The Substitution of ICT Capital for Routine Labor: Transitional Dynamics and Long-Run Implications

April 24, 2014

Abstract: The invention of information, communication, and computing technology (ICT) has made it possible to use automated processes to replace labor in certain "routine" tasks, which require following exact, well-defined procedures. We study the implications of this for the labor income share as well as the allocation of labor across routine and non-routine occupations. We document a substantial decline in the routine labor income share since 1979 as well as a simultaneous rise in the the non-routine labor income share. At the same time, the ICT capital income share nearly doubled while the non-ICT capital income share remained at its historical levels. We use these trends to calibrate a neoclassical growth model, in which ICT capital and routine labor are imperfect substitutes. We further allow for exogenous changes in the production intensity of non-routine labor. Our calibration suggests that the decline in the aggregate labor income share is a result of the automation of routine tasks. However, the reallocation of labor toward non-routine occupations is due primarily to the increase in the production intensity of non-routine labor as opposed to the accumulation of ICT.

JEL: J24, J31, J82, O33
Keywords: labor share, polarization, ICT

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[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, Roberto Fattal Jaef, Nir Jaimovich, Aart Kraay, Michael Sposi, Alan M. Taylor as well as seminar participants at the World Bank and at the ABCDE Conference on the Role of Theory in Development Economics for extremely helpful comments and suggestions.

1. Introduction

The increasing importance of computers in production has raised many questions about the future: will computers replace workers? How many? What will happen to the share of labor income in production? What are the limits to computerization, if any? And, how will computerization change the standards of living?

With these questions in mind, this paper focuses on a particular channel through which the future may be shaped by the process of computerization: the substitution of information and communications technology (ICT) capital for routine labor.[1] Similar to Autor and Dorn (2013) we postulate a production structure in which computers are imperfect substitutes for "routine" labor, classified as labor that is primarily employed in carrying out exact, pre-specified procedures.[2] Put differently, we *define* routine labor as preforming tasks that can—at least in principle—be performed by a computer. We will refer to these tasks broadly as routine inputs.

There is substantial empirical evidence documenting the substitution of ICT capital for routine labor in the US over the last few decades.[3] However, the quantitative importance of this substitution with respect to the labor income share and the reallocation of labor across occupations remains highly controversial. At the center of the debate is the possibility that a surge in international trade and the possibility of offshoring have led to a change in the pattern of specialization that accounts for the changes in the relative income shares of capital and labor and the restructuring of the labor market (see for example Goldin and Katz (2008) and Krugman (2008) for opposing views).

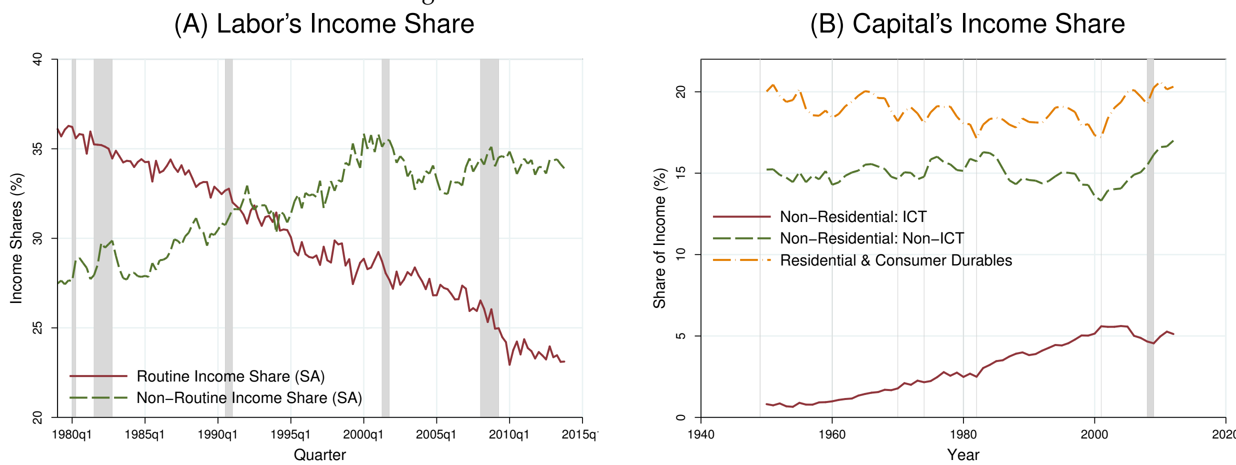
In light of this controversy, we focus our attention narrowly on the substitution of ICT capital for routine labor, imposing as little structure as possible on the evolution of factor intensities. Our primary assumption is that routine labor and ICT capital both produce the same production input ("routine tasks"). We allow for exogenous evolution in the intensity in which the economy

[1] Of course, the general notion that technological progress leads to the substitution of capital for labor is not new (see for example Zeira, 1998). Our focus is on a particular type of techology, ICT, and a particular type of labor, routine labor.

[2] See Acemoglu and Autor (2011) for a comprehensive survey of the literature embracing the "tasks approach", which concludes that "routine" tasks, as we define them here, play a key role for trends in employment and wages over the past three decades.

[3] See for example Autor and Dorn (2013), Autor et al. (2003), Michaels et al. (2014), as well as the extensive survey by Acemoglu and Autor (2011) and references therein.

Figure 1: The Division of Income in the US



Notes: Occupation specific income shares are based on earnings data in the monthly CPS merged outgoing rotation group (MORG) extracts provided by the NBER and rescaled to match the aggregate income share in the Non-Farm Business Sector (BLS). The data are seasonally adjusted using the U.S. Cenusus X11 method. 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 2. The construction of capital-type specific income shares is described in Section 3. The underlying data are nominal gross capital stocks and depreciation rates, drawn from the BEA's detailed fixed asset accounts.

demands routine tasks, reflecting the possibility of a changing pattern of specialization. We do not take a stance on whether changes in the demand for routine inputs result from the offshoring of these tasks (as suggested by Krugman (2008), Autor et al. (2013), or Elsby et al. (2013), among others) or from complementarity between ICT and skilled non-routine labor (as suggested by Krusell et al. (2000), Acemoglu (1998, 2002), Beaudry et al. (2010), or Gaggl and Wright (2014), among others). Rather, we take the evolution of the economy's routine/non-routine production-intensities as given and focus exclusively on the substitutability of routine labor and ICT capital in the production of routine tasks.

We begin by documenting the trends in factor shares. Panel A of Figure 1 highlights a stark decline in the routine labor income share: in 1979, the routine labor income share was around 38%. By 2012, the routine labor income share fell to 23%. At the same time, we estimate that the income share of ICT capital has increased from 2.5% to 5%. To construct these income shares we measure occupation specific income shares directly from earnings data in the U.S. Current Population Survey (CPS) and we provide a framework to measure capital specific income shares

based on the U.S. Bureau of Economic Analysis' (BEA) detailed fixed asset accounts.

Overall, the income share of "routine tasks"—defined as the sum of the routine labor income share and the ICT capital income share—has fallen by 12.5% since 1979. Figure 1 illustrates that the primary counterpart of this decline was a rise the non-routine labor income share, while the non-ICT capital share has remained roughly constant. This suggests that, while ICT capital is absorbing a larger share of income accruing to routine tasks, there has been a substantial decline in the intensity in which the economy demands routine tasks, perhaps due to specialization in the production of goods that require relatively more non-routine labor (Autor et al., 2013).

To interpret these trends, we consider a constant elasticity of substitution (CES) production structure for routine inputs, and estimate the elasticity of substitution between routine labor and ICT capital. Based mostly on trends in relative income shares, we provide OLS and GMM estimates suggesting that the elasticity of substitution between ICT capital and routine labor is between 1.5 and 4.5. In other words, while we estimate that ICT capital and routine labor are gross substitutes, they are far from perfect substitutes: there are some routine tasks in which labor has an inherent comparative advantage, in the sense that it would require large amounts of computers to substitute for these tasks.

We embed this CES structure for routine inputs into an aggregate production function that is Cobb-Douglas in non-routine labor, non-ICT capital and routine tasks. We allow for the factor intensities to be time-varying, reflecting the possibility of a changing pattern of specialization. We use a GMM approach to estimate all structural parameters of our production framework, including capital-augmenting and labor-augmenting technological progress. Our estimates suggest that capital-augmenting technological progress did not play a major role throughout our sample period; rather, growth was driven by the accumulation of ICT and non-ICT capital.[4] We use our estimation to calibrate a standard neoclassical growth model and simulate transition paths of inputs and factor shares that closely match their empirical counterparts—especially until the mid-2000s. This suggests that our framework may serve as a useful lens to analyze the observed

[4]The view that technological progress requires capital accumulation resonates with Zeira (1998). In our model, the main driver of ICT and non-ICT capital accumulation is the decline in the price of ICT goods, rather than capital-biased technical change.

trends in inputs and factor payments. Specifically, we construct counterfactuals that abstract away from the change in non-routine labor intensity, which enable us to evaluate the extent to which the observed trends are mostly due to the substitution of ICT capital for routing labor or, alternatively, the changing patterns of specialization.

Looking at the past few decades, the calibration suggests several conclusions. First, the accumulation of ICT capital was the primary driver for the decline in the aggregate labor income share—recently documented as a worldwide phenomenon by Karabarbounis and Neiman (2014)—while the change in specialization seems to have had a neutral effect on the labor income share. Second, the decline in routine labor income is attributable, in roughly equal parts, to the changing pattern of specialization and the accumulation of ICT. Finally, the reallocation of labor from routine to non-routine occupations is due primarily to the change in factor intensities, rather than to direct crowding out by computers.

Looking forward, our calibrated model provides potentially interesting long-run predictions (with all the usual caveats attached): abstracting away from any further declines in the price of ICT investment goods, the steady state level of ICT per effective unit of labor is about 140% of its current level. However, the calibration suggests only modest output and consumption gains associated with further accumulation of ICT capital. Moreover, despite the accumulation of ICT, the transition to the steady state does not predict substantial reallocation of labor from routine to non-routine occupations. This suggests that the tasks currently performed by routine labor are ones in which labor has a strong comparative advantage relative to computers. Finally, the model generates a steady state labor income share of about 0.58, roughly consistent with 2012 levels, suggesting that, at current prices, the additional accumulation of ICT capital is unlikely to further reduce the labor income share.

Of course, it should be emphasized that our model only considers a single channel through which computerization may affect the pattern of production, specifically, the replacement of labor in routine tasks. The suggested conclusion is that while this channel was an important driver of factor income shares, it played only a minor role in the reallocation of labor from routine to non-routine occupations, which was driven primarily by the changing pattern of specialization (which

may or may not be related to ICT).

2. The Labor Income Share

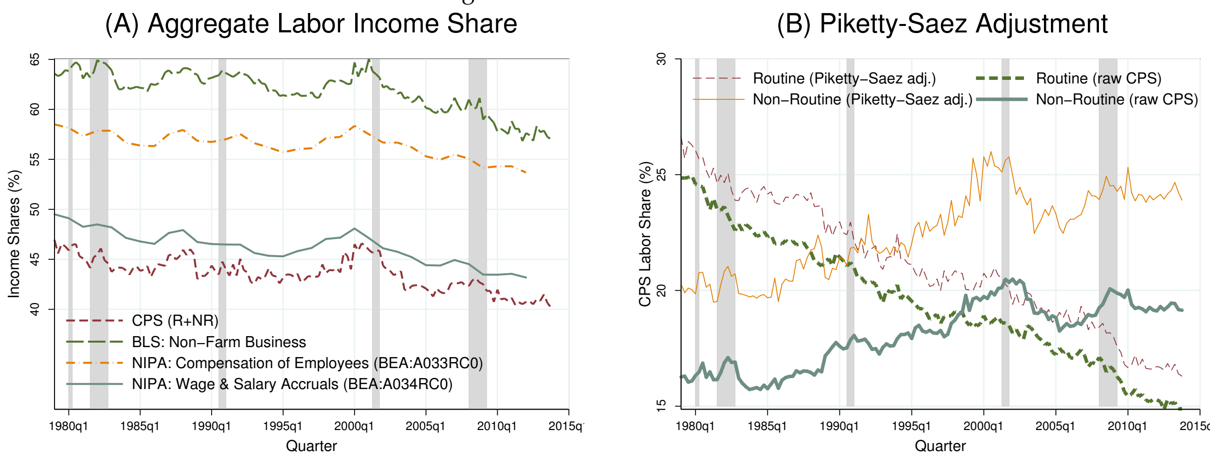
To measure the routine and non-routine labor income shares, we use the monthly U.S. Current Population Survey's (CPS) merged outgoing rotation group (MORG) extracts, provided by the NBER for the years 1979m1-2013m12, and decompose the U.S. aggregate labor share into the portion going to routine and non-routine labor, respectively. Using the CPS sampling weights, we estimate the aggregate wage bill at the detailed occupation level on a monthly frequency throughout the entire sample. These computations require 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).[5] 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 2, the aggregate labor share based on earnings data in the CPS-MORG accounts for 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

[5]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 et al. (2014).

Figure 2: Labor's Share in Income



Notes: Panel A contrasts aggregate income shares (as a fraction of GDP) based on the CPS merged outgoing rotation group (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. Cenusus X11 method. Panel B contrasts the raw earnins reflected by CPS topcoded values and our series that adjust top-coded earnings with the appropriate (updated) estimates by Piketty and Saez (2003).

extraction occupations", and "installation, maintenance, and repair occupations". We drop farm workers for all our analyses. To compute the corresponding income shares, 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 2) 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 2).[6] The resulting routine and non-routine income shares are displayed in panel A of Figure 1.

This decomposition highlights a striking feature: in the U.S., the decline in the aggregate labor share is entirely accounted for by routine occupations. This observation is perfectly consistent with a vast literature that documents the polarization of both wages and employment toward the tails of the skill distribution.[7] This line of research documents that the share of employment as well as

[6] As is customary in the literature, we exclude farming and forestry for all analyses since it only accounts for a small portion of overall income in the U.S. and because the the production structure we have in mind does not necessarily apply to the farming and forestry sector.

[7] Acemoglu (1999) was the first to document employment polarization in the U.S. over the period 1983–1993. For more recent periods, Goos and Manning (2007) find similar patterns in the UK, Goos et al. (2009) for 16 EU countries, and Autor et al. (2008) as well as Autor and Dorn (2013) for the US. Autor and Dorn (2013) further show compelling

wages at the tail-ends of the skill distribution are increasing, while "middle-skill" occupations—which largely require "routine" skills—are disappearing and suffer declining wages.

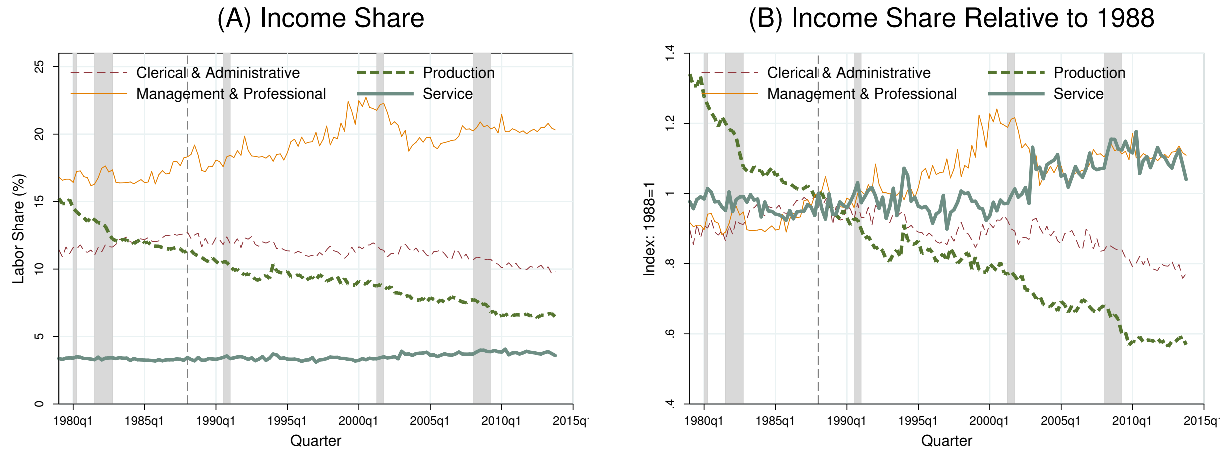
Piketty and Saez (2003) have recently put much emphasis on the rising gap between the earnings of the top 1% of earners relative to the remaining 99%. To gauge the potential impact of this recent divergence at the top of the earnings distribution on our reported trends, Panel B of Figure 2 illustrates the impact of our top-code adjustment relative to the raw values reported in the CPS.[8] It is important to note that, despite the fact that we adjust top-coded values at the individual level, our adjustment effectively results in a level shift in aggregate income shares; all the original trends are preserved after the adjustment. If the divergence of the top 1% were really driving the differential trends for routine and non-routine income shares, then we should expect a larger gap between the adjusted and raw numbers for non-routine workers than we do for routine workers. As this is not readily apparent in panel B of Figure 2 we argue that "the one percent" are not likely the main driver of our results. Nevertheless, panel B of Figure 2 highlights that the top-code adjustment is crucial in order to construct quantitatively meaningful aggregate income shares based on earnings reported in the CPS.

Moreover, several studies have recently argued that the decline in routine labor's importance in production is merely a symptom of the decline in manufacturing jobs. However, Figure 3 illustrates that the strong divergence between routine and non-routine income shares is not only due to the disappearance of classic blue collar jobs—which are primarily concentrated in the manufacturing sector. Specifically, at least since 1988, both service and managerial/professional occupations gained about 20% in income share. Thus, both abstract and manual occupations contributed about equally to the rise in the non-routine income share since 1988. Similarly, while traditional blue collar occupations lost about 40% administrative/clerical occupations lost a little more than 20% in their income share. This makes clear that, while traditional blue collar occupations are by far the dominant driver of the decline in the routine labor income share, administrative/clerical jobs still explain at least a quarter of the decline in the routine share since 1988—clearly a non-negligible

evidence that PC adoption is an important driving force for these trends. The broader literature sourrounding these findings is surveyed by Acemoglu and Autor (2011).

[8] Note that these shares are not re-scaled to match the BLS's estimate of the aggregate labor share.

Figure 3: Abstract & Manual Tasks



Notes: Panel A plots unadjusted income shares of four major occupation groups as reflected in the CPS MORG. These shares do not add to 100% as the earnings reflected in the CPS MORG does not properly measure benefits as well as proprietors' income. Panel B imposes the normalization 1988q1=1 to illustrate the clear divide between routine and non-routine tasks. The dashed vertical line indicates 1988q1.

portion.

2.1. Price-Quantity Decomposition

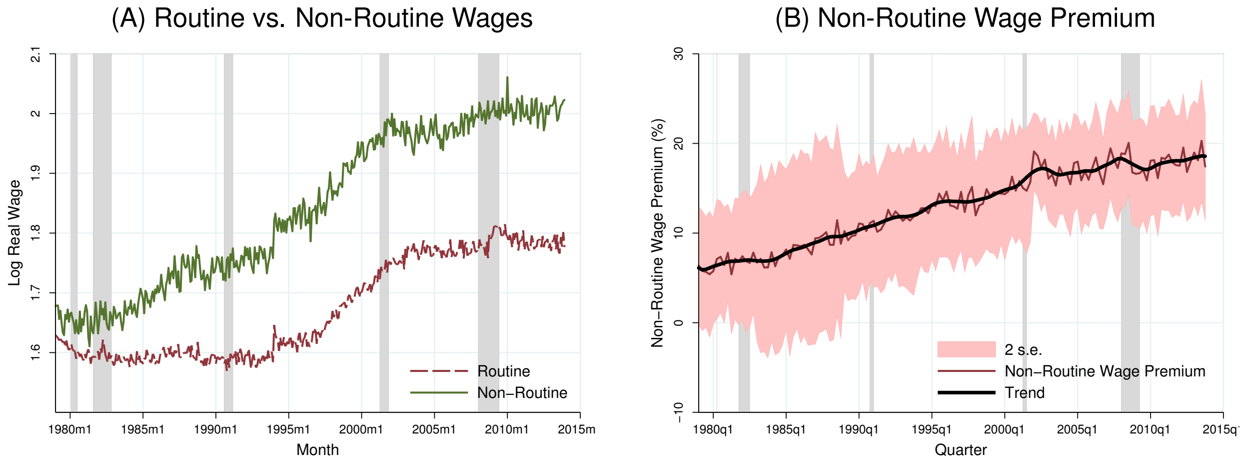
The declining routine labor income share relative to the non-routine labor income share could be driven either by a change in relative wages, a change in relative labor inputs, or both. We find that both an increasing non-routine wage premium and an increase in non-routine labor inputs contribute to this trend.

A large body of literature has documented increasing wage *polarization* over the past three decades—a relative increase in wages for high- and low-paying jobs relative to middle-income jobs.[9] It has also been established that routine jobs are disproportionately middle-income jobs, and it has often been conjectured that the process of computerization has contributed to the polarization trend (e.g., Autor et al., 2003; Autor and Dorn, 2013). Closely related, we provide evidence of an increasing non-routine wage premium, providing further support for this view.

As a baseline reference, we start with estimating simple quarterly averages of the mean hourly

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

Figure 4: The Non-Routine Wage Premium in the US



Notes: Panel A plots the unconditional quarterly mean real wage in each occupation group. Panel B graphs the coefficients from quarterly regressions of individual level real wages 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 wages are based on the monthly CPS merged outgoing rotation group (MORG) extracts provided by the NBER for the period 1979m1-2013m12. We deflate wage data with the chain type implicit price deflator for personal consumption expenditures (1979=1). 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).

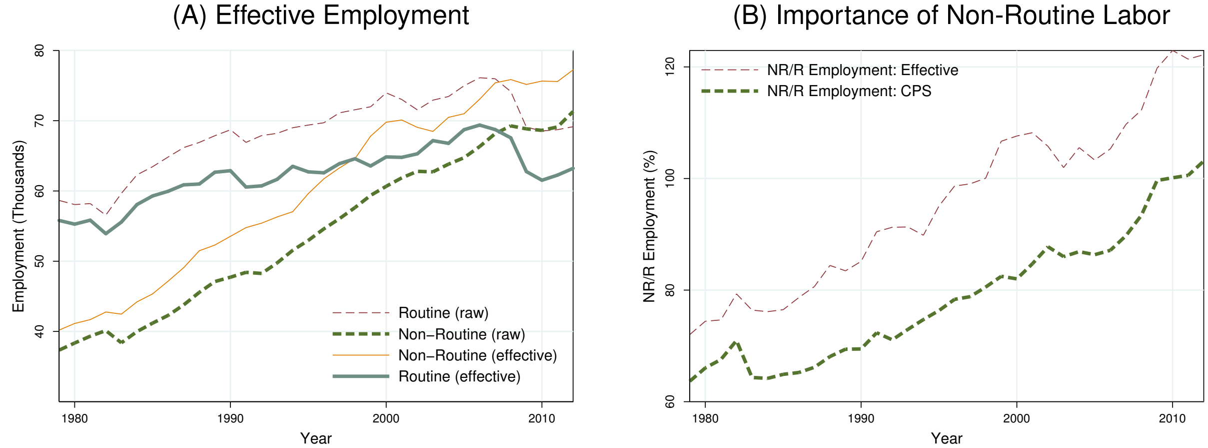
real wage for each type of labor. Panel A of Figure 4 illustrates these estimates and gives a first indication of a steadily increasing wedge between non-routine and routine pay. However, to ensure that this wedge is not simply driven by a changing composition of characteristics of routine and non-routine workers, we estimate the following set of cross-sectional wage regressions separately for each quarter, q:

$$\ln w_{i,q} = \beta_{0,q} + \beta_{1,q} NR_{i,q} + \beta_{2,q} X_{i,q} + \epsilon_{i,q} \quad \text{for } q \in \{1979q1, \ldots, 2013q4\}, \tag{1}$$

where $NR_{i,q}$ is a dummy variable indicating that individual i works a non-routine job in quarter q and $X_{i,q}$ includes a variety of control variables. In particular, we include a gender dummy, 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 (1) based on individual level data from the CPS MORG and weight by the CPS sampling weights. Panel B of Figure 4 plots the resulting time series of estimates $\hat{\beta}_{1,q}$ and

Figure 5: Routine & Non-Routine Employment



Notes: Panel A plots employment levels in routine and non-routine jobs as reflected in the CPS MORG. The graph plots both the raw CPS numbers as well as our imputed "effective" units based on equations (3) and (4). Panel B illustrates the relative importance of non-routine jobs.

the associated 95% confidence intervals based on standard errors that are clustered on industry. Not only do these estimates resemble the increasing wage premium already apparent in panel A of Figure 4, but they also highlight that the wage premium is neither entirely driven by demographic composition nor 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 $\hat{\beta}_{1,q}$ are identified 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.

We use the above estimates of the non-routine wage premium to decompose the non-routine income share into a price and quantity component. We start with measuring total employment as the sum of routine and non-routine employment from the CPS. As we are interested in measuring routine and non-routine labor in terms of "effective" units of employment—taking into account differences in human capital, etc—, we impute a series for routine and non-routine labor based on the following relationship:

$$\frac{s_{r,t}}{s_{ln,t}} = \frac{w_{r,t}L_{r,t}}{w_{nr,t}L_{nr,t}} \Leftrightarrow \frac{L_{r,t}}{L_{nr,t}} = \frac{s_{r,t}}{s_{ln,t}}\frac{w_{nr,t}}{w_{r,t}} \tag{2}$$

Using our estimated series of the routine and non-routine labor income shares, as well as the non-routine wage premium, equation (2) allows us to divide aggregate employment between "effective" routine and non-routine labor. That is, we compute

$$L_{nr,t} = \frac{E_t}{1 + \frac{L_{r,t}}{L_{nr,t}}} = \frac{E_t}{1 + \frac{s_{r,t}}{s_{ln,t}} \frac{w_{nr,t}}{w_{r,t}}} \quad (3)$$

$$L_{r,t} = L_{nr,t} \frac{s_{r,t}}{s_{ln,t}} \frac{w_{nr,t}}{w_{r,t}} \quad (4)$$

where E_t is our measure of total employment. Note that this formula measures the relative quantities of effective units of labor under the assumption that factors are paid their marginal products. More importantly, as our measure of the non-routine wage premium, $\frac{w_{nr,t}}{w_{r,t}}$, is estimated from regression models (1), this provides a "composition adjusted" measure for the two types of employment.

Figures 4 and 5 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.

3. The Capital Income Share

While we were able to measure labor income shares directly from observed earnings data, estimating the payment to different types of capital requires a more structural approach. With a single type of physical capital—as is customary in most macro analyses—it is straightforward to measure the capital income share as the reciprocal of the labor income share as they need to sum to unity. However, we are interested in separating the payments to several distinct types of capital. 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 price of the various types of capital is changing over time.

We build on three 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), which 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.[10]

Specifically, we utilize a no-arbitrage condition in competitive capital markets, and impose two assumptions regarding aggregate production: factor markets are competitive, and aggregate production exhibits constant returns to scale in all factors.[11] Suppose that, in addition to labor, L, there are 3 types of capital: ICT capital, K_c, non-ICT capital, K_n, and residential capital, K_h. If factor markets are competitive, and the production technology exhibits constant returns to scale in all factors, the share of payments to capital must satisfy the following equilibrium relation:

$$s_{K,t} = MPK_{c,t}\frac{K_{c,t}}{Y_t} + MPK_{n,t}\frac{K_{n,t}}{Y_t} + MPK_{h,t}\frac{K_{h,t}}{Y_t} = 1 - s_{L,t}, \tag{5}$$

where $s_{K,t}$ and $s_{L,t}$ denote the aggregate capital and labor income shares, respectively, Y_t is final output, and $MPK_{i,t}$ denotes the real marginal product of a unit of capital type i.

Suppose a producer buys a unit of capital type i at the going price $P_{i,t}$ and uses it in the production of the final good. The gross return on this piece of capital is then given by

$$\frac{P_t MPK_{i,t} + P_{i,t+1}(1-\delta_{i,t})}{P_{i,t}}, \tag{6}$$

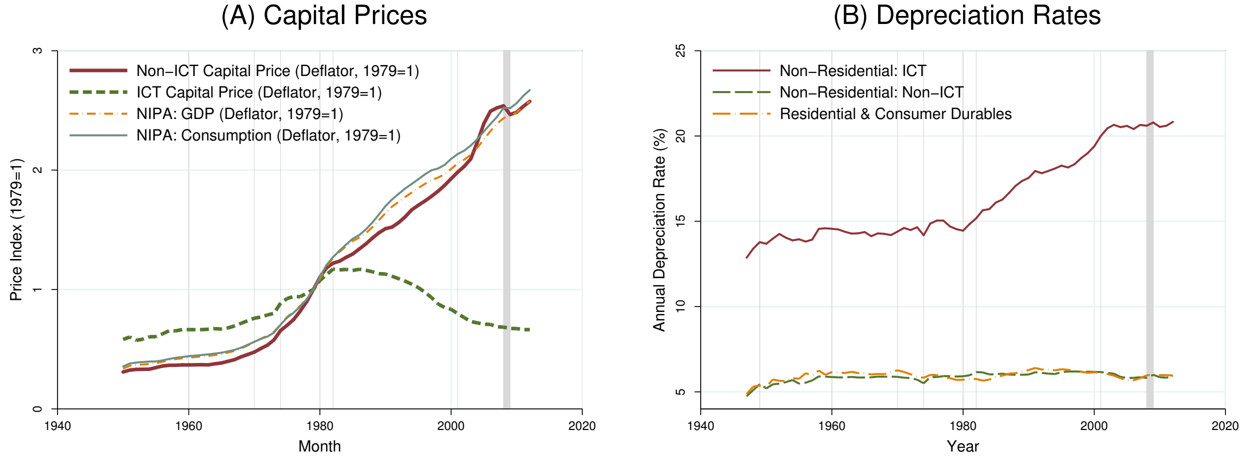
where $\delta_{i,t}$ is the depreciation rate for capital type i.[12] In an equilibrium with perfect capital markets, the return on each type of capital $i \in \{c, n, h\}$ must then equal the prevailing gross return on investment. It is important to note that this does not require the marginal product 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

[10]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.

[11]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.

[12]Notice that we use the same timing as Caselli and Feyrer (2007) here.

Figure 6: Relative Prices & Depreciation



Notes: Panel A graphs implicit price deflators by capital type, which were constructed directly from the BEA's detailed fixed-asst accounts. Price deflators from the NIPA talbes are taken from FRED. Panel B depicts asset-specific depreciation rates constructed directly from the BEA's fixed asset accounts. See Tables A.4 and A.5 in Appendix A for our grouping of assets.

relative to output and all other forms of capital (see Figure 6). Thus, no-arbitrage in perfect capital markets requires the *gross return* (6) to be equalized across all types of capital.

We show in Appendix A how equations (5) and (6) allow us to compute the income share for each type of capital, defined as $s_{i,t} = MPK_{i,t}\frac{K_{i,t}}{Y_t}$ for $i \in \{c, n, h\}$, based on the labor income share, nominal current cost values for each type of capital, capital specific depreciation rates, $\delta_{i,t}$, and a price index for ICT capital. To measure the current cost values of different types of assets we use the BEA's detailed fixed asset accounts.[10] In particular, we aggregate the BEA's detailed industry level estimates into three types of capital: we distinguish residential and non-residential assets according to the BEA's definition and within the non-residential category we separate ICT and non-ICT assets. Specifically, we consider an asset to be ICT if the BEA classifies it as software (classification codes starting with RD2 and RD4) or as equipment related to computers (certain classifications codes starting with EP and EN). See Tables A.4 and A.5 in Appendix A for complete lists of the detailed assets grouped into the two types of non-residential capital.

To construct the income shares of these assets we further need an estimate of both the depreciation rate, $\delta_{i,t}$, and expected capital gains, $E\left[P_{i,t+1}/P_{i,t}\right]$, for each type of capital. We measure depreciation rates directly form the BEA's nominal values of depreciation for each type of detailed

asset.[13] We then employ implicit price deflators, that we construct for each type of capital based on chain type price indices provided by the BEA, to measure capital type specific inflation.[14] Panel A of Figure 6 depicts the path of prices for different types of assets, where we have aggregated residential and non-residential non-ICT capital, since the prices for these types of assets largely evolve in lockstep. This figure reveals two striking insights: First, the relative price of non-ICT capital and output/consumption are essentially constant throughout the entire sample. Second, the price of ICT capital falls substantially, both in absolute terms and relative to all remaining types of assets, after the 1982 recession. Panel B of Figure 6 graphs the respective depreciation rates for each type of capital.

Based on these measures we use the derivations in Appendix A to construct the income share for each type of capital and Figure 1 illustrates the resulting estimates. One can clearly see that the income shares of non-ICT capital do not show any significant trend since at least the 1950s. During the same period, the income share of ICT capital has increased from essentially zero in the 1950s to more than 5%. This suggests that the introduction of ICT did not crowd out other forms of capital, which continued to exhibit constant income shares.

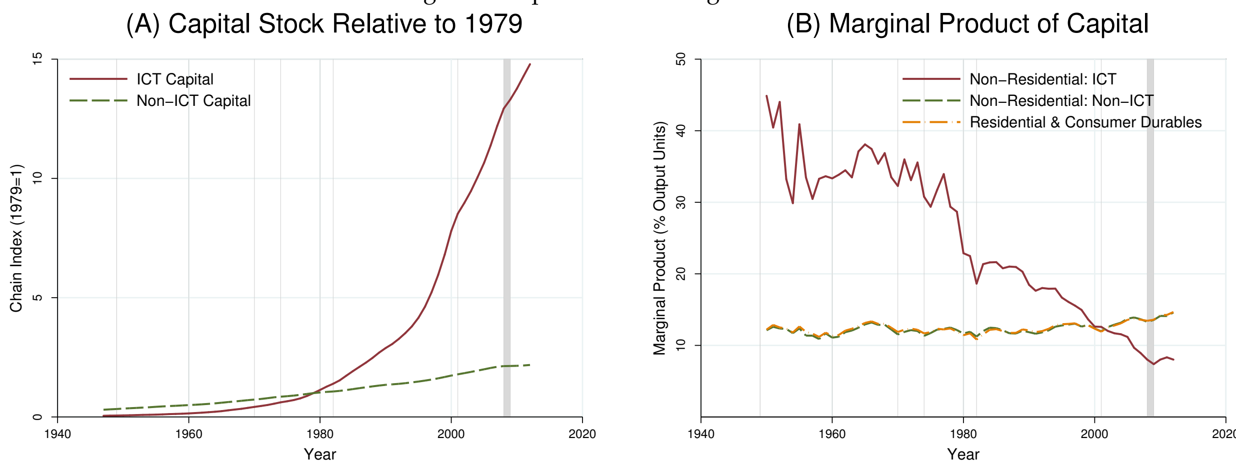
3.1. Price-Quantity Decomposition

The above results suggest a substantial increase in the income share of ICT capital relative to the income share of non-ICT capital. While we did not use the real stock of capital to compute its income share, $s_{i,t}$, we find it instructive to decompose the payments to capital, $MPK_{i,t}K_{i,t}$, into a price and quantity component. To this end, we construct a chained quantity index for the stock of both ICT and non-ICT capital based on the BEA's fixed asset accounts. Panel A of Figure 7 shows that the stock of ICT capital in 2012 is about 15 times its 1979 level. On the other hand, Panel B illustrates that the marginal product of ICT capital—measured in units of final output—fell

[13] 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.

[14] 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 A.4 and A.5 in Appendix A.

Figure 7: Capital and its Marginal Product



Notes: Panel A graphs the stock of ICT and non-ICT captial relative to its 1979 level. Panel B depicts asset-specific marginal products, $MPK_{i,t}$, in % of final output, based on equations (A.3)-(A.5) in Appendix A. The underyling data are the BEA's detailed fixed-asset accounts.

substantially over the same period. In particular, while an additional unit of ICT capital increased final output by about 40% in 1979 it only produced another 10% in 2012. This price-quantity decomposition suggests that the increase in the income share of ICT capital is due to massive accumulation of ICT, while the marginal product of ICT capital (which is the implicit rental rate of ICT capital) fell during this time.

It is further worth noting that the marginal product of ICT capital was substantially higher than that of non-ICT capital until about 2000. After 2000, ICT capital's marginal product was in fact less than that of other forms of capital (see Figure 1). Recall that the marginal product itself is not the relevant criterion for investment decisions and therefore it is not required to equalize across different types of assets. No arbitrage in competitive markets requires the gross return (6) to equalize, which is heavily influenced by the drastic changes in the relative price as well as depreciation rate of ICT capital relative to output and other forms of capital (see Figure 6).

4. A Changing Aggregate Production Function

To interpret the trends presented in the previous sections, we propose a simple Cobb-Douglas production structure in which the intensities of non-routine labor, routine "tasks"—produced by

either routine labor or ICT capital—and non-ICT capital change over time. Formally, we consider a production function of the form:

$$\begin{aligned} Y_t &= (A_{nc,t}K_{nc,t})^{\alpha_{nc,t}}(A_{l,t}L_{nr,t})^{\alpha_{nr,t}}X_t^{1-\alpha_{nc,t}-\alpha_{nr,t}} \\ X_t &= \left(\gamma\left(A_{c,t}K_{c,t}\right)^{\sigma}+(1-\gamma)\left(A_{l,t}L_{r,t}\right)^{\sigma}\right)^{\frac{1}{\sigma}} \end{aligned} \tag{7}$$

where Y_t is real output, $K_{nc,t} \equiv K_{n,t} + K_{h,t}$ and $K_{c,t}$ are non-ICT capital and ICT capital, respectively, $L_{nr,t}$ and $L_{r,t}$ denote non-routine and routine employment, and X_t represents "routine inputs" that can be performed by ICT capital or routine labor, which are imperfect substitutes. To allow for technical change we introduce both purely labor augmenting progress, $A_{l,t}$, as well as ICT and non-ICT capital augmenting technical change, $A_{c,t}$ and $A_{nc,t}$, respectively.

We allow for the factor intensities $\alpha_{nr,t}$ and $\alpha_{nc,t}$ to change over time. This reflects the possibility of a changing pattern of specialization, in which the US is increasingly specializing in the production of goods that require a more intensive use of non-routine labor inputs—perhaps due to international trade or to the introduction of new goods that change the pattern of production. In principle, this change in factor intensities may also result from ICT accumulation, that may be complementary to non-routine labor—for example, as it requires computer programmers, innovators and entrepreneurs.

We specify the production of routine inputs as a constant elasticity of substitution (CES) production function that uses routine labor and ICT capital as inputs. By definition, routine labor is labor carrying out tasks that can be carried out by a computer. However, the two may be imperfect substitutes, as certain tasks are more effectively carried out by routine labor while others are more effectively carried out by ICT capital.

A few notes are in order regarding our chosen conceptual framework. Of course, other setups may be consistent with our stylized facts. For example, a time-invariant production function with a nested CES component, in which the elasticity of substitution between non-routine labor and routine inputs is less than unity—i.e., non-routine labor and routine inputs are more complementary than Cobb-Douglas—, would likely generate similar trends in factor income shares. In this case, a rise in the non-routine labor income share would be attributed to the complementarity of

non-routine labor with ICT.

It is important to note that our framework does not rule out this possibility, as we do not take a strong stance on the source of change in specialization. The increase in the non-routine labor share could result from complementarity with routine inputs, but may also result from offshoring and international trade integration. By specifying a time-varying production function, we are able to isolate the "direct" effect of ICT accumulation on the routine labor income share, coming from the fact that ICT and routine labor preform the same tasks. Our setup further allows us to isolate the contribution of the rising non-routine labor income share, without taking a strong stance on whether or not it is coming from complementarity with ICT—which would then be an "indirect" effect of ICT on the routine labor share.

Our production structure implies that the marginal products of the four factors are given by

$$MPK_{nc,t} = \alpha_{nc,t}\frac{Y_t}{K_{nc,t}} \tag{8}$$

$$MPK_{c,t} = (1-\alpha_{nc,t}-\alpha_{nr,t})\gamma A_{c,t}^{\sigma}K_{c,t}^{\sigma-1}\frac{Y_t}{X_t^{\sigma}} \tag{9}$$

$$MPL_{nr,t} = \alpha_{nr,t}\frac{Y_t}{L_{nr,t}} \tag{10}$$

$$MPL_{r,t} = (1-\alpha_{nc,t}-\alpha_{nr,t})(1-\gamma)A_{l,t}^{\sigma}L_{r,t}^{\sigma-1}\frac{Y_t}{X_t^{\sigma}} \tag{11}$$

Throughout, we will assume perfectly competitive factor markets, in which factors are paid their marginal products. Note, however, that we are not assuming that wages are equalized across routine and non-routine labor, since these are considered different factors; we are merely assuming that the routine and non-routine wages reflect their marginal productivities. These assumptions imply the following factor income shares:

$$
\begin{aligned}
s_{nc,t} &= MPK_{nc,t}\frac{K_{nc,t}}{Y_t} = \alpha_{nc,t} && (12)\\
s_{c,t} &= MPK_{c,t}\frac{K_{c,t}}{Y_t} = (1-\alpha_{nc,t}-\alpha_{n,t})\gamma\left(\frac{A_{c,t}K_{c,t}}{X_t}\right)^{\sigma} && (13)\\
s_{nr,t} &= MPL_{nr,t}\frac{L_{n,t}}{Y_t} = \alpha_{nr,t} && (14)\\
s_{r,t} &= MPL_{r,t}\frac{L_{r,t}}{Y_t} = (1-\alpha_{nc,t}-\alpha_{n,t})(1-\gamma)\left(\frac{A_{l,t}L_{r,t}}{X_t}\right)^{\sigma} && (15)
\end{aligned}
$$

where $s_{nc,t} = s_{n,t} + s_{h,t}$ is the share of non-ICT capital.

To calibrate the parameters of the proposed productions structure we start with simple OLS estimation of σ and then move on to a more involved GMM strategy to estimate the parameters governing the exogenous sources of technological progress, $A_{i,t}$. Since both forms of technical progress are at this point unrestricted exogenous processes, we need to impose some additional structure to make estimation feasible. We follow Antràs (2004) and assume that the technology processes grow exponentially, i.e. $A_{i,t} = A_{0,i}e^{\lambda_i t+\epsilon_{i,t}}$, with $i \in \{c, l, k\}$, where $\epsilon_{i,t}$ are mean 0 shocks. For technical progress that affects non-ICT capital we only consider the cases of $A_{nc,t} = A_{c,t}$, i.e. general capital augmenting progress, as well as $A_{nc,t} = 1$, i.e. only ICT capital augmenting progress. We further impose the normalization $A_{c,0} = 1$ without loss of generality.[15]

As a first attempt to identify σ, we use the equilibrium relationship between our parameters and the ratio of the routine labor income share and the ICT capital income share, as in Antràs (2004) . In particular, taking the ratio of (13) and (15) implies that:

$$
\begin{aligned}
\ln\left(\frac{s_{r,t}}{s_{c,t}}\right) &= \ln\left(\frac{1-\gamma}{\gamma}\right) + \sigma\ln\left(\frac{A_{l,t}}{A_{c,t}}\right) + \sigma\ln\left(\frac{L_{r,t}}{K_{c,t}}\right)\\
&= \ln\left(\frac{1-\gamma}{\gamma}\right) + \sigma\ln(A_{l,0}) + \sigma(\lambda_l-\lambda_c)t + \sigma\ln\left(\frac{K_{c,t}}{L_{r,t}}\right) + \nu_t && (16)
\end{aligned}
$$

where $\nu_t = \sigma\left(\epsilon_{l,t} - \epsilon_{c,t}\right)$ is a mean zero disturbance. This relationship allows us to identify σ using a simple OLS regression based directly on (16) or alternatively by taking first-differences, which

[15]Note that a change in $A_{c,0}$ would correspond to a simple change in γ.

Table 1: OLS Estimates for σ

	Dependent Variables	
	$\ln(s_{c,t}/s_{r,t})$	$\Delta\ln(s_{c,t}/s_{r,t})$
Constant	-1.706	-0.0412
	(1.081)	(0.0295)
t	0.0274	
	(0.0163)	
$\ln\left(\frac{K_{c,t}}{L_{r,t}}\right)$	0.774***	
	(0.198)	
$\Delta\ln\left(\frac{K_{c,t}}{L_{r,t}}\right)$		-0.121
		(0.313)
Implied EOS	4.419	0.892
Obs.	34	33
F-Stat.	119.4	0.2

Notes: Newey-West standard errors are reported in parentheses and significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. For each specification we also report the implied elasticity of substitution, $\varepsilon_{c,r} = 1/(1-\sigma)$, evaluated at the respective point estimate.

yields the regression model

$$\Delta\ln\left(\frac{s_{r,t}}{s_{c,t}}\right) = \sigma(\lambda_l - \lambda_c) + \sigma\Delta\ln\left(\frac{K_{c,t}}{L_{r,t}}\right) + \Delta\nu_t. \tag{17}$$

To estimate (16) and (17) we measure the stock of computers, $K_{c,t}$, using a chained quantity index of ICT assets (see Table A.4), which we construct from the BEA's detailed asset accounts, and the amount of "effective" routine labor, $L_{r,t}$, is based on equation (4). Table 1 shows the resulting OLS estimates. While the model in first differences has very little explanatory power and results in insignificant estimates, the level specification delivers a highly significant point estimate of $\hat{\sigma} = 0.774$. Since we are interested in the substitutability of ICT and routine labor it is instructive to translate this point estimate into an implied elasticity of substitution (EOS): $\hat{\varepsilon}_{c,r} = \frac{1}{1-\hat{\sigma}} = 4.419$. Since this estimate is greater than one but significantly less than infinity, this suggest strong but less than perfect substitutability between ICT and routine labor.

While the OLS estimates of regression model (16) suggest that ICT and routine labor are substitutes, the above regressions are not sufficient to identify all five parameters of the production function: γ, σ, $A_{l,0}$, λ_c, and λ_l. We therefore pursue a GMM approach that allows us to jointly identify these parameters, which requires at least five moment conditions. Our setup delivers eight moment conditions. The first two moment conditions readily follow from equations (16) and (17). Four additional moment conditions follow directly from the production function and the fact that equations (13) and (15) allow us to write X_t as a function of either ICT capital and the ICT share, $K_{c,t}$ and $s_{c,t}$, or alternatively as a function of the quantity of routine labor and the routine share, $L_{r,t}$ and $s_{r,t}$:

$$X_t = A_{c,t}K_{c,t}\left(\frac{\gamma\alpha_{x,t}}{s_{c,t}}\right)^{\frac{1}{\sigma}} \tag{18}$$

$$X_t = A_{l,t}L_{r,t}\left(\frac{(1-\gamma)\alpha_{x,t}}{s_{r,t}}\right)^{\frac{1}{\sigma}} \tag{19}$$

where $\alpha_{x,t} = 1 - \alpha_{nc,t} - \alpha_{nr,t}$. Plugging expressions (18) and(19) into the production function (7) then yields equations (20) and (21), respectively:

$$Y_t = A_{c,t}^{(\alpha_{nc,t}+\alpha_{x,t})} A_{l,t}^{\alpha_{nr,t}} K_{nc,t}^{\alpha_{nc,t}} L_{nr,t}^{\alpha_{nr,t}} K_{c,t}^{\alpha_{x,t}} \left(\frac{\gamma\alpha_{x,t}}{s_{c,t}}\right)^{\frac{\alpha_{x,t}}{\sigma}} \tag{20}$$

$$Y_t = A_{c,t}^{\alpha_{nc,t}} A_{l,t}^{(\alpha_{nr,t}+\alpha_{x,t})} K_{nc,t}^{\alpha_{nc,t}} L_{nr,t}^{\alpha_{nr,t}} L_{r,t}^{\alpha_{x,t}} \left(\frac{(1-\gamma)\alpha_{x,t}}{s_{r,t}}\right)^{\frac{\alpha_{x,t}}{\sigma}} \tag{21}$$

Given our parametrization for the exogenous growth processes, $A_{i,t}$, both expressions are log-linear in a mean zero disturbance, which allows us to use the logs of (20) and (21) as moment conditions both in levels and first differences.

Finally, under the assumption that each type of labor is paid its marginal product, the non-routine wage premium relates to the model parameters as follows:

$$\frac{w_{nr,t}}{w_{r,t}} = \frac{\gamma}{1-\gamma}\left(\frac{A_{c,t}}{A_{l,t}}\right)^{\sigma}\left(\frac{K_{c,t}}{L_{r,t}}\right)^{\sigma}\frac{s_{nr,t}L_{r,t}}{s_{c,t}L_{nr,t}} \tag{22}$$

Again, given our parameterization for $A_{i,t}$, this expression is log-linear in a mean zero disturbance and therefore yields two additional moment conditions: one in levels and one in first differences. While we only need five moment conditions to identify all model parameters we will use all eight conditions described above to increase the empirical fit of our estimated production structure.[16]

To construct GMM estimates based on the eight moment conditions described above we treat the following variables as data: employment, $L_{r,t}$ and $L_{nr,t}$, input intensities, $\alpha_{nc,t}$ and $\alpha_{nr,t}$, capital stocks, $K_{c,t}$ and $K_{nc,t}$, income shares, $s_{i,t}$ with $i \in \{r, nr, c, nc\}$, output, Y_t, and the non-routine wage premium, $w_{nr,t}/w_{r,t}$. We measure the respective amounts of "effective" labor using equations (4) and (3), and capital stocks are based on chained quantity indexes that we construct directly from the BEA's detailed fixed asset accounts (see Tables A.4 and A.5 for our grouping of assets).[17] We proxy the factor intensities with our estimated income shares of non-ICT capital and non-routine labor described in sections 3 and 2, respectively. Output data are taken from FRED and appropriately re-chained to match the normalization of our chain indexes for capital. It is worth noting that the quantity indexes are such that the prices of output, ICT, and non-ICT stocks are normalized to one in 1979, consistent with our normalization of $A_{c,0} = 1$. For the non-routine wage premium we employ annual averages of our estimated sequence of point estimates, $\hat{\beta}_{1,q}$, from regression models (1).

Our GMM estimation results are presented in Table 2. Column A presents the estimates under the assumption of labor-augmenting technical change ($\lambda_c = 0$), whereas column B allows for capital augmenting technological change (e.g., $A_{c,t} = A_{nc,t}$ augments both ICT and non-ICT capital). Finally, column C presents the estimates given the possibility of both labor augmenting technological change and ICT-augmenting technological change.

Several results deserve comment: First, notice that the point estimates for γ, σ, $\ln(A_{l,0})$, and λ_l are tightly estimated and very consistent across the three specifications. Second, while we cannot rule out the possibility of modest capital- or ICT-augmenting technological progress, the upper

[16]We experimented with a variety of possible combinations of moment conditions and the results do not change in a substantive manner if we use as little as five moment conditions. The results are available upon request.

[17]These are the same quantitiy indexes whose associated implicit price deflators we used to measure capital gains in ICT capital.

Table 2: GMM Estimates

	Exogenous Technical Progress		
	A. Labor Augmenting	B. Labor & Capital Augmenting	C. Labor & ICT Augmenting
γ	0.191***	0.190***	0.190***
	(0.0104)	(0.0105)	(0.0103)
σ	0.470***	0.465***	0.468***
	(0.0498)	(0.0513)	(0.0494)
$\ln(A_{l,0})$	-3.218***	-3.212***	-3.219***
	(0.0664)	(0.0691)	(0.0663)
λ_l	0.00953**	0.00918**	0.00963**
	(0.00435)	(0.00449)	(0.00435)
λ_k		0.0000468	0.0000460
		(0.000142)	(0.000140)
Implied Elasticity of Substitution			
Lower 95% CI	1.594	1.574	1.591
Point Estimate	1.888	1.869	1.880
Upper 95% CI	2.315	2.302	2.298
Obs.	34	34	34

Notes: The estimates are based on a Newey-West HAC robust weighting matrix and Newey-West standard errors are reported in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. For each specification we also report the implied elasticity of substitution, $\varepsilon_{c,r} = 1/(1-\sigma)$, evaluated at the respective point estimate, lower, and upper 95% confidence interval.

bound of the 95% confidence interval of the estimates of λ_k in Panels B and C is only 0.03%, which is negligible compared to the estimated rate of labor-augmenting technological progress. This finding allows us, with caution, to focus exclusively on labor-augmenting technological progress in our quantitative exercises below. This is computationally convenient as—by Uzawa's theorem—this guarantees a balanced growth path within our neoclassical framework.[18]

For each specification, Table 2 further tabulates the elasticity of substitution implied by our point estimates of σ as well as well as the upper and lower 95% confidence bound. These calculation suggest an elasticity of substitution of around 1.888 and within the range of 1.5 and 3. While these estimates are significantly smaller than the ones from our single equation OLS estimates reported in Table 1, they also imply that ICT and routine labor are more than unit elastic but are significantly less than perfect substitutes. For our quantitative exercises below we will use our

[18]See any graduate growth text for a discussion of Uzawa's theorem.

point estimates from column A in Table 2, as these estimates satisfy the joint cross-equation restrictions implied by competitive factor markets and our production structure postulated in equation (7).

5. Transitional Dynamics & Long-Run Implications

We interpret the observed trends over 1979-2013 as part of a transition to a new long-run balanced growth path in response to the advent of computers in the 1970s—and possibly other shocks that led to changes in factor intensities. This interpretation allows us to shed further light on the underlying mechanics of these developments by embedding the above production structure into an otherwise standard neoclassical growth model. In particular, our model allows us to isolate the roles of changing specialization, ICT accumulation, and labor market rigidities.

Specifically, we consider a neoclassical model, in which time is discrete and denoted $t = 0, 1, 2....$ There is a single final good used for consumption and investment. Households take the paths of the following three objects as given: the sequence of factor intensities, $\alpha_{nc,t}$ and $\alpha_{nr,t}$, the price sequence of ICT capital, $p_{c,t}$, and the sequence of ICT capital depreciation rates, $\delta_{r,t}$. In principle, the price of ICT capital is an equilibrium object, however, we think of our formulation as a reduced form version of a richer model in which there is exogenous productivity growth in the production of ICT.[19] In addition, to capture the dynamics of the wage premium, we assume an exogenous "routine labor wedge", which, for simplicity, will be modeled as an exogenous subsidy on routine labor.

There is a unit measure of identical households. Each household values its lifetime consumption stream according to the utility function:

$$U(\{A_t c_t\}_{t=0}^{\infty}) = \sum_{t=0}^{\infty} \beta^t \frac{(A_t c_t)^{1-\eta}}{1-\eta} \tag{23}$$

[19]For example, assume that ICT capital is produced using to the following technology: $k_{r,t} = A_{ICT,t} y_{r,t}$, where $y_{r,t}$ is the final good (which is used as an input of production of ICT capital). It is easy to show that, in a competitive framework, the price of ICT capital in terms of the final good is given by $p_{c,t} = \frac{1}{A_{ICT}}$, and thus the declining price sequence can be thought of as reflecting an exogenous productivity improvement in the production of ICT capital.

where $c_t = \frac{C_t}{A_t L_t}$ is consumption per effective unit of labor at time t, and $\beta \in (0, 1)$. Note that this formulation implies that the representative household cares about consumption per worker, $\frac{C_t}{L_t} = A_t c_t$. Each household is the owner of a single firm, that operates a production function identical to the aggregate production function. The firm owns the capital that it operates, and hires routine and non-routine labor at the market wages, $w_{r,t}$ and $w_{nr,t}$, which it takes as given. Wages, $w_{i,t} = \frac{W_{i,t}}{A_t}$, are specified in terms of effective units of labor, where $W_{i,t}$ is the wage in terms of the final good. In addition, the household is endowed with L_t units of labor at time t, which it can allocate between routine and non-routine labor. To match the observed wage premium, we assume that routine labor is subsidized at a rate τ_t. The subsidy is financed with a lump-sum tax.

The household seeks to maximize (23) by choosing the sequence $\{c_t, k_{nc,t+1}, k_{c,t+1}, l_{r,t}, l_{nr,t}, l^s_{r,t}, l^s_{nr,t}\}_{t=0}^{\infty}$, where $l_{r,t} = \frac{L_{r,t}}{L_t}$ and $l_{nr,t} = \frac{L_{nr,t}}{L_t}$ denote firm's labor demand, $l^s_{r,t} = \frac{L_{r,t}}{L_t}$ and $l^s_{nr,t} = \frac{L_{nr,t}}{L_t}$ denote the household's labor supply, $k_{nc,t} = \frac{K_{nc,t}}{A_t L_t}$ and $k_{c,t} = \frac{K_{c,t}}{A_t L_t}$ are the amounts of non-ICT and ICT capital per effective worker employed in production, and A_t is labor-augmenting technology. At time 0, each household is endowed with $k_{nc,0}$ and $k_{c,0}$ units of non-ICT capital and ICT capital, respectively. The household solves:

$$\max_{c_t, k_{nc,t+1}, k_{c,t+1}, l_{r,t}, l_{nr,t}, l^s_{r,t}, l^s_{nr,t}} \sum_{t=0}^{\infty} \beta^t \frac{(A_t c_t)^{1-\eta}}{1-\eta} \tag{24}$$

such that

$$c_t + (1+\lambda)(1+\lambda_p) \sum_{i=nc,c} p_{i,t} k_{i,t+1} = \pi_t + (1+\tau_t) w_{r,t} l^s_{r,t} + w_{nr,t} l^s_{nr,t} + T_t \tag{25}$$

$$\pi_t = y_t + \sum_{i=nc,c} (1-\delta_{i,t}) p_{i,t} k_{i,t} - w_{r,t} l_{r,t} - w_{nr,t} l_{nr,t} \tag{26}$$

$$y_t = k_{nc,t}^{\alpha_{nc,t}} l_{nr,t}^{\alpha_{nr,t}} (\gamma k^{\sigma}_{c,t} + (1-\gamma) l^{\sigma}_{r,t})^{\frac{1-\alpha_{nr,t}-\alpha_{nc,t}}{\sigma}} \tag{27}$$

$$l^s_{r,t} + l^s_{nr,t} = 1 \tag{28}$$

$$A_t = A_0 e^{\lambda t} \tag{29}$$

where $p_{i,t}$ is the price of capital of type i in terms of the final good, π_t is the firm's profits, λ_p is the rate of population growth and λ is the rate of labor-augmenting technological progress. Routine

and non-routine labor supplies are given by $l^s_{r,t}$ and $l^s_{nr,t}$, respectively, and $l_{r,t}$ and $l_{nr,t}$ are routine and non-routine labor demands (of course, in equilibrium, market clearing requires $l^s_{i,t} = l_{i,t}$).

Equation (25) is the household's budget constraint. The household's income consists of the firm's profits, labor income—which may be "subsidized"—and the transfer. The household divides its income between consumption and investment in next period's capital stocks.[20] Equation (26) specifies the firm's profits as the sum of output and depreciated capital, net of wage payments to routine and non-routine labor. Finally, constraint (27) is the firm's production function in effective units of labor, equation (28) is the constraint on the household's labor supply, and (29) defines the process of labor-augmenting technological progress.

Note that τ_t captures the non-routine wage premium, as the household's first order conditions with respect to routine and non-routine labor supplies require that

$$(1+\tau_t)w_{r,t} = w_{nr,t} \Rightarrow \frac{w_{nr,t}}{w_{r,t}} - 1 = \tau_t. \tag{30}$$

The "transfer" T_t is a methodological device to guarantee that the aggregate resource constraint is satisfied with equality. In particular, we assume that $T_t = -\tau_t w_{r,t}$, which simply says that the exogenous non-routine wage premium needs to be financed with real resources. If $\tau_t = 0$, the budget constraint (25) reduces to the standard budget constraint of the representative agent.

Given $k_{nc,0}$, $k_{c,0}$, λ, λ_p, $\{p_{i,t}\}$, $\{\delta_{i,t}\}$, $\{\alpha_{nr,t}\}$, $\{\alpha_{nc,t}\}$, $\{\tau_t\}$ and $\{T_t\}$, an equilibrium of this econ-

[20] It may be useful to show how this budget constraint can be derived from the more familiar setting, in which variables are specified in terms of output rather than normalized by effective units of labor. In this case, the household's budget constraint is:

$$C_t + \sum_{i=nc,c} p_{i,t}K_{i,t+1} = \Pi_t + (1+\tau_t)W_{r,t}L^s_{r,t} + W_{nr,t}L^s_{nr,t} + A_tL_tT_t$$

Dividing through by A_tL_t yields:

$$c_t + \sum_{i=nc,c} p_{i,t}\frac{K_{i,t+1}}{A_tL_t} = \pi_t + (1+\tau_t)(\frac{W_{r,t}}{A_t})(\frac{L^s_{r,t}}{L_t}) + (\frac{W_{nr,t}}{A_t})(\frac{L^s_{nr,t}}{L_t}) + T_t$$

Since $w_{i,t} = \frac{W_{i,t}}{A_t}$ and $l^s_{i,t} = \frac{L^s_{i,t}}{L_t}$, we can rewrite the above as:

$$c_t + \sum_{i=nc,c} p_{i,t}\frac{K_{i,t+1}}{A_{t+1}L_{t+1}}\frac{A_{t+1}L_{t+1}}{A_tL_t} = \pi_t + (1+\tau_t)w_{r,t}l^s_{r,t} + w_{nr,t}l^s_{nr,t} + T_t$$

Finally, by using the identities $k_{i,t+1}\frac{K_{i,t+1}}{A_{t+1}L_{t+1}}$ and $\frac{A_{t+1}L_{t+1}}{A_tL_t}$, we arrive at the household's budget constraint.

Table 3: Baseline Parameter Values

A. Fixed Parameters & Initial Values		
η	IES parameter	2
β	Discount factor	1/1.03
λ_p	Population growth	0.013
$k_{nc,0}$	Initial non-ICT capital stock	1.8220
$k_{r,0}$	Initial ICT capital stock	0.0561
B. Long-Run Values		
$\delta_{nc,\infty}$	Depreciation rate: non-ICT capital	0.056
$\delta_{r,\infty}$	Depreciation rate: ICT capital	0.204
$\alpha_{nr,\infty}$	Non-routine labor share	0.3883
$\alpha_{nc,\infty}$	Non-ICT capital share	0.3371
p_{∞}	ICT capital price	0.257
τ_{∞}	Non-routine wage premium	0.1796
C. GMM Estimates		
γ	CES scale parameter	0.19072
σ	CES substitution parameter	0.47041
λ	Growth rate of labor-augmenting productivity	0.0095271

Notes: The table reports the parameter values used in our baseline simulations. Panel A groups fixed parameters and initial conditions. The preference parameters, η and β, are standard. λ_p is the observed rate of aggregate employment growth throughout 1979-2013. The initial capital stocks are the 1979 values of our quantity indexes for the two types of capital. The long run values in panel B are the observed values in 2013, except for $\alpha_{nc,\infty}$, which is calibrated to the average value from 1979-2013. Panel C groups parameters that were estimated using GMM.

omy is defined as a set of sequences $\{c_t\}$, $\{k_{nc,t+1}\}$, $\{k_{c,t+1}\}$, $\{l_{r,t}\}$, $\{l_{nr,t}\}$, $\{l^s_{r,t}\}$, $\{l^s_{nr,t}\}$, $\{w_{r,t}\}$ and $\{w_{nr,t}\}$ that jointly solve the representative households maximization problem, the labor market clearing conditions, $l_{i,t} = l^s_{i,t}$ for $i = r, nr$, and the aggregate resource constraint $T_t = -\tau_t w_{r,t}$.

We solve for the deterministic equilibrium paths converging to the unique balanced growth path of this economy based on a number assumptions about the model parameters described below.[21] Table 3 summarizes the parameter values used in our baseline simulations. We choose standard values for the two preference parameters, β and η. Of course, there is a range of parameters used in the literature; our particular choices have the advantage that they generate a growth rate of non-ICT capital that roughly matches its empirical counterpart.

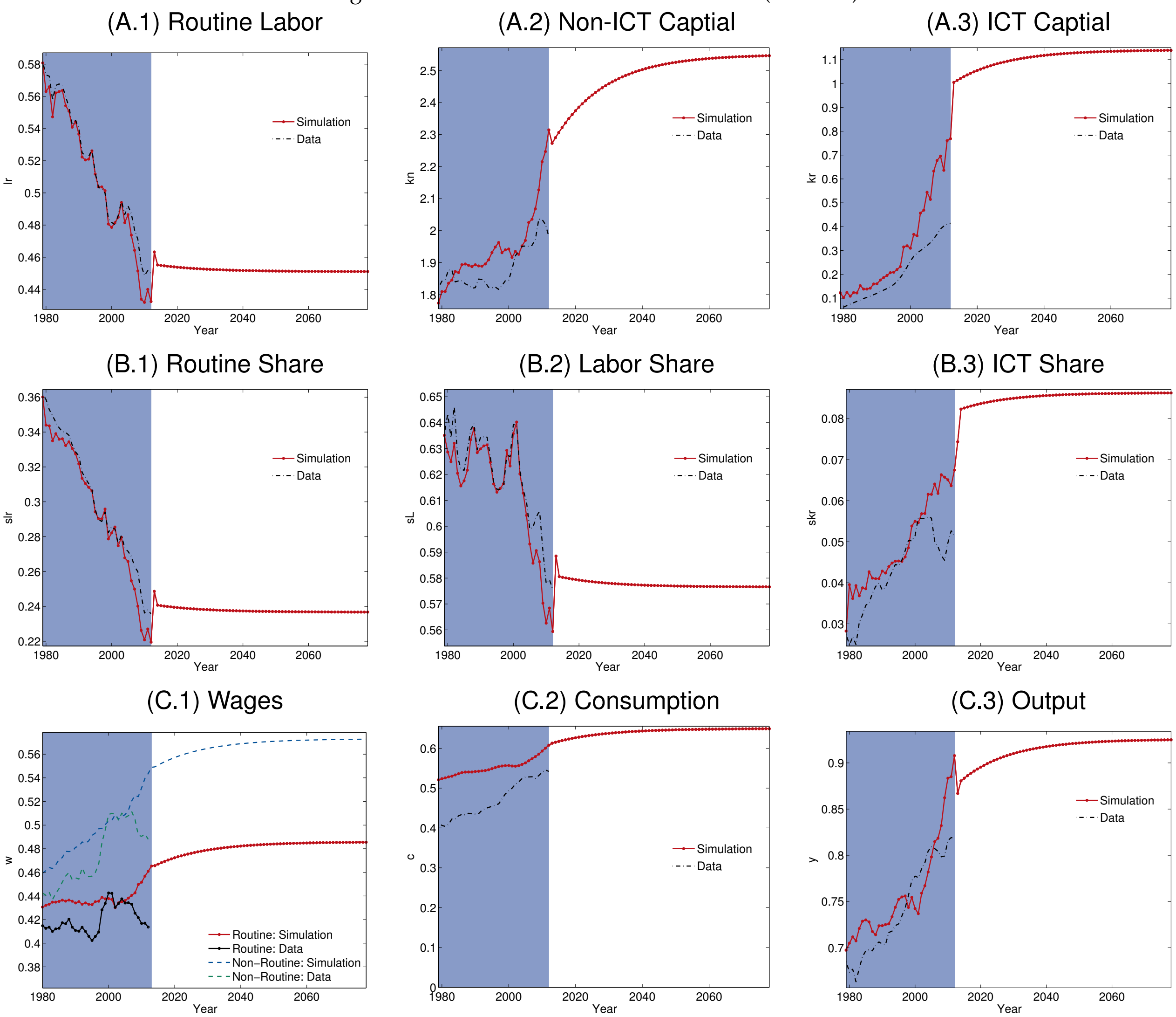
[21]For deterministic simulations, the numerical problem consists of solving a nonlinar system of simultaneous equations in n endogenous variables in T periods. We use a Newton-type method to solve the simultaneous equation system.

To compute the economy's steady state, we need to take a stance on the limiting values of our exogenous parameters. Given that $\alpha_{nc,t}$ has remained roughly constant, we take the steady state value of $\alpha_{nc,t}$ to be the average level over the period 1979-2012. We assume that the long run values $\alpha_{nr,\infty}$, $\delta_{nc,\infty}$, $\delta_{r,\infty}$, $p_{c,\infty}$, and τ_∞ match their respective 2012 levels as these parameters have either been stable throughout 1979-2012 or appear to have stabilized since 2000. Of course, alternative trajectories in which the price of ICT capital continues to decline and the non-routine wage premium begins to fall would tend to imply more ICT accumulation, and—if the rise in the non-routine labor share is due, in part, to ICT accumulation—a higher non-routine labor share as well. Our calibration therefore presents a "conservative" estimate regarding the long-run impact of ICT. Appendix C presents an alternative calibration in which the exogenous ICT capital price continues to decline for 20 years and converges to a steady state value of $p_{c,\infty} = 0.08$. It is worth noting that, while the long run predictions generated by this alternative are substantially different from those discussed here, the simulated paths are nearly perfectly aligned within the sample period (1979-2012) and the counterfactual analysis remains essentially unchanged.

For the remaining parameters, we use our GMM point estimates of λ, σ and γ, and specify λ_p to be the average growth rate of employment. We choose initial capital stocks to match the levels of their empirical counterparts in 1979. The paths of the exogenous parameters are summarized in Figure B.12 in Appendix B. After 2012, exogenous parameters are assumed to be equal to their specified long-run levels. During 1979-2012, the ICT price, the ICT depreciation rate, and the non-routine wage premium are assigned their estimated values. The factor intensities $\alpha_{nr,t}$ and $\alpha_{nc,t}$ are calibrated to match the sequences of the non-routine income share and the non-ICT capital share, respectively.

Figure 8 presents the results of the baseline calibration, against the relevant empirical counterparts. The simulated transition paths of inputs and input shares closely line up with their empirical counterparts up until the mid 2000s. At that point, the simulated path of ICT capital surpasses its empirical counterpart, resulting in a higher ICT income share and lower labor income shares. This departure could potentially be viewed as a strength of the model, as it is well understood that other forces were at play during the last part of our sample—e.g., the great recession that

Figure 8: Simulated Paths of Income Shares (Baseline)



Notes: The graphs plot the simulated transition path to the new steady state in the baseline calibration. The shaded area indicates the our estimation sample, 1979-2012. For routine and non-routine employment, the empirical counterparts are "effective" routine and non-routine employment shares based on equations (3) and (4). All remaining empirical ounterparts are constructed form the chain indexes used in the GMM estimation, divided by total employment times an estimate of A_t, which is given by $A_0e^{\lambda t}$, where $A_{l,0}$ and λ are our GMM estimates. We impute wage series for "effective" units of labor from the estimated non-routine wage premium and employment based on equations (3) and (4).

led to a slow-down in capital accumulation, and the "housing bubble" that potentially diverted investment from ICT to residential capital.

This calibration suggests a steady state labor income share of about 0.58, which is roughly comparable to its empirical level at 2012. It is interesting to note that our analysis implies natural upper and lower bounds for the future labor income share: at one extreme, if non-routine labor intensity continues to grow relative to the intensity of routine inputs to the point where "routine

inputs" have a zero share, the long-run labor income share will revert back to its historical level of roughly 0.67. If, at the other extreme, the non-routine labor income share remains at its current level but the price of ICT capital falls to zero—rather than remaining at its current level—, routine labor will be completely crowded out and the labor income share will be given by the non-routine labor income share, which is roughly 0.4.

The calibration suggests that the current levels of ICT capital are still substantially below their steady state levels: the simulated transition path suggests that ICT capital per effective unit of labor will increase by about 40% in the next 100 years. Interestingly, the massive accumulation of ICT capital is associated with only a moderate decline in routine employment, which remains roughly at its 2012 (empirical) level. The relatively moderate decline in routine employment reflects the imperfect substitutability of ICT capital and routine labor.

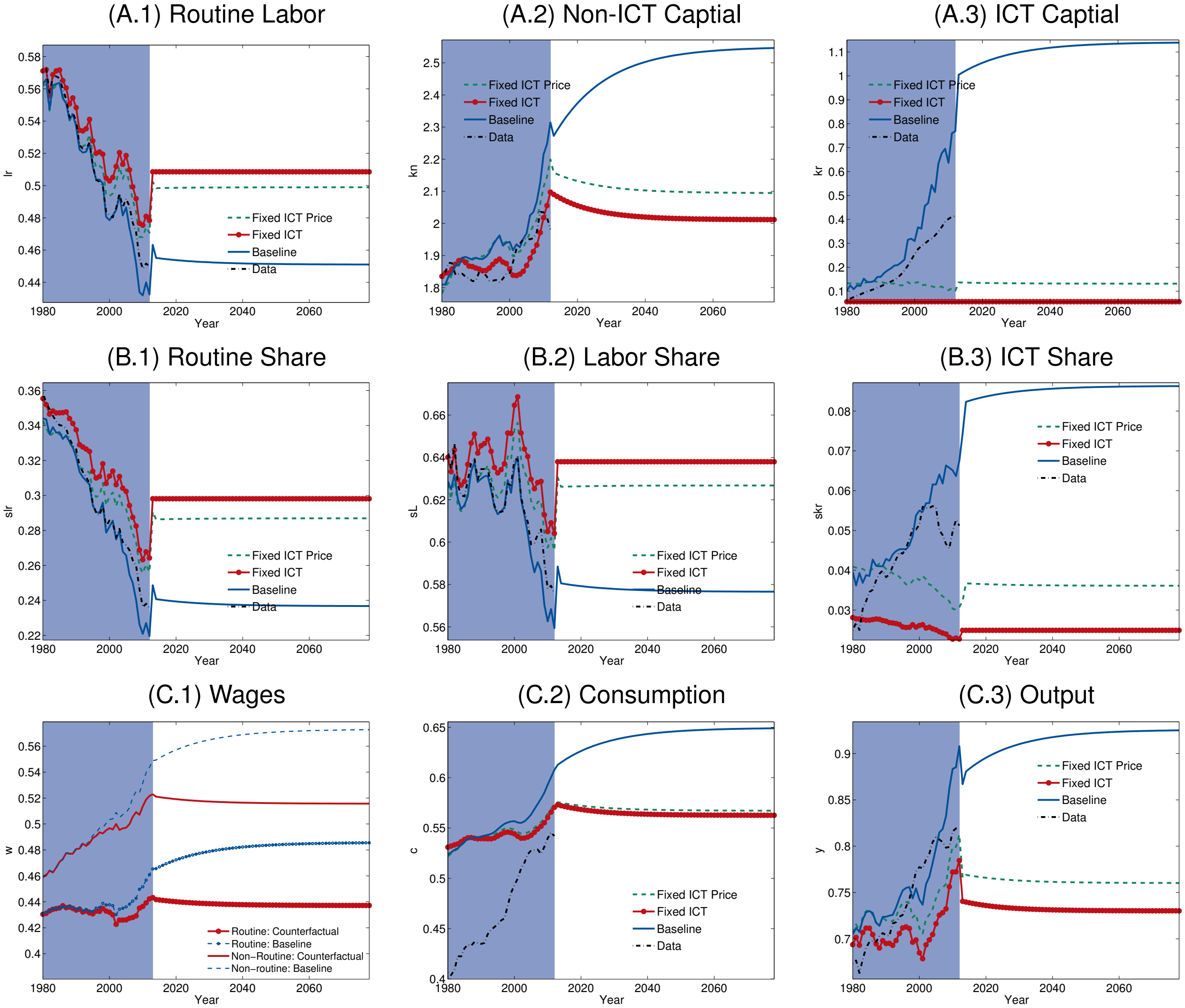
The associated increase in routine inputs and non-routine labor increases the incentives to accumulate non-ICT capital; the simulated transition path suggests close to a 10% increase in non-ICT capital (per effective unit of labor) over the next 100 years. Despite the accumulation of ICT and non-ICT capital, projected growth of output and consumption per effective unit of labor is modest. This suggests that bulk of the welfare gains from the transition to a new balanced growth path have already been realized (though, this result is sensitive to the specification of the future evolution of the ICT price; see Appendix C).

5.1. Counterfactual 1: The Role of ICT Accumulation and the Decline in the ICT Price

To study the direct effect of ICT capital accumulation on routine labor income, we consider two related counterfactuals: first, we treat ICT capital as an exogenous parameter and hold it constant at its 1979 level. Second, we allow for ICT investment to be determined endogenously, but abstract away from the decline in the relative price of ICT, holding it fixed at its 1979 level.

Figure 9 present the counterfactual transition paths, against the baseline calibration. The first thing to note is that the two counterfactuals imply remarkably similar transition paths. This sug-

Figure 9: Counterfactual: No ICT Accumulation & Fixed Price of ICT



Notes: The graphs plot the simulated transition path to the new steady state. The shaded area indicates the our estimation sample, 1979-2013. For the wage graph, the counterfactual of a constant ICT price is omitted (the counterfactual is the constant ICT scenario). For the empirical counter parts see the notes of Table 8.

gests that the declining ICT price, emphasized by Karabarbounis and Neiman (2014), played a key role in generating ICT investment.

A second observation worth noting is the more moderate decline in both the routine labor income share and the aggregate labor income share: in these counterfactuals, the aggregate labor income share declines by 4% between 1979-2012, compared to an 8% decline in the baseline calibration. Similarly, the counterfactual routine share declines only by about 9% between 1979-2012, compared to a 12% decline in the baseline calibration. These findings are consistent with the view that computerization was one of the key drivers of the declining labor income share, and the

crowding out of routine occupations.

At the same time, it is worth noting that the counterfactual paths of employment shares are quite close to the baseline calibration. This suggests that, at least during our sample period, the reallocation of labor from routine to non-routine occupations was driven in part by the increase in non-routine intensity.

It is interesting to note that, even in the absence of ICT accumulation, the aggregate labor income share declines by about 4%, despite the increase in non-routine labor intensity (α_{nr}). The reason is that the increase in the non-routine labor intensity raises the equilibrium wage for non-routine labor. Labor then reallocates from routine to non-routine occupations, leaving a larger part of the routine income share ($1 - \alpha_{nr} - \alpha_k$) to be absorbed by ICT capital. The net effect of an increase in α_{nr} turns out to be, somewhat surprisingly, a decline in the aggregate labor income share.

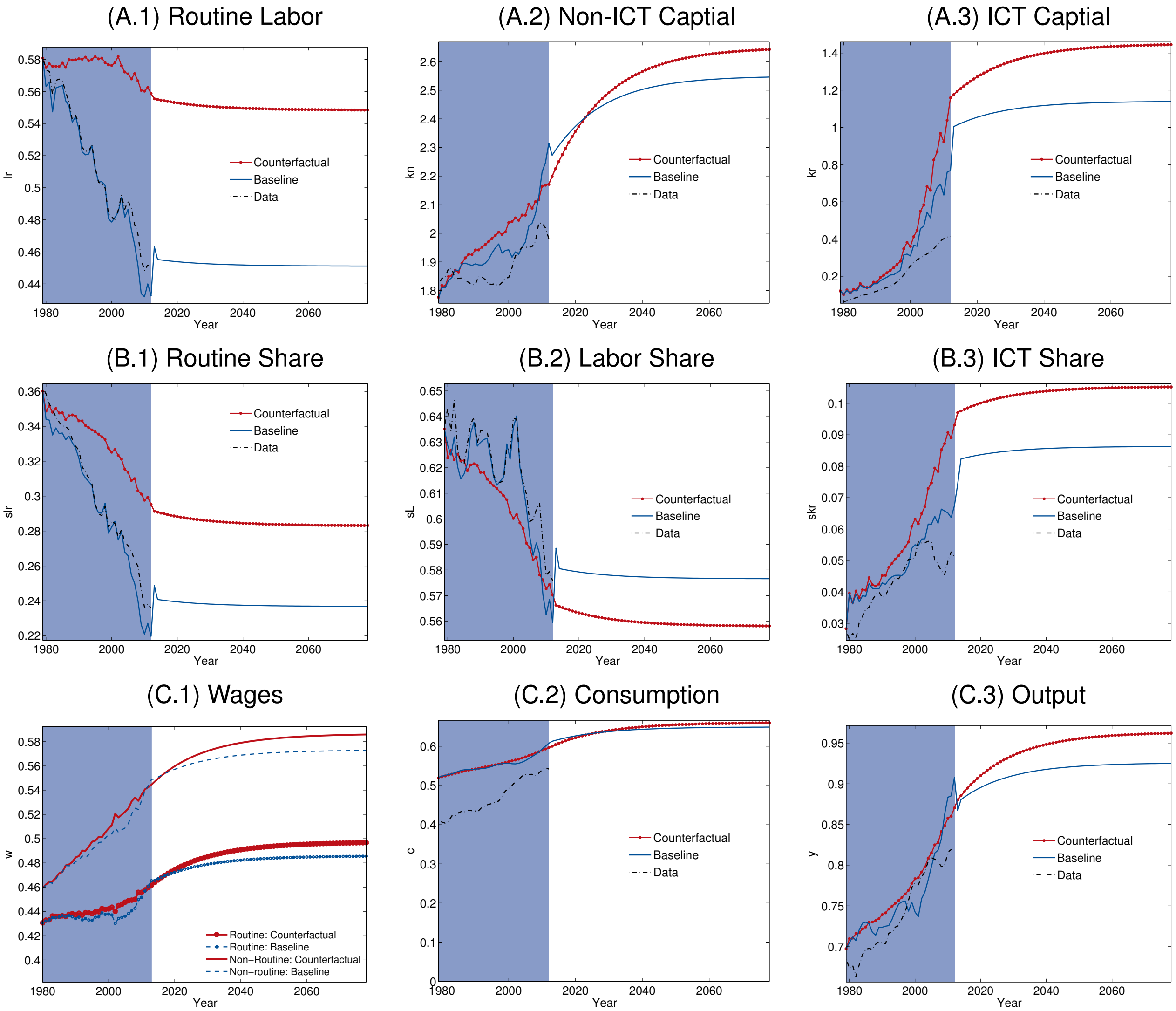
To summarize, the counterfactuals suggests that the accumulation of ICT had a sizable impact on factor income shares between 1979-2012. However, interestingly, its (direct) impact on the reallocation of labor from routine to non-routine occupations was rather moderate, suggesting that the bulk of labor reallocation may have been due to changes in the pattern of specialization.

5.2. Counterfactual 2: The Role of Changing Patterns of Specialization

As a complementary exercise, we consider the counterfactual transition path that abstracts away from changes in factor intensities, by fixing $\alpha_{nr,t}$ and $\alpha_{nc,t}$ to be constant at their 1979 levels. Figure 10 illustrates the results.

The counterfactual drop in the aggregate labor income share is similar, in the long run, to the baseline calibration. This suggests that the changing pattern of specialization had a neutral effect on the declining labor income share. At times, the changing pattern of specialization may have worked towards increasing the aggregate labor income share, as suggested by the occasional disparities between the baseline and counterfactual paths. However, the long run trends seem to be identical. This neutrality reflects two forces that cancel out: on the one hand, the increase in

Figure 10: Counterfactual: Fixed Patterns of Specialization



Notes: The graphs plot the simulated transition path to the new steady state. The shaded area indicates the our estimation sample, 1979-2013.

the non-routine intensity works towards boosting the labor income share. On the other hand, as previously noted, the increase in non-routine intensity leads to a reallocation of labor from routine to non-routine employment, reducing the fraction of the routine input share $(1 - \alpha_{nr} - \alpha_k)$ that accrues to labor. The two effects seem to exactly cancel out in the long run, suggesting that the declining labor income share is due entirely to the accumulation of ICT capital.[22]

[22] Note the nuanced relationship between the conclusion in this section and the conclusion in the previous section regarding the quantitative importance of the change in specialization to the declining labor income share. The previous section concludes that the changes in specialization without the possibility of accumulating ICT would result in a declining labor income share; however, with the accumulation of ICT, the effects of changing specialization are neutral, as ICT accumulation lowers the marginal product of ICT and increases the relative income of routine labor.

While the changing factor intensities did not seem to affect the decline in the aggregate labor income share, they seem to have had a sizable effect on the decline in the routine labor income share. The counterfactual suggests that about half of the decline in the routine income share is due to changes in factor intensities. The counterfactual path of routine employment departs substantially from the baseline: while the baseline calibration implies a 15% drop in routine employment, the counterfactual implies a mere 2% drop. This suggests that the primary force behind the reallocation of labor from routine to non-routine jobs has been the increase in the non-routine labor intensity of production.

The counterfactual generates trends in wages, consumption and output that are similar to the baseline up until 2012. However, the long run values of wages and output—and to a lesser extent, consumption—surpass the baseline. This is not surprising, as the accumulation of ICT capital would imply more output gains when production is more intensive in routine tasks.

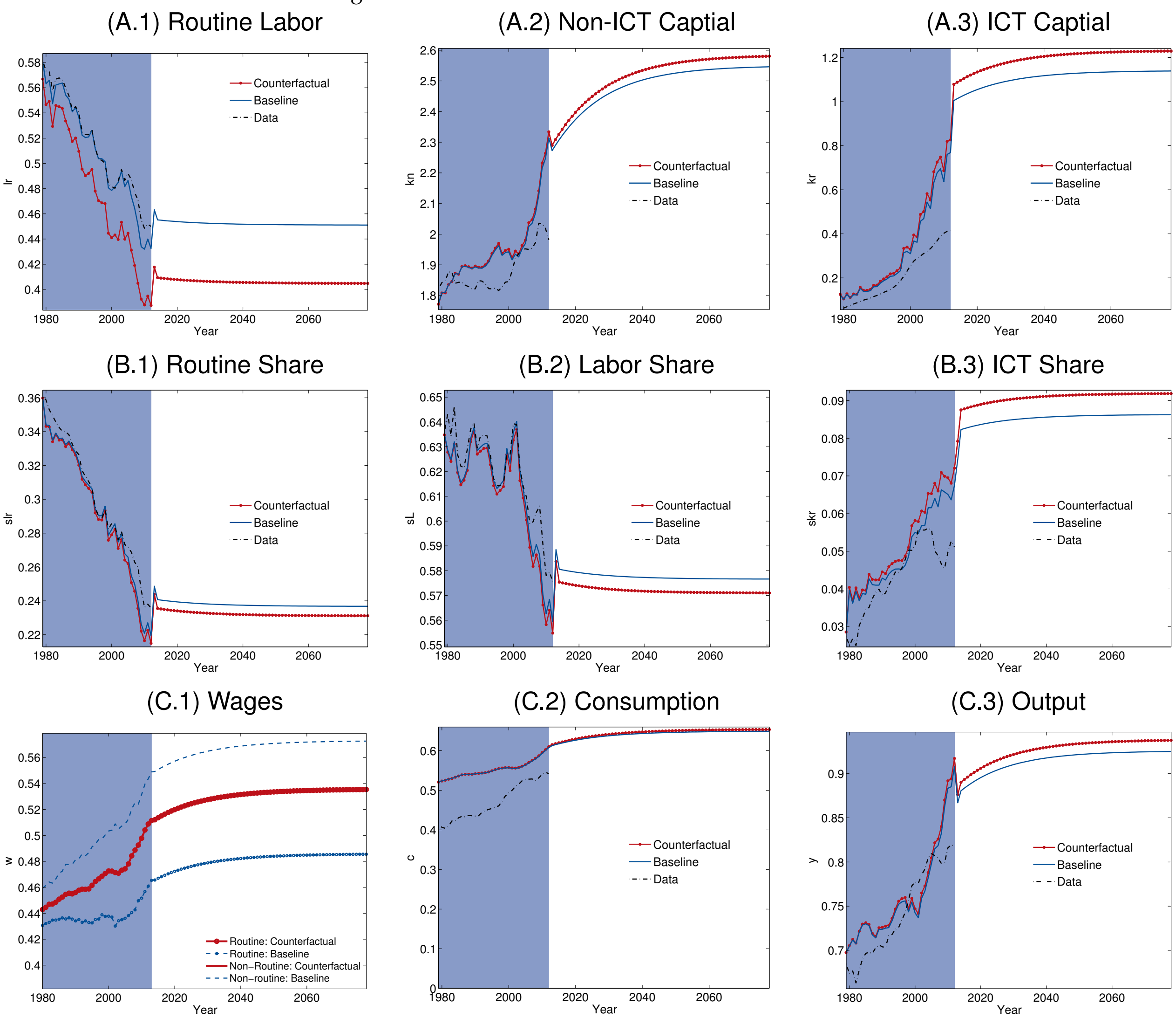
This counterfactual suggests that, while ICT accumulation and the changing pattern of specialization played similar roles in generating the decline in routine income shares, the decline in the aggregate labor share is due primarily to the substitution of ICT capital for routine labor. However, the changing pattern of specialization was the dominant force behind the reallocation of labor from routine to non-routine employment. Without the changes in factor intensities, the decline in routine labor would be more moderate, and the decline in the routine labor income share would be more moderate as well. However, the decline in the aggregate labor income share would be the same—as, absent the increase in non-routine intensity, the income share accruing to routine labor represents a higher share of total labor income.

5.3. Counterfactual 3: The Role of Labor Market Frictions

As a final counterfactual exercise, we study the role of labor rigidities by setting the non-routine wage premium to zero. Figure 11 presents the results.

While an 18% non-routine wage premium may seem large, the calibration suggests that, from the representative agent's perspective, it does not generate a large departure from the friction-

Figure 11: Counterfactual: No Labor Market Frictions



Notes: The graphs plot the simulated transition path to the new steady state. The shaded area indicates the our estimation sample, 1979-2013.

less benchmark. The most notable departure is, not surprisingly, in the routine and non-routine employment shares—and of course, by construction, in wages. Up until 2012, the counterfactual routine employment follows the baseline calibration with an increasing gap, that reaches around 5% in the long run. However, except for the very long run, the output trajectories of the baseline and the counterfactual are nearly indistinguishable. This suggests that even a relatively high non-routine wage premium generates rather minor labor misallocation, since the demand for routine labor is relatively inelastic.

6. Conclusion

This paper opens with several questions about how computerization will shape the future. While any answers to these questions are necessarily speculative, we study them through the lens of the standard neoclassical growth model, and suggest the following answers:

Will computers replace workers? How many? Our estimates suggest that the continued accumulation of ICT capital per se will likely not result in substantial crowding out of routine labor (unless, of course, the price of ICT capital goods further declines). In fact, our counterfactual analysis suggests that the reallocation of labor from routine to non-routine jobs has been due primarily to an increase in demand for non-routine labor, rather than to substitution with ICT capital. The key to this result is the imperfect substitutability between ICT capital and routine labor. We estimate the elasticity of substitution between ICT capital and routine labor to be between 1.5 and 4.5—suggesting that, while it is possible to use ICT capital to substitute for labor in routine tasks, there are some routine tasks in which labor has a relatively strong comparative advantage. Our calibration suggests that, as of 2012, most labor employed in routine jobs is already performing tasks which will be highly costly to perform with ICT.

What will happen to the share of labor income in production? We document that the decline in the labor income share is due entirely to a decline in the routine labor income share, while the non-routine labor income share has been increasing until the 2000s—and has leveled off since. Our calibration suggests that if the non-routine labor income share stays around its current levels, the aggregate labor income share is expected to remain about the same—around 0.58—, despite the increase in ICT capital. Less conservative assumptions regarding the future decline of the ICT capital price generate larger declines in the labor share. Within our framework, the non-routine labor share of 0.4 is a natural lower bound on the steady state labor income share. Our counterfactual analysis suggests that the declining labor income share since the 1980s has been due primarily to the accumulation of ICT capital, while changes in specialization had a neutral effect on the labor income share—though, they had a substantial effect on the allocation of labor and on the routine labor income share. So, while we find that the accumulation of ICT was not the primary source of

crowding out routine employment, it reduced the income share of routine labor.

What are the limits of computerization, if any? How will computerization change the standards of living? Our analysis suggests that, while computerization contributed substantially to output and consumption growth since the 1980s, absent further declines in the ICT capital price the future gains from additional ICT accumulation are relatively modest. Like all capital, ICT capital is subject to decreasing returns. While the calibration predicts the stock of ICT capital per effective unit of labor to increase by 40% until it reaches its new the steady state, the gains in terms of consumption and output are modest relative to the gains during the period 1980-2012.

Of course, our analysis considers only one aspect of computerization: the replacement of labor in routine tasks. Our conclusions suggest that while this may have been a dominant force in shaping trends in factor shares and factor allocations in recent decades, it may not generate the same drastic changes going forward.

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Appendix A. The Income Share of ICT/Non-ICT Capital

This appendix outlines our approach to measure income shares directly from BEA's nominal current cost values of detailed asset categories. No-arbitrage in perfect capital markets requires the *gross return* (6) to be equalized across all types of capital, which directly implies the following two relations:

$$\tilde{\delta}_{c,t} - \tilde{\delta}_{h,t} = \frac{P_t}{P_{h,t}} MPK_{h,t} - \frac{P_t}{P_{c,t}} MPK_{c,t} \tag{A.1}$$

$$\tilde{\delta}_{c,t} - \tilde{\delta}_{n,t} = \frac{P_t}{P_{n,t}} MPK_{n,t} - \frac{P_t}{P_{c,t}} MPK_{c,t} \tag{A.2}$$

where $\tilde{\delta}_{i,t} \equiv (1 + E_t[\pi_{i,t+1}])(1 - \delta_{i,t})$ and $E_t[\pi_{i,t+1}]$ is expected price inflation for capital type i. To see this, write (6) as $(P_t/P_{i,t})\, MPK_{i,t} + (1 - \delta_{i,t})\,(P_{i,t+1}/P_{i,t})$. Thus, for any two types of capital, i and j, no-arbitrage requires that $(P_t/P_{i,t})\, MPK_{i,t} + (1 - \delta_{i,t})\,(P_{i,t+1}/P_{i,t}) = (P_t/P_{j,t})\, MPK_{j,t} + (1 - \delta_{j,t})\,(P_{j,t+1}/P_{j,t})$, which directly implies (A.1) and (A.2)

Equation (5) combined with (A.1) and (A.2) then allows us to write the relative price adjusted marginal product of each type of capital as follows:

$$\frac{P_t}{P_{c,t}} MPK_{c,t} = (1 - s_{L,t}) \frac{P_t Y_t}{P_{nc,t} K_t} - (\tilde{\delta}_{c,t} - \tilde{\delta}_{n,t}) \frac{P_{n,t} K_{n,t}}{P_{nc,t} K_t} - (\tilde{\delta}_{c,t} - \tilde{\delta}_{h,t}) \frac{P_{h,t} K_{h,t}}{P_{nc,t} K_t} \tag{A.3}$$

$$\frac{P_t}{P_{n,t}} MPK_{n,t} = (1 - s_{L,t}) \frac{P_t Y_t}{P_{nc,t} K_t} - (\tilde{\delta}_{n,t} - \tilde{\delta}_{c,t}) \frac{P_{c,t} K_{c,t}}{P_{nc,t} K_t} - (\tilde{\delta}_{n,t} - \tilde{\delta}_{h,t}) \frac{P_{h,t} K_{h,t}}{P_{nc,t} K_t} \tag{A.4}$$

$$\frac{P_t}{P_{h,t}} MPK_{h,t} = (1 - s_{L,t}) \frac{P_t Y_t}{P_{nc,t} K_t} - (\tilde{\delta}_{h,t} - \tilde{\delta}_{c,t}) \frac{P_{c,t} K_{c,t}}{P_{nc,t} K_t} - (\tilde{\delta}_{h,t} - \tilde{\delta}_{n,t}) \frac{P_{n,t} K_{n,t}}{P_{nc,t} K_t}, \tag{A.5}$$

where $P_t Y_t$ is the nominal value of output, $P_{i,t} K_{i,t}$ is the nominal value of capital type i, $s_{L,t} \equiv W_t L_t / P_t Y_t$ is labor's share in income, and $P_{nc,t} K_t \equiv \sum_i P_{i,t} K_{i,t}$ is the nominal value of aggregate capital.

Notice that the right hand sides (RHS) of equations (A.3) through (A.5) only involve nominal shares, as well as the depreciation rates adjusted for capital gains, $\tilde{\delta}_{i,t}$. These expressions and the data described in Section 3 then allow us to compute the income share for each type of capital

using the following expressions:

$$s_{i,t} \quad = \quad MPK_{i,t}\frac{K_{i,t}}{Y_t} = \left(\frac{P_t MPK_{i,t}}{P_{i,t}}\right) \cdot \left(\frac{P_{i,t}K_{i,t}}{P_t Y_t}\right), \tag{A.6}$$

for each capital type $i \in \{c, n, h\}$. Notice that the first bracket on the RHS of equation (A.6) corresponds to the respective RHS expressions of equations (A.3) through (A.5) and the second bracket contains nominal shares. We can therefore compute the capital income share entirely based on nominal values at current cost, as well as a measure of inflation within each type of capital.

Table A.4: Relative Value of ICT Capital

	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. 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 A.4 and A.5. 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.

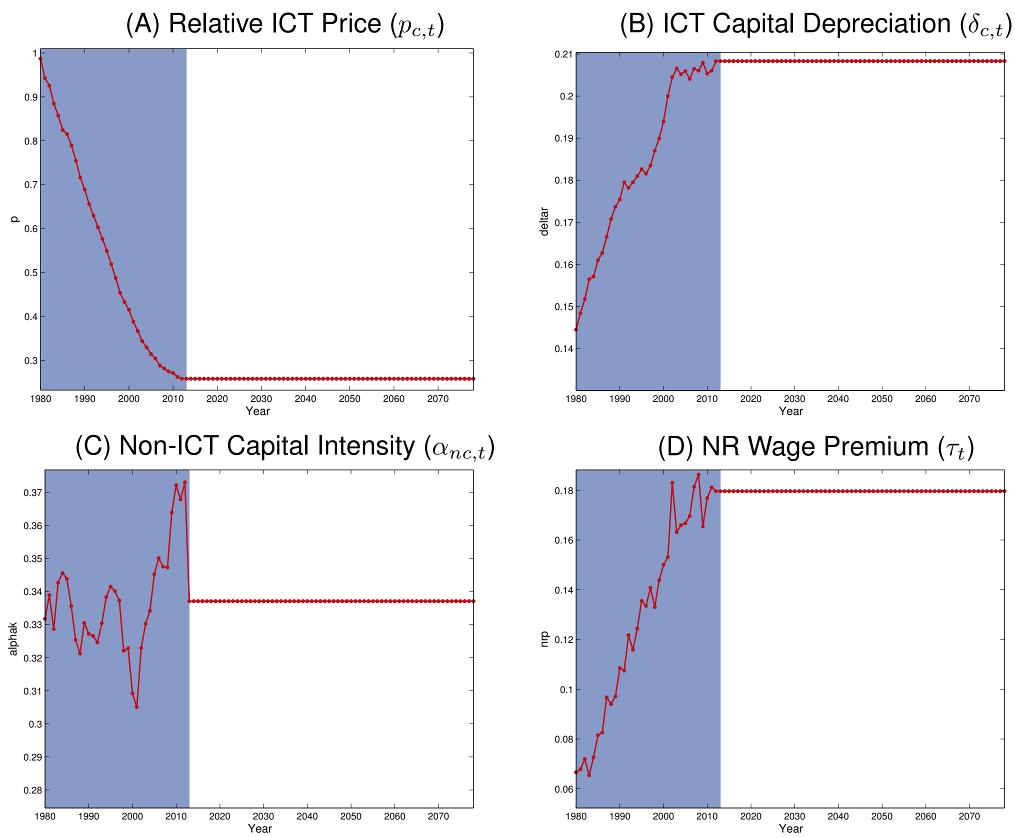
Table A.5: Relative Value of Non-ICT Capital

Non-ICT Assets	A. Average Share of Aggregate Capital (%) 1960-1980	1980-2000	2000-2013	B. Average Growth in Share (%) 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 A.4 and A.5. 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.

Appendix B. Baseline Simulation: Exogenous Paths

Figure B.12: Exogenous Paths



Notes: The graphs plot the exogenous paths for our baseline simulation. The values 1979-2013 are those observed in the data, and

Appendix C. Alternative Path for ICT Price

We consider an alternative specification in which the price of ICT capital goods continues to decline for several years after 2012, and converges to $p_c = 0.1$ at around 2030. Figure C.13 describes the exogenous paths used for the calibration. Note that the path of ICT capital depreciation (δ_c), non-ICT capital intensity (α_{nc}), non-routine labor intensity (α_{nr}) and the non-routine wage pre-

mium (τ) are the same as in the baseline specification. The only difference is in the evolution of p_c, which, rather than staying at its 2013 level of $p_c = 0.257$, decreases to $p_c = 0.08$ in the long run.

To construct the alternative price path for p_c, we fit a second order log polynomial to the observed price sequence:

$$\ln(p_{c,t}) = const + \beta_1 t + \beta_2 t^2 \tag{C.1}$$

The estimated coefficients are $const = .0530339$, $\beta_1 = -.0401107$ and $\beta_2 = -.0001642$.

We then use the estimated coefficients to extrapolate the price path for an additional 20 years, assuming that it converges to a long run level of 0.078. For consistency, the alternative price path uses fitted values rather than actual prices for the sample period as well.

Of course, which price path is "more reasonable" depends on the economic and technological forces underlying the price decline, which are outside of this model. If advancements in technology are the main force behind the price decline, there may (or may not) be substantial further price declines in ICT. If, however, the price decline is driven by the offshoring of the production of ICT goods to low-wage countries, there are clear boundaries to the price decline, especially given signs of likely future wage appreciations in many prominent ICT producers such as China.[23]

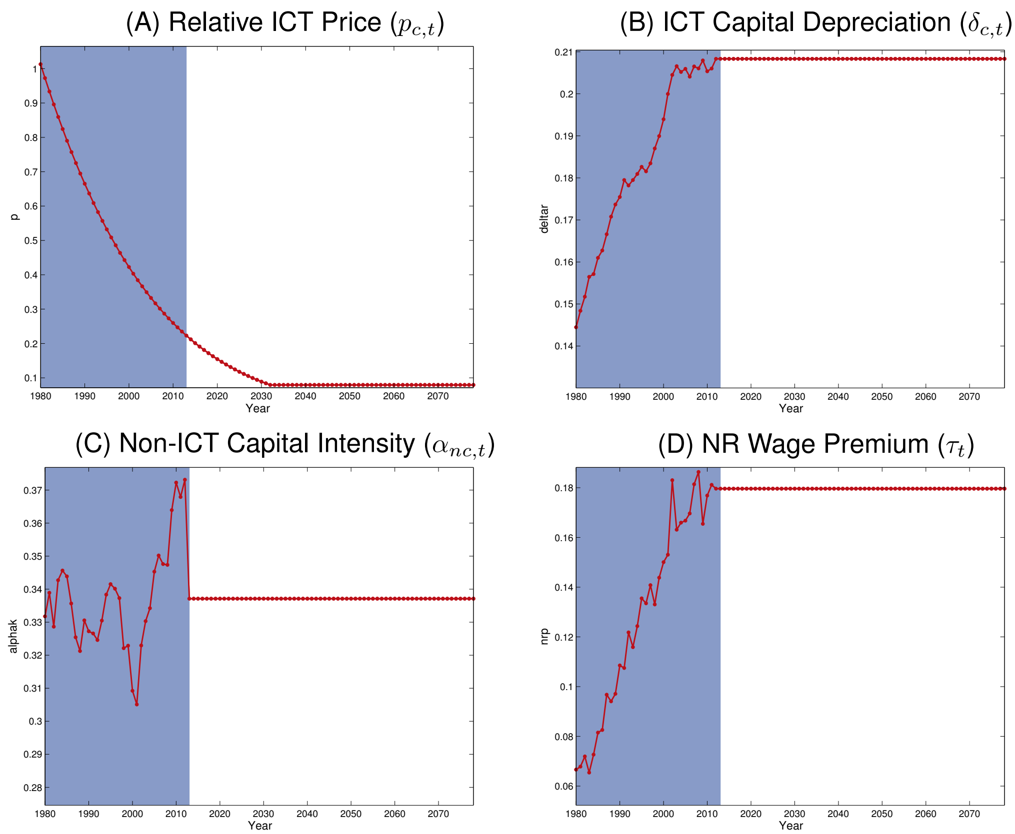
Appendix C.1. Baseline specification

Figure C.14 depicts the simulated paths from the two alternative specifications of the long-run evolution of the ICT capital price, together with the data for the sample period 1979-2012. Within the sample period 1979-2013, both simulated paths are nearly perfectly aligned. Unfortunately, the forward-looking behavior of agents does not provide useful information regarding the expectations of the future evolution of the price of ICT goods. Both specifications are equally consistent with the data.

At the same time, there are substantial differences in the long-run predictions generated by the two alternative paths. While, in the $p_{c,\infty} = 0.257$ scenario, the labor income share remains roughly at its 2012 level of 0.58, in the $p_{c,\infty} = 0.08$ scenario the labor income share declines by

[23] It is perhaps worth noting that higher log polynomial approximations of the price path generate a turning point at shortly after 2012.

Figure C.13: Alternative Exogenous Paths

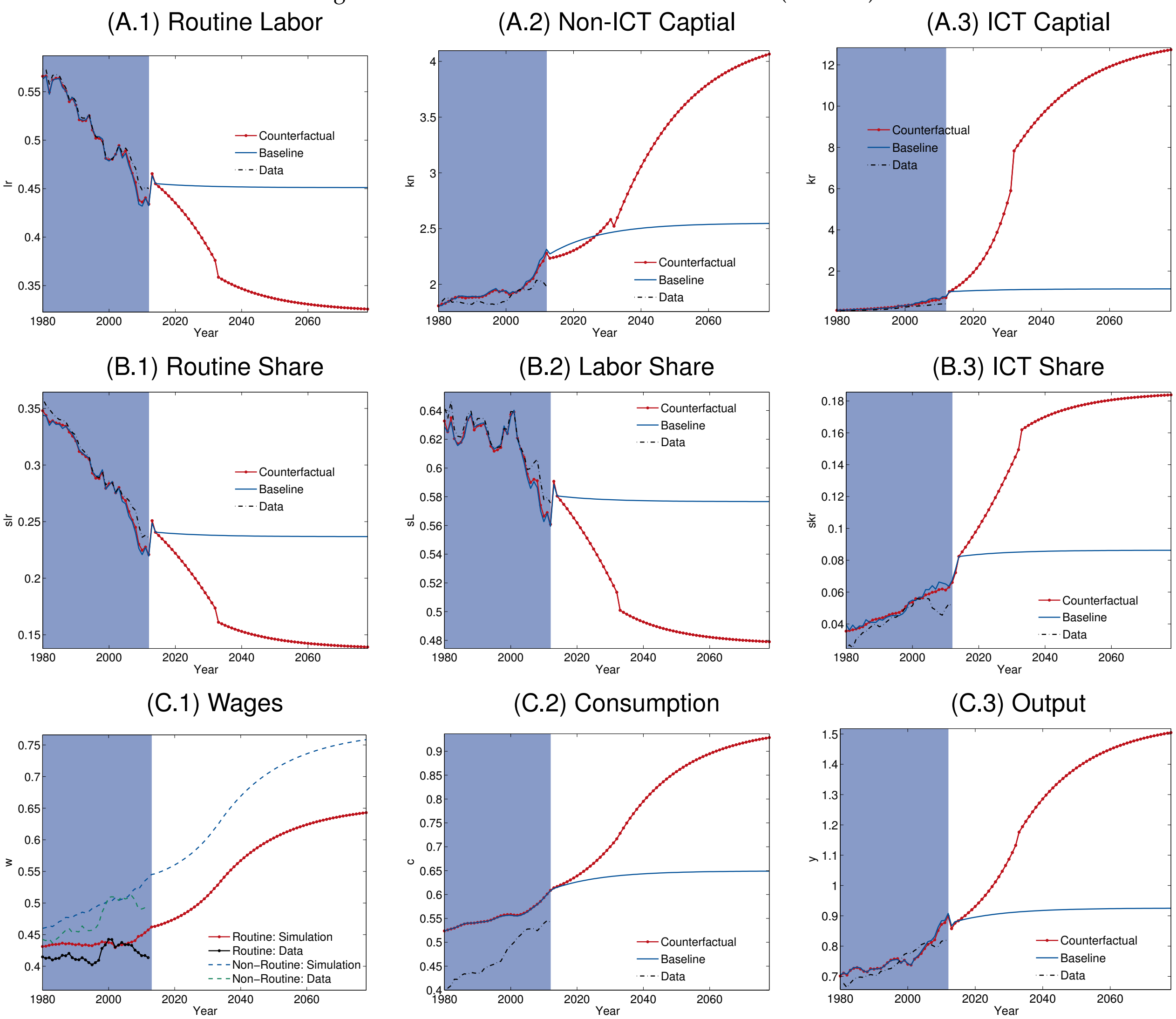


Notes: The graphs plot the exogenous paths for our baseline simulation. The values 1979-2013 are those observed in the data.

an additional 10 percentage points by 2060. Routine employment declines by an additional 15 percentage points. Output, consumption, and non-ICT capital increase dramatically.

The implication is that our long-run predictions are highly sensitive to our assumptions regarding the future evolution of the ICT capital price. However, within the sample period, future expectations regarding the evolution of the ICT capital price do not seem to generate large differences in the simulated transition paths. The following subsections illustrate the robustness of our counterfactual analysis to changes in the specification of the exogenous price paths.

Figure C.14: Simulated Paths of Income Shares (Baseline)

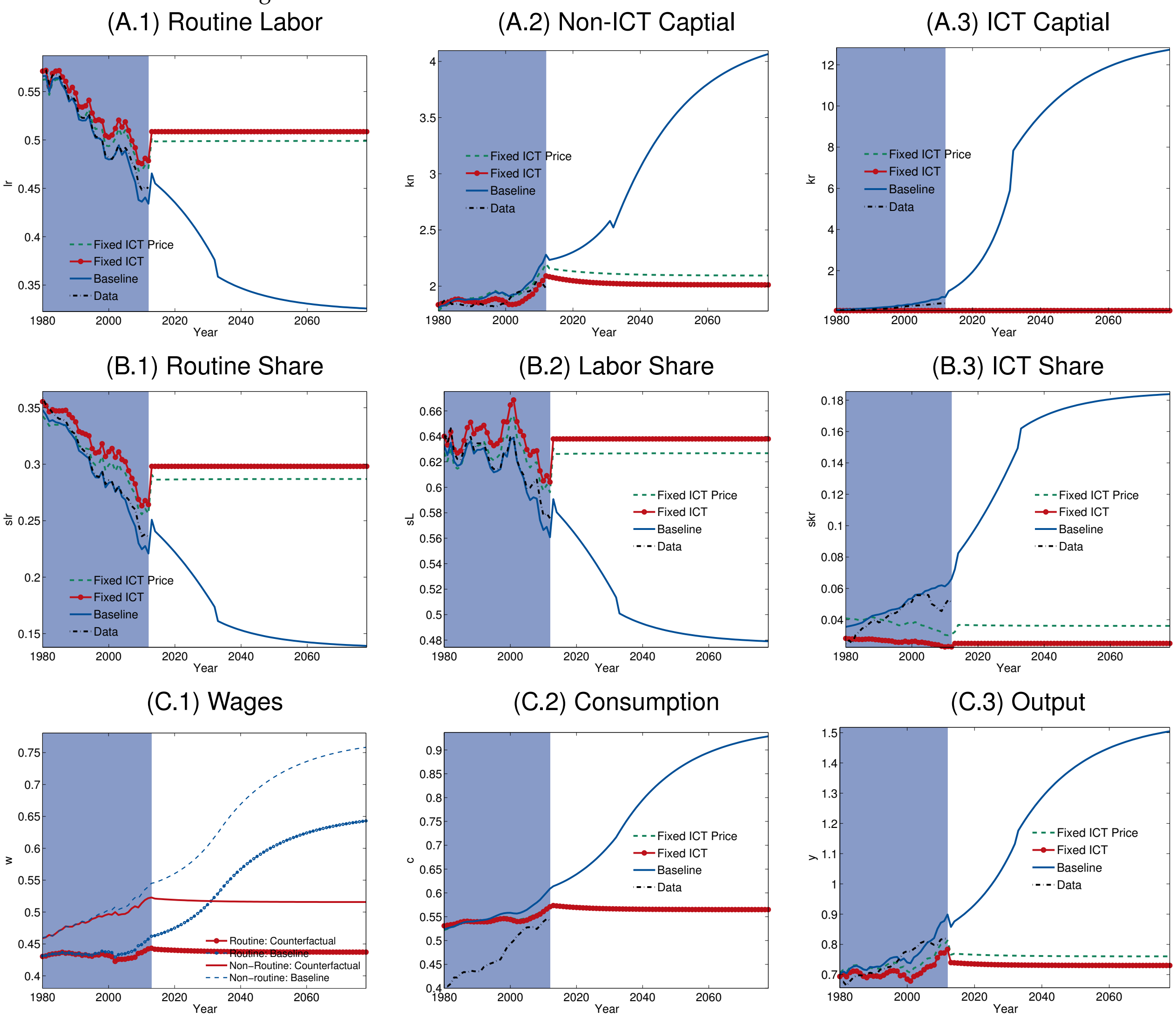


Notes: The graphs plot the simulated transition path to the new steady state in the baseline calibration. The shaded area indicates the our estimation sample, 1979-2012. For routine and non-routine employment, the empirical counterparts are "effective" routine and non-routine employment shares based on equations (3) and (4). All remaining empirical ounterparts are constructed form the chain indexes used in the GMM estimation, divided by total employment times an estimate of A_t, which is given by $A_0 e^{\lambda t}$, where $A_{l,0}$ and λ are our GMM estimates. We impute wage series for "effective" units of labor from the estimated non-routine wage premium and employment based on equations (3) and (4).

Appendix C.2. Counterfactual 1: The Role of ICT Accumulation and the Decline in the ICT Price

First, we consider the counterfactual scenarios generated from holding the ICT capital price fixed at its 1979 level, or, alternatively, holding the stock of ICT capital fixed at its 1979 level. Figure C.15 present the counterfactual transition paths, against the baseline calibration. The results emphasized in section 5.1 continue to hold here:

Figure C.15: Counterfactual: No ICT Accumulation & Fixed Price of ICT



Notes: The graphs plot the simulated transition path to the new steady state. The shaded area indicates the our estimation sample, 1979-2013. For the wage graph, the counterfactual of a constant ICT price is omitted (the counterfactual is the constant ICT scenario). For the empirical counter parts see the notes of Table 8.

1. The two counterfactual paths (fixed ICT price and fixed ICT stock) deliver close predictions within the sample period.
2. The counterfactuals generate more moderate declines in both the routine labor income share and the aggregate labor income share.
3. The counterfactual paths of employment shares are quite close to the baseline calibration.

Appendix C.3. Counterfactual 2: The Role of Changing Patterns of Specialization

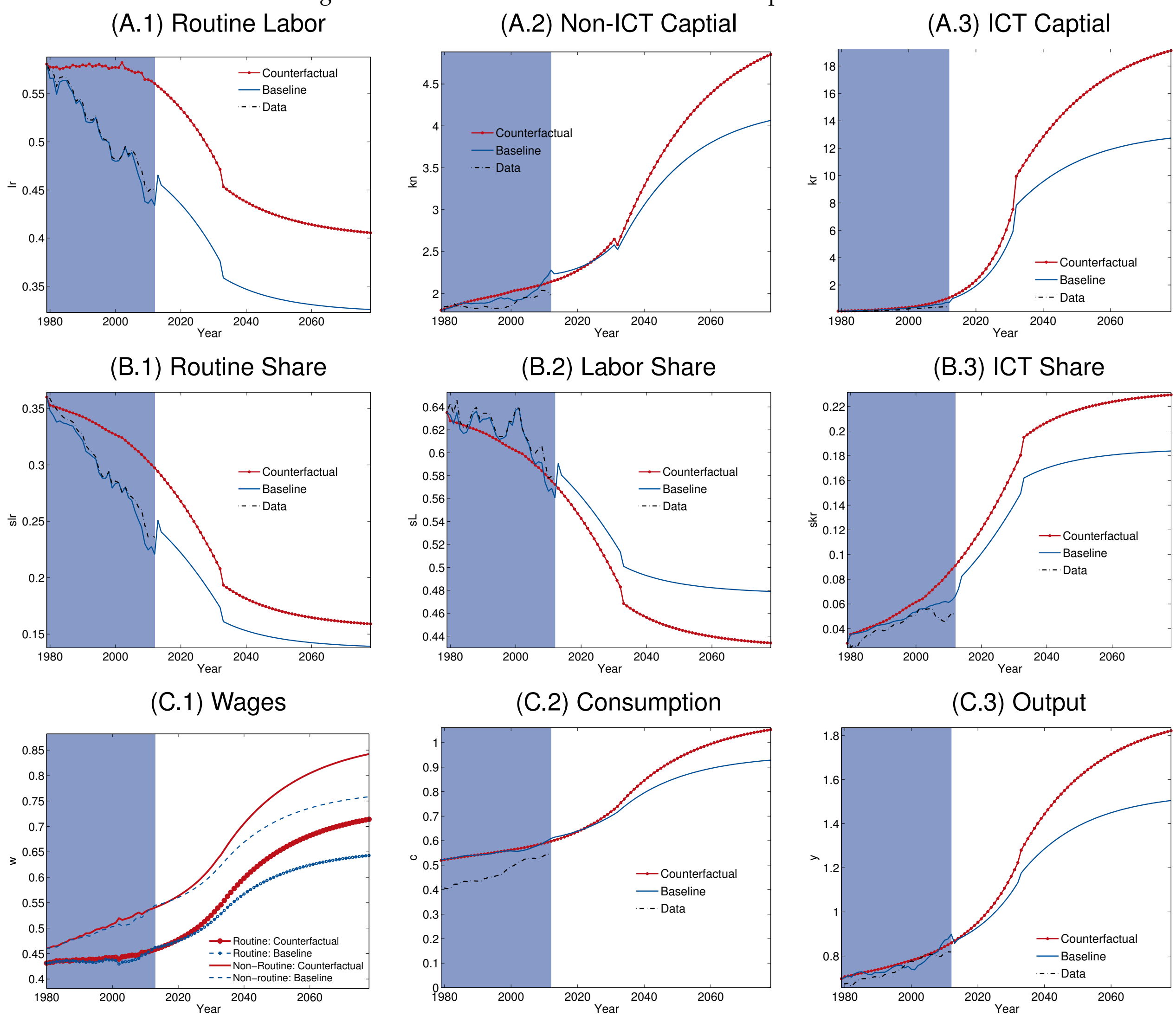
The second counterfactual discussed in section 5.2 holds the non-routine labor intensity α_{nr} fixed at its 1979 level. Figure C.16 illustrates the results for this counterfactual, given the alternative specification of the price path. Here, too, the main insights are unchanged:

1. The counterfactual drop in the aggregate labor income share during the sample period is similar to the baseline calibration.
2. The counterfactual decline in the routine labor income share during the sample period is smaller than in the baseline calibration.
3. The counterfactual generates a substantially smaller decline in routine employment.
4. The counterfactual wages, consumption and output coincide with the baseline within the sample period, but surpass the baseline in the long run.

Appendix C.4. Counterfactual 3: The Role of Labor Market Frictions

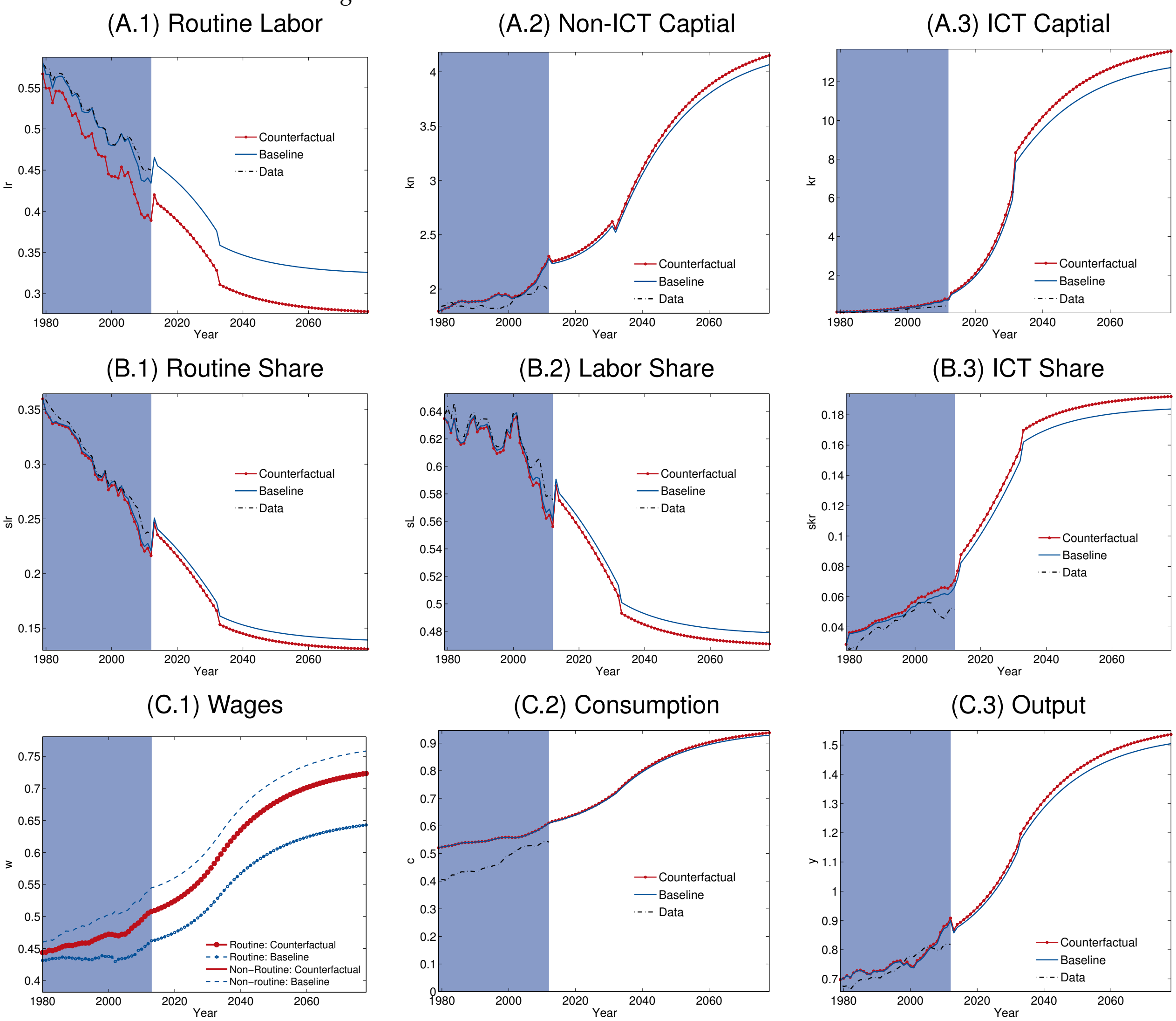
A final exercise presented in section 5.3 studies the counterfactual transition paths in an economy in which the non-routine wage premium is set to 0 in all periods. Figure C.17 presents the results given the alternative ICT price path. Here, too, the counterfactual is very similar to the baseline, with the exception of employment in routine labor.

Figure C.16: Counterfactual: Fixed Patterns of Specialization



Notes: The graphs plot the simulated transition path to the new steady state. The shaded area indicates the our estimation sample, 1979-2013.

Figure C.17: Counterfactual: No Labor Market Frictions



Notes: The graphs plot the simulated transition path to the new steady state. The shaded area indicates the our estimation sample, 1979-2013.