UNC CHARLOTTE ECONOMICS WORKING PAPER SERIES

ON THE WELFARE IMPLICATIONS OF AUTOMATION

Maya Eden
Paul Gaggl

Working Paper No. 2016-011

THE UNIVERSITY OF NORTH CAROLINA AT CHARLOTTE
BELK COLLEGE OF BUSINESS
DEPARTMENT OF ECONOMICS
9201 University City Blvd
Charlotte, NC 28223-0001
September 2016

ABSTRACT

We study the effects of information and communication technologies (ICT) on the distribution of income across factors of production in the United States. Since the 1950s, the income share of ICT saw a seven-fold increase, while it has remained trendless for other types of capital. In parallel, we document substantial reallocation of labor income from occupations relatively substitutable with ICT (routine) to ones relatively complementary (non-routine). In a general equilibrium model that matches these trends, automation accounts for half of the decline in the labor share and for 27% of growth in output per person since 1990.

On the Welfare Implications of Automation

September 9, 2016

Abstract: We study the effects of information and communication technologies (ICT) on the distribution of income across factors of production in the United States. Since the 1950s, the income share of ICT saw a seven-fold increase, while it has remained trendless for other types of capital. In parallel, we document substantial reallocation of labor income from occupations relatively substitutable with ICT (routine) to ones relatively complementary (non-routine). In a general equilibrium model that matches these trends, automation accounts for half of the decline in the labor share and for 27% of growth in output per person since 1990.

JEL: E25, E22, J24, J31, O33
Keywords: labor share, capital share, job polarization, ICT

Maya Eden[1]

The World Bank
Development Research Group
Macroeconomics and Growth Team
1818 H St. NW
Washington, DC 20433
Email: meden@worldbank.org

Paul Gaggl[1]

University of North Carolina at Charlotte
Belk College of Business
Department of Economics
9201 University City Blvd
Charlotte, NC 28223-0001
Email: pgaggl@uncc.edu

[1]This paper reflects our own views and not necessarily those of the World Bank, its Executive Directors or the countries they represent. We are grateful to Eric Bartelsman, David Berger, Ben Bridgman, Bart Hobijn, Roberto Fattal Jaef, Nir Jaimovich, Aart Kraay, Aitor Lacuesta, Juan Rubio-Ramirez, Ayşegül Şahin, Michael Sposi, Nancy Stokey, Alan Taylor as well as seminar participants at the World Bank, Vanderbilt University, Duke University, the Stockholm School of Economics (SITE), the ABCDE Conference on the Role of Theory in Development Economics, the 2014 NBER Summer Institute (CRIW), the 2014 SEA Meetings, the 2016 LAEF Macroeconomics and Business CYCLE conference (UCSB), the 4th WB-BE Research Conference on "Labor markets: Growth, Productivity and Inequality", and the 2016 Econometric Society Summer Meetings for extremely helpful comments and suggestions.

1. Introduction

The advent of information and communication technologies (ICT) is widely viewed to have had transformational effects on the distribution of income across factors of production. The discussion of this topic has centered around two mechanisms: first, ICT may have lowered the demand for tasks that can easily be automated relative to those that cannot, thus leading to a reallocation of labor income across occupations (e.g., Autor and Dorn, 2013).[1] Second, the automation of certain tasks may have led to a decline in the overall demand for labor, thus reallocating income from labor to ICT capital and lowering the labor income share (e.g., Karabarbounis and Neiman, 2014).[2]

Within a framework that allows for both of these channels to operate, we ask how the adoption of ICT since the 1950s has affected the distribution of income across factors of production, as well as growth in per-capita output and consumption in the United States. We begin with documenting the evolution of income shares since the 1950s, disaggregating capital and labor inputs based on their relationship with ICT. We then offer a structural interpretation of the observed trends, which allows us to comment on the effects of automation. In particular, our quantitative analysis suggests that ICT accumulation since the 1950s is responsible for sizable output and consumption gains and about half of the decline in the labor income share. Moreover, we highlight that the direct output and consumptions gains from ICT accumulation are amplified substantially by concurrent non-ICT investments—a general equilibrium effect that is absent in traditional growth accounting exercises. In fact, we show that this indirect effect has become more prominent in recent years, especially since the 2000s, a period in which we find that ICT explains about 1/3 of US growth in output per person.

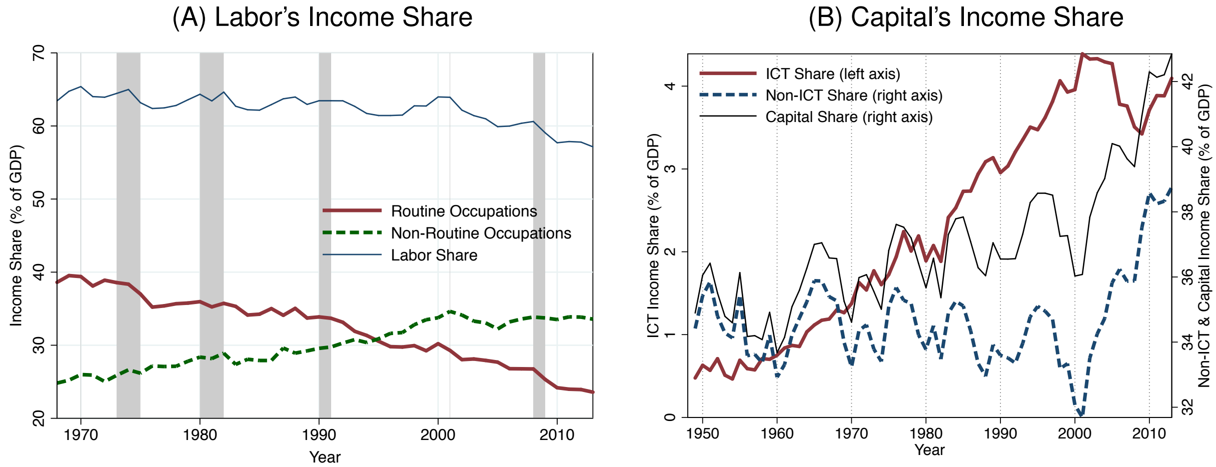
We distinguish four factors of production: ICT and non-ICT capital, as well as "routine" and "non-routine" labor, following the organizing framework of Acemoglu and Autor (2011), which is based on extensive research documenting the relative substitutability of ICT with different types of tasks.[3] On the

[1]While many older contributions provide mostly conditional correlations, Akerman, Gaarder and Mogstad (2015) as well as Gaggl and Wright (2016) are two recent examples providing estimates for the causal effects of ICT investments on the employment and wage distribution. Their estimates confirm many of the earlier results (based mostly on conditional correlations) surveyed by Acemoglu and Autor (2011).

[2]Further examples are Elsby, Hobijn and Sahin (2013) as well as Bridgman (2014).

[3]Acemoglu and Autor (2011) survey an extensive literature in labor economics sourounding the classification of occupations according to their task content and their interactions with ICT. The very aggregate classification we choose here is based on what they consider the "consensus aggregation" emerging out of this literature.

Figure 1: The Division of Income in the US



Notes: Occupation specific income shares are based on CPS earnings data from the annual march supplement (1968 and after) and rescaled to match the aggregate income share in the Non-Farm Business Sector (BLS). The underlying earnings data are top-code adjusted using Piketty and Saez's (2003) updated estimates of the US income distribution. Non-routine workers are those employed in "management, business, and financial operations occupations", "professional and related occupations", and "service occupations". Routine workers are those in "sales and related occupations", "office and administrative support occupations", "production occupations", "transportation and material moving occupations", "construction and extraction occupations", and "installation, maintenance, and repair occupations" (Acemoglu and Autor, 2011). For details see Section 3. The construction of capital-type specific income shares is described in Section 2. The underlying data are nominal gross capital stocks and depreciation rates, drawn from the BEA's detailed fixed asset accounts.

capital side, we find that the ICT capital income share has increased by almost a factor of 7 since 1950 (Panel B of Figure 1 and Table 1), while the non-ICT capital income share remained trend-less. On the labor side, our decomposition suggests that there has been a steep decline in the income share of "routine" labor, which performs tasks that are relatively prone to automation, countered by an equally rapid increase in the income share of "non-routine" labor (Panel A of Figure 1 and Table 1).

To interpret these findings, we calibrate a production function that matches the observed trends in the *relative* income shares of ICT capital and both routine and non-routine labor. By focusing on relative rather than absolute income shares and excluding non-ICT capital, our calibration strategy attributes only the rise in the ICT capital income share to automation, allowing for part of the decline in the aggregate labor income share to reflect other factors. Given that our measurement of relative income shares is insensitive to the measurement of the aggregate labor income share, this strategy is immune to the recent critiques regarding the potential mis-accounting of self-employment income, which may potentially be driving the bulk of the decline in the measured labor income share (Elsby et al., 2013). Through the lens of our model, we can gauge the effects of automation without taking a strong stance on this measurement issue.

Table 1: The Division of Income in the US

	Labor Share	Capital Share	Labor Share		Capital Share	
			Routine	Non-Routine	ICT	Non-ICT
1950	63.95	36.05			0.57	35.48
1968	63.44	36.56	38.61	24.82	1.2	35.37
2013	57.15	42.85	23.58	33.57	3.86	38.99
Percentage Point Change						
1968-2013	-6.29	6.29	-15.04	8.75	2.67	3.62
1950-2013	-6.8	6.8			3.29	3.5

Notes: The table summarizes the long run trends in labor and cpaital shares as depicted in Figure 1. See the notes to Figure 1 for details on the data construction. Since our earnings data based on the CPS start in 1968 we report the disaggregated labor shares only for the period 1968-2013.

At the same time, our calibration strategy attributes the entire reallocation of labor to automation, ignoring the potential contributions of other factors. There has been some debate regarding the quantitative relevance of different factors to the changing occupational composition. While some papers argue that technology has been the driving force behind the shift from routine to non-routine occupations (e.g., Autor and Dorn, 2013), others suggest the importance of offshoring and international trade (e.g., Autor, Dorn and Hanson, 2013). We emphasize that our paper does not provide new evidence in support of one view or another. Rather, our paper contributes to this debate by deriving new testable predictions associated with the technology-based view. In particular, we compute the elasticities of substitution between different factors of production that are necessary in order to generate the trends in the data in a general equilibrium model of automation. Our results show that if one is to subscribe to the view that automation is the sole driver of the reallocation of labor income, then one must accept that routine and non-routine labor are highly substitutable, and that both routine and non-routine labor are substitutable to varying degrees with ICT. While testing these predictions is beyond the scope of this paper, we hope that their derivation will further the debate by providing a benchmark for interpreting the general equilibrium implications of different empirical estimates of elasticities of substitution.

In addition, the distinction between routine and non-routine labor is useful for decomposing the sources of the declining routine labor income share, under the assumption that the reallocation of labor across occupations is caused by differences in substitutability with ICT. Our calibration suggests that of the 15pp measured decline in the routine labor income share over the period 1968-2013 (see Table 1), 13.9pp can be attributed to automation (while 1.1pp are due to factors outside the model): 3.3pp reflect an increase in the income share of ICT capital while 10.6pp reflect an increase in the income share of non-routine labor. In addition, of the 6.3pp decline in the aggregate labor share over the same period (see Table 1), our model suggests that ICT accounts for 3.3pp, while the remaining 3pp are explained by factors outside the model. Thus, we conclude that ICT accounts for about half of the decline in the aggregate labor share over the period 1968-2013.

Our framework further allows us to comment on the contribution of ICT toward aggregate output and consumption growth. Given the low income share of ICT, traditional growth accounting exercises tend to attribute only a small portion of growth to the accumulation of ICT capital.[4] Using steady-state comparative statics in our model, we illustrate that such growth accounting exercises understate the overall output gains from ICT by about 50%, as they fail to account for the effect of ICT accumulation on the accumulation of non-ICT capital. On the one hand, our model predicts that ICT explains about 8% (0.17pp of 2.02% per year) of the average growth in per-capita real GDP over the period 1950-2016. On the other hand, our simulations also highlight that ICT contributed less than 4% to overall growth until the 1980s but comprised more than 40% (0.46pp of 1.1% per year) of US growth during the 2000s and more than 30% since 2010 (0.38pp of 1.22% per year). Interestingly, we find that the growth contribution of indirect non-ICT investments has become increasingly important starting in the 1980s—a general equilibrium effect typically not accounted for by traditional growth accounting exercises.

Finally, we note that our calibration implies an elasticity of substitution between ICT capital and labor of about 1.85. However, since ICT capital is a relatively small share of the aggregate capital stock (about 2.5% on average within our sample), this elasticity is consistent with an elasticity of substitution between aggregate capital and labor that is close to unity (1.09). We note that this value is in line with a number of previous studies that estimate an aggregate elasticity of close to one (e.g., Berndt, 1976).

This paper is most closely related to the literature on the general equilibrium effects of declining capital prices (e.g., Krusell, Ohanian, Ríos-Rull and Violante, 2000; Autor and Dorn, 2013; Karabarbounis and Neiman, 2014). Our main departure from this literature is an explicit focus on the distinction between ICT and non-ICT capital. Karabarbounis and Neiman (2014) and Autor and Dorn (2013) consider an aggregate

[4] There is a long literature trying to assess the growth impact of ICT. For some recent examples see Colecchia and Schreyer (2002), Basu, Fernald, Oulton and Srinivasan (2003), Jorgenson and Vu (2007), Bloom, Sadun and Van Reenen (2012), as well as Acemoglu, Autor, Dorn, Hanson and Price (2014) and references therein.

capital input. Closer to our decomposition, Krusell et al. (2000) distinguish between equipment and structures.[5] The ICT capital class considered in this paper is a subset of the broader class of equipment. Our focus on this narrower category is motivated by the rich literature emphasizing that ICT features unique interactions with different types of labor (Acemoglu and Autor, 2011; Akerman et al., 2015; Gaggl and Wright, 2016). Consistent with Krusell et al. (2000), our analysis suggests that technology has more transformative effects on the distribution of labor income than on the distribution of income between capital and labor. However, while the analysis in Krusell et al. (2000) does not find an effect on the labor income share, our model suggests that ICT also changes the distribution of income between capital and labor, consistent with Karabarbounis and Neiman (2014). However, we note that our calibration implies a substantially lower elasticity of substitution between aggregate capital and labor (close to unity).

2. Decomposing The Capital Income Share

Conceptually, the payment to each type of capital is comprised of both a unit payment (the rental rate of capital) and the (real) stock of capital—analogous to the wage rate and the physical amount of labor provided by the worker. Both of these items are challenging to measure, especially when the relative prices of the various types of capital are changing over time. To accomplish this, we build on two standard assumptions, that have been used to measure the returns to capital at least since the seminal work by Hall and Jorgenson (1967) and Christensen and Jorgenson (1969) and will allow us to directly measure capital type specific income shares from the BEA's current cost values for the stocks of detailed assets in the US.[6] Specifically, we impose the standard constant returns assumption and a no-arbitrage condition for investment in different types of assets.[7]

Suppose that there are several types of capital, denoted K_i, with $i = 1, ..., I$. If the aggregate production

[5] In a similar analysis, vom Lehn (2015) also distinguishes between equipment and structures.

[6] Official documenation for the BEA's methodology to construct these estimates is available at http://www.bea.gov/national/pdf/Fixed_Assets_1925_97.pdf. Most macroecnomic studies using capital stocks utilize a simpler version of the perpetual inventory method than the BEA's estimates, usually based on linear constant depreciation and aggregate real investment rates. We prefer the BEA's estimates for several reasons: first, they are provided at the detailed asset level; second, they allow for time varying non-linear depreciation patterns; finally, these estimates allow us to directly use nominal stocks at current cost, rather than chain-weighted quantity indexes.

[7] For a few more recent contributions that use the same basic strategy to compute the return to specific types of captial in various contexts see for example Jorgenson (1995), O'Mahony and Van Ark (2003), and Caselli and Feyrer (2007). We outline the basic idea of our implementation to measure capital type specific income shares here and provide detailed derivations in Appendix A.

technology exhibits constant returns to scale in all factors, the share of payments to capital must satisfy the following equilibrium relation:

$$s_{K,t} = \sum_{i}^{I} \frac{R_{i,t} K_{i,t}}{P_t Y_t} = 1 - s_{L,t}, \tag{1}$$

where $s_{K,t}$ and $s_{L,t}$ denote the aggregate capital and labor income shares, respectively, Y_t is final output with associated price P_t, and $R_{i,t}$ denotes the (nominal) rental rate of capital type i. Note that, if factor markets are competitive, the real rental rate $(R_{i,t}/P_t)$ is equal to the physical marginal product of a unit of capital. However, our approach does not require this assumption.

Suppose an investor buys a unit of capital type i at the going price $P_{i,t}$ and rents it out for a period at the real rental rate $R_{i,t}$. The gross return after production and re-sale of this piece of capital is then given by

$$\frac{R_{i,t} + P_{i,t+1}(1 - \delta_{i,t})}{P_{i,t}}, \tag{2}$$

where $\delta_{i,t}$ is the depreciation rate for capital type i.

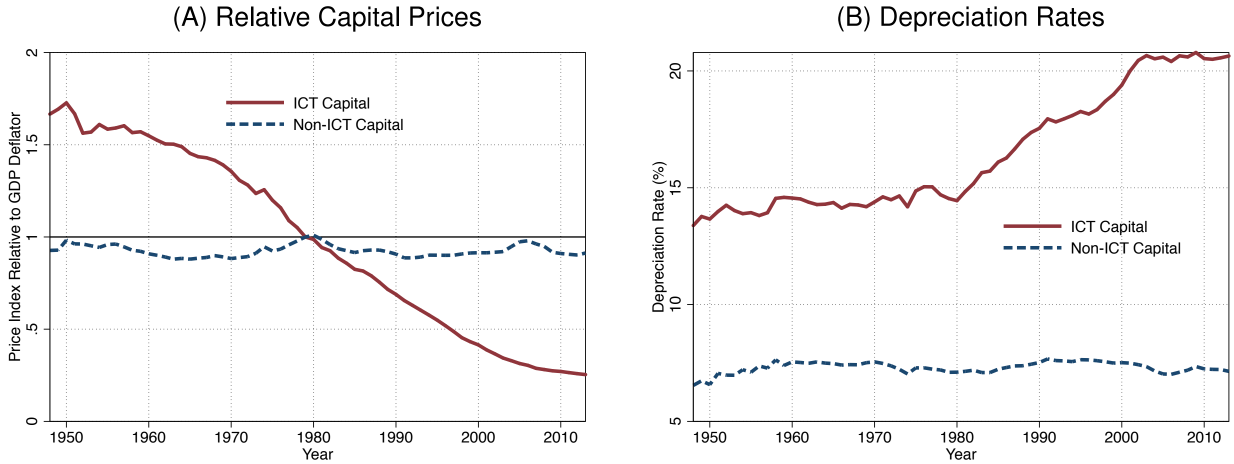
In an equilibrium in which investors can choose between different assets, the return (2) on each type of capital must equal the prevailing gross return on investment. It is important to note, however, that this does not require the (physical) marginal product of each type of capital to be equalized. In the standard neoclassical growth model, marginal products need to equalize since capital has a constant price relative to output and there is only one rate of depreciation. In our context, both the price as well as the depreciation rate of ICT is changing drastically relative to output and all other forms of capital (see Figure 2). Thus, no-arbitrage in investment requires the *gross return* (2) to be equalized across all types of capital.

We show in Appendix A how equations (1) and (2) allow us to compute the income share for each type of capital, defined as $s_{i,t} = \frac{R_{i,t} K_{i,t}}{P_t Y_t}$, using the labor income share, nominal current cost values for each type of capital, capital specific depreciation rates, and a price index for ICT capital as data inputs.

To measure the current cost values of different types of assets we use the BEA's detailed fixed asset accounts. We aggregate the BEA's detailed industry level estimates into three types of capital, classified according to the BEA's definition: residential assets, consumer durables and non-residential assets. Within the non-residential and consumer durables categories we separate ICT and NICT assets.

Within non-residential assets we consider an asset to be ICT if the BEA classifies it as software (clas-

Figure 2: Relative Prices & Depreciation



Notes: Panel A graphs implicit price deflators by capital type expressed as a fraction of the GDP deflator, which were constructed directly from the BEA's detailed fixed-asst accounts. The BEA GDP deflator is taken from FRED. Panel B depicts asset-specific depreciation rates constructed directly from the BEA's fixed asset accounts. See Tables G.8 and G.9 in Appendix G and the text for our grouping of assets. The dashed vertical lines indicate the year 1968.

sification codes starting with RD2 and RD4) or as equipment related to computers (classifications codes starting with EP and EN). See Tables G.8 and G.9 in Appendix G for complete lists of the detailed assets grouped into the two types of non-residential capital. Within consumer durables we classify the following assets as ICT: PCs and peripherals (1RGPC); software and accessories (1RGCS); calculators, typewriters, other information equipment (1RGCA); telephone and fax machines (1OD50).

The construction of capital income shares requires estimates of the depreciation rates, $\delta_{i,t}$, as well as estimates of expected capital gains, $E\left[P_{i,t+1}/P_{i,t}\right]$. We measure depreciation rates directly form the BEA's nominal values of depreciation for each type of detailed asset.[8] We then employ implicit price deflators that we construct for each type of capital based on chain type price indices provided by the BEA.[9]

Panel A of Figure 2 depicts the path of prices for ICT and NICT assets relative to the GDP deflator.[10] This figure immediately reveals two important insights: First, the price of NICT capital relative to output

[8]In particular, we measure depreciation rates based on the BEA's nominal values for depreciation and net capital stocks. That is, we compute $\delta_{i,t} = (P_{i,t}Dep_{i,t})/(P_{i,t}(NetStock_{i,t} + Dep_{i,t})$. Since both measures are reported in year-end nominal values, the price terms cancel.

[9]Notice that this involves constructing appropriate chain type quantity aggregates and associated implicit price deflators for each capital type, derived from the BEA's estimates of stocks and prices for the detailed assets listed in Tables G.8 and G.9 in Appendix G.

[10]See Appendix C for alternative aggregation schemes, highlighting the distinction between residential and non-residential capital as well as equipment and structures, which all reveal the same qualitative result.

is essentially constant throughout the entire sample. This regularity will allow us to ignore changes in the NICT capital price, and focus our analysis on changes in the ICT capital price. Second, the relative price of ICT falls substantially, especially during the 1970s and 1980s. Since a real quantity index holds productive capacity constant, this price decline reflects technological improvements in the production of computing power and ICT capital. Our quantitative analysis will focus on the general equilibrium effects of these technological improvements, as measured by this trend.

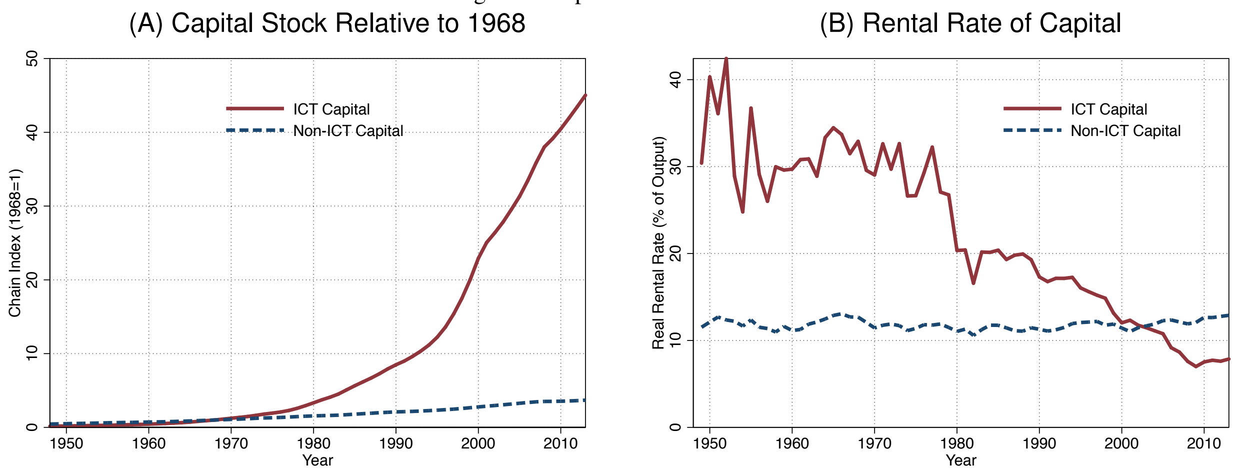
Panel B of Figure 2 graphs the respective depreciation rates for each type of capital. The depreciation rate of ICT capital is substantially higher than the depreciation rate of NICT capital. This will tend to imply that ICT capital goods constitute a larger share of investment than of the aggregate capital stock. These divergent trends therefore imply that an aggregate capital price index weighted by investment shares will have a sharper decline than a price index weighted by capital shares. Despite the fact that "investment prices" (i.e., investment weighted price indexes) are more common and easier to measure, a stock weighted index is the relevant price to study investment behavior within a neo-classical framework, as we do here.

Based on these measures, we use the derivations in Appendix A to construct the income share for each type of capital and panel B of Figure 1 illustrates the resulting estimates (also see Table 1). One can clearly see that the income share of NICT capital does not show any significant trend throughout the entire sample. During the same period, the income share of ICT capital was on a steady upward trend and has increased roughly seven-fold, from 0.57% in 1950 to 3.86% by 2013. This implies that the introduction of ICT did not significantly crowd out other forms of capital, whose income share fluctuated around a trend-less long run average of around 35%.

This accounting exercise suggests that roughly half of the decline in the labor income share is attributable to the rise in the ICT income share. The remainder is due to a rapid rise in the NICT income share, particularly after 2001. Consistent with the findings of Rognlie (2015), a further decomposition of the increase in the NICT capital income share in the post 2001 period reveals that this rise is accounted for entirely by a rise in the income share of structures and residential capital (see Appendix C for further details). After removing structures and residential capital income, the NICT capital income share is stationary. If one assumes that trends in real estate income are unrelated to automation, this measurement exercise suggests that about half of the decline in the labor income share is potentially attributable to the declining ICT price.

Given the stark trends in income shares (Figure 1 and Table 1), we find it instructive to decompose the

Figure 3: Capital and its Rental Rate



Notes: Panel A graphs the stock of ICT and non-ICT captial relative to its 1968 level. Panel B depicts asset-specific real rental rates $(R_{i,t}/P_t)$ in % of final output, derived from expressions (A.5)-(A.6) in Appendix A. The underyling data are the BEA's detailed fixed-asset accounts. The dashed vertical lines indicate the year 1968.

payments to capital, $(R_{i,t}/P_t)K_{i,t}$, into a price and quantity component. To this end, we construct chained quantity indexes for the stocks of ICT and NICT capital based on the BEA's fixed asset accounts. Panel A of Figure 3 shows that the stock of ICT capital in 2012 is more than 40 times its 1950 level. Panel B illustrates that the rental rate of ICT capital—measured in units of final output—fell substantially over the same period. This price-quantity decomposition suggests that the increase in the income share of ICT capital is due to the accumulation of ICT capital that outpaced the decline in its rental rate.

Finally, in our calibration, we will postulate a one-sector aggregate production structure that matches the trends depicted in panel A of Figure 1. To justify such an approach, we illustrate that the disaggregated trends in the capital income shares are not merely a result of changes in the industrial composition but rather a within-industry phenomenon. To this end, Appendix D presents the measurement of industry-specific ICT and NICT shares based on the BEA's detailed fixed asset accounts and establishes that the aggregate trends in ICT and NICT income illustrated in Figure 1 and Table 1 are robust to the inclusion of industry fixed-effects.

3. Decomposing The Labor Income Share

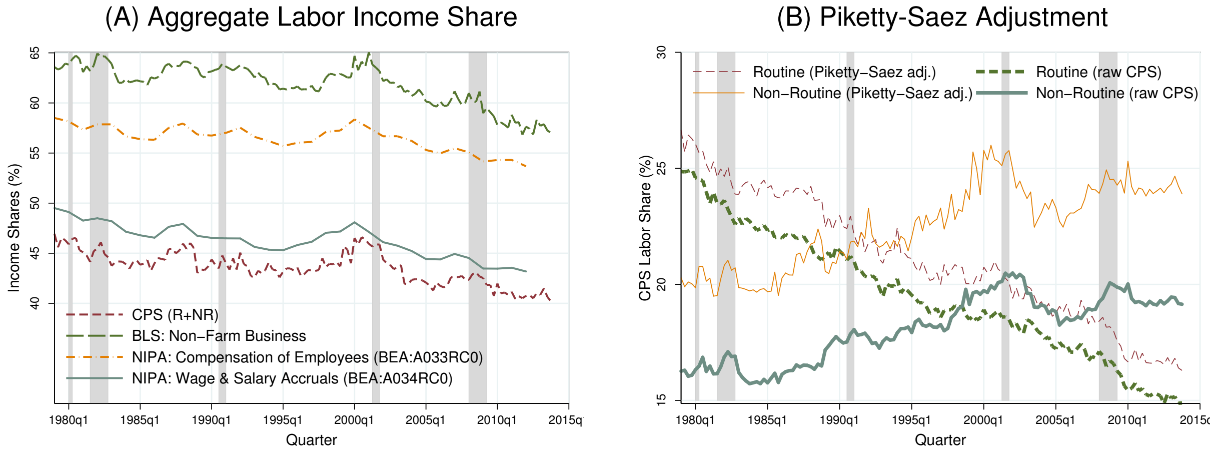
An extensive literature in labor economics has recently identified unique interactions between ICT and two types of labor as one of the main sources for dramatic shifts in the earnings distribution within virtually all developed countries around the world (Acemoglu and Autor, 2011). The first type of labor executes primarily "routine" tasks, that require following exact, pre-specified decision trees (or routines). By their very nature, these tasks are prone to automation and numerous empirical studies have shown that investments in ICT tend to replace such tasks, and therefore jobs (e.g., Autor and Dorn, 2013, and references therein). On the other hand, the second type of labor is intensive in non-routine tasks, that require substantial amounts of judgement, creativity or interpersonal skills, which are less readily automated. This assertion is backed by an equally large body of empirical evidence shwoing that investments in ICT complement these tasks and tend to increase the demand for jobs specializing in such tasks (e.g., Akerman et al., 2015; Gaggl and Wright, 2016, and references therein).

To incorporate this distinction into our production framework, we measure the income shares of routine and non-routine labor. To do so, we consider two alternative measures of earnings at the occupation level in the U.S. Current Population Survey (CPS): annual earnings from the march supplements (MARCH) starting in 1968 (provided by IPUMS, Ruggles, Alexander, Genadek, Goeken, Schroeder and Sobek, 2010), and weekly earnings for the outgoing rotation groups (MORG) starting in 1979 (provided by the NBER). We use the CPS sampling weights and construct an estimate of the aggregate wage bill at the detailed occupation level, which requires several non-trivial adjustments to the raw data. First, since the U.S. Department of Labor's (DOL) classification of occupations changes several times during our sample period, we aggregate individuals into a panel of 330 consistent occupations, designed by Dorn (2009).[11] Second, and more crucial for our analysis, we follow Champagne and Kurmann (2012) and adjust top coded earnings based on Piketty and Saez's (2003) updated estimates of the cross-sectional income distribution.

Based on these adjusted earnings numbers, we then compute the aggregate annual wage bill and divide it by nominal GDP, to construct the share of wage and salary earnings in aggregate income. As illustrated in panel A of Figure 4, the aggregate labor share based on earnings data in the CPS-MORG accounts for

[11] We thank Nir Jaimovich for providing a crosswalk between Dorn's (2009) occupation codes and the latest Census classification that is used in the CPS since 2011. This crosswalk is the same as in Cortes, Jaimovich, Nekarda and Siu (2014).

Figure 4: Labor's Share in Income



Notes: Panel A contrasts aggregate income shares (as a fraction of GDP) based on the CPS outgoing rotation groups (MORG), aggregates reported in the NIPA tables, as well as a BLS estimate for the total non-farm business sector that includes benefits, self employed, proprietors income, and other non-salary labor income. The aggregate series are drawn from FRED. The series labeled "CPS (R+NR)" is constructed from our occupation specific earnings based on the monthly CPS MORG extracts provided by the NBER. The data are seasonally adjusted with the U.S. Census X11 method. Panel B contrasts the raw earnings reflected by CPS topcoded values and our series that adjust top-coded earnings with the appropriate (updated) estimates by Piketty and Saez (2003).

stable 70% of the one based on total non-farm business labor income (which includes benefits, pensions, self employed income, etc.). Moreover, the two series are almost perfectly correlated over time.

To compute the routine and non-routine income shares we define routine and non-routine workers as suggested by Acemoglu and Autor (2011). That is, we consider workers employed in "management, business, and financial operations occupations", "professional and related occupations", and "service occupations" as non-routine; and we define routine workers as ones employed in "sales and related occupations", "office and administrative support occupations", "production occupations", "transportation and material moving occupations", "construction and extraction occupations", and "installation, maintenance, and repair occupations". Note that this classification emerges out of an extensive literature, surveyed in Acemoglu and Autor (2011), that originated from the seminal work by Autor, Levy and Murnane (2003). They and many other contributions in this line of research use detailed information on the task content of at least 300 detailed occupations (depending on the study) obtained from the Dictionary of Occupational Titles (DOT) and its successor O*Net. The classification used here is the "consensus aggregation" suggested by Acemoglu and Autor (2011) that captures the key insights from the more detailed micro analyses. We drop farm workers for all our analyses for comparability with the BLS measure of the labor income share.[12] To compute the income shares corresponding to each occupation group, we simply compute the aggregate annual wage bill within each occupation group and divide it by nominal GDP.

Finally, we proportionately rescale both group specific income shares (which originally add up to the series labeled "CPS(R+NR)" in panel A of Figure 4) so that they match the share of (non-farm business) labor income in GDP, as estimated by the BLS (top line in panel A of Figure 4). The resulting routine and non-routine income shares using the MARCH earnings measure are displayed in panel A of Figure 1 and Figure A.11 in Appendix B illustrates that income shares based on the MORG earnings measure reveal a virtually identical picture. Consistent with the literature in labor economics, we find that, in the U.S., the decline in the aggregate labor share is entirely accounted for by routine occupations, while the income share of non-routine labor has been rising (also see Table 1).

For our calibration, it will be useful to decompose these trends in income shares into trends in wages and trends in labor inputs. The declining routine labor income share relative to the non-routine labor income share could be driven either by a change in relative wages, a change in relative labor inputs, or both. We find that both an increasing non-routine wage premium and an increase in non-routine labor inputs contribute to this trend.

As a baseline reference, we start with estimating simple averages of log real earnings for each type of labor. Panel A of Figure 5 illustrates these estimates and gives a first indication of a steadily increasing wedge between non-routine and routine pay. Since routine occupations comprise primarily of middle-income jobs, this regularity is consistent with a large body of literature that documents an increase in wages for high- and low-paying jobs relative to middle-income jobs.[13]

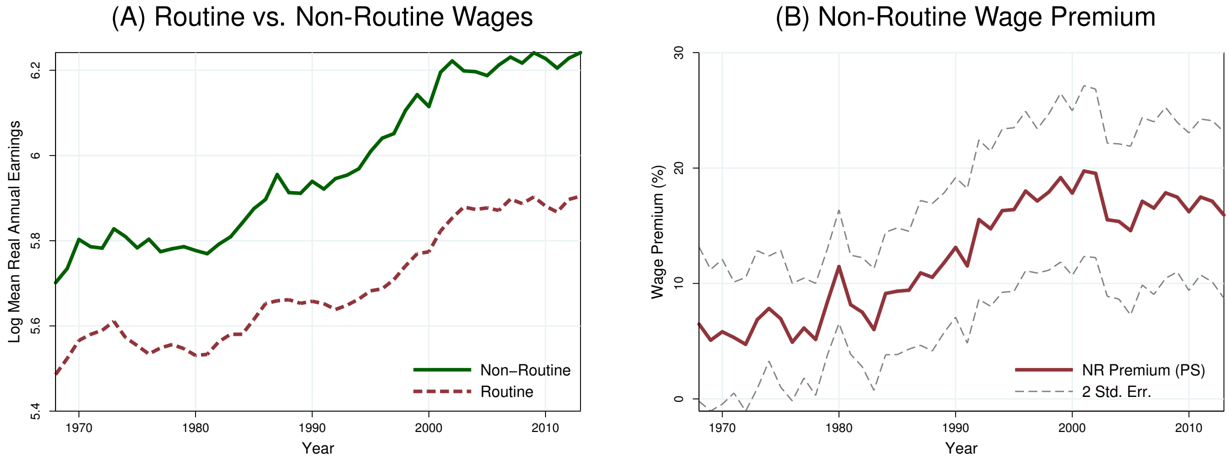
To ensure that this wedge is not simply driven by a changing composition of characteristics of routine and non-routine workers, we estimate the following set of cross-sectional wage regressions separately for each year, t:

$$\ln w_{i,t} = \beta_{0,t} + \beta_{1,t}\boldsymbol{NR}_{i,t} + \beta_{2,t}X_{i,t} + \epsilon_{i,t} \quad \text{for } t \in \{1968, \ldots, 2013\}, \tag{3}$$

[12] We note that the aggregation into the two groups of routine and non-routine occupations is also supported by separate evidence provided by Gaggl and Kaufmann (2015), who use cyclical employment dynamics to classify detailed occupations into clusters with common dynamic trends.

[13] See Acemoglu and Autor (2011) for a comprehensive summary of this literature.

Figure 5: The Non-Routine Wage Premium in the US



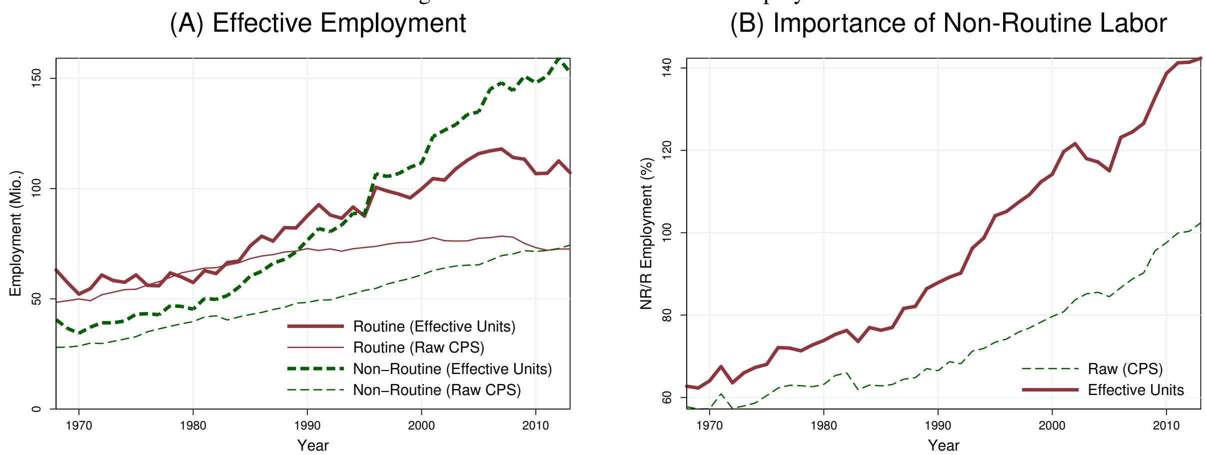
Notes: Panel A plots the unconditional mean of log real annual earnings in each occupation group. Panel B graphs the coefficients from annual regressions of individual level log real earnings on a non-routine dummy and a host of demographic control variables, including flexible functional forms in industry, age, and education. Occupation and individual specific earnings are based on the the annual march supplements in the CPS (MARCH) provided by IPUMS (Ruggles et al., 2010). We deflate eranings data with the chain type implicit price deflator for personal consumption expenditures. Non-routine workers are those employed in "management, business, and financial operations occupations", "professional and related occupations", and "service occupations". Routine workers are those in "sales and related occupations", "office and administrative support occupations", "production occupations", "transportation and material moving occupations", "construction and extraction occupations", and "installation, maintenance, and repair occupations" (Acemoglu and Autor, 2011).

where $NR_{i,t}$ is a dummy variable indicating that individual i works a non-routine job in year t and $X_{i,t}$ includes a variety of control variables. In particular, we include gender, race, and full time employment dummies, we control for the weeks worked, a full set of industry fixed effects (50 industries constructed from SIC industry codes by the NBER), as well as forth order polynomials in age, education, and the interaction of education and age.

We estimate regressions (3) based on individual level data from the annual CPS march supplements and weight by the CPS sampling weights.[14] Panel B of Figure 5 plots the resulting time series of estimates $\hat{\beta}_{1,t}$ and the associated 95% confidence intervals based on standard errors that are clustered on industry. These estimates highlight that the rising relative wage for non-routine labor is not entirely driven by the rising skill premium or by specific industries. The latter observation is of particular importance, as it highlights that the wage premium is not simply due the steady decline in manufacturing as the estimates $\hat{\beta}_{1,t}$ are identified

[14] Note that in an earlier version we estimated these regressions at the quarterly level based on the CPS MORG. The results are qualitatively equivalent but we prefer the longer time horizon provided by the annual march supplements. The CPS MORG results are available form the authors upon request.

Figure 6: Routine & Non-Routine Employment



Notes: Panel A plots employment levels in routine and non-routine jobs as reflected in the CPS. The graph plots both the raw CPS numbers as well as our imputed "effective" units based on equations (6) and (7). Panel B illustrates the relative importance of non-routine jobs.

from within industry variation. These estimates therefore suggest that part of the increase in the non-routine income share is driven by a steadily increasing gap between routine and non-routine pay.

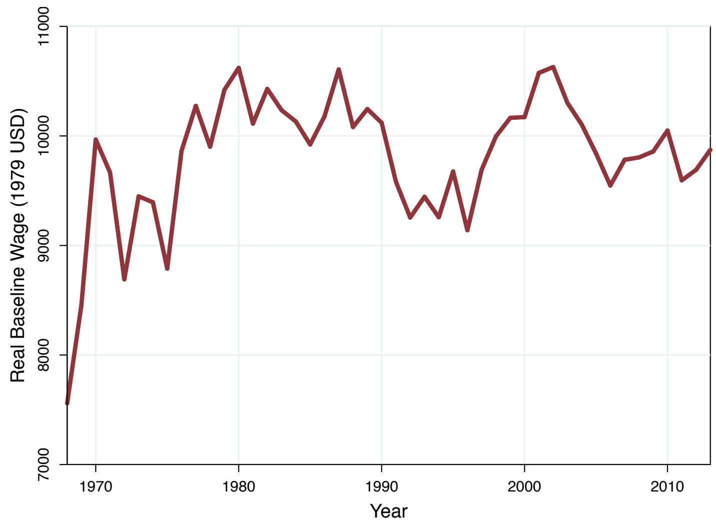
Our estimates suggest that the non-routine wage premium rose from around 6.5% in 1968 to 16% in 2013. Given the sheer size and persistence of this premium we find it unlikely to be driven by frictions (like barriers to entry). In our calibration exercise, we will therefore assume flexible labor markets and attribute the non-routine wage premium to some form of unobserved ability (e.g. managerial skills, "people" skills, etc.).

Similarly, to measure the trends in labor inputs we distinguish between raw labor (employment) and "effective" units of labor, which take into account differences in worker attributes. In a frictionless world, an "effective" unit of labor needs to be paid a fixed wage w_t and therefore, the ratio of non-routine to routine labor in effective units is given by

$$\frac{s_{r,t}}{s_{ln,t}} = \frac{w_{r,t}L_{r,t}}{w_{nr,t}L_{nr,t}} = \frac{w_t(e_{r,t}L_{r,t})}{w_t(e_{nr,t}L_{nr,t})} = \frac{L^e_{r,t}}{L^e_{nr,t}}, \tag{4}$$

where $e_{r,t}$ and $e_{nr,t}$ are effective units of labor embodied in routine and non-routine workers, respectively. Panel B of Figure 6 illustrates the time path of this ratio, revealing that non-routine labor inputs have increased relative to routine labor inputs, both in terms of raw labor and in terms of effective units of labor.

Figure 7: Real Baseline Wage



Notes: The figure plots $\hat{w}_t = \hat{\beta}_{0,t}$ based on estimates from regression model (3) with $X_{it} = 0$ for our baseline worker: a 19-year-old, white, male, full-time, routine, manufacturing worker with a high school degree, who works 50-52 weeks per year. Real earnings are based on the U.S. GDP deflator with 1979=1.

For our calibration exercise below, it will be useful to construct the time paths of routine and non-routine labor in effective units, as well as a sequence of real wages per effective unit of labor. We obtain an estimate for w_t directly from regression model (3). To do so, we normalize X_{it} such that $X_{it} = 0$ corresponds to our "reference worker": a 19-year-old, white, male, full-time, routine, manufacturing worker with a high school degree, who works 50-52 weeks per year. This allows us to interpret our estimated constant in regression (3) as the baseline wage, that is $\hat{w}_t = \hat{\beta}_{0,t}$. Figure 7 illustrates the resulting baseline real wage series and we note that our estimates are in line with a vast literature in labor economics that finds stagnating real wages for the "middle class" starting in the early 1970s (Levy and Murnane, 1992).

Based on the identity $w_t L_t^e = \sum_i w_{it} L_{it}$, aggregate effective employment is then given by

$$L_t^e = \frac{\sum_i w_{it} L_{it}}{w_t} \tag{5}$$

which allows us to compute the effective levels of routine and non-routine employment as

$$
\begin{aligned}
L^e_{nr,t} &= \frac{1}{1+\frac{s_{r,t}}{s_{ln,t}}} L^e_t && (6)\\
L^e_{r,t} &= L^e_t - L^e_{nr,t} && (7)
\end{aligned}
$$

Panel A of Figure 6 illustrates the time paths for routine and non-routine employment, both in actual and effective units of labor.

Figures 5 and 6 clearly illustrate that the increase in non-routine labor's share in income is due to a substantial increase in both the non-routine wage premium as well as non-routine employment relative to routine employment.

4. A Calibrated Production Function

This section lays out a procedure for calibrating an aggregate production function based on observed trends in income shares. Given the relative stability of the non-ICT capital income share, we postulate a production function that is a Cobb-Douglas aggregate of non-ICT capital and a CRS production function in the remaining inputs. The calibration targets long-run trends in the relative income shares of ICT capital, routine- and non-routine labor. Specifically, using lower case letters to indicate variables expressed in per-worker terms, we assume an aggregate production function given by:

$$y = k_n^{\alpha} x^{1-\alpha}, \tag{8}$$

where y is output, k_n is non-ICT capital and x is an input produced by ICT (k_c) as well as routine (ℓ_r) and non-routine (ℓ_{nr}) labor inputs. To parametrize this composite input we consider two alternative specifications that have been proposed in the literature. Frist, Autor and Dorn (2013) consider the following nested CES specification:

$$x = (\mu(\chi k_c^{\rho} + (1-\chi)\ell_r^{\rho})^{\frac{\varphi}{\rho}} + (1-\mu)\ell_{nr}^{\varphi})^{\frac{1}{\varphi}} \tag{9}$$

where $\mu, \chi \in [0, 1]$ and $\rho, \varphi \leq 1$. The interpretation is one in which non-routine labor interacts with "routine inputs", which can be produced by either routine labor or ICT capital. For example, a (non-routine) applied economist is more productive if there is more data available; it is immaterial whether the data is collected by (routine) human surveyors or by an online survey. ICT affects the productivity of non-routine labor only through increasing the supply of routine inputs, while routine labor is directly substitutable with ICT.

An alternative specification, in the spirit of Krusell et al. (2000), is a nested CES in which non-routine labor interacts directly with ICT:

$$x = (\eta \ell_r^\theta + (1-\eta)(\gamma k_c^\sigma + (1-\gamma)\ell_{nr}^\sigma)^{\frac{\theta}{\sigma}})^{\frac{1}{\theta}} \tag{10}$$

where, again, $\eta, \gamma \in [0,1]$ and $\theta, \sigma \leq 1$. Here, non-routine labor interacts directly with ICT capital, and routine labor interacts with a "non-routine" input that is produced jointly by ICT capital and non-routine labor. For example, secretaries producing printed documents using typewriters are substitutable with writers directly producing their documents using word processors. In this case, the direct interaction between non-routine labor and ICT capital makes routine labor redundant. More generally, this functional form captures technologies that directly affect the productivity of non-routine labor, performing tasks that would be less feasible for routine labor. For example, complicated computations such as a multivariate regressions would require a lot of patience and brainpower without a computer, rendering them practically unfeasible for routine labor. Similarly, communication technologies that allow for instantaneous sharing of ideas and information provide a service that is not feasibly provided by human messengers.

The two specifications parameterize the various interactions between labor and ICT in slightly different ways. Equation (9) postulates a constant elasticity of substitution between ICT and routine labor, $1/(1-\rho)$, while the elasticity between ICT and non-routine labor is an endogenous, time varying object. Conversely, equation (10) postulates the opposite, i.e., that the elasticity of substitution between ICT and non-routine labor is constant, $1/(1-\sigma)$, while the elasticity of ICT and routine labor may vary over time. Despite these subtle differences, both specifications allow for substitutability between routine labor and ICT, and complementarity (or relatively less substitutability) between non-routine labor and ICT. We are therefore a-priori agnostic and propose a calibration strategy to choose the specification that best fits trends in relative income shares. However, it turns out that our calibration for specification (9) requires implausible parameter values ($\rho > 1$) to fit the targeted trends. In the interest of space, we therefore restrict the discussion below to specification (10) and relegate the analogous calibration of specification (9) to Appendix F.

Specifically, we use a two-step procedure based on the first order conditions of a competitive firm producing output y with technology (8). Taking wages and rental rates as given, the firm's optimality conditions for the case of specification (10) imply that the following conditions must hold:[15]

$$\ln\left(\frac{s_c}{s_{nr}}\right) = \ln\left(\frac{\gamma}{1-\gamma}\right) + \sigma \ln\left(\frac{k_c}{\ell_{nr}}\right) \tag{11}$$

$$\ln\left(\frac{s_r}{s_{x_{nr}}}\right) = \ln\left(\frac{\eta}{1-\eta}\right) + \theta \ln\left(\frac{\ell_r}{x_{nr}}\right) \tag{12}$$

where s_i is the income share of input $i \in \{k_c, \ell_{nr}, \ell_r, x_{nr}\}$, with $x_{nr} = (\gamma k_c^\sigma + (1-\gamma)\ell_{nr}^\sigma)^{\frac{1}{\sigma}}$ and associated income share $s_{x_{nr}} = s_c + s_{nr}$. Analogous expressions hold for specification (9) and details are shown in Appendix F. We then use measured trends in income shares and quantities from the previous sections to calibrate the four parameters γ, σ, η, and θ using the following two steps:

1. Estimate γ and σ using OLS and compute the implied time series for $x_{nr} = (\gamma k_c^\sigma + (1-\gamma)\ell_{nr}^\sigma)^{\frac{1}{\sigma}}$
2. Estimate η and θ using OLS, conditional on the implied series for x_{nr} from step 1

Table 2 reports the results based on this procedure for specification (10) in four alternative versions. Panel A uses all data as measured in the previous sections, panel B uses a fitted log linear trend rather than the measured data, while panels C and D fit only the first and last data/trend point, respectively. While our goal is a calibration based on trends, ignoring short-term fluctuations, notice that the estimated parameter values are extremely similar across the four alternative specifications. We prefer specification B as it is based on a log linear trend rather than the measured data and it is not exclusively based on the two end-points of our sample, which may introduce bias in both two-point regressions shown in panels C and D.

Notice that these calibrated parameters imply an elasticity of substitution between ICT capital and non-routine labor to be around 1.56 and an elasticity of substitution between routine labor and x_{nr} (a CES composite of ICT and non-routine labor) of around 8.3. While the latter elasticity is not necessarily an object of particular interest, we will devote Section 5.2 to comment on the implications of these estimates for two elasticities that have received significant attention in the recent literature: the elasticity of substitution between aggregate capital and labor (e.g., Karabarbounis and Neiman, 2014; Oberfield and Raval, 2014) as

[15]See Appendix E for more details.

Table 2: Calibration of Production Parameters

	A. Data: 1968-2013		B. Trend: 1968-2013		C. Data: 1968/2013		D. Trend: 1968/2013	
	(A.1)	(A.2)	(B.1)	(B.2)	(C.1)	(C.2)	(D.1)	(D.2)
	$\ln\left(\frac{s_c}{s_{nr}}\right)$	$\ln\left(\frac{s_r}{s_{xnr}}\right)$	$\ln\left(\frac{s_c}{s_{nr}}\right)$	$\ln\left(\frac{s_r}{s_{xnr}}\right)$	$\ln\left(\frac{s_c}{s_{nr}}\right)$	$\ln\left(\frac{s_r}{s_{xnr}}\right)$	$\ln\left(\frac{s_c}{s_{nr}}\right)$	$\ln\left(\frac{s_r}{s_{xnr}}\right)$
$\ln(k_c/\ell_{nr})$	0.367***		0.358***		0.354		0.358	
	(0.038)		(0.000)					
$\ln(\ell_r/x_{nr})$		0.879***		0.880***		0.884		0.879
		(0.007)		(0.003)				
Constant	-5.763***	0.119***	-5.685***	0.124***	-5.717	0.113	-5.685	0.130
	(0.333)	(0.002)	(0.000)	(0.001)				
Obs.	46	46	46	46	2	2	2	2
Estimated Parameters & Implied Elasticities								
γ	0.003		0.003		0.003		0.003	
σ	0.367		0.358		0.354		0.358	
EOS(k_c, ℓ_{nr})	1.579		1.558		1.549		1.558	
η		0.530		0.531		0.528		0.532
θ		0.879		0.880		0.884		0.879
EOS(x_{nr}, ℓ_r)		8.269		8.307		8.596		8.263

Notes: The table shows OLS estimates of the parameters in equations (11) and (12) and the two-step procedure described in the text: in step one, we estimate (11); in step two, we estimate (12) conditional on the results from step one. Newey-West standard errors are reported in parethesis below estimated coefficients in panels A and B. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

well as the elasticity of ICT and routine labor (e.g., Autor and Dorn, 2013). We note that, in our framework, both of these elasticities are endogenous, time varying objects.

5. Counterfactual Analysis

We embed our calibrated production structure in a neoclassical growth model to study the effects of the declining ICT price. Formally, we consider a representative agent model, in which an infinitely lived household solves the following optimization problem:

$$\max_{c_t, k_{i,t+1}, l_{i,t}} \sum_{t=0}^{\infty} \beta^t u(c_t)$$

Table 3: Calibration of Remaining Parameters

Parameter	Calibration	
β	0.9747	
$u(c)$	$\ln(c)$	
δ_n	.059	(mean of non-ICT depreciation, BEA data)
α	0.349	(mean of non-ICT share)
λ_l	0.028	(trend US population growth)
$p_{c,t}$	$\in [0.254, 1.727]$	(BEA data, 1950-2013)
$\delta_{c,t}$	$\in [.134, 0.208]$	(BEA data, 1950-2013)

Notes: The ICT price and depreciation rates are measured directly based on the BEA's fixed asset accounts.

subject to $\ell_{r,t} + \ell_{nr,t} = 1$, $y_t = Ak_n^\alpha x_t^{1-\alpha}$, equation (10), and the budget constraint

$$c_t + (1+\lambda_l)\sum_i p_{i,t}k_{i,t+1} = y_t + \sum_i p_{i,t}(1-\delta_{i,t})k_{i,t}. \tag{13}$$

All variables are in per-worker terms: c_t is consumption per-worker, $k_{i,t}$ is the capital stock per-worker of type i, y_t is output per-worker and $\ell_{r,t}$ and $\ell_{nr,t}$ are the employment shares in routine and non-routine occupations. The parameter λ_l is the growth rate of labor, while A is a scaling parameter.

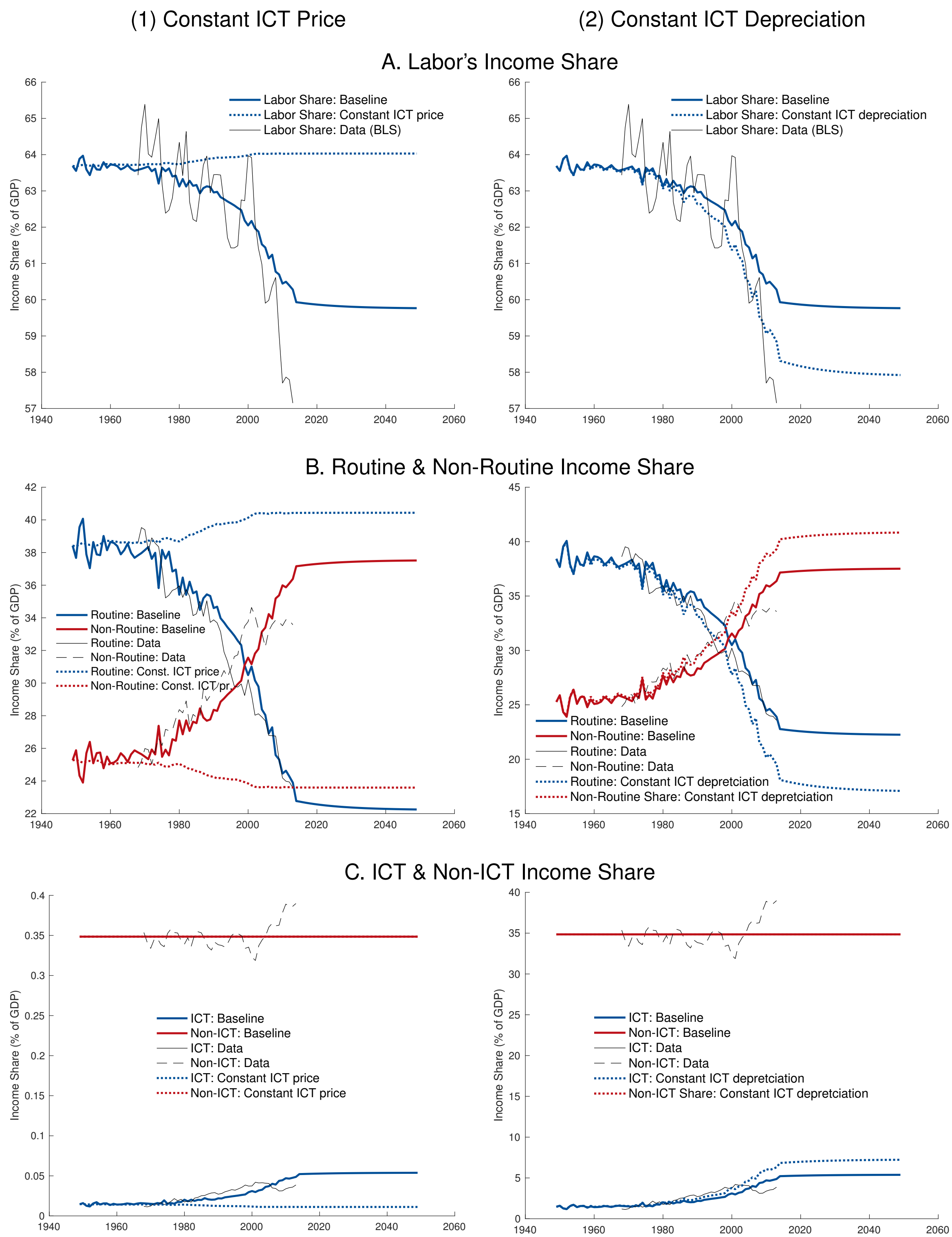
In our quantitative analysis we allow for two sources of exogenous variation. The first and most relevant is the decline in the price of ICT capital, $p_{c,t}$. As also mentioned by Karabarbounis and Neiman (2014), while prices are conceptually endogenous variables, in this context the price of ICT can be interpreted as the real transformation rate of output into ICT capital. Thus, a declining ICT price captures technological progress in the production of ICT capital.[16] The second source of exogenous variation that we consider is time variation in the depreciation rate of ICT capital, which, as we document, is quite substantial (see Figure 2).[17]

To assess the implications of the declining ICT price, we can therefore compare our baseline simulation with a counterfactual scenario in which the ICT price remains constant at its 1950 level. Our simulations are based on the calibration of the core production parameters (panel B of Table 2) and the values reported

[16] Formally, assume that $k_{c,t+1} - (1-\delta_c)k_{c,t} = a_t y_t^c$, where y_t^c is the output spent on ICT investment. A competitive market for the production of ICT capital goods would imply an ICT price of $p_c = \frac{1}{a}$.

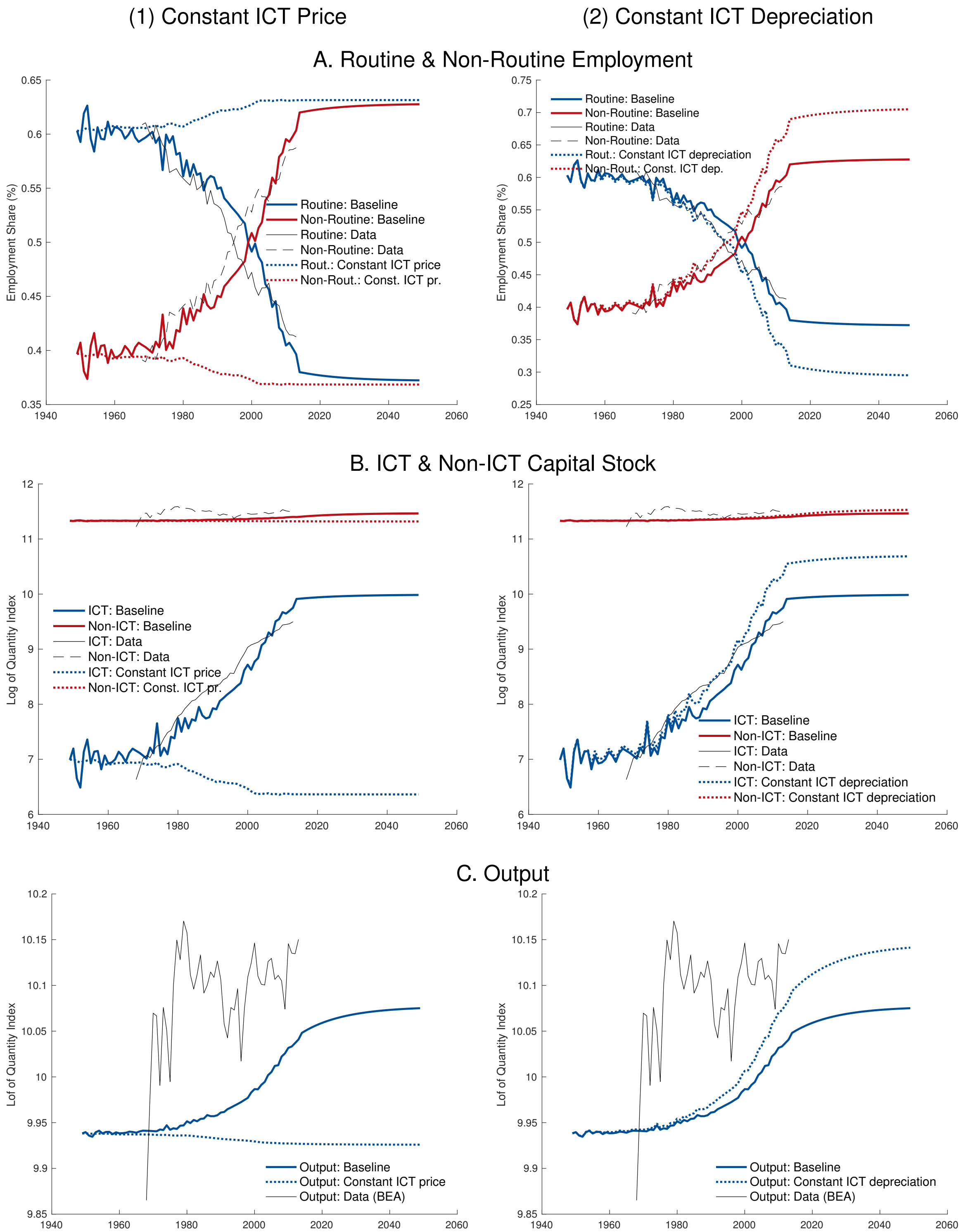
[17] We do this to improve the fit in our calibration but this does not materially affect our main results concerning the impact of the declining ICT price. We will illustrate this point below.

Figure 8: Counterfactuals: Income Shares



Notes: Each figure shows our baseline simulation (solid red and blue), data (thin black), and counterfactual simulations (dashed red and blue). All Simulations are initialized in a steady state consistent with the ICT price and depreciation in 1948.

Figure 9: Counterfactuals: Quantities



Notes: Each figure shows our baseline simulation (solid red and blue), data (thin black), and counterfactual simulations (dashed red and blue). All Simulations are initialized in a steady state consistent with the ICT price and depreciation in 1948.

in Table 3. The value of β, the discount factor, is calibrated based on our estimates of the returns to capital.[18] Given our focus on long run trends, we assume log utility, or a unitary inter-temporal elasticity of substitution, which is consistent with the wide range of empirical estimates (see, for example, the discussion and references listed by Guvenen, 2006). Moreover, log utility is a useful benchmark for expositional purposes, as income and substitution effects cancel out. For the depreciation rate of non-ICT capital we take the average value of our BEA-based estimates. Likewise, we calibrate the non-ICT capital intensity, α, using the average of our estimated non-ICT capital income share, ignoring any short term fluctuations around this average. As initial conditions for capital, we compute a steady state that is consistent with the 1950 values of the price and depreciation rate of ICT.

Figures 8 and 9 illustrate our simulated transition paths. All simulations are initialized in a steady state that is consistent with the price and depreciation rate of ICT in 1950. Each figure then displays two alternative transition paths alongside the data series used to calibrate the production function (1968-2013). Our baseline simulation takes the relative price and depreciation rate of ICT as estimated by the BEA and assumes that these series remain constant from 2013 on. That is, the final steady state is consistent with the 2013 price and depreciation rate of ICT. Column 1 of Figures 8 and 9 then contrasts the baseline with a counterfactual in which the relative price of ICT remains fixed at its initial (1950) level but the depreciation rate varies as measured in the data, again remaining fixed after 2013. A comparison of these two transition paths provides an estimate for the direct impact of the declining ICT price on predicted outcomes.

These simulations reveal a number of interesting insights. At around 1980, the price of ICT capital starts falling rapidly. In response, agents accumulate ICT capital, and the path of ICT starts diverging from its counterfactual. Since non-ICT capital is complementary to x, the accumulation of ICT capital raises the returns to non-ICT capital, and the stock of non-ICT capital increases as well. As a result of ICT and non-ICT capital accumulation, output increases relative to its counterfactual. Section 5.1 highlights the quantitative importance of indirect non-ICT investments for growth accounting exercises.

Table 4 shows that the falling ICT price leads to a divergence in the income shares of routine and non-routine labor, roughly consistent with the magnitudes observed in the data. The net effect on the aggregate

[18] The steady state Euler equation implies that $\beta(1 + r) = 1$, where r is the return to capital. We assume that the returns to capital before 1980 are roughly at their steady state level and calibrate β based on this relation.

Table 4: The Effects of the Declining ICT Price

A. Output & Consumption

	Log. Output			Log. Consumption		
	Baseline	Counterf.	Diff.	Baseline	Counterf.	Diff.
Initial SS	9.9383	9.9383	0	9.648	9.648	0
Final SS	10.0751	9.9259	0.1492	9.7351	9.6388	0.0963
% Change	+13.6848	-1.2319	+14.9167	8.7156	-0.9186	+9.6342

B. ICT and NICT Capital

	Log. ICT			Log. Non-ICT		
	Baseline	Counterf.	Diff.	Baseline	Counterf.	Diff.
Initial SS	6.99	6.99	0	11.3313	11.3313	0
Final SS	9.9843	6.3622	3.6221	11.4655	11.319	0.1464
% Change	+299.4309	-62.7841	+362.215	+13.4186	-1.224	+14.6427

C. Labor Share

	Agg. Labor Share			Routine Share			Non-Routine Share		
	Baseline	Counterf.	Diff.	Baseline	Counterf.	Diff.	Baseline	Counterf.	Diff.
Initial SS	63.69	63.69	0	38.42	38.42	0	25.27	25.27	0
Final SS	59.77	64.03	-4.26	22.25	40.44	-18.19	37.51	23.6	13.91
Change	-3.92	0.34	-4.26	-16.17	2.02	-18.19	+12.24	-1.67	+13.91

D. Capital Share

	ICT Share		
	Baseline	Counterf.	Diff.
Initial SS	1.46	1.46	0
Final SS	5.38	1.12	4.26
Change	+3.92	-0.34	+4.26

Notes: The table shows steady state changes for the baseline and counterfactual (constant ICT price) simulations. To gauge the impact of ICT on output, consumption, the stocks of ICT and non-ICT capital, labor and capital shares we compute the difference between the initial and final steady state for both simulations, along with the difference in differences.

labor income share is a 4.26 percentage point decline between 1950 and the final steady state, countered by an increase in the ICT capital income share of equal magnitude. In the data, we measured a 6.8 percentage point decline between 1950 and 2013 (see Table 1), suggesting that the falling price of ICT alone explains about half of the measured decline in the aggregate labor share (3.3pp over the period 1950-2013 in our baseline simulation).

In terms of welfare, the model suggests that the declining ICT price has lead to net steady state consumption and output gains of 9.7% and 14.9%, respectively. The output gains reflect larger ICT *and* non-ICT capital stocks, together with appropriate adjustments in the allocation of labor across routine and non-routine occupations. In Section 5.1 we will further discuss this observation, highlighting the quantitative importance of complementary non-ICT investment for the overall long run growth effect of the falling price of ICT.

To gauge the influence of the substantially increasing depreciation rate of ICT capital, column 2 of Figures 8 and 9 illustrates an alternative counterfactual simulation, in which we let the price of ICT follow its observed path but keep the rate of ICT depreciation fixed at its 1950 level. This exercise confirms that rising ICT depreciation works in the opposite direction of the effects of falling ICT prices, but quantitatively dampens the effects by a relatively small margin.

5.1. Growth Accounting & The General Equilibrium Multiplier

Economists have long sought to gauge the overall contribution of information and communication technologies (ICT) to output and consumption and most existing estimates are based on growth accounting exercises in the spirit of Solow (1957)—a decomposition of the growth in output into the marginal contributions of each production input. However, due to the low aggregate income share of ICT, this technique tends to attribute only a small portion of output growth to the accumulation of ICT capital (e.g., Colecchia and Schreyer, 2002; Basu et al., 2003; Jorgenson and Vu, 2007; Acemoglu et al., 2014). In this section, we start with an illustration based on steady state comparative statics, highlighting that traditional growth accounting exercises understate the long-run aggregate output gains from ICT by about 50%, in large part because they fail to account for an important general equilibrium effect: investments in ICT capital tend to trigger complementary non-ICT (NICT) investments.[19] While the steady state comparative statics are instructive, we we will also use our simulations to illustrate the quantitative importance of this general equilibrium effect

[19] Note that the work by Stiroh (2002) as well as Brynjolfsson and Hitt (2003) have found comparatively large gains from ICT by resorting to growth accounting exercises at the firm or industry level. However, the discrepancies between micro and macro estimates based on traditional growth accounting exercises are not surprising and possibly have a different interpretation. Intuitively, a growth accounting exercise at the industry (or firm) level will attribute a larger growth contribution of ICT to more ICT intensive industries, even if all industries had the same amount of ICT investment. The implied aggregate effects will then depend on the cross-sectional distribution of the output share of industries (or firms) with various ICT intensities. The argument we make in this paper is that even in industries with a low ICT intensity, the growth contribution of ICT may be substantial if there are sufficient complementarities with non-ICT.

along the transition path and put it in relation to observed growth in output per-capita in the US.

A growth accounting exercise is an accounting framework that attributes changes in output to changes in inputs. The growth accounted for by a marginal unit of ICT capital is:

$$\frac{\partial \ln y}{\partial \ln k_i} = (1-\alpha)\frac{\partial \ln x}{\partial \ln k_i} \tag{14}$$

To assess the indirect effect of ICT on non-ICT capital accumulation, recall that, in our neoclassical growth model, the steady state condition for NICT capital is given by:

$$\alpha k_n^{\alpha-1} x^{1-\alpha} = const \Rightarrow \ln k_n = const + \ln x \tag{15}$$

Using the above, we can quantify the general equilibrium (GE) effect of the growth in k_i as follows:

$$\begin{aligned} \frac{\partial \ln y}{\partial \ln k_i} + \frac{\partial \ln y}{\partial \ln k_n}\frac{\partial \ln k_n}{\partial \ln k_i} &= (1-\alpha)\frac{\partial \ln x}{\partial \ln k_i} + \alpha\frac{\partial \ln x}{\partial \ln k_i} \qquad (16) \\ &= \frac{\partial \ln x}{\partial \ln k_i} \end{aligned}$$

This expression suggests the following simple relationship between the direct accounting effect and the general equilibrium effect:

$$\text{GE growth contribution of } k_i = \frac{\text{Direct growth contribution of } k_i}{1-\alpha} \tag{17}$$

Given that non-ICT capital accounts for the bulk of capital income, our calibration suggests that $\alpha \approx 0.3485$. Thus, the general equilibrium contribution of ICT will be roughly 1.5 times its direct accounting contribution. In our simulation, the income share of ICT is roughly 0.03, and the growth in ICT capital is close to 300%. The direct effect is therefore approximately $0.03 \cdot 300\% = 9\%$. The contribution of non-ICT capital accumulation is $0.3485 \cdot 13\% \approx 4.5\%$. The GE contribution of ICT to growth is the sum of the two contributions, amounting to approximately 13.5%.

It is also possible to decompose the general equilibrium welfare gains from ICT into a direct contribution from ICT capital accumulation and an indirect contribution from NICT capital accumulation. At the steady state, consumption is given by:

$$c = y - \delta_i p_i k_i - \delta_n k_n \tag{18}$$

The direct marginal contribution of ICT capital accumulation to steady state consumption is:

$$\frac{\partial \ln c}{\partial \ln k_i} = \frac{\left(\frac{\frac{\partial y}{\partial k_i}}{p_i} - \delta_i\right) p_i k_i}{c} \tag{19}$$

It is useful to observe that, at the steady state,

$$\frac{\frac{\partial y}{\partial k_i}}{p_i} - \delta_i = \frac{\partial y}{\partial k_n} - \delta_n = \frac{1}{\beta} - 1 \tag{20}$$

Using this steady state condition to substitute for the expression in equation (19) and using a first order Taylor approximation, the direct contribution of ICT capital accumulation to steady state consumption is approximately:

$$\text{Direct welfare contribution} = \frac{(\frac{1}{\beta} - 1) p_i k_i}{c} \Delta \ln k_i \tag{21}$$

Deriving a similar expression for the contribution of NICT capital, the general equilibrium contribution is:

$$\begin{aligned} \text{GE welfare contribution} &= \frac{\left(\frac{1}{\beta} - 1\right) K}{c} \left(\frac{p_i k_i}{K} \Delta \ln k_i + \frac{k_n}{K} \Delta \ln k_n\right) \\ &\approx \frac{\left(\frac{1}{\beta} - 1\right) K}{c} \left(\frac{p_i k_i}{K} + \frac{k_n}{K} \frac{\partial \ln x}{\partial \ln k_i}\right) \Delta \ln k_i \end{aligned} \tag{22}$$

where $K = p_i k_i + k_n$ denotes the value of the aggregate capital stock, and the final expression uses the first order Taylor approximation for $\ln k_n$ with respect to changes in $\ln k_i$.

A back-of-the-envelope calculation suggests that the GE welfare gains from automation are roughly 2.8 times higher than the direct welfare gains. Assuming that ICT capital is 2.5% of the capital stock (the average value in our simulation), the first term in brackets is $p_i k_i / K = 0.025$. The second term in brackets is approximately equal to $k_n / K = 0.975$ times the ICT capital income share out of f, which is roughly $s_i/(1 - \alpha) = 0.03/(1 - 0.35) = 0.046$; thus the second term is roughly 0.045.

It is worth noting that it is possible to do this calculation using data rather than simulated variables.

Table 5: Contribution of ICT to Output Growth

		Growth Contribution of ICT		
	USA		% of USA	
Decade	% growth	perc. points	total	pp. due to NICT
	(1)	(2)	(3)	(4)
1950s	1.01	0.03	2.50	0.13
1960s	3.66	0.03	0.88	0.09
1970s	2.29	0.06	2.72	0.59
1980s	2.80	0.09	3.33	1.30
1990s	2.21	0.23	10.26	2.58
2000s	1.10	0.46	42.26	8.54
2010s	1.22	0.38	31.24	11.37
1950-2016	2.02	0.17	8.17	2.04

Notes: Column 1 shows the implied, constant, annual growth rate of real GDP per capita for various time periods in the US. Column 2 shows model predicted growth in GDP per capita due to the falling price of ICT. Column 3 expresses ICT's contribution (column 2) as a percent of USA (column 1). Column 4 is based on an alternative counterfactual simulation in which the stock of NICT capital is fixed at it's initial steady state value. The difference in the growth contribution between the baseline simulation and this counterfactual can be attributed to complementary NICT investments.

Since our simulated ICT stocks and income shares closely align with the data, the results would be similar. The added value of the simulation is in attributing the accumulation of ICT to falling capital prices, and justifying the plausibility of the steady state assumptions used in this analysis.

While the above steady state comparative statics illustrate the potential impact of the GE multiplier for long-run gains from ICT, we also find it instructive to illustrate its importance along the transition between steady states. Based on our baseline simulation illustrated in Figure 9, Table 5 puts the ICT-induced output growth (as predicted by our simulation) in relation to observed growth in real GDP per-capita in the United States. This comparison suggests that ICT accounted for at best 3% of US growth until the 1980s, while ICT was responsible for roughly 1/3 of US growth since 2000 (see column 3 of Table 5). Moreover, our framework also allows us to assess what portion of this growth contribution is due to the indirect accumulation of NICT capital. We accomplish this by simulating another counterfactual, in which we exogenously keep the NICT stock at its initial (1950) steady state level. The difference between this counterfactual and our baseline simulation illustrates the portion of ICT induced growth that is strictly due to complementary NICT investments. Column 4 of Table 5 shows that this contribution was relatively minor prior to the 1980s but significantly contributed to the substantial growth contribution of ICT in the most recent decades.

5.2. The Elasticity of Substitution Between Capital and Labor

A large literature, going back at least to Blanchard (1997) and Caballero and Hammour (1998), has discussed the central role of capital-labor substitutability for the division of income between capital and labor. However, despite its importance, the elasticity of substitution between these two factors is hard to estimate in practice, and the values reported in the literature range anywhere between 0.5 and 1.5.[20] Thus, we find it useful to discuss this elasticity within the context of our model. Like in the framework of Miyagiwa and Papageorgiou (2007) or Oberfield and Raval (2014) the aggregate elasticity of substitution is an endogenous, time-varying object. To compute the elasticity of substitution between capital and labor, we specify an aggregate production function in two inputs as:

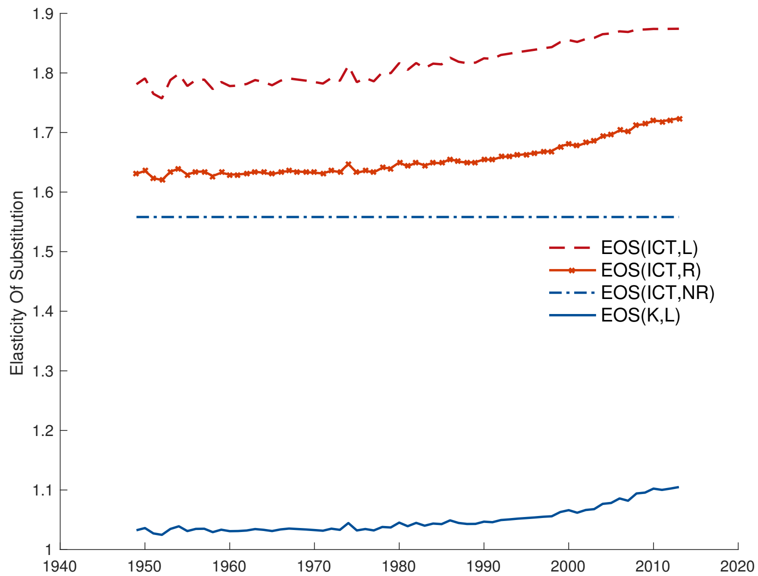
$$\begin{aligned} F(K, L) &= y(\ell_r^*, \ell_{nr}^*, k_i^*, k_n^*) \qquad (23) \\ \text{where } (\ell_r^*, l_{nr}^*, k_i^*, k_n^*) &= \arg \max_{\ell_r, \ell_{nr}, k_i, k_n} y + (1-\delta_n)k_n + (1-\delta_i)p_{i,t}k_i \\ \text{s.t. } L &= \ell_r + \ell_{nr} \\ \text{and } K &= p_{i,t-1}k_i + k_n \end{aligned}$$

Note that the optimality conditions with respect to capital and labor inputs imply that the rates of return to capital are equalized and that the marginal products of labor are equalized. We can thus solve for the marginal products, $MPL(K, L)$ and $MPK(K, L)$. The elasticity of substitution between capital and labor can then be obtained by numerically solving for the change in relative income shares, $[MPL(K, L) \times L]/[MPK(K, L) \times K]$, induced by a change in relative quantities, L/K. Using a similar representation based on the same logic, we can also compute the elasticities of substitution between ICT and different labor inputs.

Interestingly, we find an (average) aggregate elasticity of very close to unity, not far from the original estimates found by Berndt (1976). As Figure 10 illustrates, the implied aggregate elasticity starts at 1.03 in 1950 and rises to 1.1 in 2013, with an average value of 1.09. We note that Karabarbounis and Neiman (2014) illustrate, that a model with homogeneous aggregate labor and capital inputs requires an aggregate elasticity

[20] See for example, Berndt (1976), Antràs (2004), Klump, McAdam and Willman (2007), Karabarbounis and Neiman (2014), Piketty (2014), Oberfield and Raval (2014), or Alvarez-Cuadrado, Long and Poschke (2015), Herrendorf, Herrington and Valentinyi (2015).

Figure 10: Implied Elasticities of substitution



Notes: The Figure reports four elasticities of substitution within our model. The elasticity between ICT and non-routine labor is constant by construction. The elasticities between ICT and both types of labor, as well as aggregate capital and labor are computed using the procedure explained in Section 5.2.

of about 1.25 in order to predict approximately half of the observed fall in the aggregate labor share.[21] In contrast, we present a model in which technological progress is driven exclusively by falling ICT prices, which predicts about half of the observed fall in the aggregate US labor share, despite an approximately unitary elasticity of substitution.

Finally, our calibrated model also predicts that ICT is relatively more substitutable with routine labor compared to non-routine labor (see Figure 10), consistent with the task framework advocated by Acemoglu and Autor (2011).

[21] We note that, while similar, the two exercises can't be compared directly. For example, Karabarbounis and Neiman (2014) use investment prices (i.e., an investment share weighted aggregate price index) while we use the price of the ICT and non-ICT stocks. Investment weighted price indexes produce a much larger drop in the aggregate price index than stock weithed indexes. Thus, a direct, stock-weighted aggregation of our prices would require an even larger elasticity of substitution in order to rationalize half of the fall in the labor share in a model with aggregate capital and labor as the only production inputs. However, given the structure of our neo-classical growth model, the price of the ICT stock is the relevant price measure to conduct steady state comparative statics.

6. Concluding Remarks

The discussion of the social costs and benefits of automation can roughly be divided into two issues: the effects on aggregate consumption and the distributional implications. The general consensus is that, while there is likely a positive effect on aggregate consumption, there are some adverse distributional implications. The net welfare implications depend on the relative quantitative importance of the two.

In this paper we set out to derive a ballpark estimate for the overall quantitative benefits of automation, by employing a representative agent model in which redistribution of income is frictionless. We assess the long-run welfare gains from automation at about 14.9% gain in output per worker and 9.6% gain in consumption per worker. This welfare gain takes into account the transitional costs of accumulating ICT capital, but not the R&D costs associated with generating the decline in the ICT capital price, which we treat as exogenous. Moreover, our framework allows us to trace the quantitative importance of ICT in contributing to output an consumption growth at each point in time since 1950. We find that the growth contribution of ICT was relatively minor until the 1980s but accounts for about one third of growth in output per-capita since the 2000s. It is also important to note that complementary non-ICT investments—a general equilibrium effect that is hard to measure directly—substantially contributed to the overall growth impact of the "ICT Revolution".

Even though our representative agent framework is unable to account for distributional costs, it is informative regarding potential distributional implications. Our analysis suggests that while ICT may have a large effect on the distribution of labor income, it has only a moderate effect on the distribution of income between capital and labor.

Our results further suggest that automation is unlikely to be the sole cause of the declining labor income share. In particular, our measurement suggests that only half of the decline in the labor income share is directly countered by an increase in the ICT capital income share. The remainder is due to an increase in the non-ICT capital income share, particularly in the post-2001 period and primarily driven by housing. This suggests that, in order to fully understand the sources of the declining labor income share, it is necessary to study the mechanisms driving changes in non-ICT capital income, in particular residential capital income. We leave this challenge for future work.

References

Acemoglu D, Autor D. 2011. *Skills, Tasks and Technologies: Implications for Employment and Earnings*, volume 4 of *Handbook of Labor Economics*, chapter 12. Elsevier, 1043–1171.
URL http://ideas.repec.org/h/eee/labchp/5-12.html

Acemoglu D, Autor D, Dorn D, Hanson GH, Price B. 2014. Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing. *American Economic Review* **104**: 394–99.
URL http://ideas.repec.org/a/aea/aecrev/v104y2014i5p394-99.html

Akerman A, Gaarder I, Mogstad M. 2015. The Skill Complementarity of Broadband Internet. *The Quarterly Journal of Economics* **130**: 1781–1824.
URL https://ideas.repec.org/a/oup/qjecon/v130y2015i4p1781-1824.html

Alvarez-Cuadrado F, Long NV, Poschke M. 2015. Capital-Labor Substitution, Structural Change and the Labor Income Share. IZA Discussion Papers 8941, Institute for the Study of Labor (IZA).
URL https://ideas.repec.org/p/iza/izadps/dp8941.html

Antràs P. 2004. Is the u.s. aggregate production function cobb-douglas? new estimates of the elasticity of substitution. *The B.E. Journal of Macroeconomics* **4**: 1–36.
URL http://ideas.repec.org/a/bpj/bejmac/vcontributions.4y2004i1n4.html

Autor D, Dorn D, Hanson GH. 2013. Untangling Trade and Technology: Evidence from Local Labor Markets. IZA Discussion Papers 7329, Institute for the Study of Labor (IZA).
URL http://ideas.repec.org/p/iza/izadps/dp7329.html

Autor DH, Dorn D. 2013. The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review* **103**: 1553–97.
URL http://ideas.repec.org/a/aea/aecrev/v103y2013i5p1553-97.html

Autor DH, Levy F, Murnane RJ. 2003. The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics* **118**: 1279–1333.
URL http://ideas.repec.org/a/tpr/qjecon/v118y2003i4p1279-1333.html

Basu S, Fernald JG, Oulton N, Srinivasan S. 2003. The Case of the Missing Productivity Growth: Or, Does Information Technology Explain why Productivity Accelerated in the US but not the UK? NBER Working Papers 10010, National Bureau of Economic Research, Inc.
URL http://ideas.repec.org/p/nbr/nberwo/10010.html

Berndt ER. 1976. Reconciling Alternative Estimates of the Elasticity of Substitution. *The Review of Economics and Statistics* **58**: 59–68.
URL https://ideas.repec.org/a/tpr/restat/v58y1976i1p59-68.html

Blanchard OJ. 1997. The medium run. *Brookings Papers on Economic Activity* **1997**: 89–158.

Bloom N, Sadun R, Van Reenen J. 2012. Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review* **102**: 167–201.
URL http://ideas.repec.org/a/aea/aecrev/v102y2012i1p167-201.html

Bridgman B. 2014. Is Labor's Loss Capital's Gain? Gross versus Net Labor Shares. BEA Working Papers 0114, Bureau of Economic Analysis. URL http://ideas.repec.org/p/bea/wpaper/0114.html

Brynjolfsson E, Hitt LM. 2003. Computing productivity: Firm-level evidence. *The Review of Economics and Statistics* **85**: 793–808. URL http://ideas.repec.org/a/tpr/restat/v85y2003i4p793-808.html

Caballero RJ, Hammour ML. 1998. Jobless growth: appropriability, factor substitution, and unemployment. *Carnegie-Rochester Conference Series on Public Policy* **48**: 51 – 94. ISSN 0167-2231. URL http://www.sciencedirect.com/science/article/pii/S0167223198000165

Caselli F, Feyrer J. 2007. The marginal product of capital. *The Quarterly Journal of Economics* **122**: 535–568. URL http://ideas.repec.org/a/tpr/qjecon/v122y2007i2p535-568.html

Champagne J, Kurmann A. 2012. Reconciling the divergence in aggregate us wage series. Working Paper. URL http://www.andrekurmann.com/files/wp_files/CESpaper_27July2012.pdf

Christensen LR, Jorgenson DW. 1969. The measurement of us real capital input, 1929–1967. *Review of Income and Wealth* **15**: 293–320.

Colecchia A, Schreyer P. 2002. ICT Investment and Economic Growth in the 1990s: Is the United States a Unique Case? A Comparative Study of Nine OECD Countries. *Review of Economic Dynamics* **5**: 408–442. URL http://ideas.repec.org/a/red/issued/v5y2002i2p408-442.html

Cortes GM, Jaimovich N, Nekarda CJ, Siu HE. 2014. The micro and macro of disappearing routine jobs: A flows approach. Working Paper 20307, National Bureau of Economic Research. URL http://www.nber.org/papers/w20307

Dorn D. 2009. Essays on inequality, spatial interaction, and the demand for skills. Dissertation 3613, University of St. Gallen.

Eden M, Gaggl P. 2015. Do poor countries really need more IT ? the role of relative prices and industrial composition. Policy Research Working Paper Series 7352, The World Bank. URL http://ideas.repec.org/p/wbk/wbrwps/7352.html

Elsby MW, Hobijn B, Sahin A. 2013. The decline of the us labor share. *Brookings Papers on Economic Activity* .

Gaggl P, Kaufmann S. 2015. The Cyclical Component of Labor Market Polarization and Jobless Recoveries in the US. Economics Working Paper 2015-004, UNC Charlotte. URL https://belkcollegeofbusiness.uncc.edu/economic-working-papers/wp-content/uploads/sites/850/2012/10/wp2015-004.pdf

Gaggl P, Wright GC. 2016. A short run view of what computers do: Evidence from a uk tax incentive. Forthcoming in *American Economic Journal: Applied Economics* . URL https://belkcollegeofbusiness.uncc.edu/pgaggl/wp-content/uploads/sites/867/2014/09/UK_ICT_AEJA_Revision_Final.pdf

Guvenen F. 2006. Reconciling conflicting evidence on the elasticity of intertemporal substitution: A macroeconomic perspective. *Journal of Monetary Economics* **53**: 1451–1472. URL http://ideas.repec.org/a/eee/moneco/v53y2006i7p1451-1472.html

Hall RE, Jorgenson DW. 1967. Tax policy and investment behavior. *The American Economic Review* **57**: pp. 391–414. ISSN 00028282.
URL http://www.jstor.org/stable/1812110

Herrendorf B, Herrington C, Valentinyi Á. 2015. Sectoral Technology and Structural Transformation. *American Economic Journal: Macroeconomics* **7**: 104–33.
URL https://ideas.repec.org/a/aea/aejmac/v7y2015i4p104-33.html

Jorgenson DW. 1995. *Productivity: Postwar US economic growth*, volume 1. Mit Press.

Jorgenson DW, Vu K. 2007. Information Technology and the World Growth Resurgence. *German Economic Review* **8**: 125–145.
URL http://ideas.repec.org/a/bla/germec/v8y2007ip125-145.html

Karabarbounis L, Neiman B. 2014. The global decline of the labor share. *The Quarterly Journal of Economics* **129**: 61–103.
URL http://qje.oxfordjournals.org/content/129/1/61.abstract

Klump R, McAdam P, Willman A. 2007. Factor Substitution and Factor-Augmenting Technical Progress in the United States: A Normalized Supply-Side System Approach. *The Review of Economics and Statistics* **89**: 183–192.
URL https://ideas.repec.org/a/tpr/restat/v89y2007i1p183-192.html

Krusell P, Ohanian LE, Ríos-Rull JV, Violante GL. 2000. Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica* **68**: 1029–1054.
URL http://ideas.repec.org/a/ecm/emetrp/v68y2000i5p1029-1054.html

Levy F, Murnane RJ. 1992. U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations. *Journal of Economic Literature* **30**: 1333–81.
URL http://ideas.repec.org/a/aea/jeclit/v30y1992i3p1333-81.html

Miyagiwa K, Papageorgiou C. 2007. Endogenous aggregate elasticity of substitution. *Journal of Economic Dynamics and Control* **31**: 2899–2919.
URL https://ideas.repec.org/a/eee/dyncon/v31y2007i9p2899-2919.html

Oberfield E, Raval D. 2014. Micro Data and Macro Technology. NBER Working Papers 20452, National Bureau of Economic Research, Inc.
URL https://ideas.repec.org/p/nbr/nberwo/20452.html

O'Mahony M, Van Ark B. 2003. *EU productivity and competitiveness: an industry perspective: can Europe resume the catching-up process?* Office for Official Publications of the European Communities Luxembourg.

Piketty T. 2014. *Capital in the Twenty-First Century*. Harvard University Press. ISBN 9780674369559.
URL https://books.google.com/books?id=J222AgAAQBAJ

Piketty T, Saez E. 2003. Income inequality in the united states, 1913-1998. *The Quarterly Journal of Economics* **118**: 1–39.
URL http://ideas.repec.org/a/tpr/qjecon/v118y2003i1p1-39.html

Rognlie M. 2015. Deciphering the fall and rise in the net capital share. In *Brookings Papers on Economic Activity*. Conference Draft.
URL http://www.brookings.edu/~/media/projects/bpea/spring-2015/2015a_rognlie.pdf

Ruggles S, Alexander JT, Genadek K, Goeken R, Schroeder MB, Sobek M. 2010. Integrated public use microdata series: Version 5.0 [machine-readable database]. Technical report, University of Minnesota, Minneapolis.
URL https://cps.ipums.org/cps/

Solow RM. 1957. Technical change and the aggregate production function. *The Review of Economics and Statistics* **39**: 312–320.

Stiroh KJ. 2002. Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say? *American Economic Review* **92**: 1559–1576.
URL https://ideas.repec.org/a/aea/aecrev/v92y2002i5p1559-1576.html

vom Lehn C. 2015. Labor Market Polarization, the Decline of Routine Work, and Technological Change: A Quantitative Evaluation. 2015 Meeting Papers 151, Society for Economic Dynamics.
URL http://ideas.repec.org/p/red/sed015/151.html

Appendix A. Construction of Capital Income Shares

This appendix outlines our approach to measure income shares directly from the BEA's nominal current cost values of detailed asset categories. As discussed in Section 2, our measurement exercise relies on two assumptions: First, no-arbitrage in capital markets requires the *gross return* (2) to be equalized across all types of capital, which can be written more compactly as

$$(1+\pi_{i,t})\frac{R_{i,t}}{P_{i,t}} + CG_{i,t} = R_t \tag{A.1}$$

where $(1+\pi_{i,t}) \equiv P_{i,t+1}/P_{i,t}$ is gross price inflation and $CG_{i,t} = (1+\pi_{i,t})(1-\delta_t)$ are capital gains for capital of type i.

Second, we impose constant returns to scale in aggregate production (equation (1)), and thus the following condition must hold:

$$s_{K,t}P_tY_t = \sum_{i\in I} R_{i,t}K_{i,t} \tag{A.2}$$

where $s_{K,t}$ is a measure of the income share paid to reproducible capital. Equations (A.1) and (A.2) directly imply the following expression for the relative price adjusted rental rates for each capital type $i = \{c, n\}$:

$$\mathit{PR}_{c,t} = \frac{R_{c,t}}{P_{c,t}} = \frac{P_{n,t}K_{n,t}}{\tilde{P}_t\tilde{K}_t}(CG_{n,t} - CG_{c,t}) + (1+\pi_{n,t})s_{K,t}\frac{P_tY_t}{\tilde{P}_t\tilde{K}_t} \tag{A.3}$$

$$\mathit{PR}_{n,t} = \frac{R_{n,t}}{P_{n,t}} = \frac{P_{c,t}K_{c,t}}{\tilde{P}_t\tilde{K}_t}(CG_{c,t} - CG_{n,t}) + (1+\pi_{c,t})s_{K,t}\frac{P_tY_t}{\tilde{P}_t\tilde{K}_t} \tag{A.4}$$

where $\tilde{P}_t\tilde{K}_t \equiv (1+\pi_{n,t})P_{c,t}K_{c,t} + (1+\pi_{c,t})P_{n,t}K_{n,t}$. Based on (A.3) and (A.4) we then compute the income shares for each type of capital as

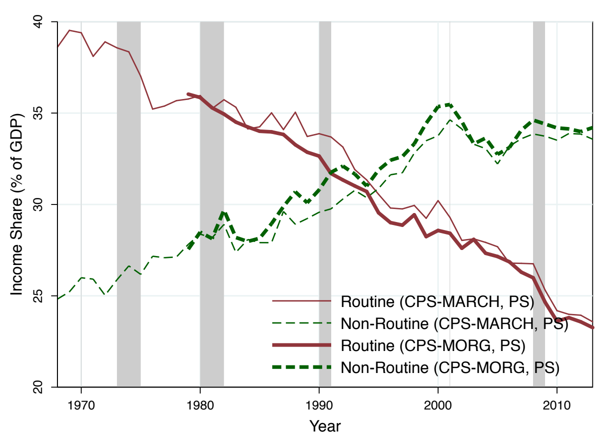
$$s_{c,t} = PR_{c,t} \frac{P_{c,t}K_{c,t}}{P_t Y_t} \tag{A.5}$$

$$s_{n,t} = PR_{n,t} \frac{P_{n,t}K_{n,t}}{P_t Y_t} \tag{A.6}$$

where we use the following data inputs:

1.	$(1 + \pi_{i,t})$	ICT/non-ICT prices based on the BEA's fixed asset accounts
2.	$(1 - \delta_{i,t})$	depreciation rates from the BEA's fixed asset accounts accounts
3.	$P_{i,t}K_{i,t}$	nominal capital stocks from the BEA's fixed asset accounts accounts
4.	$P_t Y_t$	nominal GDP from the BEA
5.	$s_{K,t}$	measured as the reciprocal of the official BLS labor share

Figure A.11: Labor's Income Share: MORG vs. MARCH

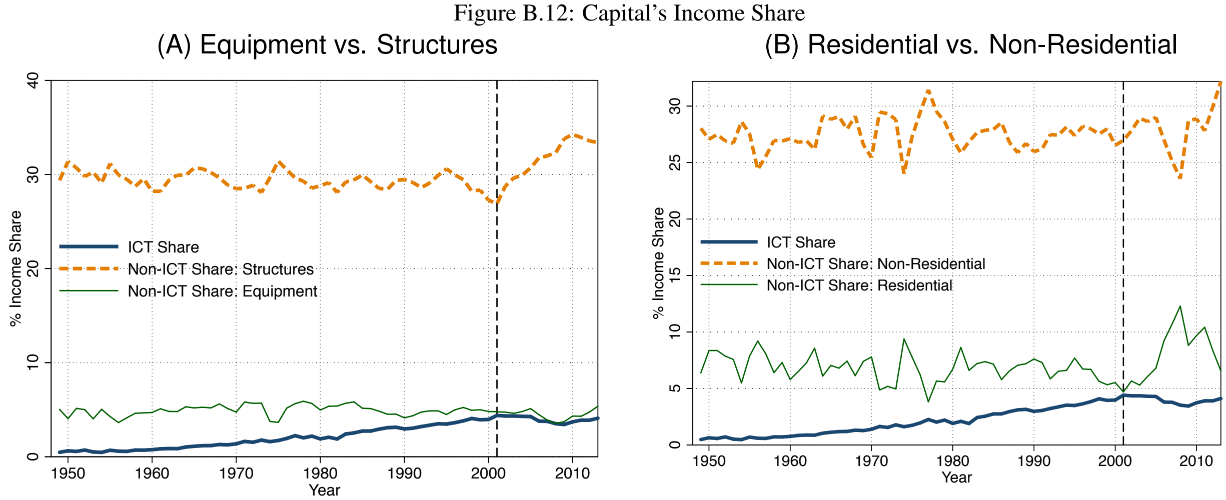


Notes: Occupation specific income shares are based on CPS earnings data from the annual march supplement (1968 and after) and the monthly outgoing rotation groups (MORG, starting in 1979) extracts and rescaled to match the aggregate income share in the Non-Farm Business Sector (BLS). The underlying earnings data for both series are top-code adjusted using Piketty and Saez's (2003) updated estimates of the income distribution (PS). The MORG series shows annual averages of monthly data that was seasonally adjusted using the U.S. Cenusus X11 method. The graphs are constructed analogously to panel A in Figure 1. For details see Section 3.

Appendix B. CPS Outoing Rotation Groups vs. March Supplements

Figure A.11 illustrates a comparison of the disaggregate labor income shares based on two alternative measures of earnings. The details for the data construction are discussed in Section 3. The thick lines are the shares reported in panel A of Figure 1 and are based on the march supplements in the CPS (MARCH). The thin lines use usual weekly earnings from the outgoing rotation groups (MORG).

Figure B.12: Capital's Income Share



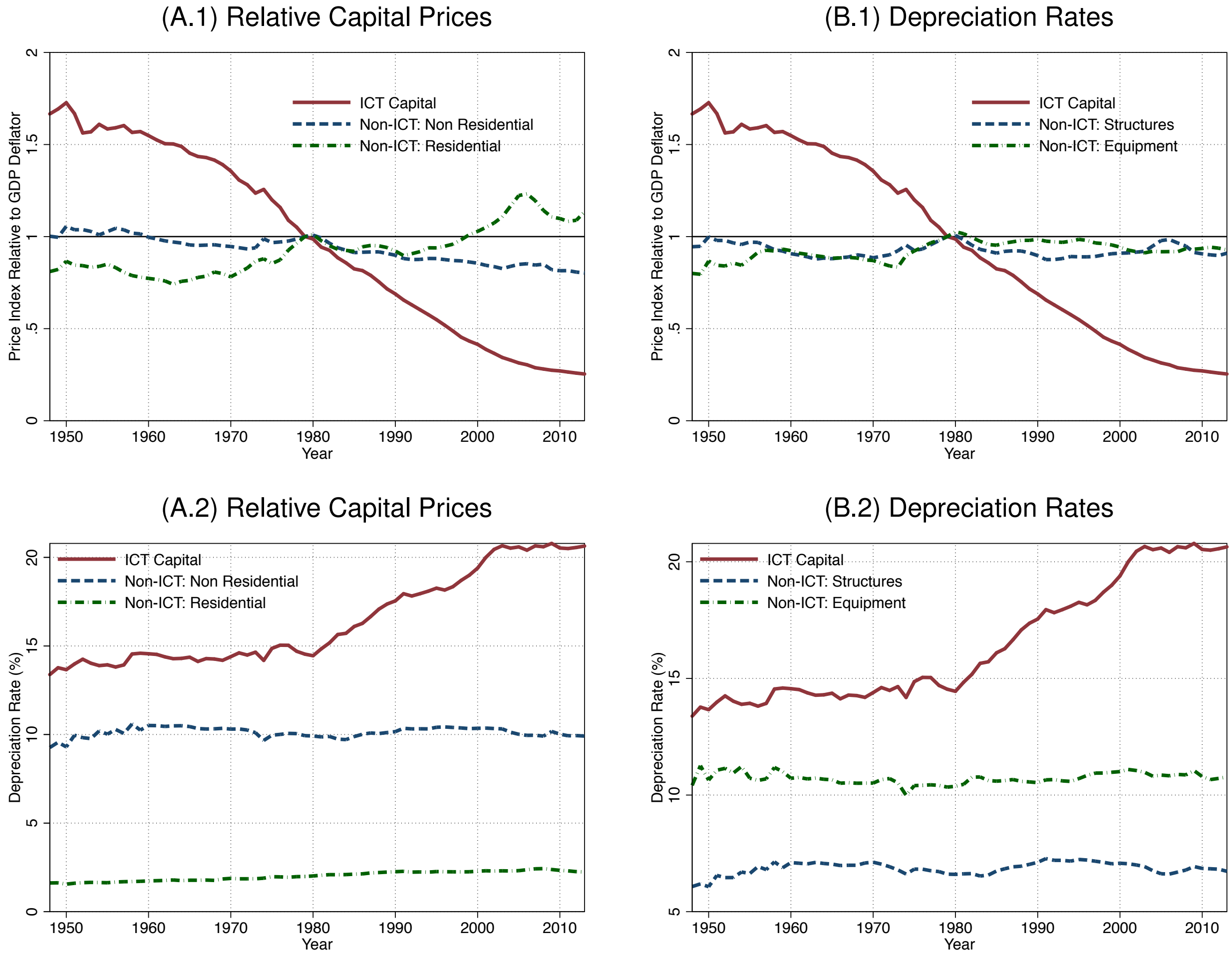
Notes: Panel A decomposes the non-ICT share into equipment and structures. Panel B decomposes the non-ICT share into residential and non-residential capital. The computations are based on the methodology described in Section 2 and the underlying data are nominal gross capital stocks and depreciation rates, drawn from the BEA's detailed fixed asset accounts. The vertical dashed line indicates the year 2001.

Appendix C. The Role of Housing

Rognlie (2015) has recently argued that housing may be the main driver for an increase in the net capital share—the capital income share, net of depreciation—since 1970. In light of this, we briefly discuss the role of housing within the context of our analysis. To this end, we use the methodology described in Section 2 to decompose the NICT share into residential and non-residential assets and alternatively equipment and structures.

Figure B.12 illustrates the resulting decompositions, again based on the BEA's fixed asset accounts, and highlights a number of important observations: first, NICT equipment (panel A) as well as non-residential NICT assets (panel B) are completely trend-less; second, consistent with the findings of Rognlie (2015), the

Figure C.13: Relative Prices & Depreciation (Housing)



Notes: Panels A.1 and B.1 graph implicit price deflators by capital type relative to the GDP deflator, which were constructed directly from the BEA's detailed fixed-asst accounts. The BEA GDP deflator is taken from FRED. Panels A.2 and B.2 depicts asset-specific depreciation rates constructed directly from the BEA's fixed asset accounts.

increase in the NICT capital income share in the post 2001 period is accounted for entirely by structures (panel A) and residential capital (panel B). Since the "housing share" is unlikely to be reflective of automation, our calibration in Section 4 assumes that the part of the decline in the labor share which is attributable to ICT accumulation is only the portion that is directly countered by an increase in the ICT share.

In addition, the decomposition in panel A also emphasizes that a decomposition into equipment and structures, which ignores the distinction between ICT and NICT, as suggested by Krusell et al. (2000), will blur this picture, as the income share of NICT equipment is trend-less throughout the entire sample.

Finally, we note that this more disaggregated decomposition takes into account heterogeneous prices and

Table D.6: Within Industry Trends in Capital Income Shares

	ICT Share		Non-ICT Share	
	(1)	(2)	(3)	(4)
Ann. Trend Growth (%)	3.873***	3.873***	0.0692	0.0692
	(0.327)	(0.193)	(0.205)	(0.0601)
Industry FEs		yes		yes
Observations	1197	1197	1197	1197

Notes: The table shows regressions of 100 times the log ICT and non-ICT shares on a time trend for an annual panel of 19 broad sectors over the period 1949-2012. Columns 1 and 3 report pooled regressions while columns 2 and 4 condition on a complete set of fixed effects for 19 broad sectors. Sector specific income shares are based on the BEA fixed asset accounts and the BEA's estimates of sector specific value added and constructed as in Eden and Gaggl (2015). Standard errors are HAC robust and significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

depreciation rates for the different types of assets as measured by the BEA and depicted in Figure C.13. This price decomposition further emphasizes that essentially all of the fall in equipment prices is concentrated in ICT, further justifying our focus on falling ICT prices, rather than those of equipment as a whole.

Appendix D. The Role of Industrial Composition

In Section 4, we calibrate a one-sector aggregate production structure that matches the trends depicted in panel A of Figure 1. To justify such an approach, we illustrate that the disaggregated trends in the capital share are not merely a result of changes in the industrial composition but rather a within-industry phenomenon, by constructing industry specific ICT and NICT shares as in Eden and Gaggl (2015) based on the BEA's detailed fixed asset accounts. We then estimate the average annual growth rates in these income shares both with and without industry fixed effects. Table D.6 illustrates that the ICT share was growing at about 3% annually while the NICT share showed no significant trend growth over the period 1948 - 2012. Importantly, columns 3 and 4 illustrate that this finding does not change after we control for a complete set of industry fixed effects. In fact, we find that the levels of ICT intensity vary vastly across the various industries, but the differential trends in ICT and NICT income shares are predominantly a within industry phenomenon.

Appendix E. Marginal Products

In this section we illustrate the first order conditions of a profit maximizing producer facing our production structure for the case of specification (10). The production function is then given by

$$
\begin{aligned}
y &= k^{\alpha} x^{1-\alpha} &\text{(E.1)}\\
x &= \left[\eta \ell_r^{\theta} + (1-\eta) x_{nr}^{\theta}\right]^{\frac{1}{\theta}} &\text{(E.2)}\\
x_{nr} &= \left[\gamma k_c^{\sigma} + (1-\gamma) \ell_{nr}^{\sigma}\right]^{\frac{1}{\sigma}} &\text{(E.3)}
\end{aligned}
$$

and the associated marginal products are

$$
\begin{aligned}
MPK_k &= \alpha \frac{y}{k} &\text{(E.4)}\\
MPK_c &= p_{x_{nr}} \gamma \left(\frac{k_c}{x_{nr}}\right)^{\sigma-1} &\text{(E.5)}\\
MPL_{nr} &= p_{x_{nr}} (1-\gamma) \left(\frac{\ell_{nr}}{x_{nr}}\right)^{\sigma-1} &\text{(E.6)}\\
MPL_r &= p_x \eta \left(\frac{\ell_r}{x}\right)^{\theta-1} &\text{(E.7)}
\end{aligned}
$$

where the two auxiliary prices $p_{x_{nr}}$ and p_x are defined as

$$
\begin{aligned}
p_x &= \frac{\partial y}{\partial x} = (1-\alpha)\frac{y}{x} &\text{(E.8)}\\
p_{x_{nr}} &= \frac{\partial y}{\partial x_{nr}} = p_x (1-\eta) \left(\frac{x_{nr}}{x}\right)^{\theta-1} &\text{(E.9)}
\end{aligned}
$$

A profit maximizing produce will therefore face the following first order conditions:

$$
\begin{aligned}
R_k &= \alpha \frac{y}{k} &\text{(E.10)}\\
R_c &= p_{x_{nr}} \gamma \left(\frac{k_c}{x_{nr}}\right)^{\sigma-1} &\text{(E.11)}\\
w_{nr} &= p_{x_{nr}} (1-\gamma) \left(\frac{\ell_{nr}}{x_{nr}}\right)^{\sigma-1} &\text{(E.12)}\\
w_r &= p_x \eta \left(\frac{\ell_r}{x}\right)^{\theta-1} &\text{(E.13)}
\end{aligned}
$$

These conditions directly imply the following two relations

$$\frac{R_c}{w_{nr}} = \frac{p_x(1-\eta)\left(\frac{x_{nr}}{x}\right)^{\theta-1}\gamma\left(\frac{k_c}{x_{nr}}\right)^{\sigma-1}}{p_x(1-\eta)\left(\frac{x_{nr}}{x}\right)^{\theta-1}(1-\gamma)\left(\frac{\ell_{nr}}{x_{nr}}\right)^{\sigma-1}} = \frac{\gamma}{(1-\gamma)}\cdot\left(\frac{\ell_{nr}}{k_c}\right)^{\sigma-1} \tag{E.14}$$

$$\frac{w_r}{p_{x_{nr}}} = \frac{p_x\eta\left(\frac{\ell_r}{x}\right)^{\theta-1}}{p_x(1-\eta)\left(\frac{x_{nr}}{x}\right)^{\theta-1}} = \frac{\eta}{1-\eta}\cdot\left(\frac{\ell_r}{x_{nr}}\right)^{\theta-1} \tag{E.15}$$

or equivalently

$$\frac{R_c k_c}{w_{nr}\ell_{nr}} = \frac{s_c}{s_{nr}} = \frac{\gamma}{(1-\gamma)}\cdot\left(\frac{k_c}{\ell_{nr}}\right)^{\sigma} \tag{E.16}$$

$$\frac{w_r\ell_r}{p_{x_{nr}}x_{nr}} = \frac{s_r}{s_{x_{nr}}} = \frac{\eta}{1-\eta}\cdot\left(\frac{\ell_r}{x_{nr}}\right)^{\theta} \tag{E.17}$$

Taking logs yields expressions (11) and (12) in the main text.

Appendix F. Autor-Dorn Calibration

Analogously to our preferred specification discussed in the text (10) we illustrate the analogous two-step calibration procedure for equation (9). In this case, the following conditions must hold for a competitive producer:

$$\ln\left(\frac{s_c}{s_r}\right) = \ln\left(\frac{\chi}{1-\chi}\right) + \rho\ln\left(\frac{k_c}{\ell_r}\right) \tag{F.1}$$

$$\ln\left(\frac{s_{x_r}}{s_{nr}}\right) = \ln\left(\frac{\mu}{1-\mu}\right) + \varphi\ln\left(\frac{x_r}{\ell_{nr}}\right) \tag{F.2}$$

where s_i is the income share of input $i \in \{k_c, \ell_{nr}, \ell_r, x_{nr}\}$, with $x_r = (\chi k_c^\rho + (1-\chi)\ell_r^\rho)^{\frac{1}{\rho}}$ and associated income share $s_{x_r} = s_c + s_r$. Again, we use measured trends in income shares and quantities from the previous sections to calibrate the four parameters χ, ρ, μ, and φ using the following two steps:

1. Estimate χ and ρ using OLS and compute the implied time series for $x_r = (\chi k_c^\rho + (1-\chi)\ell_r^\rho)^{\frac{1}{\rho}}$
2. Estimate μ and φ using OLS, conditional on the implied series for x_r from step 1

Analogously to the table shown in the main text, Table F.7 reports the results based on this procedure for specification (9) in four alternative versions. Again, Panel A uses all data as measured in the previous

Table F.7: Calibration of Production Parameters

	A. Data: 1968-2013		B. Trend: 1968-2013		C. Data: 1968/2013		D. Trend: 1968/2013	
	(A.1)	(A.2)	(B.1)	(B.2)	(C.1)	(C.2)	(D.1)	(D.2)
	$\ln\left(\frac{s_c}{s_r}\right)$	$\ln\left(\frac{s_{xr}}{s_{nr}}\right)$	$\ln\left(\frac{s_c}{s_r}\right)$	$\ln\left(\frac{s_{xr}}{s_{nr}}\right)$	$\ln\left(\frac{s_c}{s_r}\right)$	$\ln\left(\frac{s_{xr}}{s_{nr}}\right)$	$\ln\left(\frac{s_c}{s_r}\right)$	$\ln\left(\frac{s_{xr}}{s_{nr}}\right)$
$\ln(k_c/\ell_r)$	0.527***		0.525***		0.512		0.525	
	(0.025)		(0.000)					
$\ln(x_r/\ell_{nr})$		1.204***		1.203***		1.207		1.218
		(0.019)		(0.015)				
Constant	-7.240***	-0.123***	-7.224***	-0.124***	-7.126	-0.131	-7.224	-0.148
	(0.222)	(0.007)	(0.000)	(0.004)				
Obs.	46	46	46	46	2	2	2	2
Estimated Parameters & Implied Elasticities								
χ	0.001		0.001		0.001		0.001	
ρ	0.527		0.525		0.512		0.525	
EOS(k_c, ℓ_r)	2.113		2.105		2.050		2.105	
μ		0.469		0.469		0.467		0.463
φ		1.204		1.203		1.207		1.218
EOS(x_{nr}, ℓ_r)								

Notes: The table shows OLS estimates of the parameters in equations (F.1) and (F.2) and the two-step procedure described in the text: in step one, we estimate (F.1); in step two, we estimate (F.2) conditional on the results from step one. Newey-West standard errors are reported in parethesis below estimated coefficients in panels A and B. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

sections, panel B uses a fitted log linear trend rather than the measured data, while panels C and D fit only the first and last data/trend point, respectively. While step 1 implies an elasticity of substitution between routine labor and ICT of around 2, which is slightly higher than what is implied by our main specification discussed in the text (see Section 5.2), step two implies a value of $\varphi > 1$ violating one of the parameter restrictions within the CES framework (which requires $\varphi \leq 1$). We therefore conclude that, using our calibration strategy, specification (9) cannot rationalize the trends we observe in the data.

Appendix G. Classification of ICT and Non-ICT Assets

Table G.8: ICT Assets

	Share of Aggregate Capital (%)			Average Growth in Share (%)		
ICT Assets	1960-1980	1980-2000	2000-2013	1960-1980	1980-2000	2000-2013
EP20: Communications	2.73	3.91	3.39	2.87	1.78	-2.63
ENS3: Own account software	0.24	0.75	1.56	27.26	6.68	2.58
ENS2: Custom software	0.11	0.61	1.40	34.82	8.49	2.06
EP34: Nonelectro medical instruments	0.35	0.76	1.08	4.87	2.97	2.30
EP36: Nonmedical instruments	0.51	0.92	0.92	0.62	2.41	-1.08
ENS1: Prepackaged software	0.02	0.33	0.83	32.28	14.63	-1.04
EP35: Electro medical instruments	0.11	0.36	0.66	7.25	3.43	4.28
EP1B: PCs	0.00	0.31	0.45		12.12	0.96
RD23: Semiconductor and other component manufacturing	0.05	0.23	0.43	6.58	8.21	2.75
RD22: Communications equipment manufacturing	0.26	0.21	0.27	3.27	0.89	0.24
EP31: Photocopy and related equipment	0.53	0.75	0.26	6.75	-2.11	-7.70
EP1A: Mainframes	0.19	0.36	0.24	24.00	1.91	-4.97
EP1H: System integrators	0.00	0.03	0.23		42.85	3.45
RD24: Navigational and other instruments manufacturing	0.05	0.19	0.22	3.20	5.78	-1.59
EP1D: Printers	0.07	0.22	0.19	20.75	7.20	-9.76
EP1E: Terminals	0.02	0.14	0.16	71.14	5.48	-4.62
EP1G: Storage devices	0.00	0.17	0.12		7.55	-9.55
EP12: Office and accounting equipment	0.48	0.32	0.12	-3.09	-5.00	-6.13
RD40: Software publishers	0.00	0.05	0.09		16.91	-1.13
RD21: Computers and peripheral equipment manufacturing	0.16	0.09	0.07	3.68	-3.07	-0.60
RD25: Other computer and electronic manufacturing, n.e.c.	0.01	0.01	0.02	0.91	3.24	-0.34
EP1C: DASDs	0.09	0.13	0.00	30.38	-36.26	-78.36
EP1F: Tape drives	0.06	0.03	0.00	22.77	-40.33	-186.06

Notes: The data are drawn from the BEA's detailed fixed asset accounts. ICT assets are defined as BEA asset codes starting with EP, EN, RD2, or RD4. Notice that the EP category incorporates two assets that are strictly speaking likely not ICT: EP34 and EP36. Our results do not critically hinge on these two assets and we therefore stick with the more standard BEA aggregation of EP. Assets are ranked by their average share in aggregate capital during 2000-2013. The share of aggregate captial is the value of each individual asset, as estimated by the BEA at current cost, as a fraction of the value of all assets in Tables G.8 and G.9. Panel A reports averages of these shares for three time periods. Panel B reports the average annual growth in these shares over same three time periods.

Table G.9: Non-ICT Assets

Non-ICT Assets	A. Average Share of Aggregate Capital (%)			B. Average Growth in Share (%)		
	1960-1980	1980-2000	2000-2013	1960-1980	1980-2000	2000-2013
SOO1: Office	4.75	6.99	8.28	1.59	2.14	0.12
SI00: Manufacturing	8.27	8.07	6.96	0.22	-0.44	-1.39
SM01: Petroleum and natural gas	3.91	3.63	5.20	0.12	-2.30	6.54
SU30: Electric	6.44	5.48	4.73	-0.18	-1.79	0.89
SC03: Multimerchandise shopping	2.21	2.77	3.05	1.46	0.69	0.59
EI50: General industrial equipment	3.42	3.40	2.95	0.32	-0.60	-0.75
SB31: Hospitals	1.70	2.52	2.86	3.69	1.06	0.51
SU20: Communication	2.80	2.51	2.66	0.70	-1.09	1.79
SC02: Other commercial	1.55	2.00	2.47	1.43	1.41	0.38
SB41: Lodging	1.58	1.83	2.32	1.40	1.76	0.47
EI60: Electric transmission and distribution	2.87	2.50	2.16	-0.79	-0.64	-0.21
EI40: Special industrial machinery	2.63	2.52	1.95	-0.36	-0.07	-3.33
SB20: Educational and vocational	1.56	1.36	1.92	-0.26	0.68	2.78
SC01: Warehouses	1.18	1.40	1.89	0.54	1.57	1.03
ET30: Aircraft	1.17	1.59	1.79	5.36	0.94	0.37
EO80: Other	1.09	1.44	1.75	2.30	1.18	0.71
EO12: Other furniture	1.37	1.67	1.74	-0.45	1.68	-1.35
SB42: Amusement and recreation	1.84	1.67	1.70	-0.46	0.54	-1.44
SN00: Farm	3.48	2.46	1.69	-0.63	-2.66	-2.11
RD11: Pharmaceutical and medicine manufacturing	0.23	0.65	1.68	4.70	6.63	5.22
SU40: Gas	2.70	1.89	1.66	-1.66	-1.72	0.35
SC04: Food and beverage establishments	1.19	1.51	1.58	1.47	0.84	-0.51
SB10: Religious	2.11	1.57	1.51	-0.70	-0.73	-0.82
EI30: Metalworking machinery	2.32	2.10	1.49	0.46	-1.25	-3.31
ET11: Light trucks (including utility vehicles)	0.93	1.05	1.42	0.45	2.48	-2.56
RDOM: Other manufacturing	1.47	1.50	1.19	0.00	0.04	-1.13
ET20: Autos	1.80	1.67	1.14	-1.79	-0.33	-4.27
ET12: Other trucks, buses and truck trailers	1.59	1.46	1.02	0.54	-1.43	-3.04
SU11: Other railroad	4.14	1.86	0.97	-4.62	-3.94	-3.77
SU12: Track replacement	2.66	1.39	0.97	-4.22	-2.69	-1.34
SOO2: Medical buildings	0.57	0.83	0.95	1.55	1.90	0.25
EO40: Other construction machinery	1.16	1.02	0.94	1.79	-2.11	1.37
AE10: Theatrical movies	0.97	0.67	0.86	-4.28	2.37	0.00
AE20: Long-lived television programs	0.69	0.79	0.86	0.39	1.91	-0.55
EO60: Service industry machinery	1.14	0.94	0.85	-1.61	-0.49	0.00
EI12: Other fabricated metals	1.42	1.20	0.75	0.83	-3.88	-0.19
RD80: All other nonmanufacturing, n.e.c.	0.09	0.75	0.72	3.04	8.28	-3.34
SB32: Special care	0.41	0.62	0.71	3.70	1.59	-0.74
ET50: Railroad equipment	2.12	1.09	0.66	-1.97	-4.52	-0.75
EO30: Other agricultural machinery	1.58	1.11	0.63	0.61	-4.71	-0.74
EI21: Steam engines	0.75	0.57	0.46	0.16	-3.01	0.43
SU50: Petroleum pipelines	0.95	0.57	0.45	-2.76	-3.29	1.69
AE30: Books	0.40	0.42	0.43	-0.37	1.02	-0.54
ET40: Ships and boats	0.92	0.68	0.40	-0.91	-3.72	-1.18
RD92: Other nonprofit institutions	0.22	0.35	0.38	3.94	2.25	0.23
RD31: Motor vehicles and parts manufacturing	0.40	0.44	0.36	0.45	0.79	-4.90
SM02: Mining	0.31	0.40	0.35	2.12	-1.30	1.93
RD12: Chemical manufacturing, ex. pharma and med	0.59	0.47	0.34	0.04	-0.98	-1.58
EO50: Mining and oilfield machinery	0.54	0.39	0.31	0.73	-5.74	7.21
SO01: Water supply	0.23	0.28	0.28	0.22	1.25	-0.60
EO21: Farm tractors	0.69	0.44	0.28	-0.08	-4.65	-0.28
SO02: Sewage and waste disposal	0.24	0.29	0.28	0.26	1.16	-1.21
RD32: Aerospace products and parts manufacturing	0.33	0.41	0.25	2.09	-0.28	-2.54
AE40: Music	0.21	0.20	0.20	0.14	1.37	-4.21
RD70: Scientific research and development services	0.00	0.06	0.19		11.29	4.20
SO04: Highway and conservation and development	0.15	0.18	0.18	0.27	1.20	-0.44
SB43: Air transportation	0.15	0.15	0.17	0.74	1.03	-0.69
AE50: Other entertainment originals	0.18	0.17	0.17	-1.71	1.53	-2.58
SU60: Wind and solar	0.00	0.01	0.16		12.44	25.22
EO72: Other electrical	0.12	0.19	0.14	2.74	-0.20	-1.74
SO03: Public safety	0.14	0.10	0.11	-0.96	0.17	-0.55
RD60: Computer systems design and related services	0.00	0.03	0.11		22.31	2.68
EO11: Household furniture	0.16	0.13	0.10	0.19	-2.30	-1.38
EO22: Construction tractors	0.28	0.18	0.09	0.39	-5.15	-3.98
EI22: Internal combustion engines	0.09	0.08	0.08	-0.80	-1.19	0.43
SB44: Local transit structures	0.51	0.17	0.07	-6.06	-5.15	-4.84
EI11: Nuclear fuel	0.03	0.10	0.06	27.52	-3.93	-1.86
RD91: Private universities and colleges	0.03	0.04	0.06	0.95	2.71	3.68
SOMO: Mobile structures	0.05	0.07	0.05	0.35	1.29	-3.77
SB46: Other land transportation	0.04	0.03	0.05	-0.72	1.04	2.80
RD50: Financial and real estate services	0.00	0.02	0.05		22.33	-0.88
EO71: Household appliances	0.09	0.05	0.03	-2.09	-4.08	-2.35
SB45: Other transportation	0.02	0.02	0.02	-0.70	0.56	-0.71

Notes: The data are drawn from the BEA's detailed fixed asset accounts. Assets are ranked by their average share in aggregate capital during 2000-2013. The share of aggregate captial is the value of each individual asset, as estimated by the BEA at current cost, as a fraction of the value of all assets in Tables G.8 and G.9. Panel A reports averages of these shares for three time periods. Panel B reports the average annual growth in these shares over same three time periods.