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JEL Classification: Q10, O13, O47

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Occupational exposure to capital-embodied technical change*

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Abstract

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1 Introduction

Technical change and labor market outcomes are tightly linked. One of the major drivers of technical change in the postwar era has been capital-embodied technical change (CETC), Greenwood *et al.* (1997). By changing the availability of capital goods and its costs, CETC vastly changed the tools workers use to perform their job. For example, chimney sweepers went from using manual brushes to alternate spinning brushes and high-tech cameras to detect blockage; postal workers went from paper parcel-tracking to mobile scanners at delivery; and the list continues. Yet, not much is known about workers' exposure to CETC via their occupational choice.[1] We provide the first available measures of CETC and factor complementarity at the occupation level and quantify their role for labor market outcomes in the US over the last 40 years. We find that CETC explains 91% of the gross labor reallocation across occupations observed in the US since 1982: CETC is responsible for 74% of the hollowing out in middle skill occupations and virtually all of the reallocation towards high-skill occupations between 1982 and 2015.

CETC materializes as a decline in the relative price of capital to consumption (Hulten, 1992). The availability of cheaper capital affects workers through a myriad of channels – for example, it replaces workers in certain occupations via automation, while increasing the demand of other occupations that are complementary to these new technologies, some of which are new altogether. A useful way to summarize these disparate channels is to think about workers' exposure to CETC through the cross-price elasticity of labor demand – that is, the response of the labor demand in an occupation to changes in the cost of capital. Under the assumptions of constant returns and price-taking behavior, Hicks (1932) and Robinson (1934) independently showed that this elasticity is solely a function of (i) the extent of labor substitutability to capital, (ii) the own price elasticity of labor supply, (iii) the importance of capital for production, or its cost share; and (iv) the demand elasticity for occupational output.

Our first task is to measure this cross-price elasticity across occupations. The measurement of workers' occupational exposure to CETC allows us to characterize the relevant channels through which technical change affects labor reallocation. Our second task is to quantify the importance of these channels. The cross-price elasticity of labor demand considers each occupation in isolation and abstracts from general equilibrium forces, so we run

[1] There is an extensive literature studying the effect of computerization on the labor market, but not much is known about other equipment goods. As we show in this paper, broader equipment categories – importantly, communication equipment – have indeed played a major role in shaping the labor market.

the quantification in a general equilibrium model with endogenous worker selection across occupations. Workers differ by gender, age, and education, and occupation-specific CETC along with shifts in the demand for occupational output drive the employment allocation and equilibrium wages through time.

To carry out these two tasks, we start by constructing a novel dataset of the capital stocks used for production in each occupation. Our dataset covers 24 major equipment categories considered by the BEA and 327 occupations in the Census classification, over the last 40 years in the US. For each occupation, we construct a bundle of capital goods, using information on occupation-specific tools requirements. We measure the tools required for production in each occupation in two separate years, 1977 and 2016. The Tools and Technology module of the Occupational Information Network (O*NET) readily provides this information for 2016, but the requirements in the earlier years are hard to come by. To collect such information, we apply Natural Language Processing (NLP) algorithms over the description of occupations in the 1977 Dictionary of Occupational Titles (DOT), the predecessor to O*NET. Based on these tool requirements, we build an allocation rule to distribute quality-adjusted stocks for each of the 24 equipment categories across occupations in each year, between 1982 and 2015.[2] Then we aggregate across equipment categories in each occupation to build their stock.

These capital stocks allow us to measure the capital intensity for an average worker in each occupation as well as the degree of technical change embedded in these stocks, through the decline in their price relative to consumption. We document heterogeneous paths of capital per worker across occupations, over time. Sales occupations display the fastest growth in capital per worker (1.4% per year), while transportation occupations display the slowest growth (0.4% per year). These heterogeneous paths correspond to disparate extent of CETC across occupations. We combine our newly constructed dataset with capital prices, and measure CETC across occupations.[3] The extent of CETC varies between a yearly 4.7% for mechanics and transportation and a yearly 11.4% for sales occupations. These disparities are mostly driven by the share of computers and communication equipment in their stocks. CETC in these two equipment categories is fastest, at yearly 13.6% and 12.6%, respectively.[4]

We then take on our first task of measuring workers' occupational exposure to CETC. Two ingredients of exposure can be inferred directly from our dataset: the capital share

[2]In the tradition of Greenwood *et al.* (1997) we adjust investment series by the decline in quality-adjusted price of equipment, which yields a measure of efficiency units of capital or quality-adjusted stocks.

[3]We generate a series of constant quality equipment prices following the methodology in Cummins and Violante (2002) to update the estimates of Gordon (1987).

[4]For comparison, the price of investment for computers declined by 11.5% over the same period, as reported by the BEA.

and the elasticity of substitution between capital and labor. To estimate this elasticity, we exploit time variation in capital labor ratios and the relative cost of capital to labor, in each occupation. Our estimates range from 0.54 for transportation occupations to 1.99 for precision workers. Managers, professionals and technicians all display elasticities of substitution below 1, with an average of 0.73. In the aggregate, we estimate an elasticity of substitution between capital and labor of 0.76, consistent with estimates by Oberfield and Raval (2020) based on establishment level data in the manufacturing sector.

The output demand and the labor supply elasticity remain to be inferred. Their inference brings up two challenges. First, the estimation of the demand elasticity relies on occupational output and price data, which are inherently unobservable. Second, the estimation of the labor supply elasticity is tangled by selection effects from the endogenous sorting of workers across occupations, which are also unobservable. To make progress, we specify a model of endogenous sorting of workers across occupations in the tradition of Roy (1951). First, we assume a CES aggregator of occupational output so that its demand elasticity equals the elasticity of substitution across occupational outputs. Cost minimization at the occupation level is sufficient to infer occupational output and prices from our data on occupational capital per worker. We find that occupational outputs are gross substitutes, with an elasticity of 1.33. Second, we take a Frechet distributional assumption on workers' comparative advantage across occupations to obtain a structural counterpart to the price elasticity of labor supply, which we estimate at 0.3.

We document substantial variation in exposure across occupations: the lowest cross-price elasticity of labor demand is recorded for precision production, at -4%, while the highest one is recorded for transportation, at 4.2%. In all but precision production occupations, the scale effect of a decline in the relative price of capital on labor demand dominates the substitution effect. Hence, CECT increases labor demand in these occupations, when considered in isolation. High-skill occupations record twice as high exposure as middle-skill occupations. We find that the elasticity of substitution between capital and labor is the primary channel that drives occupational heterogeneity in workers' exposure to CETC, and that, in combination with our measures of CETC, exposure generates employment polarization, e.g. the hollowing out of employment in middle skill occupations.

So what has been the impact of CETC on the US labor market? To answer this question we take on our second task and quantify the role of CETC for labor market outcomes in general equilibrium. Unlike the exposure measure, the model considers incentives for reallocation of workers of different characteristics across occupations as well as changes in equilibrium wages. We use our model to compute the equilibrium response of the labor allocation to CETC by conducting counterfactual exercises where we shut down changes in the relative price of capital to consumption. We find that CETC explains most of the observed reallocation of labor toward high-skill occupations between 1982 and 2015. CETC accounts for 74% of the reallocation out of middle-skill occupations and for an even smaller fraction of the reallocation toward low-skill occupations, accounting for 23% of it.

Our finding that CETC explains all of the gains in employment in high-skill occupations highlights that occupational choices are an important channel through which workers reap the benefits of CETC. Various studies emphasize the importance of labor market frictions linked to workers' demographic characteristics for occupational choice (Hsieh *et al.*, 2019). Arguably, such frictions prevent workers from fully responding to CETC with their occupational choices and therefore may exacerbate inequality across demographic groups. Indeed, we find that CETC generates 81% of the increase in the college premium, about 50% of the rise in the cross-sectional age premia, and also widened the gender wage gap by 1.6 p.p., between 1982 and 2016.

The richness of our structural model allows us to explore the role of other channels that are potentially important for labor reallocation across occupations. Occupational demand shifts, in the form of offshoring or related to structural change, have been posed as an important driver of employment polarization. We find that this demand channel is quantitatively important to explain the gains in employment of low-skill occupations, but it entirely misses the gains in employment of high-skill occupations.

Last, in our quantification, we compute the path for prices and stocks of occupational capital using a linear aggregator of different capital goods. We relax this assumption towards the end of the paper and allow occupational capital to be a CES composite of different capital goods, with an elasticity of substitution of 1.27, which we estimate using our newly constructed dataset. Our main findings are robust to this extension. CETC explains 9.4 p.p. less of the labor reallocation across high-, middle- and low- skill occupations on average. The richness of this extended framework allows us to distinguish the role of technological advances in different types of equipment. Consistently with Eden and Gaggl (2018) and Acemoglu and Restrepo (2018), our results indicate that CETC in computers and communication equipment have been important drivers of the returns to skill and employment reallocation in the US over the last 40 years. Communication equipment accounts for a higher share of the stock of capital across occupations and is responsible for most of the reallocation out of middle-skill occupations and toward high-skill ones.

Literature Review. Katz and Murphy (1992) were the first to highlight factor-biased technical change as a mechanism to reconcile key features of the labor market dynamics in the US, over the second-half of the 20th century, i.e. the contemporaneous increase in skill supply and the skill-premium, while Krusell *et al.* (2000) posed CETC in combination with capital-skill complementarity as an economic mechanism to rationalize such a bias. Motivated by recent changes in the earnings and employment distribution observed in industrialized economies, Acemoglu and Autor (2011) highlight that the focus on workers' skills misses important features of the labor market, advocating for a shift of focus towards jobs or occupations. A worker's occupation is a commonly used measured for those jobs, and non-monotone changes in wages and employment across occupations of different skill intensity are a major feature of labor markets in recent decades, i.e. wage and employment polarization (Krueger *et al.*, 2010, Autor and Dorn, 2013). In this paper, we provide the first direct measures of the bias of technology at the occupation level, by measuring CETC and capital-labor complementarity across occupations.

As a byproduct of constructing occupation-specific capital price indexes, we build quality-adjusted equipment stocks for each occupation over the last 40 years in the US. These stocks are key to computing other relevant structural features that determine labor demand in an occupation. The information on occupations' tools requirements from O*NET was first introduced by Aum (2017) to study the impact of software innovation on the demand for high-skill jobs. Aum *et al.* (2018) use these requirements to measure computer and software demand by occupation. Distinctively, we use tool requirements to measure occupation-specific price indexes, which we link to technological change. A novel contribution of our paper is the construction of tools requirements in 1977 from the text of the DOT by exploiting machine-learning algorithms. DOT is the predecessor to O*NET and therefore the natural data source to document changes in tool requirements. This feature allows us to tackle the changing nature of occupations and their capital requirements over time.

We use our measures of the equipment stocks and the user cost of capital to also estimate occupation-specific elasticities of substitution between capital and labor. These elasticities are an important input in measuring workers' exposure to technical change, the impact of computerization and trade on the labor market (Burstein *et al.*, 2019), off-shoring (Goos *et al.*, 2014a), and long-run changes in the structure of production of the economy (Barany and Siegel, 2018). For tractability, these elasticities are typically assumed constant across occupations. Kehrig (2018) is the first attempt to measuring heterogeneity in these elasticities for the case of computers, using cross-sectional variation. In this paper, we provide the first available measures for broad equipment categories across occupations by exploiting changes in tool requirements and investment over time. Consistent with the literature emphasizing the role of general purpose technologies (Jovanovic and Rousseau, 2005; Bresnahan, 2010 and the extensive literature cited therein), we highlight that communication equipment has become an increasingly important equipment category for workers' exposure to technical change. Communication equipment is abstracted away in studies that focus solely on computers.

Finally, our work relates to the extensive literature that highlights the task content of occupations as a measure of exposure to technology (Autor and Dorn, 2013; Atalay *et al.*, 2018; Jaimovich and Siu, 2020). The working hypothesis is that non-neutral technological change that reduces the cost of accomplishing codifiable job tasks (routine-replacing technical change) is at the heart of the decline in wages and employment observed in middle-skill occupations starting in the 1980s.[5] Our measurement complements this analysis by providing direct measures of technical change embodied in capital for a broad set of equipment categories and occupations. Indeed, we find that CETC can account for the hollowing out of middle-skill occupations, and at the same time, the sharp increase in employment and wages for high-skill occupations.

The rest of the manuscript is organized as follows. Section 2 construct our measures of stock and prices of capital at the occupation level and presents key correlations between CETC and labor market outcomes. Section 3 outlines the model. We then present the inference of model-free parameters (Section 4.1) and of model-based parameters (Section 4.2) and document exposure to CETC across occupations. Section 5 evaluates the differential role that CETC has for employment reallocation across occupations in general equilibrium. Section 6 discusses relevant model extensions and Section 7 concludes.

2 Capital stocks and CETC across occupations

In this section we document the path of the capital stock used in each occupation in the US between 1982 and 2016. We later use this data to study the role of CETC for labor market outcomes.

We focus on equipment capital and measure occupational capital stocks consistently with the aggregate investment series in NIPA. We follow the extensive literature that highlights

[5]We show that the effect of CETC for employment changes is significant even after controlling for the task content of occupations, see Online Appendix.

the capital-embodied nature of technology and the secular decline in the cost of capital goods with time, and construct time-series of quality-adjusted capital stocks. Then, we construct a novel index of the capital requirements in each occupation through time, and use it allocate these stocks to occupations. Our index is based off of the tool requirements of each occupation, which we extract from the DOT in the 1970s and from it successor, the O*NET, in the 2010s. We call the quality-adjusted stock allocated to an occupation, the stock in efficiency units of occupational capital, or occupational capital for short. Finally, we document patterns of CETC across occupations.

2.1 Data and methodology

Data sources. We combine five different data sources: a novel tool requirements dataset constructed using NLP algorithms over the textual occupational definitions of the 1977 DOT and the Tools and Technology supplement of the 23.4 O*NET; annual NIPA series of investment for 24 equipment categories; annual quality-adjusted series for the price of (new) capital constructed following Cummins and Violante (2002)'s methodology; and annual full-time equivalent workers by occupation from the March Current Population Survey (CPS) between 1982 and 2015.[6] We construct measures of hourly wages from 1982 to 2015 using labor income divided by total hours worked in the subsequent CPS. We deflate wages and the price of quality-adjusted capital by the price of personal consumption expenditures provided by the BEA.[7]

Quality-adjusted capital stocks. We start by constructing chained-weighted quality-adjusted stocks for each of the 24 equipment categories considered by NIPA. This is our measure of the stock of capital in efficiency units for each category. The stocks correspond to their nominal counterparts in 1983, our base year.[8] We apply the permanent inventory method to construct stocks through time. For that, we need a measure of the efficiency units of investment and of the physical depreciation rate, both of which are constructed following the methodology proposed in Cummins and Violante (2002), see Online Appendix A.4 for details.

An index of capital requirements in each occupation. We infer capital require-

[6]Additional data details are in the Online Appendix. We also use comparable measures form the Census, with the caveat that these are available at 10-year frequency prior to year 2000.

[7]We could alternatively deflate the series using a Consumer Price Index. The CPI raises 70% more than the price index of consumption expenditures (PCE) for the period of analysis. The change in prices in PCE is consistent with change in the chained-weighted CPI by the BLS.

[8]Because the stock is assigned to workers in 1982, our measurement implies that any investment occurred during 1982 (and showing up in the stock in 1983) was available to workers in that year.

ments in each occupation from the tools commonly used by workers in the occupation. For example, commonly used tools by a dental assistant include, among others, air compressors, dental cutting instruments, and personal computers. We define these commonly used tools as the tool requirements of the occupation. Our dataset on tool requirements includes more than 7,000 alternative commodities in the United Nations Standard Products and Services Code (UNSPSC) classification system.

The O*NET, a database collecting standardized occupation-specific descriptors, readily provides information on occupational tool requirements for the period post-2010 (Aum, 2017). The Tools and Technology module of the O*NET is available since 2006, with scattered occupational coverage in the earlier years. Occupational tool requirements in the earlier years are hard to come by. To collect such information, we use the textual definition of occupations collected in the 1977 version of the DOT. We parse out the set of tools required in each occupation by using Natural Language Processing algorithms.[9] For illustration, Figure 1 compares the occupational tool requirements implied by the O*NET and DOT datasets. It plots the fraction of tools required across 1-digit occupations for two capital categories, computers and communication equipment. For both categories, the DOT records the highest share of tools for professionals while the O*NET records it for administrative services. Through time, professionals have seen the share of tools allocate to them increase, whereas administrative services have seen it decline. These differences exemplify how technology impacts occupations by changing the nature of the activities performed, as well as the tools required to perform those tasks. We then linearly interpolate the DOT-based and O*NET-based tool requirements for each of the 324 3-digit occupations we observe to construct a time series of occupational tool requirements.[10]

We use these time-series of occupational tool requirements to construct an assignment rule for the stocks of capital across workers in different occupations. Ideally, we would like to know how a dental assistant splits his working hours in the use of cutting instruments and computers, as well as the details of the value of the capital used. This data is unfortunately

[9]We build a corpus of the universe of tools listed under Commodity Titles, i.e. United Nations Standard Products and Services Code (UNSPSC), and T2-Examples in the tools and technology module of the O*NET and use it for string-matching to the descriptions in the DOT. We experiment with different matching criteria as described in the Online Appendix. Our benchmark results exploit occupational cross-walks to disambiguate generic tool descriptions found in the DOT.

[10]These occupations are those for which we consistently observe labor and capital over time. The classification of occupations based on the O*NET-SOC system is a modification of the 2010 Standard Occupational Classification (SOC) system that allows for a link to the American Community Survey classification system. To build a consistent occupational definition through time, we use the classification and the crosswalks of the ACS classification system provided by Acemoglu and Autor (2011).

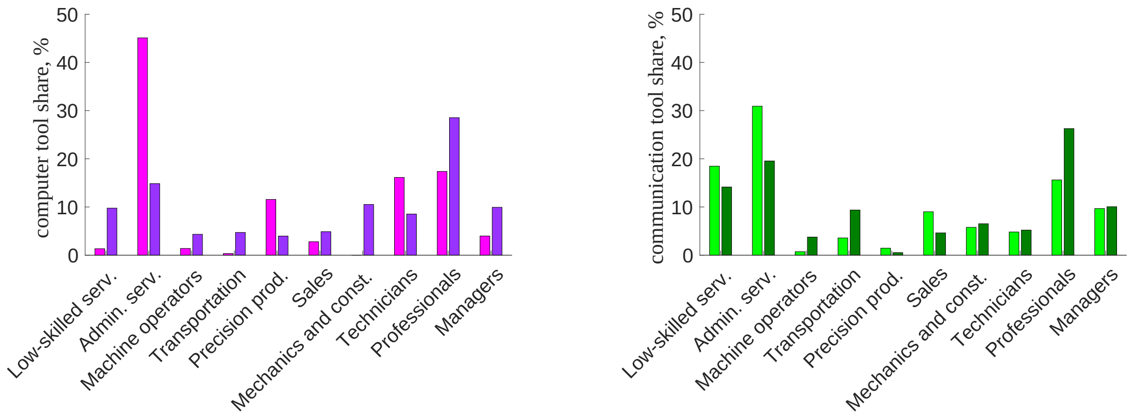


Figure 1: Changes in tool shares.

The left panel displays the share of computer tools used by a worker in each 1-digit occupation in 1977 (from the DOT) and in 2016 (from O*NET). The right panel displays the share of communication tools used by a worker in each 1-digit occupation in 1977 and 2016. Source: O*NET, DOT and own computations.

unavailable. We instead exploit the highly disaggregated nature of tool descriptions to proxy for intensity of usage. Let τ_{ojt} be the total number of tools of NIPA capital category j used by a worker in occupation o at time t – that is, $\tau_{ojt} \equiv \sum_c \mathfrak{I}^{ot}_{c\in j}$, where $\mathfrak{I}^{ot}_{c\in j}$ is an index function that takes value 1 if UNSPSC commodity c belongs to capital category j and is used in occupation o at time t.[11] Let l_{ot} be the number of full-time equivalent workers in occupation o at time t. We define the requirement for capital j in occupation o as the number of tools required by the workers in that occupation relative to the total tool required in the economy:

$$\text{req}_{jot} \equiv \frac{\tau_{ojt} l_{ot}}{\sum_o \tau_{ojt} l_{ot}}. \tag{1}$$

We distribute the stock of capital of a given category across occupations proportionally to these capital requirements. We then add up the stock across categories with an occupation to measure occupational capital at a point in time t, $k_{ot} = \sum_j k_{ojt} = \sum_j k_{jt}\text{req}_{ojt}$.[12] A few features of the assignment require further discussion. First, the capital assigned to an occupation changes whenever there is employment reallocation in other occupations, even if its employment is fixed. The reason is that the tool requirements are heterogeneous across occupations and the aggregate stock of capital is fixed at a point in time, so when workers

[11]We map UNSPSC commodities to the NIPA equipment categories using the textual definition provided by the BEA as in Aum (2017) (see the Online Appendix for details on this mapping).

[12]We have alternatively allocated investment to each occupation. Results are similar to those in this section and available on request.

reallocate across occupations the measure of tools requirements changes. Heterogeneous tool requirements are consistent with an economy where the intensity of use of capital differs across occupations. Second, for a fixed capital category, occupations that use a larger variety of tools within that category will be allocated more capital. Third, while differences in relative prices across capital categories are fully accounted for (through the value of the efficiency units of each stock), our assignment implies that no additional price heterogeneity exists across tools that belong to the same category. While this is certainly a limitation, the tool description is general enough that imputing prices would induce a fair amount of measurement error.[13] Fourth and last, changes in the relative prices of different capital goods generate fluctuations in occupational capital due to the heterogeneity in intensity of tool usage across occupations.

2.2 Salient features of occupational capital

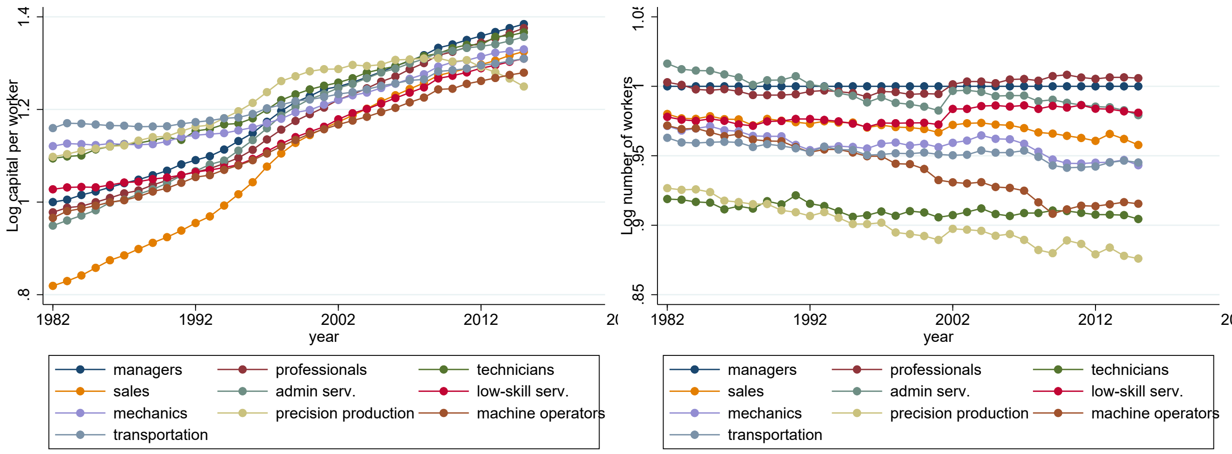
We now document the path of occupational capital and its composition by capital type through time. These data along with capital price data yields a measure of the decline in the relative price of capital to consumption in each occupation, our measure of occupational CETC.

Aggregate capital stock. To begin with, we highlight the relative importance of CETC versus nominal investment for the dynamics of the aggregate stock of capital (in efficiency units) in the US, between 1982 and 2015. We compare the dynamics for the aggregate capital over time to what we would have obtained if the price of capital would have not declined. The difference in the two series is the role of the decline in the relative price of capital to consumption, our measure of CETC. CETC explains half of the annualized growth rate of the stock of capital between 1982 and 2015 (50.7%), consistently with the importance of CETC for post-war growth experience highlighted in Greenwood *et al.* (1997).[14]

An alternative way to account for the role of CETC for the dynamics of the capital stock is to aggregate capital types between those with high rates of capital embodiment, or large decays in the price of capital relative to consumption (HCETC), and those with low rates of embodiment, or small movements in the relative price of capital to consumption (LCETC). In addition, because an extensive literature focuses on the role of computers for labor market outcomes (Beaudry *et al.*, 2010; Burstein *et al.*, 2019; Aum *et al.*, 2018; Atalay

[13] There is no description of the characteristics of the tool. For example, prices for personal computers vary widely depending on its features and capabilities, none of which are reported in the data.

[14] Given the novelty of occupational capital stocks, we also highlight the role of different channels in the allocation of stocks to occupations, see Online Appendix A.5.



(a) Stock per worker

(b) Number of workers

Figure 2: Capital stock by occupation.

Panel (a) displays the logarithm of the stock of quality-adjusted capital per worker for each occupation relative to the stock allocated to managers in 1982. Panel (b) displays the logarithm of the numbers of workers in each occupation relative to the number of workers working as managers in 1982. Source: NIPA, CPS and own computations.

et al., 2018) we also single out computers and software from HCETC capital. Table E.I makes the classification explicit and shows the dynamic of prices and stocks. Panel (a) in Figure 12, in the Online Appendix, shows the dynamic for these major capital categories. While the stock of computers grew faster than the aggregate stock until the 2000s, it has slowed down since then. The growth in quality-adjusted stocks is explained by the accumulation of HCETC, and particularly, communication equipment.

Capital stocks by occupation. To ease the exposition, we group the data into 10 occupational groups, which correspond to the 1-digit non-agricultural occupational grouping in the US census – that is, managers, professionals, technicians, sales, administrative services, low-skilled services, mechanics and construction, precision workers, machine operators, and transportation.

Figure 2 shows the time series of the capital stock per worker across occupations. The levels are normalized relative to the stock allocated to a manager in 1982. Overall, the stocks of capital per worker increased in all occupations, the dispersion of occupational stocks shrank around the 2000s and increased thereafter. The increase in capital per worker was largest for administrative services and sale workers (13% and 16% per year on average, respectively). This increase in capital intensity was accompanied by declines in employment in the latter and a stable workforce in the former (relative to manager's employment).

Table 1: Capital bundles at the 1-digit occupation level.

	Share in 1982			Share in 2015		
	Computers	HCETC	LCETC	Computers	HCETC	LCETC
Managers	0.08	0.58	0.34	0.32	0.65	0.03
Professionals	0.04	0.42	0.54	0.34	0.61	0.05
Technicians	0.03	0.60	0.38	0.29	0.62	0.09
Sales	0.24	0.60	0.15	0.43	0.56	0.01
Administrative Services	0.20	0.52	0.28	0.36	0.62	0.02
Low-Skilled Services	0.01	0.47	0.52	0.35	0.56	0.09
Mechanics and repairers	0.01	0.23	0.77	0.37	0.35	0.27
Precision workers	0.14	0.38	0.48	0.54	0.29	0.16
Machine operators	0.03	0.40	0.57	0.26	0.50	0.24
Transportation	0.01	0.08	0.92	0.24	0.48	0.27
Aggregate	**0.04**	**0.31**	**0.64**	**0.34**	**0.59**	**0.07**

Notes: Columns 1 to 3 report the share of capital by type in 1982 while Columns 4 to 6 report the share of capital stocks by type in 2015. HCETC corresponds to equipment categories with high rates of capital embodiment, or large decays in the price of capital relative to consumption. LCETC corresponds to equipment categories with low rates of embodiment, or small movements in the relative price of capital to consumption. See description in Table E.I.

Capital bundles by occupation. The aggregate path of the occupational capital stocks hides compositional differences in the stocks across occupations. Occupations that are more intensive in capital that experiences larger declines in its quality-adjusted price would see their stocks increase even with a fixed employment allocation. Table 1 displays the composition of the stock of capital across occupations at different points in time. There is vast heterogeneity in the share of capital accounted for by different capital categories. For example, in 1982, the share of HCETC capital ranges from 10% in transportation to 60% in managerial occupations. Professionals, low skill services and machine operators were all relatively intensive in LCETC capital in 1982, but the importance of LCETC capital falls through time. Occupational heterogeneity in the aggregate stocks as displayed in Figure 2 primarily stems from disparities in the trajectory for HCETC capital.[15]

CETC by occupation. We measure capital-embodied technical change from the decline in the price of capital to consumption in each occupation. We construct the price of the bundle of capital in an occupation using a Fisher ideal price index, with shares equal to the share of investment in a given capital category and occupation at a point in time. Figure 3, shows the price of capital relative to consumption for the bundle of capital used by each

[15]Figure 13 plots the complete time-series of the occupational capital stocks per worker across broad categories.

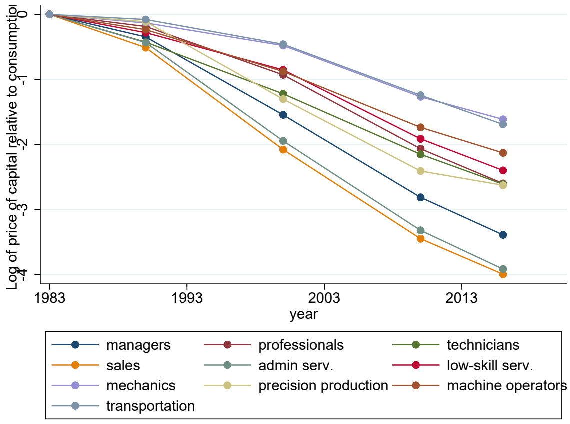


Figure 3: CETC across occupations.

The figure shows the logarithm of the relative price of capital to consumption across occupations. This is computed as a weighted average of the relative price of each capital good, where the weights are given by the composition of the capital stock in the occupation in each year. Source: Own computations.

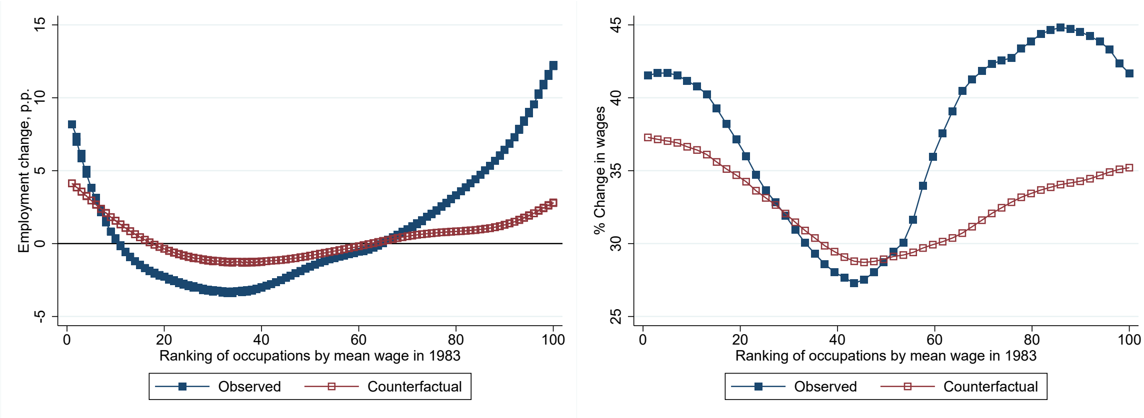
occupation. Sales and administrative services experienced the strongest decline in the relative price of capital to consumption, by more than 11% per year between 1982 and 2015. On the opposite end, mechanics and transportation occupations recorded a decline in the relative price of capital to consumption of less than 6% per year.

2.3 CETC and labor market outcomes

Given the novel nature of our stocks of occupational capital, it is worth exploring evidence for the relationship between these stock and labor market outcomes.

Table E.II, panel B, classifies occupations by the growth rate in capital-per-worker. Hourly wages increased by 0.6% per year at the bottom of the distribution, while annual wage gains reached 1.0% per year at the top of the distribution of growth rates in capital-per-worker. At the same time employment shares fell for occupations at the bottom of the distribution of growth rates of capital-per-worker and increased at the top of the distribution.

An alternative way to classify occupations is by looking into the bundle of capital goods used for production (in 2015). Panel C of Table E.II reports labor market changes for occupations that differ by the intensity of use of the three major capital categories detailed before (HCETC, LCECT and computers). There is a striking pattern. While workers in computer-intensive occupations saw their wages rise the fastest, by 0.9% per year on average, these occupations lost employment overall (with their share falling by 4.3 p.p. over the period). At the same time, workers in HCETC-intensive occupations saw their wages rise



(a) Employment polarization (b) Wage polarization

Figure 4: Change in capital-intensity and the labor market.

The left panel shows employment changes by occupation between 1982 and 2015 (polynomial fit, parameter 0.8) in blue, and reweighted employment changes by occupation assuming no change in occupations with above median changes in the capital stock per worker. The right panel shows wage changes by occupation between 1982 and 2015 (polynomial fit) in blue, and wage changes by occupation imputing the average change in wages in occupations with above median changes in the capital stock per worker.

by a similar amount, 0.8% per year and these occupations gained employment throughout (6.3 p.p.).

Finally, we consider the relevance of CETC for employment polarization by constructing a reduced-form counterfactual in the spirit of Autor and Dorn (2013). In particular, we reweight the observed employment distribution across occupations by imposing no employment change in occupations above the median of the distribution of changes occupational capital-per-worker (see Panel (a) in Figure 4). We find that employment polarization would have been weaker if abstracting from the shifts in employment in occupations that became more capital intensive. Particularly, we should have seen lower gains in employment at the top of the skill distribution, as proxied by the wage. In the same spirit, Panel (b) of Figure 4 explores the dynamics of hourly wages. If we set wage gains in occupations that experienced above median changes in capital-per-worker to the average wage gains over the period we find that wage gains would have been lower at the bottom and top of the skill distribution, and that these lower gains concentrate at the top of the skill distribution.

While both these exercises provide suggestive evidence of the link between CETC and labor market outcomes, they do not provide causal evidence. They are also not informative as of the channels through which workers become exposed to technical change via their occupational choices. Next, we present a Ricardian model of the labor market where these links are formalized.

3 A model of occupational capital, labor and output

In this section, we propose a framework that links occupational output to capital and labor inputs. Our framework extends Greenwood *et al.* (1997) to include multiple occupations that differ by their exposure to CETC and to include an heterogeneous worker's assignment to occupations in the tradition of Roy (1951). In Section 6.1, we extend our framework to explicitly model the usage of different capital goods across occupations.

3.1 Environment

Time is discrete and indexed by t. The economy is populated by a continuum of heterogeneous workers indexed by i. Workers are divided into a countable number of labor groups of cardinality H, indexed by h. A labor group is defined on the basis of the demographic characteristics of the workers. For example, we can think of h as comprising schooling e, cohort c and gender g, $h \equiv (e, c, g)$. The measure of workers of type h at a point in time is exogenously given by π_{ht}.

There is a countable set of occupations of cardinality O, indexed by o. An occupation is a technology that combines capital and labor of different types to produce an occupational good. Occupations differ in two dimensions, by the elasticity of substitution between capital and labor and by the technology embodied in capital (CETC). The first dimensions is supported by the evidence provided in Section 2. In particular, differences in the path of technology embodied in capital are supported by occupational differences in the decline in the price of capital relative to consumption. The latter dimension is supported by our estimation exercise in Section 4.1.

There are three sets of goods: a final good that can be used for consumption and to produce capital goods; O-types of occupational goods that are used in the production of the final good; and O-types of capital goods that are used in the production of each occupational good, along with labor. Capital fully depreciates after usage within the period. We relax this assumption when microfounding differences in occupational capital and CETC via occupational disparities in the capital bundles, see Section 6.2.[16]

[16]When capital of different types is combined via an occupation-specific bundle, the capital allocation problem can be split into two. First, one chooses an equilibrium capital-labor ratio in each occupation (our benchmark), and second, one chooses the composition capital. Modelling capital dynamics when capital is

Last, equipment, output, and labor markets are frictionless.

Occupational good producer. In each occupation, a representative producer uses a CES technology in capital, k_{ot}, and labor, n_{ot}, to produce the occupational good, y_{ot}:

$$y_{ot} = \left[\alpha k_{ot}^{\frac{\sigma_o - 1}{\sigma_o}} + (1-\alpha) n_{ot}^{\frac{\sigma_o - 1}{\sigma_o}}\right]^{\frac{\sigma_o}{\sigma_o - 1}}. \tag{2}$$

A producer facing an occupational price λ^y_{ot}, a price of capital-o λ^k_{ot}, and a wage per efficiency unit of labor λ^n_{ot}, chooses equipment and labor to maximize profits:

$$\max_{\{k_{ot}, n_{ot}\}} \lambda^y_{ot} y_{ot} - \lambda^k_{ot} k_{ot} - \lambda^n_{ot} n_{oht}. \tag{3}$$

Final good producer. Final consumption goods are produced combining occupational goods using a CES technology:

$$y_t = \left(\sum_o \omega_{ot}^{1/\rho} y_{ot}^{(\rho-1)/\rho}\right)^{\frac{\rho}{\rho-1}},$$

where ρ is the elasticity of substitution across occupational goods. Changes in the relative ω_o over time are isomorphic to demand shifters. They capture, for example, the increase in demand for low-skill services discussed by Autor and Dorn (2013); and the increase in demand for skill-intensive output discussed by Buera *et al.* (2015).

A producer facing a final good price λ^y_t and prices of occupational goods λ^y_{ot} maximizes profits:

$$\max_{\{y_{ot}\}_{o=1}^{O}} \lambda^y_t y_t - \sum_o \lambda^y_{ot} y_{ot}. \tag{4}$$

Capital producer. Each occupational capital is produced with a linear technology in the final good. Let q_{ot} be the rate of transformation for capital-o. Changes in q_{ot} formalize the notion of capital embodied technical change (CETC), as in Greenwood *et al.* (1997).

A producer facing a price of capital λ^k_{ot} and a price of the final good λ^y_t demands x_{ot} units of final output to maximize:

$$\max_{\{x_{ot}\}} \lambda^k_{ot} q_{ot} x_{ot} - \lambda^y_t x_{ot}. \tag{5}$$

occupation-specific implies a slower factor reallocation in response to technical change than in an economy where capital of different types are accumulated each period and then allocated and combined into bundles in each occupation in spot markets.

Workers. Workers value consumption and are endowed with one unit of time, which they inelastically supply to work in an occupation. Worker i of type h supplies $n_{oht}(i)$ efficiency units of labor when employed in occupation o at time t. Each worker draws a profile of $\{n_{oht}(i)\}_o$ across occupations at each point in time. We assume that $n_{oht}(i)$ is a random variable drawn from a univariate Frechet distribution with cumulative density function $F_{oht}(z) \approx \exp(-T_{oht}z^{-\theta})$. The draws of efficiency units of labor are independent and identically distributed across occupations and workers.[17] The parameters θ and T_{oht} govern the dispersion of efficiency units of labor across workers and across groups/occupations, respectively.

We allow the scale parameter T_{oht} to vary across groups and occupations to scale the mean efficiency units of labor at each point in time. The group-h common component of T_{oht} determines the absolute advantage of the labor group. For example, the average efficiency units supplied by a college graduate working for an hour of time might be higher than that supplied by a non-college graduate. The dispersion of T_{oht} across occupations and groups determines the structure of comparative advantage. The comparative advantage of working in occupation o relative to $o^{'}$ of labor type h with respect to labor type $h^{'}$ is:

$$\left(\frac{T_{oht}}{T_{o'ht}} \Big/ \frac{T_{oh't}}{T_{o'h't}}\right)^{\frac{1}{\theta}}, \tag{6}$$

with a comparative advantage for h if the ratio is greater than 1.

The scale parameters of the distribution of efficiency units of labor encompass differences in human capital, differences in labor productivity in the occupational technologies, as well as labor market frictions (see, Burstein *et al.*, 2019 and Hsieh *et al.*, 2019). Our framework remains agnostic as of the source of these differences. We infer the scale parameter residually to match labor market outcomes.

A worker i of type h who provides $n_{oht}(i)$ units of labor to occupation o receives compensation,

$$w_{oht}(i) \equiv n_{oht}(i)\lambda^n_{ot}.$$

Workers maximize their consumption, $c_{oht}(i) = w_{oht}(i)$ (and therefore instantaneous utility), by choosing the occupation that yields the highest compensation. Hence, given a set of wages per efficiency units $\{\lambda^n_{ot}\}^O_{o=1}$, the problem of worker i in labor group h reads:

$$o^\star_{ht}(i) \equiv \arg\max_o \{w_{oht}(i)\}. \tag{7}$$

[17] This assumption can be relaxed following Lind and Ramondo (2018).

3.2 Equilibrium

We characterize the equilibrium prices and allocations of labor and capital and their relation to the exogenous components of our model. We start by defining equilibrium, given a set of technological parameters $\{\omega_o, q_o\}_{o=1}^{O}$, a set of a scale parameters in the distribution of efficiency units of labor, $\{\{T_{oh}\}_{o=1}\}_{h=1}^{H}$, and a set of measures of workers by labor groups, $\{\pi_h\}_{h=1}^{H}$.

Definition. A competitive equilibrium consists of (1) consumption and labor decisions for workers of each type i and labor group h, $\{o_h^\star(i), c_{o_h^\star(i)h}(i)\}_{h=1}^{H}$, (2) labor, capital and output allocations across occupations, $\{\{n_o, k_o, y_o, x_o\}_{o=1}^{O}, y\}$; such that given prices $\{\{\lambda_o^n, \lambda_o^k, \lambda_o^y\}_{o=1}^{O}, \lambda^y\}$:

1. Workers maximize wages, equation 7;
2. Profits in all occupations, final output, and capital production are maximized, equations 3, 4, 5;
3. The labor market for each occupation clears, i.e., $n_o = \sum_h \int_{i \in \Omega_o^h} n_{oh}(i) \pi_h dF_{oh}(i)$, where Ω_o^h identifies the set of workers with $o_h^\star(i) = o$;
4. The market for each capital-o clears, $k_o = q_o x_o$.
5. The market for final output clears, i.e. $\sum_{ho} \int_i c_{o_h^\star(i)h}(i) + \sum_o x_o = y$.

Input and output prices across occupations. From the zero-profit condition of the producer of occupational output, we express the wage per efficiency unit of labor as a function of the price of occupational output and the price of capital:

$$\lambda_{ot}^n = \left(\left(\frac{1}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{y 1-\sigma_o} - \left(\frac{\alpha}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{k 1-\sigma_o} \right)^{\frac{1}{1-\sigma_o}}. \tag{8}$$

The wage per efficiency unit does not equalize across occupations because workers are not equally productive across them, i.e. they draw different efficiency units depending on the occupation $\{n_{oht}(i)\}_{o=1}^{O}$, as in Roy (1951).

From the zero-profit condition of the capital producer, the price of capital-o equals the inverse of the exogenous rate of transformation from consumption, $\lambda_o^k = 1/q_o$.

The optimal demand from the final good producer characterizes occupation output prices,

$$\lambda_{ot}^y = \lambda_t^y \left(\omega_{ot} \frac{y_t}{y_{ot}} \right)^{\frac{1}{\rho}}, \tag{9}$$

where λ_t^y is the price index for the final good and which we normalize to 1 at each point in time, $\lambda_t^y = (\sum_o \omega_{ot} (\lambda_{ot}^y)^{1-\rho})^{\frac{1}{1-\rho}} = 1$.

Capital-labor ratios across occupations. The optimality conditions of the occupational good producer pin down the capital to labor ratio in the occupation as a function of prices,

$$\frac{k_{ot}}{n_{ot}} = \left(\frac{\alpha}{1-\alpha} \frac{\lambda_{ot}^n}{\lambda_{ot}^k}\right)^{\sigma_o}. \tag{10}$$

Therefore, the capital-labor ratio differs across occupations as a function of the elasticity of substitution between capital and labor and factor prices.

Workers' labor supply. The probability that worker i of group h chooses occupation o is:

$$\pi_{oht} \equiv Prob(w_{oht}(i) > w_{o'ht}(i)) \;\; \forall o^{'} \neq o. \tag{11}$$

Replacing equilibrium wages and using the properties of the Frechet distribution, we solve for the occupational allocation of workers of group h:

$$\pi_{oht} = \frac{T_{oht}(\lambda_{ot}^n)^{\theta}}{\sum_{o'} T_{oht}(\lambda_{o^{'}t}^n)^{\theta}}. \tag{12}$$

The occupational choice of the worker defines the amount of efficiency units supplied to an occupation o:

$$n_{ot} = \sum_h \int_{i \in \Omega_{ot}^h} n_{oht}(i) \pi_{ht} dF_{oht}(i) = \sum_h \pi_{ht}\pi_{oht} E(n|oht) = \sum_h \pi_{ht}\pi_{oht} \left(\frac{T_{oht}}{\pi_{oht}}\right)^{\frac{1}{\theta}} \Gamma(1-\frac{1}{\theta}). \tag{13}$$

These are a function of the number of workers that choose that occupation, $\pi_{ht}\pi_{oht}$, and their average efficiency units, $E(n|oht)$. The properties of the Frechet distribution yield a close form solution for the average efficiency.

Workers' expected wages. The average wages of workers of type h in occupation o are the product of the wage per efficiency unit and the average efficiency units supplied, $w_{oht} = \lambda_{ot}^n E(n|oht)$. Using equation 13 average wages are:

$$w_{oht} = \left(T_{oht} \sum_o \lambda_{ot}^{n\theta}\right)^{\frac{1}{\theta}} \Gamma(1-\frac{1}{\theta}). \tag{14}$$

The equilibrium of the model predicts no differences in the average wages of a group h across occupations, $w_{ht} = w_{oht}$. The assumption of i.i.d. Frechet draws implies that selection effects perfectly offset differences in the scale parameters across occupations (or mean efficiency of the workers). For example, an increase in the mean worker efficiency associated to occupation o through a higher scale parameter increases the returns to working in that occupation. This increases the number of workers that choose such an occupation and therefore decreases the efficiency units of the inframarginal worker, pushing average wages down.[18]

Labor supply-elasticity. Combing equations equation 12, 13 and 14, we can characterize the elasticity of labor supply to its price for *fixed average wages across labor groups*:

$$\eta_{\pi\lambda_o^n} = \theta - 1.$$

The constant elasticity result is a direct result of the Frechet distributional assumption of workers' efficiency units across occupations.

4 Parameterization

In this section, we parameterize the model described in Section 3. This allows us to measure occupational exposure to technical change and then to quantify the impact of CETC on the labor market.

Our parameterization strategy consists of two steps. First, we use our newly constructed dataset on occupational capital to measure occupational heterogeneity in CETC and in the elasticity of substitution between capital and labor. Second, we parameterize the distribution of efficiency units of labor to match labor market outcomes and the demand structure of occupational output to match the stock of capital per worker across occupations.

4.1 Model-free inference

Model-free estimates include the elasticities of substitution between capital and labor and the price of capital in each occupation.

We constructed the quality-adjusted relative price of investment in each occupation in Section 2, Figure 3. In a similar spirit, we compute the average price of the capital stock in

[18]Different occupational wages across occupation for a labor group, as observed in the data, can be rationalized via occupational preferences that generate equilibrium compensating differentials (see Hsieh *et al.*, 2019). In a Mincerian regression run separately on the initial and final years of our sample (1983 and 2016), controlling for demographics alone accounts for approximately 80% of the explained variation in wages by a model that also controls for 1-digit occupational dummies.

each occupation. We use this price, normalized to 1 in 2015, for all capital goods to measure the growth rate of the price of each occupational capital good relative to consumption, λ^k_{ot}.

4.1.1 Elasticity of substitution between capital and labor

The elasticity of substitution is the partial equilibrium response of the capital labor ratio, $\frac{k_o}{n_o}$, to a change in the marginal rate of transformation. With the assumption of competitive factors markets, the marginal rate of transformation equals the relative factor prices, λ^n_{ot}/r_{ot}, where λ^n_{ot} is the price of a unit of labor and r_{ot} is the user cost of a unit of capital. We can then write the parameter of interest as:

$$\sigma_o \equiv \frac{d\ln(k_{ot}/n_{ot})}{d\ln(\lambda^n_{ot}/r_{ot})}.$$

To measure the elasticity, we need information on input ratios (in efficiency units) and price ratios. Non-neutral technical change has direct implications for the measurement of the capital labor ratio and is, for the most part, unobserved. To see this, rewrite the elasticity as a function of observables – that is, observable labor $\tilde{n}_{ot}$ (for example, full-time equivalent workers) and its price as well as our measure of capital in efficiency units and its price $\lambda^{\tilde{n}}_{ot}$:

$$\sigma_o \equiv \frac{d\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}\exp(\gamma^{n_o}t)}\right)}{d\ln\left(\frac{\lambda^{\tilde{n}}_{ot}\exp(\gamma^{n_o}t)}{r_{ot}}\right)}, \tag{15}$$

where $\gamma^{n_o}_t$ is labor-augmenting technical change in occupation o. This technical change shapes the bias of technology for observable CETC.[19] Diamond *et al.* (1978) formally proved the impossibility of separately identifying the elasticity of substitution and biased technical change from a time series of factor shares and observable capital-labor ratios. In a nutshell, for an arbitrary elasticity of substitution, periods of low observable capital-labor ratios $\frac{k_{ot}}{\tilde{n}_{ot}}$ can be rationalized by capital-biased technology, $\exp(\gamma^{n_o}_t) < 1$ and periods of high observable capital-labor ratios, by labor-biased technology $\exp(\gamma^{n_o}_t) > 1$.

To circumvent this impossibility result and identify the elasticity of substitution, the literature assumes a structure for the form of technical change (see Herrendorf *et al.*, 2015, Antras, 2004). In line with the literature, we assume that technical change is exponential.

[19]Given our working assumption that CETC is captured by the decline in the relative price of capital, our measure of efficiency units of capital fully embeds capital-augmenting technical change.

Then, under constant elasticity, the empirical counterpart to equation 15 is:

$$\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}}\right) = \beta_{1o} + \beta_{2o}t + \beta_{3o}\ln\left(\frac{\lambda_{ot}^{\tilde{n}}}{r_{ot}}\right) + \epsilon_{ot}, \tag{16}$$

where β_{1o} is the intercept of the regression which corresponds to a constant of integration in equation 15; β_{2o} captures labor augmenting technology as we explain above, γ_{ot}^{n}; β_{3o} is the elasticity of substitution between capital and labor, σ_o; and ϵ_{ot} is an error term with which we augmented the structural equation 15. We measure labor, $\tilde{n}_{ot}$, using full-time equivalent workers adjusted for disparities in their efficiency due to observable characteristics, i.e. age, schooling, and gender, using their relative wages as a proxy for skill (see Caselli and Coleman, 2006, among others). We compute average wages, w_{ot}, as the ratio between the total wage bill in an occupation and our measure for labor $\tilde{n}_{ot}$. Finally, we construct a measure of the user cost of capital r_o using a standard no-arbitrage condition for the price of capital assuming a real interest rate of 2% per year. All series are available from 1982 to 2015 and the occupation is mapped to the 1-digit occupational classification system of the Census. Details of the data construction are relegated to the Online Appendix.

The estimation of regression equation 16 exposes an obvious endogeneity problem. Observed capital labor ratios are endogenous to their relative factor prices. In general, the elasticity will not be identified unless one uses an exogenous shift in the supply of capital or labor. Therefore, the OLS estimates are biased and the direction of that bias is unknown. We use two alternative instruments, which we interpret as exogenous supply shifters. First, we use 16-year lagged birthrates and adjust them by the share of employment in a given occupation in 1982 to construct an exogenous shifter of the working age population. Second, we use the 1-year lagged value of the observable capital-labor ratio.[20]

For the aggregate economy, we obtain an OLS point-estimate of 1.01 and an IV point-estimate of 0.79.[21] These estimates are consistent with prior exercises in Antras (2004), using time-series variation, and with Oberfield and Raval (2020), exploiting cross-sectional variation in the manufacturing sector.

Table 2 presents our baseline estimates of the elasticity of substitution across occupations. The OLS estimates of the occupational elasticities fall below one, ranging from 0.25 to 0.73. The point estimates increase in all occupations when instrumenting for the possible en-

[20] Our baseline estimates are robust to alternative IVs that shift the supply of skills in the economy. Specifically, we obtain similar results when using the 16-year lagged birth rate adjusted by the share of employment in an occupation in 1982 times the share of college educated workers in an occupation relative to the total number of college-educated in 1982. Results are available upon request.

[21] We implement a two-stage least squares regression.

Table 2: Elasticity of substitution between capital and labor.

	OLS	confidence interval		IV	confidence interval		F-statistic	
							Cragg-Donald	Kleinbergerg
Aggregate	0.44***	*0.27*	0.61	0.77*	0.49	1.03	23	.
Managers	0.31***	0.13	0.50	0.79	0.36	1.23	13	8
Professionals	0.50***	0.35	0.65	0.66***	0.49	0.82	45	41
Technicians	0.51***	0.29	0.72	0.75*	0.49	1.03	24	24
Sales	0.68	0.29	1.07	1.17	0.82	1.51	29	36
Admin Service	0.37***	0.05	0.69	1.32	0.67	1.97	8	11
Low-skilled Serv	0.57***	0.38	0.76	0.73**	0.50	0.97	42	22
Mechanics & Repairers	0.73***	0.60	0.87	0.80***	0.68	0.93	88	110
Precision	0.39***	0.03	0.74	1.99***	1.00	3.00	8	18
Machine Operators	0.25***	0.10	0.39	0.57***	0.35	0.80	13	15
Transportation	0.43***	0.30	0.56	0.54***	0.44	0.65	44	15
Stock-Yogo weak ID test critical values				10% maximal IV size			19.9	
				15% maximal IV size			11.6	

Authors' estimation of equation 16. Columns (1-3) present the OLS estimates and the 99% confidence intervals; Columns (4-6) contain the IV estimates and 99% confidence intervals using the instruments described in the text. Column (7-8) contains the F-statistic for weak instruments under homoscedastic errors, Cragg-Donald and robust to heteroscedasticity, Kleinbergerg. The bottom of the table reports the Stock-Yogo critical value for a 10% and 15% bias in the IV estimates.

dogeneity. The lowest elasticities (highest complementarity) are reported for transportation and machine operators (at 0.54 and 0.57, respectively), followed by professionals, low-skill services and technicians. For sales, administrative services and precision production occupations we estimate substitutability between capital and labor, but the estimates of the first two occupations are noisy. The elasticity of substitution in precision production raises to 1.99, statistically different from 1, when instrumenting.

Discussion. The structural equation 15 is consistent with two econometric models, equation 16 and its inverse,

$$\ln\left(\frac{r_{ot}}{\lambda_{ot}^{\tilde{n}}}\right) = \bar{\beta}_{1o} + \bar{\beta}_{2o}t + \bar{\beta}_{3o}\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}}\right) + \bar{\epsilon}_{ot} \tag{17}$$

As pointed out by Antras (2004), the R^2 of the estimation equations 16 and 17 are identical and satisfy, $R^2 = \bar{R}^2 = \beta_{3o}\bar{\beta}_{3o} = \frac{\sigma_o}{\bar{\sigma}_o}$. Therefore, the estimate of the elasticity of substitution that we use as our benchmark is lower than the one obtained from equation 17. However, when using an exactly identified IV-regression, the estimates are identical irrespective of whether relative prices are on the left-hand side or the right-hand side of the econometric model.[22] Indeed, acknowledging the biases in the estimates associated to alternative representations of the same equation, Leon-Ledesma *et al.* (2010) propose the estimation of a system of equations including the production function itself and the optimality conditions for each input. Unfortunately, the inherent unobservability of occupational prices and output yields this approach unfeasible for us.

In the remaining of the discussion, we focus on the IV estimates. With one endogenous variable and two instruments, i.e. lagged observable capital-labor ratios and lagged birth rates, the Cragg-Donald Wald-type test for weak-instruments is desirable under the assumption of homoscedasticity.[23] Table 2 presents the value of the statistic and the critical value for a 10% maximal IV size as tabulated by Stock and Yogo (2005). In all cases we reject the null that the maximum relative bias in the estimate is 10% or larger. The magnitude of the F-stats is large relative to the threshold throughout.

A commonly used strategy when estimating the elasticity of substitution between capital and labor is to exploit cross-sectional variation across geographical locations in production units, as in Oberfield and Raval (2020), or in the occupational composition, as in Kehrig (2018). One interpretation of these estimates is that they correspond to the "long-term" elasticity of substitution, whereas the one identified from time-series variation corresponds to the "short-term" elasticity of substitution. Indeed, adjustments in input ratios that do not respond to changes in prices within a unit of time (in our case, a year) would be abstracted away by the latter estimation. Assumptions on factor mobility and standard Bartik-style instruments are enough to identify the parameter of interest in the cross-section. Such an identification strategy is challenging for us because we do not observe capital usage in each location. At best, our cross-sectional estimation can exploit variation across locations in their 3-digit occupational composition. Indeed, despite we can certainly assign stocks to workers across locations based on tools requirements, workers in a given 3-digit Census occupation would have identical capital allocations across locations at a point time (because their tool's requirements are the same across locations).

An alternative way to identify the longer term responses of inputs to price changes is to estimate equation 16 including 5-years lags in observed input ratios, while instrumenting

[22] When using an over-identified IV-regression, as we do in our benchmark, the estimates vary only slightly across specifications.

[23] We also report heteroscedastic robust Wald-type test as in Kleibergen-Paap.

prices for the supply shifter in the working-age population as before:[24]

$$\ln\left(\frac{k_{ot}}{l_{ot}}\right) = \bar{\beta}_{1o} + \bar{\beta}_{2o}t + \bar{\beta}_{3o}\ln\left(\frac{w_{ot}}{r_{ot}}\right) + \bar{\beta}_{4o}\ln\left(\frac{k_{ot-5}}{l_{ot-5}}\right) + \bar{\epsilon}_{ot}$$

Under this specification, one could interpret $\frac{\bar{\beta}_{3o}}{1-\bar{\beta}_{4o}}$ as the long run elasticity. Our benchmark point estimates are similar to this alternative long-run counterparts, suggesting that the shorter-term movements in input and price ratios that we exploit are close to the longer-run ones. The exception is machine operators, for whom the long-run elasticity of substitution is 1.3 (relative to 0.6 in the benchmark), albeit not significantly different from one.

Another approach to the estimation of the elasticity of substitution focuses on the differential intensity of input usage across output goods, as reflected in the direct requirements matrix of the input-output tables. An assumption on the correlation between the bias in technology across goods and cross-sectional variation in input shares is still needed for identification of the elasticity of substitution between capital and labor. Hubmer (2020) assumes no correlation between capital intensity and the labor bias in the production of goods and finds an aggregate elasticity of substitution between capital and labor above one.[25] In the case of occupations, a parallel assumption implies that more capital intensive occupations do not display stronger labor bias, e.g. they do not hire workers with relatively more skills. We find such an assumption problematic given the complementarities between skill and capital that Krusell *et al.* (2000) document.

Finally, we discuss the implications of our estimates for the labor share. Our aggregate estimates for the elasticity of substitution between capital and labor suggest complementarity, as well as the estimates of 7 out of 10 1-digit occupations. The consistency between these findings and the decline in the labor share reported in the US (Sahin *et al.*, 2013) depends on the relative strength of labor and capital-augmenting productivity trends, which combined with the value of the elasticity of substitution yields the bias of technology (equation 17 can be rewritten as a function of the factor shares). In the aggregate, we find that labor-augmenting technology grew at 14.9% per year between 1982 and 2015, while the efficiency of capital (the inverse of the realtive price of capital) increased of 11.5% per year over the same period. The 3.4% faster increase in labor-augmenting technology relative to

[24] See a similar discussion for the dynamic panel estimates in Oberfield and Raval (2020).

[25] Hubmer (2020) assumes no correlation between capital intensity and capital bias but argues that even when these are correlated, the empirical magnitude of that correlation would likely not change the estimates of substitutability between capital and labor. A positive correlation between the labor bias in technology and capital intensity, i.e. more capital intensive goods are produced with workers of higher skills, could however flip the sign of the estimate, from above one to below one.

capital-augmenting technology and the aggregate complementarity between capital and labor implies labor-biased technology and is consistent with the decline in the aggregate labor share.[26] Table E.IV reports our estimates of the bias of technology across occupations. The fastest growth in labor efficiency is reported for professionals, low-skill services and mechanics. This trend combined with their relatively high complementarity to capital explains the decline in the labor share in these occupations. Among occupations where labor is substitutable to capital, the strength of CETC is stronger than improvements in the efficiency of labor in sales occupations, consistent with a decline in their labor share. In addition, we also note that the labor share in administrative services and precision workers increases after 2000, consistent with the pattern of substitutability and the fastest growth in the efficiency of labor identified in the data.[27]

4.2 Model-based inference

We start by parameterizing the distribution of efficiency units of labor, determined by the shape parameter of the Frechet distribution, θ, and the scale parameters, $\{\{\{T_{oht}\}_{o=1}^{O}\}_{h=1}^{H}\}_{t=\{1982,2015\}}\}$. The shape parameter governs the magnitude of the right tail of the distribution of efficiency units of labor: a lower θ induces a fatter tail and therefore more dispersion in talent draws. To estimate its value, we use maximum likelihood to fit an inverse Weibull distribution on the wage residuals predicted from a Mincerian regression with age, age squared, dummies for sex and education, and 1-digit occupation fixed effects. We run these estimates for each year, between 1982 and 2015, and take the average over the period at $\theta = 1.30$.

The model defines a link between the labor market outcomes of workers of a given group h and their associated scale parameters of the Frechet distribution, T_{oht} (equations 12 and 14). We consider 12 labor groups, as defined by three of their demographic characteristics: age, gender and schooling attainment. We group age in three groups: 16- to 29-years old, 30- to 49-years old and 50- to 65-years old. We group schooling attainment into two groups: less-than 4-year of college and 4-year of college or more. We use the occupational choice and average wages of workers to parameterize the profile of T_{oht}, given wages per efficiency units in each occupation.

We choose a profile of wages per efficiency units across occupations, w_{oht}, so that the

[26] We are unaware of estimates of the trends in factor augmenting technology in the US. Doraszelski and Jaumandreu (2018) document a labor bias of between 1.5% and 2% per year using firm-level estimates for Spain.

[27] Incidentally, these occupations are relatively intensive in computers and software, equipment categories that experience a slow-down in the decline in prices after 2000, see Figure 3.

model matches the capital per worker across occupations, $\frac{k_{ot}}{\ell_{ot}}$. The equilibrium of the model specifies that the capital-labor ratio differs across occupations as a function of the elasticity of substitution between capital and labor and factor prices (equation 10). The capital-labor ratio maps to capital per worker for a value of the average efficiency units of labor in each occupation. This last term is not directly observable in the data and is a result of worker's selection into different occupations. The properties of the Frechet distribution allows us to link the selection effect of each worker group to their occupational choice, and therefore measure differences in efficiency units of labor per-worker from data on occupational choices (equation 13).

Details on the inference of the scale parameters of the Frechet distribution are in Online Appendix C. Figure 10 in the Online Appendix depicts the evolution of the scale parameters of the Frechet distribution, separately for the group and the occupation components.

We now turn to the inference of the parameters of the production function of final output. We first estimate the elasticity of substitution across occupational output, ρ, from the first order condition for the final good producer, equation 9:

$$\ln \lambda^y_{ot} y_{ot} = \ln \lambda^y_{o_b t} y_{o_b t} + (1-\rho) \ln \left(\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}} \right) + \ln \frac{\omega_{ot}}{\omega_{o_b t}}.$$

Through the lens of the model, we observe all the elements of the above equation except from the demand shifters. We calculate the value of output across occupations, $\lambda^y_{ot} y_{ot}$, from data on capital and labor expenditures at the occupation level, under the assumption of cost minimization. We measure the ratio of prices of occupational output, $\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}}$, from our previously inferred wage per efficiency units of labor and its link to the price of capital and that of occupational output (see equation 8).

We estimate the following regression equation:

$$\ln \lambda^y_{ot} y_{ot} = \beta_{1o} + \beta_2 t + \beta_3 \ln \left(\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}} \right) + \epsilon_{ot},$$

where $\epsilon_{ot} \equiv \ln \frac{\omega_{ot}}{\omega_{o_b t}} + \nu_{ot}$, and ν_{ot} is an error term, normally distributed, mean-zero, and i.i.d. across observations. Our model predicts that changes in equilibrium occupational prices depend on changes in the unobserved demand shifters. We expect the error term and the covariate $\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}}$ to be correlated and so the resulting estimate of ρ to be biased, with unknown direction. To address this endogeneity issue, we follow Burstein *et al.* (2019) and use a Bartik-style instrument based on the average price of capital in each occupation with equipment weights fixed at 1982 levels. Our estimation considers ten occupations, over 36 years, between 1982 and 2015. The OLS yields an estimate for the elasticity of substitution of 0.97 (se: 0.0165) while the IV yields an estimate of 1.33 (se: 0.0926).[28]

Last, to pin down the demand shifters, ω_{ot}, we use the first-order conditions of optimization of the final good producer (equation 9) and the price of occupational output implied by the wage per efficiency units of labor.

4.3 Occupational exposure to technical change

Our parameterization strategy implies a measure for occupational exposure to CETC – that is, the cross-price elasticity of labor demand. Hicks (1932) shows that, under the assumptions of constant returns and price-taking behavior, this elasticity can expressed as:

$$-\frac{d\ln(n_o)}{d\ln(\lambda_o^k)} = \frac{\eta_{\pi\lambda_o^n}(\rho-\sigma_o)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}}{\rho+\eta_{\pi\lambda_o^n}+(\sigma_o-\rho)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}}^{29}, \tag{18}$$

where (i) σ_o is the extent of labor substitutability to capital in occupational output production, (ii) $\eta_{\pi\lambda_o^n}$ is the own price elasticity of labor supply, (iii) $\frac{\lambda_o^k k_o}{\lambda_o^y y_o}$ is the importance of capital for production, or its cost share and (iv) ρ is the demand elasticity for occupational output.

The capital share and the elasticity of substitution between capital and labor can be inferred directly from the data. Through the lens of the structural model, we are able to measure the two remaining components. The distributional assumptions for workers' efficiency characterize the selection effects of occupational sorting and the supply elasticity for fixed average wages across labor groups, $\eta_{\pi\lambda_o^n} = \theta - 1 = 0.30$. The elasticity of output demand equals the elasticity of substitution across occupational outputs in our model, ρ.

Figure 5, left panel, shows the occupational exposure to CETC in each occupation. In the figure, 1-digit occupations are ranked by increasing skill requirements, following Autor (2015). There is substantial variation in exposure across occupations: the lowest exposure is recorded for precision production, at -4%, while the highest is recorded for transportation, at 4.2%. Occupational heterogeneity in the elasticity of substitution is an important driver

[28] The elasticity of substitution across occupational output has not been well pinned down in the literature. Typically a value greater than 1 is assumed, which accords with our finding. Goos *et al.* (2014b), Aum *et al.* (2018) and Burstein *et al.* (2019) are exceptions. Goos *et al.* (2014b), Aum *et al.* (2018) find an elasticity less than 1. Burstein *et al.* (2019) estimate an elasticity of $\rho = 1.78$ assuming a Cobb-Douglas structure in the production of occupational output. Our estimate is the first that exploits capital stock data.

[29] Derivations in Online Appendix B.

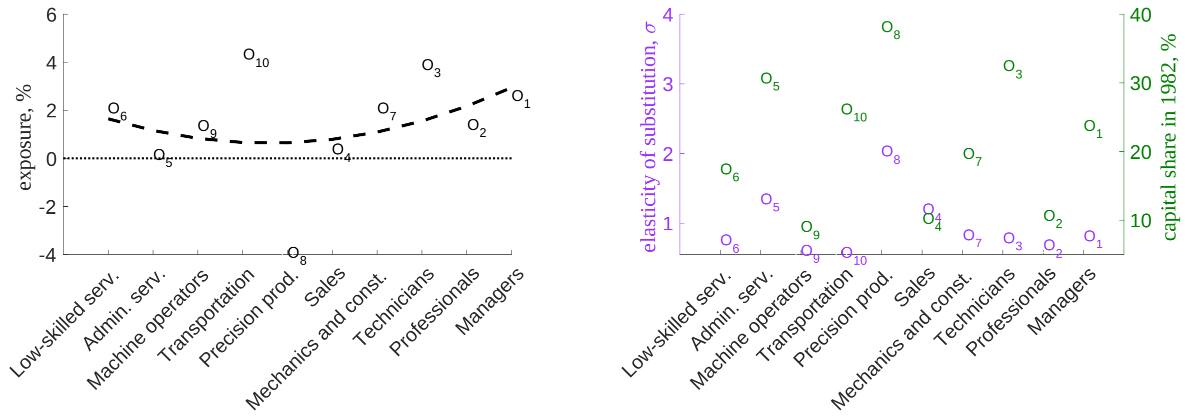


Figure 5: Occupational exposure to CETC.

The left panel plots occupational exposure to CETC (equation 18) across 1-digit occupations ordered by increasing skill requirements. The striped line is cubic polynomial fit. The right panel plots the sources of occupational heterogeneity in exposure: the elasticity of substitution and the capital share in 1982.

of these differences (Figure 5, right panel). For all but one occupation the elasticity of substitution between capital and labor is lower than the elasticity of substitution across occupational output, $\rho = 1.33$, with the implication that the scale effect of a decline in the relative price of capital on labor demand dominates the substitution effect. Hence, CECT increases labor demand in these occupations, when considered in isolation. Precision production is the only occupation for which, instead, the substitution effect dominates the scale effect.

The capital share in 1982 also plays an important role in shaping occupational heterogeneity in exposure. For example, consider professionals and technicians. These occupations have elasticities of substitution between capital and labor among the lowest ones, which, for a fixed capital share imply high exposure to CECT. However, professionals also record a low capital share relative to technicians, which decreases the power of the scale effect and therefore exposure to CETC and employment gains. Overall, occupational exposure is U-shaped across occupations ranked by their average wage and skill content.

5 The role of CETC for labor market outcomes

In this section, we use the model described in Section 3 and parameterized in Section 4 to quantify the impact of CETC on labor re-allocation and the evolution of wage premia across labor groups in the US. We close the section by evaluating other forces that may have contributed to these labor market outcomes.

Quantification of the role of CETC. To assess the quantitative importance of CETC for labor market outcomes, we conduct a counterfactual exercise. We take the model economy in 2015 and remove the decline in the quality-adjusted price of capital, which is our proxy of CETC – that is, we set $\lambda^k_{o2015} = \lambda^k_{o1982}$. This exercise allows us to isolate the implications of CETC for occupational choice and wages of workers of different demographic groups. We start by considering the role of CETC for the polarization of US employment, as documented by Acemoglu and Autor (2011). Over the last half century, employment at the bottom and top of the skill distribution increased, while there was a hollowing out of middle skill occupations. The top panel of Table 3, column *Data*, document this pattern. Between 1982 and 2015, low-skill occupations (low-skill services) and high-skill occupations (professionals and managers) gain 3.51 p.p. and 10.37 p.p. in their employment shares, respectively. Column *CECT*, in the same table, reports the contribution of CECT to this pattern, that we isolate via the counterfactual. CETC is consistent with employment polarization, as it generates an increase in the employment share for low- and high- skill occupations. However, CETC has been much more relevant for high-skill occupations. The model predicts that employment reallocation toward high-skill occupations due to CETC alone was of 9.45 p.p. – that is, 92% of the observed reallocation. CETC had a lesser role in the reallocation out of middle-skill occupations, accounting for 74% of it, and even a smaller one in the reallocation toward low-skill occupations, accounting for 23% of it.

Figure 6 gives a visual representation of the role of CECT for employment polarization. It plots employment changes across occupations of increasing skill requirements, as reported in the data (blue line with filled markers) and as generated by CECT alone (red line with hollow markers). CECT generates an inflow of employment toward high-skill occupations of a magnitude similar to the one observed in the data. CETC is also consistent with the hollowing out of middle skill occupations, although the model predicts lower employment losses for machine operators and transportation, than observed in the data.

Workers of different demographic characteristics differ in their occupational choices (see, among others, Hsieh *et al.*, 2019). As CECT tends to be more relevant for high-skill occupations, it may have a different impact on the labor market outcomes of workers of different demographic characteristics. The bottom panel of Table 3 reports the absolute change in employment allocation across occupations generated by CETC for workers of different education, age and gender. We find that CETC had a stronger role in the reallocation for more educated, older, and male workers. CETC accounts for more than twice as much of

Table 3: The role of CETC for employment reallocation.

	Data	CECT	CECT/Data
Fraction moving into:			
High-skill	10.37	9.45	91.07
Middle-skill	-13.89	-10.24	73.76
Low-skill	3.51	0.80	22.68
Abs average movement:			
All	2.78	2.53	90.92
Non-college graduates	2.55	2.47	96.74
College graduates	1.17	2.78	237.83
16- to 29-year old	3.56	2.49	70.02
30- to 49-year old	2.52	2.48	98.42
50- to 65-year old	2.54	2.61	102.45
Females	4.14	2.81	67.71
Males	1.99	2.32	116.75

Note: Column "CETC" reports the outcome attributed to the decline in the price of capital relative to consumption via the counterfactual. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction when we shut down CETC. "High-skill" occupations are managers and professionals. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations. Entries are in percent.

the reallocation of college graduates than of non-college graduates, for 32p.p. more of the reallocation of 50- to 65-year-old workers compared to 16- to 29-year-old workers, and almost twice as much of the reallocation of male workers compared to female workers. This finding is a reflection of more educated, older, and male workers choosing high-skill occupations more frequently and highlights the importance of the occupational choice for workers to access the returns of CETC.

In our model, differences in the occupational choices across demographic groups are rationalized via a residual component of the productivity shifters that determines the comparative advantage. Various studies highlight how this residual component reflects labor market frictions linked to the demographic characteristics (see, among others Hsieh *et al.*, 2019). Such frictions prevent workers to fully respond to CETC with their occupational choices and therefore exacerbate inequality in labor market outcomes across demographic groups. Table 4 shows the impact of CECT on the wage premia across labor groups. In the data, the college premium increased by 35 p.p. between 1983 and 2015, the cross-sectional age premium increased by 12 p.p. for 30- to 49-year old workers and by 19 p.p. for 50- to 65-year old workers. CETC generates 81% of the increase in the college premium and about

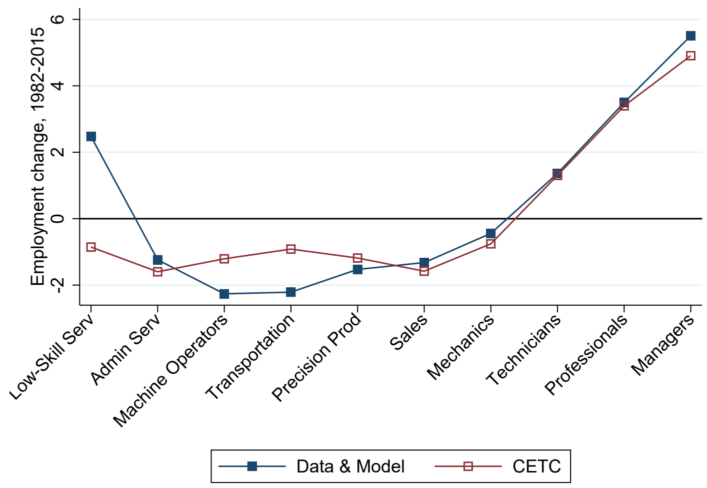


Figure 6: Employment polarization.

In blue, with filled markers, we plot 100 times the change in share of employment between 1982 and 1982. In red, with hollow markers, we plot the same outcome attributed to the CETC via the counterfactuals. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction when we shut down CETC. Employment changes are smoothed by a locally weighted smoother, lowess, following Autor (2015). Non-smoothed numbers are presented in Table E.VI, columns "Data" and "CETC", in the Online Appendix.

1/2 of the rise in the cross-sectional age premia. Over the same period of time, the gender wage gap decreased of 29 p.p.. Our model generates an increase of the gender wage gap due to CETC because males are more likely to work in high-skill occupations, where wages increase as a consequence of technical change.[30]

Lastly, a recent literature highlights the importance of younger workers in the reallocation of labor across occupations and sectors (Hobijn *et al.*, Adao *et al.*, 2020). In our calculations, CETC is a more important driver of the reallocation of older workers because older workers tend to be more prevalent in high-skill occupations, and therefore measure a comparative advantage in these occupations.[31] When we shut down heterogeneity across occupations (in the elasticity of substitution and the extent of CETC), CETC generates a similar reallocation for workers of different age groups.

We conclude by aggregating the effects of CECT we described above to summzarize the role of CETC for the reallocation of US labor between 1982 and 2015. Table 3 shows that the

[30]Note that despite the model matches wage premia across labor groups by construction, it does not match occupational premia. The perfomance on occupational wage premia and the role of CETC are in Table E.V in the Online Appendix.

[31]For example, 20.7% of 16- to 29-year old workers choose high-skill occupations compared to 33.9% of 30- to 49-year old workers, in 1982.

Table 4: The role of CETC for the wage premia across demographic groups.

	Data	CETC	CETC/Data
College premium	35.16	28.98	82.43
Age premium			
30- to 49-year old	11.77	7.15	60.74
50- to 65-year old	19.01	5.12	26.92
Gender wage gap	-29.37	1.58	-5.38

Note: The table reports percentage variation in the college premium, the age premia, and the gender wage gap between 1982 and 2015. Column "CETC" reports the outcome attributed to CETC via the counterfactual. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction when we shut down CETC. Entries are in percent.

average absolute change in employment allocation across occupations over this time period is 2.8%. CETC accounts for 91% of this employment reallocation (2.5 p.p.).

How does CETC operate? CETC influences the labor market outcomes via two channels: the heterogeneity in the elasticity of substitution between capital and labor across occupations and the bundle of capital used in each occupation, which drives heterogeneity in the decline of the relative price of capital to consumption across occupations. To isolate the quantitative role of these two channels, we design three alternative experiments: first, we equalize the path of the relative price of capital to consumption across occupations by feeding the same path of the relative price across all capital goods (*Identical CETC*); second, we input a common elasticity of substitution of capital and labor across occupations, (*Identical elasticity*); third, we input both a common relative price of capital and elasticity of substitution in all occupations, (*Identical elasticity*). We set the common elasticity of substitution to $\sigma = 1.08$, which is estimated by imposing a common elasticity parameter in regression equation 16, Section 4. We quantify the importance of CETC in each of these alternative experiments by again shutting down the decline in the relative price of capital to consumption. Table 5 reports the contribution of CETC in the three alternative experiments, along with the baseline.[32]

The heterogeneity in the elasticity of substitution across occupations is most important for the direction and the magnitude of the reallocation of labor across occupations. When we force identical elasticities of substitution in all occupations, CETC is attributed an outflow

[32] In each of the alternative experiments, we recalibrate the model following the calibration strategy in Section 4. Our estimate of the elasticity of substitution of occupational output when the elasticity of substitution between capital and labor is identical across occupations increases to $\rho = 3.81$, with a standard error of 0.0894.

Table 5: The role of CETC: channels.

	Data	Baseline	Identical: elasticity	Identical: CETC	Identical: elasticity and CETC
Fraction moving into:					
High-skill	10.37	9.45	0.50	8.81	0.47
Middle-skill	-13.89	-10.24	-0.07	-10.17	-0.23
Low-skill	3.51	0.80	-0.43	1.36	-0.24
Abs average movement:					
All	2.78	2.53	0.34	3.26	0.19
Non-college graduates	2.55	2.47	0.40	3.41	0.24
College graduates	1.17	2.78	0.28	3.09	0.14
16- to 29-year old	3.56	2.49	0.34	3.39	0.20
30- to 49-year old	2.52	2.48	0.33	3.17	0.18
50- to 65-year old	2.54	2.61	0.35	3.32	0.20
Females	4.14	2.81	0.36	3.49	0.20
Males	1.99	2.32	0.34	3.10	0.19

Note: entries are in percent. All columns aside from "Data" report the outcome attributed to the decline in the price of capital relative to consumption via the counterfactual. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction when we shut down CETC. Column Baseline shows our baseline results, columns Identical elasticity, Identical CETC, and Identical elasticity and CETC show the results for the alternative exercises. "High-skill" occupations are managers and professionals. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations. Entries are in percent.

of employment from low skill occupations, opposite to our baseline findings. Moreover, in this alternative experiment, CETC generates less than 1/10 of the inflow of employment toward high-skill occupations, compared to more than 9/10 in the baseline. Finally, CETC also generates more reallocation for college graduates compared to non-college graduates in this alternative experiment, opposite to our baseline findings.

The importance of the heterogeneity in the elasticity of substitution across occupations for the direction of labor reallocation operates through workers' exposure to CETC. In our benchmark, exposure to CETC of middle-skill occupations is about half that of high- and low-skill occupations. When we shut down heterogeneity in the elasticity of substitution this gap in exposure flips, with middle-skill occupations recording a 49% higher exposure. As a consequence, the outflow of employment from middle-skill occupations weakens to a magnitude lower than the outflow from low-skill occupations. This experiment still generates an inflow of employment to high-skill occupation as these occupations record the strongest decline in the relative price of capital to consumption.[33]

[33]High-skill occupations record the highest relative price decline, 9.12% per year. Low-skill occupations

To evaluate the quantitative implications of heterogeneity in exposure to CETC for labor reallocation, we combine our estimates of exposure with the decline in the price of capital relative to consumption and we reweight the predicted gains in employment so that total net employment reallocation equals zero. The predicted employment change is the Hicks (1932)'s prediction for the impact of CETC on each occupation. Figure 7 presents these results for occupations ranked by increasing skill requirements in green small markers. In the figure, we also plot the reallocation of workers in the data in blue filled markers; and the reallocation generated by CETC through the lens of the our model in red hollow markers as before. The shape of the employment changes predicted from exposure is consistent with the predictions of the structural model. However, the magnitude of the employment changes is always smaller than in the structural model. This is particularly so for high-skill occupations, for which exposure generates an inflow of employment of only 1.3 p.p., compared to 9.4 p.p. in the baseline. The computation based on exposure also misses most of the outflow of employment from administrative services and sales, which is instead predicted by the structural model, and also overestimates the outflow of employment from precision production. Overall, exposure only generates 1/5 of the outflow of employment from middle-skill occupations predicted by the structural model.

The difference in the role of CETC for labor reallocation that we infer using exposure compared to using our general-equilibrium framework is that the former considers occupations in isolation and so it misses feedback effects on the reallocation of labor. Our exercise shows that these feedback effects are quantitatively important.

5.1 Other forces at play

In the previous section we established that CETC has played a major role in shaping labor market outcomes in the US over the last half century. However, not all labor market outcomes can be traced back to CETC. In this section, we quantify the contribution of other exogenous forces in the model to labor market outcomes via counterfactual exercises.

In the first exercise, we remove changes in the scale parameters of the distribution of efficiency units of labor associated to occupations, $T_{o2015} = T_{o1982}$, and in the demand shifters in final production, $\omega_{o2015} = \omega_{o1982}$ ("Demand"). In the second exercise, we remove changes in the scale parameters associated to worker types, $T_{g2015} = T_{g1982}$ ("Demographics"). In the third exercise, we remove changes in the structure of worker comparative advantage,

record instead the weakest price decline, 7.3% per year. Middle-skill occupations record a price decline of 8.1% per year

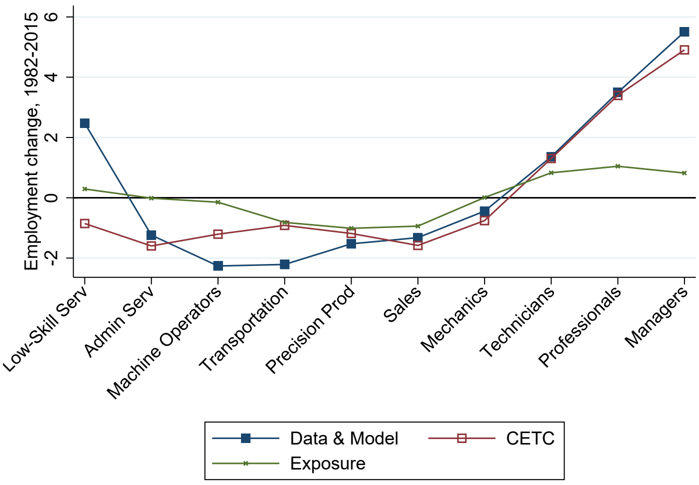


Figure 7: Exposure vs general equilibrium employment changes.

In blue, with filled markers, we plot 100 times the change in share of employment between 1982 and 2015. In red, with hollow markers, we plot the same outcome attributed to the CETC via the counterfactuals. In green, we plot the same outcomes attributed to the CETC via exposure. Changes in employment shares are smoothed by a locally weighted smoother, lowess.

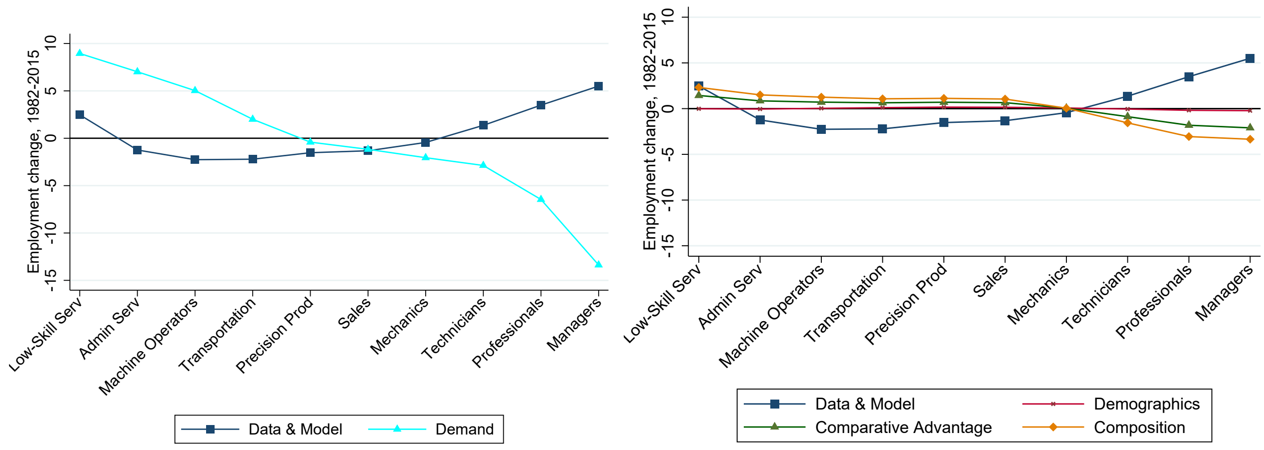
$\tilde{T}_{og2015} = \tilde{T}_{og1982}$ ("CA"). Lastly, in the fourth exercise, we remove changes in the weights of the different labor groups, $\pi_{g2015} = \pi_{g1982}$ ("Composition"). For each exercise, we discuss the implications in relation to the occupational choice of workers of different types.[34][35]

Figure 8 shows the contribution for employment polarization of the occupational demand shifters, in the left panel, and of all other exogenous forces, in the right panel. [36] Consistently with the hypothesis in Autor and Dorn (2013), we find that demand shifters were responsible for the increase in employment at the bottom of the skill distribution. The model predicts that the demand shifts towards low-skill occupations should have generated a 6.83 p.p. increase in the share of workers allocated to them; in the data, this change was 3.51 p.p.. Demand shifters entirely miss the employment gains at the top of the skill distribution, as well as the hollowing out in middle skill occupations. About 60% of the employment losses at the top of the skill distribution that follow from the demand shifters are redirected toward

[34]Details on the decomposition of the scale parameter of the Frechet distribution in the occupation, group, and comparative advantage components are in Online Appendix C.

[35]Our main findings are robust to run the counterfactual exercises sequentially – that is, starting from the baseline economy in 2015 and shutting down the various exogenous channel to return to the 1982 baseline economy. Table E.VII in the Online Appendix compares the results of the two set of counterfactual exercises.

[36]The employment changes are smoothed by a locally weighted smoother, lowess, following Autor (2015), to make them comparable to Figure 6 on the contribution of CETC. Unsmoothed series are available in the Online Appendix, Table E.VI.



(a) The role of demand shifters

(b) The role of other forces

Figure 8: Other forces at play.

In blue, with filled markers, we plot 100 times the change in share of employment between 1982 and 2015. In other colors, we plot the same outcome attributed to various forces via the counterfactuals. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction. Employment changes are smoothed by a locally weighted smoother, lowess, following Autor (2015). Non-smoothed numbers are presented in Table E.VI in the Online Appendix.

higher employment in the middle-skill occupations.

The right panel of Figure 8 shows that exogenous forces beyond CETC and demand shifters play a secondary role in the US employment polarization. We therefore conclude that, on average, CETC and demand effects are the most important determinants of workers reallocation from middle skill occupations to high and low skill occupations.

6 Discussion

There is a growing literature studying the role of computers, automation and general purpose technologies for labor market outcomes, Aghion *et al.* (2002), Eden and Gaggl (2018), Acemoglu and Restrepo (2018), Aum *et al.* (2018), Burstein *et al.* (2019). In measuring capital, these studies typically rely on survey data for a handful of equipment goods, mostly computers. One of the key advantages of our measurement is that we see disaggregated data for all equipment categories and that our series are consistent with NIPA's measurement of equipment stocks.

To study the effect of particular equipment categories on labor market outcomes, we modify the commodity space of the economy in Section 3 to model occupational capital as an endogenous composite of different capital goods. In Section 6.1, we document the contribution of CETC that relates to specific capital goods for the reallocation of labor in the US between 1982 and 2015. In Section 6.2 we discuss the implications of capital accumulation for the equilibrium allocations.

6.1 Multiple capital goods

Consider a countable set of capital goods of cardinality J indexed by j. These capital goods map to the 24 NIPA equipment categories, including for example computers and communication equipment. Each capital good is produced with a linear technology in the final good, with a rate of transformation q_{jt} specific to each capital good. Occupational capital is an occupation-specific CES aggregator of a subset of capital goods, Ω_{ot}^k of cardinality J_{ot}:

$$k_{ot} = \left(\sum_{j \in \Omega_{ot}^k} \xi_{jot}^{1/\phi} k_{jot}^{(\phi-1)/\phi} \right)^{\frac{\phi}{\phi-1}}, \quad \text{for: } \sum_{j \in \Omega_{ot}^k} \xi_{jot} = 1.$$

The equipment producer now chooses the quantity of each capital good used in the occupation, along with the stock of capital and labor.

The competitive equilibrium is analogous to the one described in the benchmark, except that the capital markets are now indexed by the capital type rather than the occupation. As before, the equilibrium price of capital relative to consumption equals the inverse of the rate of transformation, $\lambda_{jt}^k = 1/q_{jt}$. Given the price of each capital good, the optimal capital allocation in an occupation and the price of occupational capital satisfy:

$$\frac{\xi_{jot}}{\xi_{j'ot}} = \frac{k_{jot}}{k_{j_bot}} \left(\frac{\lambda_{jt}^k}{\lambda_{j't}^k} \right)^{\phi}, \quad \lambda_{ot}^k = \left(\sum_{j \in \Omega_{ot}^k} \xi_{jot} . \lambda_{jt}^{1-\phi} \right)^{\frac{1}{1-\phi}} \tag{19}$$

Hence, given these prices, the equilibrium allocations in this extension of the model are as in the baseline. The capital labor ratio and the relation of the wage per efficiency unit and the occupational price follow from equations 10 and 8. In this sense, the problem of capital allocation within each occupation can be split into two. First, solving for the value of the capital labor ratio, and second, solving for the mix of capital types within the occupational composite, as in equation 19.

We now turn to the quantification of this extended version of the model. We first parameterize the CES aggregator for capital and then run the calibration procedure in Section 4.2. We use the parameterized model to run counterfactual exercises analogous to those of Section 5 and quantify the role of CETC in each capital good on the reallocation of labor across occupations.

To infer the elasticity of substitution across capital goods, we use the ratio of the first order condition for the occupational good producer across capital goods, equation 19:

$$\ln \lambda_{jt}^k k_{jot} = \ln \lambda_{jt}^k k_{j_b ot} + (1-\phi) \ln \left(\frac{\lambda_{jt}^k}{\lambda_{j_b t}^k} \right) + \ln \frac{\xi_{jt}}{\xi_{j_b t}}.$$

We observe all the elements of the above equation, except for the shares by capital type, $\frac{\xi_{jt}}{\xi_{j_b t}}$. Therefore, we estimate the following regression equation:

$$\ln \lambda_{jt}^k k_{jot} = \beta_{1j} + \beta_2 t + \beta_3 \ln \left(\frac{\lambda_{jt}^k}{\lambda_{j_b t}^k} \right) + \epsilon_{jt},$$

where $\epsilon_{jt} = \ln \frac{\xi_{jt}}{\xi_{j_b t}} + \nu_{jt}$, and ν_{jt} is an error term, normally distributed, mean-zero, and i.i.d. across observations. We take changes in the ratio of capital prices over time, $\frac{\lambda_{jt}^k}{\lambda_{j_b t}^k}$, as exogenously determined by changes in technology. We then estimate regression equation above in first differences, using OLS. We consider 24 capital goods, over 34 years, between 1982 and 2015 and estimate an elasticity of substitution of $\phi = 1.27$ (se: 0.025). Given the estimate of ϕ, we set the capital shares in each occupation to match the expenditure shares for each capital good.

The paramaterization of the CES aggregator for the stock of capital implies a path for prices and stocks of occupational capital that is different from our baseline, which was constructed using a linear aggregator. The CES aggregator generates a stronger average decline in the relative price of capital to consumption and a smaller dispersion across occupations in both the price and the stock. The yearly decline in the price of capital goes from 7.0% in our baseline to 10.2% with the CES aggregator, on average across occupations. The log variance of the price in 1982 reduces from 0.70 in the baseline to 0.18 with the CES aggregator, while the log variance of the stock halves.

Table 6 shows the contribution of CETC for the reallocation of labor, separately for all capital goods (column *all*) and for the two capital goods with the strongest impact on allocations: *computers and software* and *communication* equipment. First, our findings on the role of CETC for labor reallocation are robust to modelling the occupational capital

Table 6: CETC across capital goods.

	Data	Baseline CETC	Multiple capital goods all CETC	computers and software	communication
Fraction moving into:					
High-skill	10.37	9.45	6.25	1.52	2.52
Middle-skill	-13.89	-10.24	-7.77	-2.08	-3.27
Low-skill	3.51	0.80	1.52	0.56	0.75
Managers	4.70	4.26	-1.02	0.24	0.24
Professionals	5.67	5.19	7.28	1.29	2.28
Technicians	-0.07	0.70	0.29	0.13	0.12
Sales	-1.28	-4.06	-4.55	-0.90	-1.29
Administrative Services	-4.63	-6.23	-8.29	-1.90	-3.45
Low-Skilled Services	3.51	0.80	1.52	0.56	0.75
Mechanics and Construction	-1.62	-0.97	-0.87	0.05	-0.02
Precision Production occs	-2.00	-1.37	-0.69	-0.30	-0.13
Machine operators	-4.08	0.53	2.09	0.27	0.35
Transportation	-0.21	1.15	4.25	0.57	1.16

Note: entries are in percent. Columns "Baseline" and "Multiple capital goods" present the outcome attributed to the decline in the price of capital relative to consumption via the counterfactuals. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction when we shut down CETC. "High-skill" occupations are managers and professionals. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations.

bundle. The model with multiple capital goods predicts that CETC generates 60% of the flow of labor toward middle-skill occupations (compared to 91% in the baseline), 56% of the flow of labor out of middle-skill occupations (compared to 74% in the baseline), and 43% of the flow of labor toward low-skill occupations (compared to 23% in the baseline). The slightly smaller effect we measure for CETC in the framework with multiple capital substitutable goods is due to the fact that we also estimate a lower elasticity of substitution across occupational goods in final output, 0.81 compared to 1.33 in the baseline.

We then use our model with multiple capital goods to evaluate the role of computer and communication equipment for the reallocation of labor. Table 6 shows that CETC in both capital goods generates a reallocation of labor out of middle-skill occupations and into high- and low- skill occupations. However, the effect of communication equipment CETC is stronger. This is particularly so for high- and middle- skill occupations, where CETC in communication equipment generates an effect that is 65% and 57% higher than that of CETC in computer, respectively. This difference is mainly due to the differential effect that technology embodied in these two types of capital has on professionals and administrative services. These two occupations record the highest shares of communication equipment, in the CES aggregator of capital in 2015, at levels higher than 50%.

Overall, the average absolute change in employment allocation across occupations generated by CETC is higher for communication equipment (0.99 p.p.) than for computers, (0.62 p.p.). Our results highlight the importance of studying broader equipment categories, other than computers and software. This is particularly important for the post-2000 period, where the stock of computers and software experienced a slow in growth while communication equipment has continued its linear trend and has now surpassed the efficiency units value of the stock of computers, see Figure 12 in the Online Appendix.

6.2 Capital accumulation

A distinctive feature of equipment is its durability. To the extent that technology is embodied in capital, technology is also vintage specific. Measures of efficiency units of capital, as in Greenwood *et al.* (1997), have the advantage of summarizing complicated features of the vintage composition of the stock into a single aggregate. This is the approach that we take both in the baseline model and the extension discussing multiple capital goods.

An important feature of the embodied nature of technology is that technological changes shift the returns to capital accumulation. Capital accumulation and output growth would necessarily be unbalanced in an environment where there are multiple capital goods and therefore multiple trends for investment-specific technical change, as well as arbitrary elasticities of substitution across different inputs and outputs. This feature poses a major challenge in characterizing the equilibrium path of the economy.

To make progress, we restrict the parameter space of the economy to an aggregator of capital at the occupation level, and an aggregator of occupational output that display unitary elasticity, i.e. Cobb-Douglas. In addition, we restrict the occupation specific component of the scale parameter of the distribution of talent to grow at the same rate as the measure of investment-specific technical change at the occupation level. Therefore, technological growth is Hicks-neutral.

As we show in the Online Appendix, this economy displays a BGP where final output, occupational output and capital grow at constant albeit different rates. As in Greenwood *et al.* (1997) capital grows faster than output and the return to capital declines at constant rates. Because the shares of occupational output are constant along the BGP (due to the Cobb-Douglas structure of the demand), occupational prices exactly offset the effect of CETC on occupational output. Capital-labor ratios, measured in efficiency units, are constant along the equilibrium path as they are in our baseline economy. Finally, the detrended version of this economy is observationally equivalent to the economy discussed in section 6.1.

7 Conclusions

We document two new facts. First, there is substantial heterogeneity in the capital bundles used by different occupations, and therefore in CETC. Second, workers' exposure to CETC varies considerably across occupations, as a function of heterogeneity in the intensity of capital use and in the elasticity of substitution between capital and labor. Through the lens of a general equilibrium model of occupational choice, we find that CETC accounts for 91% of the gross labor reallocation across occupations observed in the US since 1982. CETC is particularly important in explaining the gains in employment at the top of the skill distribution.

Occupations with higher skill requirements experienced strongest CETC. These occupations also gained employment overall. Our structural model rationalizes these gains in employment through capital-labor complementarity, as well as a relatively substitutable occupational output. As the demand for higher skill occupations shifted upwards, both capital and labor reallocated toward those occupations. How changes in the demand for skills feed back into the pace of CETC is still an open question.

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Online Appendix

A Data construction

A.1 Data description and sources

All data mentioned in this section are publicly available and were retrieved from the Bureau of Economic Analysis, Census Bureau, FRED and O*NET websites as of March 30th 2020.

A. National Income and Product Accounts (NIPA-BEA).

1. Table 2.1. Current-Cost Net Stock of Private Fixed Assets, Equipment, Structures, and Intellectual Property Products by Type.

2. Table 2.7. Investment in Private Fixed Assets, Equipment, Structures, and Intellectual Property Products by Type.

3. Depreciation rates estimates from BEA by equipment type `https://apps.bea.gov/national/pdf/BEA_depreciation_rates.pdf`.

4. Table 2.4. Current-Cost Depreciation of Private Fixed Assets, Equipment, Structures, and Intellectual Property Products by Type.

B. Prices.

1. Personal consumption expenditures: Nondurable goods (chain-type price index), Federal Reserve Economic Data (FRED), annual series 1958-2016.

2. Annual Quality-Adjusted Price Index for Investment by equipment type. Own estimates following the methodology in Cummins and Violante (2002).

C. Labor Market Outcomes.

1. We use the Annual Social and Economic Supplement (ASEC) from the Current-Population Survey as available in Flood *et al.* (2019), 1983-2016.

2. Occupational crosswalks between occupational classifications in CPS from Acemoglu and Autor (2011) up to 2002. After that we use the classification from Deming (2017).

D. Use of Tools by NIPA Equipment type at the occupational level.

- Measures of tool requirements per occupation from the text of the 1977 Dictionary of Occupational Titles.

- Tools and Technology module in O*NET 23.4 as our measure of tool usage in 2016.

- Crosswalk between NIPA equipment type and commodity family in O*NET, adjusted from Aum (2017).
- Crosswalk between occupations in O*NET (soc-code) from Acemoglu and Autor (2011). For new soc-code we use the Dictionary of Occupational Titles (DOT) 2016 and its correspondence to DOT 2010 to express all soc-code in O*NET as occupations 2010 (occ2010).

A.2 Tool requirements in the DOT 1977

We use Natural Language Processing algorithms to construct data on tool requirements in 1980 from the occupational definitions in the Dictionary of Occupational Titles. We exploit the spacy NLP package in phyton. We first tokenize and lemmatize the text to prepare it for analysis. This avoids matches to be confounded by differences in case/capitalization, number (singular vs. plural), punctuation, or word form. We collect all nouns in sentences and match them to the Commodity titles or T2 Examples available in the O*NET dataset.[37] This builds a corpus which we use for string-matching. That is, we look for matches to Commodity Titles or T2 Examples within the text describing a DOT job.[38] In addition to identifying exact matches of T2 Examples and Commodity Titles, an additional set of search terms is also created from the set of T2 Examples and/or Commodity Titles, as described below.

Constructing search terms. Many T2 Examples and Commodity Titles involve both more general and specific variants of some type of object. For example, the set of T2 Examples contains both the more general term 'straightedges' and the more specific forms 'precision straightedges', 'steel straightedges', and 'aluminum straightedges'. In such a case, a DOT job description that simply includes the term 'straightedges' would match against the more general form. But many other terms occur only in the specific form, e.g., there are 38 T2 Examples associated with some type of computer ('desktop computers', 'laptop computers', 'personal computers', 'parallel computers', etc.), but no general term that is simply 'computer' or 'computers'. Unfortunately, many of the DOT job definitions make references to these more general forms, and therefore do not match against either T2 Examples or Commodity Titles. To address this problem we create an additional set of search terms.

Most of the composite terms (e.g., 'desktop computers', 'digital video cameras', 'commercial fish or shark hooks') are of the form where the general noun in question is the last word in the term. Therefore, two additional sets of search terms have been created, which contain all the unique last words of the set of T2 Examples and Commodity Titles, respectively.

Many of the general terms have trailing words which are themselves rather generic, such

[37]We could alternatively run the matching on the full universe of commodities listed on UNSPSC but both of them yield very similar results.

[38]While we are interested in identifying tools that are being used by workers, at present, no attempt is being made to prune down to a subset of words within DOT job definitions that are either (a) nouns or (b) objects of verbs, since the NLP tools considered (spacy and NLTK) do not appear to do a robust enough job in this sort of part-of-speech (POS) tagging and dependency parsing.

as ‘equipment’, ‘system’, or ‘machine’. To avoid large numbers of uninformative matches to these sorts of words, a number of trailing words have been removed from the set of search terms. At present, this consists of the following list: ‘machine’, ‘accessory’, ‘equipment’, ‘system’, ‘kit’, ‘analyzer’, ‘unit’, ‘tool’, ‘device’, ‘supply’, ‘apparatus’, ‘meter’, ‘instrument’, ’machinery’, ‘therapy’, ‘recorder’, ‘challenge’, ‘use’, ‘tester’, ‘set’, ‘product’, ‘component’, ‘console’, ‘work’, ‘surface’, ‘procedure’, ‘test’, ‘facility’, ‘plant’, ‘application’, ‘assist’, ‘chart’, ‘material’, ‘standard’, ‘assembly’, ‘environment’. These are words that are sufficiently generic that they could be associated with a more specific term for a tool in almost any context, with no real information about function. A secondary criterion, which motivated the creation of this list in the first place, is that many of the entries in this list (if included in the search) have the largest number of matches against the DOT job definitions. That is, because the words are sufficiently generic, they occur in many different unrelated job definitions.

DOT-to-O*NET crosswalk search. In addition to searching DOT terms for matches in T2 Example or Commodity Title, a DOT-to-O*NET crosswalk is also performed to determine if a DOT term is associated with the subset of T2 Examples and Commodity Titles linked to the O*NET-crosswalked occupation. The intent of this is to provide some support for a particular match among many, by indicating that the same term is associated both with a DOT occupation and an O*NET occupation to which it is linked. A crosswalk is made from DOT to O*NET, using the data provided at data.widcenter.org (/download/soc2010/dotsoc10.xls). All T2 Examples and Commodity Titles associated with the O*NET occupation identified through the crosswalk are examined, to determine if there is a match.

A.3 Details of the series

A) Assignment of tool requirements to occupations by equipment type. We build a tool-based index of occupational equipment requirements for each NIPA equipment type. To do so, we proceed in four steps. First, we classify the tools listed in each occupation into one of the 24 equipment categories in NIPA by updating and expanding the cross-walk between commodity family and NIPA equipment provided Aum (2017), see online appendix for details. The tool requirements in each occupation stem from the 1977 Dictionary of Occupational Titles and from the Tools and Technology supplement of O*NET (2016). We linearly interpolate these tool requirements to generate an annual time series of the tool requirements in each occupation. Albeit a crude interpolation, we find that the requirements predicted for 2006 are consistent with the information from the 2006 O*NET Tool and Technology requirements supplement (which is used for validation purposes only). The DOT measures that we construct have no information on software, so we assign them the tool requirements’ for computers in 1982.[39] Second, we sum all the tools used in each equipment at the occupational level defined by the soc-code 2016 (standard classification of occupations) of the O*NET in 2016. Third, we implement a crosswalk from soc-code 2016 to soc-codes 2010, which can be matched to the 2010 census classification of occupations following the

[39] Our results are robust to assuming zero requirements for software back then.

US Census crosswalk. [40] Fourth, once we aggregate occupations in O*NET 2016 to the 2010 census classification, we implement the occupational crosswalk from Deming (2017) to further aggregate the 2010 census classification into a comparable occupational classification for the annual data from the ASEC-CPS, 1980-2016. [41]. This process generates an index of the occupational tools for 24 NIPA equipment and 342 occupations.

B) Labor market outcomes. Data on wages and employment come from the Annual Social and Economic Supplement from the CPS, for years 1983 to 2016. We use "asecwt" to weight observations and generate full-time equivalent measures of workers multiplying the person weight by the average number of weekly hours in the previous year divided by 40 (hours per week) and the number of weeks worked in a year divided by 51 (weeks per year). Hourly wages are computed as total labor income divided by the average hours worked in a year multiplied by the number of weeks worked in a year. Labor income corresponds to the pre-tax wage and salary income deflated using the price of consumption for non-durable goods.

We keep workers of at least 16-years old and at most 65-years old. We eliminate observations where average weekly hours are less than 30. We assign a value of 80 hours whenever workers report higher than 80 hours in a week. We implement the following data trimming. We drop observations with missing data for income or n.i.u., and trim the top and bottom 1% of the distribution of labor income.

A.4 Stocks in efficiency units

Given the nominal series for investment $\tilde{x}_{jt}$ we construct measures of efficiency units of investment using the quality adjusted price of investment.

$$x_{jt} \equiv \frac{\tilde{x}_{jt}}{\lambda^k}$$

To deflate nominal investment, we use the chained-weighted price of capital, Figure 11.To properly compute quality-adjusted stocks, capital prices need to be adjusted by changes in the quality of investment. We use extrapolations of the series of quality-adjusted capital prices constructed by Gordon (1987), following the methodology proposed in Cummins and Violante (2002).[42] The price of consumption corresponds to a chained-weighted price index of personal consumption expenditures (known as PCE).

Measures of capital depreciation available from the BEA account for both economic and physical obsolescence. To correct the measurement and obtain estimates for physical depreciation we rely again on quality-adjusted prices of investment. In an economy with linear production technology for investment, the change in the quality-adjusted price through time captures changes in the quality of the stocks, and therefore obsolescence. Let δ_{jt} be the

[40] Between 2016 and 2010 only a few new soc-codes were created. For these new soc-codes, we first look at its correspondence to the DOT and then match the DOT to soc-code 2010.

[41] Deming (2017) updates the broadly use crosswalks from Autor (2015) up to 2002 to be comparable to the remainder of the years

[42] This entail using a linear projection of the series of investment prices adjusted by quality into the corresponding deflators available from NIPA. More details in the online appendix.

physical depreciation of capital j in period t; d_{jt} be the depreciation rate reported by BEA. Physical depreciation satisfies:

$$d_{jt} = 1 - (1 - \delta_{jt})\frac{q_{jt-1}}{q_{jt}}.$$

We assume a linear technology to transform consumption goods into investment at rate q_{jt}, in the tradition of Greenwood *et al.* (1997). Then, the quality-adjusted relative price of capital relative to consumption, $\frac{\lambda^k}{\lambda^y}$ is the inverse of the rate of transformation q_{jt}, or CETC.

With these ingredients, we use the law of motion for capital to construct stocks,

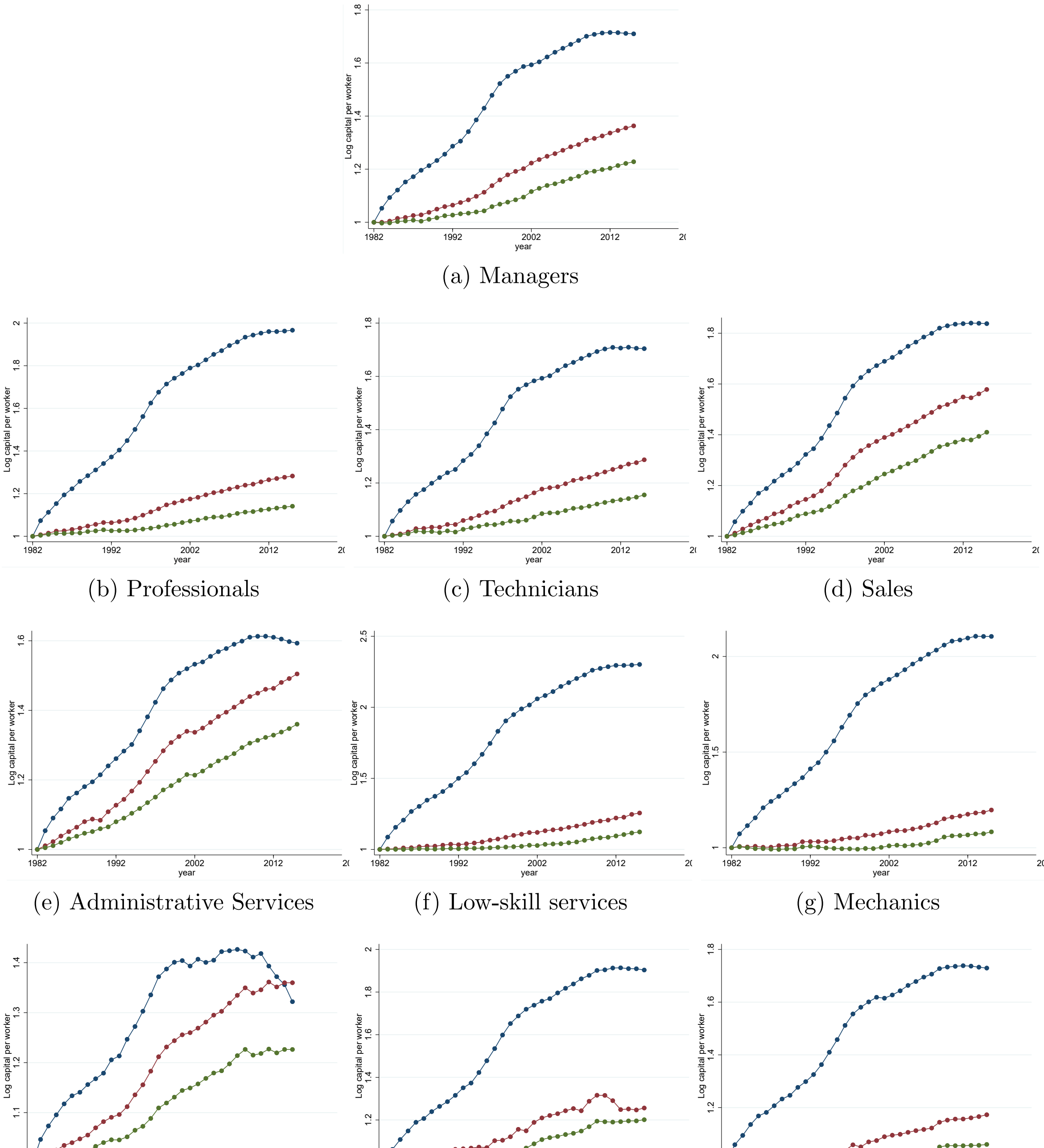
$$k_{jt+1} = k_{jt}(1 - \delta_{jt}) + x_{jt}.$$

A.5 Assignment of stocks to occupations

Our assignment of stocks (equation 1) implies the allocation changes due to disparities in CETC across capital types through its impact in the quality-adjusted value of each of the stocks, k_j. The capital allocation also moves in response to shifts in the share of employment across occupations, by changing the distribution of tools for each capital type. Figure 9 illustrates the role of these channels comparing the dynamics of the occupational stock to what we would have been obtained if either (a) the capital requirements were held constant to its 1982 levels ($\text{req}_{jot} = \text{req}_{jo1982}$, red line) or (b) in addition, the level of nominal investment was held constant to its 1982 level (green line).[43]

The difference between the benchmark data and a constant requirements series is the tool and employment reallocation effect. When in addition the nominal investments are held fixed, the dynamics of the stocks is explained by the decline in the relative price of capital to consumption, our measure of CETC.

[43] In constructing fixed capital requirements we reweight the proportion of tools allocated to each 3 digit allocation within a (1-digit) occupation so that it replicates the distribution of shares in 1982.



(a) Managers

(b) Professionals

(c) Technicians

(d) Sales

(e) Administrative Services

(f) Low-skill services

(g) Mechanics

(h) Precision

(i) Machine Operators

(j) Transportation

Figure 9: Allocation of capital to occupations.

Each panel corresponds to an occupation. The stock of capital per worker, normalized to 1982, is in blue. The stock of capital fixing the capital-requirements share to its 1982 level in red. The stock of capital per worker fixing the capital requirements and the nominal investment to their 1982s level is in blue.

B Derivations

B.1 Cross-price elasticity of labor demand

Suppose capital, k, and labor, n, are used to produce output via a constant returns to scale technology. Let y be the quantity produced, at price p_y; and let r, w be the prices of labor and capital. Suppose capital and labor are paid their marginal products.

The assumptions that the production structure is constant returns and inputs are paid their marginal costs imply that:

$$y = n\frac{\partial y}{\partial n} + k\frac{\partial y}{\partial k}. \tag{20}$$

Differentiating the above equation with respect to capital,

$$\frac{\partial y}{\partial k} = n\frac{\partial^2 y}{\partial n \partial k} + k\frac{\partial^2 y}{\partial k^2} + \frac{\partial y}{\partial k},$$

and therefore:

$$k\frac{\partial^2 y}{\partial k^2} = -n\frac{\partial^2 y}{\partial n \partial k}. \tag{21}$$

The total differential of output satisfies:

$$dy = dn\frac{\partial y}{\partial n} + dk\frac{\partial y}{\partial k},$$

$$p_y dy = wdn + rdk. \tag{22}$$

We totally differentiate equation 20 and replace 22 to obtain:

$$ydp_y = ndw + kdr.$$

As in Chirinko and Mallick (2011), we can rewrite this equation as a function of the cross-elasticity of interest. Let the price-elasticity of labor supply be $\eta_{nw} = -\frac{\frac{dn}{n}}{\frac{dw}{w}}$; the demand elasticity for output $\rho = -\frac{\frac{dy}{y}}{\frac{dp_y}{p_y}}$; and the cross-price elasticity of labor demand, $\eta^c = -\frac{\frac{dn}{n}}{\frac{dr}{r}}$. Then,

$$\frac{p_y dy}{\rho} = -\frac{wdn}{\eta_{nw}} + \frac{rdk}{\eta^c}\frac{kdn}{ndk}. \tag{23}$$

Using the assumption of constant returns, we obtain a value for the last term in the above equation:

$$\frac{p_y y}{rk} = \frac{nw}{kr} + 1.$$

Define the share of labor expenses in the value of output as $\kappa = \frac{nw}{p_y y}$, then:

$$\frac{kdn}{ndk} = \frac{wdn}{rdk}\frac{1-\kappa}{\kappa},$$

and we can rewrite equation 23 as

$$\frac{p_y dy}{\rho} = -\frac{wdn}{\eta_{nw}} + \frac{wdn}{\eta^c}\frac{1-\kappa}{\kappa} \tag{24}$$

Finally, consider the change in labor that results from an exogenous change in capital. We start from the expression for the supply elasticity of labor $dn = \frac{n\eta_{nw}}{w}dw$ and expand the total differential dw by replacing the price of labor for its marginal product $dw = d\left(p_y \frac{\partial y}{\partial n}\right)$. Replace equation 21 and define the elasticity of substitution between capital and labor, $\sigma = \frac{p_k p_n}{p_y^2 y \frac{\partial^2 y}{\partial n \partial k}}$ to obtain:

$$\frac{p_y dy}{\rho} = \frac{rdk}{\sigma} - \frac{wdn}{\kappa}\left(\frac{1}{\eta_{nw}} + \frac{1-\kappa}{\sigma}\right) \tag{25}$$

Combining equations 22, 24 and 25 yields the expression for the elasticity in equation 18.

B.2 Model

We describe the derivations for allocation of workers across occupations and their average wages. We start from equation 11. Without loss of generality, we solve for the probability of a worker to choose occupation 1,

$$Prob\left(n_{o'ht}(i) < n_{1ht}(i)\frac{\lambda_{1t}^n}{\lambda_{o't}^n}\right), \ \forall o$$

Therefore,

$$\pi_{1ht} = \int F_{oht}^1\left(n, \frac{\lambda_{1t}^n}{\lambda_{2t}^n}n, ...\frac{\lambda_{1t}^n}{\lambda_{ot}^n}n|h\right) dn$$

where F_{oht}^1 is the projection of the CDF on the first argument. Using the assumption of independence in the efficiency unit draws and the extreme distribution we can solve for these probabilities in closed form:[44]

$$\pi_{1ht} = \frac{T_{1ht}(\lambda_{1t}^n)^\theta}{\sum_o T_{oht}(\lambda_{ot}^n)^\theta},$$

or, more generally,

$$\pi_{oht} = \frac{T_{oht}(\lambda_{ot}^n)^\theta}{\sum_{o'} T_{o'ht}(\lambda_{o't}^n)^\theta}.$$

Similarly, we compute the expected efficiency units of workers of group h who choose occupation o:

$$E(n|oht) = \int_0^\infty \tau dG_{hot}(\tau),$$

where G_{hot} is the CDF of workers of type h who choose occupation o; also a Frechet with

[44] Lind and Ramondo (2018) show how to compute these probabilities for arbitrary patterns of correlation.

scale parameter $\overline{T}_{oht} = \sum_{o'} T_{oht}(\frac{\lambda^n_{o't}}{\lambda_{ot}})^{\theta}$. It follow that:

$$E(n|oht) = \left(\frac{T_{oht}}{\pi_{oht}}\right)^{\frac{1}{\theta}} \Gamma(1-\frac{1}{\theta}).$$

This expression for the average efficiency units of workers allocated to each occupation determines the average wages of workers type h choosing occupation o:

$$w_{oht} \equiv \varkappa_{oht} E(\tau|oht) = \left(T_{oht}\sum_{o} \lambda^{n\ \theta}_{ot}\right)^{\frac{1}{\theta}} \Gamma\left(1-\frac{1}{\theta}\right).$$

The determinants of occupational choice. We analyze the drivers of occupational choice in our framework. To do so, it is useful to describe the allocation of workers of group h via the probability of choosing occupations relative to a baseline occupation at time t, $\{\Xi_{oht}\}_{o=1}^{O}$:

$$\Xi_{oht} \equiv \frac{\pi_{oht}}{\pi_{o_b ht}} = \frac{T_{oht}\lambda^{n\theta}_{ot}}{T_{o_b ht}\lambda^{n\theta}_{o_b t}}.$$

Define g_x to be the growth rate of a variable x between period t and $t+1$. The change in the allocation of workers between periods t and $t+1$ for group h is:

$$g_{\Xi_{oh}} = g_{T_{oh}} - g_{T_{o_b h}} + \theta\left(g_{\lambda^n_o} - g_{\lambda^n_{o_b}}\right).$$

Hence, an occupation gains employment relative to a baseline group if the scale parameter grows faster than the baseline, i.e. the labor productivity of the workers in that group and occupation; or if the gains in the wage in efficiency units are larger than for a baseline group. The tail of the distribution of efficiency units of labor θ is indeed the price elasticity of the labor supply as summarized by Ξ.

Given the zero-profit condition in occupational output, the gains in wages per efficiency units across occupations are a function of the change in the price of occupational output and the price of capital (see equation 14). On a first order approximation, these gains are:

$$g_{\lambda^n_o} = sh^y_{ot} g_{\lambda^y_o} - sh^k_{ot} g_{\lambda^k_o},$$

where $sh^y_{ot} = \frac{(\frac{1}{1-\alpha})^{\sigma_o}\lambda^{y\ 1-\sigma_o}_{ot}}{\lambda^{n1-\sigma}_{ot}}$ and $sh^k_{ot} = \frac{(\frac{\alpha}{1-\alpha})^{\sigma_o}\lambda^{k\ 1-\sigma_o}_{ot}}{\lambda^{n1-\sigma}_{ot}}$. Therefore, we can express the change in the allocation of labor as:

$$g_{\Xi_{oh}} = \theta\left(\frac{1}{\theta}g_{T_{oh}} - \frac{1}{\theta}g_{T_{o_b h}} + sh^y_{ot}g_{\lambda^y_o} - sh^y_{o_b t}g_{\lambda^y_{o_b}} - (sh^k_{ot}g_{\lambda^k_o} - sh^k_{o_b t}g_{\lambda^k_{o_b}})\right).$$

For fixed shares sh^y_{ot} and sh^k_{ot} and occupational output price, workers move to occupation o, if the price of capital declines in the occupation or the scale parameter increases. To fix ideas, consider the Cobb-Douglas case, $\sigma_o = 1\ \forall o$, for which we obtain:

$$g_{\Xi_{oh}} = \theta\left(\frac{1}{\theta}g_{T_{oh}} - \frac{1}{\theta}g_{T_{o_b h}} + \frac{\alpha}{1-\alpha}(g_{\lambda^y_o} - g_{\lambda^y_{o_b}}) - \frac{1}{1-\alpha}(g_{\lambda^k_o} - g_{\lambda^k_{o_b}})\right).$$

For a fixed price of occupational output, workers flow to occupation o proportionally to the increase in scale parameter associated to the occupation. Workers flow occupation o in relation to the growth rate of the relative price of capital in the occupation, with elasticity $-\frac{\theta}{1-\alpha}$.

To analyze the aggregate response of occupational choice, rather than that of one labor group, we aggregate the responses across labor groups. Describe the allocation of workers to occupations by $\{\Xi_{ot}\}_{o=1}^{O}$, for:

$$\Xi_{ot} \equiv \sum_h \Xi_{oht}\pi_{ht} = \sum_h \frac{T_{oht}\lambda_{ot}^{n\theta}}{T_{o_b ht}\lambda_{o_b t}^{n\theta}}\pi_{ht}.$$

Using a log-linear approximation, we obtain the change in the allocation of workers:

$$g_{\Xi_{ot}} = \sum_h sh_{oht}(\pi)(g_{\Xi_{oh}} + g_{\pi_{ht}}),$$

where $sh_{oht} = \frac{\Xi_{oht}\pi_{ht}}{\Xi_{ot}}$. Hence, changes in the allocation of workers are fully described by the within group change $g_{\Xi_{oh}}$ and the exogenous change in the measure of each group, $g_{\pi_{ht}}$.

B.3 Multiple capital goods

We describe the balanced growth path allocation with capital accumulation. Assume that final output is a Cobb-Douglas aggregator of occupational output:

$$y_t = \prod_o y_{ot}^{\omega_o}.$$

Occupational output is a CES aggregator of capital and labor as in the benchmark economy:

$$y_{ot} = \left[k_{ot}^{\frac{\sigma_o - 1}{\sigma_o}} + \exp(\gamma_o^n t)\tilde{n}_{ot}^{\frac{\sigma_o - 1}{\sigma_o}}\right]^{\frac{\sigma_o}{\sigma_o - 1}}.$$

Capital at the occupation level is a Cobb-Douglas aggregator of capital of different types:

$$k_{ot} = \prod_{J_{ot}} k_{ojt}^{a_{oj}}$$

The law of motion for capital of each type is:

$$k_{jt+1} = \frac{x_{jt}}{q_{jt}} + k_{jt}(1-\delta)$$

where changes in q_{jt} over time are a measure of investment-specific technical change in capital j and x_{jt} is investment in capital j at time t. Last, workers maximize the present-discounted value of lifetime utility from consumption,

$$\sum_{t=0}^{\infty} \beta^t \log(c_t(i)),$$

where β is the preference discount factor and $\log(c_t)$ is the per-period utility.

The market clearing conditions for the economy are:

$$c_t + \sum_j x_{jt} = y_t$$

$$\sum_o k_{ojt} = k_{jt}$$

The optimality condition for capital accumulation

$$\frac{\lambda_t}{\beta\lambda_{t+1}} = \frac{q_{jt+1}}{q_{jt}}\left[(1-\delta) + \omega_o \frac{y_{t+1}}{y_{ot+1}}\left(\frac{y_{ot+1}}{k_{ot+1}}\right)^{\frac{1}{\sigma_o}} \frac{k_{ot+1}}{k_{jt+1}} \frac{a_{oj}}{q_{jt+1}}\right]$$

where β is the discount factor.

The return to capital j declines at the rate of investment specific technical change, q_{jt+1}. We are left to show that $\frac{y_{t+1}}{y_{ot+1}}\left(\frac{y_{ot+1}}{k_{ot+1}}\right)^{\frac{1}{\sigma_o}} \frac{k_{ot+1}}{k_{jt+1}}$ grows at rate $\gamma_{t+1}^{q_j}$ so that the LHS of the Euler equation is constant. Given the production technology for occupational output the growth rate of output satisfies,

$$g_{y_o} = sh_{k_o} g_{ko} + sh_{n_o} g_{n_o}.$$

Assume that the average talent drawn to an occupation grows at a constant rate that satisfies, $g_{n_o} \equiv \gamma_o^n = g_{k_o}$. This assumptions implies that technological changes is neutral. The production technology for final output and the aggregator for capital imply:

$$\gamma_y = \prod_o \gamma_{y_o}^{\omega_o},$$

$$\gamma_{k_o} = \prod_j \gamma_{k_{oj}}^{a_{oj}},$$

where γ are constant growth rates. We can rewrite the growth rate of the term of interest as

$$\frac{\prod_o \gamma_{y_o}^{\omega_o}}{\gamma_{y_o}} \frac{\gamma_{k_o}}{\gamma_{k_j}}.$$

We have shown that $\gamma_{y_o} = \gamma_{k_o}$. The feasibility condition for capital implies $\gamma_{kj} = \frac{\gamma_y}{\gamma^{q_j}}$, therefore

$$\frac{\gamma_y}{\gamma_{kj}} = \gamma^{q_j}.$$

C Parameterization of the model

Elasticity of substitution between capital and labor: instruments. To solve endogeneity problems of relative input prices to the capital-labor ratio we construct the following instruments.

Lagged Capital-Labor ratio. We use 1-year lags for the capital-labor ratios in each occupation measured as described in the body of the paper.

Birth Rates. We use lagged birth rates br to pin down exogenous variation in the supply of labor. The instrument in year t is:

$$br_{t-\underline{a}},$$

where $\underline{a}$ is the minimum age in the sample (16). These two instruments are used in the pooled regression across 1-digit occupations, where we impose a common elasticity of substitution across occupations.

Birth Rates (occupations) We modify the instrument described before multiplying by the share of employment allocated to a 1-digit occupation in 1980.

$$br_{t-\underline{a}}sh^{l}_{o1980},$$

where $sh^l_{ot} = \frac{l_{ot}}{l_t}$ and l_{ot} as workers in occupation o at time t, while l_t is the total number of workers at t.

Scale parameters of the Frechet distribtuion. The model defines a link between the occupational choice of workers of a given group h and the scale parameters, T_{oht}:

$$\frac{\pi_{oht}}{\pi_{o_b ht}} = \frac{T_{oht}}{T_{o_b ht}} \left(\frac{\lambda^n_{ot}}{\lambda^n_{o_b t}}\right)^{\theta}, \tag{26}$$

where o_b is a baseline occupation, which we set to be low-skill services (the occupation with the lowest average wage in 1982). The equation above delivers two important points for our inference. First, the level of the scale parameters for a group of individuals (absolute advantage) does not influence the occupational choice. That is, the fact that high-school may, on average, be endowed with lower efficiency units for labor than college graduates does not have a bearing on the different occupational choice of the two groups. Second, the link between the scale parameters and the occupational choice in equation 26 relies on a measure of wages per efficiency units across occupations.

To pin down the absolute advantage across labor groups, we use wage differentials. Equation **??** shows that the level of the scale parameters influence the average wage a group receives. In particular, one can infer the scale parameters across labor groups in an occupation from data on average wages and the relative frequency of that occupation:

$$\frac{w_{ht}}{w_{h_b t}} = \left(\frac{\sum_o T_{oht}(\lambda^n_{ot})^{\theta}}{\sum_o T_{oh_b t}(\lambda^n_{ot})^{\theta}}\right)^{\frac{1}{\theta}} = \left(\frac{T_{o_b ht}}{T_{o_b h_b t}} \frac{\pi_{o_b h_b}}{\pi_{o_b h}}\right)^{\frac{1}{\theta}},$$

where h_b is a baseline demographic group, which we set to be a young, male, worker without a four-year college degree. The above equation links differences in the scale parameter across groups in occupation o_b at time t, $\frac{T_{o_b ht}}{T_{o_b h_b t}}$, to average wages and frequency of occupation o_b for the groups.

To complete the inference of the scale parameters, we need to pin down the level of efficiency units in each year, $T_{o_b h_b t}$. To do so, we use the specification of average wages (equation **??**), which links the wages of our baseline labor group to $T_{o_b h_b t}$ and the wage per efficiency unit in our baseline occupation. To measure the latter, we use data on capital per worker. Combining the wage equation with the capital per worker equation, we write:

$$\frac{k_{o_b t}}{\ell_{o_b t}} = \lambda_{o_b t}^{n\sigma_{o_b}-1} w_{h_b t} \left(\frac{\alpha_{o_b}}{1-\alpha_{o_b}} \frac{1}{\lambda_{ot}^k} \right)^{\sigma_{o_b}} \left(\sum_o \frac{\pi_{oh_b t}}{\pi_{o_b h_b t}} \right)^{-\frac{1}{\theta}} \frac{n_{o_b t}}{\ell_{o_b t}}.$$

With a measure of $\lambda^n_{o_b t}$ at hand, we can then pin down the evolution of $T_{o_b h_b t}$ as a residual between the observed change in wages for young, male workers without a college degree and the change in the wage per efficiency units and frequency of managerial occupation for the group. We normalize $T_{o_b h_b t}$ in the in 2015 to 1.

Wages per efficiency units. We choose a profile of wages per efficiency units across occupations so that the model is consistent with capital per worker across occupations, $\frac{k_{ot}}{\ell_{ot}}$. Replacing equation 12 into equation 10, we write differences in capital per worker across occupations as a function of relative wages per efficiency units and observable variables:

$$\frac{k_{ot}}{\ell_{ot}} / \frac{k_{o_b t}}{\ell_{o_b t}} = \left(\frac{\alpha}{1-\alpha} \frac{\lambda_{ot}^n}{\lambda_{ot}^k} \right)^{\sigma_o} \left(\frac{\alpha}{1-\alpha} \frac{\lambda_{o_b t}^n}{\lambda_{o_b t}^k} \right)^{-\sigma_{o_b}} \frac{n_{ot}}{\ell_{ot}} \left(\frac{n_{o_b t}}{\ell_{o_b t}} \right)^{-1} \left(\frac{\lambda_{ot}^n}{\lambda_{o_b t}^n} \right)^{-1}, \tag{27}$$

where $\ell_{ot} = \sum_h \pi_{oht}\pi_{ht}$. The first two terms on the RHS are the capital labor ratios, for labor measured in efficiency units. They are a function of the wage per efficiency units and observables. We observe the price of capital in our dataset and assign a value of 0.24 to the capital share in the production of the occupational good, as estimated by Burstein *et al.* (2019). The remaining terms in equation 27 give the ratio of the average efficiency units supplied by workers to each occupation. This term is not directly observable in the data and is a result of worker's selection into different occupations. The properties of the Frechet distribution allows us to link the selection effect to the occupational choice, and therefore measure differences in per-worker efficiency units from data on occupational choices, given the wage per efficiency unit:

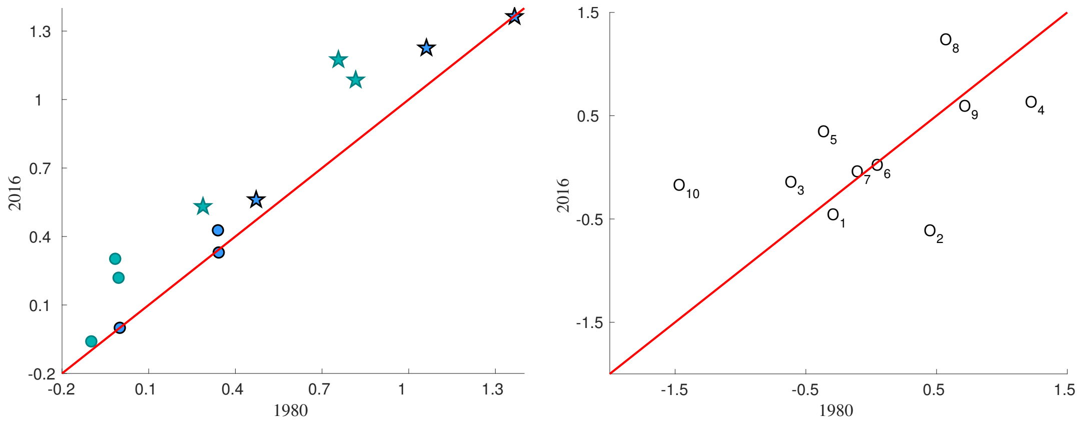
$$\frac{n_{ot}}{\ell_{ot}} = T_{o_b h_b t} \sum_h \pi_{oht}\pi_{ht} \left(\frac{T_{o_b ht}}{T_{o_b h_b t}} \right)^{\frac{1}{\theta}} \left(\frac{1}{\pi_{o_b ht}} \right)^{\frac{1}{\theta}}.$$

With these numbers at hand, equation 27 yields a measure of the variation in the price of labor across occupations scaled by the elasticity of substitution, $\frac{\lambda_{ot}^{n\sigma_o -1}}{\lambda_{o_b t}^{n\sigma_{o_b}-1}}$. With equation 26, we are able to parameterize the dispersion of the scale parameter across occupations for each labor groups and year, up to differences in the elasticity of substitution σ_o.

Outcomes. Figure 10 plots the group and occupation component of the scale parameter of the Frechet distribution. To isolate those two components, we specify T_{oht} to be the product of an occupational component, T_{ot}, a labor group component, T_{ht} and a residual component, $\tilde{T}_{oht}$. In particular, we define the scale parameter for labor group h in occupation o at time t as:

$$T_{oht} = T_{ot} T_{ht} \tilde{T}_{oht}.$$

In the above equation, T_{ht} is the average efficiency units of labor of group h. The profile $\{T_{ht}\}_{h=1}^G$ describes the pattern of absolute advantage across the groups. The pattern of



(a) Labor group component, $\log(T_h)$ (b) Occupation component, $\log(T_o^{\sigma_o-1})$

Figure 10: Scale parameters.

The left panel shows the logarithm of the labor group component of the scale parameter in the distribution of the efficiency units of labor, $\ln(T_h)$. Lighter (green) color indicates females and darker (blue) color indicates males; stars indicate individuals with a 4-year college degree or more and circles indicate individuals without a college degree. The right panel shows the logarithm of the occupation component of the scale parameter in the distribution of the efficiency units of labor transformed to the elasticity, $\ln(T_o^{\sigma_o-1})$. o_i indicates occupation numbered i in the 1-digit Census classification. Our baseline occupation (o_6, low-skill services) have normalized $T_o = 1$. Occupation numbers follow the ordering of occupations in the tables, such as Table 3.

comparative advantage across labor groups is instead described by $\tilde{T}_{oht}$. Last, the profile $\{T_{ot}\}_{o=1}^{O}$ describes the average efficiency units across occupation. For example, an increase in T_o associated to managers implies that individuals become more efficient in managerial occupations, across all groups.[45] To measure the components of T, we estimate, in each year, the following regression equation:[46]

$$\ln T_{oht} = \beta_{ot} d_{ot} + \beta_{ht} d_{ht} + \epsilon_{oht},$$

where the ds are dummies for occupational groups and worker groups and the βs their coefficients. β_o and β_h corresponds to the logarithm of T_o and T_h, respectively.

Figure 10, panel (a), shows the labor group component of the scale parameter, T_h. It increases with the schooling of the group on average, and is higher for males than for females. These findings are mostly a reflection of the structure of wages in the data. The elasticity to which wage differentials across labor groups translate into differences in T_h is shaped by θ. In 2015, the component associated to college graduates is 79 p.p. higher than that associated to individuals without a college degree. The gap in wages between these two groups is 57p.p.

[45]Note that our model does not specify the channel through which an increase in T_o happens. Labor my become more efficient in an occupation due to the accumulation of human capital related to that occupation or because the occupational technology improves and the execution of occupational tasks simplifies.

[46]In estimating the regression by which we measure the components of T, we weight each observations by the measure of workers of each labor type choosing an occupations.

in the same year. The group component associated to males is 11 p.p. higher than that associated to females, while the gender wage gap is of 18 p.p., in 2015. Between 1982 and 2015 the gender wage gap halves and the gap in efficiency units decreases of two thirds.

Figure 10, panel (b), shows the occupation component of the scale parameter in the distribution of the efficiency units of labor transformed by the elasticity of substitution between capital and labor, $T_o^{\sigma_o - 1}$. The dispersion of the occupation component at each point in time is a reflection of the dispersion in the evolution of the price and quantity of capital as well as of the occupational choice. Technicians, administrative services, mechanics, precision production and transportation calibrate an increase in their demand shifters between 1983 and 2016, relative to low-skill services. These are occupations that experience a weaker decline in the price and a weaker increase in the stock of capital and so measure a higher wage per efficiency unit (equation 27), which push down the occupation component (equation 26). The adjustment by the occupational choice pushes up the occupation component (equation 26). This adjustment is stronger for precision production and machine operator, and pushes, respectively, down and up the change of the occupational component between 1982 and 2016.

D Tables and Figures

Table E.I: Equipment assignment by CETC.

Description	Nipa Code	Price	Stock
		1982-2015 annual % change	
i) Computers and peripheral equipment	4	-13.60	18.16
Software	99	-4.94	11.55
ii) High—CETC			
Communication equipment	5	-12.65	14.95
Aircraft	26	-9.53	10.89
Engines and turbines	14	-5.92	5.42
Special industry machinery, n.e.c.	18	-4.81	4.76
Service industry machinery	40	-4.30	5.37
Photocopy and related equipment	10	-4.21	1.50
Medical equipment and instruments	6	-4.21	8.95
Nonmedical instruments	9	-4.21	6.54
iii) Low—CETC			
Electrical transmission and industrial apparatus	20	-3.67	4.40
Fabricated metal products	13	-3.27	0.13
Autos & trucks	22-25	-3.25	5.04
Ships and boats	27	-2.93	1.38
General industrial	19	-2.01	2.40
Other nonresidential equipment	29	-1.86	3.85
Mining and oilfield machinery	39	-1.73	2.81
Office and accounting equipment	11	-1.66	-0.53
Electrical equipment, n.e.c.	41	-1.44	1.15
Metalworking machinery	17	-1.32	0.26
Railroad equipment	28	-1.21	-0.19
Furniture and fixtures	30	-1.06	1.90
Construction machinery	36	-0.74	1.24
Agricultural machinery	33	-0.74	-0.70

Table E.II: CETC and changes in the labor market 1982-2015.

	c Wage growth per year	c Wages	Employment share	
			all	c skilled workers
	c (median, p.p.)	% change 1982-2015		
	(1)	(2)	(3)	(4)
Panel A: All occupations				
	0.8	28.2	0.0	5.6
Panel B: Occupations ordered by change in capital-per-worker				
Bottom third	0.6	20.9	-4.5	3.5
Middle third	0.8	27.0	2.8	7.9
Upper third	1.0	38.3	1.6	7.6
Panel C: Occupations ordered by the type of capital with highest share				
Computer-intensive	0.9	35.1	-4.3	5.6
HCETC intensive	0.8	27.7	6.3	6.3
LCETC intensive	0.6	22.9	-2.1	3.5

Notes: Column (1) reports average wage changes for workers in a given category. Column (2) reports the change in the share of workers. Column (3) reports the change in the share of high-skill workers in a given category. Column (4) reports the change in the share relative to the total in the economy, so the ratio of a given category to the average change reported in column (3) line 1. Panel B classifies occupations the degree of CETC in the bundle of goods used in the occupation. Panel C classifies occupations using the relative intensity across equipment categories.

Table E.III: CETC regressions with task content.

	employment share, p.p. change							
	all				Skilled			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Capital-measures								
Change in capital-per-worker	-0.01	-0.03			0.32	0.18		
	(0.02)	(0.03)			(1.00)	(1.07)		
Decline in the relative price of capital	-0.01	0.01			-1.81*	-1.10		
	(0.02)	(0.02)			(1.00)	(1.04)		
By Type								
Low CETC								
Change in capital-per-worker			-0.04	-0.15			10.85*	11.81*
			(0.14)	(0.15)			(6.19)	(6.32)
Decline in the relative price of capital			-0.00	-0.01			1.78**	1.76**
			(0.02)	(0.02)			(0.86)	(0.85)
High CETC								
Change in capital-per-worker			-0.04*	-0.06**			0.91	0.96
			(0.03)	(0.03)			(1.16)	(1.17)
Decline in the relative price of capital			0.00	0.02			0.02	0.13
			(0.02)	(0.02)			(1.00)	(1.06)
Computers								
Change in capital-per-worker			-0.01	0.06			-6.46**	-6.91**
			(0.08)	(0.08)			(3.26)	(3.36)
Decline in the relative price of capital			-0.01	-0.00			-1.30	-1.04
			(0.02)	(0.02)			(1.02)	(1.06)
Tasks intensity								
Abstract		0.05**		0.03		0.34		-0.16
		(0.02)		(0.02)		(0.83)		(0.95)
Manual		0.01		0.00		-0.67		-1.08
		(0.02)		(0.02)		(0.84)		(0.88)
Routine		-0.08***		-0.08***		-0.18		0.10
		(0.02)		(0.02)		(0.82)		(0.91)
Observations	327	313	274	264	327	327	274	264

Notes: Author's estimations based on CPS data 1983 and 2016. The table shows the point estimates of a OLS regression across 3-digit occupations of changes in the outcome variable. Outcomes variable is changes in employment (columns 1-4), changes in college-educated workers (columns 5-8). Panel A presents results for an index of CETC intensity ranking occupations by percentage change in stock of equipment between 1982 and 2015. Panel B shows results by type of capital good. Columns 3-4 and 7-8 include controls for the task intensity of the occupation. Standard errors in parenthesis. *** indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level

Table E.IV: Estimated bias in technology.

	Elasticity (1)	Labor-Augmenting, γ_n (2)	Capital-Augmenting, γ_k (3)	Difference (2)-(3)
Managers	0.79	0.13	0.10	0.03
Professionals	0.66***	0.19	0.08	0.11
Technicians	0.75	0.10	0.08	0.02
Sales	1.17	-0.01	0.11	-0.12
Admin Service	1.32	0.15	0.11	0.04
Low-skilled Serv	0.73**	0.17	0.07	0.10
Mechanics & Repairers	0.80***	0.18	0.05	0.13
Precision	1.99***	0.14	0.08	0.07
Machine Operators	0.57***	0.13	0.06	0.07
Transportation	0.54***	0.04	0.05	-0.01

Columns (1) presents the IV estimates and the 95% confidence intervals of the elasticity of substitution between capital and labor; Column (2) contains the estimates of the time trend in regression equation 16 which corresponds to improvements in the efficiency of labor as discussed in the text. Column (3) contains the annual decline in quality-adjusted price of equipment to consumption, CETC. The difference between these two is presented in Column (4). A positive difference indicates faster growth in labor efficiency than capital efficiency.

Table E.V: The role of CETC for the occupational premia.

	Data	Model	CETC	CETC/Data
Managers	14.49	11.19	8.39	57.87
Professionals	20.01	14.16	11.33	56.62
Technicians	-3.46	7.33	3.13	-90.41
Sales	2.11	6.98	4.19	198.43
Administrative Services	1.04	14.07	0.37	35.50
Mechanics and Construction	-13.98	-6.70	1.83	-13.08
Precision Production occs	-17.11	-6.68	1.28	-7.47
Machine operators	-11.98	2.57	0.35	-2.90
Transportation	-14.34	-5.31	0.98	-6.82

Note: The table reports percentage variation in the occupational premia between 1982 and 2015. Occupational premia are reported as percentage difference from low-skill services. Column “CETC” reports the outcome attributed to CETC via the counterfactual. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction when we shut down CETC. Entries are in percent.

Table E.VI: Forces driving labor reallocation across occupations.

	Data	CETC	demand	demographics	CA	composition
Fraction moving into						
Managers	4.70	4.26	-15.25	-0.14	-1.18	-1.63
Professionals	5.67	5.19	-1.17	-0.43	-4.42	-7.88
Technicians	-0.07	0.70	-2.76	-0.04	0.05	0.23
Sales	-1.28	-4.06	-8.14	0.06	0.31	0.71
Administrative Services	-4.63	-6.23	12.54	-0.39	0.15	0.74
Low-Skilled Services	3.51	0.80	6.83	0.11	1.66	2.55
Mechanics and Construction	-1.62	-0.97	2.20	0.34	1.27	1.90
Precision Production occs	-2.00	-1.37	2.32	0.06	0.40	0.52
Machine operators	-4.08	0.53	0.55	0.11	0.47	0.83
Transportation	-0.21	1.15	2.89	0.33	1.29	2.04
High-skill	10.37	9.45	-16.42	-0.57	-5.60	-9.50
Middle-skill	-13.89	-10.24	9.59	0.46	3.94	6.96
Low-skill	3.51	0.80	6.83	0.11	1.66	2.55

Note: All columns present the outcome attributed to the various forces via the counterfactuals. This equals the difference between the benchmark model prediction (which by construction matched the data), and the counterfactual prediction. The description of all the counterfactuals in the columns is in the text. "High-skill" occupations are managers and professionals. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations. Entries are in percent.

Table E.VII: Alternative counterfactual exercises.

	Data	CETC	demand	demographics	CA	composition
From 2015 baseline						
Fraction moving into:						
High-skill	10.37	9.45	-16.42	-0.57	-5.60	-9.50
Middle-skill	-13.89	-10.24	9.59	0.46	3.94	6.96
Low-skill	3.51	0.80	6.83	0.11	1.66	2.55
Sequential						
Fraction moving into:						
High-skill	10.37	9.45	-11.93	11.03	-2.22	4.05
Middle-skill	-13.89	-10.24	6.74	-8.61	1.72	-3.50
Low-skill	3.51	0.80	5.19	-2.42	0.50	-0.55

Note: All columns present the outcome attributed to the various forces via the counterfactuals. **From 2015 baseline** refers to the counterfactuals described in the main text. **Sequential** refer to alternative counterfactuals where the various forces are shut down sequentially, one after the other. All columns present the outcome attributed to CETC via the counterfactual. "High-skill" occupations are managers and professionals. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations. Entries are in percent.

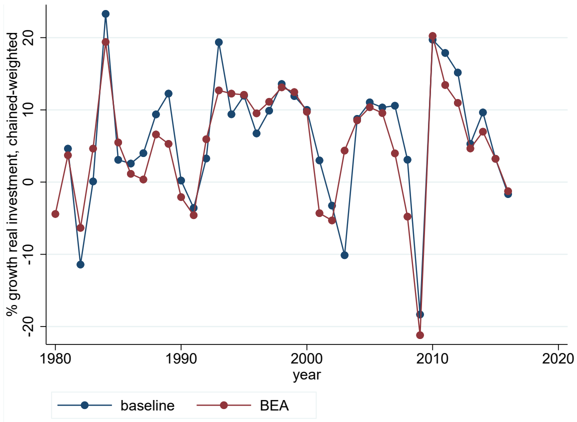
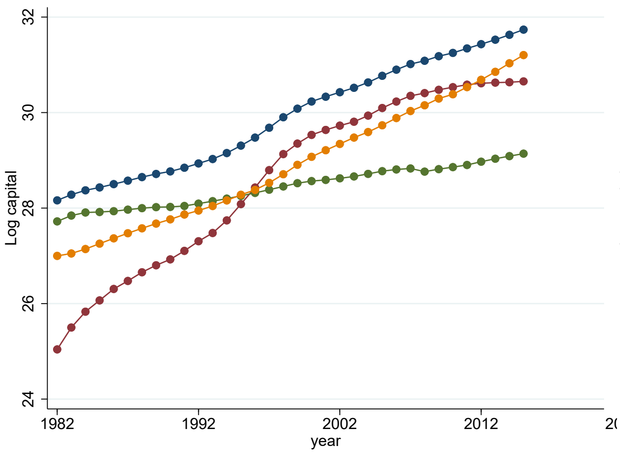
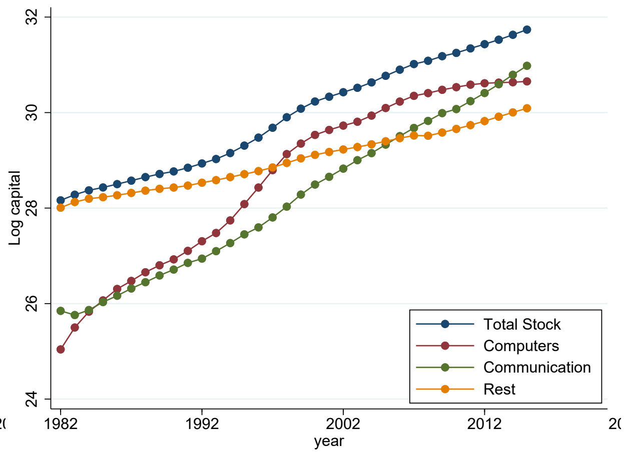


Figure 11: Investment

BEA% growth in real equipment investment and our quality-adjusted measures of investment, chained-weighted.



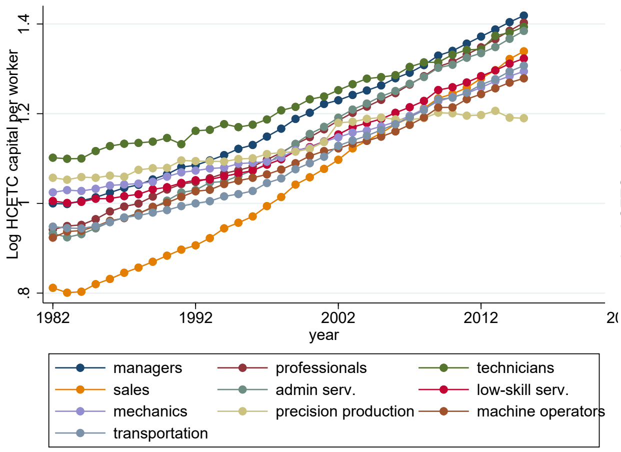
(a) The role of CETC



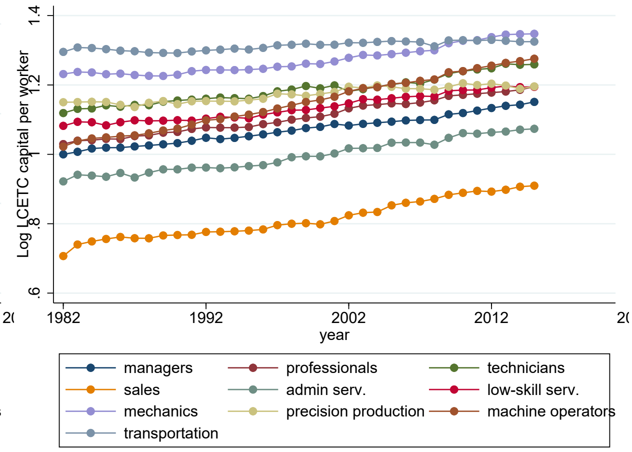
(b) Communication equipment vs. computers & software

Figure 12: Capital stock by type.

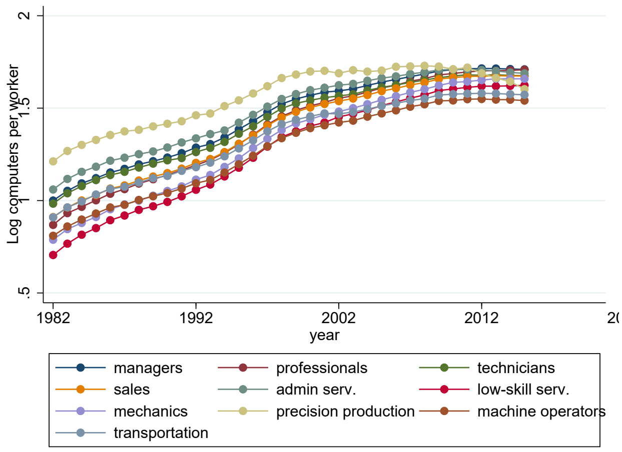
Panel (a) displays the log of the stock of quality-adjusted capital by broad equipment categories. Panel (b) displays the log of the stock of quality-adjusted capital for computer and software, communication equipment, and other equipment. Source: NIPA and own computations. Source: NIPA and own computations.



(a) High-CETC



(b) Low-CETC



(c) Computers

Figure 13: Composition of equipment per worker by occupation.

Series for the stock of quality-adjusted equipment per worker by broad category across occupations.