Online Appendix

Occupational exposure to capital-embodied technological change

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1 Data construction

1.1 Data description and sources

All data mentioned in this section are publicly available and were retrieved from the Bureau of Economic Analysis, Census Bureau, Federal Reserve Economic Data (FRED), World Development Indicators (WDI) and O*NET websites as of March 30th 2020. The text of the Dictionary of Occupational Titles (DOT) was retrieved from Inter-university Consortium for Political and Social Research (ICPSR) at University of Michigan.

A. Fixed-Asset tables from U.S. Bureau of Economic Analysis (2021a), 1985-2016.

1. Table 2.1. Current-Cost Net Stock of Private Fixed Assets, Equipment, Structures, and Intellectual Property Products by Type.
2. Table 2.7. Investment in Private Fixed Assets, Equipment, Structures, and Intellectual Property Products by Type.
3. Depreciation rates estimates from BEA by equipment type `https://apps.bea.gov/national/pdf/BEA_depreciation_rates.pdf`.

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B. Prices.

1. Personal consumption expenditures: Nondurable goods (chain-type price index), from U.S. Bureau of Economic Analysis (2021b), annual series 1958-2016.

2. Annual Quality-Adjusted Price Index for Investment by equipment type. Estimates by DiCecio (2009) following the methodology in Cummins and Violante (2002), 1985-2016.

C. Labor market outcomes.

1. We use the Annual Social and Economic Supplement (ASEC) from the Current-Population Survey as available in **?**, 1985-2016.

2. Occupational crosswalks between occupational classifications in CPS from Deming (2017).

D. Use of tools by BEA equipment category at the occupational level.

1. Measures of tool requirements per occupation from the digitized text of the 4th edition of the DOT from U.S. Department of Labor (1991) (`https://www.icpsr.umich.edu/web/ICPSR/studies/6100`). This includes 85% of the sample of occupational descriptions last updated in 1977 and 15% of the sample updated between 1984 and 1987.

2. Tools and Technology module in O*NET 23.4 as our measure of tool usage in 2015 from U.S. Department of Labor (2016).

3. Crosswalk between BEA equipment type and commodity family in O*NET presented in Table 1. The cross-walk exploits the commodity family classification available through the United Nations Standard Products and Services Code (UNSPSC), and maps into its 8-digit commodity classification.

4. Crosswalk between occupations in O*NET (soc-code) from **?**. For new soc-code we use the DOT 2016 and its correspondence to DOT 2010 to express all soc-code in O*NET as occupations 2010 (occ2010).

D. Instruments.

1. Birth rates: Series code SPDYNCBRTINUSA from World Development Indicators (2021) measuring the number of live births per 1000 people.

2. Exports: Series code NE.EXP.GNFS.ZS from World Bank National Accounts (2021) measuring exports of goods and services as a share of GDP.

1.2 Tool requirements in the DOT

We use Natural Language Processing algorithms to construct data on tool requirements in 1980 from the occupational definitions in the DOT. We exploit the spacy NLP package in phyton. We first tokenize and lemmatize the text to prepare it for analysis. This avoids matches to be confounded by differences in case/capitalization, number (singular vs. plural), punctuation, or word form. We collect all nouns in sentences and match them to the Commodity titles or T2 Examples available in the O*NET dataset.[1] This builds a corpus which we use for string-matching. That is, we look for matches to Commodity Titles or T2 Examples within the text describing a DOT job.[2] In addition to identifying exact matches of T2 Examples and Commodity Titles, an additional set of search terms is also created from the set of T2 Examples and/or Commodity Titles, as described below.

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

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

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

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

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

have the largest number of matches against the DOT job definitions. That is, because the words are sufficiently generic, they occur in many different unrelated job definitions.

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

1.3 Details of the series

1.3.1 Quality-adjusted capital stocks per equipment category

We use the current cost investment series (billion of US dollars) by equipment category available under Table 2.7. of the Fixed-Assets tables. Because the stock is assigned to workers in 1984, our measurement implies that any investment occurring during 1984 (and showing up in the stock in 1985) was available to workers in that year. We initialize the stock of capital in efficiency units to equalize its nominal value in 1984 for each equipment category. We also initialize the investment series to equalize its nominal value in the initial year $x_{j1984} = \tilde{x}_{j1984}$, where $\tilde{x}$ is the nominal value of investment. For each equipment category, we use DiCecio (2009)'s price series to deflate investment into efficiency units:

$$x_{jt} = \frac{\tilde{x}_{jt}}{p^k_{jt-1}}.$$

Then, we use the permanent inventory method to construct stocks for each equipment category

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

1.3.2 Tool requirements over time

First, we classify the tools listed in each occupation into one of the 24 equipment and software categories in the Fixed-Assets tables by updating and expanding the cross-walk between commodity family and BEA equipment provided by Aum (2017). The tool requirements in each occupation are available from the 1977 DOT and from the Tools and Technology supplement of O*NET (2016). To construct tool requirements in every year in our sample, we linearly interpolate these tool requirements in each occupation. Albeit a crude interpolation, we find that the requirements predicted for 2006 are consistent with the information from the 2006 O*NET Tools and Technology requirements supplement (which is used for validation purposes only). The DOT measures that we construct have no information on software, so we assign them the tool requirements' for computers in 1984.[3] Second, we sum all the tools used in each equipment at the occupational level defined by the soc-code 2016 (standard classification of occupations) of the O*NET in 2016.

1.3.3 Labor market outcomes

Data on wages and employment come from the Annual Social and Economic Supplement from the CPS, for years 1985 to 2016. We use "asecwt" to weight observations and generate full-time equivalent measures of workers multiplying the person weight by the average number of weekly hours in the previous year divided by 40 (hours per week) and the number of weeks worked in a year divided by 51 (weeks per year). Hourly wages are computed as total labor income divided by the average hours worked in a year multiplied by the number of weeks worked in a year. Labor income corresponds to the pre-tax wage and salary income deflated using the price of consumption for non-durable goods.

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

[3] Our results are robust to assuming zero requirements for software in 1977.

Table 1: Concordance between NIPA category and tools' commodity family

Nipa line/ Family code	Title nipa line/Title commodity family code
Nipa line 4	**Computers and peripheral equipment**
43210000	Computer Equipment and Accessories
Nipa line 5	**Communication equipment**
43190000	Communications Devices and Accessories
43200000	*Information tech. or broadcasting or telecomm.*
43220000	*Data Voice or Multimedia Network Equipment*
45110000	Audio and visual presentation and composing
46170000	*Security surveillance and detection*
55110000	*Electronic reference material*
55120000	*Signage and accessories*
Nipa line 6	**Medical Instruments**
42150000	Dental equipment and supplies
42160000	Dialysis equipment and supplies
42170000	Emergency and field medical services products
42180000	Patient exam and monitoring products
42190000	Medical facility products
42200000	Medical diagnostic imaging and nuclear medicine
42210000	Independent living aids for the physically challenged
42220000	Intravenous and arterial administration products
42230000	Clinical nutrition
42240000	Orthopedic and prosthetic and sports medicine
42250000	Physical and occupational therapy and rehabilitation
42260000	Postmortem and mortuary equipment and supplies
42270000	Respiratory and anesthesia and resuscitation
42280000	Medical sterilization products
42290000	Surgical products
42300000	Medical training and education supplies
42310000	Wound care products
Nipa line 9	**Non-Medical Instruments**
41100000	Laboratory and scientific equipment
41110000	Measuring and observing and testing instruments
41120000	Laboratory supplies and fixtures
Nipa line 10	**Photocopy and related Equipment**
45100000	Printing and publishing equipment
45120000	Photographic or filming or video equipment
45140000	Photographic filmmaking supplies
Nipa line 11	**Office & accounting equipment**
44100000	Office machines and their supplies and accessories
44110000	Office and desk accessories
44120000	Office supplies

Nipa line/ Family code	Title Nipa line/Commodity Family code
Nipa line 13	**Fabricated metal products**
27110000	Hand tools
27120000	Hydraulic machinery and equipment
27140000	Automotive specialty tools
31150000	Rope and chain and cable and wire and strap
31160000	Hardware
31170000	Bearings and bushings and wheels and gears
31180000	*Packings glands boots and covers*
40140000	Fluid and gas distribution
40170000	Pipe piping and pipe fittings
Nipa line 14	**Engines & turbines**
26100000	*Power sources*
26110000	Batteries and generators and kinetic power
26130000	Power generation
26140000	Atomic and nuclear energy machinery
Nipa line 17	**Metalworking machinery**
23240000	Metal cutting machinery and accessories
23250000	Metal forming machinery and accessories
23280000	Metal treatment machinery
Nipa line 18	**Special industry machinery, n.e.c.**
23100000	Raw materials processing machinery
23120000	Textile and fabric machinery and accessories
23130000	Lapidary machinery and equipment
23140000	Leatherworking repairing machinery and equipment
23150000	Industrial process machinery and equipment
23180000	Industrial food and beverage equipment
23190000	Mixers and their parts and accessories
23210000	Electronic manufacturing machinery and equipment
23220000	Chicken processing machinery and equipment
23230000	Sawmilling and lumber processing machinery
23260000	Rapid prototyping machinery and accessories
32110000	*Discrete semiconductor devices*
Nipa line 19	**General industrial, incl. materials handling eq.**
23110000	Petroleum processing machinery
23160000	Foundry machines and equipment and supplies
23200000	Mass transfer equipment
23270000	Welding and soldering and brazing machinery
23290000	Industrial machine tools
24100000	Material handling machinery and equipment
24110000	Containers and storage
24130000	Industrial refrigeration
24140000	Packing supplies
27130000	Pneumatic machinery and equipment
31140000	Moldings
40100000	Heating and ventilation and air circulation
40150000	Industrial pumps and compressors
40160000	Industrial filtering and purification

Table 1: Concordance between NIPA category and tools' commodity family (continued)

Nipa line/ Family code	Title nipa line/Title commodity family code
Nipa line 20	**Electrical transmission, and ind. apparatus**
26120000	Electrical wire and cable and harness
31250000	*Pneumatic and hydraulic and electric control systems*
32100000	*Printed circuits and integrated circuits*
32120000	*Passive discrete components*
Nipa line 26	**Aircrafts**
25130000	Aircraft
25200000	Aerospace systems and components and equipment
Nipa line 27	**Ships & boats**
25110000	Marine transport
Nipa line 28	**Railroad equipment**
25120000	Railway and tramway machinery and equipment
Nipa line 29	**Other equipment**
32140000	*Electron tube devices and accessories*
42120000	*Veterinary equipment and supplies*
49120000	*Camping and outdoor equipment and accessories*
53100000	*Clothing*
53110000	*Footwear*
53120000	*Luggage and handbags and packs and cases*
53130000	*Personal care products*
53140000	*Sewing supplies and accessories*
54100000	*Jewelry*
54110000	*Timepieces*
Nipa line 30	**Furniture & fixtures**
30160000	*Interior finishing materials*
30170000	*Doors and windows and glass*
30180000	*Plumbing fixtures*
56100000	Accommodation furniture
56110000	Commercial and industrial furniture
56120000	Classroom and instructional furniture and fixtures
56130000	Merchandising furniture and accessories
Nipa line 33	**Agric. machinery**
21100000	Agricultural and forestry and landscape
21110000	Fishing and aquaculture equipment
Nipa line 36	**Construction machinery**
22100000	Heavy construction machinery and equipment
30120000	*Roads and landscape*
30190000	*Construction and maintenance support equipment*
30240000	*Portable Structure Building Components*

Nipa line/ Family code	Title Nipa line/Commodity Family code
Nipa line 39	**Mining & oilfield machinery**
20100000	Mining and quarrying machinery and equipment
20110000	Well drilling and operation equipment
20120000	Oil and gas drilling and exploration equipment
20140000	Oil and gas operating and production equipment
Nipa line 40	**Service industry machinery**
31240000	Industrial optics
47110000	*Industrial laundry and dry cleaning equipment*
47120000	*Janitorial equipment*
48100000	Institutional food services equipment
48110000	Vending machines
48120000	*Gambling or wagering equipment*
49130000	*Fishing and hunting equipment*
49140000	*Watersports equipment*
49150000	*Winter sports equipment*
49160000	*Field and court sports equipment*
49170000	*Gymnastics and boxing equipment*
49180000	*Target and table games and equipment*
49200000	*Fitness equipment*
49210000	*Other sports*
49220000	*Sports equipment and accessories*
49240000	*Recreation and playground and swimming and spa*
60100000	*Teaching aids and materials and accessories*
60120000	*Arts and crafts equipment and accessories*
60130000	*Musical Instruments and parts and accessories*
60140000	*Toys and games*
Nipa line 41	**Electrical equipment, n.e.c.**
32130000	Electronic hardware and component
32150000	Automation control devices
39120000	Electrical equipment and components and supplies
39130000	Electrical wire management devices
52140000	Domestic appliances
52150000	Domestic kitchenware and kitchen supplies
52160000	Consumer electronics
Nipa line 99	**Software**
43230000	Software
Nipa line 22+25	**Trucks and Cars**
25100000	Motor vehicles
25170000	Transportation components and systems
25180000	Vehicle bodies and trailers
25190000	Transportation services equipment

Notes: The table reports the concordance between NIPA equipment investment types and the classification system used in the O*NET Tools and Technology database (UNSPSC). The concordance updates and expands the cross-walk between commodity family and BEA equipment provided by Aum (2017). The new commodity family codes not considered by Aum (2017) are marked in italics.

2 Additional empirical results

2.1 Dynamics of the capital stock

Aggregate capital. We compare the implied changes in the aggregate stock of capital as reported by the BEA, the quality-adjusted stocks reported by Cummins and Violante (2002), and our own quality-adjusted stocks, which rely on price deflators from DiCecio (2009) for an extended time frame; see Table 2.

Table 2: Annual changes in the stock of capital, alternative measures

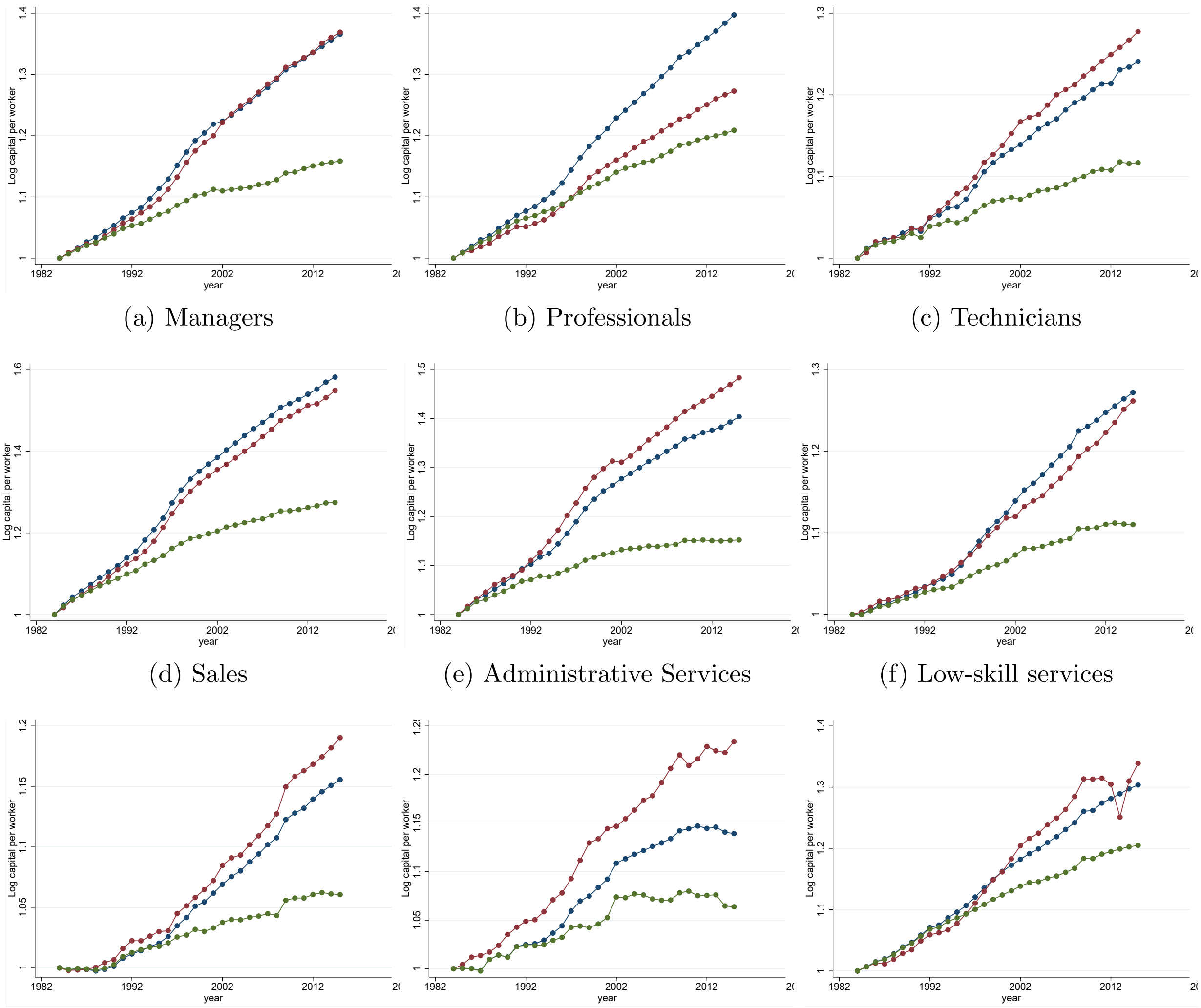
	1984-1989	1990-2000	2001-2009	2010-2015
Non-quality adjusted:				
1. NIPA Table 5.10	5.9	5.1	5.4	3.6
Quality-adjusted:				
2. Cummins & Violante	7.5	10	.	.
3. Own	8.3	10.2	8.4	8.5

Notes: The top panel reports growth rates without quality-adjustment in the price of investment while the bottom panel reports growth rates deflated with quality-adjusted prices. Line 1 reports the growth rate of the capital stock reported in Table 5.10 (NIPA) by the BEA; Line 3 reports the estimate in Cummins and Violante (2002) (only available until 2000). Line 3 reports our computation of the growth rate of the aggregate stock of capital using a Tornqvist quantity index on the quality-adjusted equipment series and analogous to that used for the computation of occupational equipment stocks. Entries are in percent.

Occupational capital. Our assignment rule for the capital stocks across occupations (occupational capital requirements) implies that the allocation changes due to disparities in CETC across equipment categories, through its impact in the quality-adjusted value of each of the stocks. The occupational capital requirements also move in response to shifts in the share of employment across occupations, by changing the occupational distribution of tools for each equipment category. Figure 1 illustrates the role of these channels by comparing the dynamics of the occupational capital per worker to what we would have been obtained if either (a) the occupational capital requirements were held constant to its 1984 levels ($\text{req}_{ojt} = \text{req}_{oj1984}$, red line) or (b) in addition, the level of nominal investment was held constant to its 1984 level (green line).[4]

The difference between the benchmark occupational capital per worker (blue) and the constant requirements series (red) is the tool and employment reallocation effect. This reallocation effect is positive for administrative services, low-skill services, and precision production occupations, i.e. occupational tools increased relative to their 1984 level; and particularly so after the 2000s for machine operators, technicians, mechanics, and transportation. The contribution of this reallocation effect for the growth in occupational capital per worker is 26%, on average across these occupations. The reallocation effect is negative for professionals

[4]In constructing fixed capital requirements we reweight the proportion of tools allocated to each 3-digit occupation within a 1-digit occupation so that it replicates the distribution of shares in 1984.



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

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

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

Figure 1: Allocation of capital to occupations.

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

and sales occupations i.e. occupational tools decreased relative top their 1984 levels. The contribution of this reallocation effect for the growth in occupational capital per worker is -17.7%, on average across these occupations. When in addition nominal investments are held fixed (green), the dynamics of the stocks are explained by the decline in the relative price of investment to consumption. The contribution of the decline in the relative price of investment to the change in the occupational stock per worker averages 41% across occupations, and it is as low as 19% for machine operators and as high as 57% for administrative service occupations.

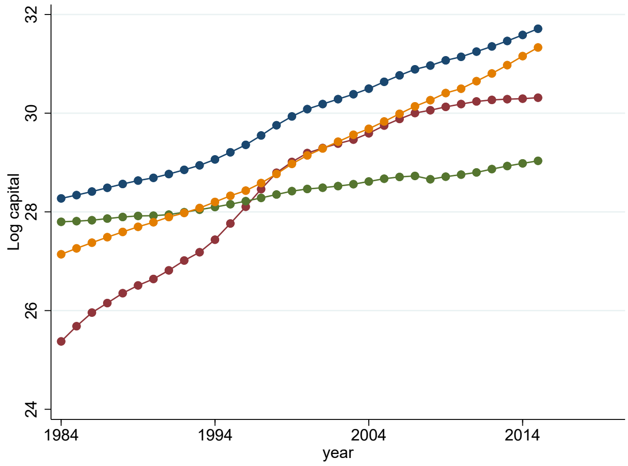


Figure 2: Quality adjusted stocks by category.

The figure shows the quality-adjusted stock of equipment (logs) in blue; the quality-adjusted stock of computers and software (logs) in red; the quality-adjusted stock of communication equipment (logs) in yellow; and the remaining equipment categories in green. Source: BEA and own computations.

2.2 Capital bundles by occupation

The aggregate path of occupational capital hides compositional differences in the stocks across occupations. To assess the role of CETC for the dynamics of occupational capital we aggregate equipment categories to include three capital groups: those with high rates of CETC, or large decays in the price of investment relative to consumption (HCETC), and those with low rates of CETC, or small movements in the relative price of investment to consumption (LCETC).[5] In addition, because an extensive literature focuses on the role of computers for labor market outcomes (Beaudry *et al.*, 2010; Burstein *et al.*, 2019; Aum *et al.*, 2018; Atalay *et al.*, 2018) we also single out computers and software from HCETC capital. Table 3 makes the classification explicit and shows the dynamic of prices and stocks. While the stock of computers grew faster than the aggregate stock until the 2000s, it has slowed down since then. The growth in quality-adjusted stocks is explained by the accumulation of HCETC, and particularly, communication equipment.

Occupations that are more intensive in equipment categories that experienced larger declines in their quality-adjusted price of investment should see their stocks increase even with a fixed employment allocation. Table 4 displays the composition of the occupational capital by capital type at different points in time. There is vast heterogeneity in the share of capital expenses accounted for by different capital types. For example, in 1984, the share of HCETC capital ranges from 12% in mechanics and transportation to 54% in managerial occupations. Professionals, low skill services and machine operators were all relatively intensive in LCETC capital in 1984, but the importance of LCETC capital falls through time. Heterogeneity in occupational capital as displayed in Figure 2 primarily stems from disparities in the trajectory for HCETC capital.

[5]Formally, stocks with investment price declines relative to consumption that are above the median for the sample period are grouped together, HCETC, and those below the median are also grouped together, LCETC.

Table 3: Equipment assignment by CETC.

Description	**Fixed-Asset Code**	**Price of Investment**	**Usercost**	**Stock per worker**
		1984-2015 annual % change		
i) Computers and peripheral equipment	4	-13.17	-13.96	17.07
Software	99	-4.87	-4.97	11.36
ii) High—CETC				
Communication equipment	5	-13.71	-11.62	20.16
Aircraft	26	-9.42	-9.43	11.90
Engines and turbines	14	-5.05	-5.45	4.69
Special industry machinery, n.e.c.	18	-4.87	-4.97	11.36
Nonmedical instruments	9	-4.35	-3.36	6.73
Photocopy and related equipment	10	-4.35	-3.63	1.44
Medical equipment and instruments	6	-4.35	-3.36	9.37
Service industry machinery	40	-4.29	-4.31	5.86
iii) Low—CETC				
Electrical transmission and industrial apparatus	20	-3.19	-3.02	3.87
Autos & trucks	22-25	-2.95	-3.70	4.51
Fabricated metal products	13	-2.63	-3.05	-0.18
Ships and boats	27	-2.57	-2.03	1.34
Other nonresidential equipment	29	-1.82	-2.14	4.14
Office and accounting equipment	11	-1.50	-2.00	-1.21
General industrial	19	-1.29	-2.15	1.93
Electrical equipment, n.e.c.	41	-1.20	-1.08	0.74
Mining and oilfield machinery	39	-1.11	-1.40	3.06
Railroad equipment	28	-1.09	-1.32	0.35
Metalworking machinery	17	-0.83	-2.00	-0.02
Furniture and fixtures	30	-0.73	-0.45	1.56
Construction machinery	36	-0.30	-1.34	2.72
Agricultural machinery	33	-0.30	-1.33	-0.96

Notes: Column 1 presents a description of the equipment category while column 2 reports the corresponding code in the fixed-asset tables of the BEA. Column 3 presents the change in the quality-adjusted relative price of investment to consumption, column 4 presents the change in the user cost of capital and column 5 presents the change in the stock per worker.

Table 4: Capital bundles at the 1-digit occupation level

	Share in 1984			Share in 2015		
	Computers	HCETC	LCETC	Computers	HCETC	LCETC
Managers	0.20	0.54	0.27	0.15	0.57	0.28
Professionals	0.10	0.40	0.50	0.10	0.54	0.37
Technicians	0.08	0.55	0.37	0.05	0.49	0.45
Sales	0.46	0.34	0.21	0.35	0.46	0.19
Administrative services	0.44	0.33	0.23	0.23	0.40	0.36
Low-skilled services	0.02	0.41	0.56	0.08	0.37	0.55
Mechanics and transportation	0.02	0.12	0.87	0.04	0.12	0.84
Precision workers	0.05	0.34	0.61	0.06	0.36	0.58
Machine operators	0.06	0.34	0.61	0.03	0.29	0.68
Average (all)	**0.08**	**0.26**	**0.65**	**0.09**	**0.37**	**0.54**

Notes: Columns 1 to 3 report the share of capital expenses by capital type in 1984 while Columns 4 to 6 report the share of capital expenses by type in 2015. HCETC corresponds to equipment categories with high rates of CETC, or large decays in the price of investment relative to consumption. LCETC corresponds to equipment categories with low CETC, or small movements in the relative price of investment to consumption. See description in Table 3.

2.3 Elasticity of substitution between capital and labor

Table 5 run robustness checks for the estimates of the elasticity of substitution when we allow for a trend break in 2000, the time at which we observe a slow-down in the decline in the price of computers as well as when we allow for a quadratic trend instead of a linear trend in technical change. Our results are robust to this more flexible specification

We also study the potential confounding effects of our measures of the elasticity of substitution between capital and labor and other dimensions of occupational heterogeneity, namely the task content of occupations Autor *et al.* (2003). Table 5 shows estimates of the elasticity of substitution where the estimation equation (5) is augmented to include a measure of the routine task intensity (RTI) of each 1-digit occupation. Following Autor *et al.* (2006), $RTI_{ot} = \ln(routine_{ot}) - \ln(manual_{ot}) - \ln(abstract_{ot})$, where $routine_{ot}$, $manual_{ot}$, and $abstract_{ot}$ indicate the average normalized task score of occupation o in year t.[6] We find that the resulting estimates of the elasticity of substitution are only slightly more complementary than our benchmark, particularly so in high-skill occupations. We conclude that our estimates are robust to these controls and importantly, that our estimates pick up a novel dimension of heterogeneity across occupations.

Estimates of the bias in technology. Table 6 presents the estimates for the log difference in the trend of labor-augmenting and capital-augmenting technology. Using the notation for equation (4) in the body of the paper, the bias in technology equalizes $\frac{\beta_{2o}}{\beta_{3o}} = \gamma_o$.

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

Table 5: Estimates of σ_o, robustness.

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

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

A positive estimate of γ_o is evidence of labor-augmenting technical change while a negative estimate is evidence of capital-augmenting technical change. If the elasticity of substitution between capital and labor is below one (complements) and $\gamma_o > 0$ (labor-augmenting) then technology is capital-biased, implying a decline in the share of total expenses in the occupation accrued to labor. Our estimates suggest a decline in the share accrued to labor in all occupations but machine operators.

2.4 Further evidence on CETC and labor market outcomes

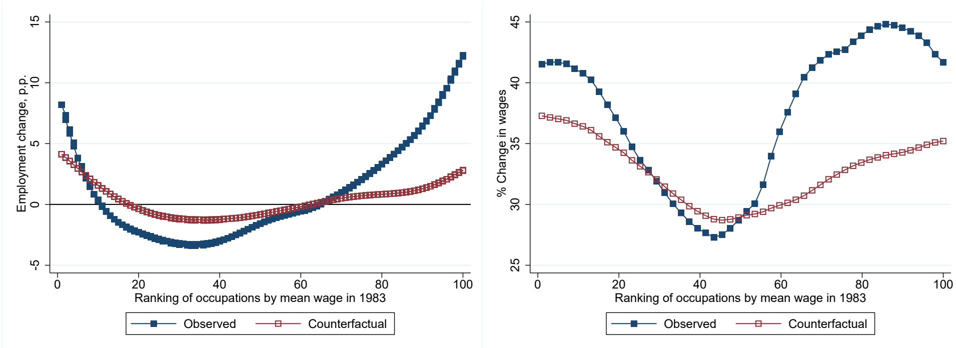
Employment and wage dynamics. We consider the relevance of CETC for the polarization of the US labor market by constructing reduced-form counterfactuals in the spirit of Autor and Dorn (2013). In particular, we reweight the observed employment distribution across occupations by imposing no employment change in occupations above the median of the distribution of changes occupational capital per worker (see Panel (a) in Figure 3). We find that employment polarization would have been weaker if abstracting from the shifts in employment in occupations that became more capital intensive. Particularly, we should have seen lower gains in employment at the top of the skill distribution, as proxied by the wage. In the same spirit, Panel (b) of Figure 3 explores the dynamics of hourly wages. If we set wage gains in occupations that experienced above median changes in capital per worker to the average wage gains over the period we find that wage gains would have been lower at the bottom and top of the skill distribution, and that these lower gains concentrate at the top of the skill distribution.

Task content. Table 7 explore the reduced-form relationship between capital-deepening,

Table 6: Log-difference in labor vs. capital augmenting technology

	σ_o	γ_o, %
Aggregate	0.88	1.35
	0.18	*0.01*
Managers	0.93	1.48
	0.25	*0.02*
Professionals	0.86	4.51
	0.17	*0.01*
Technicians	0.65	4.41
	0.21	*0.01*
Sales	1.38	-0.92
	0.16	*0.02*
Admin Service	2.18	-5.74
	0.50	*0.05*
Low-skilled Serv	1.32	-1.04
	0.37	*0.02*
Mechanics & Transp.	0.73	0.71
	0.39	*0.02*
Precision	2.06	-2.28
	0.63	*0.03*
Machine Operators	1.41	0.37
	0.61	*0.03*

Notes: This table presents the estimates for the log difference in the trend of labor-augmenting and capital-augmenting technology, $\frac{\beta_{2o}}{\beta_{3o}} = \gamma_o$, Column (3), and repeats the IV-estimates for the elasticity of substitution between capital and labor in the main body of the paper, Column (2).



(a) Employment polarization

(b) Wage polarization

Figure 3: Change in capital-intensity and the labor market.

Panel (a) shows employment changes by occupation between 1984 and 2015 (polynomial fit, parameter 0.8) in blue, and reweighed employment changes by occupation assuming no change in occupations with above median changes in the capital per worker. Panel (b) shows wage changes by occupation between 1984 and 2015 (polynomial fit) in blue, and wage changes by occupation imputing the average change in wages in occupations with above median changes in the capital per worker.

measured as the change in capital-per-worker, and CETC, measured as the decline in the user cost of capital, with labor market outcomes. Outcome variables are the change in employment, the change in college-educated workers, and the change in wages for workers in each 3-digit occupational Census category between 1984 and 2015. These outcomes are regressed against our measures of capital-deepening and CETC, with and without controls for the task intensity of an occupation. Measures of task intensity are constructed following the methodology in Acemoglu and Autor (2011). The main take aways from this analysis is that occupations that become more intensive in capital also gained employment on average, they also became more skill-intensive, and their average wages increased. At the same time, the relationship between the decline in the user cost of capital and these outcomes is noisily estimated, consistent with the lack of correlation between employment changes and technical change in Section 2 of the paper. Importantly, the correlation between capital-deepening and employment outcomes remains even after controlling for the task content of these occupations.

Table 7: CETC regressions with task content.

	employment share, p.p. change all		college educated		wages % change	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
a. Capital-measures						
Change in capital-per-worker	0.09***	0.07***	3.19***	2.89***	10.53***	8.71***
	(0.02)	(0.02)	(0.64)	(0.66)	(2.16)	(2.21)
Decline in the user cost of capital	0.00	-0.00	-0.08	-0.28	1.19	1.08
	(0.02)	(0.02)	(0.64)	(0.67)	(2.19)	(2.26)
b. Tasks intensity						
Abstract		0.03		1.01		5.65**
		(0.02)		(0.68)		(2.29)
Manual		0.02		-0.56		-5.58**
		(0.02)		(0.72)		(2.42)
Routine		-0.06***		-0.43		-3.04
		(0.02)		(0.68)		(2.30)
Observations	316	303	316	303	316	303

Point estimates of a OLS regressions at 3-digit occupations of an outcome variable and measures of changes in capital intensity and technical change. Outcomes include changes in employment (columns 1-2), changes in college-educated workers (columns 3-4) and wages (columns 5-6). Task intensity is constructed following Acemoglu and Autor (2011). Columns 2, 4 and 6 include controls for the task intensity. Standard errors in parenthesis. *** indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

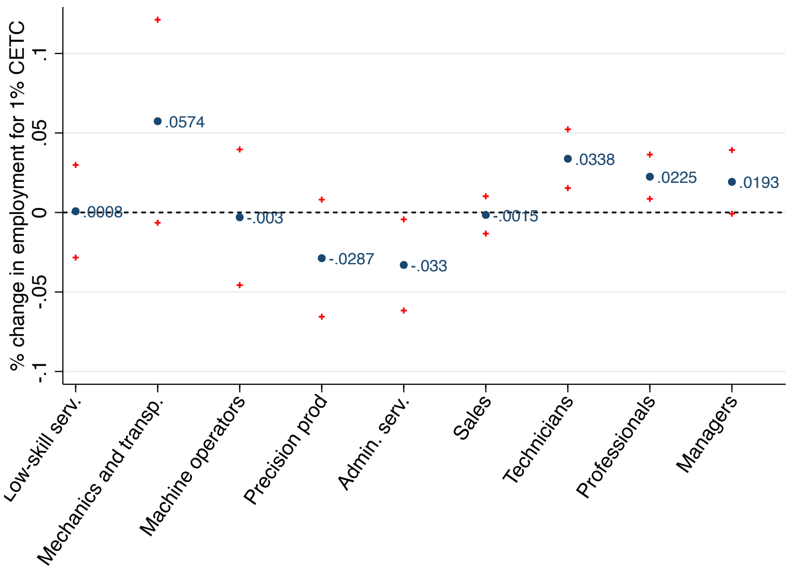


Figure 4: Occupational exposure to CETC, fixed $\frac{\lambda^k k}{\lambda_o y_o} = 0.24$.

Note: Authors' estimation of exposure fixing the expenditure share of capital to 0.24 across occupations. Percentage change in employment for a 1% decline in the relative cost of capital to consumption, i.e. CETC. A positive (negative) entry indicates employment gains (losses) from CETC. Point estimates and 95% confidence intervals (+).

3 Derivations

3.1 Cross-price elasticity of labor demand

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

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

$$y = n\frac{\partial y}{\partial n} + k\frac{\partial y}{\partial k}. \tag{1}$$

Differentiating the above equation with respect to capital,

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

and therefore:

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

The total differential of output satisfies:

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

$$p_y dy = wdn + rdk. \tag{3}$$

We totally differentiate equation 1 and replace 3 to obtain:

$$ydp_y = ndw + kdr.$$

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

$$\frac{p_y dy}{\rho} = -\frac{wdn}{\eta_{nw}} + \frac{rdk}{\eta^c}\frac{kdn}{ndk}. \tag{4}$$

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

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

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

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

and we can rewrite equation 4 as

$$\frac{p_y dy}{\rho} = -\frac{wdn}{\eta_{nw}} + \frac{wdn}{\eta^c}\frac{1-\kappa}{\kappa}. \tag{5}$$

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

$$\frac{p_y dy}{\rho} = \frac{rdk}{\sigma} - \frac{wdn}{\kappa}\left(\frac{1}{\eta_{nw}} + \frac{1-\kappa}{\sigma}\right). \tag{6}$$

Combining equations 3, 5 and 6 yields the expression for exposure.

4 Quantitative exercise

4.1 Parameterization

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

$$\frac{\pi_{oht}}{\pi_{o_b ht}} = \frac{T_{oht}}{T_{o_b ht}}\left(\frac{\lambda^n_{ot}}{\lambda^n_{o_b t}}\right)^{\theta}, \tag{7}$$

where o_b is a baseline occupation, which we set to be low-skill services (the occupation with the lowest average wage in 1984). The equation above delivers two important points for our inference. First, the level of the scale parameters for a group of individuals (absolute advantage) does not influence the occupational choice. That is, the fact that high-school may, on average, be endowed with lower efficiency units for labor than college graduates does not have a bearing on the different occupational choice of the two groups. Second, the link between the scale parameters and the occupational choice in equation 7 relies on a measure of wages per efficiency units across occupations.

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

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

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

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

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

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

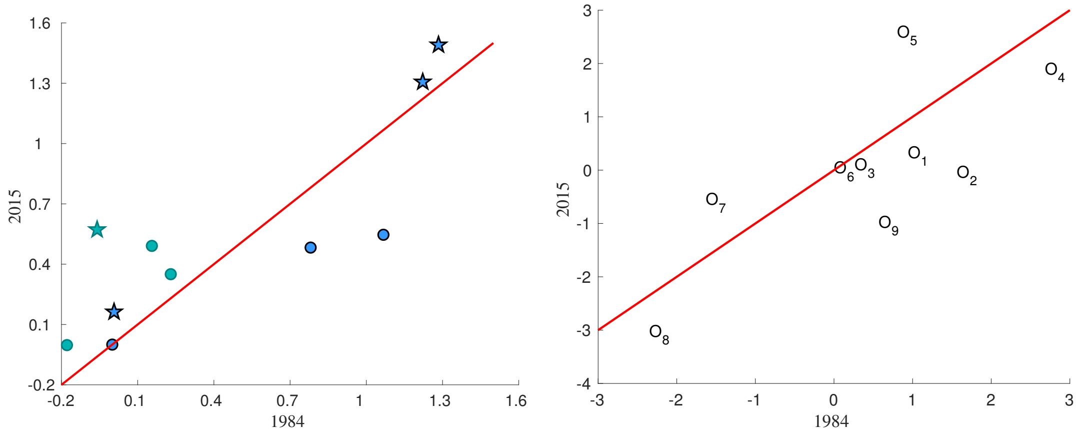
Wages per efficiency units. We choose a profile of wages per efficiency units across occupations so that the model is consistent with capital per worker across occupations, $\frac{k_{ot}}{\ell_{ot}}$. Replacing the equilibrium occupational choice into equation for the capital per efficiency units, we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

$$\frac{k_{ot}}{\ell_{ot}} / \frac{k_{o_b t}}{\ell_{o_b t}} = \left(\frac{\alpha}{1-\alpha} \frac{\lambda_{ot}^{n}}{\lambda_{ot}^{k}}\right)^{\sigma_o} \left(\frac{\alpha}{1-\alpha} \frac{\lambda_{o_b t}^{n}}{\lambda_{o_b t}^{k}}\right)^{-\sigma_{o_b}} \frac{n_{ot}}{\ell_{ot}} \left(\frac{n_{o_b t}}{\ell_{o_b t}}\right)^{-1} \left(\frac{\lambda_{ot}^{n}}{\lambda_{o_b t}^{n}}\right)^{-1}, \tag{8}$$

where $\ell_{ot} = \sum_h \pi_{oht}\pi_{ht}$. The first two terms on the RHS are the capital labor ratios, for labor measured in efficiency units. They are a function of the wage per efficiency units and observables. We observe the price of capital in our dataset and assign a value of 0.24 to the capital share in the production of the occupational good, as estimated by Burstein *et al.* (2019). The remaining terms in equation 8 give the ratio of the average efficiency units supplied by workers to each occupation. This term is not directly observable in the data and is a result of worker's selection into different occupations. The properties of the Frechet distribution allows us to link the selection effect to the occupational choice, and therefore measure differences in per-worker efficiency units from data on occupational choices, given the wage per efficiency unit:

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

With these numbers at hand, equation 8 yields a measure of the variation in the price of labor across occupations scaled by the elasticity of substitution, $\frac{\lambda_{ot}^{n\sigma_o-1}}{\lambda_{o_b t}^{n\sigma_{o_b}-1}}$. With equation 7, we are able to parameterize the dispersion of the scale parameter across occupations for each



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

Figure 5: Scale parameters.

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

labor groups and year, up to differences in the elasticity of substitution σ_o.

Outcomes. Figure 5 plots the group and occupation component of the scale parameter of the Frechet distribution. To isolate those two components, we specify T_{oht} to be the product of an occupational component, T_{ot}, a labor group component, T_{ht} and a residual component, $\tilde{T}_{oht}$. In particular, we define the scale parameter for labor group h in occupation o at time t as:

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

In the above equation, T_{ht} is the average efficiency units of labor of group h. The profile $\{T_{ht}\}_{h=1}^{G}$ describes the pattern of absolute advantage across the groups. The pattern of comparative advantage across labor groups is instead described by $\tilde{T}_{oht}$. Last, the profile $\{T_{ot}\}_{o=1}^{O}$ describes the average efficiency units across occupation. For example, an increase in T_o associated to managers implies that individuals become more efficient in managerial occupations, across all groups.[7] To measure the components of T, we estimate, in each year, the following regression equation:[8]

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

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

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

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

Figure 5, panel (a), shows the labor group component of the scale parameter, T_h. It increases with the schooling of the group on average, and is higher for males than for females. These findings are mostly a reflection of the structure of wages in the data. The elasticity to which wage differentials across labor groups translate into differences in T_h is shaped by θ. In 2015, the component associated to college graduates is 40p.p. higher than that associated to individuals without a college degree. The gap in wages between these two groups is 57p.p. in the same year. The group component associated to males is 31p.p. higher than that associated to females, while the gender wage gap is of 18p.p., in 2015. Between 1984 and 2015 the gender wage gap decreases of three seventh and the gap in efficiency units reduces of 2/3.

Figure 5, panel (b), shows the occupation component of the scale parameter in the distribution of the efficiency units of labor transformed by the elasticity of substitution between capital and labor, $T_o^{\sigma_o - 1}$. The dispersion of the occupation component at each point in time is a reflection of the dispersion in the evolution of the price and quantity of capital, the elasticity of substitution, as well as of the occupational choice. For example, consider administrative services and mechanics, which are the two occupations that calibrates an increase in its demand shifter relative to low-skill services, between 1984 and 2015. These occupations both measure a slow increase in the wage per efficiency unit (equation 8), which push up the path of the occupation component (equation 7). Administrative services record the biggest changes in price and quantity of capital, as well as the highest elasticity of substitution. On the opposite end, mechanics and transportations record the smallest changes in price and quantity of capital along with the second smallest elasticity of substitution.

4.2 Alternative parameterization

We test the robustness of our results for the drivers of labor reallocation over time against different strategies for estimating the elasticity of substitution between capital and labor across occupations. We consider the two alternative estimation strategies mentioned above. *Alternative (1)* extends our regression equation (eqn 5 in the paper) to include a break in the time trend in year 2000 – that is, we estimate γ_o for the period before 2000 and for the period after 2000. *Alternative (2)* extends our regression equation (eqn 5 in the paper) to include controls for the routine task intensity (RTI) index of each occupation. Table 8 reports the drivers of the employment reallocation and of changes in wage premia between 1984 and 2015 under our baseline and the two alternative estimation strategies. Overall, CETC is attributed 95% of the gross employment reallocation between 1984 and 2014 via our baseline exercise, 115% via the *Alternative (1)* exercise and 64% via the *Alternative (2)* exercise. Looking across occupations of different skill levels, the fraction of the flows into high-skill occupations that are attributed to CETC via the counterfactual exercises is 72% in the baseline, 78% in the *Alternative (1)* exercise, and 56% in the *Alternative (2)* exercise. The most noticeable difference between the results of the *Alternative (2)* exercise and those of our baseline (and of the *Alternative (1)* exercise) is on the employment flow into low-skill occupations for which the former predicts an inflow and the latter predicts and outflow. Turning to wages, the role attributed to CETC for the changes in the college premium and in the occupational wage premium is consistent across the different sets of estimates of the elasticity of substitution, with our baseline exercise being on the conservative side. The two alternative exercises predict a smaller role for CETC in rising the age premium for older workers and the *Alternative (2)* exercise predicts a smaller role of CETC in rising the gender wage gap.

Table 8: The drivers of labor reallocation: Alternative specifications of the elasticity of substitution, σ_o.

	model		CECT	
		baseline	alternative (1)	alternative (2)
Fraction moving into				
High-wage	10.06	7.23	7.83	5.58
Middle-wage	-13.58	-7.82	-9.14	-4.71
Low-wage	3.52	0.59	1.31	-0.88
Abs average movement				
All	3.04	2.89	3.51	1.96
Change in				
Occupation premium				
High-wage	16.25	9.01	11.31	9.17
Middle-wage	4.50	7.52	9.36	1.30
College premium	30.58	18.96	21.72	21.70
Age premium				
30- to 49-year olds	7.95	4.63	4.86	3.66
50- to 65-year olds	13.83	0.37	-0.65	-0.35
Gender wage gap	-28.01	14.51	17.79	0.30

Note: Column "model" reports the percentage variation in the outcome of interest (employment or wages), between 1984 and 2015. All other columns present the outcome attributed to CET via the counterfactual exercise. The description of the counterfactual exercise is in the text. *baseline* refers to our baseline economy calibrated under our baseline estimates for the elasticity of substitution between capital and labor, σ_o. *alternative (1)* refers to our baseline economy calibrated under the *Alternative (1)* estimates for σ_o. *alternative (2)* refers to our baseline economy calibrated under the *Alternative (2)* estimates for σ_o. "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.

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. vol. 4B, *12*, 1st edn., Elsevier, pp. 1043–1171.

Atalay, E., Phongthiengtham, P., Sotelo, S. and Tannenbaum, D. (2018). New technologies and the labor market. *Journal of Monetary Economics*, **97**, 48 – 67.

Aum, S. (2017). *The Rise of Software and Skill Demand Reversal*. Mimeo.

—, Lee, S. Y. T. and Shin, Y. (2018). Computerizing industries and routinizing jobs: Explaining trends in aggregate productivity. *Journal of Monetary Economics*, **97**, 1 – 21.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, **103** (5), 1553–97.

—, Katz, L. F. and Kearney, M. S. (2006). The polarization of the U.S. labor market. *American Economic Review*, **96** (2), 189–194.

—, Levy, F. and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, **118** (4), 1279–1333.

Beaudry, P., Doms, M. and Lewis, E. (2010). Should the personal computer be considered a technological revolution? evidence from u.s. metropolitan areas. *Journal of Political Economy*, **118** (5), 988–1036.

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

Chirinko, R. S. and Mallick, D. (2011). The elasticity of derived demand, factor substitution, and product demand: Corrections to Hicks' formula and Marshall's Four Rules. *Labour Economics*, **18** (5), 708–711.

Cummins, J. G. and Violante, G. L. (2002). Investment-Specific Technical Change in the US (1947-2000): Measurement and Macroeconomic Consequences. *Review of Economic Dynamics*, **5** (2), 243–284.

Deming, D. (2017). Replication Data for: "The Growing Importance of Social Skills in the Labor Market".

DiCecio, R. (2009). Sticky wages and sectoral labor comovement. *Journal of Economic Dynamics and Control*, **33** (3), 538 – 553.

U.S. Bureau of Economic Analysis (2021a). Nipa tables. https://apps.bea.gov/iTable/?reqid=19&step=2&isuri=1&categories=survey.

U.S. Bureau of Economic Analysis (2021b). Personal consumption expenditures: Chain-type price index [pcepi]. https://fred.stlouisfed.org/series/PCEPI.

U.S. Department of Labor (1991). Dictionary of occupational titles: Revised fourth edition [dataset]. https://doi.org/10.3886/ICPSR06100.v1.

U.S. 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.

World Bank National Accounts (2021). *Exports of goods and services (% of GDP) - United States, 1960-2020 [NE.EXP.GNFS.ZS]*. Used under the cc by 4.0 license, World Bank, https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS?name_desc=true&locations=US.

World Development Indicators (2021). Crude birth rate for the united states [spdyncbrtinusa]. https://fred.stlouisfed.org/series/SPDYNCBRTINUSA.