Occupational exposure to capital-embodied technical change*

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Abstract

Much of technological progress is embodied in capital and realized through the availability of new, more efficient, capital goods. How does capital-embodied technical change (CETC) impact the labor market? We study workers' exposure to CETC at the occupation level by unpacking the cross-price elasticity of occupational labor demand. To do so, we construct a novel dataset of the stocks and prices of different types of capital used by workers in each occupation. Our dataset yields the first available occupational estimates of CETC and of the elasticity of substitution between capital and labor. CETC varies substantially across occupations, but it is the heterogeneity in the elasticity of substitution which fuels differences in workers' exposure and ultimately sets the direction of the labor reallocation triggered by CETC. We evaluate the impact of CETC in a general equilibrium model of endogenous sorting of workers across occupations of different CETC and substitutability between capital and labor. CETC explains 87% of labor reallocation in the US between 1984 and 2015: it is responsible for 73% of the gains in employment in high-skill occupations, and for 57% of the employment losses in middle-skill occupations. A forecasting exercise for the US economy in 2005 suggests that occupational disparities in the pace of CETC over the previous 10 years are a strong predictor of occupational employment flows over the subsequent 10 years.

JEL codes: O13, O47, Q10.

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1 Introduction

Technological progress and labor market outcomes are tightly linked. In the post-war era, technological progress has been mostly embodied in factors of production, such as capital (Greenwood *et al.*, 1997). By changing the availability of capital goods and its costs, capital-embodied technical change (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. 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 30 years. CETC varies substantially across occupations, but it is the heterogeneity in factor complementarity that ultimately sets the direction of the labor reallocation triggered by CETC. CETC explains 87% of the gross labor reallocation across occupations observed in the US since 1984: it is responsible more than 2/3 of the gains in employment in high-skill occupations and for more than 1/2 of the employment losses in middle-skill occupations between 1984 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, 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 occupational labor demand – that is, the response of occupational labor demand to changes in the cost of capital. Under the assumptions of constant returns and price-taking behavior, 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 input share; and (iv) the demand elasticity for occupational output (Hicks, 1932 and Robinson, 1934).

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 the quantification in a general equilibrium model that is consistent with our concept of exposure and features 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 30 years in the US. For each occupation, we construct capital requirements by equipment category, exploiting information on the occupation-specific tools that workers use in their jobs. We measure occupational tools 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 tool information in the earlier years is 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 the occupational capital requirements, we build an allocation rule to distribute capital for each of the 24 equipment categories across occupations in each year, between 1984 and 2015. Then, we aggregate across equipment categories in each occupation to build their stocks.[1]

With our dataset at hand, we 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 and the elasticity of substitution between capital and labor. To measure the former, we work under the assumption of constant returns so that labor and capital expenses equal the value of output. Capital expenses are computed using our newly constructed stocks and estimates of the user cost of capital by equipment category in the tradition of Jorgenson (1963).[2] In 1984, the capital share ranges from 5% in sales occupations to 43% in mechanics and transportation occupations. Capital shares change substantially over time: between 1984 and 2015, they decrease by 9.7p.p. in mechanics and transportation occupations and by 7.6p.p in precision occupations and increase by more than 11p.p. for professionals and machine operators. We exploit this time variation along with changes in the relative price of capital to labor to estimate their elasticity of substitution in each occupation. Our estimates range from 0.65 for technicians to 2.2 for administrative services. Middle- and low-skill occupations are substitutable to capital on average, with an average elasticity of 1.5; while high-skill occupations are complementary to capital, with an average elasticity of 0.81.[3]

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

[2] Our estimates of the user cost are based off of a series of constant quality equipment prices, which we build following the methodology in Cummins and Violante (2002) to update the estimates of Gordon (1987).

[3] In the aggregate, we estimate an elasticity of substitution between capital and labor of 0.88, consistent

Inferring the output demand and labor supply elasticities 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 and its price. We find that occupational outputs are gross substitutes, with an elasticity of 1.34. 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, ranging from a negative exposure of -3.5% for precision production occupations to the most positive exposure of 5.7% for mechanics and transportation occupations. Exposure is positive in five occupations out of nine – managers, professionals, technicians, low-skilled services, mechanics and transportation – with the implication that the positive scale effect of a decline in the relative price of capital dominates the negative substitution effect and so CETC increases labor demand. We combine exposure with CETC and compute the reallocation of labor implied by changes in labor demand to find it to be consistent with the polarization of employment observed in the US labor market over the last 30 years. Employment flows toward occupations with lower substitutability between capital and labor, and so higher exposure. Prima facie, the phenomena of employment polarization is consistent with either heterogeneous substitutability of capital and labor across occupations, emphasized in Autor *et al.* (2003) and of which we provide the first available estimates; or with a common elasticity of substitution of capital and labor across occupations, faster capital deepening in occupations that loose employment and complementarity in output across occupations, as in Goos *et al.* (2014). Our estimates favor the substitution channel rather than the scale channel as a driving force for employment polarization.

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

with estimates by Oberfield and Raval (2020) based on establishment level data in the manufacturing sector; and Leon-Ledesma *et al.* (2010) using normalized production functions and aggregate data.

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. We find that CETC explains 73% of the observed reallocation of labor toward high-skill occupations between 1984 and 2015. CETC also accounts for 57% of the reallocation out of middle-skill occupations and for a small fraction of the reallocation toward low-skill occupations, 11% of it. An in-sample forecasting exercise attests to the centrality of CETC for the labor market dynamics of high-skill occupations. Standing in 2005, information on the pace of CETC in the previous 10 years is enough to adequately forecast employment flows in high- and middle- skill occupations over the subsequent 10 years.

Our finding that the role of CETC for employment flows varies across occupations of different skill 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 54% of the increase in the college premium, about 1/3 of the rise in the cross-sectional age premia, and also widened the gender wage gap by 12.5p.p., between 1984 and 2015.

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 (Autor and Dorn, 2013; Comin *et al.*, 2020). We find that this demand channel is quantitatively important to explain the gains in employment of low-skill occupations, but it misses most of the gains in employment of high-skill occupations.

Last, we tease out the role of technological advances in each equipment type, by extending our baseline model and specifying occupational capital as a CES composite of different capital goods, with an elasticity of substitution of 1.13, which we estimate using our newly constructed dataset. Consistently with Eden and Gaggl (2018) and Acemoglu and Restrepo (2018), our results indicate that CETC in computers, communication equipment, and software have been important drivers of the returns to skill and employment reallocation in the US over the last 30 years. Distinctively to previous studies, we show that CETC becomes quantitatively relevant to predict labor reallocation only in combination with heterogeneous elasticities of substitution between capital and labor across occupations. In other words, the magnitude of measured disparities in CETC across capital types and occupations can not in itself rationalize employment dynamics as it does not systematically correlate with observed employment flows.

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 toward workers' jobs. 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 (Autor *et al.*, 2006, 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 and exposure to CETC, we build quality-adjusted equipment stocks for each occupation over the last 30 years in the US. These stocks are key to computing other relevant structural features that determine labor demand in an occupation. The information on occupational tools in the O*NET was first exploited by Aum (2017) to study the impact of software innovation on the demand for high-skill jobs. Aum *et al.* (2018) further use these tools to measure computer and software demand by occupation. Distinctively, we use occupational tools to measure occupation-specific capital price indexes, which we link to technological change. In addition, a novel contribution of our paper is the construction of occupational tools in 1977, from the text of the DOT by using machine-learning algorithms. The DOT is the predecessor to the O*NET and therefore the natural data source to document changes in occupational tools. This feature allows us to tackle the changing nature of occupations and their capital requirements over time.

Our estimates of the occupation-specific elasticities of substitution between capital and labor are an important input in measuring workers' exposure to technical change, in the form of computerization, trade (Burstein *et al.*, 2019) and off-shoring (Goos *et al.*, 2014), and, more generally, to 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. 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.

Finally, our work relates to the extensive literature that highlights the task content of occupations as a measure of exposure to technology and computerization as the driving force of job polarization (Autor *et al.*, 1998, 2003; Autor and Dorn, 2013). Consistently with the literature, we find that employment reallocated away from occupations that became computer-intensive. However, we find that employment reallocated into occupations that became intensive in other equipment categories that displayed similar or faster raise in stocks and similar degree of technical change than computer equipment. The effect of capital-deepening is significant even after accounting for the task content of occupations.

The rest of the manuscript is organized as follows. Section 2 constructs stocks and prices of capital at the occupation level and presents key correlations between CETC and employment flows. Section 3 estimates the elasticity of substitutions between capital and labor across occupations. We use the findings in these sections to measure occupational exposure to CETC and quantify the partial-equilibrium effects of technical change on the labor market (Section 4). Section 6 evaluates the differential role that CETC has for employment reallocation across occupations in general equilibrium, using the model outlined and parameterized in Section 5. Section 7 discusses relevant model extensions and Section 8 concludes.

2 Capital stock and CETC across occupations

In this section, we document the path of the capital stock used in each occupation as well as its user cost in the US between 1984 and 2015. We focus on equipment capital and measure occupational capital stocks consistently with the aggregate investment series in the Fixed-Asset Tables (BEA). We follow the extensive literature that highlights 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. To allocate these stocks to occupations, we construct a novel index of the capital requirements in each occupation through time. Our index is based off of the tool commonly used in each occupation, which we extract from the DOT in the 1970s and from it successor, the O*NET, in the 2010s.

2.1 Data and methodology

Data sources. We combine four different data sources: a novel dataset on occupational tool usage that we construct using Natural Language Processing (NLP) algorithms over the textual occupational definitions of the 1977 DOT and the Tools and Technology supplement of the 23.4 O*NET; annual Fixed-Assets (BEA) 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 labor market statistics computed from the March Current Population Survey (CPS) between 1984 and 2015. Labor market statistics include full-time equivalent workers by occupation as well as hourly wages, which we measure by dividing labor income 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.[4]

Quality-adjusted capital stocks. We start by constructing chained-weighted quality-adjusted stocks for each of the 24 equipment categories considered by the BEA. This is our measure of the stock of capital in efficiency units (capital, for short) for each equipment category. The stocks correspond to their nominal counterparts in 1985, our base year.[5] We apply the permanent inventory method to construct efficiency units through time. For that, we need a measure of the efficiency units of investment and of the physical depreciation rate. We construct chained-weighted measures of efficiency units of investment by deflating nominal investment with quality-adjusted prices of each of the 24 equipment categories. We adjust BEA depreciation rates by the change in the quality-adjusted price of equipment, i.e. a measure of economic obsolescence, to obtain estimates of physical depreciation by equipment. Quality-adjusted prices and physical depreciation rates follow the methodology proposed by Cummins and Violante (2002), see Appendix A.1 for details.

An index of capital requirements across occupations. We refer to the capital requirements of an occupation as to the fraction of the aggregate stock of each capital category used by the occupation. We infer these requirements from the tools used by workers in the occupation. For example, commonly used tools by a dental assistant include air

[4] Additional details on our datawork on the CPS 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.

[5] Because the stock is assigned to workers in 1984, our measurement implies that any investment occurring during 1984 (and showing up in the stock in 1985) was available to workers in that year.

compressors, dental cutting instruments, and personal computers. We collect information on these tools across occupations in the US over the last 30 years. Our dataset includes more than 7,000 tools, which correspond to commodities in the United Nations Standard Products and Services Code (UNSPSC) classification system and are linked to the equipment categories considered by the BEA.[6]

The O*NET, a database collecting standardized occupation-specific descriptors, readily provides information on occupational tools 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. To collect occupational tools in the 1980s (the beginning of our sample), we use the textual definition of occupations collected in the 1977 version of the DOT. We parse out the set of the tools used in each occupation by applying NLP algorithms.[7] For illustration, Figure 1 compares the occupational tools measured in the O*NET and DOT datasets. It plots the fraction of tools used across 1-digit occupations for two capital categories, computers and communication equipment. For both categories, the DOT records the highest share of tools for administrative services while the O*NET records it for professionals. Through time, a worker in a professional occupation have seen the share of computers and communication equipment tools allocated to him increase, whereas a worker in an administrative service occupation has seen it decline. These differences exemplify how technology impacts occupations by changing the nature of the activities performed, as well as the tools used to perform those tasks. To generate measures of occupational tools through the sample period we linearly interpolate the DOT-based and O*NET-based occupational tools for each of the 324 3-digit occupations we observe.[8]

We then use our time-series of occupational tools to construct occupational capital requirements. Let τ_{ojt} be the number of tools of BEA 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. Let l_{ot} be the number of full-time equivalent workers in occupation o at time t.

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

[7] We build a corpus of the universe of tools listed under Commodity Titles, i.e. 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.

[8] 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).

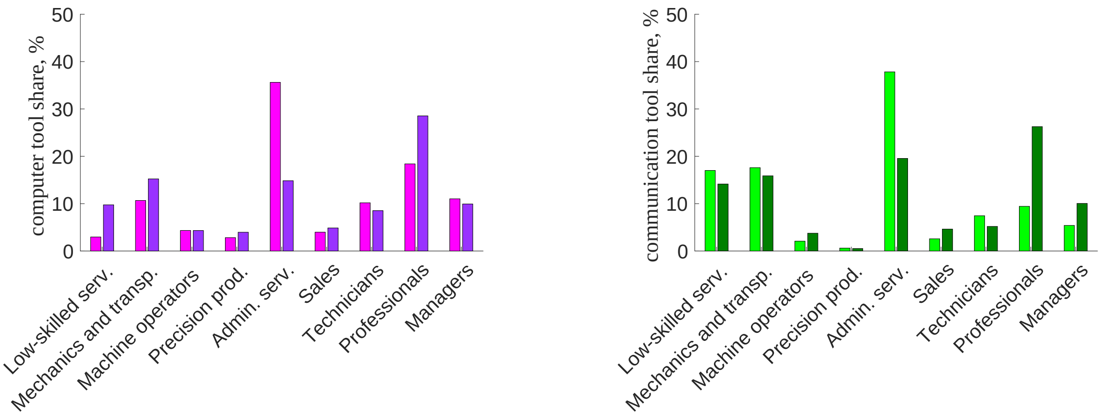


Figure 1: Changes in tool shares.

The left panel displays the share of computer tools used by a worker in each 1-digit occupation in 1977 (from the DOT, lighter colors) and in 2016 (from O*NET, darker colors). 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.

We define the requirement for capital j in occupation o as the number of tools used by the workers in that occupation relative to the total tool used in the economy:

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

These capital requirements are the base of our assignment rule for the stocks of capital across occupations.

We distribute the stock of capital of a given category across occupations proportionally to the capital requirements in that category. We then construct a Tornqvist quantity index for the capital stock in each occupation using the expenditure share of each equipment type in the occupation as weights for the growth rates of each equipment category, following Oulton and Srinivasan (2003). The construction of these weights requires us to measure the usercost of capital for each equipment category as described in Appendix A.1.

A few features of our assignment require further discussion. First, the measurement of occupational capital requirements is challenged by the absence of data on the amount of time a worker uses a particular capital good. Our assignment rule exploits the highly disaggregated nature of tool descriptions to proxy for intensity of usage. For a fixed capital category, occupations that use a larger variety of tools within that category will be allocated more capital. For the case of computers, our assignment is comparable to that based off use a binary answer to a question in the October Supplement of the CPS on whether a worker uses a computer at work or not (Autor *et al.*, 1998; Burstein *et al.*, 2019).[9] Second, 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 usage is heterogeneous across occupations and the aggregate stock of capital is fixed at a point in time, so when workers reallocate across occupations the fraction of tools used changes. Heterogeneous tool usage is consistent with an economy where the intensity of use of capital differs across occupations. 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.[10] 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 by capital category across occupations.

2.2 Salient features of occupational capital

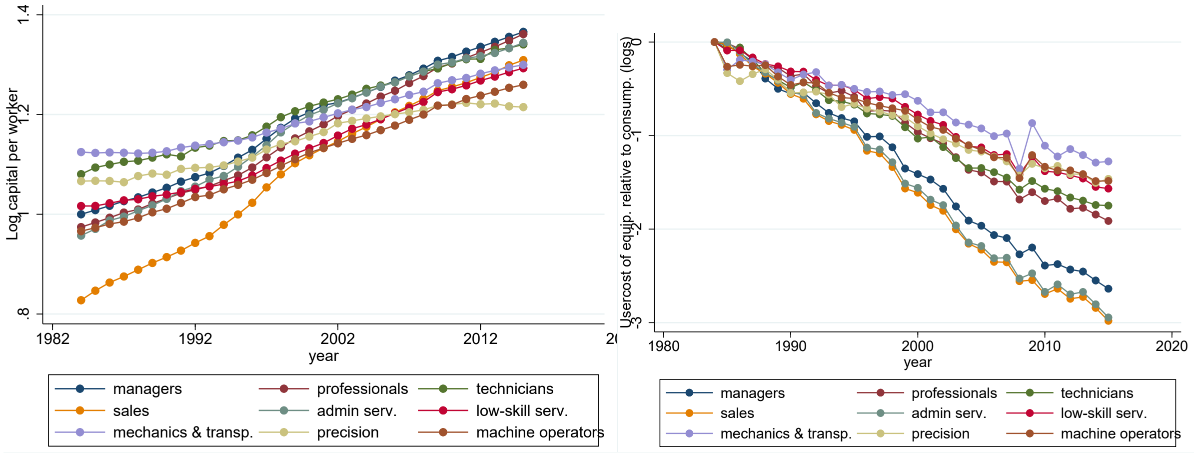
We now document the path of occupational capital and that of the user cost of occupational capital relative to consumption in each occupation, our measure of occupational CETC. To ease the exposition, we group the data into 9 occupational groups, which correspond to the 1-digit non-agricultural occupational grouping in the US census – that is, managers, professionals, technicians, sales, administrative services, low-skilled services, mechanics and transportation, precision workers, and machine operators.

Capital per worker by occupation. Panel (a) in 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 1984. Overall, the stocks of capital per worker increased in all occupations and their dispersion shrank throughout the period. The increase in capital per worker was largest for administrative services, professionals, and sales workers (1.1%, 1.1%, and 1.4% annualized growth rates between 1984 and 2015, respectively). Capital-per-worker in precision production occupations and mechanics and transportation occupations grew the least, with annualized growth rates of 0.4% and 0.5%, respectively.

CETC by occupation. We measure capital-embodied technical change from the decline

[9]We compare the assignment of the stock of computers across occupations using our tool shares and using the CPS October Supplement and find that the allocations are strongly correlated, both in levels at different points in time, and in changes for an occupation across time; see the Online Appendix.

[10]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.



(a) Stock per worker

(b) CETC

Figure 2: Capital stock and CETC 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 1984. Panel (b) displays the logarithm of the user cost of capital relative to consumption across occupations. Source: BEA and own computations.

in the user cost of capital to consumption in each occupation, Panel (b) in Figure 2. We construct the usercost of the bundle of capital in an occupation using the ratio between the total expenses in capital in an occupation and the stock of capital in the occupation constructed using a Tornqvist quantity index as explained Appendix A.1.[11] Managers, sales, and administrative services occupations experienced the strongest decline in the relative user cost of capital to consumption, by more than 8% per year between 1984 and 2015. On the opposite end, mechanics and precision production occupations recorded a decline in the relative user cost of capital to consumption of 2.9% and 3.4% per year, respectively.[12]

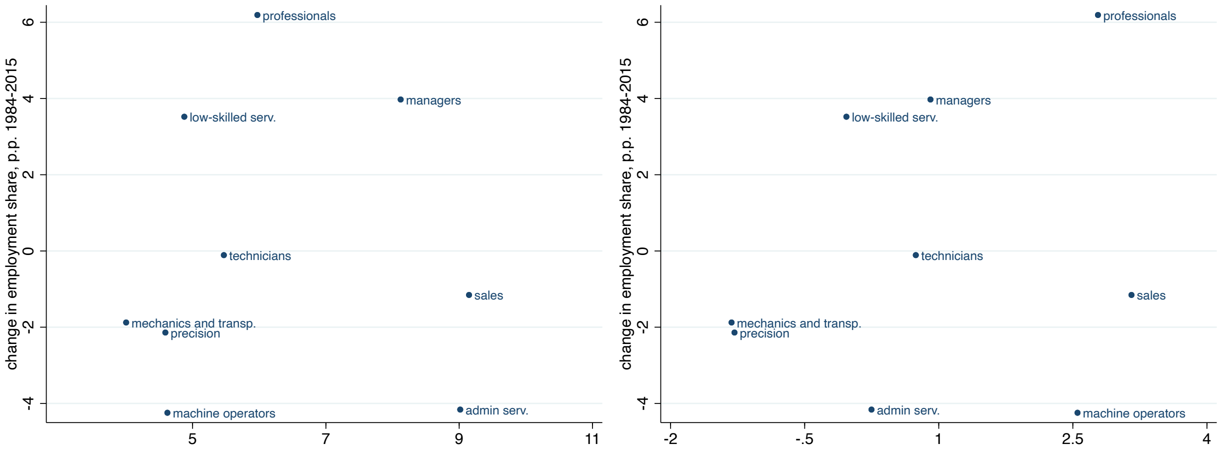
Relationship to employment.[13] Given the novel nature of our stocks of occupational capital as well as their user cost relative to consumption (CETC), it is worth exploring evidence for the relationship between these measures and labor market outcomes.

Figure 3 panel (a) displays the change in the employment share between 1984 and 2015 for each of the 9 1-digit occupations plotted against CETC. Prima facie, there is little association between the extent of CETC and employment flows across occupations. For example, the extent of CETC was similar for low-skill services and precision production occupations, but the

[11]This implied usercost is almost identical to a Tornqvist price index, with shares equal to the expenditure share of a given capital category and occupation at a point in time, see Appendix A.1.

[12]These disparities are related to heterogeneity in capital bundles across occupations as reported in the Online Appendix.

[13]For brevity, we only report features on the association between CETC and labor market outcomes that are central to our analysis. We defer to Appendix A.2 for a broader evaluation.



(a) CETC (b) Input expense ratio

Figure 3: Employment shares by occupation.

Panel (a) displays the change in the share of employment between 1984 and 2015 in each 1-digit occupation against the annualized decline in the user cost of capital relative to consumption. Panel (b) displays the change in the share of employment between 1984 and 2015 in each 1-digit occupation against the percentage change in the input expense ratio (capital expenses divided the wage-bill) in each occupation between 1984 and 2015. All entries are in percent. Source: BEA, CPS, and own computations.

share of employment in the latter decreased, while the share in the former increased.[14] Heterogeneity in CETC across occupations that gained and lost employment is likely grounded in differences in capital-labor substitutability across occupations, as hypothesized by Autor *et al.* (2003) and Autor *et al.* (2008).

Figure 3 panel (b) displays the same employment changes plotted against the change in the input expense ratio, i.e. capital expenses divided by the wage-bill in each occupation. We see again vast heterogeneity in employment gains and losses for occupations that became more capital intensive. For example, the change in the input expense was comparable for professionals and machine operators, but the share of employment in the latter decreased while the share in the former increased. On the flip side, occupations that displayed similar declines in their share of employment had vastly different changes in input expense ratios. For example, the share of employment decreased similarly for machine operators and administrative service occupations, but the ratio of capital expenses to labor expenses increased substantially more in the former (2.5p.p. per year versus 0.25p.p. per year).

Heterogeneity in the path of capital per worker across occupations is partially explained by differences in the composition of the stock of capital. Occupations that are more in-

[14]In levels, the only occupation that lost employment sustainedly through the period was machine operators, particularly post-2000.

tensive in capital categories that experienced stronger CETC also record faster growth in their capital per worker. This heterogeneity persists even when looking at more disaggregated occupational data: across 327 occupations, employment shares fell for occupations at the bottom of the distribution of growth rates in capital-labor ratios and increased at the top of the distribution, see Panel B in Table E.I. This disparate association between changes in capital and employment across occupations is again consistent with occupational heterogeneity in the substitutions patterns between capital and labor. Importantly, these differences in employment changes coexisted with wage gains across all occupations (about 1% per year, on average), and these wage gains were largest in occupations with highest changes in capital-labor ratios and the highest gains in skilled workers, consistently with capital skill complementarity as a driver of skill-biased technical change Katz and Murphy (1992); Krusell *et al.* (2000).

There is an extensive literature linking capital-deepening and employment reallocation. Notably, the routinization hypothesis sustains that workers that engage in tasks that are routine intensive are more likely to be replaced by machines, particularly computers and robots (Autor *et al.*, 2008, Autor *et al.*, 2003). This hypothesis is consistent with the observation that employment has flown out of computer-intensive occupations, which we also confirm with our data. However, the gains in employment and wages in occupations intensive in other types of capital that displayed levels of CETC comparable to that of computers, suggest that other dimensions of occupational heterogeneity may play a role in understanding the link between employment reallocation, CETC, and capital-deepening. For example, panel C of Table E.I shows that while workers in computer-intensive occupations saw their wages rise the fastest, by 1% per year on average, these occupations lost employment overall (with their share falling by 3.6p.p. between 1984 and 2015). At the same time, workers in occupations intensive in other capital goods with strong CETC, including communication equipment, also saw their wages rise by a similar amount, 0.8% per year, but these occupations gained employment throughout (5.5p.p. over the period). This heterogeneity highlights the need for estimates of occupation-specific elasticities of substitution between capital and labor, which we discuss in the next section.

3 Elasticity of substitution between capital and labor

The heterogeneous occupational paths of CETC, capital-per-worker, and employment suggest that substitution patterns between capital and labor may differ across occupations. In this section, we estimate these occupation-specific elasticities using our newly constructed dataset.

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, $\lambda^n_{ot}/\lambda^k_{ot}$, where λ^n_{ot} is the price of a unit of labor and λ^k_{ot} is the user cost of a unit of capital. We can then write the parameter of interest as:

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

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 observable variables – that is, observable labor $\tilde{n}_{ot}$ (for example, full-time equivalent workers) and its price $\lambda^{\tilde{n}}_{ot}$ as well as our measure of capital in efficiency units and its user cost:

$$\sigma_o \equiv \frac{d\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}}\right)}{d\ln\left(\frac{\lambda^{\tilde{n}}_{ot}\exp(\gamma_{ot})}{\lambda^k_{ot}}\right)}, \tag{2}$$

where γ_{ot} is the log difference between labor and capital-augmenting technical change in occupation o and, jointly with the elasticity of substitution, shapes the bias of technology. 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, declining observable capital-labor ratios $\frac{k_{ot}}{\tilde{n}_{ot}}$ can be rationalized by capital-augmenting technical change, a decline in $\exp(\gamma_{ot})$, and increasing observable capital-labor ratios, by labor-augmenting technical change, an increase in $\exp(\gamma_{ot})$.

To circumvent this impossibility result and identify the elasticity of substitution, the literature imposes structure on the path of factor-augmenting technical change (see Herrendorf *et al.*, 2015, Antras, 2004). In line with the literature, we assume that we assume that factor-augmenting technical change is exponential, i.e. $\exp(\gamma_{ot}) = a_o \exp(\gamma_o t)$ for some initial level $a_o > 0$. Then, under constant elasticity, the empirical counterpart to equation 2 is:

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

where β_{1o} is the intercept of the regression which corresponds to a constant of integration in equation 2; β_{2o} identifies γ_o for an estimate of σ_o; β_{3o} is the elasticity of substitution between capital and labor, σ_o; and ϵ_{ot} is an error term with which augments the structural equation 2. 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 Antras, 2004, among others). We compute the price of measured labor, $\tilde{\lambda}^n_{ot}$, as the ratio between the total wage bill in an occupation and our measure for labor $\tilde{n}_{ot}$. Finally, we use our measures of the usercost of capital and stocks in each occupations constructed in Section 2. All series are available from 1984 to 2015 and the occupation is mapped to the 1-digit occupational classification system of the Census.

The estimation of regression equation 3 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. To overcome this potential endogeneity we propose two alternative instruments, which we interpret as exogenous supply and demand shifters in occupational labor. First, we use the interaction between 16-year lagged birthrates and the predicted employment in an occupation computed from the product of the 1984 share of employment of a given education level in the occupation and the total supply of workers of that educational level in the economy in each year. Second, we use a shifter in the demand for the output produced in an occupation based on the interaction of the economy-wide exports (as % of GDP) and the predicted occupational demand for labor computed by interacting the 1984 sectoral employment shares of the occupation with the change in the total number of workers in each sector in each year. A valid instrument should be exogenous to the system and correlated with the regressors. We take fertility choices as exogenous and argue that changes in the size of the population and the skills available in the economy are likely correlated with the labor services available in each occupation. Similarly, we consider aggregate trade shocks as exogenous to the workings of the labor market and argue that changes in US exports of goods and services as a share of GDP and the size of the production sectors in the economy, measured by the number of workers in each sector, are likely correlated with the labor services available in each occupation. Since occupational employment differs in its sectorial composition, a shift in sectorial demand generates heterogeneous employment demand across occupations.

Table 1 presents our baseline estimates of the elasticity of substitution across occupations. For the aggregate economy, we obtain an OLS point-estimate of 0.56 and an IV point-estimate of 0.88. The IV estimate is 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. Focusing on the results from the instrumented regression equation, the lowest elasticities (highest complementarity) are reported for technicians and mechanics and transportation (at 0.65 and 0.73, respectively), followed by professionals and managers. For the remaining occupations we estimate substitutability between capital and labor. The point estimates are significantly different from a unitary elasticity for technicians, sales, administrative services, and precision production workers. We also run Wald type tests to assess whether point estimates are significantly different from each other. We find that the elasticity of substitution between capital and labor is significantly lower for managers, professionals and technicians, than in administrative services, sales, and precision occupations. We also find that the point estimate for mechanics and transportation occupations is significantly lower to that in administrative services and precision occupations.

Discussion. The structural equation 2 is consistent with two econometric models, equation 3 and its inverse,

$$\ln\left(\frac{r_{ot}}{\lambda^{\tilde{n}}_{ot}}\right) = \bar{\beta}_{1o} + \bar{\beta}_{2o}t + \bar{\beta}_{3o}\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}}\right) + \bar{\epsilon}_{ot}. \tag{4}$$

As pointed out by Antras (2004), not much can be said about the relative magnitudes of the OLS estimates for β_{3o} and $\bar{\beta}_{3o}$ on statistical grounds. 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. 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 that includes 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. First we run statistical tests for the strength of the proposed instruments, then we test for potential spurious correlation in the variable of interest. Formally, with one endogenous variable and one instrument the Kleibergen-Paap Wald-type test for weak-instruments is desirable under possible heteroscedasticity. Table 1 presents the value of the statistic and the critical value for a variety of maximal IV sizes as tabulated by Stock and Yogo (2005). In all cases but for mechanics and transportation we reject the null that the maximum relative bias in the estimate is 15%

Table 1: Elasticity of substitution between capital and labor.

	OLS	**IV**	Kleibergen-Paap	Dickey-Fuller
Aggregate	0.56	**0.88**	29.20	-2.57
	0.11	*0.18*		
Managers	0.48	**0.93**	23.74	-1.90
	0.11	*0.25*		
Professionals	0.64	**0.86**	24.96	-2.98
	0.10	*0.17*		
Technicians	0.30	**0.65**	15.98	-2.93
	0.10	*0.21*		
Sales	1.00	**1.38**	43.24	-2.34
	0.11	*0.16*		
Admin Service	0.92	**2.18**	16.47	-2.22
	0.19	*0.50*		
Low-skilled Serv	0.71	**1.32**	10.74	-2.96
	0.21	*0.37*		
Mechanics & Transp.	0.04	**0.73**	5.94	-4.47
	0.11	*0.39*		
Precision	0.44	**2.06**	12.06	-5.27
	0.19	*0.63*		
Machine Operators	0.05	**1.41**	7.48	-2.75
	0.10	*0.61*		

Note: Authors' estimation of equation 3. Columns (1) presents the OLS estimates and the corresponding std. errors for the estimate; Columns (2) contains the IV estimates using the instruments described in the text. Column (3) contains the F-statistic for weak instruments robust to heteroscedasticity, Kleibergen. The relevant Stock-Yogo critical value for a 15%, 20% and 25% bias in the IV estimates are 8.96, 6.66 and 5.53, respectively. Column (4) contains the Dickey-Fuller test statistic for a test of a unit root in the error for the IV estimated equation. The 5% and 10% critical values are -1.95 and -1.6 respectively.

or larger. For mechanics we reject the null that the maximum relative bias in the estimate is 25% or larger. Another important threat to the validity of the estimates is the possibility of spurious correlation induced by unit roots in the time series of relative prices and input ratios. For the IV specification, we construct tests for the presence of unit roots in the error of the regression equation following Dickey and Fuller (1979) and report the statistics in Table 1. For all occupations as well as in the aggregate we reject the null of a unit root in the error of the regression.

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 because workers in a 3-digit Census occupation would have identical capital allocations across locations at a point time.[15]

Finally, we loop back and discuss the implications of our elasticity estimates for the occupational heterogeneity in capital per worker and employment flows. We focus on the labor share, which combines information on both factor quantities and prices (equation 4 can be rewritten as a function of the factor shares). Our aggregate estimates for the elasticity of substitution between capital and labor suggest complementarity, as well as the estimates of 4 out of 9 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 technical change, which combined with the value of the elasticity of substitution yields the bias of technology. In the aggregate, we find a 1.35% faster increase in labor-augmenting technology relative to capital-augmenting technology. This finding jointly with the aggregate complementarity between capital and labor implies capital-biased technology and is consistent with the decline in the aggregate labor share. Prior literature that focuses on the estimation of aggregate production functions has generated estimates for the bias of technology in the US and are very much in line with ours, see Klump *et al.* (2012) for a review. Leon-Ledesma *et al.* (2010) (using a normalization of the production function and data between 1960 and 2004) estimates a difference between labor-augmenting and capital-augmenting technology of 0.9%.[16]

[15]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.Identification requires an assumption on the correlation between the bias in technology across goods and cross-sectional variation in input shares, Hubmer (2020) assumes none. In the case of occupations, a parallel assumption implies that more capital intensive occupations do not hire workers with relatively more skills, which is problematic given the complementarities between skill and capital that Krusell *et al.* (2000) document.

[16]We present occupation-specific estimates of the bias of technology in the Online Appendix.

4 Occupational exposure to CETC

In this section, we use the findings in Sections 2 and 3 to measure occupational heterogeneity in the exposure to CETC and quantify the partial-equilibrium effects of technical change on the US labor market between 1984 and 2015.

As described in the introduction, we conceptualize occupational exposure to CETC in the cross-price elasticity of labor demand – that is, the response of the labor demand in an occupation to changes in the user cost of capital. Under the assumptions of constant returns, price-taking behavior, and cost minimization, Hicks (1932) and Robinson (1934) independently show that this elasticity can be expressed as a function of four components:

$$-\frac{d\ln(n_o)}{d\ln(\lambda_o^k)} = \frac{\eta_{n\lambda^n}(\rho-\sigma_o)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}}{\rho+\eta_{n\lambda^n}+(\sigma_o-\rho)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}},\text{[17]} \tag{5}$$

where (i) σ_o is the extent of labor substitutability to capital in occupational output production, (ii) $\eta_{n\lambda^n}$ 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 in the occupation, or its cost share and (iv) ρ is the demand elasticity for occupational output. On the one hand, a decline in the cost of capital decreases the labor demand via a substitution effect, a function of the elasticity of substitution between capital and labor in the occupation σ_o. On the other hand, it increases labor demand through a scale effect associated to the higher demand for occupational output in response to lower production costs, a function of the demand elasticity for occupational output ρ. Ultimately, the relative magnitude of these two elasticities determines which of the two effects dominates and therefore if exposure rises labor demand in the occupation ($\sigma_o < \rho$) or reduces it ($\sigma_o > \rho$).

We bring exposure to the data by assuming that all three elasticities that enter its specification are constant in time. The elasticity of substitution between capital and labor across occupations as well as the capital share have been directly estimated from our dataset (Section 3). These two sets of parameters are the source of heterogeneity in exposure across occupations.

The remaining two parameters that characterize exposure, ρ and $\eta_{n\lambda^n}$, cannot be estimated directly in the data as their inference requires information on occupational output and on selection effects due to workers' occupational sorting, which are intrinsically unobservable. For their inference, we use a structural model where exposure arises endogenously

[17] Derivations in the Online Appendix.

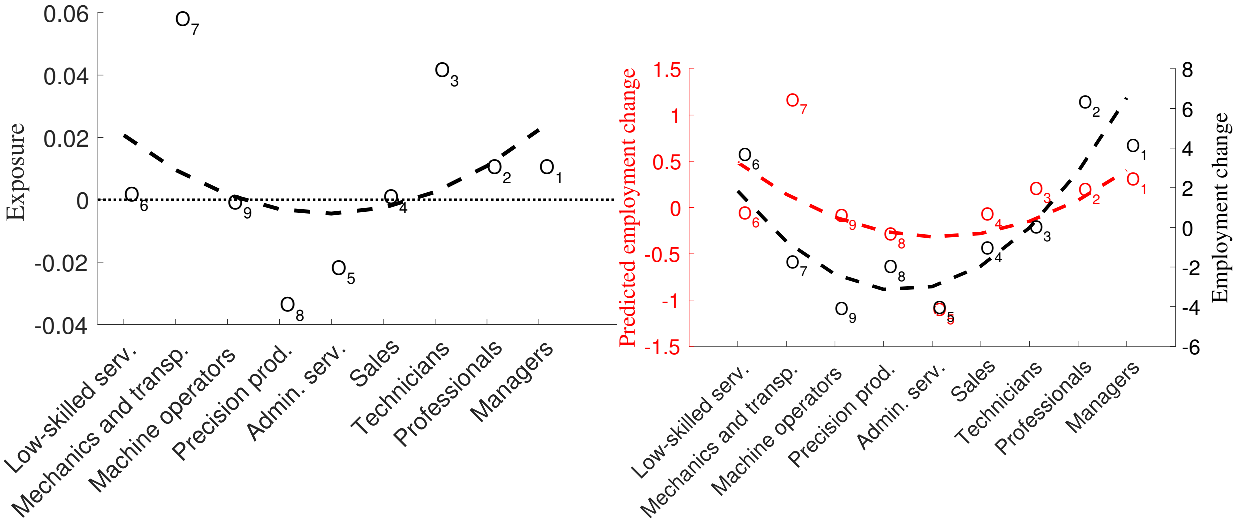


Figure 4: Occupational exposure to CETC and CECT-powered employment reallocation.

The left panel plots occupational exposure to CETC (equation 5) across 1-digit occupations ordered by increasing skill requirements. Exposure is computed using the capital share in 1984, the initial year in our sample. The right panel plots the change in the share of employment between 1984 and 2015 attributed to CETC by the Hicks's prediction (left axis) and that observed in the data (right axis). The striped lines are cubic polynomial fit.

and is consistent with equation 5, as described in Section 5. Our estimate of the labor supply elasticity is $\eta_{n\lambda^n} = 0.30$ and of the demand elasticity for occupational output is $\rho = 1.34$. We defer to Section 5 the details of our estimation strategy. To identify the former elasticity, we take a Frechet distributional assumption on workers' comparative advantage across occupations and construct a structural counterpart to the price elasticity of labor supply, which we then estimate from residual wage inequality, as in Hsieh *et al.* (2019). To identify the latter elasticity, we exploit time-series variation in occupational expenditure shares and occupational output prices. The novelty of our approach relies on our ability to measure occupational capital and so occupational expenditure shares.

We start by reporting exposure to CETC in each occupation, Figure 4 left panel. In the figure, 1-digit occupations are ranked by increasing skill requirements, following Autor (2015). Exposure is positive in five occupations out of nine: managers, professionals, technicians, low-skilled services, mechanics and transportation. In these occupations, the elasticity of substitution between capital and labor is lower than the demand elasticity for occupational output, with the implication that the positive scale effect of a decline in the relative cost of capital on labor demand dominates the negative substitution effect and therefore CETC increases labor demand. Sales, administrative services, precision production, and machine operators are occupations for which, instead, the substitution effect dominates the scale effect, even though only by a small amount, and CETC has a negative impact on labor demand. Low-skill services, sales, and machine operators measure scale and substitution effects of similar sizes and so a small elasticity of labor demand to CETC.[18]

Exposure to CETC varies substantially across occupations: it ranges from a negative exposure of -3.5% recorded for precision production to the most positive exposure of 5.7% recorded for mechanics and transportation. Heterogeneity in the elasticity of substitution between capital and labor is the main determinant of these differences: occupations with higher elasticity have smaller exposure to CETC. Exposure also varies with the capital share in each occupation, albeit the correlation is weaker (see the Online Appendix). Combined, the elasticity of substitution and the capital share generate an exposure to CETC that is U-shaped across occupations ranked by their average wage and skill content. The exposure of high-skill occupations (i.e. managers, professionals, and technicians) and that of low-skill occupations is positive, averaging 2% in the former and 0.1% in the latter, while the exposure of middle-skill occupations (i.e. the remaining occupations) is negative, at an average of -0.1%.

Next, we combine exposure with CETC to compute the yearly changes in occupational labor demand generated by CETC.[19] Then, we cumulate these changes over the 1984-2015 period and re-weight them so that total net employment reallocation equals zero. The predicted employment change is the Hicks (1932)'s (partial equilibrium) prediction for the impact of CETC on each occupation. Figure 4, right panel, presents these results for occupations ranked by increasing skill requirements in black markers along with the reallocation of workers in the data in red markers.

The direction of employment reallocation generated by Hicks's prediction is consistent with the data. This direction is mostly set by occupational heterogeneity in exposure, rather than in the extent of CETC. Consider for example the occupations that experienced the strongest CETC, at a rate above 8% per year: managers, sales, and administrative workers. Despite experiencing similar CETC, these occupations record changes in labor demand that are at opposite extremes due to their differential exposure. Sales have an exposure that is very close to zero, implying a very small elasticity of labor demand to CETC. Administrative services, instead, record the highest decrease in demand across all

[18]Our finding that CETC mostly increased labor demand is robust to alternative estimates of a demand elasticity for occupational output that are less than but close to 1. Goos *et al.* (2014)'s estimate of the labor demand elasticity at 0.9 extends the list of occupations with negative exposure in our framework by one occupation only (sales). That is, our estimates still indicates that the scale effect has been at least as strong as the substitution effect between 1984 and 2015.

[19]The yearly rate of CETC in an occupation is as reported in Section 2 (plotted in Figure 2).

occupations, at 0.21p.p. per year, combining the second highest negative exposure with strong CETC; while the average exposure of managers implies the third-highest change in labor demand. Similarly, precision production, mechanics and transportation, and machine operators experience similar levels of CETC but they record very different changes in labor demand, of -0.16%, 0.23%, and -0.01% respectively. We conclude that the key driver in the heterogeneity in labor demand across occupations is exposure rather than the extent of CETC.

Yet the magnitude of employment reallocation set by exposure is always smaller than that in the data. For example, in high-skill occupations the Hicks (1932)'s prediction generates an inflow of employment of only 0.62p.p., compared to 10.05p.p. in the data. An important limitation of the Hicks's prediction is its partial equilibrium nature, which considers occupations in isolation and abstracts from important feedback effects in labor reallocation across occupations. In the remaining part of the paper we address this limitation. We re-evaluate the impact of CETC on the labor market in a general equilibrium model where these effects are considered and exposure endogenously responds to CETC through the capital share.

5 A model of occupational capital, labor and output

In this section, we lay out and parameterize 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 7.1, we extend our framework to explicitly model the usage of different capital goods across occupations.

5.1 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 technology embodied in capital (CETC) and by the elasticity of substitution between capital and labor. This is supported by the evidence provided in Sections 2 and 3.

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 7.2.[20]

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}:

$$y_{ot} = \left[\alpha k_{ot}^{\frac{\sigma_o - 1}{\sigma_o}} + (1-\alpha) n_{ot}^{\frac{\sigma_o - 1}{\sigma_o}} \right]^{\frac{\sigma_o}{\sigma_o - 1}}. \tag{6}$$

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:

$$\max_{\{k_{ot}, n_{ot}\}} \lambda^y_{ot} y_{ot} - \lambda^k_{ot} k_{ot} - \lambda^n_{ot} n_{ot}. \tag{7}$$

Note that this description of behaviour and technology of the occupational output producer is sufficient for the model to generate a specification of exposure to CETC as in equation 5.

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. This elasticity is the

[20] 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 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.

model equivalent of the demand elasticity for occupational output in occupational exposure, equation 5. Changes 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_t^y and prices of occupational goods λ_{ot}^y maximizes profits:

$$\max_{\{y_{ot}\}_{o=1}^{O}} \lambda_t^y y_t - \sum_o \lambda_{ot}^y y_{ot}. \tag{8}$$

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_{ot}^k and a price of the final good λ_t^y demands x_{ot} units of final output to maximize:

$$\max_{\{x_{ot}\}} \lambda_{ot}^k q_{ot} x_{ot} - \lambda_t^y x_{ot}. \tag{9}$$

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.[21] 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, shifting 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' for labor type h with respect to labor type h' is:

$$\left(\frac{T_{oht}}{T_{o'ht}} / \frac{T_{oh't}}{T_{o'h't}}\right)^{\frac{1}{\theta}}, \tag{10}$$

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

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:

$$o^\star_{ht}(i) \equiv \arg\max_o \{w_{oht}(i)\}. \tag{11}$$

5.2 Parameterization

We parameterize the model equilibrium to the US economy, over the 1984-2015 period. The definition and characterization of the equilribium is standard and, for brevity, described in the Appendix, Section B.1. 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. The parameterization of the model delivers the two components of exposure to CETC, equation 5, that remain to be inferred – that is, the labor supply elasticity and the demand elasticity of occupational output.

We map the estimates of the elasticity of substitution in Table 1 to σ_o in each occupation. In Section 2, we constructed the user cost of the quality-adjusted capital in each occupation, in units of consumption (figure 2). We map this price to the price of each occupational capital good relative to consumption in the model, λ^k_{ot}.

Next, we parameterize the distribution of efficiency units of labor, as determined by the shape parameter of the Frechet distribution, θ, and the scale parameters, $\{\{\{T_{oht}\}^O_{o=1}\}^H_{h=1}\}_{t=\{1984,2015\}}\}$. 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 1984 and 2015, and take the average over the period at $\theta = 1.30$. This is consistent with Hsieh *et al.* (2019) and Burstein *et al.* (2019) who, using a similar identification strategy, infer the estimate θ to be 1.24 and 2, respectively. Combining our estimate of θ with the specification of the labor supply elasticity in our model, we deduce $\eta_{n\lambda_o^n} = \theta - 1 = 0.30$.

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 19 and 21). 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 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 18). 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 20).[22]

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 17:

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

[22] Details on the inference of the scale parameters of the Frechet distribution are in Appendix B.2. Figure 10 in the appendix depicts the evolution of the scale parameters of the Frechet distribution, separately for the group and the occupation components.

The covariation of the value of occupational output with relative occupational prices gives an estimate of the elasticity of substitution across occupational. The value of output across occupations, $\lambda^y_{ot} y_{ot}$, can be readily measured from our dataset on capital and labor expenditures at the occupation level, under the assumption of competitive markets. However, occupational output prices, λ^y_{ot}, are intrinsically unobserved. To overcome this challenge, we rely on the structure of our model, which links these prices to our previously inferred wage per efficiency units of labor and to the price of capital (see equation 16).

We are then able to estimate the following regression equation:

$$\ln\left(\frac{\lambda^y_{ot} y_{ot}}{\lambda^y_{o_b t} y_{o_b t}}\right) = \beta_1 + \beta_{2o} t + \beta_3 \ln\left(\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}}\right) + \epsilon_{ot}, \tag{12}$$

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. We control for occupation-specific time trend in equation 12 to capture trends in unobserved occupation-specific demand shifters. Note that our model predicts that changes in equilibrium occupational prices depend on changes in the unobserved demand shifters. We then expect the error term to be correlated with $\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}}$ and 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 cost of capital in each occupation with equipment weights within each occupation fixed at 1984 levels.[23]

Our estimation considers eight occupations, over 32 years, between 1984 and 2015. The OLS yields an estimate for the elasticity of substitution of 1.11 (se: 0.008) while the IV yields an estimate of 1.34 (se: 0.061).[24] Burstein *et al.* (2019) estimate the elasticity of substitution using the same method, under a Cobb-Douglas production structure for occupational output. They obtain an estimate of 1.78, which is close to our estimate. Note, however, that under a Cobb-Douglas production structure the wage per efficiency units of labor cannot be inferred from capital per worker, and therefore can only be measured up to a value for the scale parameters of the Frechet distribution.[25]

Last, to pin down the demand shifters, ω_{ot}, we use the first-order conditions of optimization of the final good producer (equation 17) along with the price of occupational output

[23]We construct a Tornqvist price index using the expenditure share of each equipment type in each occupation in 1984 as weights for the growth rates of each equipment price,

[24]The first-stage regression of the 2-stage least squares returns a p-value on the coefficient for the instrument of 0.009 and an R^2 of 0.80.

[25]Alternative estimates are in Goos *et al.* (2014) and Lee and Shin (2019), who estimate the demand elasticity using data on routine tasks' intensity and computer capital, respectively, and find an elasticity lower than 1.

implied by the wage per efficiency units of labor and our estimate of elasticity of substitution across occupational output.

6 The role of CETC for labor market outcomes

In this section, we use the model described in Section 5 to quantify the impact of CETC on labor re-allocation and the evolution of wage premia across labor groups in the US. This is the general equilibrium counterpart of the analysis developed in Section 4. We close the section by evaluating other forces that may have contributed to these labor market outcomes.

Our main findings are based on a set of counterfactual exercises, where we take the 2015 economy and progressively remove all exogenous forces in the model, by setting their value to that in the 1984 economy. These exogenous forces are: the decline in the user costs of quality-adjusted capital, λ^k_{ot}, ("CETC"); the change in the scale parameters of the distribution of efficiency units of labor associated to occupations, T_{ot}, and in the demand shifters in final production, ω_{oT} ("Demand"); the change in the scale parameters associated to worker types, T_{gt} ("Demographics"); the change in the structure of worker comparative advantage, $\tilde{T}_{ogt}$ ("CA"); the change in the weights of the different labor groups, π_{gt} ("Composition").[26] Because each of these forces interact non-linearly with each other, their role for labor market outcomes depends on the value of the remaining forces. To account for these non-linear interactions we remove these forces in different ordering and compute the effect of a particular force by averaging across different orderings.[27]

6.1 CETC

We start by considering the role of CETC for the polarization of US employment (Acemoglu and Autor, 2011). The top panel of Table 2, column *Data*, reports that, between 1984 and 2015, low-skill occupations (low-skill services) and high-skill occupations (professionals, managers, and technicians) gain 3.52p.p. and 10.06p.p. in their employment shares, respectively. Column *CETC*, in the same table, reports the contribution of CETC to this pattern, i.e. the difference between the data and the counterfactual employment allocation. CETC is consistent with employment polarization, as it generates an increase in the employment

[26] Details on the decomposition of the scale parameters of the Frechet distribution in the occupation, group, and comparative advantage components are in Appendix B.2.

[27] The interaction effects are quantitatively relevant. The Online Appendix compares our findings to those based on a set of counterfactual exercises where we remove each of the exogenous forces starting from the 2015 economy.

Table 2: The role of CETC for employment reallocation.

	Data	CETC	CETC/Data
Fraction moving into:			
High-skill	10.06	7.31	72.72
Middle-skill	-13.58	-7.72	56.85
Low-skill	3.52	0.41	11.55
Abs average movement:			
All	3.04	2.64	86.95
Non-college graduates	2.61	3.22	123.23
College graduates	1.03	1.87	180.90
16- to 29-year old	3.97	2.65	66.79
30- to 49-year old	2.86	2.32	81.03
50- to 65-year old	2.29	2.70	117.98
Females	4.33	3.20	74.01
Males	2.17	2.10	96.85

Note: Column "CETC" reports the outcome attributed to the decline in the price of capital relative to consumption via the counterfactual exercise. "High-skill" occupations are managers, professionals, and technicians. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations. Entries are in percent.

share for low- and high- skill occupations. CETC has been most relevant for high-skill occupations. The model predicts that employment reallocation toward high-skill occupations due to CETC was of 7.31p.p. – that is, 73% of the observed reallocation. CETC had a lesser role in the reallocation out of middle-skill occupations, accounting for 57% of it, and even a smaller one in the reallocation toward low-skill occupations, accounting for 12% of it. Figure 5 gives a visual representation of the role of CETC for employment polarization. It plots employment changes across occupations of increasing skill requirements, as reported in the data (black dashed line) and as generated by CETC alone (red dotted line).

Workers of different demographic characteristics differ in their occupational choices (see, among others, Hsieh *et al.*, 2019). As CETC 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 2 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 of more educated, older, and male workers. CETC accounts for 58p.p. more of of the reallocation of college graduates than of non-college graduates, for 52p.p. more of the reallocation of

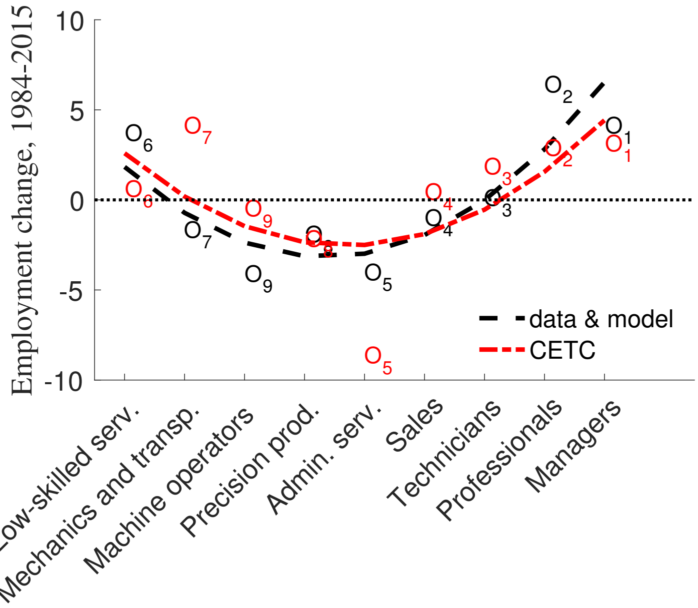


Figure 5: Employment polarization.

"Data & model" plots 100 times the change in share of employment between 1984 and 2015; "CETC" plots the same outcome attributed to the CETC via the counterfactual exercise. Lines are cubic polynomial fits.

50- to 65-year-old workers compared to 16- to 29-year-old workers, and for 23p.p. more 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 3 shows the impact of CETC on the wage premia across labor groups. In the data, the college premium increased by 31p.p. between 1984 and 2015, the cross-sectional age premium increased by 8p.p. for 30- to 49-year old workers and by 14p.p. for 50- to 65-year old workers. CETC generates 54% of the increase in the college premium and about 1/3 of the rise in the cross-sectional age premia. Over the same period of time, the gender wage gap decreased of 28p.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

Table 3: The role of CETC for the wage premia across demographic groups.

	Data	CETC	CETC/Data
College premium	30.58	16.49	53.93
Age premium			
30- to 49-year old	7.95	4.12	51.86
50- to 65-year old	13.83	1.26	9.09
Gender wage gap	-28.01	12.48	-44.56

Note: The table reports percentage variation in the college premium, the age premia, and the gender wage gap between 1984 and 2015. Column "CETC" reports the outcome attributed to CETC via the counterfactual exercises. Entries are in percent.

increase as a consequence of technical change.

To conclude our evaluation of the role of CETC for labor market outcomes, we test its predictive capacity on employment flows via an in-sample prediction exercise. Standing in 2005, we ask how well we would had predicted occupational employment over the subsequent 10 years in the US using only the information on occupational CETC over the previous 10 years. To do so, we take the calibrated model economy in 2005 and input the path of CETC that is implied by the average yearly decline in the user cost of capital relative to consumption we observe over the 1995-2005 period, to forecast employment reallocation between 2006 and 2015. The results are in Figure 6, which plots the predicted employment changes (dotted lines) along with the data (solid lines). CETC is a strong predictor of employment in high-skill occupations: it predicts 3.8p.p. of the realized 5.0p.p. rise in the employment share of these occupations, between 2005 and 2015. CETC is also able to predict the outflow of employment from middle-skill occupations over the same period, 64% of the realized one, but predicts an outflow of employment from low-skill occupations of 0.35p.p. in contrast to the realized inflow of 0.34p.p..

Partial vs general equilibrium quantification. Aggregating the effects of CETC across occupation, we summzarize the role of CETC for the reallocation of US labor between 1984 and 2015. Table 2 shows that the average absolute change in employment allocation across occupations over this time period is 3.0%. CETC accounts for 87% of this employment reallocation (2.6p.p.).

The contribution of CETC to labor market outcomes using our general-equilibrium framework is more than five times the number we obtain when using the Hicks's prediction (see Section 4). The Hicks's prediction considers occupations in isolation and therefore misses

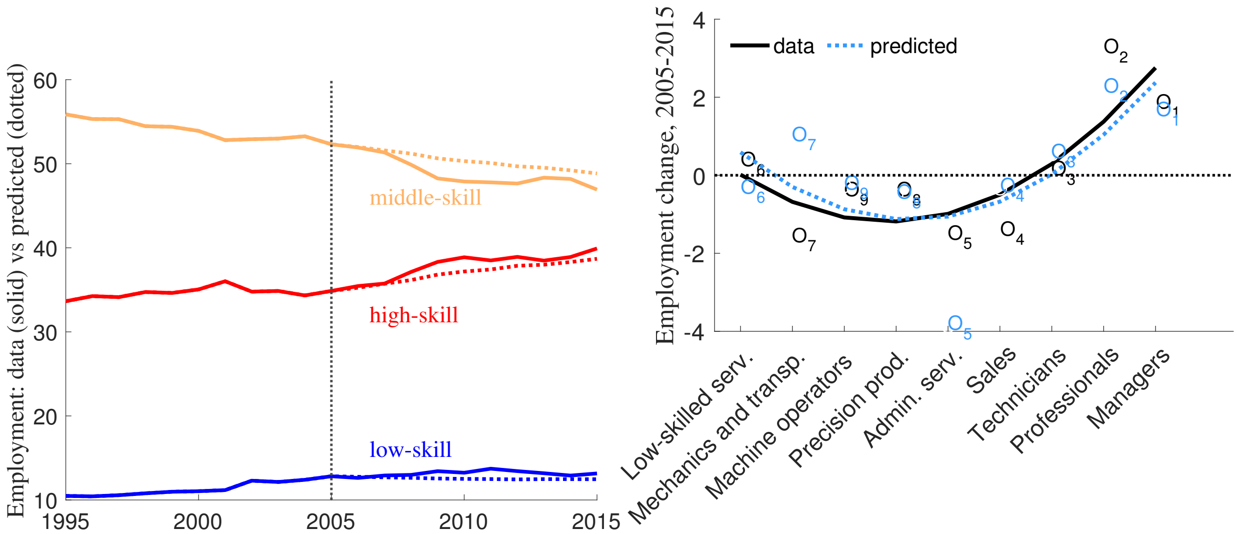


Figure 6: Forecasting exercise.

The left panel plots 100 times the employment share in the data and as predicted by our in-sample forecasting exercise, between 1995 and 2015. Forecasting starts in 2006 and uses CETC data from 1995 to 2015. The right panel plots the same statistics but as a difference between 2015 and 2005 and separately for 1-digit occupations; lines are cubic polynomial fits.

feedback effects across occupations for labor reallocation. In particular, the elasticity of employment to a decline in the cost of using capital in an occupation is computed fixing employment and output prices in all other occupations in the Hicks exercise, whereas those are allowed to endogenously change in our general-equilibrium estimates. Our exercise shows that these feedback effects are quantitatively important.

At the same time, the direction of employment flows implied by our model and by the Hicks's formulae are mostly consistent. We conclude then that we can use the concept of exposure developed in Section 4 and the channels therein highlighted to understand the workings of CETC in the labor market.

Quantification of the channels. In Section 4, we established that CETC influences labor market outcomes through heterogeneity in occupational exposure, which shapes the scale and substitution effects in each occupation. Through the lens of the model, heterogeneity in exposure is driven solely by the heterogeneity in the elasticity of substitution between capital and labor across occupations. At the same time, for a given level of exposure, CETC is heterogeneous across occupations due to differences in the bundle of capital used in each occupation, which influence the observed decline in the relative price of capital to consumption across occupations

To isolate the quantitative role of these two source of heterogeneity, we design three alternative experiments: first, we equalize the path of the relative user cost of capital to consumption across occupations (*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 user cost of capital and elasticity of substitution in all occupations, (*Identical elasticity*). We set the common elasticity of substitution to $\sigma = 0.81$, which is estimated by imposing a common elasticity parameter in regression equation 3, Section 3.[28] We quantify the importance of CETC in each of these alternative experiments by shutting down the decline in the relative price of capital to consumption – that is, by setting $\lambda^k_{o2015} = \lambda^k_{o1984}$, and computing the difference between the data and the counterfactual in 2015. Table E.III in the Appendix reports the contribution of CETC in the three alternative experiments.[29]

Consistently with our findings in Section 4, the heterogeneity in the elasticity of substitution across occupations is the most important driver for the direction and the magnitude of the reallocation of labor across occupations. When we force identical elasticities of substitution in all occupations, CETC generates about a 1/3 of the inflow of employment toward high-skill occupations generated in the baseline.

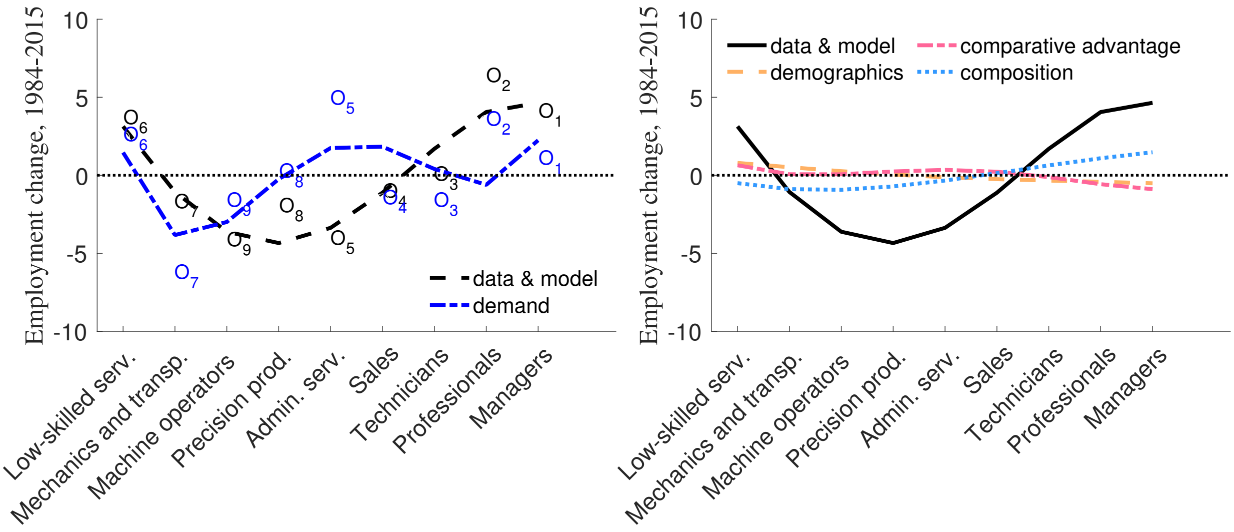
6.2 Other forces at play

In the previous section we established that CETC has played a major role in shaping labor market outcomes in the US over the 30 years. 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.

Figure 7 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. Consistently with the hypothesis in Autor and Dorn (2013) and the recent work of Comin *et al.* (2020), we find that demand shifters were responsible for the increase in employment at the bottom of the skill distribution. The model predicts that demand shifts towards low-skill occupations should have generated a 2.41p.p. increase in the share of workers allocated to them; in

[28] We use 16-years lagged birthrates interacted with the share of employment in an occupation in 1984 as an instrument and include occupation-specific time trends.

[29] In each alternative experiment, we recalibrate the model following the calibration strategy in Section 5.2. We keep the elasticity of substitution across occupational output as in the baseline, at $\rho = 1.34$, for comparability. Note that our counterfactual exercises on the alternative experiments abstract from interaction effects among the exogenous forces in the model. These effects are inconsequential to the conclusions we take from the alternative experiments.



(a) The role of demand shifters (b) The role of other forces

Figure 7: Other forces at play.

"Data & model" plots the fifth-degree polynomial fit of 100 times the change in share of employment between 1984 and 2015; the remaining lines plot the quadratic polynomial fit of the same outcome attributed to the various forces via the counterfactuals described in the text.

the data, this change was 3.52p.p. Demand shifters mostly miss the employment gains at the top of the skill distribution, as well as the hollowing out in middle skill occupations. Employment losses at the middle of the skill distribution that follow from the demand shifters are redirected equally toward higher employment in both high- and low- skill occupations, This is in contrast to the data, where see a flow into high-skill occupations that is 74% of the outflow from middle-skill occupations.

The right panel of Figure 7 shows that exogenous forces beyond CETC and demand shifters mostly play a secondary role in the US employment polarization. The only effect worth noting is that of changes in the weights of the different labor groups ("Composition" effects), which generate an outflow of employment from middle-skill occupations of a magnitude of 20% that observed in the data (mostly accounted by mechanics, transportation, and machine operators) and an inflow of employment toward high-skill occupations of a magnitude of 31% that observed in the data (mostly accounted by managers and professionals).[30]

Overall, we conclude that, on average, CETC, demand effects, and demographic compositional effects are the most important determinants of workers reallocation from middle skill occupations to high and low skill occupations. CETC is the most important contributor of

[30]Details on the quantifications of each of the effects by occupation are in Table E.II in the Appendix.

changes in the reallocation of labor in high-skill occupations.

7 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 BEA'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 5 to model occupational capital as an endogenous composite of different capital goods. In Section 7.1, we document the contribution of CETC that relates to specific capital goods for the reallocation of labor in the US between 1984 and 2015. In Section 7.2 we discuss the implications of capital accumulation for the equilibrium allocations.

7.1 Multiple capital goods

Consider a countable set of capital goods of cardinality J indexed by j. These capital goods map to the 24 BEA 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^k_{ot} of cardinality J_{ot}:

$$k_{ot} = \left(\sum_{j \in \Omega^k_{ot}} \xi_{jot}^{1/\phi} k_{jot}^{(\phi-1)/\phi} \right)^{\frac{\phi}{\phi-1}}.$$

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:

$$\frac{\xi_{jot}}{\xi_{j'ot}} = \frac{k_{jot}}{k_{j_b ot}} \left(\frac{\lambda_{jt}^k}{\lambda_{j't}^k} \right)^{\phi}, \quad \lambda_{ot}^k = \left(\sum_{j \in \Omega_{ot}^k} \xi_{jot} \lambda_{jt}^{1-\phi} \right)^{\frac{1}{1-\phi}} \tag{13}$$

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 18 and 16. 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 13.

To quantify this extended version of the model, we first parameterize the CES aggregator for capital and then run the calibration procedure in Section 5.2. We use the parameterized model to run counterfactual exercises analogous to those of Section 6 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 13:

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

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

$$\ln \left(\frac{\lambda_{jt}^k k_{jot}}{\lambda_{jt}^k k_{j_b ot}} \right) = \beta_1 \ln \left(\frac{\lambda_{jt}^k}{\lambda_{j_b t}^k} \right) + \epsilon_{jt}, \tag{14}$$

where $\epsilon_{jot} = \ln \frac{\xi_{jot}}{\xi_{j_b ot}} + \nu_{jot}$, 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 using OLS. We consider 24 capital goods, over 9 occupations and 32 years, between 1984 and 2015 and estimate an elasticity of substitution of $\phi = 1.13$ (se: 0.017).[31] Given

[31] Including a time-trend in regression equation 14 gives an estimate for the elasticity of substitution across capital goods of 1.42 (se: 0.030). If the trend is allowed to vary by occupation and capital good, we estimate a value of 1 (se: 0.014).

Table 4: CETC across capital goods.

	Data	CETC in: computers	communication	software
Fraction moving into:				
High-skill	10.16	0.70	0.81	1.12
Middle-skill	-13.82	-0.61	-0.73	-0.97
Low-skill	3.52	-0.09	-0.08	-0.15
Managers	3.97	0.27	0.32	0.38
Professionals	6.19	0.30	0.41	0.54
Technicians	-0.11	0.14	0.08	0.20
Sales	-1.15	-0.12	-0.12	-0.19
Administrative serv.	-4.16	-0.67	-0.80	-0.79
Low-skilled serv.	3.52	-0.09	-0.08	-0.15
Mechanics and transp.	-1.88	0.32	0.29	0.17
Precision production	-2.14	-0.09	-0.05	-0.10
Machine operators	-4.24	-0.05	-0.05	-0.07
Fraction moving into:				
High-wage	10.06	0.70	0.81	0.16
Middle-wage	-13.58	-0.61	-0.73	-1.49
Low-wage	3.52	-0.09	-0.08	-0.30

Note: entries are in percent. Columns under "CETC" present the outcome attributed to CETC via the counterfactual exercise. "High-skill" occupations are managers, professionals, and technicians. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations.

the estimate of ϕ, we set the occupational efficiency by capital type, ξ_{jot} to match our newly documented occupational expenditure shares by capital good and occupational capital stocks (Figure 2).

First, note that under our calibration the inferred role for CETC in all capital goods is identical to the one measured in our baseline model with occupational capital goods. We then use our model with multiple capital goods to evaluate the role of specific capital goods for the reallocation of labor. To do so, we run a counterfactual where we shut down, one at a time, the CETC in each capital good – that is, we set $\lambda_{j2015} = \lambda_{j1984}\ \forall j$, and consider the implications for employment reallocation between 1985 and 2015. Table 4 shows the contribution of CETC, separately for the three capital goods with the strongest impact on allocations: *computers*, *communication* equipment, and *software*. The direction of employment reallocation generated by CETC in the three capital goods is identical. However, the magnitude of these reallocations are not. CETC in computer generates the smallest reallocation of employment, communication equipment comes second in order of magnitude, while software comes first. This difference in magnitude is particularly relevant for administrative services and professionals. CETC in both communication and software generates an employment outflow from administrative service occupations that is more than 0.10p.p. stronger than that generated by computers. In professional occupations, CETC in software generates an employment inflow that is more than 0.10p.p. stronger than that generated by communication equipment and more than 0.20p.p. stronger than that generated by computers.[32]

Our results highlight the importance of studying broader equipment categories, other than computers. This is particularly important for the post-2000 period, where the stock of computers and software experienced a slow down in growth while communication equipment has continued its linear trend and has now surpassed the efficiency units value of the stock of computers.

7.2 Capital accumulation

A distinctive feature of equipment is its durability.

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 7.1.

[32] Different in magnitudes across CETC are also recorded for technicians, transportation, and mechanics, but the model generates counterfactual directions of the employment flows.

8 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 87% of the gross labor reallocation across occupations observed in the US since 1984. 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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Appendix

A Data

A.1 Data construction

Stocks in efficiency units. Given the nominal series for investment we construct measures of efficiency units of investment using the quality adjusted price of investment. 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) and updated in DiCecio (2009).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 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}.

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

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

where x_{jt} is the quality-adjusted investment series for a particular equipment category j. Available equipment categories are described in the Online Appendix.

We exploit information on tools to allocate capital of different equipment categories to each occupation at a point in time as described by req_{jot} in Section 2. Then we construct the stock of equipment in each occupation using a Tornqvist quantity index. Following, Oulton and Srinivasan (2003), the weights in the index correspond to the expenditure share of each equipment category $\omega_{oj} = \frac{r_j k_{ojt}}{\sum_{j' \in o} r_{j'} k_{oj't}}$, using estimates of the usercost of capital that follow from the standard no-arbitrage condition Jorgenson (1963):

$$r_{jt} = \frac{p_{jt-1}}{p^c_{t-1}} \left[R - (1 - \bar{\delta}_{jt}) \frac{\frac{p_{jt}}{p^c_t}}{\frac{p_{jt-1}}{p^c_{t-1}}} \right],$$

where p^c is the price of consumption, p_j is the price of equipment good i, and $\bar{\delta}$ corresponds to the average depreciation in the relevant decade of analysis.[33] We average the depreciation rates to smooth the effect of annual fluctuations in economic depreciation on the residual estimate for physical depreciation. The gross return on a safe asset is set at 2% per year, for $R = 1.02$. Hence, the growth rate of the stock at a point in time is $\gamma^k_{ot} = \sum_j \omega_{oj}\gamma^k_{ojt}$, where γ^k_{ojt} is the growth rate in the quality-adjusted stock of equipment j in occupation o at time t. We construct the stock of capital in each occupation by imposing that the stock in 1984 equals its nominal stock $\tilde{k}_{o1984}$, and iterating forward:

$$k_{ot} = k_{ot-1}e^{\gamma^k_{ot}}, \quad k_{o1984} = \tilde{k}_{o1984}.^{34} \tag{15}$$

Assignment of stocks to occupations. Our assignment rules for the capital stocks across occupations (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. 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 8 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 1984 levels ($\text{req}_{jot} = \text{req}_{jo1984}$, red line) or (b) in addition, the level of nominal investment was held constant to its 1984 level (green line).[35]

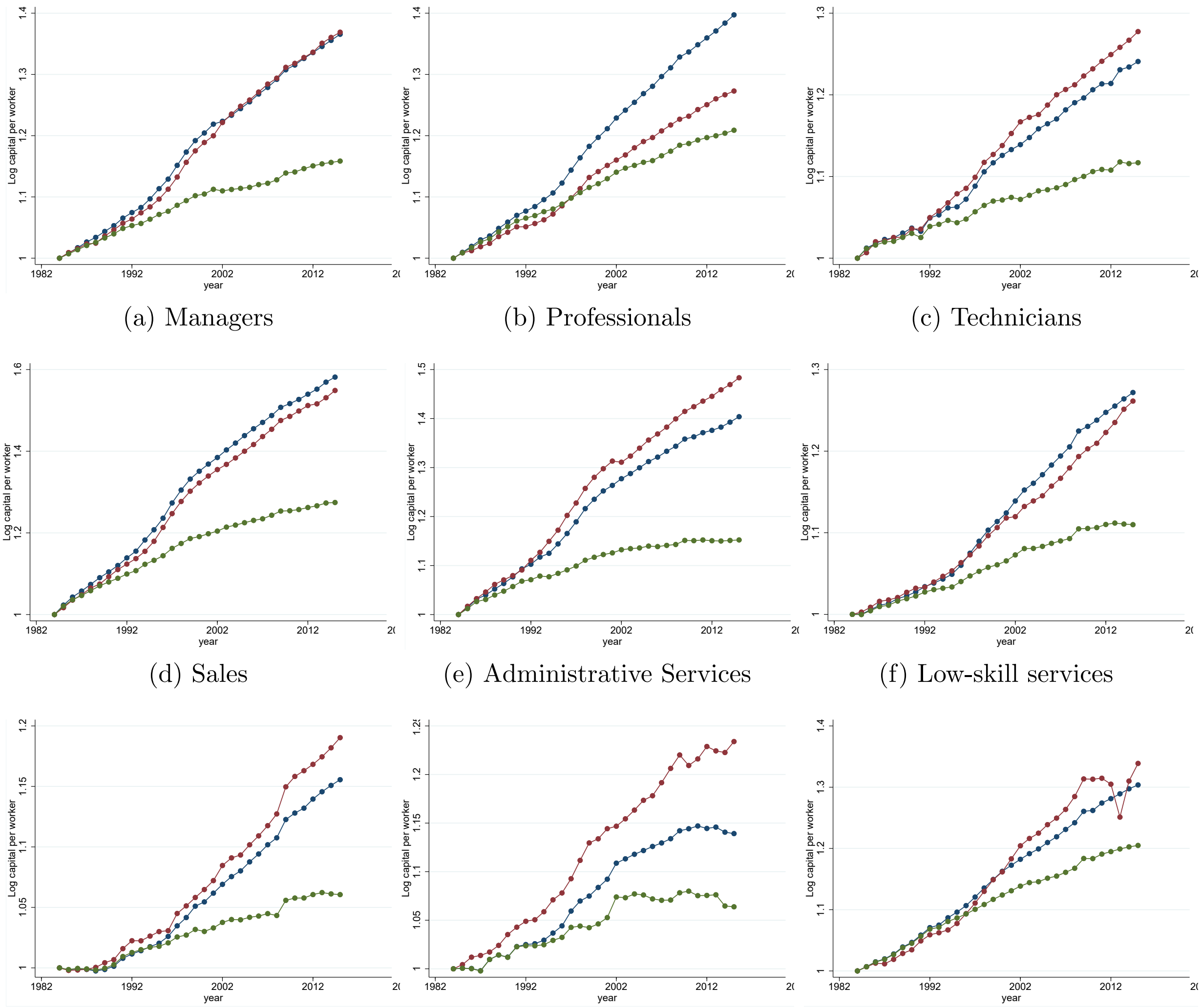
The difference between the benchmark data (blue) and a constant requirements series (red) is the tool and employment reallocation effect. This reallocation effect is positive for administrative services, low-skill services and precision production occupations, i.e. occupational tools increased relative to their 1984 level; and particularly so after the 2000s for machine operators, technicians, mechanics and transportation. The contribution of this reallocation for the growth in capital per worker is 26%, on average across these occupations. The reallocation effect is negative for professionals and sales occupations i.e. occupational tools decreased relative top their 1984 levels. The contribution of this reallocation for the growth in capital per worker is -17.7%, on average across these occupations. When in addition nominal investments are held fixed (green), the dynamics of the stocks are explained by the decline in the relative price of capital to consumption. The contribution of the decline in the relative price of capital to the change in the stock per worker across occupations averages 41%, and it is as low as 19% for machine operators and as high as 57% for administrative service occupations.

CETC at the occupational level. Our measure of CETC tracks the decline in the user cost of capital for the bundle of capital used in each occupation. Particularly, we compute a measure of the usercost of capital (in units of consumption) of the quality-adjusted capital services used in each occupation. We construct the usercost of the bundle of capital in an

[33] Our choice of weights in the Tornqvist quantity index is also consistent with those suggested by Gabaix and Koijen (2019).

[34] To compute the value of the nominal stock in 1984 in each occupation we use the tool requirements to assign the current cost stock of equipment of each category across occupations in 1984. We sum its dollar value to compute the nominal stock.

[35] 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 1984.



(a) Managers (b) Professionals (c) Technicians

(d) Sales (e) Administrative Services (f) Low-skill services

(g) Mechanics and transp. (h) Precision (i) Machine Operators

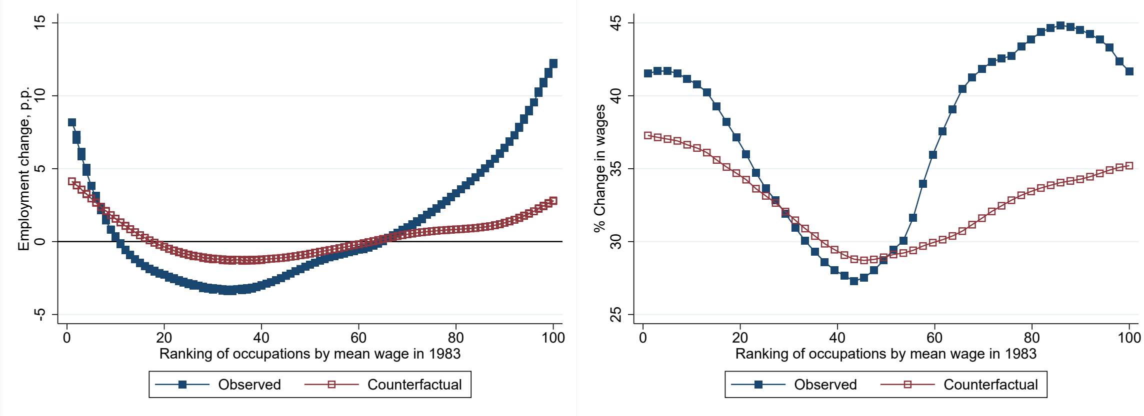
Figure 8: Allocation of capital to occupations.

Each panel corresponds to an occupation. The stock of capital per worker, normalized to 1984, is in blue. The stock of capital fixing the capital-requirements share to its 1984 level in red. The stock of capital per worker fixing the capital requirements and the nominal investment to their 1984s level is in green.

occupation using the ratio between the total expenses in capital in an occupation and the stock of capital in the occupation constructed using a Tornqvist quantity index.

A.2 Further evidence on CETC and the labor market

We consider the relevance of CETC for the polarization of the US labor market by constructing reduced-form counterfactuals in the spirit of Autor and Dorn (2013). In particular, we reweight the observed employment distribution across occupations by imposing no employ-



(a) Employment polarization

(b) Wage polarization

Figure 9: Change in capital-intensity and the labor market.

The left panel shows employment changes by occupation between 1984 and 2015 (polynomial fit, parameter 0.8) in blue, and reweighed 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 1984 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.

ment change in occupations above the median of the distribution of changes occupational capital per worker (see Panel (a) in Figure 9). 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 9 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.

A.3 Elasticity of substitution between capital and labor

Labor inputs. We construct measures of efficiency units of full-time equivalent workers using male young college-educated workers as the base group in each occupation. We adjust the efficiency units of labor of other demographics using the ratio of their average wages in a given occupation to the wages of the base group.

Wage per efficiency unit in each occupation. Constructed by dividing the wage-bill in an occupation year by our measure of efficiency units of full-time equivalent workers.

Capital services. We construct a measure of capital services in an occupation as the Torqvinst quantity index of quality-adjusted capital stocks for different equipment categories in the occupation.

User cost of capital. For consistency with the measurement of average wages, we compute the user cost of capital in an occupation as the ratio between capital expenses and the occupation-specific Torqvinst quantity index of capital in an occupation.[36] Capital expenses in an occupation are computed as the sum across equipment categories of the product of the stock of quality-adjustment equipment of a given category in an occupation and the user cost of capital for that equipment category at each point in time.

A.3.1 Instruments

To address the endogeneity concerns of the capital-labor ratio and relative input prices, we construct the following instruments.

Supply IV. For the aggregate estimate of the elasticity of substitution we use lagged birth rates, br, to proxy exogenous variation in the supply of labor. The instrument in year t is:

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

where $\underline{a}$ is the minimum working age in the sample (i.e. 16 years).

We modify this instrument when used for occupational-level regression to proxy exogenous variation in the supply of labor in a specific occupation. We do so by multiplying it by the share of employment of an educational level e allocated to the occupation in 1984 times the aggregate supply of skills at time t measured as the overall number of workers with education level e who have at least 24 years old. Education levels correspond college-educated workers, and those with less than college:

$$\log(br_{t-\underline{a}} \sum_{e} sh^{l}_{oe1984} n_{et}),$$

where $sh^{l}_{oet} = \frac{n_{oe1984}}{n_{o1984}}$ is the share of workers in occupation o and education e in 1984. This instrument is used in pooled regressions across 1-digit occupations, where we impose a common elasticity of substitution across occupations as well as in the benchmark regressions for each occupation in isolation. This instrument is weak in two occupations, namely, low skill services and mechanics and transportation. Therefore, we create an alternative instrument

Demand IV. We generate a measure of the demand for labor in an occupation using information on the sectorial composition of occupations in 1984, the sectorial composition of the labor force in each year, and exports as a share of GDP in each year. Sectors s are distributed between agriculture, manufacturing, low and high skill services following the industry codes available in CPS, which correspond to the 1990 Census Bureau industrial classification scheme. We construct a measure of the share of workers in a given occupation that are employed in a sector in 1984, $sh_{os1984} = \frac{n_{os1984}}{n_{o1984}}$, and multiply it by the number of workers in a sector and the share of exports in GDP, X_t at each point in time. We add these measures up within each 1-digit occupation and take the logs to construct a measure

[36]By construction, the user cost computed this way is almost identical to what one obtains through a Torqvinst price index for the user cost of capital in an occupation based on the user cost of each equipment category.

of exogenous changes in occupational labor demand:

$$\log(\sum_s sh_{os1984} n_{st} X_t).$$

B Model

B.1 Equilibrium

We characterize the equilibrium prices and allocations of labor and capital.[37] 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 11;
2. Profits in all occupations, final output, and capital production are maximized, equations 7, 8, 9;
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:

$$\lambda_{ot}^n = \left(\left(\frac{1}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{y 1-\sigma_o} - \left(\frac{\alpha}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{k 1-\sigma_o} \right)^{\frac{1}{1-\sigma_o}}. \tag{16}$$

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,

$$\lambda_{ot}^y = \lambda_t^y \left(\omega_{ot} \frac{y_t}{y_{ot}} \right)^{\frac{1}{\rho}}, \tag{17}$$

[37]Derivations in the Online Appendix.

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

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,

$$\frac{k_{ot}}{n_{ot}} = \left(\frac{\alpha}{1-\alpha}\frac{\lambda_{ot}^n}{\lambda_{ot}^k}\right)^{\sigma_o}. \tag{18}$$

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:

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

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

$$\pi_{oht} = \frac{T_{oht}(\lambda_{ot}^n)^\theta}{\sum_{o'} T_{o'ht}(\lambda_{o't}^n)^\theta}. \tag{19}$$

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

$$n_{ot} = \sum_h \int_{i\in\Omega_{ot}^h} n_{oht}(i)\pi_{ht}dF_{oht}(i) = \sum_h \pi_{ht}\pi_{oht}E(n|oht) = \sum_h \pi_{ht}\pi_{oht}\left(\frac{T_{oht}}{\pi_{oht}}\right)^{\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta}). \tag{20}$$

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 20 average wages are:

$$w_{oht} = \left(T_{oht}\sum_o \lambda_{ot}^{n\theta}\right)^{\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta}). \tag{21}$$

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.[38]

[38] Different occupational wages across occupation for a labor group, as observed in the data, can be

Labor supply-elasticity. Combing equations equation 19, 20 and 21, we can characterize the elasticity of labor supply to its price for *fixed average wages across labor groups*:

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

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

B.2 Parameterization

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

$$\frac{\pi_{oht}}{\pi_{o_bht}} = \frac{T_{oht}}{T_{o_bht}} \left(\frac{\lambda_{ot}^n}{\lambda_{o_bt}^n} \right)^\theta, \tag{22}$$

where o_b is a baseline occupation, which we set to be low-skill services (the occupation with the lowest average wage in 1984). 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 22 relies on a measure of wages per efficiency units across occupations.

To pin down the absolute advantage across labor groups, we use wage differentials. The level of the scale parameters influences 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:

$$\frac{w_{ht}}{w_{h_bt}} = \left(\frac{\sum_o T_{oht}(\lambda_{ot}^n)^\theta}{\sum_o T_{oh_bt}(\lambda_{ot}^n)^\theta} \right)^{\frac{1}{\theta}} = \left(\frac{T_{o_bht}}{T_{o_bh_bt}} \frac{\pi_{o_bh_b}}{\pi_{o_bh}} \right)^{\frac{1}{\theta}},$$

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, $\frac{T_{o_bht}}{T_{o_bh_bt}}$, 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, $T_{o_bh_bt}$. To do so, we use the specification of average wages, which links the wages of our baseline labor group to $T_{o_bh_bt}$ and the wage per efficiency

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 (1984 and 2015), 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.

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 $\lambda_{o_b t}^{n}$ 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 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 19 into equation 18, we write differences in capital per worker across occupations as a function of relative wages per efficiency units and observable variables:

$$\frac{k_{ot}}{\ell_{ot}} / \frac{k_{o_b t}}{\ell_{o_b t}} = \left(\frac{\alpha}{1-\alpha} \frac{\lambda_{ot}^{n}}{\lambda_{ot}^{k}} \right)^{\sigma_o} \left(\frac{\alpha}{1-\alpha} \frac{\lambda_{o_b t}^{n}}{\lambda_{o_b t}^{k}} \right)^{-\sigma_{o_b}} \frac{n_{ot}}{\ell_{ot}} \left(\frac{n_{o_b t}}{\ell_{o_b t}} \right)^{-1} \left(\frac{\lambda_{ot}^{n}}{\lambda_{o_b t}^{n}} \right)^{-1}, \tag{23}$$

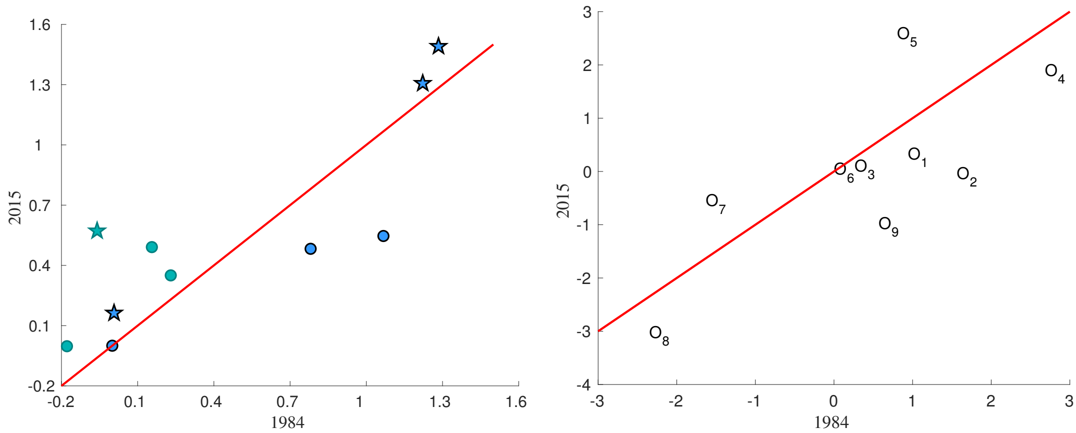
where $\ell_{ot} = \sum_h \pi_{oht}\pi_{ht}$. The first two terms on the RHS are the capital labor ratios, for labor measured in efficiency units. They are a function of the wage per efficiency units and observables. We observe the price of capital in our dataset and assign a value of 0.24 to the capital share in the production of the occupational good, as estimated by Burstein *et al.* (2019). The remaining terms in equation 23 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 23 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 22, 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:

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



(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 2.

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 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.[39] To measure the components of T, we estimate, in each year, the following regression equation:[40]

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

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.

[39] Note that our model does not specify the channel through which an increase in T_o happens. Labor may 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.

[40] 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 2015, the component associated to college graduates is 40p.p. higher than that associated to individuals without a college degree. The gap in wages between these two groups is 57p.p. in the same year. The group component associated to males is 31p.p. higher than that associated to females, while the gender wage gap is of 18p.p., in 2015. Between 1984 and 2015 the gender wage gap decreases of three seventh and the gap in efficiency units reduces of 2/3.

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, the elasticity of substitution, as well as of the occupational choice. For example, consider administrative services and mechanics, which are the two occupations that calibrates an increase in its demand shifter relative to low-skill services, between 1984 and 2015. These occupations both measure a slow increase in the wage per efficiency unit (equation 23), which push up the path of the occupation component (equation 22). Administrative services record the biggest changes in price and quantity of capital, as well as the highest elasticity of substitution. On the opposite end, mechanics and transportations record the smallest changes in price and quantity of capital along with the second smallest elasticity of substitution.

C Tables and Figures

Table E.I: CETC and changes in the labor market 1984-2015.

	Wage growth per year	Wages	Employment share	
			all	skilled workers
	(median, p.p.)	1984-2015 % change	(median p.p.)	
	(1)	(2)	(3)	(4)
Panel A: All occupations				
	0.8	28.7	0.0	6.1
Panel B: Occupations ordered by change in capital-per-worker				
Bottom third	0.7	24.2	-4.8	3.4
Middle third	0.7	24.7	2.2	7.6
Upper third	1.0	36.3	2.4	8.6
Panel C: Occupations ordered by intensity of use of capital categories with different CETC				
computers	1.0	34.9	-3.6	5.1
high CETC	0.8	28.2	5.5	7.4
low CETC	0.6	21.7	-2.0	3.5

Notes: Column (1) reports annualized change in average wages for workers in a given category. Column (2) reports the cumulated change in wages over the 1984-2015 period. Column (3) reports the change in employment shares while Column (3) reports the change in the share of high-skill workers in a given category. Panel B classifies occupations by the change in capital per worker over the sample period. Panel C classifies occupations by the intensity of use of capital with different CETC in 2015.

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

	Data	CETC	demand	demographics	CA	composition
Fraction moving into						
Managers	3.97	2.98	0.89	-0.28	-0.83	1.21
Professionals	6.19	2.69	3.42	-1.09	-0.80	1.96
Technicians	-0.11	1.64	-1.79	-0.02	0.13	-0.08
Sales	-1.15	0.22	-1.61	0.19	0.18	-0.13
Administrative services	-4.16	-8.86	4.75	-0.31	0.26	-0.07
Low-skilled services	3.52	0.41	2.41	0.49	0.60	-0.40
Mechanics and transp.	-1.88	3.96	-6.40	1.48	0.18	-1.09
Precision production	-2.14	-2.33	0.06	0.09	0.32	-0.30
Machine operators	-4.24	-0.71	-1.74	-0.60	-0.05	-1.14
High-skill	10.06	7.31	2.53	-1.38	-1.49	3.08
Middle-skill	-13.58	-7.72	-4.94	0.85	0.89	-2.74
Low-skill	3.52	0.41	2.41	0.49	0.60	-0.40

Note: All columns present the outcome attributed to the various forces via the counterfactual exercise. The description of all the counterfactuals in the columns is in the text. "High-skill" occupations are managers, professionals, and technicians. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations. Entries are in percent.

Table E.III: The role of CETC: channels.

	Data	Identical: elasticity	Identical: CETC	Identical: elasticity and CETC
Fraction moving into:				
High-skill	10.16	1.44	6.58	1.49
Middle-skill	-13.69	-0.48	-5.07	0.44
Low-skill	3.52	-0.96	-1.51	-1.93
Abs average movement:				
All	3.04	0.44	2.10	0.95
Non-college graduates	2.61	0.52	2.27	1.03
College graduates	1.03	0.36	1.86	0.85
16- to 29-year old	3.97	0.48	2.13	0.95
30- to 49-year old	2.86	0.43	2.07	0.94
50- to 65-year old	2.29	0.44	2.14	0.97
Females	4.33	0.45	2.10	1.06
Males	2.17	0.43	2.11	0.87

Note: entries are in percent. All columns aside from "Data" report the outcome attributed to CETC via the counterfactual exercises. Columns Identical elasticity, Identical CETC, and Identical elasticity and CETC show the results for the alternative exercises. "High-skill" occupations are managers, professionals, and technicians. "Low-skill" occupations are low-skill services. All remaining occupations are "Middle-skill" occupations. Entries are in percent.