Occupational exposure to capital-embodied technical change*

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September 2022.

Abstract

Factor-biased technical change is at the core of the post-war US labor market dynamics and, in recent years, occupations have become a key dimension for the anatomy of labor market outcomes. 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) and of the elasticity of substitution between capital and labor at the occupational level. We document that CETC varies substantially across occupations, but it is the heterogeneity in the elasticity of substitution that fuels differences in workers' exposure to technical change. 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. Between 1984 and 2015, CETC induced a gross labor reallocation of 2.8p.p. in the US versus the 3.0p.p. observed in the data. With identical elasticities of substitution across occupations, CETC only generates a reallocation of 0.49p.p.. CETC was also responsible for two-thirds of the rise in the college premium and was a force towards widening the gender wage gap.

JEL codes: O13, O47, Q10.

*We thank our discussant Mathias Kehrig, as well as Levon Barseghyan, Philipp Kircher, Fabian Lange, Tim Lee, Yongseok Shin, and Mathieu Taschereau-Dumouchel for detailed comments on this project. We benefitted from conversations with seminar participants at the SITE macro workshop, MMF workshop, the NBER SI 2020 and 2021 meetings, Universidad Torcuato Di Tella, the University of Melbourne, the University of Wisconsin, Stony Brook, McGill University, the Rotman School of Management, the IADB, the SED. We thanks Luming Chen and Jisu Hwang for research assistance and Chris Myers for technical assistance. We thank the Institute of Social Sciences at Cornell University for financial support. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of Banco de Mexico. The resulting dataset of occupational capital, its user cost, its code, and documentation are available online at www.capitalbyoccupation.weebly.com.

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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 occupational heterogeneity for the anatomy of new labor market phenomena, e.g. employment and wage polarization (Acemoglu and Autor, 2011). In this paper, we study how factor-biased technical change across occupations relates to these labor market phenomena 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. Pinpointing to the drivers of employment reallocation and wage inequality is of first order relevance to the understanding of where occupational demand and returns have moved and where they will likely move as technical change evolves. This understanding informs policies geared towards skill-acquisition, e.g. worker retraining programs and the design of higher education programs.

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 measures of occupational capital that cover all equipment categories 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 disparities in CETC. The direction of labor reallocation triggered by occupational CETC is ultimately steered by the occupational disparities in the elasticity of substitution between capital and labor that we estimate. We find that, between 1984 and 2015, CETC induced a gross labor reallocation of 2.8p.p. in the US versus the 3.0p.p. observed in the data. With identical elasticities of substitution across occupations, CETC only generates a reallocation of 0.49p.p.. Over the same period of time, CETC was also responsible for two-thirds of the rise in the college premium and was a force towards widening the gender wage gap.

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 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 competitive markets (Hicks, 1932; Robinson, 1934). Our dataset allows inference of those four objects and, therefore, a characterization of the sources of occupational heterogeneity in workers' exposure to technical change. Our second task is the quantification of the magnitudes of labor reallocation and wage inequality implied by CETC in a general equilibrium model that is consistent with exposure and that features endogenous worker selection across occupations. The cross-price elasticity considers occupations in isolation and so misses shifts in the price of labor and occupational output that guide worker reallocation across occupations. Further, our model allows to study CETC in tandem with other forces driving worker reallocation and wage inequality, e.g. occupational demand (offshoring) and demographical shifts.

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. Under the assumptions of constant returns and competitive markets, two ingredients of exposure can be inferred directly from our dataset: the capital expenditure

[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.

share and the elasticity of substitution between capital and labor. We estimate the latter by exploiting time variation in the ratio of capital to labor expenses along with changes in the relative user cost of capital to labor in each occupation.[2] Middle- and low-skill occupations are substitutable to capital on average, with an average elasticity of 1.5; while high-skill occupations are complementary to capital, with an average elasticity of 0.81.[3] 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), and labor-biased technical change at 1.9% per year, consistent with the aggregate decline in the labor expenditure share (Sahin *et al.*, 2013).

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.[4] 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 workers' exposure to CETC across occupations: exposure is positive for managers, professionals, technicians, mechanics, transportation, and low-skill services occupations; and it is negative for precision production, machine operators, sales, and administrative occupations. A positive exposure implies that the positive scale effect of a decline in the user cost of capital dominates the negative substitution effect, and

[2]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). 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]Importantly, our estimates of the elasticity of substitution are robust to including controls 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.

[4]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.

so CETC increases labor demand (even when capital and labor are substitutable). Exposure is U-shaped when ranking occupations by their skill-requirements, measured from average wages at the beginning of the sample period. Hence, it is qualitatively consistent with the polarization of employment observed in the US labor market over the last 30 years.

Then, how sizeable has the impact of CETC on the US labor market been? To answer this question we take on our second task and quantify the role of CETC for labor market outcomes in general equilibrium. We find that CETC explains 78% of the observed reallocation of labor towards high-skill occupations between 1984 and 2015. CETC also accounts for 61% of the reallocation out of middle-skill occupations and for a small fraction of the reallocation toward low-skill occupations, 12% of it. For this latter reallocation, shifts in occupational demand are important, but they can only explain a negligible amount of the employment gains in high-skill occupations. Over the same period of time, CETC also fuelled wage inequality: it generated 62% of the increase in the college premium and about 1/3 of the rise in the cross-sectional age premium, mostly via the rise in the wage per efficiency units in managerial and professional occupations. In addition, CETC widened the gender wage gap of 14.5p.p. by increasing the wage per efficiency units in mechanics, transportation, and managerial occupations, where women are relatively less productive than men.

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 between 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 findings favor the substitution channel rather than the scale channel for CETC as a driving force of employment polarization. In a nutshell, we estimate higher capital-labor complementarity in high- and low-skill occupations than in middle-skill occupations and, consequently, CETC moves employment out of middle-skill occupations and into low- and high-skill occupations. In our analysis, we also document a difference in the capital expenditure shares and in the magnitudes of CETC across occupations, but the former is not a significant determinant of exposure and the latter is not systematically correlated with employment flows.

Last, we tease out the role of technical change in each equipment category by extending our baseline model to specify occupational capital as a CES composite of different capital goods, with an elasticity of substitution of 1.13, which we estimate using our dataset. This exercise allows us to compare our findings to previous studies that have focused on narrower equipment categories. 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 in the price of computers and other categories of equipment, including communication, optical, and medical instruments, have become increasingly important for labor market outcomes. Further, we find that CETC in computers contributed 20% to the rise in the college premium, a lower contribution than the 60% that Burstein *et al.* (2019) estimate. These findings demonstrate the value of considering broad categories of equipment, relative to case studies that focus only on computers or robots (Autor *et al.*, 2006; Aum *et al.*, 2018; Burstein *et al.*, 2019; Acemoglu and Restrepo, 2018).[5]

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 and presents estimates of occupational exposure to CETC. Section 5 evaluates the differential role that CETC has for employment reallocation and wage inequality across occupations using the model outlined and parameterized in Section 4. Section 6 discusses relevant model extensions and Section 7 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

[5]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.

of occupational capital and its user cost, replication code, and documentation are available online at www.capitalbyoccupation.weebly.com.

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 occupational caiptal 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 occupational capital, γ_o^k, is the weighted sum of the growth rate of individual equipment services j in the occupation, γ_{oj}^k, where the weights are determined by the expenditure shares of the different categories, ω_{oj}.[6]. That is:

$$\gamma_{ot}^k = \sum_j \omega_{ojt}\gamma_{ojt}^k, \quad \text{for: } \omega_{ojt} = \frac{\lambda_{jt}^k k_{ojt}}{\sum_{jt} \lambda_{jt}^k k_{ojt}},$$

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

$$\lambda_{jt}^k = \frac{p_{jt-1}^k}{\lambda_{t-1}^c}\left[R - (1-\bar{\delta}_{jt})\frac{\frac{p_{jt}^k}{\lambda_t^c}}{\frac{p_{jt-1}^k}{\lambda_{t-1}^c}}\right],$$

[6]The choice of weights follows Oulton and Srinivasan (2003)

where λ^c is the price of consumption, p_j^k is the (quality-adjusted) price of equipment category j, and $\bar{\delta}$ corresponds to the average physical depreciation in the relevant decade of analysis.[7] The gross return on a safe asset is set at 2% per year, for $R = 1.02$.

In each occupation, the level of capital in 1984 is initialized by equalizing it to the total capital expenditures on all equipment categories in the occupation. This is equivalent to normalizing the user cost of capital in the initial period in each occupation to one. Then, iterating forward,

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

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:

$$\lambda_{ot}^k = \frac{\sum_j \lambda_{jt}^k k_{ojt}}{k_{ot}}.^{8} \tag{2}$$

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

[7] 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.

[8] 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.

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 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 $\frac{q_{jt-1}}{q_{jt}} = \frac{p^k_{jt}}{\lambda^y_t} \frac{\lambda^c_{t-1}}{p^k_{jt-1}}$ and λ^c_{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.[9]

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.[10] 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.[11]

[9] 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).

[10] 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.

[11] These occupations are those for which we consistently observe labor and capital over time. The classifi-

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.

cation 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).

Second, the reader may wonder how the 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.[12] 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.

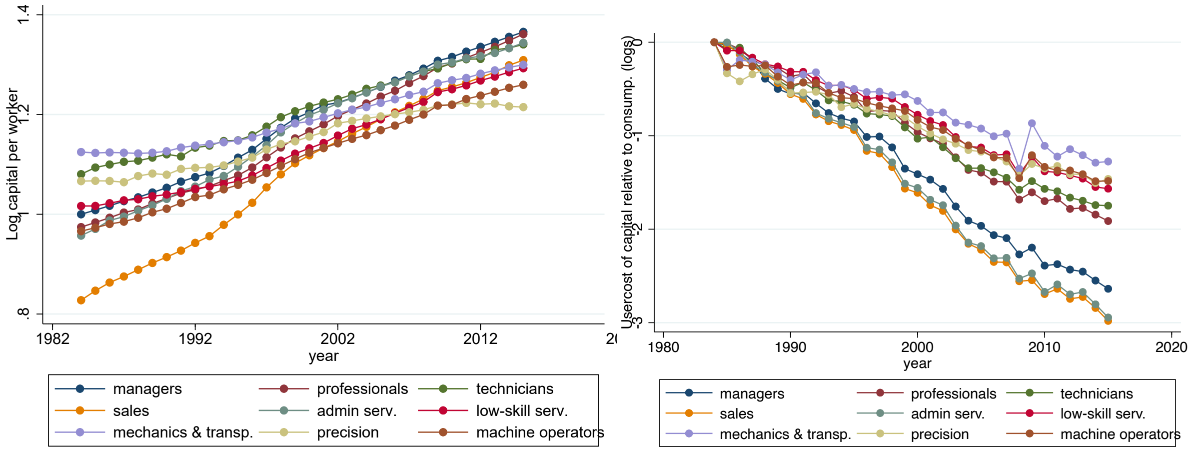
Third, what is the impact of employment offshoring on the measure of occupational capital? Insofar as offshoring replaces domestic workers in an occupation with foreign workers performing the same job, tool requirements do not change. The assignment of the stock of capital to those workers moves proportionally to the hours of the workers that remain in the economy, and therefore their capital labor ratios remain unchanged.

Fourth and last, 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.[13]

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.

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

[13] There is no description of the characteristics of the tool. For example, prices for personal computers vary widely depending on its features and capabilities, none of which are reported in the data. In an effort to control for the disparities in efficiency units of capital provided by different tools within an equipment category, we have matched tools to prices of a "flagship" good from the bundles used by the International Comparison Program, covering 10 equipment categories and approximately 40% of the tool-occupation observations. Our assignment is robust to this adjustment with a mean square error in the tool assignment averaging 0.001. Results are available upon request.



(a) Capital per worker

(b) CETC

Figure 1: Capital and CETC by occupation.

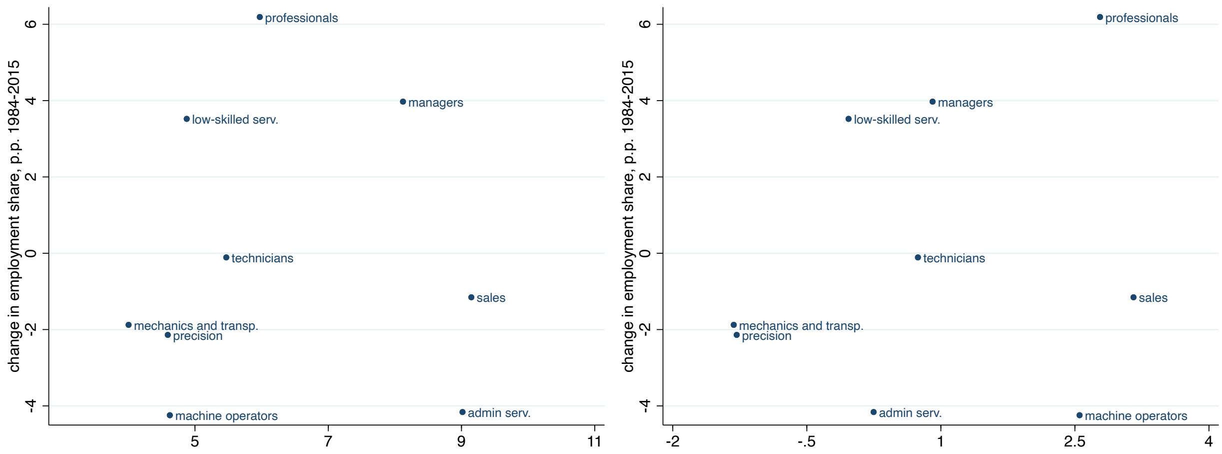
Panel (a) displays the logarithm of occupational capital per worker relative to managers in 1984. Panel (b) displays the logarithm of the user cost of capital relative to consumption across occupations. Source: BEA and own computations.

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 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) 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.

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.[14] 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 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

[14]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.

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).[15]

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 most relevant to CETC is the degree of substitutability between capital and labor, as hypothesized by Autor *et al.* (2003) and Autor

[15]Appendix B presents the changes in input-expense ratios across gender and education groups. We again corroborate the heterogeneity in the aggregate. Relative to men, females display more variation in employment changes as well as in input-expense ratios over the period. Relative to highly educated workers, low educated workers display more variation in employment changes and similar movements in input-expense ratios over the period.

et al. (2008). In Section 3.1, we then estimate occupation-specific elasticities of substitution between capital and labor and then link those elasticity to workers' exposure to technical change.

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.[16] 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

[16] 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 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.

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."[17] 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 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 Capital-labor substitutability and workers' exposure

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 and use them to document workers' exposure to CETC.[18]

3.1 Elasticity of substitution between capital and labor

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

[17] 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.

[18] Estimates of the elasticity of substitution between capital and labor at the 2-digit level of disaggregation are available through our web.

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 $a_o > 0$.[19] 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,

[19]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 Online Appendix.

$\tilde{n}_{ot}$, 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.[20] 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}:

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

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:

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

[20] 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.

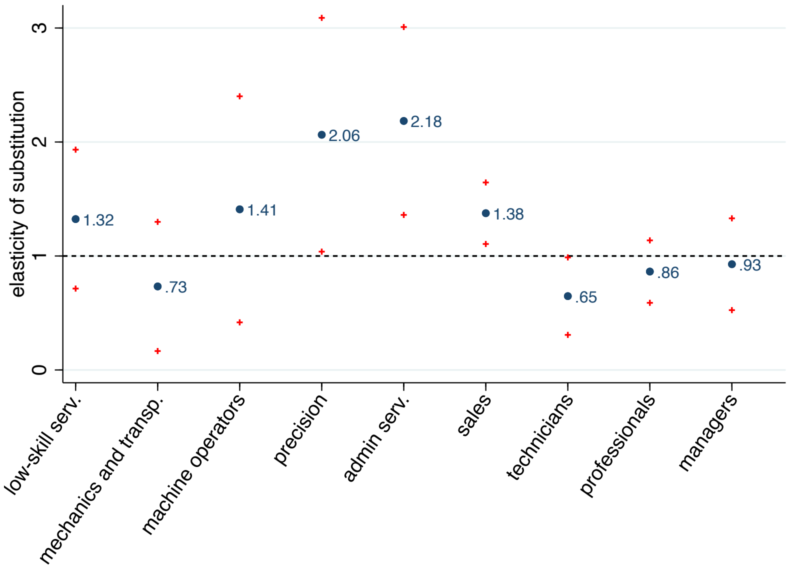


Figure 3: Elasticities of substitution between capital and labor.
Note: Authors' estimation of equation 5. Point estimates and 95% confidence intervals (+).

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. Figure 3 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 occupations (at 0.65 and 0.75, 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 occupations.

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 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.[21]

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 B.III 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 es-

[21] These results are also consistent with the estimates of the elasticity of substitution computed at a 2-digit level of disaggregation (see the Online Appendix). Finding a valid IV across occupations is the main challenge to disaggregating occupations further, but encouraged for future work.

timate 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 B.III. 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). There, assumptions on factor mobility and standard Bartik-style instruments are enough to identify the parameter of interest. Such an identification strategy is challenging for us because we do not observe capital usage in each location. One interpretation of estimates based in cross-sectional variation is that they correspond to the "long-term" elasticity of substitution, whereas those identified from time-series variation corresponds to the "short-term" elasticity of substitution.

Finally, we discuss the implications of our elasticity estimates for the occupational heterogeneity in capital per worker and employment flows. We focus on the labor share, which combines information on both factor quantities and prices. Our aggregate estimate 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 by, among others, Sahin *et al.* (2013), depends on the relative strength of labor and capital-augmenting technical change, and the bias of technology through the value of the elasticity of substitution. 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 studying the estimation of the aggregate production function in the US has generated estimates for the bias of technology that are very much in line with ours, see Klump *et al.* (2012) for a review.[22]

[22]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.

3.2 Workers' exposure to CETC

As described in the introduction, we conceptualize workers' exposure to CETC in the occupational 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 behaviour, and cost minimization, Hicks (1932) and Robinson (1934) independently show that this elasticity can be expressed as a function of four components:

$$-\frac{d\ln(n_o)}{d\ln(\lambda_o^k)} = \frac{\eta_{n\lambda^n}(\rho-\sigma_o)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}}{\rho+\eta_{n\lambda^n}+(\sigma_o-\rho)\frac{\lambda_o^k k_o}{\lambda_o^y y_o}},^{23} \tag{7}$$

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 expenditure share and (iv) ρ is the demand elasticity for occupational output. The direction of workers' exposure to CETC is summarized by standard substitution and scale effects. 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 raises labor demand in the occupation ($\sigma_o < \rho$) or reduces it ($\sigma_o > \rho$).

We map the price of occupational capital relative to consumption, λ_{ot}^k, to the user cost of quality-adjusted capital in each occupation in units of consumption (Figure 1). We measure the sources of occupational heterogeneity in exposure from our dataset: we map the estimates of the elasticity of substitution in Table B.III to σ_o in each occupation and we compute the capital expenditure shares from our estimates of the stock of capital, prices, and the assumption of constant returns in occupational output production. The remainder two components of exposure to CETC cannot be directly inferred from the data: the labor supply elasticity and the demand elasticity of occupational output. There has been an extensive discussion as of suitable values for these elasticities, see Chetty *et al.* (2011) for a review of the labor supply elasticity, and Lee and Shin (2019) and Burstein *et al.* (2019) for the occupational demand elasticity. We parameterize them consistently with the structural model that follows, for $\eta_{n\lambda^n} = 0.3$ and $\rho = 1.34$.

Figure 4 documents exposure in each occupation. We find that, a 1% decline in the

[23] Derivations in the Online Appendix.

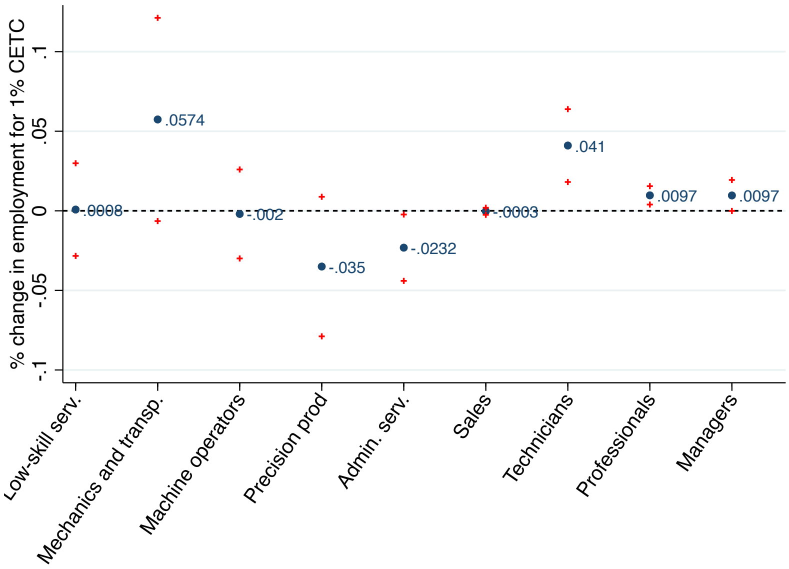


Figure 4: Occupational Exposure to CETC.

Note: Authors' estimation of equation 7. Percentage change in employment for a 1p.p. decline in the user cost of capital relative to consumption, i.e. CETC. Exposure is computed using the capital expenditure share in 1984. A positive (negative) entry indicates employment gains (losses) from CETC. Point estimates and 95% confidence intervals (+) computed using the Delta method (Oehlert, 1992).

user cost of capital induces an increase of 0.06% in employment demand for mechanics and transportation occupations, and a 0.04% increase in the demand for employment among technicians. Among professionals and managers, the gains are milder, at a 0.01% increase in employment demand for the same decline in the user cost of capital. On the opposite end, a 1% decline in the user cost of capital induces a 0.04% and a 0.02% decline in the demand for employment in precision production and administrative services occupations, respectively. Other occupations, including low-skill services, machine operators, and sales, face no changes in employment demand on balance. Importantly, heterogeneity in the elasticity of substitution between capital and labor is the main determinant of these occupational differences in exposure to CETC: occupations with higher elasticity have smaller exposure. Indeed, when we keep the capital expenditure share constant across occupations, the ranking of occupations by exposure remains unchanged and exposure changes, on average, by only 0.01p.p. relative to the benchmark.[24]

Our measures of exposure to CETC are quantitatively small, even if scaled by the average annual decline in the user cost of capital in our sample of 6.2%. We study their effects on

[24] We report measures of exposure computed with an identical expenditure share of capital across occupations in the Online Appendix. Exposure to CETC is higher for managers, professionals and administrative services occupations than in the benchmark and lower for technicians and precision production occupations.

employment reallocation through the lens of the general equilibrium model that follows and, in Section 5, find that general equilibrium forces are central to the magnitudes of the CETC-induced labor market outcomes.

4 A model of occupational capital, labor, and output

We now lay out and parameterize a framework that links occupational labor demand and occupational wage premium to CETC in general equilibrium. Our framework extends Greenwood *et al.* (1997) to include multiple occupations that differ by their exposure to CETC and heterogeneous worker's assignment to occupations in the tradition of Roy (1951).

4.1 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 3.1.

There are three sets of goods: a final good that can be used for consumption and to produce capital goods; O-types of occupational goods that are used in the production of the final good; and O-types of capital goods that are used in the production of each occupational good, along with labor. Capital fully depreciates after usage within the period.[25] Last, equipment, output, and labor markets are frictionless.

Occupational good producer. In each occupation, a representative producer uses a

[25] Building a dynamic model of capital accumulation and occupational choice is challenging, see Kleinman *et al.* (2021) for a recent study featuring both decisions, where workers are hand-to-mouth. Further combining the framework with differential occupational capital-embodied technical change and non-unitary elasticities of substitution between capital and labor brings up additional challenges in terms of the existence of balance growth, as in Uzawa (1961).

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

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

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 as well as the demand elasticity for each occupational output. It is assumed that this elasticity is symmetric across occupations.[26] Changes in 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), off-shoring forces as in Goos *et al.* (2014), and the increase in demand for skill-intensive output discussed by Buera *et al.* (2021).

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:

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

[26] Occupation-specific demand elasticities can be accommodated via a Kimball aggregator (Kimball, 1995). This approach requires taking a stand on the relationship between occupational demand elasticity and worker productivity. Alternatively, an heterogeneous nesting of occupational output can accommodate heterogeneous demand elasticities within a CES framework.

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. 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. These scale parameters encompass differences in workers' human capital and differences in the labor productivity of the occupational technologies (see, Burstein *et al.*, 2019). Our framework remains agnostic and 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 $\{\lambda^n_{ot}\}_{o=1}^{O}$, the problem of worker i in labor group h reads:

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

4.2 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 distribution of efficiency units of labor to match labor market outcomes and the demand structure of occupational output to match capital per worker across occupations.

In the model, the labor supply elasticity in each occupation corresponds to $\eta_{n\lambda_o^n} = \theta - 1$, for θ the shape parameter of the Fréchet distribution. 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 gender 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 $\theta = 1.30$.[27] Combining our estimate of θ with the specification of the labor supply elasticity in our model, we deduce $\eta_{n\lambda_o^n} = \theta - 1 = 0.30$.[28]

Next, we parameterize the scale parameters of the Fréchet distribution of efficiency units of labor, $\{\{\{T_{oht}\}_{o=1}^{O}\}_{h=1}^{H}\}_{t=\{1984,2015\}}\}$. The model defines a link between the labor market outcomes of workers of a given group h and their associated scale parameter, T_{oht} (equations 21 and 15). 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 olds, 30- to 49-years olds, and 50- to 65-years olds. We group schooling attainment into two groups: less-than 4-year of college and 4-year of college or more. We use the occupational choice and average wages of workers to parameterize the profile of T_{oht}, given wages per efficiency units in each occupation.

We choose a profile of wages per efficiency units across occupations, w_{oht}, so that the model matches the capital per worker across occupations, $\frac{k_{ot}}{\ell_{ot}}$. The equilibrium of the model specifies that the capital-labor ratio differs across occupations as a function of the elasticity of substitution between capital and labor and factor prices (equation 20). 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 and the result of worker's selection into different occupations. The properties of the Fréchet distribution link the selection effect of each worker-group to their occupational choices, and therefore differences in efficiency units of labor per-worker can be inferred from occupational choices (equation 22).[29]

[27] 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.

[28] A labor market participation choice can be accommodated following Hsieh *et al.* (2019). See Caunedo and Keller (2022) for a discussion of its implications for parameter identification and measures of exposure.

[29] Details on the inference of the scale parameters of the Fréchet distribution and on the profile of wages

Finally, we parameterize the elasticity of substitution across occupational output, ρ, from the first order condition for the final good producer, equation 19:

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

The 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 18). 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 trends 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. Therefore we expect correlation between the error term and $\frac{\lambda^y_{ot}}{\lambda^y_{o_b t}}$, biasing the estimate for ρ, with a bias of 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, where the bundle of equipment comprising each occupational capital is kept constant following its composition in 1984.

Our estimation considers a baseline (low-skill services) and eight additional occupations, over 32 years, between 1984 and 2015. The OLS yields an estimate for the elasticity of substitution of 1.11 (se: 0.008) while the IV yields an estimate of 1.34 (se: 0.061).[30] Burstein *et al.* (2019) obtain an estimate of 1.78, using the same method but constraining occupational output to a Cobb-Douglas form. Under a Cobb-Douglas production function, the wage per efficiency units of labor cannot be inferred from capital per worker, and therefore can only be measured up to the value of the scale parameters of the Fréchet distribution.[31]

per efficiency unit are in the Online Appendix.

[30] 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.

[31] Alternative estimates are in Goos *et al.* (2014) and Lee and Shin (2019), using data on routine tasks' intensity and computer capital, respectively. Both of them, find an elasticity lower than 1. The novelty of our approach relies on our ability to measure occupational capital and therefore occupational expenditure

Last, to pin down the demand shifters, ω_{ot}, we use the first-order conditions of the final good producer (equation 19) 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.

To conclude, we turn to occupational wages, that albeit not directly targeted by our calibration strategy, represent an important determinant of the capital expenditure share and so of occupational exposure to CETC. The model does not allow for differences in wages within group across occupations based on the assumption of i.i.d. Fréchet efficiency draws, which implies that worker selection perfectly offsets differences in the average efficiency of workers across occupations. Hence, the occupational wage premia in the model is purely driven by worker compositional effects by labor groups, as in Burstein *et al.* (2019). Table B.IV compares these occupational premia to the ones observed in the data. We find that, except for low-skill services and managerial occupations, the implied occupational wages in the model are close to the data, with a mean squared error of 0.96. The model overestimates wages in low-skill services by 40% and underestimates the wages of managers by 18%; which directly affects the implied capital expenditure share, resulting to be 3p.p. higher for managers and 5p.p. lower for low-skill services in the model than in the data, in 1984. In terms of wage growth between 1984 and 2015, the model endogenously generates a higher wage growth for high-skill occupations relative to other occupations (with an average annual wage growth of 1.19% versus the 1.17% observed in the data). The model overestimates the wage growth in middle skill occupations, with an average wage growth of 0.93% compared to 0.60% in the data, mostly driven by administrative services.

5 The role of CETC for labor outcomes

What has been the impact of CETC on labor market outcomes? We answer this question through counterfactuals, focusing first on the effects on labor reallocation and later on wage inequality. For each labor market outcome, we start with quantifing the role of CETC in the aggregate and for different labor groups, emphasizing heterogeneity in outcomes given the occupational choices of these groups. Then, we highlight the channels through which CETC affects these labor market outcomes to shed light on mechanisms. Finally, we describe the role of other forces that may have contributed to these labor market outcomes, including offshoring and changes in the demographical composition of the labor force.

shares.

Table 1: The role of CETC for employment reallocation.

	Model	CETC		
		baseline	identical elasticity	identical CETC
Fraction moving into				
High-skill	10.06	7.82	0.56	8.30
Middle-skill	-13.58	-8.24	-0.25	-8.38
Low-skill	3.52	0.41	-0.31	0.08
Abs average movement				
All	3.04	2.80	0.49	2.85
Non-college graduates	2.61	3.41	0.53	3.47
College graduates	1.03	1.97	0.45	2.17
16- to 29-year old	3.97	3.00	0.53	3.04
30- to 49-year old	2.86	2.63	0.49	2.72
50- to 65-year old	2.29	3.01	0.43	3.02
Females	4.33	3.86	0.41	4.02
Males	2.17	2.41	2.41	2.51

Note: Column "Model" reports the change in the employment share between 1984 and 2015. Column "baseline" reports the outcome attributed to CETC via the counterfactual exercise. Columns "identical elasticity" and "identical CETC" show the contribution of CETC under 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.

Our main counterfactual takes the 2015 economy and progressively removes all exogenous forces in the model, setting their value to that in the 1984 economy. These exogenous forces are: the decline in the user cost of capital relative to consumption, 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 labor gorups, 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").[32] Because each of these forces interact non-linearly with each other, their role for labor market outcomes depends on the value of the remaining forces. To account for these non-linear interactions we remove these forces in different order and compute the effect of a particular force by averaging across different orderings.

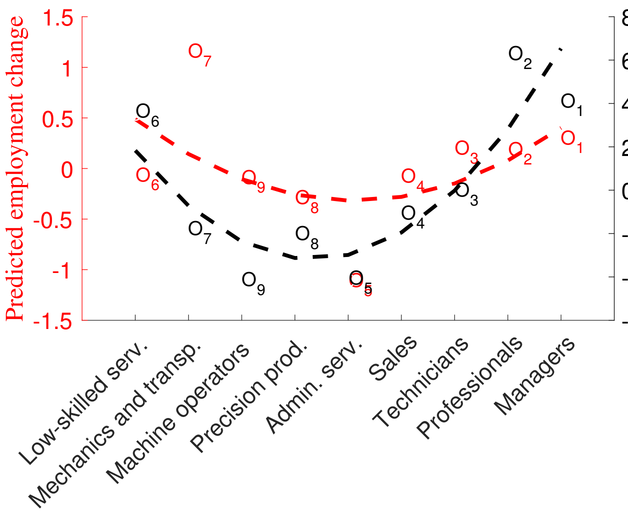
5.1 The impact of CETC on labor reallocation

The top panel of Table 1, column *Data*, reports that between 1984 and 2015, low-skill occupations (low-skill services) and high-skill occupations (professionals, managers, and technicians) gained employment relative to other occupations; while middle-skill occupations lost employment. This is what has been coined the polarization of US employment by Acemoglu and Autor (2011). Column *CETC, baseline*, in the same table, reports the contribution of CETC to this pattern. CETC is consistent with employment polarization, as it generates an increase in the employment shares for low- and high- skill occupations. CETC has been most relevant for high-skill occupations. The model predicts that employment reallocation toward high-skill occupations due to CETC was 7.82p.p. – that is, 78% of the observed 10.06p.p. reallocation. CETC had a lesser role in the reallocation out of middle-skill occupations, accounting for 61% of it, and even a smaller one in the reallocation toward low-skill occupations, accounting for 12% of the 3.52p.p. in the data. Aggregating the effects of CETC across occupations, Table 1 shows that the average absolute change in the employment share across occupations over this period is 3.0p.p. and that CETC accounts for 92% of this employment change (2.8p.p.).

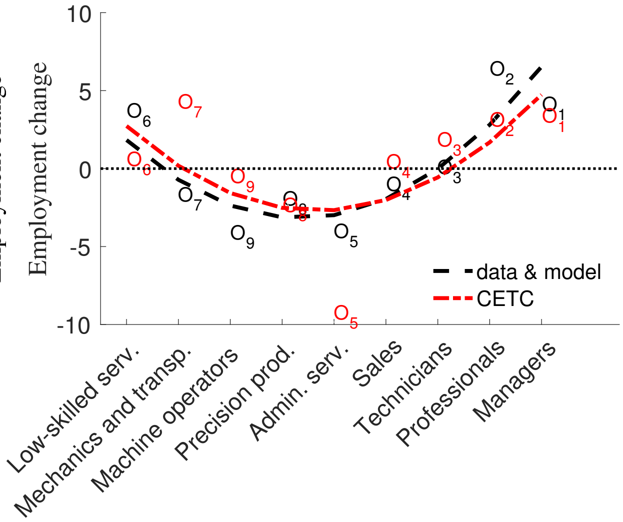
The bottom panel of Table 1 reports the average, across occupations, of the absolute change in employment generated by CETC for workers of different schooling, age, and gender. CETC had a stronger role in the reallocation of more educated, older, and male workers. This finding is a reflection of these labor groups choosing high-skill occupations more frequently, which are the occupations in which CETC raises the wage per efficiency units the most. As in the data, the reallocation generated by CETC is higher for the non-college educated than for the college educated: 1.97% compared to 1.03% in the data for the college educated, and 3.4% compared to 2.6% in the data for the non-college educated. The CETC-induced employment reallocation is also consistent with the observed higher reallocation of women compared to men: CETC generates a reallocation of 3.86% vs. 4.33% in the data for women, and a reallocation of 2.4% vs. 3.1% in the data for men.

Channels. CETC influences labor market outcomes via two channels: heterogeneity in occupational exposure, which shapes the scale and substitution effects in each occupation, and heterogeneity in the extent of occupational CETC. To isolate the quantitative role of these two channels, we design two alternative experiments: first, we input a common elasticity of substitution of capital and labor across occupations (*identical elasticity*); second,

[32] 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.



(a) Hicks' measure



(b) model

Figure 5: CETC-powered employment reallocation, Hicks and model.

The left 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 right panel plots the change in the share of employment between 1984 and 2015 attributed to CETC by our general equilibrium model and that observed in the data. The striped lines are cubic polynomial fit.

we equalize the path of the user cost of capital relative to consumption across occupations (*identical CETC*). 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 3.1. We quantify the importance of CETC in each of these alternative experiments by running an identical exercise to our main counterfactual. Table 1, columns *CETC, identical elasticity* and *CETC, identical CETC* report the contribution of CETC in the two alternative experiments.[33]

The heterogeneity in the elasticity of substitution across occupations is the most important driver for both direction and magnitude of the reallocation of labor across occupations. For example, when we force identical elasticities of substitution in all occupations, CETC generates less than a 1/3 of the inflow of employment toward high-skill occupations generated in the baseline.

Hicks measure vs. General equilibrium. It is natural to wonder whether one can do away with the general equilibrium model that we propose here and reach similar conclusions on the workings of CETC from the exposure measure in Hicks (1932). To

[33] In each alternative experiment, we recalibrate the model following the calibration strategy in Section 4.2. We keep the elasticity of substitution across occupational output as in the baseline, for comparability.

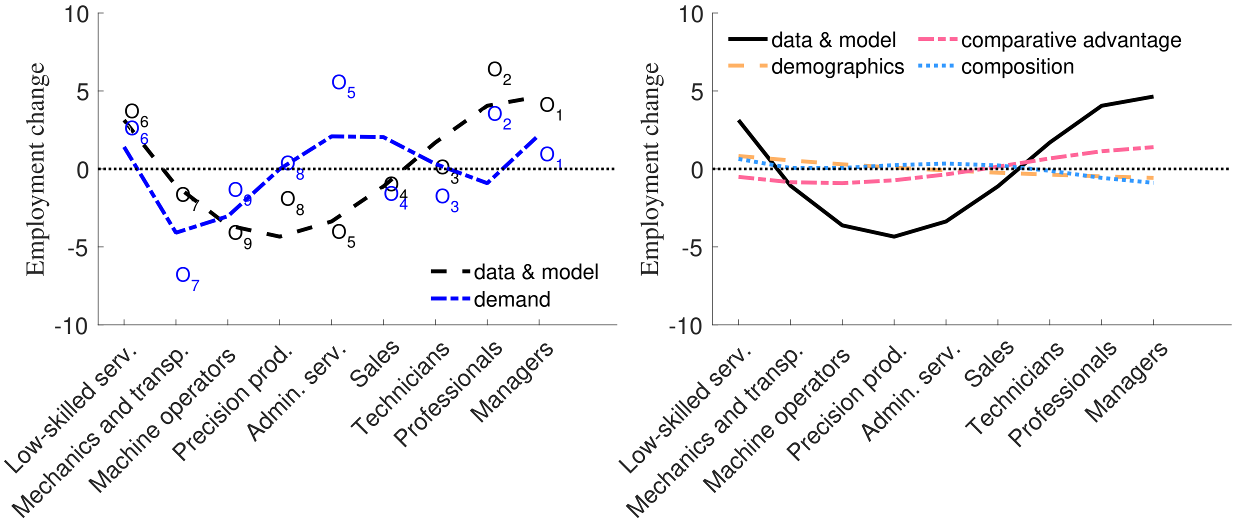
compute the implications for employment reallocation of the Hicks' exposure measure, we combine exposure with CETC to evaluate the yearly changes in occupational labor demand; we cumulate these changes over the 1984-2015 period and re-weight them so that total net employment reallocation equals zero. Figure 5 gives a visual representation of the role of CETC for employment polarization in the Hicks' exposure measure and in our general equilibrium framework. 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 general equilibrium response is in the left panel while the response based on Hicks' exposure is in the right panel of this figure, red markers.

The direction of employment reallocation generated by the Hicks' exposure measure is consistent with the general equilibrium response to CETC. Importantly, this direction is mostly set by occupational heterogeneity in exposure, rather than in the extent of CETC, in line with the channels that we highlighted using our general equilibrium model. Yet, the response of employment based on our general equilibrium model is more than five times that based on the Hicks' exposure measure. We conclude that the Hicks' exposure measure is informative for the direction of employment flows generated by CETC, but for quantification it is important to consider the general equilibrium effects of shifts in employment and output prices in all other occupations in response to CETC in a given occupation

Other forces at play. While CETC has played a major role in shaping labor market outcomes in the US over the past 30 years, not all labor market outcomes can be traced back to CETC. 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 (details in Table B.V, in the Appendix).

Consistently with the hypothesis in Autor and Dorn (2013) and the recent work of Comin *et al.* (2020), we find that demand shifters are responsible for the increase in employment at the bottom of the skill distribution. The model predicts that demand shifters towards low-skill occupations generate a 2.46p.p. increase in the share of workers allocated to them; in the data, this change is of 3.52p.p., between 1984 and 2015. Demand shifters mostly miss the employment gains at the top of the skill distribution, as well as the hollowing out in middle skill occupations. Employment losses at the middle of the skill distribution that follow from the demand shifters are redirected equally toward higher employment in both high- and low- skill occupations. This is in contrast to the data, where the flow into high-skill occupations is 74% of the outflow from middle-skill occupations.

The right panel of Figure 6 shows that exogenous forces beyond CETC and demand



(a) Demand shifters (b) Remaning 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.

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 19% relative to the data (mostly accounted by mechanics, transportation, and machine operators) and an inflow of employment toward high-skill occupations of 31% relative to he data (mostly accounted by managers and professionals).

Overall, we conclude that CETC, demand effects, and changes in the demographical composition of the labor force 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. Learning the sources shaping skill demand can inform skill-acquisition policies in response to secular trends in these sources, as we discuss in Section 6. In our framework, the nature of workers' skills or talents is attached to their occupational choice, a primal dimension to think about the future conditions of the labor market and employment demand (National Academies of Sciences and Medicine, 2017).

5.2 The impact of CETC on wage inequality

CETC influences the occupational wage per efficiency unit and, jointly with the profile of workers' comparative advantage, shapes average wages across labor groups. Indeed, the equilibrium of our model implies that average wages of labor group h can be written as the occupational average of wages per efficiency unit λ_{ot}^{n}, weighted by the average efficiency units brought into production by the labor group, i.e. the scale parameter of the distribution of efficiency units T_{oht}:

$$w_{ht} = \left(\sum_{o} T_{oht} \lambda_{ot}^{n\theta} \right)^{\frac{1}{\theta}} \Gamma(1 - \frac{1}{\theta}), \tag{15}$$

Table 2 shows the impact of CETC on the wage premium across labor groups. In the data, the college premium increased by 31p.p. between 1984 and 2015, with CETC accounting for 62% of this increase. The richness of our framework allows us to pinpoint the occupational skills that are affected by CETC, a finer concept than that of workers' education attainment (the object of seminal work as Krusell *et al.*, 2000), while considering heterogeneity across workers of different demographics. We find that the strongest contributor to the rise in the college premium is the CETC-induced rise in the wage per efficiency units in professional and managerial occupations. For example, the college premium of middle-aged men increased by 37.6p.p. between 1984 and 2015. Without the change in wages in professional occupations such a premium would have increased by only 10.5p.p.; and without the change in wages in managerial occupations it would have increased by 20.5p.p.. The strongest CETC-induced deterrents to the rise in the college premium are changes in the wage per efficiency units in mechanics and transportation occupations, affecting mostly men; and changes in administrative services and low-skill services occupations, affecting mostly women.

Over the same period of time, the gender wage gap decreased by 28p.p.. CETC raises the gender wage gap, as men are more productive in occupations where wages per efficiency unit increase the most as a consequence of technical change. On the one hand, CETC raises the wage per efficiency units in mechanics and transportation occupations, which widens the gender wage gap for the non-college educated, as well as the wage in managerial occupations, which widens the gender wage gap for the college educated. For example, for middle aged high-school educated women, the gender wage gap closes by 12.5p.p., but without the change in the wage per efficiency units in mechanics and transportation occupations, the gender wage gap would have closed even further, by 29.1p.p.. On the other hand, CETC raises the wage per efficiency units in professional and administrative services occupations, which closes the gender wage gap, mostly among older workers, irrespective of their level of education. From

Table 2: The role of CETC for wage inequality.

Change in:	Model	CETC		
		baseline	identical elasticity	identical CETC
College premium	30.58	18.96	3.51	18.34
Age premium				
30- to 49-year olds	7.95	4.63	-1.47	4.08
50- to 65-year olds	13.83	0.37	-4.58	-1.20
Gender wage gap	-28.01	14.51	-3.34	16.56
Occupation premium				
High-skill	16.25	8.84	2.24	8.71
Middle-skill	4.50	6.34	-0.38	6.27

Note: Column "Model" reports percentage change in the college premium, the age premia, the gender wage gap, and the occupation premia, between 1984 and 2015. Column "baseline" reports the outcome attributed to CETC via the counterfactual exercises. Columns "identical elasticity" and "identical CETC" show the contribution of CETC under 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.

this angle, CETC helped realize women's comparative advantage, similarly to the brain-biased technical change discussed in Rendall (2010). Overall, the first effect is stronger and, therefore, CETC has been a contributor to widening the gender wage gap.

Finally, 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 relative to younger workers between 1984 and 2015. CETC generated about 1/3 of the rise in this cross-sectional age premia. In our calculations, this rise is mostly driven by the CETC-induced increase in the wage per efficiency unit in managerial occupations. For example, for middle-aged college-educated workers, the age premium increased by 1.2p.p. for males and by 13.7p.p. for females. Without the change in the wage per efficiency units in managerial occupations, this premium would have decreased by 6.1p.p. for males and increased by 8.7p.p. for females. At the same time, a force towards closing the age premia comes from the CETC-induced rise in the wage per efficiency units in low-skill services among the high-school educated; in sales occupations among college-educated women, and in professionals occupations among college-educated males. The heterogeneity in outcomes across labor groups with regards to the cross-sectional age premia, highlights disparities in the ability to reallocate across occupations as wage premia shift in response to technical change. Worker retraining costs have been posed as an important driver to the observed lower worker reallocation of older workers relative to younger workers across sectors and occupations (Hobijn *et al.*, 2018, Adao *et al.*, 2020).

Turning to the occupational wage premia, we recall that the equilibrium of our model predicts no differences in the average wages of a labor group across occupations. Hence, the effect that CETC has on the occupational wage premia depends on the way it determines wages by labor groups and the probability of each group to choose a specific occupation. Table 2 shows that CETC generates 54% of the increase in the wage of high-skill occupations relative to that of low-skill occupations and it generates a stronger increase in the wage premium of middle-skill occupations relative to low-skill occupations (6.35p.p. compared to 4.50p.p. in the data).

Lastly and in line with the findings on employment polarization, the channel through which CETC influences wage inequality relates mostly to occupational heterogeneity in the elasticity of substitution between capita land labor. Table 2, columns *identical elasticity* and *identical CETC* show that the effect of CETC on demographic and occupation premium remains unchanged when CETC is equated across occupations.

Other forces at play. Table B.V in the Appendix shows the contribution of other exogenous forces in the model, along with CETC, to changes in the wages across labor groups. CETC is the second most important force behind the increase in the college premium, surpassed only by demand effects, that generate an increase in the premium of a magnitude of 91% that observed between 1984 and 2015. Of a similar magnitude but of opposite sign is the effect of changes in the composition of the labor force, which decreases the college premium, in line with Burstein *et al.* (2019)'s findings. Changes in workers' comparative advantage raise the college premium of a similar magnitude as CETC, possibly picking up the rise in inequality among college-educated workers (see Lemieux, 2008, among others).

Despite CETC widens the gender wage gap, all other exogenous forces in the model close it. In particular, demand effects account for 90% of the closing in the gender wage gap between 1984 and 2015, in line with the important role of structural change and the rise in services highlighted by Ngai and Petrongolo (2017). Changes in the demographical composition of the working women, such as the reversal in the the gender gap in schooling (Goldin *et al.*, 2006), also contribute to the decline in the gender wage gap: they accounted for 20% of the closing of the gender wage gap. Lastly, of a similar magnitude is the contribution of changes in the productivity of working women relative to men, in line with the selection effects on female labor force participation measured in Blau and Kahn (1997).

Lastly, changes in the productivity and comparative advantage by labor group were the important factors for the rise in the age premium of the 30- to 49-year olds, along with CETC (generating 73% and 54% of the observed rise, respectively), as well as for the rise in the age premium of the 50- to 65-year olds (generating 100% and 71% of the observed rise, respectively). On the other end, changes in the composition of the labor force by labor groups substantially reduced the age premia, supporting the findings in Böhm and Siegel (2021).

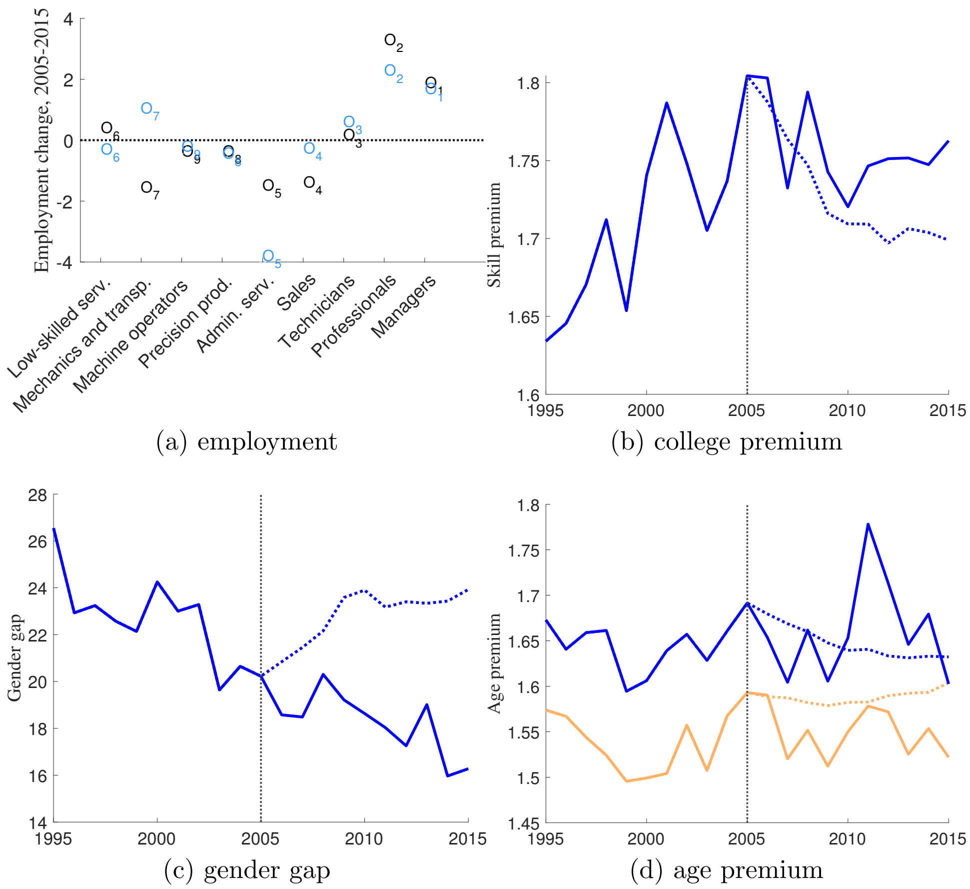
6 Discussion

Our unified framework, where CETC is studied in tandem with other forces, can be exploited to diagnose future trends in the demand for occupational skills. Understanding these trends is important for directing investment in the acquisition of occupation-specific skills. We start our discussion by analyzing the ability of CETC to yield observed trends in labor reallocation and wage inequality via an in-sample prediction exercise. We then exploit the variability in the nature of capital used by different occupations to unpack the role of technical change in different equipment categories and highlight differences to studies that have exclusively focused on computerization.

6.1 Trends in occupational demand

Standing in 2005, we ask how occupational employment over the subsequent 10 years relates to the trend in occupational CETC over the previous 10 years. To do so, we take the calibrated model economy in 2005 and the average yearly decline in the user cost of capital relative to consumption we observe over the 1995-2005 period, to predict employment reallocation between 2006 and 2015. The results are in Figure 7, first panel, which plots the predicted employment changes (in darker color) along with the data (in lighter color). Trends in CETC account for 3.8p.p. of the realized 5.0p.p. increase in the employment share in high-skill occupations between 2005 and 2015. Trends in CETC also account for 64% of the outflow of employment from middle-skill occupations over the same period, but induce an inflow rather than an outflow of employment in mechanics and transportation occupations. Lastly, trends in CETC account for an outflow of employment from low-skill occupations of 0.35p.p. in contrast to the realized inflow of 0.34p.p..

Looking at the implications for wages, trends in CETC generate the slowdown in the growth rate of the college premium measured in the data after 2005. The college premium grows by 17p.p. between 1995 and 2005 and it shrinks by 4.17p.p. between 2005 and 2015. Trends in CETC over the previous decade imply a decrease in the college premium of 10p.p.,



(a) employment (b) college premium

(c) gender gap (d) age premium

Figure 7: Labor market outcomes and trends in CETC.

The first panel plots 100 times the employment share in the data (darker color) and as predicted using the trend of CETC between 1995 and 2015 (lighter color). The remaining panels plot the wage differentials in the data (solid line) and as predicted by our in-sample predication exercise between 1995 and 2015 (striped lines). The gender wage gap is the gap in wages between females and males multiplied by 100.

between 2005 and 2015. Trends in CETC are also consistent with the trend in the age premia, with a relatively flat trend for the premium of the middle aged and a slight decrease in the trend for the premium of older aged individuals. Lastly, trends in CETC generate an increase in the gender wage gap, while the gender wage gap continues its declining trend in the data after 2005. The reason is that CETC induces an increase in the wage per efficiency units in mechanics, transportation, and managerial occupations, for which women measure relatively less productivity than men.

6.2 Multiple capital goods

Consider a modification of the framework in Section 4, which features 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:

$$\frac{\xi_{ojt}}{\xi_{j'ot}} = \frac{k_{ojt}}{k_{j_b ot}} \left(\frac{\lambda^k_{jt}}{\lambda^k_{j't}} \right)^{\phi}, \quad \lambda^k_{ot} = \left(\sum_{j \in \Omega^k_{ot}} \xi_{ojt} \lambda_{jt}^{1-\phi} \right)^{\frac{1}{1-\phi}} \tag{16}$$

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 20 and 18. 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 16.

To quantify this extended version of the model, we first parameterize the CES aggregator for capital and then run the calibration procedure in Section 4.2. 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 16:

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

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

$$\ln\left(\frac{\lambda_{jt}^{k} k_{ojt}}{\lambda_{jt}^{k} k_{j_b ot}}\right) = \beta_1 \ln\left(\frac{\lambda_{jt}^{k}}{\lambda_{j_b t}^{k}}\right) + \epsilon_{jt}, \tag{17}$$

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).[34] Given the estimate of ϕ, we set the occupational efficiency by capital goods, ξ_{ojt} to match our newly documented occupational expenditure shares by capital good and occupational capital stocks.

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 labor market outcomes. To do so, we shut down, one at a time, the CETC in each capital good – that is, we set $\lambda_{j2015} = \lambda_{j1984}$ for each j, along with other exogenous forces in the model, and consider the implications for employment reallocation and wage inequality in the US between 1985 and 2015. Table 3 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.

A similar order of magnitudes can be found for the role of CETC on wage inequality:

[34] Including a time-trend in regression equation 17 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 3: CETC across capital goods.

	Model	CETC		
		computers	communication	software
Fraction moving into				
High-skill	10.06	1.03	1.11	1.40
Middle-skill	-13.58	-1.00	-1.08	-1.32
Low-skill	3.52	-0.04	-0.03	-0.08
Change in				
Occupation premium				
High-skill	16.25	2.78	3.01	3.30
Middle-skill	4.50	-0.75	-0.74	-0.84
College premium	30.58	6.16	6.65	7.71
Age premium				
30- to 49-year olds	7.95	-0.63	-0.52	-0.37
50- to 65-year olds	13.83	-2.83	-2.74	-2.63
Gender wage gap	-28.01	-3.53	-3.53	-4.03

Note: Column "Model" reports the percentage variation in the outcome of interest (employment or wages), between 1984 and 2015. 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. Entries are in percent.

CETC in computers explains 20% of the rise in the college premium between 1984 and 2015, in comparison to 22% and 25% for communication equipment and software, respectively. Importantly, our results on the role of computer capital for the college premium stands in contrast with previous work by Burstein *et al.* (2019). Using hours worked by workers who report using a computer on the job as a proxy for computer capital productivity, they find that productivity shifts in computers account for 60% of the change in the college premium. Instead, using direct measures of the decline in the relative price of computer equipment to consumption as a measure of equipment productivity, we find a quantitatively smaller role. The difference is driven not only by the nature of the shock fed into the model, but also by the occupational heterogeneity in capital-labor substitutability that we uncover in the data as Burstein *et al.* (2019), differently from us, assume unitary elasticities in all occupations. Given their identification of the productivity shock, it is possible that improvements in the quality of software are also accounted for in their measure and our findings suggest that software has indeed been an important determinant of the college premium. Overall, our results highlight the importance of studying broader equipment categories, other than computers.

7 Conclusions

We document two new facts. First, there is substantial heterogeneity in the capital bundles used by different occupations and, therefore, in the extent of CETC. Second, workers' exposure to CETC varies considerably across occupations, as a function of heterogeneity in the elasticity of substitution between capital and labor. Through the lens of a general equilibrium model of occupational choice, we find that CETC-powered changes in the labor market were steered by the occupational elasticities of substitution between capital and labor. CETC reallocates employment toward high-skill occupations, which have the strongest capital-labor complementarities, and out of middle-skill occupations, which measure more substitutability, by a magnitude close to the one observed in the data. Employment inflows towards low-skill occupations are, instead, mostly explained by shifts in occupational demand. How changes in the demand for skills feedback into the pace and direction of CETC is an open question for future research.

How skill acquisition, either through schooling or on the job training, responds to changes in occupational demand is also an open question. Albeit an efficient framework, our model can be readily expanded to think about skill acquisition, as in Dvorkin and Monge-Naranjo (2019), or, more broadly, about whether policies can be geared to address short- and medium-run skill deficits. Our findings of a differential effect of CETC for workers of different age, may be an important input to studies focusing on workers' retraining costs as well as on the transition dynamics induced by technical change on the labor market.

Finally, the link between technical change and inequality is endogenous in our framework. Studies that extend our baseline framework to market incompleteness, e.g. financial frictions affecting skill acquisition, may provide new insights on the optimal pace of technical change (Beraja and Zorzi, 2022).

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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:

$$\lambda_{ot}^n = \left(\left(\frac{1}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{y1-\sigma_o} - \left(\frac{\alpha}{1-\alpha} \right)^{\sigma_o} \lambda_{ot}^{k1-\sigma_o} \right)^{\frac{1}{1-\sigma_o}}. \tag{18}$$

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,

$$\lambda_{ot}^y = \lambda_t^y \left(\omega_{ot} \frac{y_t}{y_{ot}} \right)^{\frac{1}{\rho}}, \tag{19}$$

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,

$$\frac{k_{ot}}{n_{ot}} = \left(\frac{\alpha}{1-\alpha}\frac{\lambda^n_{ot}}{\lambda^k_{ot}}\right)^{\sigma_o}. \tag{20}$$

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:

$$\pi_{oht} = \frac{T_{oht}(\lambda^n_{ot})^\theta}{\sum_{o'} T_{o'ht}(\lambda^n_{o't})^\theta}. \tag{21}$$

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

$$n_{ot} = \sum_h \int_{i\in\Omega^h_{ot}} n_{oht}(i)\pi_{ht} dF_{oht}(i) = \sum_h \pi_{ht}\pi_{oht} E(n|oht) = \sum_h \pi_{ht}\pi_{oht}\left(\frac{T_{oht}}{\pi_{oht}}\right)^{\frac{1}{\theta}}\Gamma(1-\frac{1}{\theta}). \tag{22}$$

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.

Labor supply-elasticity. Combing equations equation 21, 22 and 15, we can characterize the elasticity of labor supply to its price for *fixed average wages across labor groups*:

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

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

B Tables and Figures

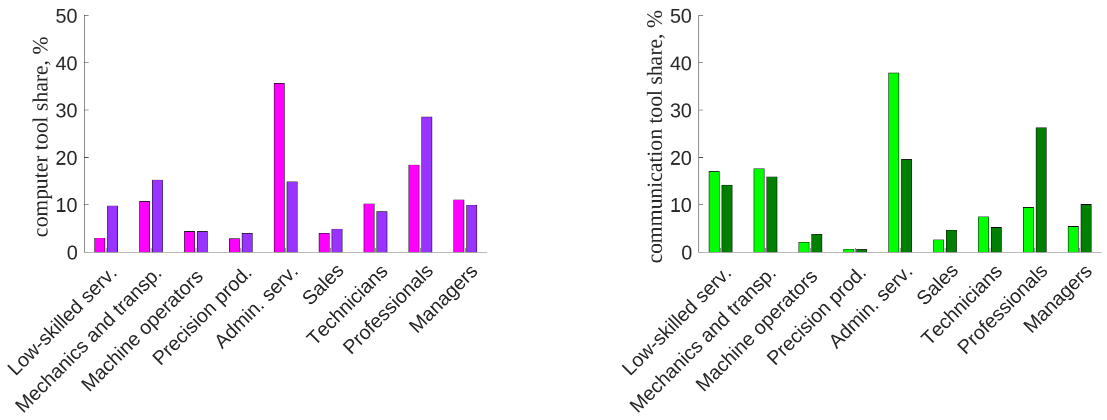

Figure B.I: Changes in tool shares.

Note: 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.

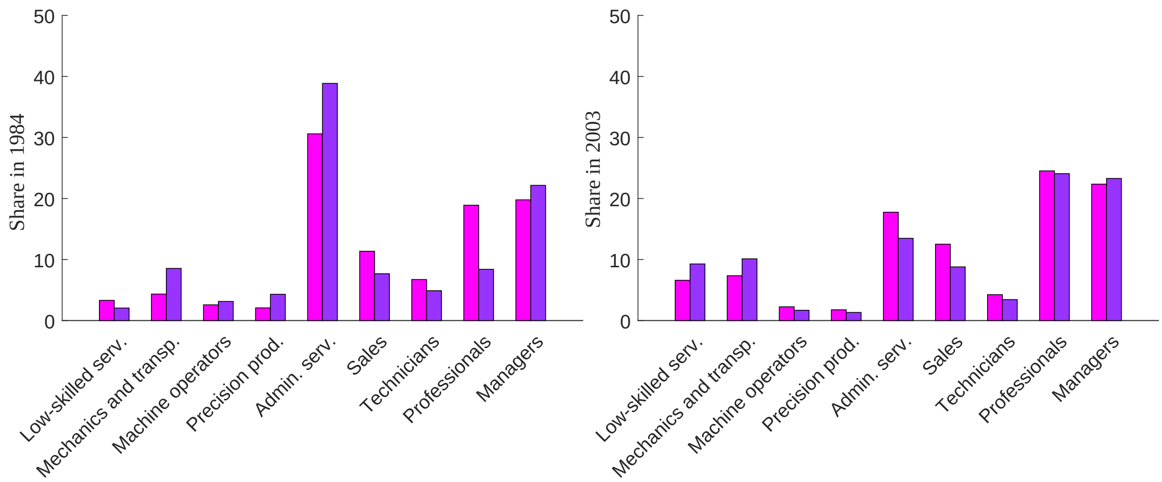

Figure B.II: Comparison tool share and computer use.

Note: 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.

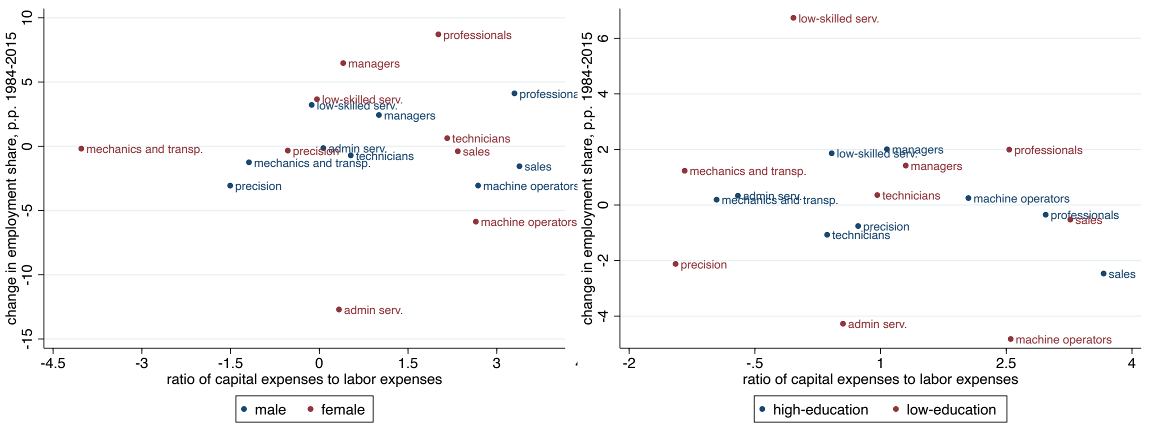

Figure B.III: Input-expense ratios across demographic groups.

Note: Percentage 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.

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

Note: 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**	0.37	0.67	**0.09**	0.46
Professionals		0.42	**0.03**	**0.01**	0.26	0.76	**0.06**	0.38
Technicians			**0.01**	**0.01**	0.11	0.84	**0.03**	0.23
Sales				0.13	0.89	**0.13**	0.29	0.96
Admin serv.					0.16	**0.02**	0.88	0.33
Low-skill services						0.26	0.30	0.90
Mechanics & Transportation							**0.06**	0.31
Precision								0.45

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

Table B.III: Elasticity of substitution between capital and labor.

	OLS	**IV**	Kleibergen Paap Paap	Dickey Fuller
Aggregate	0.45	**0.82**	8.3	-2.69
	0.09	*0.24*		
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.

Table B.IV: Model fit on occupational wages and capital expenditure shares.

	Wages 1984		Wage growth 1984-2015		Capital share 1984		Capital share growth 1984-2015	
	data	model	data	model	data	model	data	model
Managers	13.38	11.03	1.33	1.22	12.41	15.48	3.38	4.54
Professionals	11.24	11.56	1.53	1.26	10.81	11.16	11.29	12.95
Technicians	9.80	9.52	0.72	1.04	28.49	30.44	4.90	2.94
Sales	10.20	9.95	0.86	1.07	4.50	4.90	6.49	6.36
Administrative services	7.97	7.94	0.85	1.30	16.24	17.19	1.07	-0.81
Low-skill services	6.28	8.82	0.92	0.84	25.99	21.05	-0.20	0.21
Mechanics and transportation	9.21	9.68	0.51	0.69	43.39	43.74	-9.70	-10.94
Precision production	10.38	9.96	0.38	0.64	29.95	32.23	-7.69	-9.48
Machine operators	8.18	8.74	0.40	0.94	15.61	15.58	13.17	9.96

Note: Entries in all columns but those in the column "Wages" are in percent. Wage growth between 1984 and 2015 indicates the annualized wage growth over the indicated period. Capital share growth between 1984 and 2015 indicates the difference between the capital expenditure share in 2015 and that in 1984.

Table B.V: Forces driving labor reallocation across occupations.

	Model	CETC	demand	demographics	composition	CA
Fraction moving into						
High-skill	10.06	7.82	2.17	-1.53	3.08	-1.49
Middle-skill	-13.58	-8.24	-4.63	1.01	-2.61	0.89
Low-skill	3.52	0.41	2.46	0.52	-0.47	0.60
Change in						
Occupation premium						
High-skill	16.25	8.84	10.09	0.10	-11.21	8.43
Middle-skill	4.50	6.34	-6.27	0.18	-0.81	5.06
College premium	30.58	18.96	27.72	-6.47	-25.63	16.01
Age premium						
30- to 49-year olds	7.95	4.63	-0.25	5.77	-6.47	4.28
50- to 65-year olds	13.83	0.37	-3.37	13.82	-6.86	9.88
Gender wage gap	-28.01	14.51	-25.24	-11.01	-5.56	-0.71

Note: Column "Model" reports the percentage variation in the outcome of interest (employment or wages), between 1984 and 2015. All other columns report the outcome attributed to each force via the counterfactual. The description of the counterfactual and the forces considered are 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.VI: The role of CETC for occupational wages.

	Model	baseline	CETC identical elasticity	identical CETC	demand	demographics	composition	CA
Managers	15.06	8.88	2.08	8.79	6.53	-0.44	-9.32	9.41
Professionals	17.52	11.91	2.93	11.18	11.01	-0.05	-15.45	10.10
Technicians	6.52	2.06	1.13	2.39	5.33	0.61	-1.96	0.47
Sales	7.88	4.52	1.14	4.95	2.58	-1.38	-1.07	3.22
Administrative services	13.19	-48.72	0.58	-48.69	54.01	2.05	-1.14	6.98
Mechanics and transportation	-4.71	5.21	-0.98	5.27	-13.02	-0.78	-0.39	4.28
Precision production	-6.49	-55.18	-0.79	-55.00	49.62	0.36	-0.77	-0.52
Machine operators	3.09	-7.18	-0.61	1.88	20.88	-9.10	-9.37	7.85

Note: Column "Model" reports the percentage variation in occupational wages relative to low-skill services, between 1984 and 2015. All other columns present the outcome attributed to the various forces, via the counterfactual. The description of the counterfactual and the forces considered are in the text. Columns identical elasticity and identical CETC show the contribution of CETC under the alternative exercises. Entries are in percent.