Occupational exposure to capital-embodied technical change*

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Abstract

Factor-biased technical change is at the core of the US labor market dynamics in the post-war era. Concurrently, workers' occupations have become a key dimension for the anatomy of labor reallocation and inequality. This paper furthers our understanding of the heterogeneity in factor-biased technical change across occupations by providing the first direct measures of capital-embodied technical change (CETC) as well as of the elasticity of substitution between labor and capital at the occupational level. We find that CETC vary substantially across occupations and over time, but it is the heterogeneity in the elasticity of substitution that fuels differences in workers' exposure to technical change 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. In an economy with a common elasticity of substitution between capital and labor, measured differences in CETC can only explain 14.5% of the observed labor reallocation.

JEL codes: O13, O47, Q10.

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1 Introduction

A long tradition in labor economics and macroeconomics argues that factor-biased technical change is at the core of the US labor market dynamics in the post-war era (Katz and Murphy, 1992; Hornstein *et al.*, 2005). A more recent literature emphasizes the importance of workers' occupational heterogeneity for the anatomy of new labor market phenomena, e.g. employment and wage polarization (Acemoglu and Autor, 2011). In this paper, we aim at furthering our understanding of the heterogeneity in factor-biased technical change across occupations by providing the first direct measures of capital-embodied technical change (CETC) as well as of the elasticity of substitution between capital and labor at the occupational level.

CETC is a salient source of factor biased technical change (Krusell *et al.*, 2000) and materializes as a decline in the relative price of capital to consumption (Hulten, 1992). CETC may, at the same time, induce worker replacement in certain occupations, increase the demand of certain occupations, or create new occupations altogether. A thorough assessment of these effects is limited by the absence of data on the capital used in occupational production. Current assessments are either narrow in their focus on particular equipment/technology (e.g. Autor *et al.*, 1998; Kehrig, 2018); or rely on auxiliary data (notably the task characteristics of an occupation, e.g. Autor *et al.*, 2003; Autor, 2015). We provide the first-available measures of occupational capital, that cover all equipment types available in the economy and that are consistent with NIPA equipment and software aggregates. We document that the bundle of capital used in different occupations is heterogeneous and this heterogeneity leads to a substantial disparity in the decline of the user cost of capital. Despite such disparity in CETC, it is the heterogeneity in factor substitutability that ultimately sets the direction of the labor reallocation triggered by CETC. Using our estimates of the occupational elasticity of substitution between capital and labor, we find that CETC explains 87% of the gross labor reallocation across occupations observed in the US since 1984. In an economy with a common elasticity of substitution, measured differences in occupational CETC can only explain 14.5% of the observed labor reallocation.

Our first task is to discern the relevant channels through which CETC affects the labor market. To do so, we summarize workers' exposure to technical change through the cross-price elasticity of occupational labor demand – that is, the response of occupational labor demand to changes in the user cost of capital. This elasticity is only 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, under the assumptions of constant returns and price-taking behavior

(Hicks, 1932; Robinson, 1934). Our dataset allows inference of those four objects and so pinpointing of the channels at the heart of occupational heterogeneity in worker's exposure to technical change. Our second task is the quantification of these channels. The cross-price elasticity considers occupations in isolation and so misses important general equilibrium forces that were at play in the reallocation of workers over the past 30 years. Hence, we run the quantification in a general equilibrium model that is consistent with our concept of exposure and features endogenous worker selection across occupations.

We start by constructing a novel dataset of occupational capital. Our dataset covers the 24 major equipment and software categories considered by the Bureau of Economic Analysis (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 2015. The Tools and Technology module of the Occupational Information Network (O*NET) readily provides this information for 2015, but tool information in the earlier years is hard to come by. An important contribution of our paper is to collect such information, applying Natural Language Processing (NLP) algorithms over the description of occupations in the 1977 Dictionary of Occupational Titles (DOT), the predecessor to O*NET.[1] 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 occupational capital.

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 dataset and estimates of the user cost of capital by equipment category in the tradition of Jorgenson (1963). 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

[1] The Tools and Technology module of the O*NET was first exploited by Aum (2017) to study the impact of software innovation on the demand for high-skill jobs. We expand the set of tools he matched to equipment categories to include missing commodities in communication, service industry, and construction machinery accounting for 12% of the current stock in 2016 as measured in the NIPA fixed asset tables.

professionals and machine operators. We exploit this time variation along with changes in the relative user cost of capital to labor to estimate their elasticity of substitution in each occupation. 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.[2] Importantly, our estimates of the elasticity of substitution are robust to including control for the occupational task content (Autor *et al.*, 1998, 2003; Autor and Dorn, 2013), suggesting that our estimates pick up a novel dimension of heterogeneity across occupations.

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.[3] 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 services and its user cost. We find that occupational outputs are gross substitutes, with an elasticity of 1.34. Second, we take a Fréchet 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 worker's exposure to CETC 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 for managers, professionals, technicians, low-skilled services, mechanics and transportation; with the implication that the positive scale effect of a decline in the user cost of capital dominates the negative substitution effect, and so CETC increases labor demand (even when capital and labor are substitutable). We combine exposure with CETC and compute

[2]In the aggregate, we estimate an elasticity of substitution between capital and labor of 0.88, consistent with estimates by Oberfield and Raval (2020) and Leon-Ledesma *et al.* (2010). Our results are consistent with the aggregate decline in the labor share (Sahin *et al.*, 2013) through labor-biased technical change, which we estimate at 1.9% per year. Kehrig (2018) is the first attempt to measuring heterogeneity in the elasticities of substitution between capital and labor but his measure focuses solely on computers. A key advantage of our measurement is the inclusion of the entire stock of equipment in the economy.

[3]The unobservability of occupational output and prices also impede reduced-form estimates of the impact of the decline in the user cost of capital on labor demand, as implemented in Goos *et al.* (2014) using industrial output in the context of the declining user cost of routinizeable and offshorable tasks.

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.

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 how sizable has the impact of CETC been 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. The model considers incentives for reallocation of workers of different characteristics across occupations as well as changes in equilibrium wages. We find that CETC explains 73% of the observed reallocation of labor towards 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. In addition, we find that CETC fueled wage inequality: it generated 54% of the increase in the college premium, about 1/3 of the rise in the cross-sectional age premia, and also widened 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 dataset. Consistently with Eden and Gaggl (2018), our results indicate that CETC in computers, communication equipment, and software have been important drivers of employment reallocation and of the evolution of the returns to skill in the US over the last 30 years. However, since 2000, there has been a slow-down in the decline of the relative price of computers and, other categories of equipment, including communication, optical and medical instruments have become increasingly important for labor reallocation. This finding demonstrate the value of studying CETC by considering broad measures of equipment, relative to case studies that focus on computers and robots only (Autor *et al.*, 2006; Aum *et al.*, 2018; Burstein *et al.*, 2019; Acemoglu and Restrepo, 2018).[4] Distinctively from studies that focus on the adoption of capital-intensive modes of production, we show that the magnitude of measured disparities in CETC and capital labor ratios across capital types, occupations and time can not in itself rationalize employment dynamics over the last 30 years. It is only when CETC is paired with heterogeneous elasticities of substitution between capital and labor that CETC becomes a quantitatively relevant source for labor reallocation.

The rest of the manuscript is organized as follows. Section 2 constructs occupational capital and its user cost and presents key correlations between occupational 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 and CETC across occupations

In this section, we document the path of the capital used in each occupation as well as its user cost in the US between 1984 and 2015. We focus on equipment and measure occupational capital consistently with the aggregate investment series in the Fixed-Asset tables of the BEA. We follow the extensive literature that highlights the capital-embodied nature of technology and the secular decline in the cost of investment over 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 tools commonly used in each occupation, which we extract from the DOT in the 1970s and from it successor, the O*NET, in the 2010s. The resulting dataset of occupational capital and its user cost, replication code, and documentation are available online at www.capitalbyoccupation.weebly.com.

[4] Estimates from annual capital expenditure survey (ACES) suggest that robotic equipment accounts for 0.7% of total equipment expenses in the US in 2019, and that half of those expenses are concentrated in the manufacturing sector. Computers are an important contributor to the overall stock of equipment but the slow-down in the decline of computer prices implies a slow-down in investment-specific technical change.

Our dataset combines four 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 information from 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 from linear projections of quality-adjusted price series from Gordon (1987) onto NIPA price deflators for equipment (as in Cummins and Violante, 2002); and annual labor market statistics computed from the March Current Population Survey (CPS) between 1984 and 2015.

2.1 Methodology

We start by defining an occupation to be a production unit that uses capital and labor to produce output. We call the capital services used in an occupation "occupational capital", denoted by k_o. We assume it to be a constant returns to scale aggregator of the capital services used in production from individual equipment categories j, denoted by k_{oj}. This assumption along with that of competitive markets imply that the growth rate of the occupational capital, γ^k_o, is the weighted sum of the growth rate of individual equipment services j in the occupation, γ^k_{oj}, where the weights are determined by the expenditure shares of the different categories, ω_{oj}.[5] That is:

$$\gamma^k_{ot} = \sum_j \omega_{ojt}\gamma^k_{ojt}, \quad \text{for: } \omega_{ojt} = \frac{\lambda^k_{jt} k_{ojt}}{\sum_{jt} \lambda^k_{jt} k_{ojt}},$$

where λ^k_j is the user cost of capital for equipment category j.To measure this user cost, we use the standard no-arbitrage condition (Jorgenson, 1963):

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

where λ^c is the price of consumption, λ^k_j is the (quality-adjusted) price of equipment of type j, and $\bar{\delta}$ corresponds to the average physical depreciation in the relevant decade of analysis.[6]

[5] The choice of weights follows Oulton and Srinivasan (2003) and is also consistent with those suggested by Gourio and Ronglie (2020).

[6] We average the depreciation rates to smooth the effect of annual fluctuations in economic depreciation on the residual estimate for physical depreciation. Results are robust to allowing for annual changes in depreciation rates.

The gross return on a safe asset is set at 2% per year, for $R = 1.02$.

In each occupation, we initialize occupational capital in 1984 to equalize the amount of capital expenditures on all capital categories in the occupation. Then, iterating forward,

$$k_{ot} = k_{ot-1} e^{\gamma^k_{ot}}, \quad \text{for: } k_{o1984} = \sum_j \lambda^k_{j1984} k_{oj1984}. \tag{1}$$

Finally, we define CETC in each occupation, or occupational CETC, to be the decline in the user cost of capital relative to consumption in the occupation. We construct the user cost of occupational capital using the ratio between the total expenses in capital in an occupation and occupational capital:

$$\lambda^k_{ot} = \frac{\sum_j \lambda^k_{jt} k_{ojt}}{k_{ot}}.^{7} \tag{2}$$

To implement our methodology, we need a measure of the occupational stocks for each equipment category, k_{ojt}. We first construct aggregate quality-adjusted stocks by category, k_{jt}, and then assign their services across occupations as we describe next.

2.1.1 Quality-adjusted capital stocks per equipment category

We construct 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. We initialize the stocks in 1984 to equalize their nominal counterparts in 1985, our base year. Because the stock of capital 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.

We apply the permanent inventory method to construct stocks over time. This requires a measure of the efficiency units of investment and of the physical depreciation rate. We assume a linear technology to transform consumption goods into investment at rate q_{jt}, in the tradition of Greenwood *et al.* (1997). Hence, the efficiency units of investment in equipment j can be obtained by deflating nominal investment by its quality-adjusted price, p^k_{jt}. The measures of depreciation reported by BEA, d_{jt}, reflect both physical depreciation, δ_{jt}, and economic depreciation. We adjust these measures to compute physical depreciation

[7] This implied user cost is almost identical to that computed using a Tornqvist price index, with shares equal to the expenditure share of each equipment category in the occupation. Also note that the choice of the initial stock for occupational capital, equation 1, implies that the usercost of capital is normalized to 1 in each occupation in the initial period.

as follows:

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

where the measure of economic depreciation induced by the availability of more efficient capital is $\frac{q_{jt-1}}{q_{jt}} = \frac{p^k_{jt}}{\lambda^y_t} \frac{\lambda^y_{t-1}}{p^k_{jt-1}}$ and λ^y_{t-1} is the price of consumption.

2.1.2 Occupational assignment

We build an allocation rule for the aggregate quality-adjusted stocks of equipment to the occupations based on the occupational capital requirements.

An index of occupational capital requirements. We refer to the capital requirements of an occupation as the fraction of the aggregate stock of each equipment 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 compressors, dental cutting instruments, and personal computers. 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.[8]

We collect information on these tools across occupations in the US over the last 30 years. The O*NET, a database collecting standardized occupation-specific descriptors, readily provides information on occupational tools for the period post-2010 through its Tools and Technology module (available since 2006 but with scattered occupational coverage in the earlier years). To collect occupational tools in the beginning of our sample, 1980s, 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.[9] 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.[10]

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

[9]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.

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

For illustration, Figure B.I in the Appendix compares the occupational tools measured in the O*NET and DOT datasets for 1-digit occupations. It plots the fraction of tools used for two equipment 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. Over time, a worker in a professional occupation has 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 tasks performed, as well as the tools used to perform those tasks.

We use our time-series of occupational tools to construct occupational capital requirements. Let τ_{ojt} be the number of tools of BEA equipment 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 equipment 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. 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:

$$\text{req}_{ojt} \equiv \frac{\tau_{ojt} l_{ot}}{\sum_o \tau_{ojt} l_{ot}}. \tag{3}$$

We distribute the stock of capital of a given category to an occupation proportionally to these capital requirements, $k_{ojt} = \text{req}_{ojt} k_{jt}$.

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 equipment for. Our assignment rule exploits the highly disaggregated nature of tool descriptions to proxy for intensity of usage. An implication is that occupations that use a larger variety of tools within an equipment category will be allocated more capital. However, notice that capital is assigned equipment by equipment and therefore differences in total tool counts across equipment categories has no influence on the assignments. For example, the total count of tools in 2015 for non-medical equipment doubles that of medical equipment (373 vs. 170). If we were to double the number of tools for the latter category while keeping the distribution across occupations identical, occupational capital would remain unchanged.

Second, the reader may wonder how do tool counts get affected by task automation? The automation of some of the tasks executed by a worker in his job changes the nature of the job and so directly influences the aggregation mapping from the finer (10-digit) title information available in the DOT and the O*NET to the coarser 3-digit occupation classification system of the Census. To the extent that a 3-digit occupation is not fully automated, automation only implies a change in the tools used by a worker.[11] For example, an accountant may now use computer software that automates tasks previously done on paper. Our tool counts pick up this effect by extracting tool information in both the 1970s and in the 2010s. At the same time, when all the tasks executed by a worker in a 3-digit occupation get automated, the operation of the machine is usually overseen by a worker, either in the same role or in another role within the production process. For example, film projectionists have been mostly replaced by digital cinema projectors and the basic operation of these projectors is performed by a theatre's front-of-house and managerial staff. Our tool counts sensibly assign equipment to the 3-digit occupation of its operator.

Third, while differences in relative prices across equipment 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.[12]

We validate our measurement of occupational capital using available information on usage of computers by occupation and the capital stock by industry in Section 2.3.

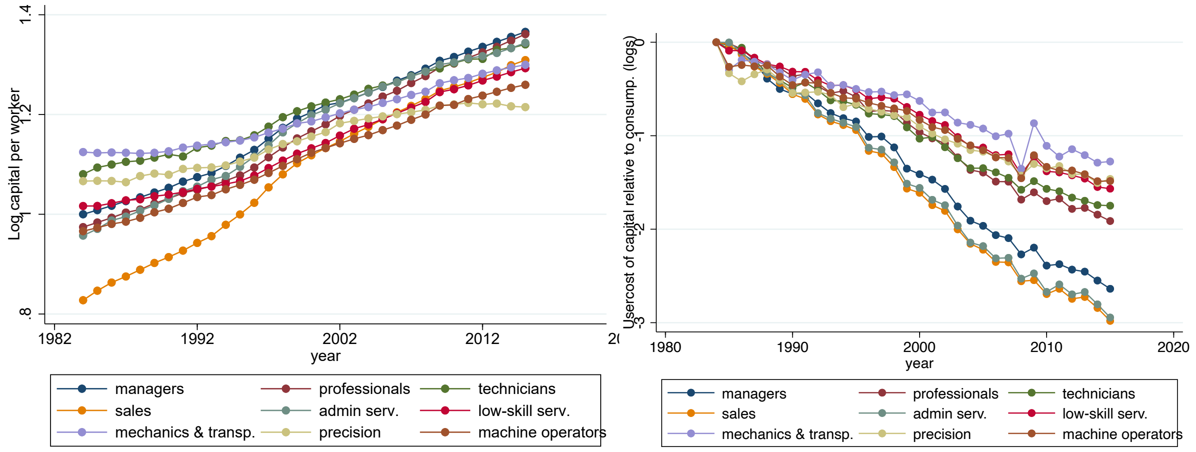
2.2 Salient features of occupational capital

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. Panel (a) in Figure 1 shows the time series of occupational capital per worker across occupations. The levels are normalized relative to the per-worker occupational capital of managers in 1984. Overall, occupational capital per worker increased in all occupations and the dispersion across occupations shrank throughout the period. The

[11]Indeed, Atalay *et al.* (2018) using newspaper job advertisement information find that most of the changes in nature of jobs happens within occupations.

[12]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) Capital per worker

(b) CETC

Figure 1: Capital and CETC by occupation.

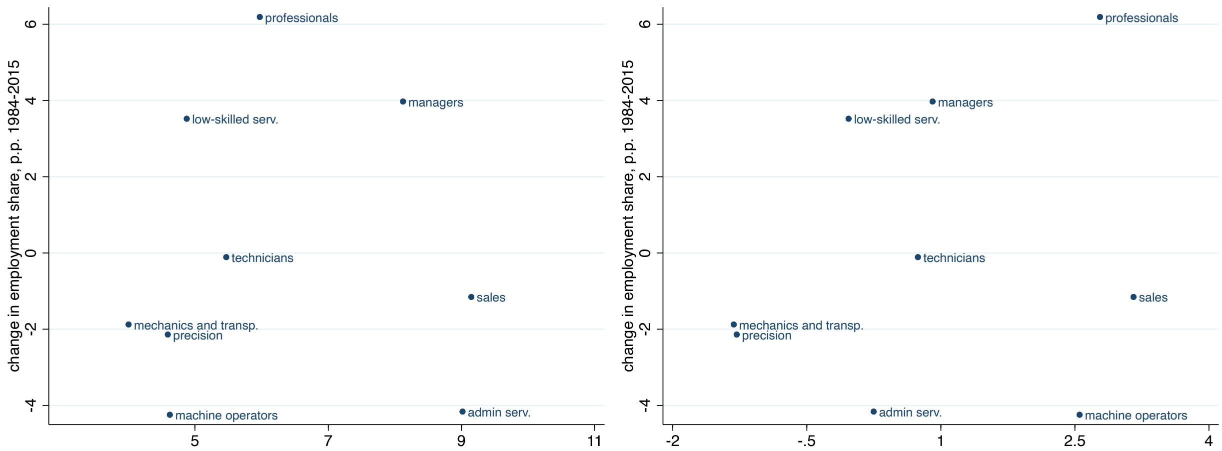
Panel (a) displays the logarithm of occupational capital per worker relative to managers in 1984. Panel (b) displays the logarithm of the user cost of capital relative to consumption across occupations. Source: BEA and own computations.

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. Panel (b) in Figure 1 displays the path of CETC for different occupations. 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.

Relationship to employment. Given the novel nature of our measurement of occupational capital and its user cost relative to consumption (CETC), it is worth exploring evidence for the relationship between these measures and labor market outcomes.[13] Figure 2 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

[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 the Online Appendix for a broader evaluation, including the relationship between CETC and outcomes when including controls for the task intensity of the occupation.



(a) CETC

(b) Input expense ratio

Figure 2: 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 by the wage bill) in each occupation between 1984 and 2015. All entries are in percent. Source: BEA, CPS, and own computations.

the share of employment in the latter decreased, while the share in the former increased. A similar conclusion is drawn when looking at the change in the input expense ratio, i.e. capital expenses divided by the wage bill in each occupation (Figure 2, panel b). 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 and employment across occupations 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 B.I. 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.*, 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, suggests 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 B.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).

The dimension of occupational heterogeneity more relevant to CETC is the degree of substituatibily between capital and labor, as hypothesized by Autor *et al.* (2003) and Autor *et al.* (2008). In Section 3, we then estimate occupation-specific elasticities of substitution between capital and labor.

2.3 Validation of occupational capital

Given the novelty of our measurement of occupational capital, we assess their comparability to alternative measures of capital and technical change used in the literature.

Implications for alternative disaggregations of the capital stock. By construction, our stocks aggregate to the BEA fixed asset tables for aggregate equipment by category (except, of course, through quality adjustments). We view this feature as a major advantage to users that would like to enrich otherwise standard macro models of the economy with occupational heterogeneity, and to users that would like to include capital in standard labor models of occupational heterogeneity.

An alternative disaggregation of the aggregate capital stock in the economy relies on the industries that use it. BEA provides fixed asset tables at the industry level, combining investment by asset type from NIPA and various sources of industry investment. While these measures are not free of imputation challenges, as described in BEA (2003), we find it worthwhile to compare our implied industrial allocation of capital to these measures.[14] We compute stocks in each 2-digits industry by aggregating up a measure occupational capital and exploiting the occupational composition of the industry. For comparability we assign nominal stocks of equipment instead of quality-adjusted ones, and abstract from agriculture and mining. The current-cost net stock of private equipment by industry in the fixed assets tables and our industry (nominal) stocks display a correlation of 0.84 in 1984, 0.79 in 2000, and 0.48 in 2016. Because these changes in correlation reflect changes in the composition of the stock of capital by equipment across industries over time, we also explore the allocation of each of the 24 equipment categories across industries. We find that the cross-industry correlation between the stock of a given equipment category computed in NIPA and using our allocation rule is stable in time for most equipment categories, e.g. communication displays a correlation of 0.6 in 1984 and 0.55 in 2016; medical equipment displays a correlation of 0.99 in both 1984 and 2016; while the correlation for aircrafts is 0.98 in 1984 and 0.81 in 2016. The one noticeable decline in such a correlation is observed for computers, with a correlation of 0.72 in 1984 and 0.3 in 2016. Cognizant of the note of caution that the BEA poses on the industrial equipment stocks due to a significantly lower imputation quality than those in the aggregate, we use an alternative validation for computer capital.

Alternative measures of computer capital. We compare the assignment of the stock of computers across occupations using our tool shares to the information in the October CPS Supplement (October Supplement) in 1984 and 2003, which asks employed workers whether they "use a computer at/for his/her/your main job."[15] As in our main analysis, we restrict the sample to employed individuals working full time (more than 35 hours a week) who are between 16 and 65 years old. We use this sample to estimate the distribution across 1-digit occupations of the total working hours of computer usage, each year. Figure B.II compares the share of computer usage and our measure of occupational tools in 1984 and 2003 (the last year available). The distribution of the tool measure across occupations is similar to that of computer usage with a correlation of 0.9 in 1984 and 0.96 in 2003. Moreover, the

[14] BEA (2003) explains that some industry sources provide information for selected benchmark years like economic Census; others provide information for interpolations between and extrapolations from the benchmark years. Wherever possible, the investment control totals are based on capital expenditures data collected from each industry, e.g. the ACES. Where these data are not available, the estimates are derived as the change in net stocks plus depreciation from industry balance sheet data as recorded regulatory offices, e.g. IRS.

[15] The computer module is also available in the CPS of 1989, 1993, 1997 and 2001. We focus on the earliest and latest modules for presentation purposes, but results are robust to using intermediate years.

correlation is also near one when considering changes over time: 0.96 for changes between 1984 and 2003. These strong correlations bring confidence to our newly constructed dataset, the main advantage of which is the breath of equipment considered relative to the October Supplement and the availability of data post-2003.

3 Elasticity of substitution between capital and labor

Heterogeneous occupational paths of CETC, capital-per-worker, and employment suggest that substitution patterns between capital and labor may differ across occupations. Next, we estimate these key elasticities for each 1-digit occupation.

The elasticity of substitution is the partial equilibrium response of the capital labor ratio to a change in the marginal rate of transformation. With the assumption of competitive factor markets, the marginal rate of transformation equals the relative input prices. To measure this elasticity, we need the information on input and price ratios in efficiency units, k_{ot}/n_{ot} and $\lambda^n_{ot}/\lambda^k_{ot}$. Non-neutral technical change has direct implications for this measurement 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 occupational capital and its user cost:

$$\sigma_o \equiv \frac{d\ln(k_{ot}/n_{ot})}{d\ln(\lambda^n_{ot}/\lambda^k_{ot})} = \frac{d\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}}\right)}{d\ln\left(\frac{\lambda^{\tilde{n}}_{ot}\exp(\gamma_{ot})}{\lambda^k_{ot}}\right)}, \tag{4}$$

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 (unobserved) biased technical change from a time series of factor shares and observable capital-labor ratios. 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, i.e. a decline in $\exp(\gamma_{ot})$; while increasing observable capital-labor ratios can be rationalized by labor-augmenting technical change, i.e. 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). Accordingly, we assume that factor-augmenting technical change is exponential, i.e. $\exp(\gamma_{ot}) = a_o \exp(\gamma_o t)$ for some initial level $a_o > 0$.[16] Then, under constant elasticity, the empirical counterpart to equation 4 is:

$$\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}}\right) = \beta_{1o} + \beta_{2o}t + \beta_{3o}\ln\left(\frac{\lambda^{\tilde{n}}_{ot}}{\lambda^{k}{}_{ot}}\right) + \epsilon_{ot}, \tag{5}$$

where β_{1o} is the intercept of the regression which corresponds to a constant of integration in equation 4; 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 that augments the structural equation 4.

To construct the series in the regression we aggregate our 3-digit series for quantities and prices to the 1-digit occupational classification system of the Census. We measure labor, $\tilde{n}_{ot}$, as full-time equivalent workers adjusted for efficiency due to observable characteristics, i.e. age, schooling, and gender. We use wages relative to males aged 16-24 with less-than-college as a proxy for skill/efficiency (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 user cost of capital and occupational capital constructed in Section 2. All series are available from 1984 to 2015.

Endogeneity. The estimation of regression equation 5 exposes an obvious endogeneity problem. Observed relative factor prices are endogenous to the capital labor ratios in each occupation. In general, the elasticity will not be identified unless one uses an exogenous shift in either the supply of capital or labor. In each 1-digit occupation, we construct an instrument for an exogenous shift in the supply of occupational labor.[17] We use the interaction between 16-year lagged live births per 1000 people, br_{t-16}, and the predicted employment in an occupation computed from the product of the 1984 share of employment of a given education level e (i.e., college or less-than-college) in the occupation, sh^l_{oe1984}, and the total number of workers of that educational level in the economy in each year, n_{et}:

$$\log(br_{t-16}\sum_e sh^l_{oe1984} n_{et}).$$

[16] The identifying restriction assumes that factor-augmenting technical change occurs at a constant proportional rate. We run robustness checks when we allow for a trend break in 2000, the time at which we observe a slow-down in the decline in the price of computers. Our results are robust to this more flexible specification, see Appendix B.III.

[17] While it may seem that this supply shifter affects the LHS of the estimation equation 5, in an exactly identified IV regression the estimated elasticity is the same whether capital-labor ratios are the LHS variable and relative prices are the RHS variable, or viceversa. We favor specification 5 because the mapping between the regression coefficients and the elasticity of substitution is linear, and therefore the computation of standard errors and hypothesis testing is straightforward.

A standard Kleibergen Paap F-statistic test suggests that this instrument is not strong for two occupations, namely low-skill services and mechanics and transportation (see details in the discussion that follows). For those occupations we construct a shifter in the supply of labor driven by an output demand shock in occupations other than the one under consideration. To do so, we exploit heterogeneity in the industrial composition of employment in an occupation. First, we predict the number of workers demanded by occupations other than the one under consideration using the total employment in each industry s, n_{st}, and the share of employment in these occupations that is employed in industry s in 1984, sh_{o^-s1984}. Second, we multiply this measure by the economy-wide level of exports as % of GDP, X_t, which we use as our output demand shifter:

$$\log(X_t \sum_s sh_{o^-s1984} n_{st}).$$

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 the size of the industries in the economy, measured by the number of workers in each industry, are likely correlated with the labor services available in each occupation. We discuss the statistical strength of these instruments after presenting the point estimates.

Results. Table 1 presents our baseline estimates of the elasticity of substitution for each occupation. 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.

Two features of these estimates are worth exploring. First, what are the implications for an aggregate measure of the elasticity of substitution of capital and labor? and second, are the occupational estimates different, in a statistical sense? We compute the estimate of the elasticity for the aggregate economy constructing economy-wide counterparts to the capital labor ratios and the relative prices for our sample period, 1984-2015. We use 16-year lagged live births per 1000 people to instrument for possible endogeneity. The IV point-estimate is

Table 1: Elasticity of substitution between capital and labor.

	OLS	**IV**	Kleibergen Paap 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**	9.22	-2.96
	0.21	*0.37*		
Mechanics & Transp.	0.04	**0.73**	6.65	-4.46
	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 5. 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.

0.88, slightly higher but consistent with recent exercises in Antras (2004) using time-series variation (0.8 for 1948-1998), Leon-Ledesma *et al.* (2010) using a normalized production function approach (0.6-0.7 for 1960-2004), and with Oberfield and Raval (2020) exploiting cross-sectional variation in the manufacturing sector (0.75 by 2007). To assess the heterogeneity in the occupational estimates of the elasticity of substitution, we run Wald type tests where we compare pair-wise each of the estimates (see Table B.II). We find that the elasticity of substitution between capital and labor is significantly lower for managers, professionals and technicians, than for administrative services, sales, and precision occupations. We also find that the point estimate for mechanics and transportation occupations is significantly lower than those in administrative services and precision occupations.

Discussion. The structural equation 4 is consistent with two econometric models, equation 5 and its inverse,

$$\ln\left(\frac{\lambda^{k}{}_{ot}}{\lambda^{\tilde{n}}_{ot}}\right) = \bar{\beta}_{1o} + \bar{\beta}_{2o}t + \bar{\beta}_{3o}\ln\left(\frac{k_{ot}}{\tilde{n}_{ot}}\right) + \bar{\epsilon}_{ot}. \tag{6}$$

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. 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. 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.

For the remainder of these 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% 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.

Finally, we loop back and discuss the implications of our elasticity estimates for the occupational heterogeneity in capital per worker and employment flows. First, we focus on the labor share, which combines information on both factor quantities and prices (equation 6 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 that are very much in line with ours, see Klump *et al.* (2012) for a review.[18]

Last, we focus on the potential confounding effects of our measures of the elasticity of substitution between capital and labor and other dimensions of occupational heterogeneity, namely the task content of occupations Autor *et al.* (2003). Table B.III shows estimates of the elasticity of substitution where the estimation equation 5 is augmented to include a measure of the routine task intensity (RTI) of each 1-digit occupation. Following Autor *et al.* (2006), $RTI_{ot} = \ln(routine_{ot}) - \ln(manual_{ot}) - \ln(abstract_{ot})$, where $routine_{ot}$, $manual_{ot}$, and $abstract_{ot}$ indicate the average normalized task score of occupation o in year t.[19] We find that the resulting estimates of the elasticity of substitution are only slightly more complementary than our benchmark, particularly so in high-skill occupations. We conclude that our estimates are robust to these controls and importantly, that our estimates pick up a novel dimension of heterogeneity across occupations.

[18] We present occupation-specific estimates of the bias of technology in the Online Appendix. In all but one occupation the estimate of the elasticity and the bias of technology implies a decline in the labor share.

[19] Task scores are measured for all 3-digit occupations in 1980. Changes in the employment composition imply that task inputs for 1-digit occupations vary in time. Tasks are measured on a zero to ten scale. We follow Autor *et al.* (2003) and replace the score of the occupations with the lowest task scores by the 5th percentile of each score.

4 Occupational exposure to CETC

We now 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:

$$-\frac{d\ln(n_o)}{d\ln(\lambda_o^k)} = \frac{\eta_{n\lambda^n}(\rho-\sigma_o)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}}{\rho+\eta_{n\lambda^n}+(\sigma_o-\rho)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}}, \tag{7}$$ [20]

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 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 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). The remaining two parameters, 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. We instead use a structural model where exposure arises endogenously. To ease the exposition, we defer the details of the estimation strategy to 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 start by reporting exposure to CETC in each occupation, Figure 3 left panel. In the figure, 1-digit occupations are ranked by increasing skill requirements, following Autor

[20]Derivations in the Online Appendix.

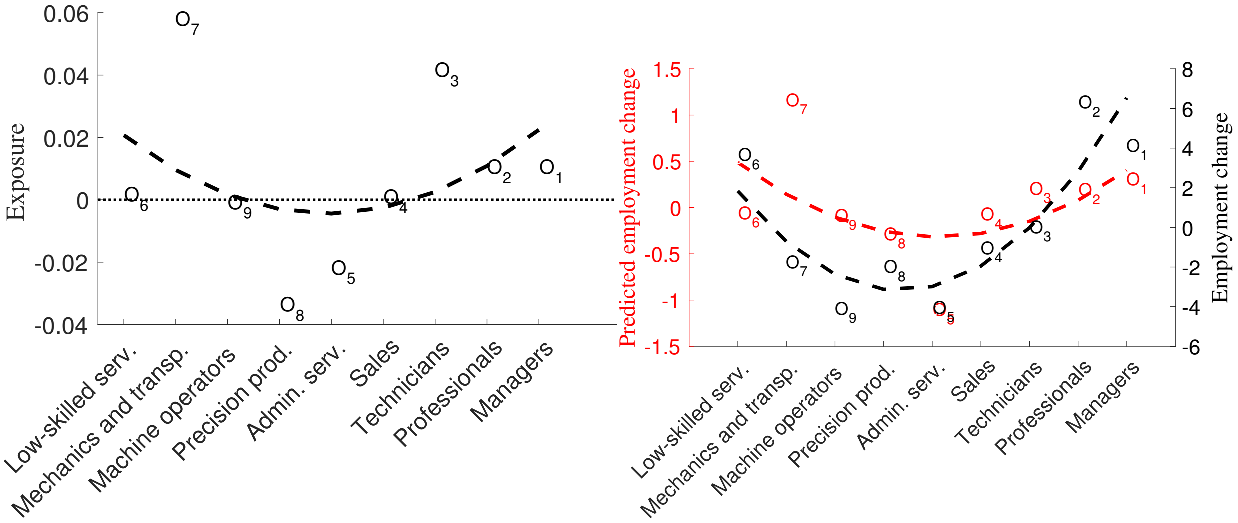


Figure 3: Occupational exposure to CETC and CETC-powered employment reallocation.

The left panel plots occupational exposure to CETC (equation 7) 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.

(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.[21]

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. Further, exposure is U-shaped across occupations ranked by their average wage and skill content. The exposure of high-skill occupations

[21]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.

(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%. 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.

Next, we combine exposure with CETC to compute the yearly changes in occupational labor demand generated by CETC. We cumulate these changes over the 1984-2015 period and re-weight them so that total net employment reallocation equals zero. The predicted employment changes are the Hicks (1932)'s (partial equilibrium) predictions for the impact of CETC on each occupation and are presented in Figure 3, right panel, black markers. The direction of employment reallocation generated by Hicks's prediction is consistent with the data (red markers). Importantly, 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 occupations, at 0.21p.p. per year, combining the second highest negative exposure with strong CETC. We conclude that the key driver of 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. An important limitation of the Hicks (1932)'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.[22]

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}:

$$y_{ot} = \left[\alpha k_{ot}^{\frac{\sigma_o - 1}{\sigma_o}} + (1 - \alpha) n_{ot}^{\frac{\sigma_o - 1}{\sigma_o}} \right]^{\frac{\sigma_o}{\sigma_o - 1}} . \tag{8}$$

A producer facing an occupational price λ_{ot}^{y}, a price of capital-o λ_{ot}^{k}, and a wage per

[22]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.

efficiency unit of labor λ^n_{ot}, chooses equipment and labor to maximize profits:

$$\max_{\{k_{ot},n_{ot}\}} \lambda^y_{ot} y_{ot} - \lambda^k_{ot} k_{ot} - \lambda^n_{ot} n_{ot}. \tag{9}$$

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 7.

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 model equivalent of the demand elasticity for occupational output in occupational exposure, equation 7. 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^y_t and prices of occupational goods λ^y_{ot} maximizes profits:

$$\max_{\{y_{ot}\}_{o=1}^{O}} \lambda^y_t y_t - \sum_o \lambda^y_{ot} y_{ot}. \tag{10}$$

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

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

$$\max_{\{x_{ot}\}} \lambda^k_{ot} q_{ot} x_{ot} - \lambda^y_t x_{ot}. \tag{11}$$

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 Fréchet 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.[23] 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:

$$\left(\frac{T_{oht}}{T_{o'ht}} / \frac{T_{oh't}}{T_{o'h't}}\right)^{\frac{1}{\theta}}, \tag{12}$$

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:

$$o^{\star}_{ht}(i) \equiv \arg\max_{o}\{w_{oht}(i)\}. \tag{13}$$

5.2 Parameterization

We parameterize the model equilibrium to the US economy, over the 1984-2015 period. The definition and characterization of the equilibrium is standard and, for brevity, described in Appendix A. 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

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

distribution of efficiency units of labor to match labor market outcomes and the demand structure of occupational output to match occupational capital per worker across occupations. The parameterization of the model delivers the two components of exposure to CETC, equation 7, 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 1). 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 Fréchet distribution, θ, and the scale parameters, $\{\{\{T_{oht}\}_{o=1}^{O}\}_{h=1}^{H}\}_{t=\{1984,2015\}}\}$. 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 $\theta = 1.30$.[24] Combining our estimate of θ with the specification of the labor supply elasticity in our model, we deduce $\eta_{n\lambda^n_o} = \theta - 1 = 0.30$.[25]

The model defines a link between the labor market outcomes of workers of a given group h and their associated scale parameters of the Fréchet distribution, T_{oht} (equations 20 and 22). 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

[24] Our estimate of the shape parameter of the Fréchet distribution is consistent with Hsieh *et al.* (2019) and Burstein *et al.* (2019) who, using a similar identification strategy, parameterize it at 1.24 and 2, respectively.

[25] A labor market participation choice can be accommodated in our environment as in Hsieh *et al.* (2019). The measure of occupational exposure to CETC remains unchanged with this additional margin, as well as the identification of the labor supply elasticity (through the residual wage variation) and the demand elasticity of occupational output (through the production technology).

of substitution between capital and labor and factor prices (equation 19). 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 Fréchet 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 21).[26]

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 18:

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

The covariation of the value of occupational output with relative occupational prices gives an estimate of the elasticity of substitution across occupations. 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 17).

We are then able to estimate the following regression equation:

$$\ln\left(\frac{\lambda^y_{ot} y_{ot}}{\lambda^y_{o_b t} y_{o_b t}}\right) = \beta_1 + \beta_{2o} t + \beta_3 \ln\left(\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}}\right) + \epsilon_{ot}, \tag{14}$$

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 14 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.

Our estimation considers eight occupations, over 32 years, between 1984 and 2015. The

[26] Details on the inference of the scale parameters of the Fréchet distribution and on the profile of wages per efficiency unit are in the Online Appendix.

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).[27] 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. 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 Fréchet distribution.[28]

Last, to pin down the demand shifters, ω_{ot}, we use the first-order conditions of optimization of the final good producer (equation 18) along with the price of occupational output 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").[29] 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

[27]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.

[28]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. The novelty of our approach relies on our ability to measure occupational capital and so occupational expenditure shares.

[29]Details on the decomposition of the scale parameters of the Fréchet distribution in the occupation, group, and comparative advantage components are in the Online Appendix.

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.

interactions we remove these forces in different ordering and compute the effect of a particular force by averaging across different orderings.[30]

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 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

[30]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.

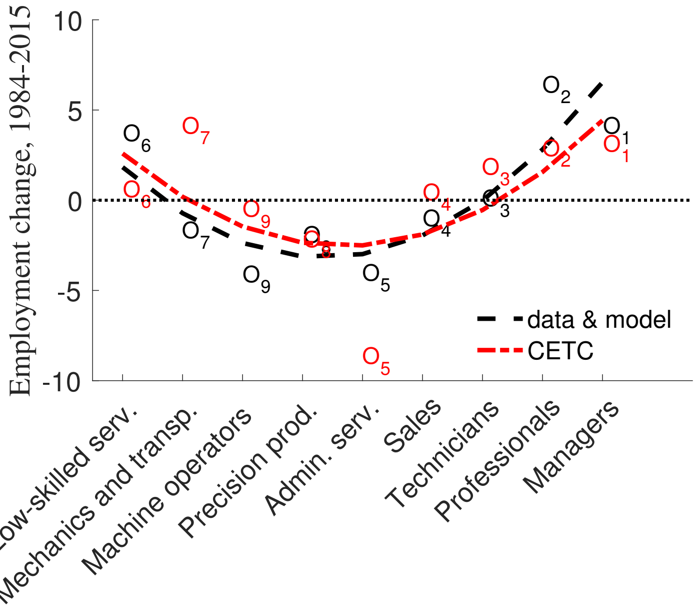


Figure 4: Employment polarization.

"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.

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 4 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).

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 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 com-

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.

parative 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 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 5, 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,

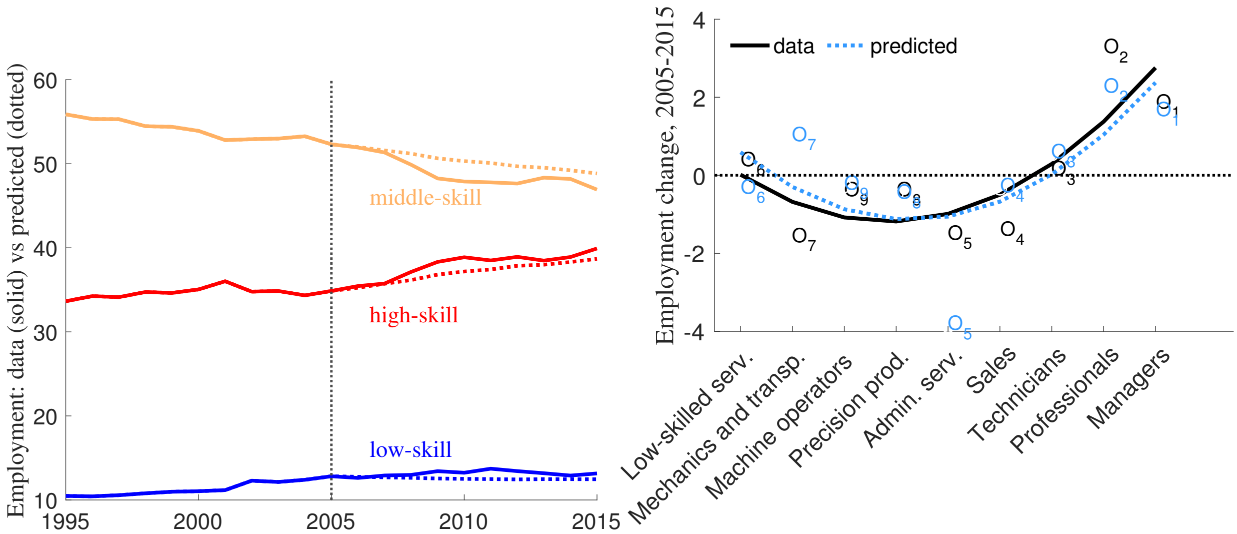


Figure 5: Forecasting exercise.

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.

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). In this latter prediction, 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.

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, rather than through heterogeneity in the extent of CETC. We now test this finding in our general equilibrium model. To isolate the quantitative role of these two sources 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 5, Section 3.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 B.V in the Appendix reports the contribution of CETC in the three alternative experiments.[31]

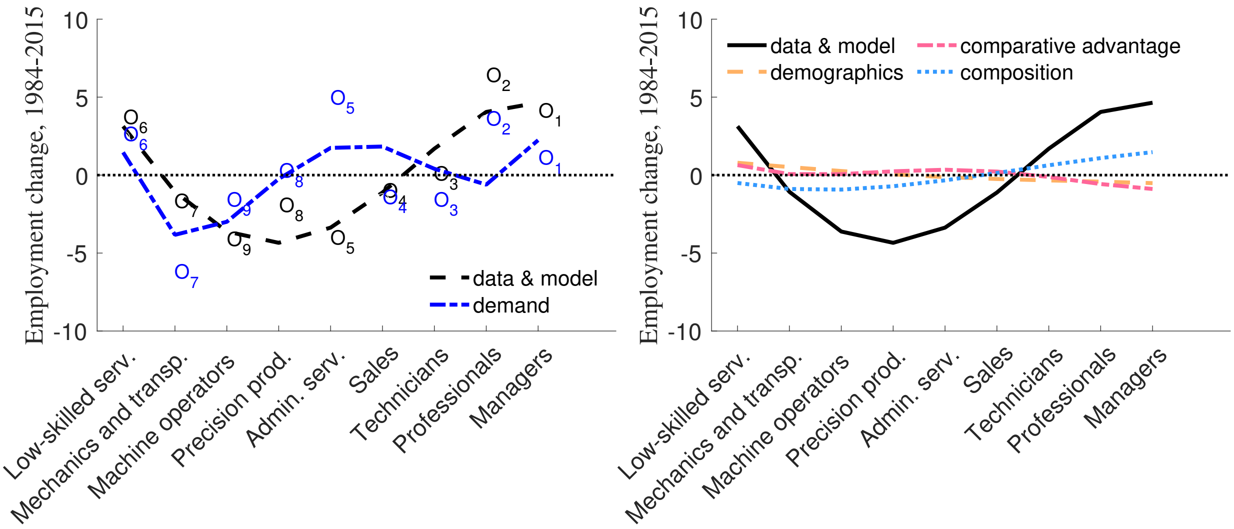
Consistently with our findings in Section 4, the heterogeneity in the elasticity of substitution across occupations is the most important driver for the direction and the magnitude of the reallocation of labor across occupations. When we force identical elasticities of substitution in all occupations, 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 maojr 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 6 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 the data, this change was 3.52p.p. Demand shifters mostly miss the employment gains

[31] 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 6: 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.

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 6 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).[32]

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

[32] Details on the quantifications of each of the effects by occupation are in Table B.IV in the Appendix.

7 Discussion

One of the key advantages of our measures of occupational capital 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}:

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

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, $\lambda^k_{jt} = 1/q_{jt}$. Given the price of each capital good, the optimal capital allocation in an occupation and the price of occupational capital satisfy:

$$\frac{\xi_{ojt}}{\xi_{j'ot}} = \frac{k_{ojt}}{k_{j_b ot}} \left(\frac{\lambda^k_{jt}}{\lambda^k_{j't}} \right)^{\phi}, \quad \lambda^k_{ot} = \left(\sum_{j \in \Omega^k_{ot}} \xi_{ojt} \lambda_{jt}^{1-\phi} \right)^{\frac{1}{1-\phi}} \tag{15}$$

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 19 and 17. 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 15.

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 15:

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

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

$$\ln\left(\frac{\lambda_{jt}^k k_{ojt}}{\lambda_{jt}^k k_{j_b ot}}\right) = \beta_1 \ln\left(\frac{\lambda_{jt}^k}{\lambda_{j_b t}^k}\right) + \epsilon_{jt}, \tag{16}$$

where $\epsilon_{ojt} = \ln\frac{\xi_{ojt}}{\xi_{j_b ot}} + \nu_{ojt}$, 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).[33] Given the estimate of ϕ, we set the occupational efficiency by capital type, ξ_{ojt} to match our newly documented occupational expenditure shares by capital good and occupational capital stocks (Figure 1).

First, the static nature of our model implies that, under our calibration, the inferred role for CETC across 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

[33] Including a time-trend in regression equation 16 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.

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.[34]

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

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 maojr 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.

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 Model derivations

Equilibrium definition. We define the 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, $\{\pi_h\}_{h=1}^{H}$.

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 13;
2. Profits in all occupations, final output, and capital production are maximized, equations 9, 10, 11;
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:

$$\lambda_{ot}^n = \left(\left(\frac{1}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{y1-\sigma_o} - \left(\frac{\alpha}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{k1-\sigma_o} \right)^{\frac{1}{1-\sigma_o}}. \tag{17}$$

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,

$$\lambda_{ot}^y = \lambda_t^y \left(\omega_{ot} \frac{y_t}{y_{ot}} \right)^{\frac{1}{\rho}}, \tag{18}$$

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,

$$\frac{k_{ot}}{n_{ot}} = \left(\frac{\alpha}{1-\alpha}\frac{\lambda^n_{ot}}{\lambda^k_{ot}}\right)^{\sigma_o}. \tag{19}$$

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 Fréchet distribution, we solve for the occupational allocation of workers of group h:

$$\pi_{oht} = \frac{T_{oht}(\lambda^n_{ot})^{\theta}}{\sum_{o'} T_{o'ht}(\lambda^n_{o't})^{\theta}}. \tag{20}$$

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

$$n_{ot} = \sum_h \int_{i\in\Omega^h_{ot}} n_{oht}(i)\pi_{ht}dF_{oht}(i) = \sum_h \pi_{ht}\pi_{oht}E(n|oht) = \sum_h \pi_{ht}\pi_{oht}\left(\frac{T_{oht}}{\pi_{oht}}\right)^{\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta}). \tag{21}$$

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 Fréchet 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, $w_{oht} = \lambda^n_{ot}E(n|oht)$. Using equation 21 average wages are:

$$w_{oht} = \left(T_{oht}\sum_o \lambda^{n\theta}_{ot}\right)^{\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta}). \tag{22}$$

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. Fréchet 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.[35]

[35]Different occupational wages across occupation for a labor group, as observed in the data, can be rationalized via occupational preferences that generate equilibrium compensating differentials (see Hsieh

Labor supply-elasticity. Combing equations equation 20, 21 and 22, 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 Fréchet distributional assumption of workers' efficiency units across occupations.

B Tables and Figures

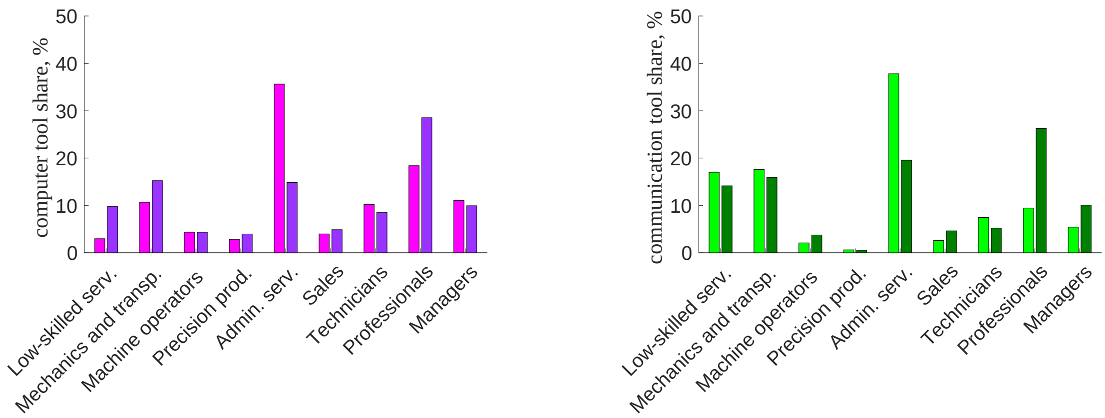

Figure B.I: Changes in tool shares.

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.

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.

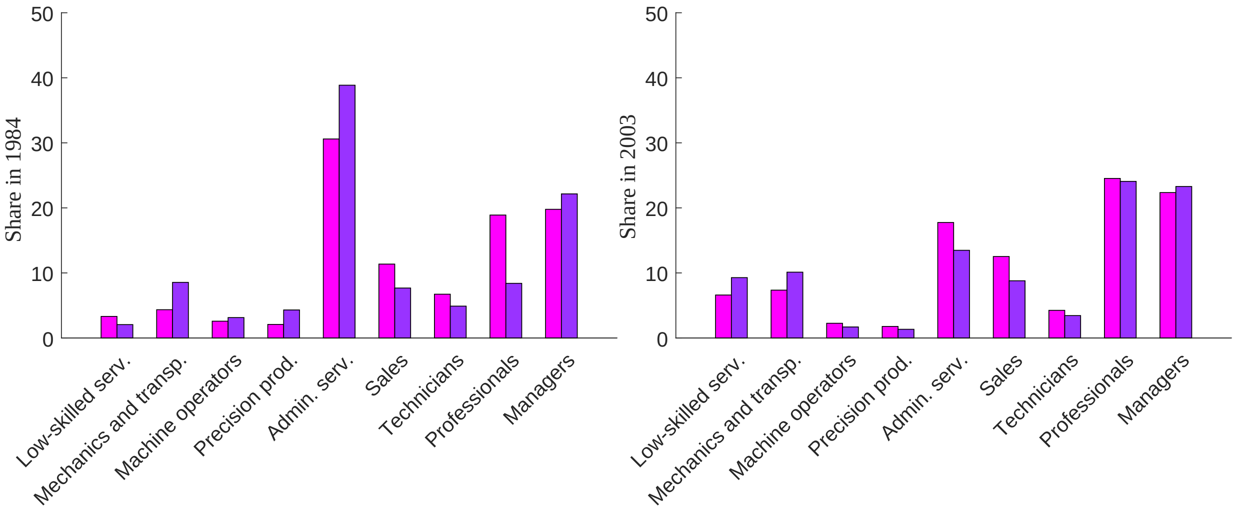

Figure B.II: Comparison tool share and computer use.

The figure shows the distribution of hours of work using computers according to historical data using the CPS October supplement (light colors) and the distributions of computer tools used by workers in each 1-digit occupation based on DOT and O*NET (darker colors). The left panel shows data for 1984 for computer use and 1984 for tool shares. The right panel displays each measure in 2003. Source: O*NET, DOT, CPS and own computations.

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

	Wage growth per year	Wages	Employment share	
			all	skilled workers
		1984-2015		
	(median, p.p.)	% 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 B.II: Wald Test for equality of elasticities, p-values

	Professionals	Technicians	Sales	Admininstrative services	Low-skill services	Mechanics & Transportation	Precision	Machine Operators
Managers	0.83	0.38	0.13	**0.03**	0.38	0.59	**0.09**	0.46
Professionals		0.42	**0.03**	**0.01**	0.26	0.67	**0.06**	0.38
Technicians			**0.01**	**0.01**	0.11	0.90	**0.03**	0.23
Sales				0.13	0.89	**0.08**	0.29	0.96
Admin serv.					0.16	**0.02**	0.88	0.33
Low-skill services						0.22	0.30	0.90
Mechanics & Transportation							**0.06**	0.31
Precision								0.45

The table reports the p-values associated to a pair-wise Wald test for equality of the elasticity estimate, β_3 in equation 4. Bold entries correspond to pairs where the null of equality of the estimates is rejected.

Table B.III: Estimates of σ_o, robustness.

	baseline		RTI controls		quadratic trend		trend break 2000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Managers	0.93	*0.25*	0.85	*0.14*	0.97	*0.27*	1.30	*0.59*
Professionals	0.86	*0.17*	0.64	*0.33*	0.90	*0.18*	0.58	*0.39*
Technicians	0.65	*0.21*	0.71	*0.22*	0.64	*0.21*	0.67	*0.54*
Sales	1.38	*0.16*	1.20	*0.11*	1.43	*0.18*	1.91	*0.33*
Admin Services	2.18	*0.50*	1.57*	*0.22*	2.31	*0.55*	3.66	*1.49*
Low-skill Services	1.32	*0.37*	1.28	*0.40*	1.07	*0.38*	1.27	*0.60*
Mechanics & Transportation	0.73	*0.35*	0.86	*0.47*	0.43	*0.30*	0.65	*0.38*
Precision	2.06	*0.63*	2.10	*0.57*	2.02	*0.61*	2.06	*0.99*
Machine Operators	1.41	*0.61*	1.62	*0.72*	1.50	*0.64*	2.17	*1.64*

The table reports the baseline estimates of the elasticity of substitution between capital and labor in each occupation (Column 1) and their standard errors (Column 2), alongside the estimates from alternative specifications of regression equation 5. Columns (3) and (4) present estimates and standard errors when controlling for a measure of the routine task intensity (RTI) of the occupation, as described in the Section 3. Columns (5) and (6) report results when we allow for a quadratic time trend in regression 5 while Columns (7) and (8) allow for a break in the time trend in 2000, which marks the beginning of the slow-down in the decline of the price of computers. * Instrumented with the stock of warehouses in the economy.

Table B.IV: 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 B.V: The role of CETC: channels.

	Data	Identical:		
		elasticity	CETC	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.