TITLE

Occupational exposure to capital-embodied technical change

AUTHORS

Caunedo, J; Jaume, D; Keller, E

JOURNAL

American Economic Review

DEPOSITED IN ORE

04 April 2023

American Economic Review 2023, 113(6): 1642–1685
https://doi.org/10.1257/aer.20211478

Occupational Exposure to Capital-Embodied Technical Change†

By Julieta Caunedo, David Jaume, and Elisa Keller*

We study differences in exposure to factor-biased technical change among occupations by providing the first measures of capital-embodied technical change (CETC) and of the elasticity of substitution between capital and labor at the occupational level. We document sizable occupational heterogeneity in both measures, but quantitatively, it is the heterogeneity in factor substitutability that fuels workers' exposure to CETC. In a general equilibrium model of worker sorting across occupations, CETC accounts for almost all of the observed labor reallocation in the US between 1984 and 2015. Absent occupational heterogeneity in factor substitutability, CETC accounts for only 17 percent of it (*JEL* I26, J16, J24, J31, O33)

A long-standing tradition in labor economics and macroeconomics posits that factor-biased technical change is a key driver of US labor market dynamics in the postwar era (Katz and Murphy 1992; Hornstein, Krusell, and Violante 2005). A more recent literature highlights the significance of occupational heterogeneity for the anatomy of the new labor market phenomena of 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. Understanding the factors driving employment reallocation and wage inequality is crucial for identifying current and future trends in occupational demand as technical change continues to evolve. This knowledge is essential for the formulation

*Caunedo: Rotman School of Management, University of Toronto (email: julieta.caunedo@utoronto.ca); Jaume: Banco de Mexico (email: djaumep@banxico.org.mx); Keller: Department of Economics, University of Exeter (email: e.keller@exeter.ac.uk). Mikhail Golosov was the coeditor for this article. 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 benefited from conversations with seminar participants at the SITE macro workshop, "The Macroeconomic Consequences of Technological Change," 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, and the SED, University of Bristol, Queen Mary University London, and Hitotsubashi University. We thank Luming Chen and Jisu Hwang for research assistance and Chris Myers and Nikhil Verma 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.
†Go to https://doi.org/10.1257/aer.20211478 to visit the article page for additional materials and author disclosure statements.

of effective policies aimed at skill acquisition, such as worker retraining and 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 simultaneously lead to job displacement in certain occupations, increase the demand of certain occupations, and even generate demand for new occupations altogether. A comprehensive evaluation of these effects is hindered by the lack of information on the specific capital utilized across different occupations. Current assessments are either narrow in their focus on particular equipment (e.g., Autor, Katz, and Krueger 1998; Kehrig 2018); or rely on auxiliary data, notably the task content of occupations (e.g., Autor, Levy, and Murnane 2003; Autor 2015). We provide measures of occupational capital that encompass all equipment categories present in the economy and align with the equipment and software aggregates in the National Income and Product Accounts (NIPA). We document heterogeneity in the types of capital used across different occupations, and that this heterogeneity results in disparities in occupational CETC. The movement of labor across occupations caused by CETC is determined by the occupational disparities in the elasticity of substitution between capital and labor, as estimated by us. We find that, between 1984 and 2015, CETC induced a gross labor reallocation of 2.9 percentage points in the United States, which is consistent with the 3.0 percentage points observed in the data. With identical elasticities of substitution across occupations, CETC only generates a reallocation of 0.50 percentage points. Over the same period of time, CETC was also responsible for half of the rise in the college premium and was a force toward widening the gender wage gap.

Our first task is to discern the key channels through which CETC affects the labor market. To do so, we summarize workers' exposure to CETC through the cross-price elasticity of occupational labor demand—that is, the response of occupational labor demand to changes in the user cost of capital. This elasticity is a function of (i) the extent of labor substitutability to capital; (ii) the elasticity of labor supply; (iii) the importance of capital for production, or its expenditure share; and (iv) the demand elasticity for occupational output, under the assumptions of constant returns and competitive markets (Hicks 1932; Robinson 1933). Our dataset enables inference of these four objects and, as such, provides a characterization of the sources of occupational heterogeneity in workers' exposure to CECT. Our second task is to quantify the extent of labor reallocation and wage inequality caused by CETC, using a general equilibrium model that is consistent with exposure and that considers the self-selection of workers across occupations. The cross-price elasticity considers occupations in isolation and therefore misses shifts in the prices of labor and output across occupations that guide worker reallocation. Further, our model allows for the examination of CETC in conjunction with other factors that influence worker reallocation and wage inequality, such as occupational demand (offshoring) and demographic 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, in the US over the last 30 years. We construct capital requirements by equipment category for each occupation, utilizing information on the specific tools used in the job. We measure these 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 by applying natural language processing (NLP) algorithms over the description of occupations in the 1977 Dictionary of Occupational Titles (DOT), the predecessor to O*NET. Using these occupational capital requirements, we establish an allocation rule for distributing capital of the 24 equipment categories across occupations annually, from 1984 to 2015. Then, we calculate occupational capital by combining the allocated capital across equipment categories.[1]

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 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. In middle- and low-skill occupations labor is substitutable to capital, with an average elasticity of 1.5, whereas in high-skill occupations, it is complementary, with an average elasticity of 0.81. 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, McAdam, and Willman (2010), and labor-biased technical change proceeding at 1.9 percent per year, consistent with the aggregate decline in the labor expenditure share (Sahin, Elsby, and Hobijn 2013).[2]

Two challenges arise when inferring the output demand and labor supply elasticities. First, the estimation of the demand elasticity relies on occupational output and price data, which are inherently unobservable.[3] Second, the estimation of the labor supply elasticity is complicated by selection effects caused by the 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 maps to the elasticity of substitution across occupational outputs. Cost minimization at the occupational level is sufficient to infer occupational output and prices from our data on occupational capital 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

[1] The O*NET's tools and technology module was initially utilized by Aum (2017) to examine the effect of software innovation on the demand for high-skilled jobs. We expand upon this study by broadening the set of tools matched to equipment categories to include missing commodities in the categories of communication, service industry, and construction machinery, which make up 12 percent of the stock in 2016, as reported in the NIPA fixed asset tables.

[2] Capital expenses are computed using our newly constructed dataset and measures 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 elasticity of substitution between capital and labor but these measures focus solely on computers. A key advantage of our measurement is the inclusion of the entire stock of equipment in the economy. Importantly, our estimates of the elasticity of substitution are robust to including controls for the occupational task content (Autor, Katz, and Krueger 1998; Autor, Levy, and Murnane 2003; Autor and Dorn 2013), suggesting that our estimates pick up a novel dimension of heterogeneity across occupations.

[3] The absence of data on 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, Manning, and Salomons (2014) using industrial output in the context of the declining user cost of routinizable and offshorable tasks.

occupations to obtain a structural counterpart to the 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 so CETC increases labor demand (even when capital and labor are substitutable). Exposure follows a U-shaped pattern when occupations are ranked by skill requirement, as determined by average wages at the start of the sample period. This pattern is consistent with the observed polarization of employment in the US labor market over the past 30 years.

Then, how sizable has the impact of CETC on the US labor market been? To answer this question, we move on to our second task and quantify the effect of CETC on labor market outcomes in general equilibrium. We find that CETC accounts for 72 percent of the observed shift of labor toward high-skill occupations between 1984 and 2015. CETC also explains 58 percent of the shift away from middle-skill occupations and a smaller fraction of the shift toward low-skill occupations (17 percent of it). While changes in occupational demand play a central role in this latter shit, they only account for a small percentage of the employment growth in high-skill occupations. Over the same period, CETC also fueled wage inequality by driving 51 percent of the increase in the college premium and about half of the rise in the cross-sectional age premium, primarily through the rise in wages per efficiency units in managerial and professional occupations. Furthermore, CETC widened the gender wage gap by 17.5 percentage points, by raising the wages per efficiency units in mechanics, transportation, and managerial occupations, in which 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, as proposed in Autor, Levy, and Murnane (2003), for which we provide the first available estimates; or with a common elasticity of substitution between capital and labor across occupations, where faster capital deepening occurs in occupations that lose employment and there is complementarity in output across occupations, as proposed in Goos, Manning, and Salomons (2014). Our findings indicate that the substitution channel, rather than the scale channel, is the primary mechanism through which CETC drives employment polarization. Quantitatively, heterogeneity in exposure driven by the elasticity of substitution is the main driver of employment reallocation. We estimate that high- and low-skill occupations have stronger capital-labor complementarity than middle-skill occupations, which results in CETC shifting employment out of middle-skill occupations and into low- and high-skill occupations.

Finally, we investigate the contribution of technical change in each equipment category by expanding our baseline model to define occupational capital as a CES composite of various capital goods, with a substitution elasticity of 1.13, as estimated from our dataset. This analysis enables us to evaluate our results against 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 had a significant impact on the reallocation of employment and changes in skill-based wages in the United States over the past 30 years. However, since 2000, there has been a slowdown in the decline in the price of computers and so other categories of equipment, including communication, optical, and medical instruments, have gained increasing importance for labor market outcomes. Further, we find that CETC in computers and software contributed 22 percent to the rise in the college premium, a lower contribution than the 60 percent that Burstein, Morales, and Vogel (2019) estimate. These findings demonstrate the value of considering broad categories of equipment, relative to case studies that focus on specific equipment goods (such as computers or robots, Autor, Katz, and Kearney 2006; Aum, Lee, and Shin 2018; Burstein, Morales, and Vogel 2019; Acemoglu and Restrepo 2018).[4]

The rest of the paper is organized as follows. Section I constructs occupational capital and its user cost and presents key correlations between occupational CETC and employment flows. Section II estimates the elasticity of substitutions between capital and labor across occupations and presents estimates of occupational exposure to CETC. Section IV evaluates the differential role that CETC has for employment reallocation and wage inequality across occupations using the model outlined and parameterized in Section III. Section V discusses relevant model extensions and Section VI concludes.

I. 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 United States between 1984 and 2015. We focus on equipment and measure occupational capital consistently with the aggregate investment series in the fixed-asset tables published by the BEA. We follow the extensive literature that highlights the capital-embodied nature of technology and the secular decline in the cost of investment, and construct time series of quality-adjusted capital stocks by equipment category. To allocate these stocks to occupations, we construct a novel index of the capital requirements in each occupation over time. Our index is based off of the tools commonly used in each occupation, which we extract from the US Department of Labor (1991) DOT in the 1970s and from it successor, the US Department of Labor (2016)'s O*NET, in the 2010s.

Our dataset combines four data sources: a novel dataset on occupational tool usage that we construct using NLP algorithms over the textual occupational definitions of the 1977 DOT along with the information from the tools and technology supplement of the 23.4 O*NET; annual fixed-assets series of investment for 24 equipment categories (BEA); annual quality-adjusted series of the price of (new) capital constructed from linear projections of quality-adjusted prices 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 (Flood et al. 2019).

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

A. *Methodology*

We start by defining an occupation as 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 capital to be a constant returns to scale aggregator of the capital services of 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 average of the growth rate of individual equipment services in the occupation γ_{oj}^k, where the weights are the expenditure shares in the individual equipment categories ω_{oj}.[5] That is,

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

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):

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

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.[6] The gross return on a safe asset is set at 2 percent 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,

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

Finally, we define CETC in each occupation, or occupational CETC, to be the decline in the user cost of occupational capital relative to consumption. We construct this user cost from the ratio between the total expenses in capital in an occupation and occupational capital:[7]

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

To implement our methodology, we need a measure of the services of each equipment category across occupations, k_{ojt}. We first construct stocks in efficiency by category, k_{jt}, and then assign their services across occupations.

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

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

[7] This implied user cost is almost identical to that computed using a Tornqvist price index, with shares equal to the expenditure share of each equipment category in the occupation.

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 these 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 then 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, Hercowitz, and Krusell (1997). Hence, the efficiency units of investment in equipment j can be obtained by deflating nominal investment by its quality-adjusted price, p^k_{jt}.

The measures of depreciation reported by the BEA, d_{jt}, reflect both physical depreciation, δ_{jt}, and economic depreciation, $q_{jt-1}/q_{jt} = \left(p^k_{jt}/\lambda^y_t\right)\left(\lambda^c_{t-1}/p^k_{jt-1}\right)$. We adjust these measures to compute physical depreciation as follows:

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

Occupational Assignment.—We build a rule for allocating the aggregate services of the stocks of equipment to occupations based on an index of their occupational capital requirements.

An Index of Occupational Capital Requirements: We refer to the capital requirements of an occupation as the fraction of aggregate services of each equipment category used by the occupation. We infer these requirements from the tools used by workers in the occupation. For example, commonly used tools by a dental assistant include air compressors, dental cutting instruments, and personal computers. Our dataset includes more than 7,000 tools, which correspond to commodities in the United Nations Standard Products and Services Code (UNSPSC) classification system and are linked to the equipment categories considered by the BEA.[8]

We collect information on the tools used across occupations in the United States over 30 years. The O*NET, a database collecting standardized occupation-specific descriptors, readily provides information on occupational tools for the period post-2010 in 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, the 1980s, we use the textual definition of occupations collected in the 1977 version of the DOT. We parse out the set of the tools used in each occupation by applying NLP algorithms.[9] Then, to generate measures of occupational tools through the sample period we linearly interpolate the DOT-based

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

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

and the O*NET-based occupational tools for each of the 324 3-digit occupations we observe.[10]

For illustration, Figure B.I in the Appendix compares the occupational tools measured in the O*NET and DOT datasets for occupations in the one-digit census classification. 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 professional occupations has seen the share of computers and communication equipment tools allocated to him increase, whereas a worker in administrative services occupations has seen it decline. These differences exemplify how the tools used by workers in a certain occupation change with time.

We use our time series of occupational tools to construct occupational capital requirements. Let τ_{ojt} be the number of tools of equipment category j used by a worker in occupation o at time t—that is, $\tau_{ojt} \equiv \sum_c \Im^{ot}_{c \in j}$, where $\Im^{ot}_{c \in j}$ 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 to be the number of tools used by the workers in that occupation relative to the total number of tools used in the economy:

$$req_{ojt} \equiv \frac{\tau_{ojt} l_{ot}}{\sum_o \tau_{ojt} l_{ot}}. \tag{3}$$

We distribute capital services of a given category j across occupations proportionally to these capital requirements, $k_{ojt} = req_{ojt} k_{jt}$.

Discussion: First, measuring the occupational capital requirements is challenging due to the lack of data on the duration for which a worker uses a specific equipment. 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, in 2015, the total number of tools for nonmedical equipment was twice that of medical equipment, with 373 tools compared to 170. Even if we were to double the number of tools for medical equipment while maintaining the same distribution across occupations, the overall amount of occupational capital would remain unchanged.

Second, the reader may wonder how the tool counts get affected by the automation of some of the tasks executed by a worker in his job. Task automation changes the nature of the job and so directly influences the aggregation mapping from the finer (ten-digit) job title information available in the DOT and the O*NET to the

[10] The occupations we consider are those for which we consistently observe labor and capital over time. The classification of occupations based on the O*NET-SOC system is a modification of the 2010 Standard Occupational Classification (SOC) system that allows for a link to the American Community Survey (ACS) 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).

coarser three-digit census occupational classification. To the extent that a three-digit occupation is not fully automated, automation only implies a change in the tools used by a worker.[11] For example, an accountant may now use computer software that automates tasks previously done on paper. Our tool counts pick up this effect by using information in both the 1970s and in the 2010s. At the same time, when all the tasks executed by a worker in a three-digit occupation get automated, the operation of the automating 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 front house and managerial staff. Our tool counts sensibly assign equipment to the three-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, capital requirements do not change. The assignment of the stock of capital moves proportionally to the hours of the workers that remain in the domestic economy and therefore their capital labor ratios remain unchanged.

Fourth and last, while differences in 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. Despite this is certainly a limitation, the tool description is general enough that imputing prices would induce a fair amount of measurement error.[12]

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

B. *Salient Features of Occupational Capital*

We now document the paths of occupational capital and its user cost relative to consumption, our measure of occupational CETC. To ease the exposition, we group the data into nine occupational groups, which correspond to the one-digit non-agricultural occupational grouping in the US census—that is, managers, professionals, technicians, sales, administrative services, low-skilled services, mechanics and transportation, precision production, and machine operators.

Capital per Worker: Panel A in Figure 1 shows the time series of occupational capital per worker across occupations. 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 occupations (1.1 percent, 1.1 percent, and 1.4 percent annualized growth

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

[12] Our tool dataset lacks information on the specific characteristics of the tools. For example, the prices of personal computers can vary significantly based on their features and capabilities, none of which are reported in the information we have. In an effort to control for the disparities in efficiency units of capital provided by different tools within an equipment category, we match tools to prices of a "flagship" good from the bundles used by the International Comparison Program, covering ten equipment categories and approximately 40 percent 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.

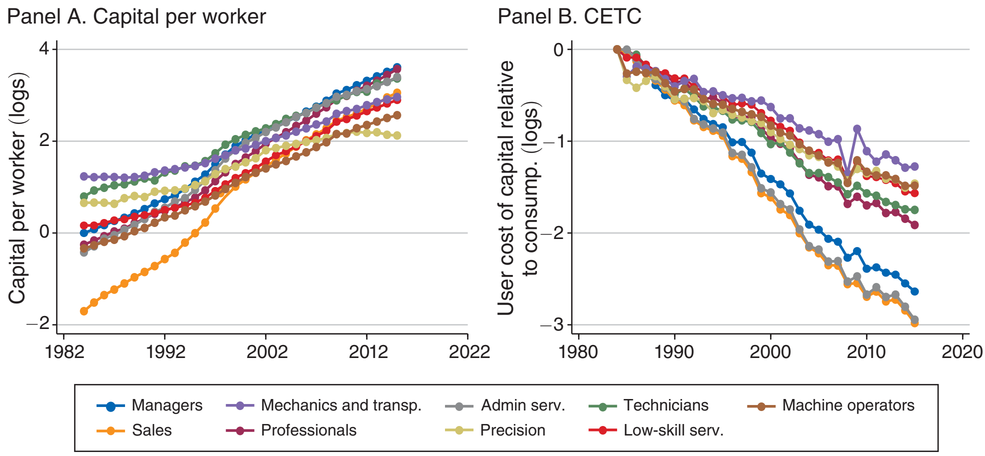

FIGURE 1. CAPITAL AND CETC BY OCCUPATION

Notes: 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.

Sources: BEA and own computations

rates between 1984 and 2015, respectively). Capital per worker in precision production occupations and that in mechanics and transportation occupations grew the least, with annualized growth rates of 0.4 percent and 0.5 percent, 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 percent per year between 1984 and 2015. On the opposite end, mechanics and precision production occupations recorded a decline in the relative user cost of capital to consumption of 2.9 percent and 3.4 percent per year, respectively.

Relationship to Employment:[13] We now document the relationship of occupational capital and CETC with labor market outcomes. Figure 2 panel A plots the change in the employment share between 1984 and 2015 for each of the nine one-digit occupations 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 ratio was comparable for professionals and machine

[13] For brevity, we only report moments that are central to our analysis. We defer to the online Appendix for a broader evaluation, including the relationship between CETC and labor market outcomes when including controls for occupational task intensity.

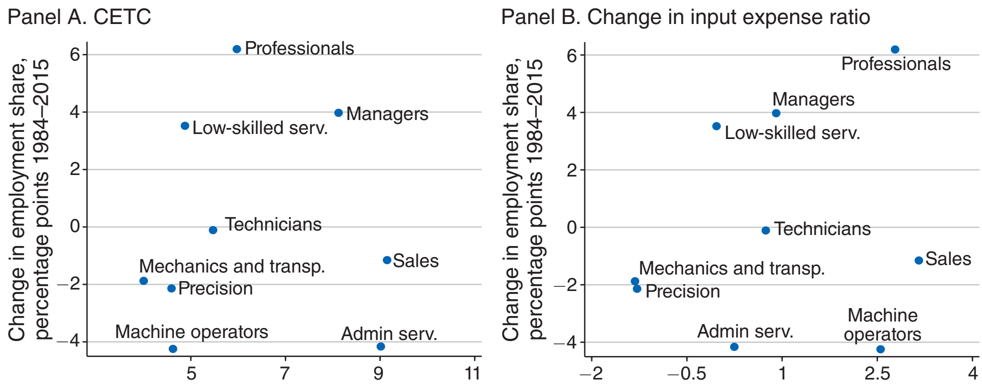

Figure 2. Employment Shares by Occupation

Notes: Panel A displays the change in the share of employment between 1984 and 2015 in each occupation against the annualized decline in the user cost of capital relative to consumption (CETC). Panel B displays the change in the share of employment between 1984 and 2015 in each 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.

Sources: BEA, CPS, and own computations

operators, but the share of employment in the latter decreased while the share in the former increased. On the flip side, occupations that displayed similar declines in their share of employment had vastly different changes in input expense ratios. For example, the share of employment decreased similarly for machine operators and administrative services occupations, but the ratio of capital expenses to labor expenses increased substantially more in the former (2.5 percentage points per year versus 0.25 percentage points per year).[14]

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 Appendix Table B.I. Importantly, these differences in employment changes coexisted with wage gains across all occupations (about 1 percent per year, on average), with the largest gains in occupations with the largest changes in capital-labor ratios and the largest 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, Levy, and Murnane 2003). This hypothesis is consistent with the observation that employment has flown out of computer-intensive

[14] Appendix B reports the changes in input-expense ratios across gender and education groups. We corroborate the heterogeneity in the aggregate. Relative to males, females display more variation in employment changes as well as in input-expense ratios, over the period. Relative to college educated workers, non-college educated workers display more variation in employment changes and similar movements in input-expense ratios over the period.

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 Appendix Table B.I shows that while workers in computer-intensive occupations saw their wages rise the fastest, by 1 percent per year on average, these occupations lost employment overall (with their share falling by 3.6 percentage points between 1984 and 2015). At the same time, workers in occupations intensive in other types of capital with strong CETC, including communication equipment, also saw their wages rise by a similar amount, 0.8 percent per year, but these occupations gained employment throughout (5.5 percentage points 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, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2008). In Section IIA, we estimate occupation-specific elasticities of substitution between capital and labor and then link these elasticities to workers' exposure to CETC.

C. *Validation of Occupational Capital*

Given the novelty of our measurement of occupational capital, we assess its comparability to alternative measures of capital used in the literature.

Implications for Alternative Disaggregations of the Capital Stock: By construction, our occupational capital stocks aggregate to the BEA fixed asset tables for aggregate equipment by category (up to, of course, 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 stocks is to focus on the industries that use these stocks. The BEA provides fixed asset tables at the industrial level, combining investment by asset type from NIPA and various sources of industrial 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 services to these measures.[15] We compute capital services in each two-digit industry by aggregating up our measure of occupational capital at the three-digit census classification and exploiting the occupational composition of each industry. For comparability we assign nominal stocks of equipment instead of quality-adjusted stocks and abstract from agriculture and mining. The nominal stock of private equipment by industry in the fixed asset tables and our industrial stocks display a correlation of 0.84 in 1984, 0.79 in 2000, and 0.48 in 2016. Because these

[15] As explained by the BEA (2003), some industries rely on data that is only available for specific benchmark years, such as census years, and thus require interpolation and extrapolation. To the extent possible, the investment totals are based on capital expenditure data collected from each industry, such as the Annual Capital Expenditure Survey. In cases where this data is not available, estimates are derived by calculating the change in net stocks plus depreciation from industrial balance sheet data, as recorded by regulatory offices, for example, the Internal Revenue Service.

changes in correlation reflect changes in the composition of the industrial stocks by equipment types 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 specific equipment category as calculated by the BEA and using our allocation rule is stable in time for the majority of equipment categories; e.g., communication displays a correlation of 0.6 in 1984 and 0.55 in 2016; medical equipment displays a correlation of 0.99 in both 1984 and 2016; while the correlation for aircrafts is 0.98 in 1984 and 0.81 in 2016. The one noticeable decline in such correlation over time 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 that of those in the aggregate, we use a different method to validate computer capital.

Alternative Measures of Computer Capital: We compare the assignment of the stock of computers across occupations that is based on our occupational capital requirements to the information in the October CPS Supplement (computer module) in 1984 and 2003, which asks workers whether they "use a computer at/for his/her/your main job." 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 of the total working hours of computer usage across one-digit occupations, each year. Appendix Figure B.II compares the share of computer usage in the CPS to that computed using our occupational tools, in 1984 and 2003 (the last year available). The two distributions are similar, with a correlation of 0.9 in 1984 and 0.96 in 2003. Moreover, the correlation is also near 1 when considering changes over time: 0.96 for changes between 1984 and 2003. These high correlations lend credibility to our newly constructed dataset, the main advantage of which is the wider range of equipment it covers compared to the October CPS Supplement and the availability of data after 2003.[16]

II. Capital-Labor Substitutability and Workers' Exposure

Heterogeneous occupational paths of CETC, capital per worker, and employment suggest that the degree of substitutability between capital and labor may differ across occupations. Next, we estimate the elasticity of substitution between capital and labor in each one-digit occupation in the census classification system and use it to document workers' exposure to CETC.[17]

A. *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 markets, the marginal rate of transformation equals the relative

[16] 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.

[17] Estimates of the elasticity of substitution between capital and labor at the two-digit census classification are available on our website at www.capitalbyoccupation.weebly.com.

input price. 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:

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

where γ_{ot} is the log difference between labor and capital-augmenting technical change in occupation o and, jointly with the elasticity of substitution σ_o, shapes the bias of the technology. Diamond, McFadden, and Rodriguez (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. Indeed, for an arbitrary elasticity of substitution, one can always design a path of $\exp(\gamma_{ot})$ that fits the path of observable capital-labor ratios $k_{ot}/\tilde{n}_{ot}$. For example, declining observable capital-labor ratios can be rationalized by labor-biased technical change—that is, a decline in $\exp(\gamma_{ot})$ with $\sigma_o < 1$ or an increase in $\exp(\gamma_{ot})$ with $\sigma_o > 1$.

To circumvent this impossibility result and identify the elasticity of substitution, the literature imposes structure on the path of factor-augmenting technical change (see Antras 2004; Herrendorf, Herrington, and Valentinyi. 2015). 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 $a_o > 0$.[18] 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).

We construct the series in the regression equation above for one-digit occupations in the census classification system. We measure labor, $\tilde{n}_{ot}$, as full-time equivalent workers adjusted for efficiency due to observable characteristics, i.e., age, schooling, and gender. We use wages relative to males aged 16–24 without a four-year college degree as a proxy for skill/efficiency (see Antrás 2004, among others). We compute the price of measured labor, $\tilde{\lambda}^n_{ot}$, as the ratio between the total wage bill in an

[18] The identifying restriction assumes that factor-augmenting technical change occurs at a constant proportional rate. We run robustness checks on this assumption where we allow for a trend break in 2000, the time at which we observe a slowdown in the decline in the price of computers. Our results are robust to this more flexible specification; see online Appendix.

occupation and $\tilde{n}_{ot}$. Finally, we use our measures of occupational capital and its user cost constructed in Section I. All series are available from 1984 to 2015.

Endogeneity: The estimation of regression equation (5) reveals a clear endogeneity issue. 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 one-digit occupation, we construct an instrument for an exogenous shift in the supply of occupational labor. 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}:

$$\log\left(br_{t-16}\sum_{e} sh^{l}_{oe1984}\, n_{et}\right).$$

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 these 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 percent of GDP, X_t, which we use as our output demand shifter:

$$\log\left(X_t \sum_{s} sh_{o^{-}s1984}\, n_{st}\right).$$

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.[19]

[19] While it may seem that this supply shifter affects the left-hand side of the estimation equation (5), in an exactly identified instrumental variable regression the estimated elasticity is the same whether capital-labor ratios are the left-hand side variable and relative prices are the right-hand side variable, or vice versa. 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.

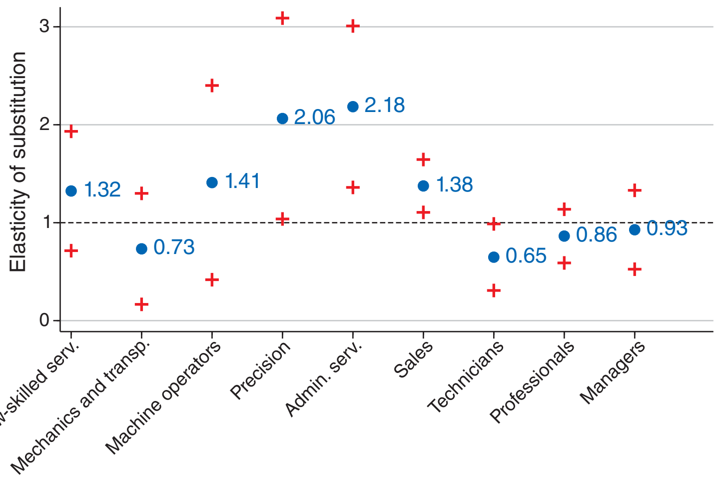

FIGURE 3. ELASTICITIES OF SUBSTITUTION BETWEEN CAPITAL AND LABOR

Notes: Authors' estimation of equation (5). Point estimates and 95 percent confidence intervals (red crosses).

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 instrumental variable (IV) point estimate is 0.88, slightly higher but consistent with recent exercises in Antrás (2004) using time-series variation (0.8 for 1948–1998), Leon-Ledesma, McAdam, and Willman (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 in 2007).

To assess the statistical 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 Appendix 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 production occupations. We also find that the point estimate for mechanics and transportation occupations is significantly lower than that for administrative services and for precision production occupations.[20]

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

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

As pointed out by Antrás (2004), not much can be said about the relative magnitudes of the ordinary least squares (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, McAdam, and Willman (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 outputs 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 regression equation.

For the remainder of this section, we focus on the IV estimates. First, we run statistical tests on the strength of the proposed instruments and 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 heteroskedasticity. Appendix 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 estimate is 15 percent or larger. For mechanics we reject the null that the maximum relative bias in the estimate is 25 percent 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 results in Appendix 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 on cross-sectional variation is that they correspond to the "long-term" elasticity of substitution, whereas those

[20]These results are also consistent with the estimates of the elasticity of substitution computed for two-digit occupations in the census classification system (see the online Appendix). Finding a valid IV across occupations is the main challenge to disaggregating occupations further, but encouraged for future work.

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 four out of nine one-digit occupations. The consistency between these findings and the decline in the labor share reported in the United States by, among others, Sahin, Elsby, and Hobijn (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 percent 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. Previous research estimating the aggregate production function in the United States has yielded similar estimates of technology bias, as reviewed in Klump, McAdam, and Willman (2012).[21]

B. *Workers' Exposure to CETC*

As described in the introduction, we conceptualize workers' exposure to CETC as 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 and competitive markets, Hicks (1932) and Robinson (1933) independently show that this elasticity can be expressed as a function of four components:[22]

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

where (i) $\sigma_o \geq 0$ is the elasticity of substitution between capital and labor in occupational output production; (ii) $\eta_{n\lambda^n}$ is the elasticity of labor supply; (iii) $(\lambda_o^k k_o)/(\lambda_o^y y_o)$ is the importance of capital for production in the occupation, or its expenditure share; and (iv) $\rho \geq 0$ is the absolute value of 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 ($\sigma_o > \rho$).

[21] We report occupation-specific estimates of the bias of technology in the online Appendix. In all but one occupation the bias of technology implies a decline in the labor share.

[22] Derivations in the online Appendix.

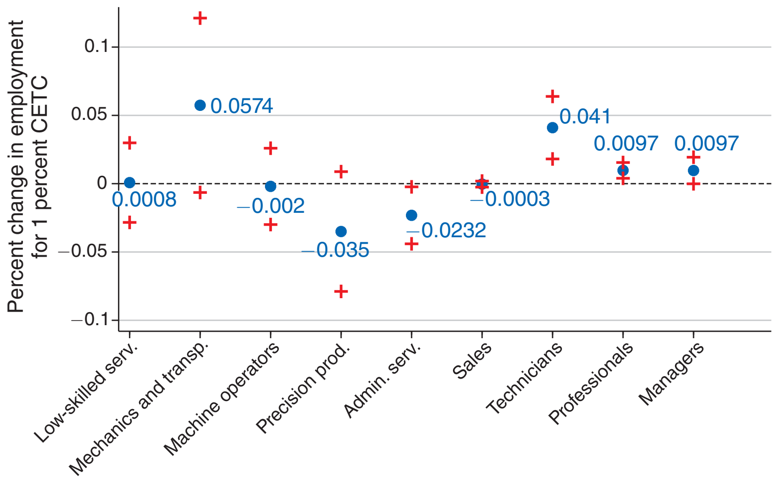

Figure 4. Occupational Exposure to CETC

Notes: Authors' estimation of equation (7). Percentage change in employment for a 1 percentage point 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 percent confidence intervals (red crosses) computed using the delta method (Oehlert 1992).

We measure the sources of occupational heterogeneity in exposure from our dataset: we map the estimates of the elasticity of substitution in Appendix Table B.III to σ_o in each occupation and we compute the capital expenditure shares from our estimates of the stock of occupational capital, its user cost, and the assumption of constant returns in occupational output production. The remainder two components of exposure 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 on the labor supply elasticity, and Lee and Shin (2019) and Burstein, Morales, and Vogel (2019) for values of 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 to CETC in each occupation. We find that, a 1 percent decline in the user cost of capital induces an increase of 0.06 percent in employment demand for mechanics and transportation occupations, and a 0.04 percent increase in employment demand for technicians. Among professionals and managers, the gains are milder, at a 0.01 percent increase in employment demand for the same decline in the user cost of capital. On the opposite end, a 1 percent decline in the user cost of capital induces a 0.04 percent and a 0.02 percent 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 0.01 percentage points relative to the benchmark.[23]

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 percent. We study their effects on employment reallocation through the lens of the general equilibrium model that follows and, in Section IV, find that general equilibrium forces are central to the magnitudes of the CETC-induced labor market outcomes.

III. A Model of Occupational Capital, Labor, and Output

We now lay out and parameterize a framework that links CETC to occupational labor demand in general equilibrium. Our framework extends Greenwood, Hercowitz, and Krusell (1997) to include multiple occupations that differ by their exposure to CETC and heterogeneous workers' assignment to occupations in the tradition of Roy (1951).

A. *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 I and IIA.

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 production of the final good; and O-types of capital goods that are used in production of each occupational good, along with labor. Equipment, output, and labor markets are frictionless. Last, capital fully depreciates after usage within the period.[24]

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

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

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

[24] Building a dynamic model of capital accumulation and occupational choice is challenging; see Kleinman, Liu, and Redding (2021) for a recent study featuring both decisions in an environment with hand-to-mouth workers. Further combining the framework with differential occupational CETC and non-unitary elasticities of substitution between capital and labor brings up additional challenges in regards of the existence of a balance growth path, as pointed out in Uzawa (1961).

A producer facing an occupational price λ_{ot}^{y}, a price of capital-o λ_{ot}^{k}, and a wage per efficiency unit of labor λ_{ot}^{n}, chooses equipment and labor to maximize profits:

$$\max_{\{k_{ot}, n_{ot}\}} \lambda_{ot}^{y} y_{ot} - \lambda_{ot}^{k} k_{ot} - \lambda_{ot}^{n} n_{ot}. \tag{9}$$

Final Good Producer: Final consumption goods are produced combining occupational goods in 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 absolute value of the demand elasticity for each occupational output. It is assumed that this elasticity is symmetric across occupations.[25] Changes in ω_o over time are isomorphic to demand shifters. They capture, for example, the increase in demand for low-skill services discussed in Autor and Dorn (2013), offshoring forces as in Goos, Manning, and Salomons (2014), and the increase in demand for skill-intensive output discussed in Buera et al. (2021).

A producer facing a final good price λ_t^y and prices of occupational goods λ_{ot}^{y} maximizes profits:

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

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 CETC, as in Greenwood, Hercowitz, and Krusell (1997). A producer facing a price of capital λ_{ot}^{k} and a price of the final good λ_t^y demands x_{ot} units of final output to maximize

$$\max_{\{x_{ot}\}} \lambda_{ot}^{k} q_{ot} x_{ot} - \lambda_t^y x_{ot}. \tag{11}$$

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

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

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 scale parameters in occupation o relative to o' for labor type h with respect to labor type h' is

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

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 for example, Burstein, Morales, and Vogel 2019).

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

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

B. *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 to measure occupational heterogeneity in CETC, in the elasticity of substitution between capital and labor, and in the price of capital. 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 corresponds to $\eta_{n\lambda^n_o} = \theta - 1$ in each occupation, for θ the shape parameter of the Fréchet distribution of efficiency units of labor. The shape parameter governs the magnitude of the right tail of this distribution: a lower θ induces a fatter tail and therefore more dispersion in the efficiency 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 one-digit occupational fixed effects. We run these estimates for each year, between 1984 and 2015, and take the average over the period at $\theta = 1.30$. Combining our estimate of θ with the specification of the labor supply elasticity in our model, we deduce $\eta_{n\lambda^n_o} = \theta - 1 = 0.30$.[26]

Next, we parameterize the scale parameters of the Fréchet distribution, $\left\{\left\{\{T_{oht}\}_{o=1}^{O}\right\}_{h=1}^{H}\right\}_{t=\{1984\}}^{2015}$. The model defines a link between the labor market

[26]Our estimate of the shape parameter of the Fréchet distribution is consistent with Hsieh et al. (2019) and Burstein, Morales, and Vogel (2019) who, using a similar identification strategy, parameterize it at 1.24 and 2, respectively. A labor market participation choice can be accommodated; see Caunedo and Keller (2022) for a discussion of its implications for parameter identification and measures of exposure.

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 3 of their demographic characteristics: age, gender, and 4-year college completion. We group age in 3 groups: 16-to-29-year-olds, 30-to-49-year-olds, and 50-to-65-year-olds. 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 capital per worker across occupations k_{ot}/ℓ_{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 due to workers' self-selection into different occupations. However, 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 can be inferred from occupational choices (equation (22)).[27]

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

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

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 $\epsilon_{ot} \equiv \ln(\omega_{ot}/\omega_{o_b t}) + \nu_{ot}$, 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 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 $\lambda^y_{ot}/\lambda^y_{o_b t}$, biasing the estimate for ρ in an unknown direction. To address this endogeneity issue, we follow Burstein, Morales, and Vogel (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.

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

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 (standard error: 0.008) while the IV yields an estimate of 1.34 (standard error: 0.061).[28] Burstein, Morales, and Vogel (2019) obtain an estimate of 1.78, using the same method but constraining occupational output to a Cobb-Douglas form. Under Cobb-Douglas, 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.[29]

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 outputs.

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 assumption of i.i.d. Fréchet efficiency draws does not allow for differences in wages within groups across occupations in equilibrium: workers' selection perfectly offsets differences in the average efficiency of workers across occupations. Therefore, the model's occupational wage premium is solely determined by the composition of labor groups. Appendix Table B.IV compares occupational wages 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 those in the data, with a mean squared error of 0.96. The model overestimates wages of low-skill services by 40 percent and underestimates wages of managers by 18 percent; with a direct counterpart in the capital expenditure shares (3 percentage points higher for managers and 5 percentage points lower for low-skill services in the model than in the data in 1984). Looking at wage growth between 1984 and 2015, the model generates a higher wage growth for high-skill occupations relative to other occupations (with an average annual wage growth of 1.19 percent versus the 1.17 percent observed in the data). The model overestimates the wage growth in middle skill occupations, with an average wage growth of 0.93 percent compared to 0.60 percent in the data, mostly driven by administrative services.

IV. The Role of CETC for Labor Market Outcomes

What has been the effect of CETC on labor market outcomes? We answer this question through counterfactuals, focusing on the effects on labor reallocation and wage inequality. For each of these two labor market outcomes, we start by quantifying the role of CETC, emphasizing heterogeneity in outcomes across labor groups. Then, we highlight the channels through which CETC affects the two labor market outcomes to shed light on mechanisms. Finally, we describe the role of other forces that may have contributed to the two labor market outcomes, including offshoring and changes in the demographic composition of the labor force.

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

[29] Alternative estimates are in Goos, Manning, and Salomons (2014) and Lee and Shin (2019), using data on routine task intensity and computer capital, respectively. Both of them find an elasticity lower than 1. We rely on measures occupational capital and therefore occupational expenditure shares.

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 price of occupational capital relative to consumption λ_{ot}^{k} ("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 groups T_{ht} ("demographics"); the change in the structure of worker comparative advantage $\tilde{T}_{oht}$ ("CA"); the change in the weights of the different labor groups π_{ht} ("composition"). Because each of these forces interact nonlinearly with each other, their role for labor market outcomes depend on the value of the remaining forces. To account for these nonlinear interactions we remove these forces in different order and compute the effect of a particular force by averaging across different orderings.[30]

A. *The Impact of CETC on Labor Reallocation*

The top panel of Table 1, column "model", 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, i.e., the "polarization of US employment" (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. It has been most relevant for high-skill occupations: the model predicts that employment reallocation toward high-skill occupations due to CETC was 7.23 percentage points—that is, 72 percent of the observed 10.06 percentage point reallocation. CETC had a lesser role in the reallocation out of middle-skill occupations, accounting for 58 percent of it, and even a smaller one in the reallocation toward low-skill occupations, accounting for 17 percent of the 3.52 percentage point increase in the data. Aggregating the effects of CETC across occupations, Table 1 reports that the average absolute change in the employment share across occupations over this period is 3.0 percentage points and that CETC accounts for 95 percent of this employment change (2.9 percentage points).

The bottom panel of Table 1 reports the average absolute change in employment generated by CETC for workers of different schooling, age, and gender across occupations. CETC had a stronger role in the reallocation of more educated, older, and male workers. These labor groups are more likely to choose high-skill occupations, where CETC has the greatest impact on wages per efficiency unit. As in the data, the reallocation generated by CETC is higher for non-college graduates than for college graduates: 1.97 percent compared to 1.03 percent in the data for college graduates, and 3.5 percent compared to 2.6 percent in the data for non-college graduates. The CETC-induced employment reallocation is also consistent with the observed higher reallocation of women compared to men: CETC generates a reallocation of 4.1 percent versus 4.3 percent in the data for women, and a reallocation of 2.5 percent versus 3.1 percent in the data for men.

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

TABLE 1—THE ROLE OF CETC FOR EMPLOYMENT REALLOCATION

	Model	CETC: Baseline	CETC: Identical elasticity	CETC: Identical CETC
Fraction moving into				
High-skill	10.06	7.23	0.40	7.42
Middle-skill	−13.58	−7.82	0.17	−7.79
Low-skill	3.52	0.59	−0.57	0.37
Absolute average movement				
All	3.04	2.89	0.50	3.00
Non-college graduates	2.61	3.46	0.54	3.55
College graduates	1.03	1.97	0.43	2.17
16-to-29-year-olds	3.97	3.04	0.53	3.15
30-to-49-year-olds	2.86	2.71	0.50	2.82
50-to-65-year-olds	2.29	3.08	0.49	3.23
Females	4.33	4.10	0.46	4.40
Males	2.17	2.47	2.47	2.63

Notes: 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.

Channels: CETC influences labor market outcomes via two channels: heterogeneity in occupational exposure, which determines the relative magnitudes of 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 between capital and labor across occupations ("identical elasticity"); second, 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 $\sigma = 0.82$, which is estimated by imposing a common elasticity parameter in regression equation (5), Section IIA. 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.[31]

Variation in elasticity of substitution across occupations is the key factor in determining both the extent and direction of labor redistribution. For instance, if all occupations have the same elasticity of substitution, CETC produces less than 10 percent of the employment shift to high-skill occupations observed in the baseline.

Hicks Measure versus General Equilibrium: It is reasonable to question whether the conclusions about the role of CETC for the labor market can be drawn from the exposure measure in Hicks (1932). To address this question, we combine our measures of Hicks' exposure in Section IIB with occupational CETC to compute the implications for employment reallocation of the Hicks' exposure measure. We evaluate the yearly changes in occupational labor demand, cumulate them over the

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

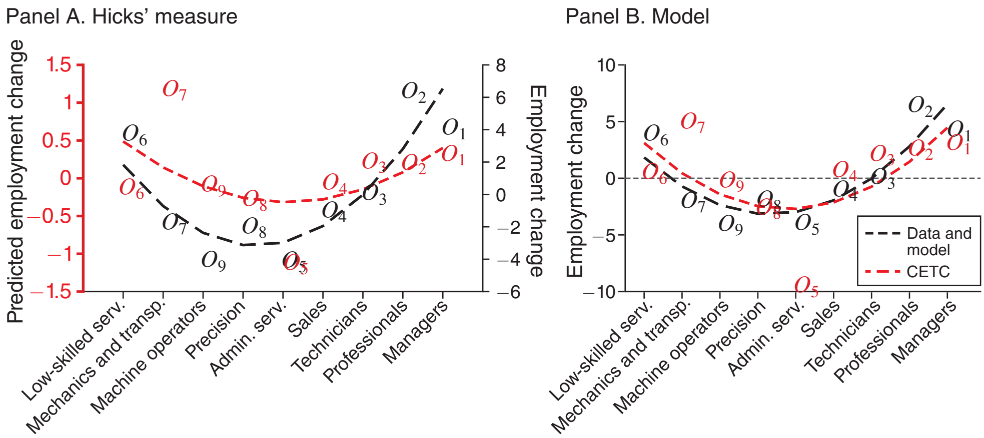

Figure 5. CETC-Powered Employment Reallocation, Hicks' Measure and Model

Notes: 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. Entries are in percent.

1984–2015 period, and reweight 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, red (lighter) 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 the general equilibrium effects of shifts in employment and output prices in all occupations are important for quantification.

Other Forces at Play: While CETC has played a major role in shaping occupational employment in the United States over the past 30 years, not all employment patterns can be traced back to it. Figure 6 shows the impact of occupational demand shifters on employment polarization in the left panel, and all other external factors in the right panel (details in Table B.V in the Appendix).

We find that demand shifters are responsible for the increase in employment at the bottom of the skill distribution, which is consistent with the hypothesis in Autor and Dorn (2013) and the recent work of Comin, Danieli, and Mestieri (2020). The model predicts that demand shifters toward low-skill occupations generate a 2.92 percentage point increase in the share of workers allocated to them; in the data, this change is of 3.52 percentage points, between 1984 and 2015. Demand shifters

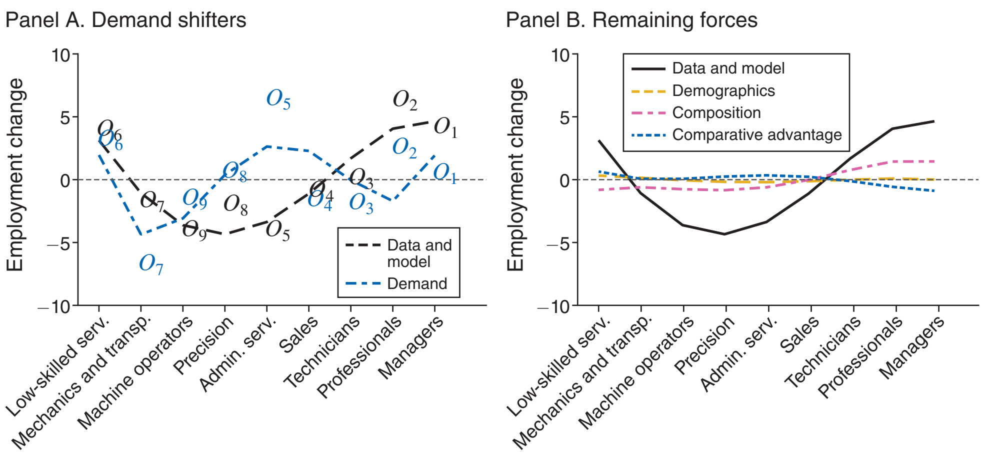

FIGURE 6. OTHER FORCES AT PLAY

Notes: "Data and 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. Entries are in percent.

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 mostly toward low-skill occupations. This is in contrast to the data, where the flow into high-skill occupations is 74 percent of the outflow from middle-skill occupations.

The right panel of Figure 6 shows that exogenous forces beyond CETC and demand shifters mostly play a secondary role in the US employment polarization. The only effect worth noting is that of changes in the weights of the different labor groups ("composition" effects), which generate an outflow of employment from middle-skill occupations of 20 percent relative to the data (mostly accounted by mechanics, transportation, and machine operators) and an inflow of employment toward high-skill occupations of 35 percent relative to the data (mostly accounted by managers and professionals).

Overall, we conclude that CETC, demand effects, and changes in the demographic 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 toward high-skill occupations. Understanding the drivers of skill demand can guide skills acquisition policies to adapt to secular trends, as discussed in Section V. Our framework links workers' skills and talents to their occupational choice, making it a crucial factor to consider for predicting labor market and employment demand changes (National Academies of Sciences and Medicine 2017).

B. *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}:

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

Table 2 reports the impact of CETC on average wages across labor groups. In the data, the college premium increased by 31 percentage points between 1984 and 2015, with CETC accounting for 51 percent of this increase. Our comprehensive framework enables us to pinpoint the specific occupational skills impacted by CETC, a more refined concept than workers' education level studied in Krusell et al. (2000), while accounting for heterogeneity among workers of varying 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 37.6 percentage points between 1984 and 2015. Without the change in wages in professional occupations this premium would have increased by only 10.5 percentage points; and without the change in wages in managerial occupations it would have increased by 20.5 percentage points. 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 28 percentage points. CETC widens the gender pay gap as men are more efficient in occupations where CETC leads to the largest increase in wages per efficiency unit. 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 graduates, as well as the wage in managerial occupations, which widens the gender wage gap for the college graduates. For example, for middle-aged women without a college degree, the gender wage gap closes by 12.5 percentage points, 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 29.1 percentage points. 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 this angle, CETC helped realize women's comparative advantage, similarly to the brain-biased technical change discussed in Rendall (2010). Overall, the first effect dominates; thus CETC has played a role in widening the gender wage gap.

Finally, the cross-sectional age premium increased by 8 percentage points for 30-to-49-year-old workers and by 14 percentage points for 50-to-65-year-old workers relative to younger workers, between 1984 and 2015. CETC generated about half 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 units in managerial occupations. For example, for middle-aged college-educated workers, the age premium increased by 1.2 percentage points for males and by 13.7 percentage points for females. Without the change in the wage per efficiency units in managerial occupations, this premium would have decreased by 6.1 percentage points

Table 2—The Role of CETC for Wage Inequality

Change in:		CETC		
	Model	Baseline	Identical elasticity	Identical CETC
College premium	30.58	15.56	−1.64	13.22
Age premium				
30-to 49-year-olds	7.95	5.90	0.42	5.98
50-to 65-year-olds	13.83	3.80	0.54	3.95
Gender wage gap	−28.01	17.49	1.18	21.04
Occupation premium				
High-skill	16.25	7.80	−0.84	7.37
Middle-skill	4.50	7.90	0.15	8.92

Notes: 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.

for males and increased by 8.7 percentage points for females. At the same time, a force toward closing the age premia comes from the CETC-induced rise in the wage per efficiency units in low-skill services among the non-college graduates; in sales occupations among college-educated women, and in professionals occupations among college-educated males. The disparities in age premium outcomes among labor groups reveal differences in their ability to reallocate occupations in response to wage shifts caused by technical change. Worker retraining costs are thought to be a key factor in the lower occupation reallocation rate among older workers compared to younger workers across sectors and occupations (Hobijn, Schoellman, and Vindas 2018; Adão, Beraja, and Pandalai-Nayar 2020).

Turning to the occupational wage premia, we remind the reader 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 48 percent 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 (7.89 percentage points compared to 4.50 percentage points 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 capital and labor. Table 2, columns "identical elasticity" and "identical CETC" show that the effect of CETC on demographic and occupational premia 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 and changes in comparative advantage by labor group are 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 79 percent 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, Morales, and Vogel's (2019) 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).

Although CETC widens the gender wage gap, all other exogenous forces in the model close it. In particular, demand effects account for 79 percent 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). 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). Finally, changes in the demographic composition of working women, such as the reversal of the gender gap in schooling (Goldin, Katz, and Kuziemko 2006), also contribute to the decline in the gender wage gap: they accounted for 9.1 percent of the closing of the gender wage gap.

Changes in the comparative advantage by labor group were an important factor for the rise in the age premium of the 30-to-49-year-olds, along with CETC (generating 53 percent of the observed increase), as well as for the rise in the age premium of the 50-to-65-year-olds (generating 71 percent of the observed increase). However, changes in the composition of the labor force by groups substantially reduced the age premia, supporting the findings in Böhm and Siegel (2021).

V. Discussion

Our integrated framework, which examines CETC in conjunction with other forces, can be used to predict future trends in occupational skill demand. Identifying these trends is crucial for guiding investment in acquiring 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 exploit the variability of capital types used by various occupations to analyze the impact of technical change in different equipment categories, highlighting differences from studies solely focused on computerization.

A. *Trends in Occupational Demand*

Standing in 2005, we ask how occupational employment over the subsequent ten years relates to the trend in occupational CETC over the previous ten 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 3.8 percentage points of the realized 5.0 percentage point increase in the employment share in high-skill occupations between 2005 and 2015. Trends in CETC also account for 64 percent 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

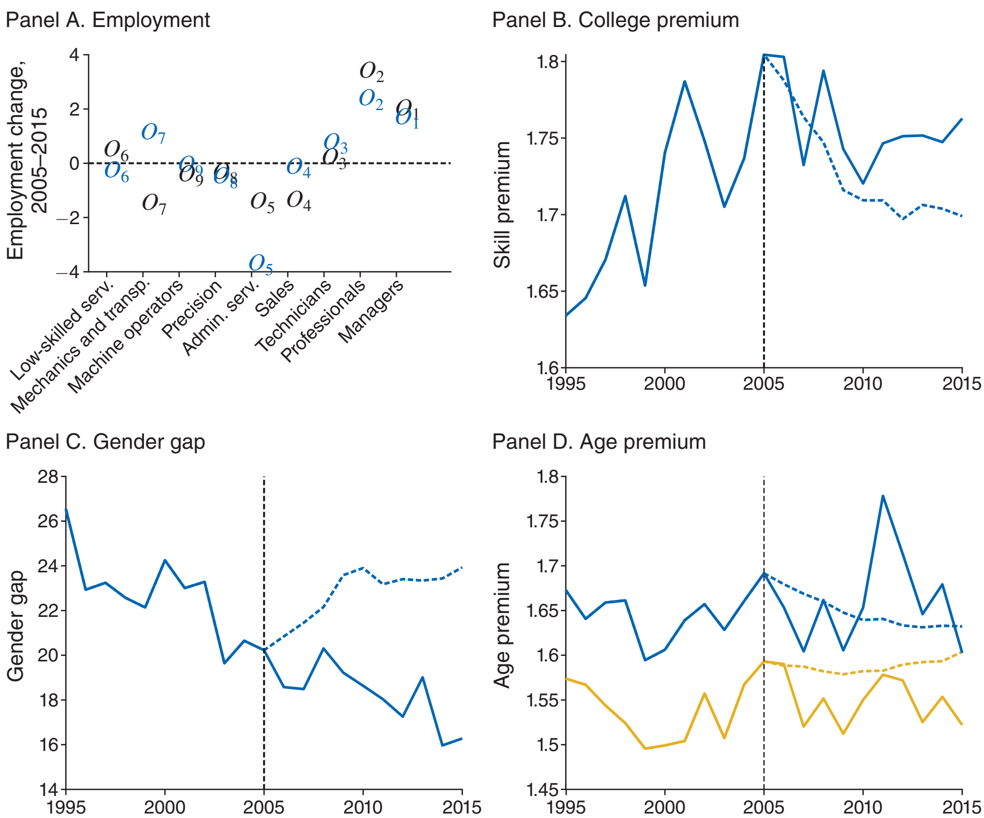

FIGURE 7. LABOR MARKET OUTCOMES AND TRENDS IN CETC

Notes: The first panel plots 100 times the employment share in the data (darker color) and is 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.

and transportation occupations. Lastly, trends in CETC account for an outflow of employment from low-skill occupations of 0.35 percentage points, in contrast to the realized inflow of 0.34 percentage points.

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 17 percentage points between 1995 and 2005 and it shrinks by 4.17 percentage points between 2005 and 2015. Trends in CETC over the previous decade imply a decrease in the college premium of 10 percentage points, 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.

B. *Multiple Capital Goods*

Consider a modification of the framework in Section III, which features a countable set of capital goods of cardinality J indexed by j. These capital goods map to the 24 BEA equipment and software categories. 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

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

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 IIIB. 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):

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

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

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

where $\epsilon_{ojt} = \ln\left(\xi_{ojt}/\xi_{j_bot}\right) + \nu_{ojt}$, 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 $\lambda^k_{jt}/\lambda^k_{j_bt}$ as exogenously determined by changes in technology. We then estimate the 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 $\phi = 1.13$ (standard error: 0.017). 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.[32]

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 evaluate the role of specific capital goods for 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 United States 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 magnitudes 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 magnitude can be found for the role of CETC on wage inequality: CETC in computers explains 10 percent of the rise in the college premium between 1984 and 2015, in comparison to 12 percent and 15 percent 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, Morales, and Vogel (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 percent 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, Morales, and Vogel (2019), differently from us, assume unitary elasticities in all occupations. Given their identification of the productivity shock, it is plausible 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.

[32] Including a time trend in regression equation (17) gives an estimate for the elasticity of substitution across capital goods of 1.42 (standard error: 0.030). If the trend is allowed to vary by occupation and capital good, we estimate a value of 1 (standard error: 0.014).

Table 3—CETC across Capital Goods

		CETC		
	Model	Computers	Communication	Software
Fraction moving into				
High-skill	10.06	0.82	0.88	1.15
Middle-skill	−13.58	−0.93	−1.01	−1.23
Low-skill	3.52	0.11	0.13	0.08
Change in occupation premium				
High-skill	16.25	1.35	1.60	1.89
Middle-skill	4.50	0.58	0.59	0.47
College premium	30.58	3.06	3.56	4.64
Age premium				
30-to-49-year-olds	7.95	0.92	1.04	1.20
50-to-65-year-olds	13.83	0.52	0.62	0.74
Gender wage gap	−28.01	0.20	0.21	−0.26

Notes: 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.

VI. 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 occupational 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. This employment reallocation is of a magnitude close to the one observed in the data. Employment inflows toward 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).

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, $\left\{\{T_{oh}\}_{o=1}\right\}_{h=1}^{H}$, and a set of measures of workers by labor groups, $\{\pi_h\}_{h=1}^{H}$.

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

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., $n_o = \sum_h \int_{i \in \Omega_o^h} n_{oh}(i) \times \pi_h dF_{oh}(i)$, where Ω_o^h identifies the set of workers with $o_h^\star(i) = o$;

4. The market for each capital-o clears, $k_o = q_o x_o$;

5. The market for final output clears, i.e., $\sum_{ho} \int_i c_{o_h^\star(i)h}(i) + \sum_o x_o = y$.

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

$$\lambda_{ot}^n = \left[\left(\frac{1}{1-\alpha}\right)^{\sigma_o} \lambda_{ot}^{y\,1-\sigma_o} - \left(\frac{\alpha}{1-\alpha}\right)^{\sigma_o} \lambda_{ot}^{k\,1-\sigma_o}\right]^{\frac{1}{1-\sigma_o}}. \tag{18}$$

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 $\left\{n_{oht}(i)\right\}_{o=1}^{O}$, 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 occupational 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,

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

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

$$\pi_{oht} \equiv \Pr\left(w_{oht}(i) > w_{o'ht}(i)\right), \ \forall o' \neq o.$$

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

$$\pi_{oht} = \frac{T_{oht}\left(\lambda_{ot}^{n}\right)^{\theta}}{\sum_{o'} T_{o'ht}\left(\lambda_{o't}^{n}\right)^{\theta}}. \tag{21}$$

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

$$\begin{aligned} n_{ot} &= \sum_h \int_{i \in \Omega_{ot}^{h}} n_{oht}(i)\pi_{ht}\, dF_{oht}(i) \\ &= \sum_h \pi_{ht}\pi_{oht} E(n \mid oht) \\ &= \sum_h \pi_{ht}\pi_{oht}\left(\frac{T_{oht}}{\pi_{oht}}\right)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right). \end{aligned} \tag{22}$$

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

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:

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

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

Appendix B. Tables and Figures

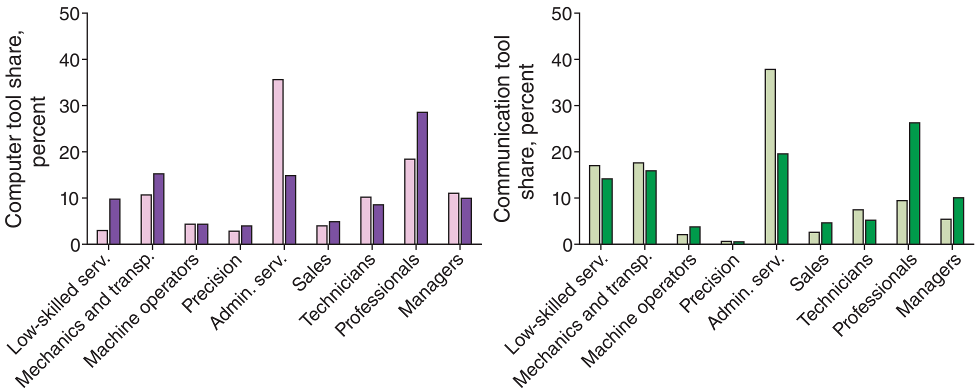

Figure B.I. Changes in Tool Shares

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

Sources: O*NET, DOT, and own computations

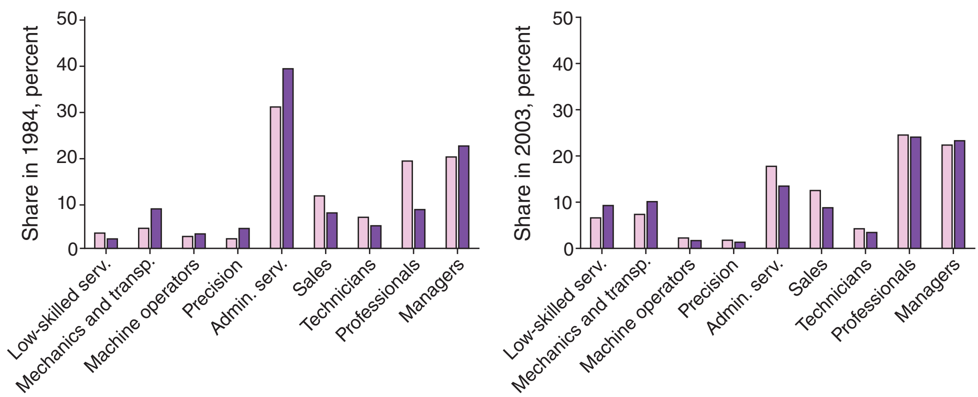

Figure B.II. Comparison Tool Share and Computer Use

Notes: The figure shows the distribution of hours of work using computers according to historical data from 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 and the right panel shows data for 2003.

Sources: O*NET, DOT, CPS, and own computations

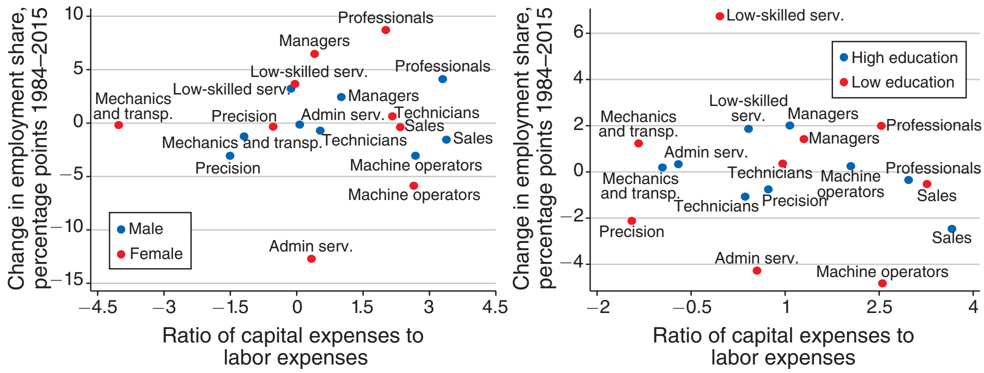

Figure B.III. Input-Expense Ratios across Demographic Groups

Notes: Percentage change in the share of employment between 1984 and 2015 in each one-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. Low education corresponds to workers with high-school or less, and High education corresponds to workers with more than high-school education. All entries are in percent.

Sources: BEA, CPS, and own computations

Table B.I—CETC and Changes in the Labor Market 1984–2015

		Wages	Employment share	
	Annual wage growth (median)	1984–2015 (percent change)	All	College-educated workers (median)
	(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	−4.8	3.3
Middle third	0.7	25.5	2.2	7.6
Upper third	1.0	36.3	2.4	8.6
Panel C. Occupations ordered by intensity of use of capital categories with different CETC				
Computers	1.0	34.9	−3.6	5.1
High CETC	0.8	28.2	5.5	7.4
Low CETC	0.6	21.7	−2.0	3.5

Notes: Entries are in percent. 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 college-educated 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	Administrative services	Low-skill services	Mechanics and transportation	Precision	Machine operators
Managers	0.83	0.38	0.13	**0.02**	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**	**0.00**	0.11	0.85	**0.03**	0.23
Sales				0.13	0.9	**0.13**	0.29	0.96
Administrative services					0.17	**0.02**	0.88	0.32
Low-skill services						0.27	0.31	0.9
Mechanics and transportation							**0.07**	0.35
Precision								0.45

Notes: The table reports the p-values associated to a pair-wise Wald test for equality of the estimates of the elasticity of substitution between capital and labor, 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	Dickey-Fuller
Aggregate	0.45	**0.82**	8.29	−2.7
	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*		
Administrative services	0.92	**2.18**	16.47	−2.22
	0.19	*0.50*		
Low-skilled services	0.71	**1.32**	9.23	−2.96
	0.21	*0.37*		
Mechanics and transportation	0.04	**0.73**	6.66	−4.47
	0.11	*0.35*		
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*		

Notes: Authors' estimation of equation (5). Column 1 presents the OLS estimates and the corresponding standard errors; column 2 contains the IV estimates using the instruments described in the text. Column 3 contains the F-statistic for weak instruments robust to heteroskedasticity, Kleibergen-Paap. The relevant Stock-Yogo critical values for a 15 percent, 20 percent, and 25 percent 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 in the IV regression. The 5 percent and 10 percent critical values are -1.95 and -1.6 respectively.

Table B.IV—Model Fit on Occupational Wages and Capital Expenditure Shares

	Wage 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

Notes: 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. Entries in all columns but those in the column "wages" are in percent.

Table B.V—Forces Driving Labor Reallocation across Occupations

	Model	CETC	Demand	Demographics	Composition	CA
Fraction moving into						
High-skill	10.06	7.23	0.86	−0.05	3.50	−1.49
Middle-skill	−13.58	−7.82	−3.78	−0.10	−2.76	0.88
Low-skill	3.52	0.59	2.92	0.15	−0.74	0.60
Change in occupation premium						
High-skill	16.25	7.80	8.13	2.09	−10.20	8.43
Middle-skill	4.50	7.90	−7.96	−0.76	0.27	5.06
College premium	30.58	15.54	24.27	3.82	−29.06	16.01
Age premium						
30-to-49-year-olds	7.95	5.90	1.02	1.96	−5.20	4.28
50-to-65-year-olds	13.83	3.80	0.06	3.53	−3.43	9.87
Gender wage gap	−28.01	17.49	−22.21	−20.03	−2.55	−0.71

Notes: 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

		CETC						
	Model	Baseline	Identical elasticity	Identical CETC	Demand	Demographics	Composition	CA
Managers	15.06	8.14	−0.43	7.94	3.97	1.02	−7.49	9.41
Professionals	17.52	11.38	−0.70	10.68	8.89	3.26	−16.11	10.10
Technicians	6.52	0.70	−0.29	0.37	3.94	1.81	−0.41	0.47
Sales	7.88	3.64	−0.19	3.74	0.58	−0.60	1.05	3.22
Administrative services	13.19	−49.29	−0.26	−49.63	52.89	3.50	−0.90	6.98
Mechanics and transportation	−4.71	8.42	0.86	10.51	−13.22	−4.53	0.34	4.28
Precision production	−6.49	−54.74	0.57	−54.21	51.06	−2.28	0.00	−0.52
Machine operators	3.09	−5.68	0.44	4.25	21.23	−11.02	−9.29	7.85

Notes: 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.

REFERENCES

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, Vol. 4B, edited by David Card and Orley Ashenfelter, 1043–171. Amsterdam: Elsevier.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6): 1488–542.

Adão, Rodrigo, Martin Beraja, and Nitya Pandalai-Nayar. 2020. "Technological Transitions with Skill Heterogeneity across Generations." NBER Working Paper 26625.

Antrás, Pol. 2004. "Is the US Aggregate Production Function Cobb-Douglas? New Estimates of the Elasticity of Substitution." *B.E. Journal of Macroeconomics* 4 (1): 1–36.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum. 2018. "New Technologies and the Labor Market." *Journal of Monetary Economics* 97: 48–67.

Aum, Sangmin. 2017. "The Rise of Software and Skill Demand Reversal." Unpublished.

Aum, Sangmin, Sang Yoon Lee, and Yongseok Shin. 2018. "Computerizing Industries and Routinizing Jobs: Explaining Trends in Aggregate Productivity." *Journal of Monetary Economics* 97: 1–21.

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29 (3): 3–30.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review* 96 (2): 189–94.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics* 90 (2): 300–323.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics* 113 (4): 1169–1213.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–333.

Bureau of Economic Analysis (BEA). 2003. *Fixed Assets and Consumer Durable Goods in the United States, 1925-97*. Washington, DC: Bureau of Economic Analysis.

Beraja, Martin, and Nathan Zorzi. 2022. "Inefficient Automation." NBER Working Paper 30154.

Blau, Francine D., and Lawrence M. Kahn. 1997. "Swimming Upstream: Trends in the Gender Wage Differential in 1980s." *Journal of Labor Economics* 15 (1): 1–42.

Böhm, Michael J., and Christian Siegel. 2021. "Make Yourselves Scarce: The Effect of Demographic Change on the Relative Wages and Employment Rates of Experienced Workers." *International Economic Review* 62 (4): 1537–68.

Buera, Francisco J., Joseph P. Kaboski, Richard Rogerson, and Juan I. Vizcaino. 2021. "Skill-Biased Structural Change." *Review of Economic Studies* 89 (2): 592–625.

Burstein, Ariel, Eduardo Morales, and Jonathan Vogel. 2019. "Changes in Between-Group Inequality: Computers, Occupations, and International Trade." *American Economic Journal: Macroeconomics* 11 (2): 348–400.

Caunedo, Julieta, David Jaume, and Elisa Keller. 2023. "Replication Data for: Occupational Exposure to Capital-Embodied Technological Change." https://doi.org/10.5281/zenodo.7591599.

Caunedo, Julieta, and Elisa Keller. 2022. "Technical Change and the Demand for Talent." *Journal of Monetary Economics* 129: 65–88.

Chetty, Raj, Adam Guren, Day Manoli, and Andrea Weber. 2011. "Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins." *American Economic Review* 101 (3): 471–75.

Comin, Diego A., Ana Danieli, and Martí Mestieri. 2020. "Income-Driven Labor Market Polarization." NBER Working Paper 27455.

Cummins, Jason G., and Giovanni L. Violante. 2002. "Investment-Specific Technical Change in the US (1947-2000): Measurement and Macroeconomic Consequences." *Review of Economic Dynamics* 5 (2): 243–84.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics* 132 (4): 1593–640.

Diamond, Peter, Daniel McFadden, and Miguel Rodriguez. 1978. "Measurement of the Elasticity of Factor Substitution and Bias of Technical Change." In *Production Economics: A Dual Approach to Theory and Applications*, Vol. 2, edited by Melvyn Fuss and Daniel L. McFadden, 125–47. Amsterdam: North-Holland.

Dickey, David A., and Wayne Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association* 74 (366): 427–31.

Dvorkin, Maximiliano A., and Alexander Monge-Naranjo. 2019. "Occupation Mobility, Human Capital and the Aggregate Consequences of Task-Biased Innovations." Federal Reserve Bank St. Louis Working Paper 2019-13.

Eden, Maya, and Paul Gaggl. 2018. "On the Welfare Implications of Automation." *Review of Economic Dynamics* 29: 15–43.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2019. IPUMS USA [dataset]. IPUMS. https://doi.org/10.18128/D030.V9.0.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the College Gender Gap." *Journal of Economic Perspectives* 20 (4): 133–56.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104 (8): 2509–26.

Gordon, Robert J. 1987. "The Postwar Evolution of Computer Prices." NBER Working Paper 2227.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell. 1997. "Long-Run Implications of Investment-Specific Technological Change." *American Economic Review* 87 (3): 342–62.

Herrendorf, Berthold, Christopher Herrington, and Ákos Valentinyi. 2015. "Sectoral Technology and Structural Transformation." *American Economic Journal: Macroeconomics* 7 (4): 104–33.

Hicks, John R. 1932. *The Theory of Wages*. London: MacMillan.

Hobijn, Bart, Todd Schoellman, and A. Vindas. 2018. "Structural Transformation by Cohort." Unpublished.

Hornstein, Andreas, Per Krusell, and Giovanni L. Violante. 2005. "The Effects of Technical Change on Labor Market Inequalities." In *Handbook of Economic Growth*, Vol. 1B, edited by Philippe Aghion and Steven N. Durlaf, 1275–370. Amsterdam: Elsevier.

Hsieh, Chang-Tai, Erik Hurst, Charles I. Jones, and Peter J. Klenow. 2019. "The Allocation of Talent and U.S. Economic Growth." *Econometrica* 87 (5): 1439–74.

Hulten, Charles R. 1992. "Growth Accounting When Technical Change Is Embodied in Capital." *American Economic Review* 82 (4): 964–80.

Jorgenson, Dale W. 1963. "Capital Theory and Investment Behavior." *American Economic Review* 53 (2): 247–59.

Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107 (1): 35–78.

Kehrig, Matthias. 2018. "Comment on 'Computerizing Industries and Routinizing Jobs: Explaining Trends in Aggregate Productivity' by Sangmin Aum, Sang Yoon (Tim) Lee and Yongseok Shin." *Journal of Monetary Economics* 97: 22–28.

Kimball, Miles S. 1995. "The Quantitative Analytics of the Basic Neomonetarist Model." *Journal of Money, Credit and Banking* 27 (4): 1241–77.

Kleinman, Benny, Ernest Liu, and Stephen J. Redding. 2021. "Dynamic Spatial General Equilibrium." NBER Working Paper 29101.

Klump, Rainer, Peter McAdam, and Alpo Willman. 2012. "The Normalized CES Production Function: Theory and Empirics." *Journal of Economic Surveys* 26 (5): 769–99.

Krusell, Per, Lee E. Ohanian, José-Víctor Rios-Rull, and Giovanni L. Violante. 2000. "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis." *Econometrica* 68 (5): 1029–54.

Lee, Sang Yoon (Tim), and Yongseok Shin. 2019. "Horizontal and Vertical Polarization: Task-Specific Technological Change in a Multi-Sector Economy." Queen Mary University of London Working Paper 888.

Lemieux, Thomas. 2008. "The Changing Nature of Wage Inequality." *Journal of Population Economics* 21 (1): 21–48.

Leon-Ledesma, Miguel A., Peter McAdam, and Alpo Willman. 2010. "Identifying the Elasticity of Substitution with Biased Technical Change." *American Economic Review* 100 (4): 1330–57.

National Academies of Sciences, Engineering, and Medicine. 2017. *Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here*. Washington, DC: National Academies Press.

Ngai, L. Rachel, and Barbara Petrongolo. 2017. "Gender Gaps and the Rise of the Service Economy." *American Economic Journal: Macroeconomics* 9 (4): 1–44.

Oberfield, Ezra, and Devesh Raval. 2020. "Micro Data and Macro Technology." *Econometrica* 89 (2): 703–32.

Oehlert, Gary W. 1992. "A Note on the Delta Method." *American Statistician* 46 (1): 27–29.

Oulton, Nicholas, and Sylaja Srinivasan. 2003. "Capital Stocks, Capital Services, and Depreciation: An Integrated Framework." *Bank of England Quarterly Bulletin* 43 (2): 227.

Rendall, Michelle Petersen. 2010. "Brain versus Brawn: The Realization of Women's Comparative Advantage." Institute for Empirical Research in Economics Working Paper 491.

Robinson, Joan. 1933. *The Economics of Imperfect Competition*. New York: St. Martin's Press.

Roy, Andrew Donald. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers* 3: 135–46.

Sahin, Aysegül, Michael W. L. Elsby, and Bart Hobijn. 2013. "The Decline of the U.S. Labor Share." Federal Reserve Bank of San Francisco Working Paper 2013-27.

Stock, James H., and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In Identification and Inference for Econometric Models, edited by Donald W. K. Andrews, 80–108. New York: Cambridge University Press.

US Census Bureau. 2016. "Industry and Occupation Code Lists Crosswalks: [2010 Census Occupation Codes with Crosswalk]." www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html (accessed June 2021).

US Department of Labor. 1991. "Dictionary of Occupational Titles: Revised Fourth Edition [dataset]." https://doi.org/10.3886/ICPSR06100.v1 (accessed June 2021).

US Department of Labor. 2016. "ONET Version 23.1 [dataset]." Used under the cc by 4.0 license, Employment and Training Administration, https://www.onetcenter.org/db_releases.html (accessed June 2021).

Uzawa, Hirofumi. 1961. "On a Two-Sector Model of Economic Growth." *Review of Economic Studies* 29 (1): 40–47.