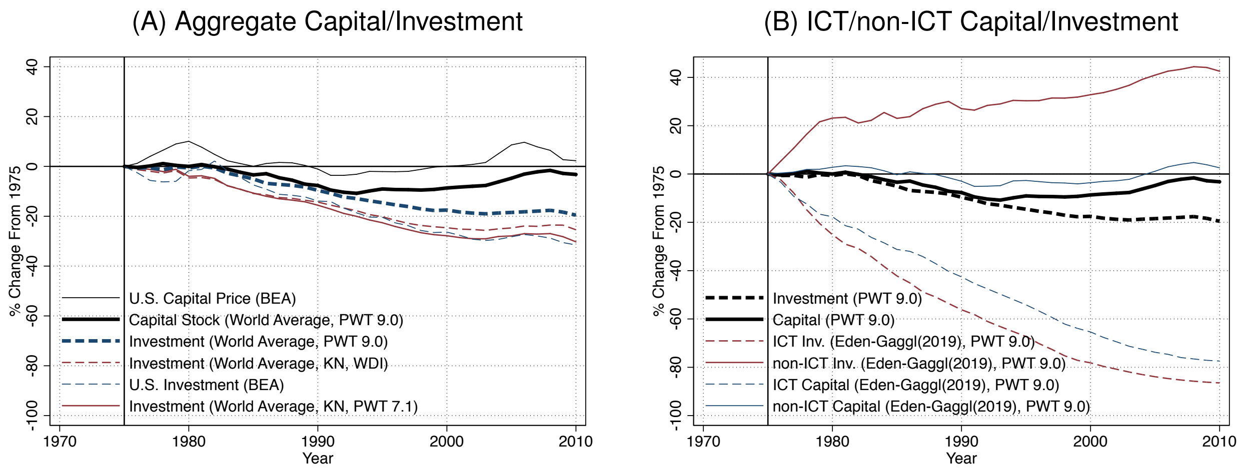
To summarize, the automation narrative in the spirit of KN relies on two important assumptions in order to explain the decline in the labor income share: first, a technological shock that results in a decline in the price of capital goods as well as a decline in the real rental rate of capital; and, second, an elasticity of substitution between capital and labor that is greater than one. The following two sections raise concerns with both of these assumptions.

3. Challenge 1: The Price of Capital

As explained in Section 2, the quantitative relevance of the automation narrative depends on the extent to which technological advances in the production of capital goods led to a decline in the price of capital. To assess this empirically, we focus on three relevant measures: the capital price, the investment price and the user cost of capital. In the aggregate model, there is no difference between capital and investment prices, and both have similar effects on the rental rate. In practice, different assets have different weights in capital, investment and rental fees.

Figure 1 documents that the price of capital has remained relatively stable since the 1970s. This challenges the view that technological advancements have made capital goods cheaper. There has, however, been some decline in the investment price (which is the focus in KN). Figure 2 is constructed in analogy to Figure 1 but adds implicit price deflators for chain indexed gross capital formation (the investment series). The difference between the investment price and the capital price may reflect different prices for different

Figure 2: Trends in Capital & Investment Prices Relative to GDP



Notes: The figure is constructed in analogy to Figure 1, adding additional data sources, as well as price indexes for gross capital formation, rather than the capital stock. In addition, panel A adds the investment price series used by KN, drawing on the World Bank's Wolrd Development Indicators (WDI) and the PWT 7.1.

vintages of capital, or systematic differences in the underlying composition of the capital stock and gross capital formation. For example, in a steady state, capital types that have higher depreciation rates will have larger weights in the investment price index than in the capital price index because they need to be replaced more often.

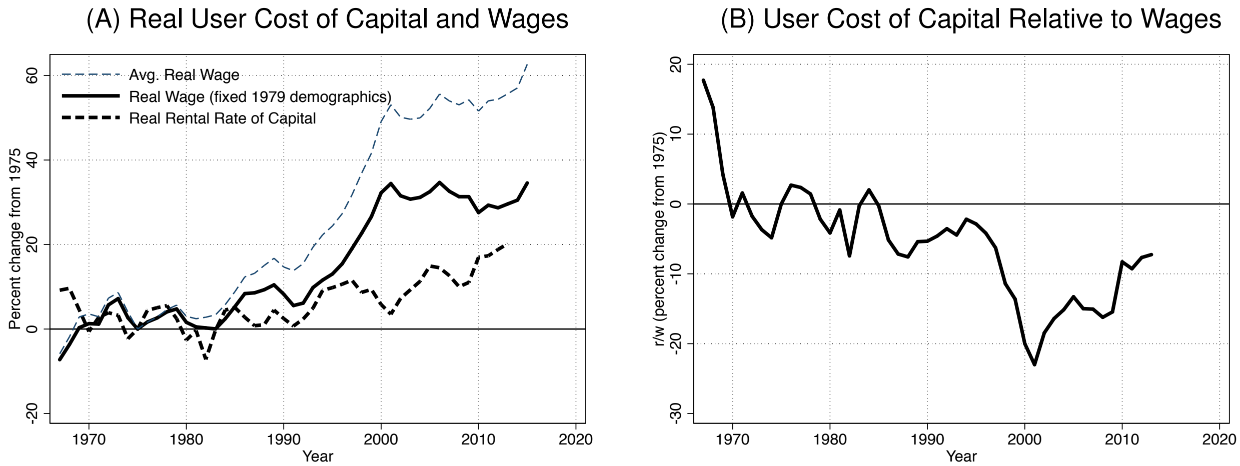
3.1. The Rental Rate of Capital

As discussed in Section 2, the automation narrative postulates that a shock to the efficiency in the production of investment goods causes both a decrease in the relative price of capital and an (endogenous) decrease in the rental rate of capital relative to wages. Note that, similar to the investment price index, the rental price index puts a larger weight on assets that have larger depreciation rates, as these assets have higher equilibrium rental fees relative to their price. The rental fees for each asset i are given by

$$r_i K_i = p_i(\bar{r} + \delta_i)K_i = \bar{r} p_i K_i + \delta_i p_i K_i \tag{11}$$

This decomposition clarifies that the weight of each asset in the rental rate index will lie somewhere between its weight in the capital index and its weight in the investment index. The first component, $\bar{r} p_i K_i$, is directly

Figure 3: The User Cost of Capital & Labor in the United States



Notes: The figure shows the rental rate of capital and the average real wage in the United States. The real wage is based on the U.S. Current Population Survey's (CPS) March supplement. We report an implicit price deflator for a labor chain index, holding fixed demographic characteristics at their 1979 level, as in Eden and Gaggl (2018), as well as the average wages, both deflated by the GDP deflator.

proportional to the capital weight, while the second component, $\delta_i p_i K_i$, is proportional to the steady state investment weight.

We estimate the aggregate rental rate of capital using the constant returns to scale property, which implies that $(1 - s_{L,t})P_t Y_t = R_t K_t$, where $s_{L,t}$ is labor's income share; Y_t is real GDP; P_t is the GDP deflator; R_t is the nominal rental rate of capital and K_t the capital stock. The constant returns to scale condition then implies that the real rental rate of capital is given by $r_t = R_t/P_t = (1 - s_{L,t})(Y_t/K_t)$.

Panel A of Figure 3 illustrates that, over the last few decades, the real rental rate of capital has been increasing. This comes in stark contrast to the mechanism envisioned in the automation narrative, according to which technological improvements in the production of capital should lead to a decline in the real rental rate (r).

However, according to the model, the change in the labor income share does not depend on the change in the rental rate (r), but rather on its change relative to the wage rate (r/w). To compute this change, we estimate the trend in wages using the U.S. Current Population Survey's (CPS) March supplements. Panel A of Figure 3 displays the resulting estimates of the real wage, alongside estimates of the real rental rate. The figure reveals that there has been an increase in wages that outpaced the increase in rental rates.

We note that the increase in the average real wage displayed in panel A may seem surprising in light of the commonly-held belief of stagnant real wages. Indeed, real wages were stagnant relative to the CPI, which is what matters for understanding the purchasing power of labor income. However, here, we are interested in the cost of labor relative to output, and therefore deflate wages using the GDP deflator, which has increased less than the CPI. In addition, we report average individual wage earnings, while many official statistics report household earnings, which have increased less than average individual wage earnings; finally, many official statistics report median wages, rather than average wages, which have increased less due to rising income inequality and a steadily rising college wage premium.

Panel B of Figure 3 illustrates a measure of the relevant price ratio for the automation narrative, r/w, using an implicit price deflator for a labor chain index based on fixed demographic bins, as displayed in panel A.[2] While this ratio has indeed declined, this decline was driven by an increase in wages rather than by a fall in rental rates.

4. Challenge 2: The Elasticity of Substitution

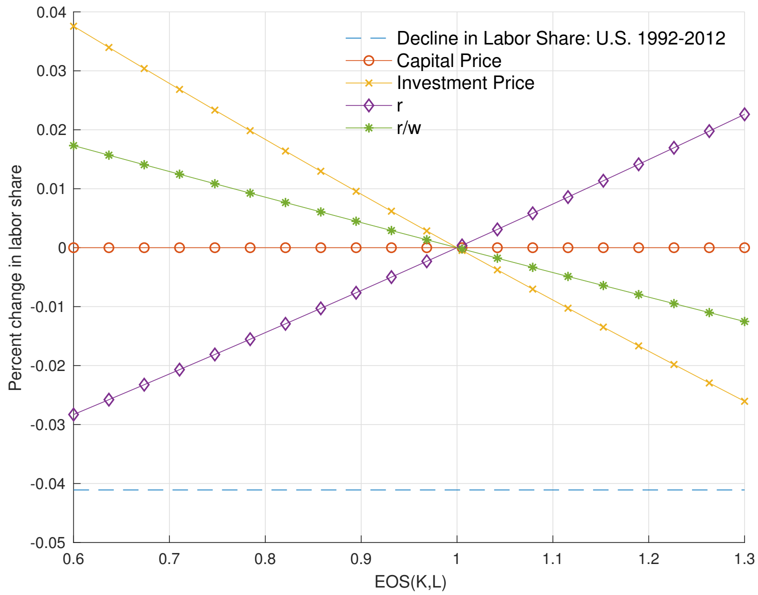
In the basic automation narrative, technological improvements in the production of capital reduce the labor share only if $EOS(K, L) > 1$. However, almost all available estimates suggest that $EOS(K, L) \leq 1$ (see for example Oberfield and Raval, 2014; Chirinko, 2008). Taken together, the automation narrative does not look promising.

Figure 4 illustrates the model's prediction for the decline in the labor income share (the percent decline in $wL/F(K, L)$), as a function of both $EOS(K, L)$ and the estimate of the price decline, p. The figure reveals that, even for a given elasticity of substitution, the prediction of the model depends crucially on the empirical interpretation of the price decline. For example, the KN specification uses the decline in investment prices and an elasticity of substitution of 1.2. With this benchmark, the model can account for a 2% decline in the labor income share in the United States—roughly half of the decline in the data.

However, if, instead, one interprets p as the capital price rather than the investment price, then the model generates no decline in the labor income share. Arguably, the most relevant measure is that of the user cost of capital (r); unfortunately, the user cost actually increases, so that, given an elasticity of substitution of 1.2, the model would actually predict an increase in the labor income share.

[2] Details for the construction of this chain index are provided in Eden and Gaggl (2018).

Figure 4: Predicted Change in the Labor Share



Notes: The figure illustrates predicted changes in the labor share based on equations (7) and (10). As a reference, we report the measured trend decline decline in the United States during the period 1992-2012, based on PWT 9.0 data reported in columns 3-5 of Table E.5 in Appendix E ($\%\Delta s_L = -2.56/62.32 \approx -0.041$).

Things look only marginally more promising if one uses the ratio of the rental rate and the wage rate (r/w), which is what directly enters the labor share calculation. In this case, the elasticity of substitution in KN generates roughly a 1% decline in the labor income share—about a quarter of the actual decline. However, one may express some unease with this result, as the trend in relative prices is driven solely by the increase in labor costs, and not by a decline in rental rates, as the model predicts.

Figure 4 also illustrates how the model's predictions are sensitive to the choice of the elasticity of substitution between capital and labor. The automation narrative requires both a decline in the price of capital and an elasticity of substitution that is greater than one. For estimates of below one, a decline in p would actually cause an increase in the labor income share. As most empirical estimates fall in this range, this presents a challenge for the automation narrative.

5. The Role of Capital Composition

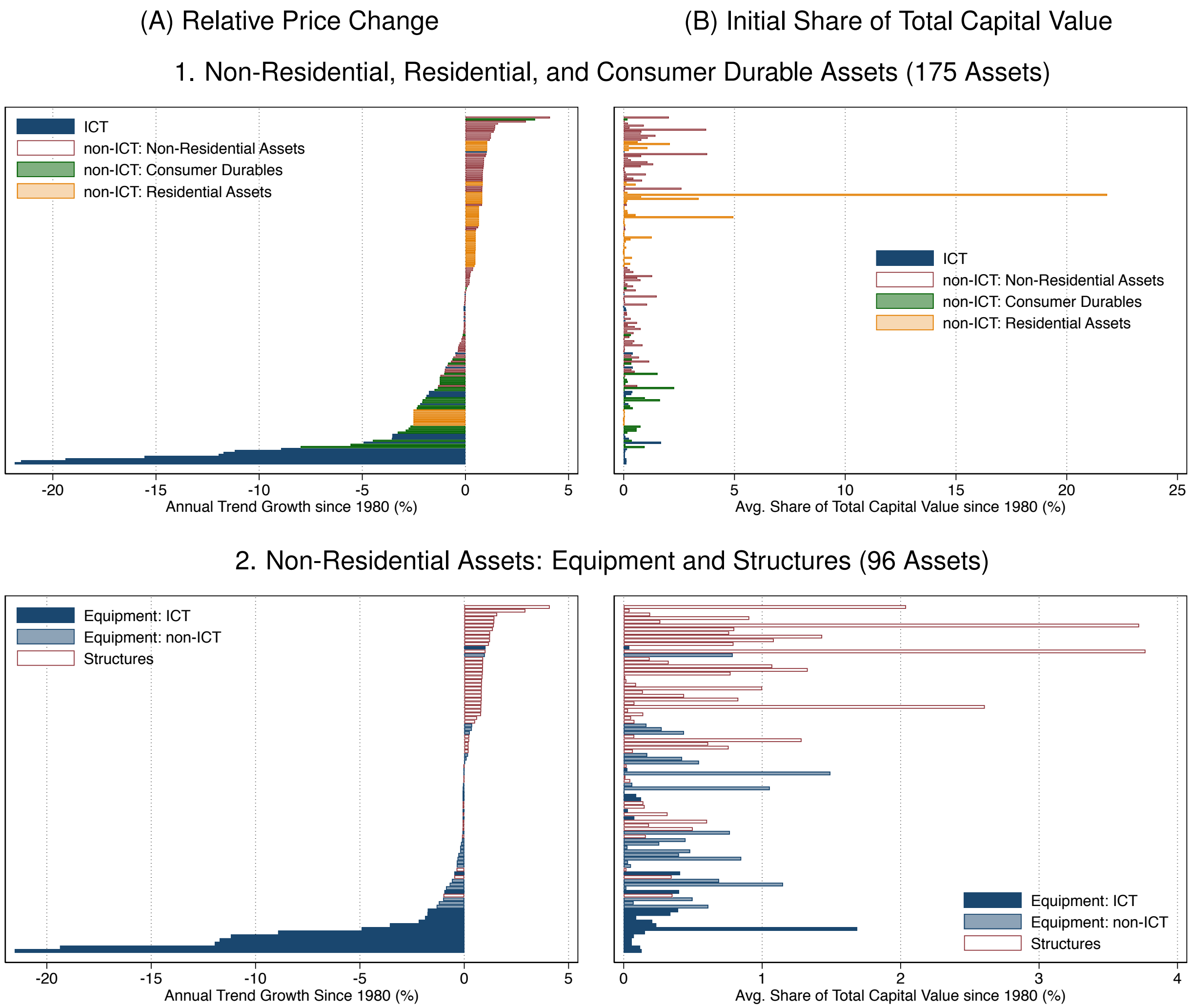
The remainder of this paper shows that augmenting the model of Section 2 to include different capital types resolves both empirical challenges discussed above. In the aggregate automation narrative, the shock to the economy is a series of technological advances in automation technology, which cause a trend decline in the rental rate of capital. However, Section 3 documents that this assertion is empirically implausible in the aggregate. In light of this concern, we document three facts: first, there is only a small set of capital assets that experienced significant trend declines in its price relative to the GDP deflator; second, this set of assets represents a small share of the aggregate capital stock; third, this small set of assets with declinig prices is primarily comprised of ICT assets.

To illustrate these facts, we begin by computing asset-specific price trends for detailed assets using data provided in the BEA fixed asset accounts, which provide annual estimates for the stock, depreciation, investment, and price of 175 assets (96 non-residential, 51 residential, and 28 consumer durables). The results are illustrated in column A of Figure 5, where annual trend growth in each asset's implicit price deflator relative to the GDP deflator is computed using a log-linear trend. The trend calculation allows us to use the longest possible asset-specific time series and still compare assets that enter or disappear from the panel throughout our sample period.

Panel 1 of Figure 5 distinguishes ICT and non-ICT assets, which are further divided into non-residential, residential, and consumer durable assets.[3] This decomposition highlights several insights: first, almost all ICT assets experienced price declines that are orders of magnitudes larger than all other assets. Moreover, non-residential, non-ICT equipment (such as industrial production machinery, etc.) did not experience notable price declines. Rather, the remaining equipment assets which experienced any price declines are consumer durables and residential equipment (such as kitchen appliances, heating furnaces, etc.). Thus, while there was some price decline in non-ICT assets, these assets are not of first order importance for production as envisioned in the automation narrative. To illustrate this point, panel 2 of Figure 5 restricts the same analysis to only the 96 non-residential assets and further illustrates the split into equipment and structures. This decomposition highlights that, from a production standpoint, ICT assets are the primary driver of any trend decline in equipment prices. In particular, notice that almost all non-residential, non-ICT

[3]The classification of ICT assets used here is described in Eden and Gaggl (2018).

Figure 5: Asset Specific Price Trends & Capital Composition in the United States (1980-2013)

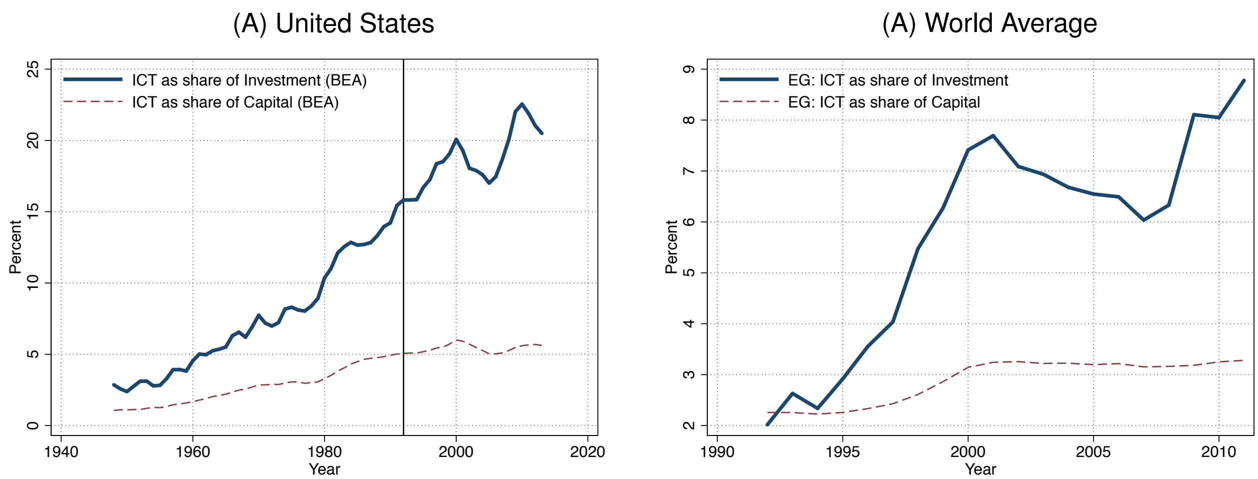


Notes: Column A shows asset specific changes in the price of capital relative to the GDP deflator, as reported in the BEA's fixed asset tables. Annual trend growth rates are based on a log-linear trend starting in 1980. Column B shows each asset's average share in the total current-cost capital value, averaged over the period 1980-2013. Assets are grouped into ICT and non-ICT equipment, as well as structures and equipment. The classification of ICT assets follows Eden and Gaggl (2018). Panel 1 lists these statistics for all 175 assets in the BEA's fixed asset tables (96 non-residential, 51 residential, and 28 consumer durables). Panel 2 restricts the set of assets to the 96 non-residential assets and distinguishes structures and equipment (ICT and non-ICT).

equipment experienced no price declines.

Figure 5 also makes clear that the relative stability of the aggregate price index, despite massive price declines in ICT equipment, is driven by the composition of the capital stock. In addition to the price trends in column A, column B shows the relative importance of each asset in aggregate capital, by reporting each

Figure 6: ICT's Share in Investment and Capital



Notes: The figure illustrates the share of ICT investment out of total investment and the value of the ICT stock out of the value of the total capital stock. Panel A reports trends based on the BEA fixed asset accounts and the vertical black line indicates 1992. Panel B uses data on ICT stocks and investment taken from Eden and Gaggl (2019), where the "world average" is respectively weighted by the capital and investment values.

asset's nominal value as a fraction of the total capital value (including residential and consumer durable assets for both panels), averaged over the period 1980-2013. This illustration immediately reveals that ICT assets comprise only a tiny share of the aggregate capital stock, and that residential structures constitute the largest share. In fact, owner occupied residential structures account for more than 20% of the aggregate capital value (see panel B of Figure 5). Thus, the mild increase in the price of structures offsets the massive declines in ICT prices, resulting in a relatively stable price of the aggregate capital stock over this period.

Moreover, this decomposition clarifies why a chain index of gross capital formation (investment) displays a larger price decline than an analogous index for the aggregate capital stock. First, ICT's share in investment is much larger than that of non-ICT and it also has increased substantially since 1980, as shown in Figure 6. In particular, as of the 1990s, ICT comprises more than 15% of total investment, while ICT barely exceeds 5 percent of the aggregate capital value. Panel B of Figure 6 illustrates that this pattern is also present around the world, though the prominence of ICT is not as dominant as it is in the United States. Second, ICT has a much larger depreciation rate (at around 21% annually by 2010) compared to non-ICT capital (which is stable at around 3% for structures and 13% for non-ICT equipment, including consumer durables) according to the BEA's estimates. This means that, in a steady state, the price of ICT capital has more weight in the investment price index than in the capital price index.

5.1. The Rental Rates of ICT and non-ICT Capital

As discussed in Section 2, declining capital prices affect the labor share through a decline in the rental rate of capital. To accomodate the disaggregated framework introduced in Section 5, we measure asset-specific rental rates using the constant returns to scale property as in Section 2 and, in addition, require that the return to investing in different assets must equalize across assets (as in Eden and Gaggl, 2018, 2019). Formally, these assumptions are summarized by the following two conditions:

$$(1 - s_{L,t})P_t Y_t = \sum_{j \in J} R_{j,t} K_{j,t} \tag{12}$$

$$\frac{R_{i,t}}{P_{i,t}} + (1 - \delta_{i,t})\frac{P_{i,t+1}}{P_{i,t}} = \frac{R_{n,t}}{P_{n,t}} + (1 - \delta_{n,t})\frac{P_{n,t+1}}{P_{n,t}} \quad \text{for all } i, n \in J \tag{13}$$

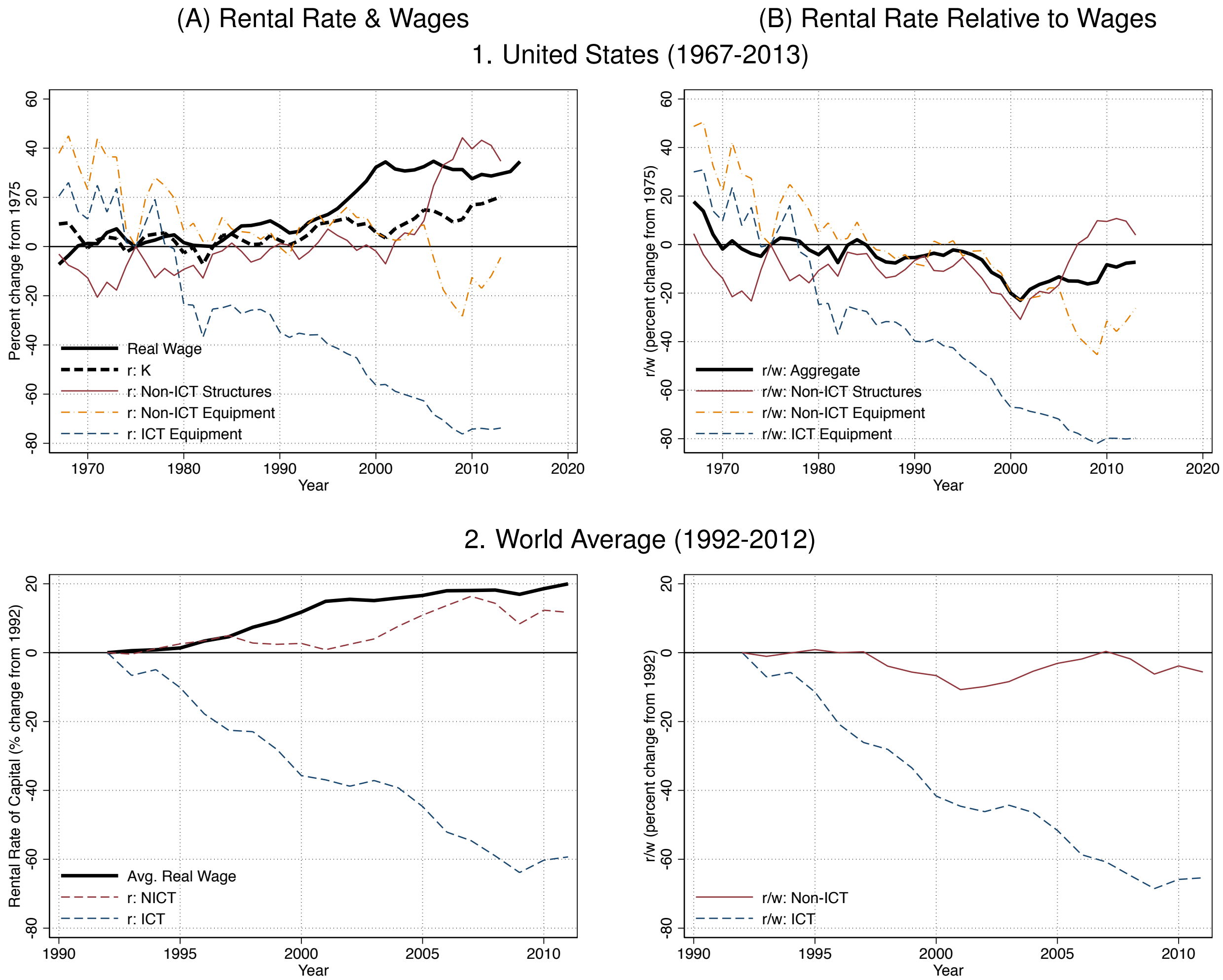
The set of available assets is denoted J, with $P_{j,t}$, $\delta_{j,t}$, and $K_{j,t}$ indicating the price, depreciation rate, and stock of asset j, respectively. $R_{i,t}$ indicates the nominal rental rate (or user cost) of asset j.[4] For each type of capital j, the above system of equations can be solved for the real rental rate, $r_{j,t} = R_{j,t}/P_t$, as a function asset specific capital stock values, $P_{j,t}K_{j,t}$, associated implicit price deflators, $P_{j,t}$, rates of depreciation, $\delta_{j,t}$, as well as the aggregate labor share $s_{L,t}$, nominal GDP, $P_t Y_t$, and the associated GDP deflator, P_t.

Two features of this measurement approach are worth emphasizing. First, it does not rely on market interest rates. This is important, as we are trying to estimate the user cost for disaggregated types of capital within a sample of more than 40 countries at various levels of development, and we are not aware of any data source that provides observed country- and asset-specific terms of financing.

Second, $R_{j,t}$ is not required to equal the marginal product of asset j. Rather, $R_{j,t}$ is the implicit user cost of asset j, which may include a (potentially time varying) markup. Thus, while our measurement approach does not rule out rents, we do assume that all rents must accrue to some factor of production, and that capital rents are proportional across different capital types. For example, if highly trained workers exploit some market power due to labor market frictions, this will be accounted for in the measured labor share.

[4] Throughout the manuscript we will use the terms user cost and rental rate interchangeably.

Figure 7: The User Cost of Various Assets & Wages



Notes: Panel 1 shows the user cost of capital for ICT equipment, non-ICT equipment, and structures, as well as the real wage in the United States, holding fixed demographic characteristics at their 1979 level following Eden and Gaggl (2018). Panel 2 shows analogous estimates for the user cost of ICT and non-ICT capital, averaged across 67 countries at various levels of development, based on data taken from Eden and Gaggl (2019). Wages in panel 2 are average annual wages (not accounting for changes in labor composition over time), computed as $w = s_L Y/L$ based on PWT 9.0 data.

Likewise, if firms have some monopsony power in labor markets that would lead to rents, then these rents will be captured as part of $R_{j,t}$ and are attributed to the owners of the respective capital stock. Put differently, any rents that are generated by some friction during the production process must ultimately be split between workers and capital owners in some way, and our measurement of $R_{j,t}$ implicitly captures the outcome of this bargaining process. We note that this procedure distributes the returns to any potentially unmeasured factors (such as consumer loyalty, reputation, etc.) across all the measured factors.[5]

For the United States, the relevant data inputs are readily available from the BEA's fixed asset accounts and NIPA, as well as the labor share form the BLS. Based on these data and the above approach, panel 1 of Figure 7 illustrates the trends for four groups of assets: aggregate capital, structures, ICT equipment, and non-ICT equipment. The figure reveals two remarkable facts: first, with the exception of the housing boom during the 2000s, the user cost of structures and non-ICT equipment displays no trend since the 1975; second, and in stark contrast, the user cost of ICT capital fell by a stunning 80% since 1975. Based on data compiled by Eden and Gaggl (2019), Panel 2 of Figure 7 illustrates remarkably similar trends for an appropriately weighted world average for the relntal rates of ICT and non-ICT, over the period 1992-2012.[6]

Finally, column B of Figure 7 plots the different rental rates relative to the wage in the in the respective country.[7] Given the sharp decline in the ICT price and the increase in wages, the rental rate of ICT relative to wages has declined by almost 80% since 1975 in the United States and by more than 60% since 1992 world wide.

6. Capital Aggregation

Section 5 establishes that virtually all of the decline in investment prices is due to ICT assets, which are at the heart of modern automation technology. In this section, we discuss how this observation invalidates the use of a production function with a single aggregate capital input.

The literature offers two general approaches for determining the appropriate level of aggregation of capital inputs, discussed in detail by Diewert (1980) and Hulten (1991). The first is due to Leontief (1947) and Shephard (1953, 1970), whose approach is based on weak separability. Loosely speaking, if several different capital inputs jointly produce an intermediate input in production (which is used, in conjunc-

[5]While our measurement exercise does not rely on any interest rate data, we note that the implied return on capital is fully consistent with independent estimates by Jordá, Knoll, Kuvshinov, Schularick and Taylor (2019). See Appendix B for a direct comparison.

[6]Reliable world wide data on ICT investment starts in 1992 and therefore the price indexes constructed by Eden and Gaggl (2019) also start in 1992.

[7]We note that the real wage in the United States is an implicit price deflator for a quantity index of labor, taken from Eden and Gaggl (2018), which fixes observable demographic characteristics at their 1979 level. Unfortunately, it is difficult construct the same quantity index for labor in many countries, due to the lack of detailed individual level surveys for a long time horizon. Instead, we impute the average, country-specific, annual real wage by using the labor share reported in the PWT 9.0 and multiplying by the ratio of real GDP to employment, i.e. $w = s_L Y/L$.

tion with labor and other capital goods, to produce the final good), then it is possible to write the aggregate production function as a function of this intermediate input and the other production inputs, rather than as a function of the distinct capital goods. Formally, if the production function for the intermediate input is $g(K_1, ..., K_m)$, then the aggregate production function can be written as $F(K_1, ..., K_n, L) = f(g(K_1, ..., K_m), K_{m+1}, ..., K_n, L)$. The intermediate input, $g(K_1, ..., K_m)$, is then interpreted as an aggregate capital input.

This approach suggests that it makes sense to aggregate capital inputs based on the type of capital services that they provide. For example, windows, floors, ceilings and electrical systems are capital goods that are combined to provide housing services, and can be aggregated into a residential housing capital good. Similarly, computer hardware and software can be aggregated into a capital good which provides computing services. The classification of capital goods according to their functionality is, to some extent, already present in the U.S. Bureau of Economic Analysis' (BEA) asset classification, which distinguishes between residential assets, non-residential assets and consumer durables, as well as between equipment and structures. However, since different capital goods play very different roles in the production process, this approach is ill-suited for motivating the use of a single capital aggregate.

The second approach for determining the appropriate level of aggregation is due to Hicks (1939). Unlike the Leontief-Shephard approach, which aggregates assets based on their role in the production process, Hicks's approach aggregates assets whose relative prices remain constant. For given rental rates, r_i with $i = 1, ..., n$, and an average rental rate of r, it is possible to write an aggregate production function with a single capital input as $F(K, L) = \max_{K_1,...,K_n} f(K_1, ..., K_n, L)$ s.t. $\sum_{i=1}^{n} \frac{r_i}{r} K_i = K$, where $f(K_1, ..., K_n, L)$ is a production function in all capital inputs. This approach arises naturally from the firm's optimization problem: for each level of labor inputs and aggregate capital payments (rK), firms should optimize with regards to how to allocate their capital spending across different capital types. Note that the aggregate production function is specified for a given vector of relative rental rates, $(r_1/r, ..., r_n/r)$. This implies that, if the relative rental rates of all capital goods are stable across time, then it is possible to write down a stable production function which treats them as a single capital aggregate—even if the weak separability condition proposed by Leontief-Shephard is violated.

The measurements in Section 5 suggest that there are substantial differences between the trends in the rental rates of ICT capital goods and non-ICT capital goods. The conditions for Hicks's aggregation theorem therefore do not hold in the data.

Consequently, neither approach can be used to motivate the use of a single capital aggregate. In what follows, we propose a modified production framework that distinguishes between ICT and non-ICT capital. We motivate the use of an ICT capital aggregate using the Leontief-Shephard approach, and the use of a non-ICT capital aggregate using Hicks's approach (see Section 8 for further detail).

7. The Correlation of Investment Price Trends and the Labor Share

KN document a cross-country correlation between the decline in investment prices and the decline in labor income shares. They interpret this cross-country correlation through the lens of a model similar to that of Section 2 and, in the spirit of equations (7) and (10), conclude that this correlation is supportive of $EOS(K, L) > 1$. In this Section, we show that this interpretation is misguided. However, we illustrate how the correlation highlighted by KN can be meaningfully interpreted in an environment with two capital goods: ICT (K_{ict}) and non-ICT (K_n). To do so, define the aggregate investment price index as

$$\zeta_t = \alpha p_{ict,t} + (1-\alpha)p_{n,t} \tag{14}$$

where $p_{ict,t}$ and $p_{n,t}$ are the relative prices of ICT and non-ICT capital, respectively, and α is the share of ICT capital in investment in a base year:

$$\alpha = \frac{p_{ict,0}I_{ict,0}}{p_{ict,0}I_{ict,0} + p_{n,0}I_{n,0}} \tag{15}$$

where $I_{j,t}$ is investment in capital of type j in year t. The percent change in the investment price between periods 0 and T is given by:

$$\begin{aligned} \hat{\zeta} &= \frac{\alpha p_{ict,T} + (1-\alpha)p_{n,T} - (\alpha p_{ict,0} + (1-\alpha)p_{n,0})}{\alpha p_{ict,0} + (1-\alpha)p_{n,0}} \\ &= \alpha\left(\frac{p_{ict,T}}{p_{ict,0}} - 1\right) + (1-\alpha)\left(\frac{p_{n,T}}{p_{n,0}} - 1\right) \\ &= \alpha\hat{p}_{ict} + (1-\alpha)\hat{p}_n \end{aligned} \tag{16}$$

Table 1: Disaggregated KN Regression

Normalized Trend in Labor share: $\hat{s}_{L,j}/(1-s_{L,0})$						
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\xi}_j$ (PWT 7.1)	0.395***					
	(0.131)					
$\hat{\xi}_j$ (WDI)		0.306**				
		(0.121)				
$\hat{\xi}_j$ (PWT 9.0)			0.209			
			(0.137)			
$\alpha_j \hat{p}_{j,ict}$				0.436		0.472
				(0.428)		(0.469)
$(1-\alpha_j)\hat{p}_{j,n}$					0.060	0.079
					(0.106)	(0.111)
Constant	-0.860	-1.528	-2.529**	-1.418	-4.046***	-1.403
	(1.362)	(1.241)	(1.226)	(2.527)	(1.070)	(2.821)
Obs.	41	41	41	41	41	41

Notes: The table shows estimates from robust regression of linearized trend changes in the labor share and linearized trend changes in aggregate investment prices (columns 1-3) as well as investment weighted ICT and NICT prices (columns 4-6). The sample only includes countries for which we have separate ICT and NICT prices and quantities. Standard errors are reported in parentheses below each coefficient and significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The discussion in Section 3 suggests that there is no trend in the non-ICT price, further implying that $\hat{\zeta} \approx \alpha \hat{p}_{ict}$. Indexing countries with j, KN estimate a parameter, σ, by regressing a normalized change in the (log) labor share ($\hat{s}_{L,j}$) on the change in aggregate investment prices, $\hat{\zeta}_j$:

$$\begin{aligned}
\frac{s_{L,j}}{1-s_{L,j}}\hat{s}_{L,j} &= \gamma + (\sigma-1)\hat{\zeta}_j + u_j \\
&= \gamma + (\sigma-1)(\alpha_j \hat{p}_{j,ict} + (1-\alpha_j)\hat{p}_{j,n}) + u_j \qquad (17) \\
&\approx \gamma + (\sigma-1)\alpha_j \hat{p}_{j,ict} + u_j \qquad (18)
\end{aligned}$$

The identification of $\sigma - 1$ comes from cross country variation in $\hat{\zeta}_j$. Without imposing $\hat{p}_{j,n} = 0$, there are two possible sources of cross-country variation in $\hat{\zeta}_j$: variation in the ICT component, $\alpha_j \hat{p}_{j,ict}$, and variation in the non-ICT component, $(1-\alpha_j)\hat{p}_{j,n}$. Based on price and investment data from Eden and Gaggl (2019), Table 1 confirms that the correlation between changes in the investment price and the labor share is effectively driven by cross-country variation in the investment share weighted ICT price.

In principle, the cross-country variation in $\alpha_j \hat{p}_{j,ict}$ can further be decomposed into variation in the investment share of ICT, α_j, and variation in the ICT price change, $\hat{p}_{j,ict}$. However, the construction of investment price indexes in the PWT (which KN use) *assumes* that the ICT price measured in the United States applies to all countries (see for example Inklaar and Timmer, 2013).[8] Consequently, when drawing on PWT price data, cross-country variation in the price decline of ICT is not a plausible source of variation; rather, the cross-country variation must come from variation in the share of ICT in the investment price, α_j.

These insights have important implications for the role of automation in explaining the global decline in the aggregate labor share. Intuitively, our decomposition of the KN regression suggests that countries which use ICT capital more intensely have experienced a larger decline in the labor income share, implying that differences in capital *composition*, rather than differences in the size of the "automation shock" are driving differences in the declining labor share. Thus, our analysis highlights that the KN correlation is therefore informative for the degree of substitutability between ICT and labor, rather than the substitutability between aggregate capital and labor. In fact, we show in the next section how this correlation can be used to calibrate $EOS(K_{ict}, L)$ in a generalized version of the model from Section 2, in which we distinguish between ICT and non-ICT capital.

8. Quantitative Implications

The remainder of this paper is devoted to illustrate that cross-country differences in the composition of capital, rather than variation in the size of the automation shock, is the key to understanding the role of automation for the world-wide decline in the labor share. In particular, we highlight the quantitative importance of the intensity with which different countries utilize ICT in production as a key driver for differences in the decline of the labor share around the world.

We consider a production framework with two capital inputs: ICT capital and non-ICT capital. We appeal to the Leontief-Shephard approach to motivate the use of an ICT capital aggregate: software and hardware are combined to produce computational services, which are an intermediate input in production.

[8] While it is difficult to test this assumption empirically due to data limitations on detailed price data, Eden and Gaggl (2019) provide some suggestive evidence based on item level price data from the World Bank's International Comparison Program (ICP), which is also the underlying data source for price data in the PWT.

To motivate the use of a non-ICT capital aggregate, we appeal to Hicks's approach. The question that we are trying to address is, how have advances in the production of ICT assets affected the labor income share? For the purpose of answering this question, we are interested in isolating the effects of the decline in the prices of ICT assets, *holding the prices of other capital goods constant*. In this hypothetical exercise, Hicks's condition applies, as the relative rental rates of non-ICT capital goods are assumed to remain constant over time.

We consider a nested CES production function for output Y_j in country j:

$$Y_j = (\eta_j K_{n,j}^{\theta} + (1-\eta_j)(\gamma_j K_{ict,j}^{\sigma} + (1-\gamma_j)L_j^{\sigma})^{\frac{\theta}{\sigma}})^{\frac{1}{\theta}} \tag{19}$$

In this specification, there are two parameters that are common across countries: σ and θ. That is, we postulate that the fundamental substitutability between ICT capital and labor (goverend by σ) as well as the degree of substiution between non-ICT capital and the ICT-labor composite (goverend by θ) is fixed across countries. In contrast, parameters $\eta_j, \gamma_j \in [0,1]$ are country-specific, and generate cross-country variation in (a) the labor share and (b) the ICT share.

The remainder of the model is analogous to that of Section 2 with the exception of capital accumulation, which now distinguishes between assets $K_{i,j}$, for $i \in \{ict, n\}$:

$$\begin{aligned} K_{i,j} &= (1-\delta_i)K_{i,j} + I_{i,j} && (20) \\ I_{i,j} &= A_i X_{i,j} = (1/p_i)X_{i,j} && (21) \end{aligned}$$

where the production of investment goods $I_{i,j}$ is governed by the asset-specific productivity parameter A_i, which is assumed to be common across countries. This productivity parameter determines the relative price of capital type i, denoted p_i. Importantly, this setup implies that cross country variation in the labor share is generated from differences in capital composition (through variation in η_j and γ_j), as suggested by the reduced form correlation from Section 7.

8.1. Calibration

We jointly calibrate the parameters of the model by performing a moment matching exercise with the following intuition: we choose η_j and γ_j to match the county-specific labor income shares and the ICT-capital income shares at the initial steady state; the initial capital stocks, $K_{n,j}$ and $K_{ict,j}$, are calibrated to match a common steady state rate of return of $1 + \bar{r}^{ss}$ (normalizing $L_j = 1$); we calibrate σ by targeting the coefficient in KN, and, finally, θ is calibrated to match the aggregate EOS in the United States (see Appendix D for details on the calculation of the aggregate EOS in a production framework with multiple capital inputs).

The necessary data for this calibration strategy are readily available from the various data sources used throughout this paper: we take the corporate labor share form KN; the ICT share from the TED; ICT investment shares from Eden and Gaggl (2019); and the implied rates of return from our measurement exercise as displayed in Figure B.10 in Appendix B.

We calculate the model-implied value for the aggregate $EOS(K, L)$ in the United States based on the initial steady state, by estimating the change in the aggregate capital-labor ratio induced by a small, common increase in the rental rates of capital relative to labor. The capital-labor ratio is defined based on a fixed-weight index of ICT and non-ICT capital, as in equation (D.8). For the target value of $EOS(K, L)$, we consider a large range of elasticities, corresponding to the range of empirical estimates (e.g., Oberfield and Raval, 2014; Chirinko, 2008). Interestingly, the quantitative results regarding the effects of automation on the labor income share are insensitive to this target.

To calculate the model-implied coefficient in KN, we calibrate the steady state labor income shares and the steady state investment prices in each country, given the initial and final ICT capital prices. As our model focuses on the effect of changes in the ICT prices, our calibration ignores any changes in non-ICT capital prices. In addition, following the construction of the PWT investment data that is used in KN, we assume that the change in the ICT capital price is common across countries (Inklaar and Timmer, 2013). Consequently, in our model, cross-country differences in the share parameters γ_j and η_j are the only sources of variation in the changes in investment prices ($\hat{\zeta}_j$). Cross-country differences in γ_j and η_j generate cross-country differences in α_j, as in equation (18).

We solve for the model's parameters using a simple grid search. Given that ICT represents a small

Table 2: Calibration

A. Fixed parameters	Value	Source
$\bar{r}^{ss}$	0.0693	return implied by equations (12) and (13). See Figure B.10.
δ_n	0.02	Eden and Gaggl (2019)
δ_{ict}	0.35	Eden and Gaggl (2019)
B. Calibrated parameters	Value or range	Target
σ	0.24	KN coefficient (0.28479)
θ	-0.4 – 0.3	$0.6 \leq EOS(K,L) \leq 1.3$
γ_j	0.03 – 0.1	ICT income shares (TED)
η_j	0.2 – 0.46	Labor income shares (KN+PWT 9.0)

Notes: The table shows ranges for fixed and calibrated parameters. See the text for details.

share of aggregate income, our initial guess sets the elasticity of substitution between aggregate capital and labor equal to the elasticity of substitution between non-ICT capital and the CES aggregate of labor and ICT capital (governed by the parameter θ). Table 2 summarizes our baseline calibration results. It is worth highlighting that, although we target only the EOS between aggregate capital and labor in the United States, the calibration suggests that the there are only minuscule differences across countries in the elasticity of substitution.

To gain some intuition for our identification strategy, it is useful to observe that, around the benchmark in which $\theta = 0$ (and thus $Y_j = K_{n,j}^{\eta_j}(\gamma_j K_{ict,j}^{\sigma} + (1-\gamma_j)L_j^{\sigma})^{\frac{1-\eta_j}{\sigma}}$), there is a local monotone relationship between each parameter and a target moment. A higher η_j implies a higher income share for non-ICT capital, and thus a lower labor income share. Note that when γ_j is small and $\theta = 0$, the production function is approximately the standard Cobb-Douglas production function, $K_{n,j}^{\eta_j}L_j^{1-\eta_j}$; in this case, a higher labor income share maps into a lower η_j.

In this benchmark case, the parameter γ_j is positively related to the share of ICT capital income. To see this, note that, in our the benchmark case in which $\theta = 0$, the marginal product of ICT capital is given by:

$$\frac{\partial Y_j}{\partial K_{ict,j}} = (1-\eta_j)\gamma_j K_{n,j}^{\eta_j}(\gamma_j K_{ict,j}^{\sigma} + (1-\gamma_j)L_j^{\sigma})^{\frac{1-\eta_j}{\sigma}-1} K_{ict,j}^{\sigma-1} \tag{22}$$

Thus, the ICT capital income share is given by:

$$\frac{\frac{\partial Y_j}{\partial K_{ict,j}} K_{ict,j}}{Y_j} = (1-\eta_j)\frac{\gamma_j K_{ict,j}^{\sigma}}{\gamma_j K_{ict,j}^{\sigma} + (1-\gamma_j) L_j^{\sigma}} \tag{23}$$

It is straightforward to show that the above expression is increasing in γ_j, at least holding $K_{ict,j}$ fixed. A higher γ_j will imply a higher steady state ICT capital stock, $K_{ict,j}$; if $\sigma > 0$ (as we have in our calibration), this would imply an even-higher ICT capital income share. This suggests a monotone relationship between the parameter γ_j and the steady-state ICT-capital income share.

Locally, the parameter θ is monotonically related to the elasticity of substitution between aggregate capital and labor (that is, for given capital stocks and given parameters γ_j, η_j and σ). To illustrate this, it is useful to go back to the benchmark of $\gamma_j = 0$ (and thus $Y_j = K_{n,j}^{\eta_j} L_j^{1-\eta_j}$) and relax the parametric restriction of $\theta = 0$. In this case, the production function becomes $Y_j = (\eta_j K_{n,j}^{\theta} + (1-\eta_j) L_j^{\theta})^{\frac{1}{\theta}}$. When $\gamma_j = 0$, the elasticity of substitution between aggregate capital and labor is the same as the elasticity of substitution between non-ICT capital and labor, which is positively related to θ in this standard CES framework. Given that the income shares of ICT capital are small, our estimates suggest small values of γ_j, which maintain the monotone relationship between θ and the elasticity of substitution between aggregate capital and labor.

Finally, around the benchmark of $\theta = 0$, there is a monotone relationship between the parameter σ, which governs the elasticity of substitution between ICT and labor, and the regression coefficient reported in KN. A larger σ implies a larger elasticity of substitution between ICT-capital and labor; thus, when σ is larger, the decline in the ICT price (which is the same across countries) will generate a larger drop in the ratio of the labor income share and the ICT income share. As the share of non-ICT capital is constant when $\theta = 0$, this would imply a larger drop in the labor income share out of output. Consequently, at the benchmark in which $\theta = 0$, countries that use ICT more intensely (higher γ_j) will experience larger drops in their labor income shares, and the magnitude of the coefficient will be increasing with σ.

As illustrated by Table 1, the positive relationship between the change in the labor income share and the change in the investment price is primarily driven by cross-country variation in the ICT share of investment. Countries that use ICT more intensely experience a larger drop in the labor income share. The magnitude is informative of the substitutability between ICT and labor. For example, if $\theta = \sigma = 0$, then there should be no relationship between the investment price decline and the decline in the labor income share: the KN

Table 3: The Impact of Falling ICT Prices on the Labor Share

	GDP (% of total)	$\frac{s_{ICT}}{s_{NICT}}$	Trend Decline in the Labor Share: 1992 to 2012 — Data 1992	Data 2012	Data Δ	Model 1992	Model 2012	Model Δ	% Explained
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
United States	30.32	10.89	62.31	59.75	-2.56	62.42	61.31	-1.11	43.37
Weighted World Avg.		9.81	60.64	57.20	-3.44	60.81	59.73	-1.08	26.98

Notes: The table shows the results from country specific calibrations, averaged across a range of values for $0.6 \leq EOS(K, L) \leq 1.3$. The figures for columns 3 - 9 are based on log linear trends, constructed as in KN. Trend changes here cover a 20 year period: 1992 to 2012. GDP and ICT shares are measured in 1992, the first year with reliable, world wide ICT expenditure data (Eden and Gaggl, 2019). ICT and NICT shares are taken from the Total Economy Database (TED). GDP is taken from the Penn World Table 9.0 (PWT9.0). Column 9 shows the fraction of the declining labor share, that is explained by falling ICT prices. Countries are sorted in descending order by their ICT intensity, measured as the ratio of ICT to non-ICT share s_{ICT}/s_{NICT} based on TED data. Country-specific results underlying the weighted world average are reported in Table E.5 in Appendix E.

regression coefficient would be 0. If, instead, $\sigma > 0$ (and $\theta = 0$), then ICT and labor are substitutes, and we would expect a positive relationship between ICT intensity and the decline in the labor income share.

The calibrated value of σ is insensitive to the choice of θ. This suggests that the cross-country correlation between falling investment prices and falling labor shares is highly informative of the elasticity of substitution between ICT capital and labor, but not very informative of the elasticity of substitution between aggregate capital and labor.

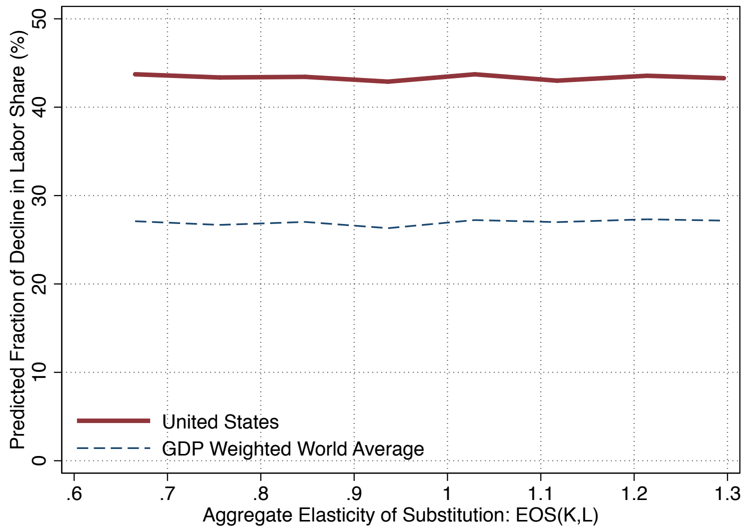
8.2. The Automation Narrative Revisited

Using the calibrated parameters, we can comment on the effect of the declining ICT price on labor income shares. Table 3 and Figure 8 summarize the results based on our sample of countries with sufficient data.[9] While Table 3 reports averages across different values for $EOS(K, L)$, Figure 8 highlights that the predictions for the decline of the labor share are not sensitive to this value.

For the United States, the model suggests that the decline in the price of ICT capital can account for roughly a one percentage point decline in the labor income share, accounting for about 40% of the actual trend decline over the period 1992 to 2012. While the results vary across countries (see Table E.5 in Appendix E) our calibration predicts that, on average, the decline in the price of ICT assets accounts for roughly 40% of the decline in the U.S. labor share and for more than one quarter of the decline in the global labor

[9] Country specific results are reported in Table E.5 in the Appendix E.

Figure 8: The Role of the Aggregate Elasticity



Notes: The figure shows the portion of the labor share predicted by the model, for calibrations with a range of different values for $EOS(K, L)$.

income share.

We note that the results for the decline of the labor share in the United States are roughly in line with other estimates from models that additionally disaggregate labor (Eden and Gaggl, 2018; vom Lehn, 2019). This suggests that distinguishing between different types of labor may be less quantitatively relevant than distinguishing between different types of capital for assessing the effects of automation on the decline in the aggregate labor share. Of course, distinguishing between different labor inputs remains absolutely necessary for understanding the differential effects of automation on different types of labor.

9. Concluding Remarks

According to the automation narrative, a decline in the price of capital led to a the replacement of workers with machines, and a subsequent decline in the labor income share. This paper begins by laying out two challenges to this view: first, the mechanism requires an elasticity of substitution between capital and labor that is substantially greater than one, while most empirical estimates are below or close to one. Second, while the automation narrative focuses on the decline in the price of capital, we estimate that the price of capital relative to output has remained roughly constant. While there has been a decline in the price of capital relative to labor, this decline has been driven entirely by a rise in the cost of labor.

We proceed by illustrating how a more nuanced view of the production structure can reconcile the automation narrative with these empirical regularities. To capture the effects of automation, it is necessary to distinguish between ICT and non-ICT capital. While the aggregate price of capital has remained roughly constant, the price of ICT capital (which constitutes a relatively small share of aggregate capital) has declined sharply. Furthermore, even if the elasticity of substitution between aggregate capital and labor is below one, ICT-capital is likely much more substitutable with labor. Our calibration suggests that, in this more nuanced framework, automation accounts for roughly 40% of the decline in the labor income share in the United States and explains more than one quarter of the decline in the global labor share.

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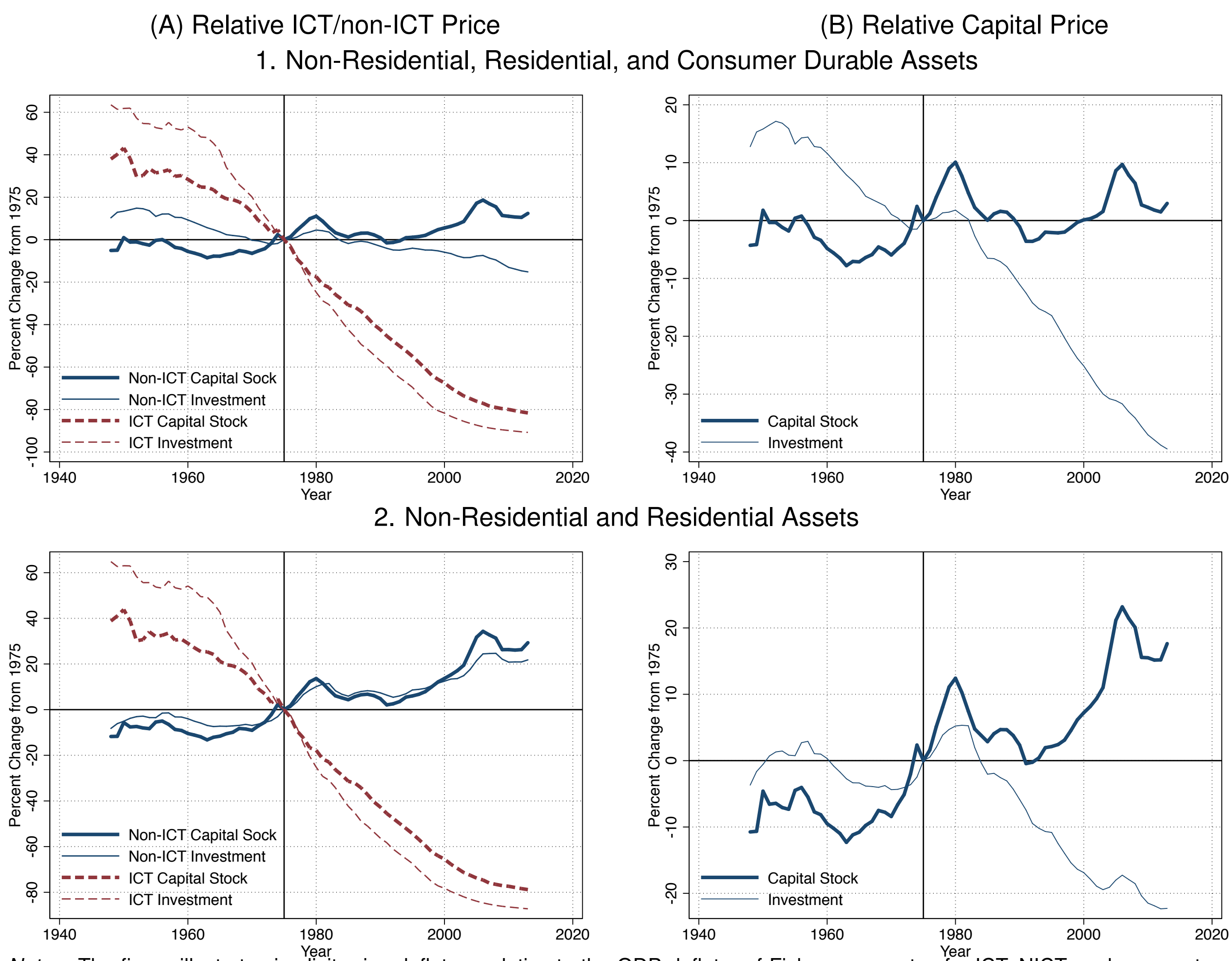
Appendix A. Relative Prices of ICT and NICT in the United States

Figure A.9 plots the relative price of ICT and non-ICT Fisher aggregates (both for the capital stock and for investment) based on the same underlying data as Figure 5. Panel 1 includes all groups of assets, while panel 2 drops consumer durable assets. Column A reports the ICT and non-ICT aggregates, while column B plots the corresponding overall national aggregates. The ICT aggregate is unaffected by the inclusion of consumer durables, yet consumer durables have a notable impact on the trend in the aggregate price index.[10] As illustrated in Figure 5, this is because consumer durables are essentially the only type of non-ICT equipment with a trend decline in its relative price. In contrast, the remaining non-ICT assets (including essentially all non-residential equipment) show a mild trend increase.

While data limitations prevent a detailed asset decomposition for many countries, it is feasible to construct the ICT and non-ICT aggregates in a sample of 67 countries at various levels of development (Eden and Gaggl, 2019). Details for the data construction are provided by Eden and Gaggl (2019) and we report the trends of appropriately weighted world averages for the relative price of ICT and non-ICT assets in panel B of Figures 1 and 2, as well as the share of ICT in capital and investment in panel B of Figure 6. The resulting trend estimates are remarkably similar to those of our BEA based estimates for the U.S. We note that the PWT 9.0 does not include consumer durables in their capital stock estimations explaining the slightly stronger trend increase relative to the BEA based estimates for the U.S. in panel A of Figure 1. Reassuringly, the PWT 9.0 trend is consistent with BEA based estimates reported in panel 2 of Figure A.9, which exclude consumer durables.

[10] We note that there are two consumer durable assets that are included in ICT: consumer owned PCs and accessories, as well as computer software. While both of these assets have very large price declines, it turns out that these two assets alone do not visibly affect the aggregate trends.

Figure A.9: Aggregate Price Trends in the United States

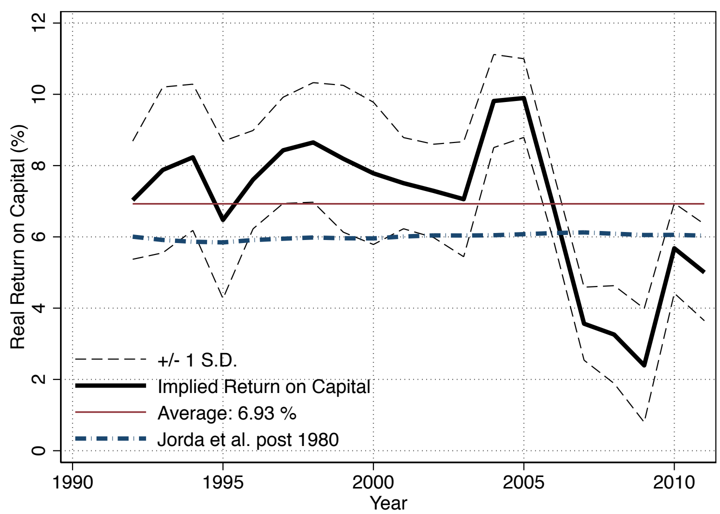


Notes: The figure illustrates implicit price deflators relative to the GDP deflator of Fisher aggregates for ICT, NICT, and aggregate capital stocks based on the BEA's fixed asset tables. Panel 1 shows non-residential, reseidential and consumer durable assets; panel 2 removes consumer durables as in the PWT 9.0. Assets are grouped into ICT and non-ICT assets following Eden and Gaggl (2018).

Appendix B. Return to Capital

Figure B.10 reports the implied real return on capital $\bar{r}$, associated with the measurement of rental rates discussed in Section 5.1, and compares it to independent estimates by Jordá et al. (2019). Reassuringly, the Jordá et al. (2019) estimate for the average return "on everything" post 1980 lies within one standard deviation of our estimates for the majority of the sample.

Figure B.10: Return to Capital Around the World



Notes: The figure reports the implied return to capital, r, and compares it to more direct estimates by Jordá et al. (2019). Data for 67 countries at various levels of develpment are taken from Eden and Gaggl (2019)

Appendix C. Replication of KN

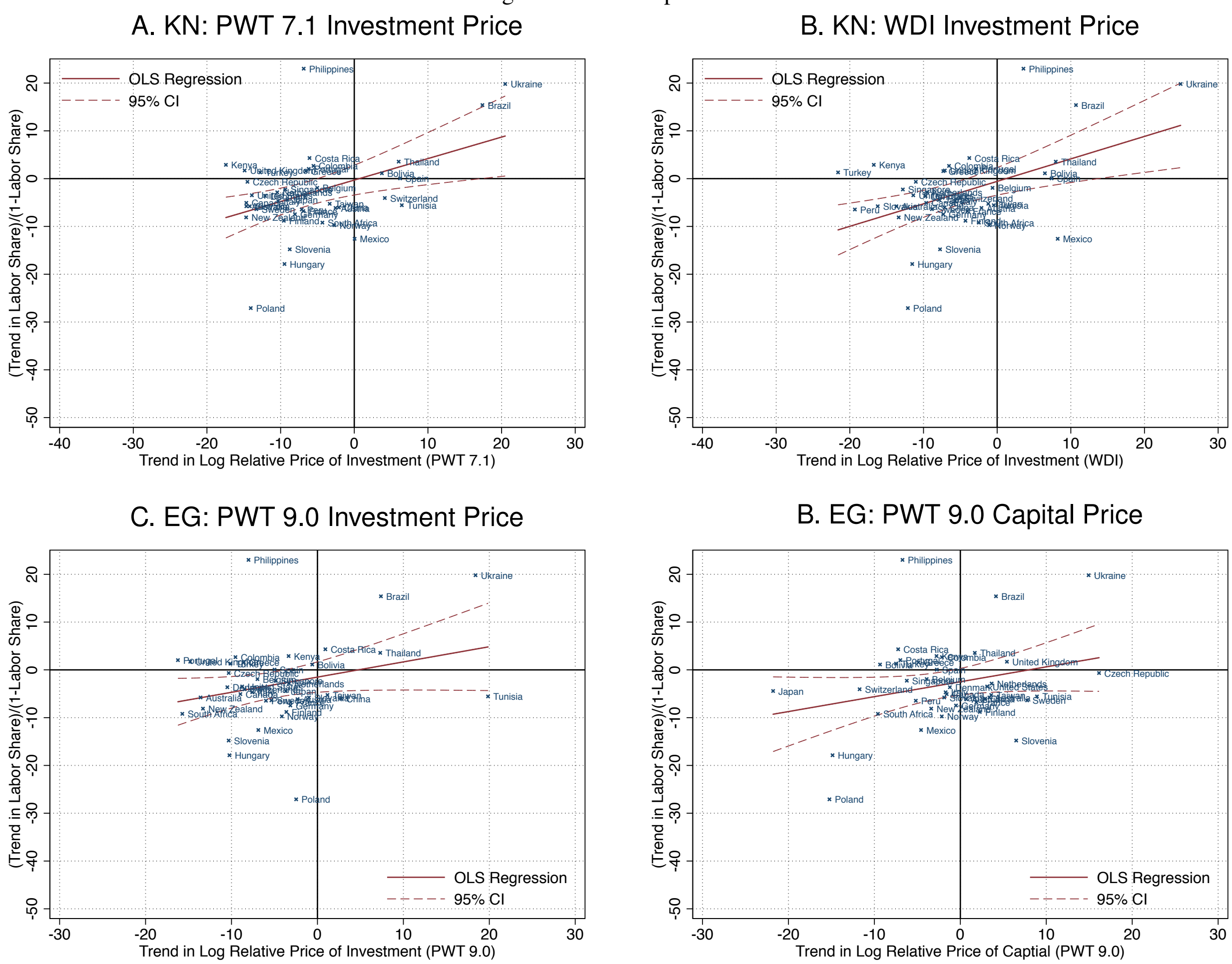
This appendix replicates the main regression results and figures in KN based KN's revised dataset as well as more recent PWT 9.0 data.

Table C.4: Replication of the KN Regression

Normalized Trend in KN Corporate Labor Share: $\hat{s}_{L,j}/(1-s_{L,0})$				
	OLS	Robust Reg.	OLS	Robust Reg.
	(1)	(2)	(3)	(4)
$\hat{\xi}_j$ (PWT 7.1)	0.280***	0.234***		
	(0.102)	(0.080)		
$\hat{\xi}_j$ (WDI)			0.341***	0.309***
			(0.078)	(0.075)
Constant	-2.060	-2.295**	-1.941*	-1.817*
	(1.321)	(1.133)	(1.108)	(1.009)
Obs.	54	57	53	55

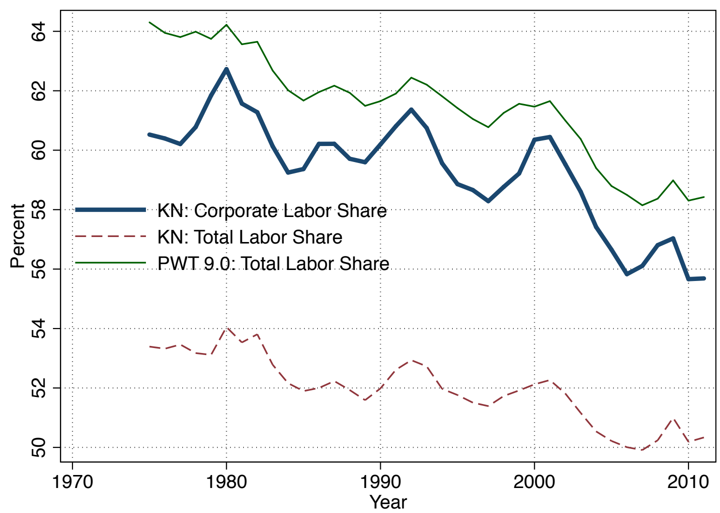
Notes: The table shows regressions of linearized trend changes in the labor share and linearized trend changes the log investment price as in KN. The data used are the revised dataset provide by KN. As in KN, we drop Kazakhstan, Kyrgyzstan, and Niger for the OLS specifications (but not for the robust regressions). For the WDI specification we further drop Bahrain as it does not have 15 years of WDI price data. Robust standard errors are reported in parentheses below each coefficient and significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Figure C.11: KN Specification



Notes: The Figure shows the KN specification for different data sources. The trend is calculated for countries with at least 15 years of data and starts in 1992 (rather than 1975), the first year for which we have international data on ICT investments and ICT shares.

Figure C.12: The Aggregate Labor Share Around The World



Notes: The Figure shows measures of the world average labor share in different international datasets: KN, PWT 7.1, PWT 9.0. All labor share figures are constructed in analogy to KN, based on panel regressions with time and country fixed effects.

Appendix D. The elasticity of substitution between aggregate capital and labor in the presence of multiple capital inputs

We formalize the notion of the elasticity of substitution between aggregate capital and labor within a framework that distinguishes between many differentiated capital inputs.

Consider an aggregate production function of the following form:

$$Y = F(L, K_1, ..., K_n) \tag{D.1}$$

where F exhibits constant returns to scale, L denotes labor inputs and $K_1, ..., K_n$ are n types of capital inputs. Factors are paid their marginal products. Using w to denote the real wage rate, this implies that:

$$\frac{\partial F(L, K_1, ..., K_n)}{\partial L} = w \tag{D.2}$$

Similarly, using r_i to denote the real rental rate of capital of type i, this implies that

$$\frac{\partial F(L, K_1, ..., K_n)}{\partial K_i} = r_i \tag{D.3}$$

Note that the above equations constitute a system of $n + 1$ equations, each equalizing the marginal product of a factor of production with its price. Given the constant returns assumption, it holds that

$$\frac{\partial F(1, \frac{K_1}{L}, ..., \frac{K_n}{L})}{\partial L} = w \text{ and, for every } i, \frac{\partial F(1, \frac{K_1}{L}, ..., \frac{K_n}{L})}{\partial K_i} = r_i \tag{D.4}$$

Thus, we have n unknowns corresponding to the capital-labor ratios $\kappa_1, ..., \kappa_n = K_1/L, ..., K_n/L$, and $n+1$ equations. Dividing through by the labor equation, we can rewrite the system as a system of n equations and n unknowns, using the following n equations corresponding to the different capital types, i:

$$\frac{\frac{\partial F(1,\kappa_1,...,\kappa_n)}{\partial K_i}}{\frac{\partial F(1,\kappa_1,...,\kappa_n)}{\partial L}} = \frac{r_i}{w} \equiv \rho_i \tag{D.5}$$

where we denote the rental rate of capital relative to wages as $\rho_i \equiv \frac{r_i}{w}$.

Given the ratios $\rho_1, ..., \rho_n$, there is a unique solution for the capital-labor ratios $\kappa_1, ..., \kappa_n$. Explicitly, let $\kappa_1^*(\rho_1, ..., \rho_n), ..., \kappa_n^*(\rho_1, ..., \rho_n)$ denote the solution to the system of equations given the relative prices $\rho_1, ..., \rho_n$. The elasticity of substitution between labor and capital of type i, denoted $EOS(K_i, L)$, is defined as the percent change in κ_i induced by a percent change in ρ_i, holding the ratios $\{\rho_1, ..., \rho_n\} \setminus \{\rho_i\}$ constant:

$$EOS(K_i, L) = -\frac{\partial \ln(\kappa_i^*(\rho_1, ..., \rho_n))}{\partial \ln(\rho_i)} \tag{D.6}$$

Note that changing ρ_i changes the entire solution to the system of equations; thus, a change in ρ_i not only affects κ_i but all of the ratios $\kappa_1, ..., \kappa_n$. However, the definition of the elasticity of substitution focuses only on the change in κ_i.

It is worth noting at this point that, as discussed by Blackorby and Russell (1989), the original Hicksian definition for the elasticity of substitution is defined only for two factors of production and there is some ambiguity in richer frameworks. The above definition characterizes the elasticity of substitution between arbitrary pairs of inputs in a framework with any number of production factors.

We next characterize the elasticity of substitution between aggregate capital and labor in this framework. To do so, it is useful to introduce the notation $\beta_i = p_i K_i / \sum_{j=1}^n p_j K_j$, where p_i is the relative price of capital of type i, and β_i denotes the expenditure share of capital type i out of the total expenditure on capital inputs. The aggregate capital stock is then given by the quantity index $K = \sum_{i=1}^n \beta_i K_i$. The capital labor index is denoted $\kappa = K/L$. Using r to denote the market interest rate, and in analogy to the aggregate model in Section 2, p_i is related to the rental rate r_i through the no-arbitrage relationship

$$r_i = p_i(\bar{r} + \delta_i) \tag{D.7}$$

Thus, again in analogy to the aggregate model in Section 2, the ratio $\rho_i \equiv \frac{r_i}{w}$ will respond to changes in p_i.

The system of n equations and n unknowns given by equation (D.5) implies a mapping between the relative prices $\rho_1, ..., \rho_n$ and the relative quantities $K_1/L, ..., K_n/L$. Fixing the weights β_i, this implies a mapping between $\rho_1, ..., \rho_n$ and the ratio $\kappa = K/L = \sum_{i=1}^n \beta_i K_i/L = \sum_{i=1}^n \beta_i \kappa_i$. Thus, we can write $\kappa^*(\rho_1, ..., \rho_n) = \sum_{i=1}^n \beta_i \kappa_i^*(\rho_1, ..., \rho_n)$. Using this notation, the elasticity of substitution between aggregate capital and labor is defined as the percent change in $\kappa^*(\rho_1, ..., \rho_n)$ induced by a uniform change in $\rho_1, ..., \rho_n$:

$$EOS(K, L) = -\frac{\partial \ln(\kappa^*(\zeta\rho_1, ..., \zeta\rho_n))}{\partial \ln(\zeta)}|_{\zeta=1} \tag{D.8}$$

Note that the derivative with respect to ζ (at the point $\zeta = 1$) corresponds to a uniform percent increase in the prices of capital relative to labor, without changing the relative prices of the different capital types. To see this, notice that, for every $\zeta > 0$, $(\zeta\rho_i)/(\zeta\rho_j) = (\zeta r_i/w)/(\zeta r_j/w) = r_i/r_j$. It is natural to define the elasticity of substitution between capital and labor based on a proportional increase in the price of capital, given that a proportional increase in the price of capital is equivalent to a decrease in the price of labor, holding capital prices fixed. Thus, this is the only way to define the elasticity of substitution in a way that maintains symmetry, a key property of the Hicksian definition for the elasticity of substitution (Blackorby and Russell, 1989).

Note that this definition holds the weights $\beta_1, ..., \beta_n$ fixed. This is because κ is a fixed-weight index of different capital types, where the weights correspond to the initial expenditure weights. Of course, a change in ζ may induce changes in the expenditure weights on different capital types; however, the aggregation of the different capital types into the aggregate capital stock will depend on the initial weights of the different capital types in the aggregate quantity index. In other words, we are not making an assumption that expenditure shares remain constant; rather that the aggregation procedure holds the weights fixed. Since the elasticity of substitution is computed based on a an infinitesimally-small price change, re-adjusting the weights is unnecessary for this computation.

Appendix E. Detailed Country-Specific Calibration Results

Table E.5: Calibration Results

	GDP (% of total)	$\frac{s_{ICT}}{s_{NICT}}$	Trend Decline in the Labor Share: 1992 to 2012						% Explained
			Data			Model			
			1992	2012	Δ	1992	2012	Δ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weighted Avg.		9.81	60.64	57.20	-3.44	60.81	59.73	-1.08	26.98
Thailand	0.52	21.55	32.24	37.21	4.97	32.49	29.54	-2.94	-59.26
Switzerland	1.28	17.91	69.17	66.55	-2.62	69.24	67.75	-1.49	56.94
Spain	3.04	11.77	61.53	61.56	0.04	61.42	60.33	-1.09	
Japan	17.59	11.66	60.50	57.09	-3.41	60.50	59.13	-1.38	40.38
Germany	10.16	10.95	65.04	59.86	-5.18	64.98	63.87	-1.11	21.38
United States	30.32	10.89	62.31	59.75	-2.56	62.42	61.31	-1.11	43.37
Slovenia	0.06	10.82	73.55	64.10	-9.44	73.58	72.74	-0.84	8.86
Philippines	0.26	10.72	26.14	33.98	7.84	28.84	27.00	-1.83	-23.38
Czech Republic	0.16	10.68	53.49	52.87	-0.62	53.63	52.12	-1.51	
Austria	0.95	10.45	60.38	55.14	-5.24	60.45	59.29	-1.16	22.10
Netherlands	1.67	10.34	61.03	58.81	-2.22	61.21	60.21	-1.00	44.79
Sweden	1.32	9.69	63.92	59.35	-4.57	63.84	62.50	-1.33	29.14
Denmark	0.71	9.51	63.66	61.03	-2.64	63.52	62.44	-1.08	40.89
Taiwan	1.01	9.32	56.28	51.72	-4.55	56.17	55.11	-1.06	23.35
Belgium	1.16	9.14	63.96	62.56	-1.40	64.07	63.02	-1.06	75.33
Australia	1.46	9.11	57.37	52.63	-4.74	57.34	56.21	-1.13	23.78
France	6.64	8.42	67.37	63.05	-4.32	67.45	66.42	-1.03	23.89
Canada	2.69	8.30	59.51	55.53	-3.99	59.33	58.53	-0.80	20.09
Portugal	0.52	7.91	59.85	61.45	1.60	59.93	59.04	-0.89	-55.67
Italy	6.19	7.48	55.09	50.91	-4.18	55.28	54.42	-0.87	20.80
New Zealand	0.19	6.02	52.66	45.44	-7.22	53.24	52.37	-0.87	12.07
Norway	0.48	5.63	52.46	43.72	-8.73	52.99	52.12	-0.88	10.03
United Kingdom	5.59	5.50	61.10	62.41	1.31	61.00	60.26	-0.75	-56.86
Tunisia	0.07	5.47	45.08	38.75	-6.32	46.83	45.95	-0.88	13.96
Bolivia	0.03	4.90	32.52	34.00	1.48	37.76	37.00	-0.76	-51.17
Slovakia	0.06	4.04	53.15	47.32	-5.82	53.52	53.01	-0.51	8.76
South Africa	0.61	3.72	55.22	45.92	-9.29	55.50	55.09	-0.41	4.42
Greece	0.55	3.17	50.89	43.14	-7.76	51.89	51.50	-0.39	5.02
Costa Rica	0.04	3.10	50.98	55.07	4.09	51.73	51.27	-0.46	-11.18
China	2.28	2.75	43.00	35.84	-7.16	45.38	45.06	-0.32	4.48
Finland	0.52	2.65	61.68	55.23	-6.45	61.82	61.50	-0.32	5.04
Mexico	1.86	2.13	41.14	24.13	-17.01	44.14	43.81	-0.34	1.99

Notes: The table shows the results from country specific calibrations, averaged across a range of values for $0.6 \leq EOS(K,L) \leq 1.3$. The figures for columns 3 - 9 are based on log linear trends, constructed as in KN. Trend changes here cover a 20 year period: 1992 to 2012. GDP and ICT shares are measured in 1992, the first year with reliable, world wide ICT expenditure data (Eden and Gaggl, 2019). ICT and NICT shares are taken from the Total Economy Database (TED). GDP is taken from the Penn World Table 9.0 (PWT9.0). Column 9 shows the fraction of the declining labor share, that is explained by falling ICT prices. Countries are sorted in descending order by their ICT intensity, measured as the ratio of ICT to non-ICT share s_{ICT}/s_{NICT} based on TED data.