Heterogeneous Effects of Capital-Embodied Innovation on Labor Market *

Hyejin Park† Younghun Shim‡

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Abstract

This paper develops an occupation-level measure of Capital-Embodied Innovation (CEI) by matching patents with capital goods based on their text similarity. The impact of CEI on labor demand is heterogeneous, depending on the similarity between capital and occupational tasks. Specifically, CEI associated with task-similar capital reduces the relative labor demand, whereas CEI related to task-dissimilar capital raises it. Between 1980 and 2015, capital used by high-wage occupations experienced more innovations in task-dissimilar capital and fewer in task-similar capital. CEI can explain 51% of the relative wage growth in high-wage occupations and significantly contributes to routine- and abstract-biased labor market changes.

Keywords: Capital-Embodied Innovation, Text Analysis of Patents, Substitution between Labor and Capital
JEL codes: J24, J31, O33, O47

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†Université de Montréal; Email Address: hyejin.park@umontreal.ca
‡International Monetary Fund; Email Address: yshim@imf.org

1 Introduction

Labor markets in developed economies have exhibited secular trends since the late 20th century. A particularly notable trend is job polarization (Goos and Manning, 2007). As depicted in Figure 1, both employment and wages have increased substantially more for occupations at the top and bottom of the wage distribution. In contrast, middle-wage occupations have seen relative declines in both employment and wages.

The primary explanation for this phenomenon focuses on a few episodes of technological changes, often embedded in capital, which have reduced demand for middle-wage occupations. Autor and Dorn (2013) points out the rise of computers that substitute routine tasks, and Acemoglu and Restrepo (2022) investigate the role of robots that replace workers in manufacturing industries. However, robots and computers account for a small fraction of capital expenditure, with 0.7% and 3% of equipment expenditures in 2019, respectively.[1] Thus, a wider range of capital needs to be covered to capture the innovation embodied in capital more precisely.

This paper constructs a measure of capital-embodied innovation (CEI) across a comprehensive set of capital goods at the occupation level and examines its heterogeneous effects across different occupations. We first group the capital goods at the occupation level from O*NET into two types based on their similarity with the occupational tasks. If capital performs a function similar to the tasks of an occupation, the capital is classified as *task-similar* for the occupation. If the function of capital is different from

[1] The computer expenditure share is from BEA fixed assets, and the robot share is from the 2019 Annual Capital Expenditure Survey of the Census Bureau. Even when combined with related equipment, such as mainframe and storage devices, computer-related equipment makes up 9.7% of total investments.

Figure 1: Job Polarization in the U.S.

A. Job Polarization

B. Wage Polarization

Notes: This figure plots log employment and wage changes between 1980 and 2015 over the wage in 1980 at the occupation level. The changes are fitted by cubic spline functions with five knots. Data source: IPUMS-USA (employment), IPUMS-CPS (wage)

occupational tasks but still is used by occupations, the capital is called *task-dissimilar*. This classification is made with text similarities between the description of capital goods from Wikipedia and occupational task descriptions from O*NET. Then, CEI is measured at the occupation level separately for different capital types by matching patents with capital goods based on text similarities between abstracts of patents and Wikipedia articles on capital goods. With this measure, we estimate the effect of CEI on labor market changes across occupations in a structural model of occupational labor demand.

Our approach complements recent work by Caunedo et al. (2023). While Caunedo et al. (2023) examine the impact of capital-embodied technical changes measured with capital prices at the occupation level, we measure innovation directly from patent data. This divergence is important for two reasons. First, changes in capital prices can stem from innovation but also from different factors including trade or shifts in market structure. Isolating technological factors behind these price changes is important for evaluations of R&D policies. Second, new technologies also change the productivity of capital in production and demand for occupational services. Our measure captures the effect of CEI on the demand for capital and occupational services even when capital prices are fixed.

Similar to this paper, Kogan et al. (2023) and Autor et al. (2024) estimate innovation at the occupation level by matching patents with the tasks of occupations, distinguishing between labor-saving and labor-augmenting innovations. While they focus on patents closely related to occupations' tasks or micro-titles, our analysis extends this scope by also accounting for innovation in capital goods that, although not directly related to occupational tasks, are still used by these occupations. Our findings indicate that 55% of innovation occurs in such capital goods, particularly those used by high-wage occupations, which significantly contributes to increased wages and employment in these occupations. Also, our analysis captures price changes of capital goods that are not driven by innovation.

We begin by building a general equilibrium model, wherein occupational service is produced using task-similar and task-dissimilar capital alongside occupational labor. The two types of capital are allowed to have different elasticities of substitution with labor. Depending on the relative magnitude of the elasticity of substitution, changes in cost efficiency of capital can either increase or decrease the demand for labor at the occupation level.

The parameters of this model are estimated in a simultaneous equation system derived from the first-order conditions of cost minimization for occupational service production. We devise shift-share instruments from academic publications and immigration shocks from Latin American countries to identify the elasticity of substitution and the effect of CEI. Exogenous shifts in academic publications that patents cite lower the cost of new patents, while exogenous shifts in Latin American immigrants increase labor supply disproportionately more in occupations in which the immigrants have a comparative advantage.

The results indicate that the elasticity of substitution between labor and task-similar capital is higher than the elasticity of substitution between occupational services. On the other hand, the elasticity of substitution between labor and task-dissimilar capital is lower than the elasticity of substitution across different occupational services. These results suggest that while lower user costs of task-similar capital reduce occupational labor demand, lower user costs of task-dissimilar capital raise it. In our framework, CEI affects occupational labor demand in three ways. First, CEI reduces the user costs of capital. Also, CEI changes the productivity of capital even with constant user costs. Lastly, CEI has an impact on the demand for occupational services. Overall, CEI on task-similar capital decreases occupational labor demand, while CEI on task-dissimilar capital increases demand.

We find that, between 1980 and 2015, occupations were heterogeneously exposed to CEI. First, CEI was heterogeneous across occupations. CEI on task-dissimilar capital (CEI-d) was biased toward high-wage occupations, whereas CEI on task-similar capital (CEI-s) was biased toward low-wage occupations. Second, occupations were differently affected by CEI depending on their capital intensity. Middle-wage occupations became relatively more intensive in task-similar capital compared to high- and low-wage occupations, while high-wage occupations became more intensive in task-dissimilar capital. At the same time, non-abstract and routine occupations had more CEI-s but less CEI-d. These occupations also had faster growth in the intensity of task-similar capital but slower growth in the intensity of task-dissimilar capital.

We run a counterfactual equilibrium of the estimated model with patent measures fixed at their levels in 1980. Our results indicate the role of CEI in reallocating labor demand toward high-wage, abstract, and non-routine occupations. CEI contributes to 42–51% of the difference in log wage changes between high-wage (fifth quintile) and middle-wage (second, third, and fourth quintiles combined) occupations. As for employment, CEI contributes to 2–8% of the difference between high- and middle-wage occupations. For task-biased labor market changes, CEI contributes to 83–94% of wage growth and 10–18% of employment growth favoring abstract occupations. Likewise, CEI produces 71–84% and 7–25% of the bias against routine occupations in wage and employment growth, respectively.

Related Literature

This paper first contributes to the literature on the sources of job polarization (e.g., Acemoglu, 1999; Autor et al., 2006; Goos and Manning, 2007; Lee and Shin, 2017; Bárány and Siegel, 2018; Keller and Utar, 2023). In particular, many papers, including Autor and Dorn (2013), Goos et al. (2014), Michaels et al. (2014), and Acemoglu and Restrepo (2022), study technical changes in specific capital goods such as computers, information technology equipment, and robots. They find that these changes have reduced the demand for middle-wage occupations, and thereby contributed to job polarization. Our research extends this body of work by developing a measure of innovation for a comprehensive range of capital goods at the occupational level. Our findings highlight the significant impact of innovation in broad types of capital goods that led to labor market changes.

Second, this paper contributes to a broader literature that studies the complementarity between capital and worker skills (Griliches, 1969; Goldin and Katz, 2008; Hornstein et al., 2005). Most papers assume that workers from different skill groups have different elasticities of substitution with capital, and the magnitude of elasticity determines how labor demand for a worker group responds to capital accumulation, (Krusell et al., 2000; Berlingieri et al., 2022; Caunedo et al., 2023). Our analysis categorizes capital goods into two types and allows these types to have different elasticities of substitution with labor. This feature allows us to capture a rich heterogeneity of complementarity between capital and labor with only two elasticities of substitution.

Lastly, this paper is related to a growing literature that applies textual analysis on patent data to measure innovation (Argente et al., 2023; Dechezleprêtre et al., 2020; Zhestkova, 2021; Bloom et al., 2021; Kelly et al., 2021; Mann and Püttmann, 2023). Existing papers match patents similar to task descriptions of occupations to measure exposure to new technologies. Webb (2019) matches occupations with technologies on artificial intelligence and robots while Kogan et al. (2023) include a broader set of new technologies for matching. Autor et al. (2024) categorize labor-augmenting and labor-saving technologies by matching patents with micro titles and tasks of occupations. Unlike these papers, we use 'Tools Used' data from O*NET to match patents with capital goods used by occupations. By doing so, our innovation measure also includes new technologies that are not similar to occupational tasks but utilized by occupational workers in the form of capital. Our results indicate that these technologies also reallocate labor demand across occupations and are quantitatively as important as new technologies similar to occupational tasks.

The remainder of the paper is organized as follows. Section 2 outlines the empirical framework. Section 3 describes the data used for the analysis and the procedure to construct CEI measures. Section 4 discusses the estimation strategy and results. Section 5 presents the results from counterfactual exercises. Section 6 concludes.

2 Empirical Framework

2.1 Overview

The economy is static and consists of firms and workers. Final goods are produced with industrial outputs. A representative firm in each industry combines occupational services to make industrial outputs. Occupational services are produced with labor and capital, where capital is a bundle of individual capital goods. For example, an aerospace company integrates tasks from aerospace engineers, engine mechanics, and janitors to produce its industrial output. Production of occupational services associated with engine mechanics requires not only engine mechanics but also services from capital bundles comprised of pressure indicators and wire cutters.

Two types of capital enter the production of occupational services. First, task-similar capital performs similar functions as occupational tasks. In contrast, task-dissimilar capital fulfills functions that are distinct from occupational tasks but are essential to producing occupational services. One capital good can be task-similar for one occupation but task-dissimilar for another. For instance, for engine mechanics involved in engine maintenance, an engine test stand is considered a task-similar capital good. However, for aerospace engineers designing new aircraft, the same engine test stand is viewed as a task-dissimilar capital good. We allow different capital bundles of these two types of capital goods to have different elasticities of substitution with labor.

Capital bundles are supplied elastically at the user costs determined by CEI below. Different occupations work with capital bundles with different compositions of capital goods. Also, each industry requires a different composition of capital goods for a given occupation. Thus, the composition and the user costs of capital bundles vary by both occupation and industry.

The labor market is distinguished by occupations but not by industries. Thus, the wage is set at the occupation level, and workers are indifferent across industries within an occupation. Workers select the occupation that offers them the highest utility, considering both wages and individual preferences. Firms in each industry hire workers of different occupations. The equilibrium occupational wages clear all occupational labor markets.

In this economy, CEI shifts occupational labor demand in three channels. First, CEI affects the user costs of capital. Second, beyond the user costs, CEI influences the productivity of capital in the production function. This happens when CEI changes the management and storage costs and the range of capital usage in occupational service production. Lastly, CEI directly shifts the relative demand for occupational services. The innovation might change how occupational services are used in industrial production even when the costs and productivity of capital are fixed. The third channel also accounts for a potential misspecification of the production function.

2.2 Capital Bundles

Competitive capital producers combine capital goods to make occupation and industry specific bundles of task-similar and task-dissimilar capital. Different capital goods are combined to produce capital bundles, k_{jio}, of capital type $j \in \{s, d\}$, s for task-similar capital and d for task-dissimilar capital, to be used by occupation o in the industry i as follows:

$$k_{jio} = A_{jio} f(x_{jio1}, \cdots, x_{jioN}) \,,$$

where A_{jio} is the factor-neutral productivity of capital bundle production, x_{jion} is the quantity of capital goods, and $f(\cdot)$ is an aggregator, which is a constant return to scale.

The user cost of the capital bundle is given by the zero profit condition:

$$r_{jio} = \sum_{n \in \mathbb{N}_{jo}} \lambda^k_{in} \frac{x_{jion}}{k_{jio}} \,, \tag{1}$$

where λ^k_{in} is the user cost of capital good n in industry i, and $\mathbb{N}_{jo}$ is a set of capital goods that are categorized as group j for occupation o. Notice that this condition holds whenever the production of a capital bundle has a constant return to scale, the zero-profit condition holds, and x_{jion}/k_{jio} is the share of capital categories. In our case, we set these shares at fixed-cost capital stocks.

To simplify the aggregation, we assume that there exists a technology base index that determines A_{jio}, the factor-neutral productivity of capital bundle production. The technology base for the capital bundle is an expenditure-weighted average of the knowledge bases for individual capital goods.

$$P_{jio} = \sum_{n \in \mathbb{N}_{jo}} \frac{\lambda_{io}^{k} x_{jion}}{r_{jio} k_{jio}} \#\text{Patent}_n = \sum_{n \in \mathbb{N}_{jo}} \kappa_{jion} \#\text{Patent}_n \,, \tag{2}$$

where $\#\text{Patent}_n$ is a measure of the capital-embodied knowledge base for capital good n and defined as the average number of patents applied to capital good n in Section 3.3. From now on, a change in technology base index P_{jio} is defined as CEI-j for $j \in \{s, d\}$. CEI shifts the user costs of capital bundles, r_{jio}, as implied by the following equation.

$$\log r_{jio} = -\gamma_{j1} \log P_{jio} + \log \omega_{jio1}, \tag{3}$$

where ω_{jio1} is the component of user costs of capital that are not explained by CEI. γ_{j1} is positive when prices of capital goods decrease with CEI-j, thereby reducing the user cost of capital. On the other hand, γ_{j1} can also be negative if depreciation rates for existing capital rise with CEI, increasing the user costs. For example, innovation in computer technology could have lowered the cost of computations. However, the value of existing computer stocks could depreciate more rapidly due to this innovation.

2.3 Labor Demand

Aggregate output Y is a Cobb-Douglas composite of industrial outputs.

$$\mathbf{Y} = \prod_i Y_i^{\alpha_i}.$$

Industrial output in sector i, Y_i aggregates occupational services with a constant elasticity of substitution, σ.

$$Y_i = \left(\sum_o \mu_{io} y_{io}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where μ_{io} is the occupation demand shifter for industry i, occupation o. Occupational service y_{io} is produced with capital and labor as in the following equation.

$$y_{io} = \left(a_{dio}^{\frac{\rho_d-1}{\rho_d}} k_{dio}^{\frac{\rho_d-1}{\rho_d}} + \Theta_{io}^{\frac{\rho_d-1}{\rho_d}} \right)^{\frac{\rho_d}{\rho_d-1}}, \tag{4}$$

$$\Theta_{io} \equiv \left(a_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}} \right)^{\frac{\rho_s}{\rho_s-1}}. \tag{5}$$

In this equation, k_{dio} denotes task-dissimilar capital with its productivity, a_{dio}, and k_{sio} is task-similar capital with its productivity, a_{sio}. l_{io} refers to the labor in sector i and occupation o. ρ_s and ρ_d are the elasticity of substitution of labor with task-similar and task-dissimilar capital, respectively. As in Krusell et al. (2000), the nested CES structure allows different substitutability between production inputs. This nested CES structure implies that the elasticity of substitution between task-dissimilar capital and task-substituting capital is also ρ_d.

A representative firm of industry i chooses labor and capital inputs to minimize the production costs given the user costs of task-similar and task-dissimilar capital, r_{sio} and r_{dio}, and the occupational wage w_o. The first-order conditions are described as the following equations.

$$\frac{r_{sio}}{w_o} = a_{sio}^{\frac{\rho_s-1}{\rho_s}} \left(\frac{k_{sio}}{l_{io}}\right)^{-\frac{1}{\rho_s}}, \tag{6}$$

$$\frac{r_{dio}}{w_o} = \left(a_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_s-\rho_d}{(\rho_s-1)\rho_d}} a_{dio}^{\frac{\rho_d-1}{\rho_d}} k_{dio}^{-\frac{1}{\rho_d}} l_{io}^{\frac{1}{\rho_s}}, \tag{7}$$

$$\frac{w_o}{w_p} = \frac{\mu_{io}}{\mu_{ip}} \left(\frac{y_{io}}{y_{ip}}\right)^{-\frac{1}{\sigma}+\frac{1}{\rho_d}} \frac{\left(a_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_d-\rho_s}{(\rho_s-1)\rho_d}}}{\left(z_{sip}^{\frac{\rho_s-1}{\rho_s}} k_{sip}^{\frac{\rho_s-1}{\rho_s}} + l_{ip}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_d-\rho_s}{(\rho_s-1)\rho_d}}} \left(\frac{l_{io}}{l_{ip}}\right)^{-\frac{1}{\rho_s}}. \tag{8}$$

Combining these three equations, we get the following equation that governs the relative labor demand within industry i.

$$\frac{w_o}{w_p} = \frac{\mu_{io}}{\mu_{ip}} \left(\frac{\tilde{y}_{io}}{\tilde{y}_{ip}}\right)^{-\frac{1}{\sigma}+\frac{1}{\rho_d}} \frac{\tilde{\Theta}_{io}^{\frac{\rho_d-\rho_s}{\rho_s\rho_d}}}{\tilde{\Theta}_{ip}^{\frac{\rho_d-\rho_s}{\rho_s\rho_d}}} \left(\frac{l_{io}}{l_{ip}}\right)^{-\frac{1}{\sigma}}. \tag{9}$$

In this equation, $\tilde{\Theta}_{io} = \Theta_{io}/l_{io}$ and $\tilde{y}_{io} = y_{io}/l_{io}$ are defined as the labor efficiencies for the inner and the outer composites of occupational service production. After imposing the first order conditions, they can be expressed as follows.

$$\tilde{\Theta}_{io} = \left(a_{sio}^{\rho_s-1} \left(\frac{r_{sio}}{w_o}\right)^{1-\rho_s} + 1\right)^{\frac{\rho_s}{\rho_s-1}}, \tag{10}$$

$$\tilde{y}_{io} = \tilde{\Theta}_{io}^{\frac{\rho_s-\rho_d}{\rho_s}} \left(a_{dio}^{\rho_d-1} \left(\frac{r_{dio}}{w_o}\right)^{1-\rho_d} + \tilde{\Theta}_{io}^{\frac{\rho_d-1}{\rho_s}}\right)^{\frac{\rho_d}{\rho_d-1}}.$$

$\tilde{\Theta}_{io}$ and $\tilde{y}_{io}$ decrease unambiguously with r_{sio} and r_{dio}, respectively. In other words, lower user costs of capital increase the labor efficiency for the inner and outer composites of occupational service production. Similarly, higher a_{sio} and a_{dio} raise $\tilde{\Theta}_{io}$ and $\tilde{y}_{io}$.

Equation (9) shows that the relative magnitudes of the elasticities of substitution shape how capital-embodied changes affect labor demand across occupations, consistent with Caunedo et al. (2023). A decrease in user costs of task-dissimilar capital increases $\tilde{y}_{io}$ and raises demand for occupational services through scale effects. If $\sigma > \rho_d$, the demand increases more elastically than the substitution toward task-dissimilar capital, increasing relative labor demand through substitution effects.

Likewise, if $\rho_s > \sigma$, substitution toward task-similar capital is stronger than an overall demand increase for occupational services. An increase in $\tilde{\Theta}_{io}$ from lower user costs of task-similar capital raises both $\tilde{y}_{io}$ and $\tilde{\Theta}_{io}$. Since $d \log \tilde{y}_{io} / d \log \tilde{\Theta}_{io} < 1$, $\rho_s > \sigma$ implies that lower user costs of task-similar capital reduce the relative labor demand.

In this framework, we also allow the CEI to directly affect the productivity of capital and demand for occupational services. For simplicity, we assume that the same technology base in Equation (2), P_{jio}, determines the productivity of the capital, a_{jio}, and the demand shifter, μ_{io}, as in the following equations.

$$\log a_{jio} = \gamma_{j2} \log P_{jio} + \log \omega_{jio2} \,, \tag{11}$$

$$\log \mu_{io} = \gamma_{s3} \log P_{sio} + \gamma_{d3} \log P_{dio} + \log \omega_{io3} \,, \tag{12}$$

where ω_{jio2} and ω_{io3} are the residual components of the capital productivity and occupation demand shifters, respectively. Positive γ_{j2} implies that the productivity of the capital increases with CEI-j, even after its effect on user costs. However, the productivity of the capital can also decrease with CEI if more advanced capital raises maintenance costs. Likewise, positive γ_{j3} means that industrial production depends more on the occupational service with a higher degree of CEI-j.

To capture the effects of CEI-s and CEI-d on labor demand across occupations, combine Equations (3), (10), and (11) and express $\tilde{\Theta}_{io}$ and $\tilde{y}_{io}$ as in the following equations.

$$\tilde{\Theta}_{io} = \left(P_{sio}^{\tilde{\gamma}_s(\rho_s-1)} \left(\frac{\tilde{\omega}_{sio}}{w_o} \right)^{1-\rho_s} + 1 \right)^{\frac{\rho_s}{\rho_s-1}}, \tag{13}$$

$$\tilde{y}_{io} = \tilde{\Theta}_{io}^{\frac{\rho_s-\rho_d}{\rho_s}} \left(P_{dio}^{\gamma_d(\rho_d-1)} \left(\frac{\omega_{dio}}{w_o} \right)^{1-\rho_d} + \tilde{\Theta}_{io}^{\frac{\rho_d-1}{\rho_s}} \right)^{\frac{\rho_d}{\rho_d-1}}.$$

In this equation, $\tilde{\gamma}_j = \gamma_{j1} + \gamma_{j2}$ and $\tilde{\omega}_{jio} = \omega_{jio1} - \omega_{jio2}$ for $j \in \{s, d\}$. $\tilde{\gamma}_j > 0$ implies that the user cost of capital per productivity unit is cheaper with more CEI-j. Then, $\tilde{\Theta}_{io}$ and $\tilde{y}_{io}$ increase in P_{sio} and P_{dio}, respectively. If we further assume $\rho_s > \sigma > \rho_d$, then cheaper user costs per productivity unit of task-similar capital associated with CEI-s reduce relative labor demand for occupation o within industry i. On the other hand, CEI-d raises labor demand.

2.4 Labor Supply and Equilibrium

The labor supply side is modeled with a standard structure of occupation choice. $\mathbf{L}$ number of ex-ante homogeneous workers are indexed by $n \in [0, \mathbf{L}]$. Worker n observes the wage of each occupation determined in the market, w_o, occupation-specific utility ξ_o, and idiosyncratic utility realized for each occupation ν_{no}. The worker chooses an occupation that gives the highest utility. Importantly, all workers receive the same wage and utility for any given occupation. Consequently, once they choose an occupation, they are indifferent across industries. The occupation choice problem can be written as follows:

$$o^* = \underset{o}{\operatorname{argmax}} \left\{ \log w_o + \log \xi_o + \nu_{no} \right\}.$$

Assuming that ν_{no} follows an i.i.d. Type 1 Extreme Value Distribution with scale parameter $1/\beta$, the following iso-elastic labor supply function is derived.

$$\frac{L_o}{\mathbf{L}} = \frac{\exp(\beta \log w_o + \beta \xi_o)}{\sum_p \exp(\beta \log w_p + \beta \xi_p)}. \tag{14}$$

The labor market equilibrium consists of occupational wages that equate the labor supply to the labor demand, which consists of industry-level demands for each occupation.

3 Data and Measurement

3.1 Data

The "Tools Used" data from O*NET serves as our primary reference for identifying the capital goods each occupation works with.[2] O*NET compiles a comprehensive list of machines or equipment vital for occupational

[2]This study uses version 25.0, which was updated in August 2020. Given that O*NET started offering "Tools Used" data in 2015, we are unable to assess the time series variation in the composition of capital goods.

roles (Dierdorff et al., 2006). To illustrate, security managers use capital goods such as security control systems, alarm systems, and video monitors. The data encompasses 4,180 distinct capital goods used by 775 occupations. Notably, each capital good is associated with a title and a corresponding United Nations Standard Products and Services Code (UNSPSC).

To measure innovation on these capital goods, we use patent data from the United States Patent and Trademark Office (USPTO).[3] This dataset includes the entire patents registered in the U.S. spanning from 1970 to 2015. The exercise uses the application year, title, and abstract of patents. The application year is used instead of the grant year since it is closer to the actual innovation year. Design patents are excluded to focus on quality improvement. In the end, we have 6.1 million utility and plant patents.

For occupational employment at the industry level in 1980 and 2015, we use the microdata from the Decennial Census of 1980 and the American Community Survey (ACS) from 2015 to 2019 for observations in 1980 and 2015, respectively. The data is downloaded from the Integrated Public Use Microdata Series (IPUMS). The ACS samples from multiple surveys are used to increase the size of the samples in each occupation by industry. Employment is measured by the number of workers with the occupation and the industry code. Each observation is used with sampling weights from the Census Bureau. The Decennial Census and the ACS are also used to construct immigrant supply instruments in Section 4. Our analysis uses prime-aged workers between the ages of 25 and 54.

Occupational wages are sourced from the microdata for the Annual Social and Economic Supplement of the Current Population Survey. The wage

[3] Bulk file is downloaded through patentsview.org.

is measured with the average weekly wage earnings and computed as the annual labor income divided by the number of weeks worked. Observations in 1980–1984 and 2015–2019 are used to calculate wages in 1980 and 2015, respectively.[4]

To account for heterogeneous labor productivity across workers with different observable characteristics, we residualize wages using the Mincerian regression, controlling for age (each age enters as dummies), education level, race, and year fixed effects as in Berlingieri et al. (2022). For this regression, we only consider full-time male workers who worked 40 weeks or more in the preceding year. Samples with zero or missing information on individual characteristics are excluded. Furthermore, observations with a nominal hourly wage below 50% of the federal minimum wage for the given year are omitted.

The occupation and industry codes are harmonized using the OCC1990 and the IND1990 variables provided by the IPUMS. The 2010 Standard Occupational Classification Code (SOC Code) on O*NET data is mapped to the OCC1990 variable using correspondence between the OCC1990 and the 2010 SOC Code variables in the ACS 2012-2018. Likewise, the IND1990 variable is converted to the NAICS code using the correspondence between the IND1990 and the NAICS in the ACS. Then, the NAICS in the ACS is aggregated to the 63 NAICS industries in National Income and Product Accounts (NIPA) by the Bureau of Economic Analysis (BEA).

For capital stocks and user costs of capital at the occupation and indus-

[4]The CPS-ASEC is not used to measure employment at the occupation and industry level because of its small sample size. The wage variables from the ACS and Decennial Census are not used because the wage variables last year are measured without information on the occupation of the last year.

try level, we use fixed-cost capital estimates from the BEA. These estimates are measured in the 2012 US dollar at the industry and the NIPA capital category level. Depreciation rates are computed by the ratio of current-cost capital depreciation to the current-cost capital stock. The stock of each category is prorated with an intensity-weighted number of workers in each occupation. Then, we follow the imputation procedure of Caunedo et al. (2023) to calculate a quantity index of capital bundles at the occupation and industry level for each capital type. The user costs of capital bundles are derived from a series of user costs at the level of capital goods with the zero-profit condition in Equation (1). The final index of capital bundles is measured as a chained index from the base year, 1980, and the average growth rate of NIPA capital categories weighted by the expenditure share. For details on the imputation process, see Appendix B.

3.2 Classifying Capital Goods: Task-Dissimilar versus Task-Similar

For each occupation, we categorize capital goods into two categories: task-similar capital and task-dissimilar capital. The capital whose function closely aligns with the tasks of an occupation is categorized as task-similar. In contrast, the capital used by an occupation whose function does not mirror the occupational tasks is labeled as task-dissimilar. One capital good may be task-similar for one occupation and task-dissimilar for another, reflecting the diverse nature of tasks across different occupations. At this point, we only allow different degrees of substitution elasticity between the two types of capital and labor and do not presuppose these relationships with occupational labor demand before the estimation.

Existing literature that matches occupations with patents based on text similarity (e.g., Webb, 2019; Kogan et al., 2023) often finds a strong labor-displacement effect of innovations. Our classification is motivated by the negative effect of new technologies performing similar tasks to those of occupations. If new technologies are *used* by workers in an occupation, new technologies may have different effects. The occupation-level list of capital goods provided by O*NET becomes a useful intermediary to identify which occupations use new technologies.

Specifically, the classification exploits the degree of text similarity between the tasks associated with an occupation and the descriptions of capital goods. We use "Task Statements" data from O*NET for occupational tasks.[5] For example, a security manager has tasks such as "Respond to medical emergencies, bomb threats, fire alarms, or intrusion alarms, following emergency response procedures." For descriptions of capital, we use Wikipedia articles, which offer product-level descriptions for text analysis (Argente et al., 2023). Utilizing the Wikipedia Application Programming Interface (API), we locate Wikipedia pages for 1,825 among 4,180 capital goods listed.[6]

We then compute text similarity between Wikipedia articles of capital goods and occupational tasks by counting the common words. A standard

[5]Version of 25.0, updated in August 2020, is used. On average, each occupation lists 23 tasks.

[6]We use the wikipediaapi package in Python, accessible at `https://pypi.org/project/wikipedia/`. The data was downloaded on 02/28/2021. Appendix Table A1 details the proportion of tools found in Wikipedia, categorized by their NIPA category. Tools related to electronics, furniture, and machinery are more frequently found, whereas those pertaining to mining, medical equipment, and aircraft are less common. For our analysis, tools without a corresponding Wikipedia page are excluded, and we calculate similarities based on the average of the remaining tools.

procedure from the natural language processing literature is used to prepare the texts for our analysis. First, we remove stopwords, words that are insignificant in delivering the content. For example, "is," "where," and "have" are classified as stopwords. Removing them prevents erroneous matches between two texts solely based on shared functional words rather than substantive content. Then, words are lemmatized to standardize word forms.[7] For example, "generating" or "generated" is changed to "generate." This step ensures that words with analogous meanings, though in different forms, align appropriately.

Next, we calculate the pairwise similarity between tasks and capital goods. Specifically, each text is vectorized to compute cosine similarity, which quantifies the share of overlapped words between two texts. Words are weighted by the frequency-inverse document frequency (TF-IDF). The weight of words i in document j, represented as ω_{ij}, is defined as follows:

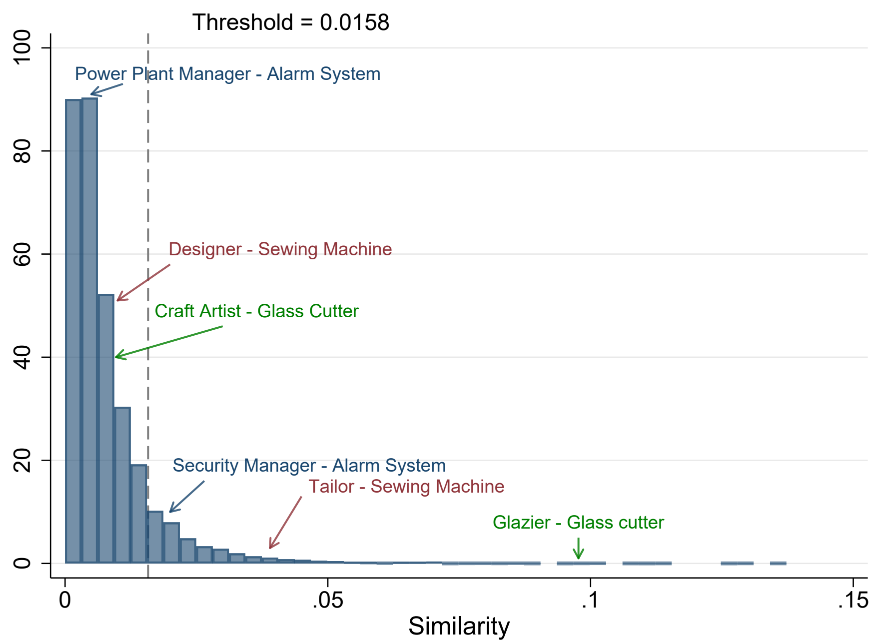
$$\omega_{ij} = \mathrm{TF}_{ij} \cdot \mathrm{IDF}_i \,, \qquad \mathrm{TF}_{ij} = \frac{f_{ij}}{\sum_i f_{ij}} \,, \qquad \mathrm{IDF}_i = \log\left(\frac{J}{\sum_j \mathbb{1}\{i \in j\}}\right) \,,$$

where J is the number of total documents. Therefore, IDF_{ij} increases when the word appears frequently within the document but decreases when it is common across other documents. This transformation helps us to match two texts that have meaningful common words. The resulting similarity score ranges from 0 to 1 by construction. A score of 0 indicates no shared words, while a score of 1 demonstrates identical texts.

After constructing similarity scores for each capital goods and task, we aggregate the similarities to the capital-occupation level. Given that each

[7] The spacy package in Python is used from `https://spacy.io/`.

Figure 2: Distribution of Similarity of Capital-Occupation Pairs



Notes. This figure plots the density of text similarity between capital goods and occupation tasks. The text similarity between the description of capital goods and each task of occupation is calculated and aggregated at the capital-occupation level.

occupation encompasses multiple tasks, it has multiple similarities with each capital good. We compute the unweighted average of these similarities across tasks to obtain similarities at the capital-occupation level.

Figure 2 shows the distribution of similarity between capital goods and occupations. The distribution is right-skewed, indicating many capital-occupation pairs do not have many overlapping words. A capital good is considered task-similar to the occupation if the similarity exceeds the 90th percentile; all other capital goods are classified as task-dissimilar.[8] Figure 2 also presents several examples of capital-occupation pairs. In this graph,

[8]The reduced-form results using different threshold can be found in Appendix D.

glass cutter is task-similar for glaziers but task-dissimilar capital for craft artists. Likewise, sewing machine is task-similar capital for tailors but task-dissimilar for designers.

Table 1 shows capital intensity among various groups of occupations. Capital intensity is the average capital stock per employee, where the capital stock is measured following Caunedo et al. (2023) as in Appendix B. As shown in Panel A, the intensity of task-similar capital was the highest for middle-wage occupations in 2015, whereas the intensity of task-dissimilar capital was the highest for high-wage occupations. Panel B and C sort occupations based on their abstract and routine scores from Autor and Dorn (2013). In Panel B, abstract occupations had the lowest intensity of task-similar capital but the highest intensity of task-dissimilar capital. Conversely, Panel C indicates that routine occupations recorded high intensities for both task-similar and task-dissimilar capital.

3.3 Measuring Capital-Embodied Innovation

Capital-embodied innovation is measured by matching patents to capital goods. To do so, we calculate text similarities between patents and capital goods, following a procedure similar to the previous section. Patents are assigned to a capital good if the similarity score of patent titles and abstracts to occupational tasks exceeds the 90th percentile across patent-capital pairs.[9] Based on the similarity scores, some patents may not be relevant to any capital goods, whereas others may be matched with multiple capital goods. We constrain the matching such that a single patent

[9] The reduced form exercises are conducted with various thresholds, but the result roughly stays the same.

Table 1: Capital Intensity over Occupations

	Similar			Dissimilar		
	1Q	2Q-4Q	5Q	1Q	2Q-4Q	5Q
	Panel A. Across Wage in 1980					
1980	8.14	7.43	7.99	25.22	26.48	21.26
2015	12.05	16.29	16.19	49.32	90.56	122.31
	Panel B. Across Abstract Score					
1980	16.27	7.44	1.32	24.63	27.65	17.31
2015	28.21	14.97	5.16	59.61	88.92	113.61
	Panel C. Across Routine Score					
1980	1.48	10.47	5.62	5.68	28.63	41.24
2015	3.00	19.31	17.64	37.02	101.22	122.30

Notes. This table presents the capital intensity for task-similar and task-dissimilar capital across occupations segmented into three groups. Capital intensity is defined as the average capital stock per employee, with values expressed in thousands of 2012 dollars. Panel A sorts occupations by their average wages in 1980, Panel B by abstract scores, and Panel C by routine scores. The columns labeled 1Q and 5Q correspond to occupations in the first and fifth quintiles, respectively, whereas the 2Q-4Q columns encompass occupations within the second to fourth quintiles.

can connect to, at most, five capital goods. As a result, 27% of patents are matched with at least one capital good. Appendix Table A2 shows the share of patents that matched at least one capital good across patent classes and periods. Appendix Figure A1 shows an example of the matching between patent and capital good.

Next, the number of patents across capital goods is aggregated at the occupation level. Note that each occupation uses multiple capital goods, which are classified into two groups: task-similar and task-dissimilar. We take the unweighted average over capital goods within each NIPA capital category for each occupation, industry, and capital group. Then, the average

Table 2: Summary Statistics of Patents Matched with Capital Goods

	Similar		Dissimilar		
	Mean	SD.	Mean	SD.	N
1970 – 1980	43.1	91.5	44.7	69.9	15,902
1980 – 1990	90.3	174.3	93.5	130.1	15,902
1990 – 2000	134.2	260.1	166.1	217.7	15,902
2000 – 2015	417.7	805.7	540.2	637.3	15,902

Notes. This table displays the summary statistics of patents matched with task-dissimilar and task-similar capital goods aggregated at the occupation-industry level. We take the average number of patents, weighted by capital expenditure share in each period.

number of patents is calculated across the NIPA categories, each category weighted by capital expenditure share in each period.[10] By taking averages across capital goods and then capital categories, our CEI measures do not reflect the variety of capital goods within capital categories and the number of capital categories within capital bundles.

Table 2 presents the summary statistics for the average number of patents on capital at the occupation and industry level. The number of patents has increased over time but with different degrees across occupations. Initially, the number of patents was comparable between task-similar and task-dissimilar capital. However, over time, task-dissimilar capital experienced faster growth in patents than task-similar capital, suggesting that more patents are made on capital goods used as task-dissimilar capital.

[10] We use capital expenditure at the occupation-industry-category level. Capital goods in UNSPSC codes are mapped to NIPA capital categories following crosswalks made in Caunedo et al. (2023).

Table 3: CEI Measure over the Wage in 1980

	Similar			Dissimilar		
	1Q	2Q-4Q	5Q	1Q	2Q-4Q	5Q
Panel A. Across Wage in 1980						
	2.22	1.58	1.76	2.91	3.24	3.69
Panel B. Across Abstract Score						
	2.49	1.44	1.86	2.80	3.31	3.63
Panel C. Across Routine Score						
	1.06	2.05	1.56	3.55	3.25	2.96

Notes. This table presents the employment-weighted averages of CEI across three bins of occupations. Panel A categorizes occupations based on their average wages in 1980, Panel B uses the abstract score, and Panel C employs the routine score. The CEI is defined in Equation (15). The columns labeled 1Q and 5Q represent the occupations in the first and fifth quintiles, respectively, while the columns under 2Q-4Q cover occupations within the second to fourth quintiles.

Finally, our measure of CEI is the following:

$$\text{CEI-j}_{io} \equiv \log\left(\frac{\sum_{n\in\mathbb{N}_{jo}} \kappa_{jion,1970-2015}\cdot \#\,\text{Patent}_{n,1970-2015}}{\sum_{n\in\mathbb{N}_{jo}} \kappa_{jion,1970-1980}\cdot \#\,\text{Patent}_{n,1970-1980}}\right), \quad j\in\{s,d\}. \tag{15}$$

In this equation, $\mathbb{N}_{jo}$ represents the set of type j capital goods used by occupation o, and κ_{jion} indicates the capital expenditure share of capital good n within type j of industry i and occupation o. # Patent$_{n,t}$ refers to the number of patents corresponding to capital n in period t. Note that CEI can vary across industries within an occupation due to differences in expenditure shares of capital categories.

Table 3 displays CEI across various occupational groups. Panel A sorts occupations by their average wages in 1980, showing that CEI-s was the highest for low-wage occupations, while CEI-d was the highest for high-wage occupations. This suggests that the innovation on task-dissimilar capital was biased toward high-wage occupations. Panel B categorizes occupations by their abstract task score calculated in Autor and Dorn (2013), and shows that abstract occupations experienced modest CEI-s but the highest CEI-d. Finally, when occupations are arranged by the routine task score, occupations in the lowest quintile experienced the lowest CEI-s but the highest CEI-d. Thus, CEI-s was biased towards low-wage, non-abstract, and routine occupations, while CEI-d was biased towards high-wage, abstract, and non-routine occupations. Autor and Dorn (2013) hypothesize a decline in the cost of substituting routine workers over time. Our findings align with this hypothesis, showing that innovation in task-similar capital was more prevalent in routine occupations.

4 Estimation

4.1 Strategy

We use the first-order conditions of the cost minimization in Section 2.3 to estimate model parameters. Specifically, Equations (6), (7), and (9) are used to estimate the elasticities of substitution for the inner CES composite, for the outer CES composite, and across different occupational services, respectively. The nested CES structure makes it possible to estimate parameters jointly in a system of linear equations. The equations can be rewritten as follows:

$$\frac{w_o}{r_{sio}} = (P_{sio})^{-\tilde{\gamma}_{s2}} \left(\frac{k_{sio}}{l_{io}}\right)^{\kappa_s} \tilde{\omega}_{sio}, \tag{16}$$

$$\frac{w_o}{r_{dio}} = \left(1 + \frac{r_{sio}}{w_o} \times \frac{k_{sio}}{l_{io}}\right)^{\kappa_d} \left(\frac{r_{dio} k_{dio}}{w_o l_{io}}\right)^{-\kappa_d} \left(\frac{k_{dio}}{l_{io}}\right)^{\kappa_s} P_{dio}^{-\tilde{\gamma}_{d2}} \tilde{\omega}_{dio}, \tag{17}$$

$$w_o = C_i P_{sio}^{\tilde{\gamma}_{s3}} P_{dio}^{\tilde{\gamma}_{d3}} (w_o l_{io})^{\kappa_a} l_{io}^{-\kappa_s} \left(1 + \frac{r_{sio}}{w_o} \times \frac{k_{sio}}{l_{io}}\right)^{\kappa_a} \tag{18}$$

$$\times \left(1 + \left(1 + \frac{r_{sio}}{w_o} \times \frac{k_{sio}}{l_{io}}\right)^{-1} \times \frac{k_{dio}}{l_{io}} \frac{r_{dio}}{w_{io}}\right)^{\kappa_a - \kappa_d} \tilde{\nu}_{io}.$$

In these equations, $\kappa_s \equiv \frac{1}{\rho_s}$, $\kappa_d \equiv \frac{\rho_d - \rho_s}{\rho_s(\rho_d - 1)}$, and $\kappa_a \equiv \frac{\sigma - \rho_s}{\rho_s(\sigma - 1)}$. Also, $\tilde{\gamma}_{j2} \equiv \gamma_{j2} \times \frac{\rho_s - 1}{\rho_s}$, and $\tilde{\gamma}_{j3} \equiv \gamma_{j3} \times \frac{\rho_s - 1}{\rho_s} \times \frac{\sigma}{\sigma - 1}$, for $j \in \{s, d\}$. $\tilde{\omega}_{sio}$, $\tilde{\omega}_{dio}$, and $\tilde{\nu}_{io}$ are the residual demand components. γ_{1s} and γ_{1d} are also jointly estimated using Equation (3). The parameters of this equation system are estimated by Seemingly Unrelated Regression (SUR) with the model-imposed linear constraints.

The residual demand components, $\tilde{\omega}_{sio}$, $\tilde{\omega}_{dio}$, and $\tilde{\nu}_{io}$, are correlated with CEI when innovation activities respond endogenously to demand shocks. For example, if the productivity of capital increases for the production of occupational services, firms invest more in the technology related to the capital. Also, with more demand for some occupational services, firms are more incentivized to make innovations on related capital goods.

Thus, we introduce a set of instrumental variables, Z_{io}, which include the publication (z_{sio} and z_{dio}) and the immigration instruments ($z_{Latin,G}$). We argue that these instrumental variables are orthogonal to the demand shocks conditional on controls.

Publication instruments are Bartik-style shift-share instruments that capture heterogeneous knowledge spillover from academic publications to patents. More academic publications in some fields lower the cost of making new knowledge in a patent class particularly more if the patent class cites disproportionately more papers from the field. Immigration instruments capture relative changes in labor supply at the occupation level when different ethnic groups have different comparative advantages, and the immigration trends are different across ethnic groups. We use immigration shocks from Latin America to construct the supply instruments. See Appendix C for more details.

Controls include industry-fixed effects and log computer stock per worker in 2015 and 1980 at the occupation and industry level. The industry-fixed effects control for industry-level demand shocks. The log computer stock captures the idea that computers affect the way workers work with capital and thereby change the productivity of capital inputs. For instance, manufacturing workers can be substituted more easily with robots if computers facilitate their control of robots. Chemical engineers benefit more from better microscopes if computers help them analyze data.

The equations are taken with logs and then differenced between 1980 and 2015 to estimate the model parameters. We prefer this long-difference specification because it is ambiguous when innovations represented in patents affect capital used by firms and labor demand. In our context, log-differencing also removes time-invariant components of measurement errors associated with the text-matching procedure. For example, if the Wikipedia articles about lasers are easier to match than the Wikipedia articles for computers and the errors are multiplicatively separable and constant over time, log-differencing the number of patents cancels out the errors. Lastly, when an

Table 4: Parameter Estimates - First Order Conditions

	ρ_s	γ_s	ρ_d	γ_d	σ
Estimate	3.302	0.272	1.650	0.282	2.679
SE	(0.267)	(0.030)	(0.041)	(0.014)	(0.163)

Notes. This table shows the estimates and the standard errors of the SUR model with Equations (16)-(18). ρ_s (ρ_d) is the elasticity of substitution between task-similar (task-dissimilar) capital and labor. σ is the elasticity of substitution between different occupational services. γ_s (γ_d) is the coefficient of CEI-s (-d) on capital-labor substitution equation.

occupation does not have any task-similar capital, Δk_{sio} is undefined and omitted from estimation.

4.2 Results

Tables 4 and 5 show the estimation results. In Table 4, the estimate for σ is smaller than the estimate for ρ_s but larger than ρ_d. These estimates are different at the 95% significance level. As discussed in Section 2.3, these values imply that the scale effect of CEI to increase the occupational service demand is smaller than the substitution effect between labor and capital for task-similar capital, but the reverse is true for task-dissimilar capital. As a result, an increase in productivity or a decrease in user cost of task-similar capital reduces relative labor demand. On the other hand, an increase in productivity or a decrease in user cost of task-dissimilar capital raises relative labor demand.

The elasticity of substitution between task-similar capital and labor is 3.3, whereas the elasticity between labor and task-dissimilar capital is 1.65. These estimates fall into a marginally higher range than the estimates in Caunedo et al. (2023). Caunedo et al. (2023) assume a single elasticity of substitution between capital and labor for each occupation and find out that the elasticity ranges from 0.7 to 2.2. They use time-series variations in birth rates and the supply of educated workers to construct the occupation-level supply shifter. Also, as in Krusell et al. (2000), they use yearly time-series variations to estimate the elasticity with capital. The estimation in this paper deals with long-term adjustments in the labor market over three decades and uses cross-sectional variations. We also construct a labor supply shifter with cross-sectional exposure to immigration from Latin America. Our higher estimates are likely to result from dealing with a longer time horizon and cross-sectional variations for estimation.

The elasticity of substitution across occupational labor inputs, σ, is also estimated at a value higher than in the literature. In Caunedo et al. (2023), the value is calibrated at 1.3, whereas this paper estimates the value of 2.7. This value is also larger than the estimates in Lee and Shin (2017), 0.7, and Burstein et al. (2019), 2. The higher estimate of the elasticity *between* occupational services is again likely a result of the longer time horizon for adjustments. On top of that, these papers use more aggregated levels of occupation codes. Caunedo et al. (2023) and Lee and Shin (2017) report results with 11 occupations. Burstein et al. (2019) have variations from 30 occupations. We have 291 occupations distinguished by three-digit occupation codes from the 1990 Census.

Because user costs of capital and relative productivity of capital both enter Equations (6) and (7), only a linear combination of γ_{j1} and γ_{j2} is identified in the first order conditions. Estimates of $\gamma_s = \gamma_{s1} + \frac{\rho_s - 1}{\rho_s}\gamma_{s2}$ and $\gamma_d = \gamma_{d1} + \frac{\rho_d - 1}{\rho_d}\gamma_{d2}$ are both positive. The positive estimates imply that the production of occupational services becomes more capital-intensive with

Table 5: Parameter Estimates - Effects of CEI

	γ_{s1}	γ_{s2}	γ_{s3}	γ_{d1}	γ_{d2}	γ_{d3}
Estimate	0.836	-0.810	-0.119	0.265	0.113	0.245
SE	(0.022)	(0.027)	(0.019)	(0.013)	(0.038)	(0.019)

Notes. This table shows the estimates and standard errors of CEI coefficients in Equations (3), (11), and (12). γ_{s1} (γ_{d1}) is the coefficient of CEI-s (CEI-d) on user costs of capital. γ_{s2} (γ_{d2}) is the coefficient of CEI-s (CEI-d) on the relative productivity of capital. γ_{s3} (γ_{d3}) is the coefficient of CEI-s (CEI-d) on demand shifter for occupational service.

CEI-s and CEI-d.

Table 5 presents the estimation results for the coefficient of CEI measures on user costs of capital, productivity of capital, and demand shifters for occupational services. γ_j^1, the effect of CEI on user cost of capital, is also estimated in the SUR system as a separate estimation between CEI measure and user costs of capital using publication instruments. Then, γ_{j2} is recovered from $\gamma_j = \gamma_{j1} + \frac{\rho_j - 1}{\rho_j}\gamma_{j2}$.

The estimates for γ_{j1} are significantly positive and sizeable. A 1% increase in CEI-s reduces the user cost of task-similar capital by 0.8%, whereas a 1% increase in CEI-d reduces the user cost of task-dissimilar capital by 0.3%. However, the estimate for γ_{s2} is negative, and the estimate for γ_{d2} is positive. γ_{s2} and γ_{d2} govern how CEI-s and CEI-d affect capital productivity in the capital-labor substitution equations after taking their effect on user costs into account. Thus, CEI-s reduces the productivity of task-similar capital relative to labor inputs, whereas CEI-d raises the productivity of task-dissimilar capital.

This negative productivity effect of CEI-s cancels out the effect of CEI-s on the user cost. The productivity effect of CEI-s is strong enough to nullify most effects of CEI-s on inner labor efficiency, $\tilde{\Theta}_{io}$, and relative labor demand in Equation (6) because $\gamma_{s1} + \gamma_{s2}$ is insignificant but positive at 0.03. On the other hand, the productivity effect of CEI-d amplifies the effect of CEI-d on occupational labor efficiency, $\tilde{y}_{io}$. Combining these results with $\hat{\rho}_s > \hat{\sigma} > \hat{\rho}_d$ implies that CEI-s (CEI-d) reduces (raises) relative labor demand by raising labor efficiency, $\tilde{\Theta}_{io}$ ($\tilde{y}_{io}$). The estimate for γ_{s3} is still negative although insignificant, while the estimate for γ_{d3} is positive. These estimates imply that CEI-s further reduces demand for occupational services while CEI-d raises it even after taking into account their effects on labor efficiencies. These results are consistent with the reduced-form findings in Appendix D.

We consider two values for the elasticity of occupational labor supply, β, 0.3 and 1. Caunedo et al. (2023) calibrates $\beta = 0.3$ at the yearly frequency and with coarser occupational codes. Since we consider labor supply adjustments over more than 30 decades with more detailed occupational codes, the supply elasticity at 0.3 is likely to be a lower bound. To capture the possibility that labor supply is more elastic to the wage changes, counterfactual equilibrium with $\beta = 1$ is also derived in Section 5.

5 Counterfactuals

5.1 CEI and Labor Market Polarization

The counterfactual exercise aims to address the following question: what happens to the labor market and the polarization measures without the contribution of CEI? To address this question, a counterfactual equilibrium is calculated with the technology base measures measures fixed at the level of

1980. Other demand and supply shocks stay at their levels of 2015.

Table 6: Counterfactual Polarization

	Wage			Employment		
	1Q	2Q-4Q	5Q	1Q	2Q-4Q	5Q
Actual Change	-0.085	-0.489	0.574	0.194	-0.656	0.462
	Panel A. Varying Supply Elasticity					
Without CEI (β=0.3)	0.258	-0.390	0.132	0.232	-0.663	0.431
Without CEI (β=1)	0.217	-0.419	0.202	0.287	-0.661	0.374
	Panel B. Similar vs. Dissimilar CEI					
Without CEI-s	0.091	-0.512	0.421	0.209	-0.669	0.460
Without CEI-d	0.132	-0.330	0.198	0.216	-0.657	0.441
	Panel C. Different Channels					
Without Δ User Costs	-0.121	-0.498	0.619	0.113	-0.537	0.424
Without Δ Productivity	0.646	-0.829	0.183	0.270	-0.698	0.428
Without Δ Occ. Demand	0.257	-0.390	0.133	0.233	-0.666	0.433

Notes. This table shows the actual and the counterfactual growth rates of wage and employment growth of occupations grouped by their wages in 1980. The counterfactual equilibrium fixes the CEI measures at their levels of 1980. The wage and employment changes are subtracted from the mean and divided by the standard deviation of occupation-level changes in each case. Columns under 1Q and 5Q denote occupations with 1980 wage levels in the first and the fifth quintiles, respectively. Columns under 2Q-4Q denote occupations between the two quintiles. Panel A summarizes counterfactual equilibria with patent measures fixed at their 1980 level for supply elasticity $\beta = 0.3$ and $\beta = 1$. Panel B fixes patent measures of either similar or dissimilar capital to the 1980 level. Panel C fixes patent measures to the 1980 level only when calculating changes in user costs, capital productivity, and occupational demand, respectively. Panels B and C assume $\beta = 0.3$.

The first row of Table 6 summarizes wage and employment changes between 1980 and 2015 for three occupation bins grouped by their residual wages in 1980. As in Autor and Dorn (2013), employment and wage changes at the occupation level take a U-shape form over the wage level in 1980. High-wage occupations with their 1980 wages in the fifth quintile have 0.57 and 0.46 standard deviations higher wage and employment growth rates than the average occupations, respectively. Low-wage occupations also exhibit higher cross-sectional wage and employment growth rates than the average. Middle-wage occupations experience lower growth in terms of both wage and employment; the wage growth rate is lower by 0.49 standard deviations than the average, and the employment growth rate is lower by 0.66 standard deviations than the average.

Panel A of Table 6 shows the counterfactual employment and wage growth when the technology base, P_{jio}, is fixed at the level of 1980 with different values of labor supply elasticity, β. Under the counterfactual equilibrium without CEI, wage and employment increase less for high-wage occupations and decrease less for middle-wage occupations. This comes from high-wage occupations having higher CEI-d and higher intensity of task-dissimilar capital. Although high-wage occupations have higher CEI-s, which lowers their labor demand, the effect of CEI-d dominates.

The wage effect is larger than the effect on employment. This is due to the calibrated value of supply elasticity β being too low to generate large responses in employment. Between 1980 and 2014, employment changes were more dispersed, exhibiting a standard deviation of 0.64, compared to wage changes, which had a standard deviation of 0.11. Thus, with considered values of supply elasticity, most employment changes result from non-wage supply shifter, ϵ_o. If $\beta = 0.3$, the difference between the relative wage growth of high-wage occupations to the middle-wage ones is decreased by 51% (=1-(0.390+0.132)/(0.489+0.574)) whereas the relative employment growth of high-wage occupations is decreased by 2% (=1-(0.663+0.431)/(0.656+0.462)). If $\beta = 1$, the relative growth of high-wage occupations decreases by 42% and 7.5% in terms of wage and employment, respectively. Thus, counterfactual equilibrium features larger employment effects and smaller wage effects if the supply elasticity is calibrated at a higher value.

Panel B of Table 6 shows polarization measures from counterfactual equilibrium when only one type of capital has the technology base measure fixed at the level of 1980. Unless specified otherwise, we set the benchmark supply elasticity at $\beta = 0.3$ following Caunedo et al. (2023) in the analyses below.

Both CEI-s and CEI-d contribute to the growth of high-wage occupations, although the effect of CEI-d is quantitatively larger than the effect of CEI-s. Firstly, the coefficients for CEI-d are larger in magnitude than the CEI-s. 1% higher CEI-d increases the labor efficiency of task service production $\tilde{y}_{io}$ by 0.38% ($\gamma_{d1} + \gamma_{d2}$ in Table 5). On the other hand, as for CEI-s, the labor efficiency is increased only by 0.03% ($\gamma_{s1} + \gamma_{s2}$) because the negative effect of CEI-s on productivity cancels out most effects on user costs. The coefficient estimate of CEI-d on demand shifter (γ_{d3}) is larger in magnitude (0.245) than the coefficient estimate of CEI-d (-0.119) in Table 5.

Panel C of Table 6 summarizes the counterfactual results when the impact of CEI changes is muted for only one of the user costs of capital, productivity, and the demand shifter in the production function at each time. Excluding the user-cost channel moderately increases relative demand for high-wage occupations. This is because, before being canceled out by negative productivity effects (γ_{s2}), the estimated effect of CEI-s on user costs (γ_{s1}) is large at 0.84. Thus, high-wage occupations are substituted more with task-similar capital when CEI-s lowers user costs.

At the same time, excluding the productivity channel raises the demand for low-wage occupations substantially while reducing the demand for middle- and high-wage occupations. This is because low-wage occupations have lower intensity of task-similar capital and lower CEI-s. Without the large negative productivity effect of CEI-s, task-similar capital reduces the relative labor demand mainly in middle- and high-wage occupations. Due to its smaller productivity effect, the role of CEI-d is limited.

The occupational demand channel has the largest effect on polarization between middle- and high-wage occupations. Without the changes in occupational demand shifters, the relative demand for high-wage occupations decreases with their higher CEI-d despite their higher CEI-s. The increase in the demand for middle-wage occupations is smaller than the increase for low-wage occupations because middle-wage occupations have lower CEI-s and higher CEI-d, all of which raise their relative labor demand.

5.2 CEI and Task-Biased Labor Market Changes

We test what task-biased labor market changes would look like without CEI between 1980 and 2015 and thereby see if CEI constitutes task-biased technical changes in Autor et al. (2003). The task bias of labor market changes is measured in the following auxiliary regression that regresses the wage and employment changes on the occupation-level abstract and routine task scores from Autor and Dorn (2013).

$$\Delta \log y_{1980-2015,o} = \alpha_0 + \alpha_1 \cdot \text{Task Score}_o + \varepsilon_o. \tag{19}$$

The estimates for α_1 summarize the correlation between abstract and routine task scores with cross-sectional changes of wage and employment at

Table 7: Counterfactual: Task-Biased Labor Market Changes

	Abstract		Routine	
	Wage	Employment	Wage	Employment
Actual Change	0.471	0.195	-0.321	-0.255
Without CEI (β=0.3)	0.013	0.159	-0.050	-0.236
Without CEI (β=1)	0.079	0.097	-0.093	-0.199

Notes. This table shows the actual and the counterfactual regression coefficients of occupation-level wage and employment growth rates on occupational task scores from Autor and Dorn (2013) as in Equation (19). The counterfactual equilibrium fixes the CEI measures at their levels of 1980. Columns $\beta = 0.3$ and $\beta = 1$ set the elasticity of occupational labor supply at 0.3 and 1, respectively.

the occupation level and thus are used as a measure of task bias of labor market changes in 1980-2015.

Table 7 shows the estimates for regression coefficients. In this period, if an occupation has one standard deviation higher score of abstract tasks, the occupation has 0.47 and 0.20 standard deviations higher wage and employment growth rates, respectively. The bias is smaller both for abstract and routine task scores in the absence of CEI. In particular, abstract and routine bias in wage growth is close to zero if CEI is absent. When $\beta = 0.3$, the model predicts that one standard deviation higher abstract (routine) task score is associated with 0.013 (-0.051) standard deviation higher (lower) wage growth without CEI. Put differently, CEI makes 97% (84%) of abstract- (routine-) biased wage changes. As for employment, CEI contributes to 18 (7.5)% of abstract- (routine-) biased changes.

6 Conclusion

This paper develops a measure of capital-embodied innovations (CEI) using a text-based matching between patents and descriptions of capital goods from Wikipedia. Then, we use this measure to study the impact of technological factors on labor market trends. Occupation-level differences in the use of capital goods give useful cross-sectional variations to identify the impact of CEI.

This paper also proposes an important factor that determines the relationship between capital-embodied changes and occupational labor demand. If capital functions similarly to the tasks of occupation, technological changes that reduce the user costs of the capital promote substitution towards capital and lower the labor demand. On the other hand, if capital fulfills functions different from occupational tasks but is still essential in performing occupational tasks, technological changes in this type of capital raise the relative labor demand for occupational labor. This distinction implies that the effect of CEI depends heavily on the relationship between the function of capital and occupational tasks.

High-wage occupations experienced higher CEI and became more capital-intensive on task-dissimilar capital than middle-wage occupations. Counterfactual analysis shows that CEI can explain 42–51% of the difference in log wage changes between high-wage and middle-wage occupations. Similarly, occupations with higher abstract scores experienced higher CEI on task-dissimilar capital. Consequently, we find that CEI explains 83–94% of the wage growth favoring abstract occupations.

With the CEI measures from patents, technological factors can be isolated from others, such as trade and outsourcing. Innovations shaped biased trends of labor market demand, which implies that innovation policies can generate biased labor market trends. As long as these policies affect innovations on various capital in a different magnitude or occupations are exposed to capital differently, innovation policies have heterogeneous consequences across occupations. Then, a supplementary policy needs to target more exposed occupations to reduce structural unemployment and lower labor market inequality. The results in this paper call for continuing research on the long-run responses of the labor market to innovation policies through CEI.

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APPENDIX

(For Online Publication)

Table A1: Share of Tools Found in Wikipedia

NIPA	Description	Found in Wikipedia (%)
20	Electrical transmission, distribution, and industrial apparatus	73.08%
4	Computers and peripheral equipment	69.64%
30	Furniture and fixtures	63.16%
27	Ships and boats	62.86%
40	Service industry machinery	60.00%
11	Office and accounting equipment	54.22%
29	Other equipment	53.13%
41	Electrical equipment, n.e.c.	53.10%
19	General industrial including materials handling equipment	52.03%
13	Fabricated metal products	49.62%
5	Communication equipment	48.59%
22,25	Trucks, buses, and truck trailers + autos	48.57%
14	Engines and turbines	46.81%
36	Construction machinery	44.44%
33	Agricultural machinery	42.86%
9	Nonmedical instruments	40.19%
10	Photocopy and related equipment	37.66%
18	Special industry machinery, n.e.c.	35.29%
39	Mining and oilfield machinery	31.13%
17	Metalworking machinery	30.61%
28	Railroad equipment	30.00%
6	Medical equipment and instruments	26.07%
26	Aircrafts	14.29%

A Details in Text Matching

This appendix reports the details of matching between capital goods and patent data. Table A1 displays the share of tools found in Wikipedia over NIPA categories.

Using the crosswalk between UNSPSC and NIPA from Caunedo et al. (2023), we assign a two-digit NIPA code to 4,180 tools. Then, we calculate the share of tools that are found in Wikipedia for each NIPA category. Table A1 shows that electronics, furniture, and machinery are more likely to be found in Wikipedia, while mining, medical equipment, and aircraft are less likely to be found in Wikipedia.

Table A2 shows the share of patents matched with at least one tools

Table A2: Patent-tool Matching Rate across Patent Class and Period

Patent Class	Matching Rate (%)			
	1970–1980	1980–1990	1990–2000	2000–2015
Human necessities	22.50	22.07	22.69	18.38
Transportation	33.19	32.75	33.48	26.80
Chemistry	6.74	7.31	8.18	9.06
Textile	28.53	30.61	31.36	26.19
Construction	32.14	31.30	31.87	24.29
Engineering	43.23	42.47	42.99	34.49
Physics	28.06	27.60	25.50	20.86
Electricity	27.48	27.74	25.87	21.87

Notes. This table presents the share of patents matched with at least one tool, by period and patent class (IPC 1 digit level).

Figure A1: Example of Text Matching between Patent and Wikipedia

Patent: Systems, apparatuses and methods for reading an amino acid sequence (10139417)
system apparatus method reading amino acid sequence embodiment present disclosure relate amino acid modified amino acid peptide protein identification sequencing mean example electronic detection individual amino acid small peptide

Wikipedia: Protein sequencer
protein sequencing practical process determining amino acid sequence part protein peptide may serve identify protein characterize post translational modification typically partial sequencing protein provides sufficient information one sequence tag identify reference database protein sequence derived conceptual translation gene

Notes. This figure shows an example of an abstract of the matched patent and Wikipedia article of the capital good. Blue texts are common words between two texts.

across period and patent classes. Patent class is IPC 1 digit level.

Table A3: Example of Matched Capital Goods and Title of Patents

Capital Goods	Title of Patent
Battery chargers	Power tool, battery, charger and method of operating the same
Belt conveyors	Conveyor belt assembly
Cash registers	Theft proof cash drawer assembly
Desktop computers	Method and system for managing windows desktops in a heterogeneous server environment
Glass cutters	Discrete glass sheet cutting
Satellite phone	Communication system with direct link to satellite
Sewing machine needles	Multiple-needle sewing machine
Smoke detectors	Smoke detector system for a house
Tire pressure gauge	Tire pressure control system, tire pressure control device and tire pressure control method
Touch screen monitors	Technologies for interacting with computing devices using haptic manipulation

Notes. This table shows examples of matched capital goods and the title of patents

B Measures of Capital Stock and User Costs

Occupation-specific capital stock and user costs are calculated using procedures in Caunedo et al. (2023). Each occupation has a set of capital goods in UNSPSC codes. These UNSPSC codes are converted to the NIPA capital category using the crosswalk in Table 1 of the Online Appendix for Caunedo et al. (2023). The 2012 fixed-price capital stock series is used to measure the quantity of capital category n for each occupation o in each year y. The capital intensity of an occupation o for the NIPA capital category n is first defined by the number of UNSPSC codes from "Tools Used" that are mapped into n. Let $\#Capital_o^{n,s}$ ($\#Capital_o^{n,c}$) denote the number of task-similar (task-dissimilar) capital goods and K_i^n the capital expenditure (based on the fixed price in 2012 USD) of industry i on capital type n.

Then, the capital stock of occupation o, industry i, capital good n is imputed as

$$x_{siont} = \frac{l_{iot}\#Capital_o^{n,s}}{\sum_p l_{ipt}\#Capital_p^{n,s} + \sum_p l_{ipt}\#Capital_p^{n,c}} K_{int} \tag{A1}$$

$$x_{diont} = \frac{l_{iot}\#Capital_o^{n,c}}{\sum_p l_{ipt}\#Capital_p^{n,s} + \sum_p l_{ipt}\#Capital_p^{n,c}} K_{int}. \tag{A2}$$

K_{int} is the current- and fixed-cost stock of of NIPA capital category n and industry i in year t. Thus, capital stocks are prorated across occupations with an intensity-weighted number of workers. If an occupation in an industry is missing from the O*NET and thus does not have any tool, the average intensity of tools in the industry is assigned to the occupation to adjust the capital stock. However, this occupation is not included in the regression analysis.

The price deflator is calculated as the ratio between current-cost and fixed-cost capital stock from the BEA and used as a capital price index. Depreciation rates are computed from depreciated capital stock data from the BEA. Specifically, the BEA depreciation rate d_{int} is calculated as the ratio of the depreciated capital stock in a year to the average between the capital stock evaluated at the end of the year and the capital stock evaluated at the end of the previous year. Because BEA-reported depreciation measures reflect both physical and economic depreciation, the physical depreciation rate is calculated using the following equation.

$$1 - \delta_{int} = (1 - d_{int}) \frac{q_{int}/\lambda_t^c}{q_{int-1}/\lambda_{t-1}^c} \tag{A3}$$

In this equation, λ_t^c is the price of consumption, and q_{int} is the price deflator.

The user cost of capital category n for industry i and year t also comes from Caunedo et al. (2023) that follows Jorgenson (1963).

$$\lambda_{int}^{k} = \frac{q_{int}}{\lambda_{t-1}^{c}} \left[R - \left(1 - \bar{\delta}_{int}\right) \frac{q_{int}^{k}/\lambda_{n}^{c}}{q_{int-1}^{k}/\lambda_{t-1}^{c}} \right]. \tag{A4}$$

$R = 1.02$ is the gross return on a safe asset, and $\bar{\delta}_{int}$ is the average (physical) deflation rate of capital category n in industry i and the decade group t belongs to. If $t = 1980, \ldots, 1989$, $\bar{\delta} = \sum_{t=1980}^{1989} \delta_{int}$ with δ_{int} the annual deflation rate. We use $\lambda_{t}^{c} = 1$.

The quantity index of capital type $j = s, d$ for occupation o and industry i in year t is given as the following equation.

$$k_{jiot} = k_{jiot-1} e^{\kappa_{jiot}^{k}}, \quad k_{jio1980} = \sum_{n} x_{jion1980} \tag{A5}$$

$$\kappa_{jiot}^{k} = \sum_{n} \frac{\lambda_{int}^{k} x_{jiont}}{\sum_{n'} \lambda_{in't}^{k} x_{jion't}} \kappa_{int}^{k}. \tag{A6}$$

κ_{int}^{k} is the growth rate of capital category n. Thus, γ_{jiot}^{k} is the expenditure-weighted average growth rate of capital type j. Unlike Caunedo et al. (2023), we normalize the occupation-level stock, not user costs of each occupation and industry, with the level in 1980. We take this approach because we are interested in the cross-sectional differences in capital stock and user cost series at the occupation level.

The user cost for the capital bundle is computed as follows.

$$r_{jiot} = \frac{\sum_{n} \lambda_{int}^{k} x_{jiont}}{k_{jiot}}. \tag{A7}$$

C Instrumental Variables

C.1 Academic Publication Shock

A simple OLS regression of labor market variables on innovation may yield a biased estimate if technical changes are directed by labor demand shocks (Acemoglu, 2002). For example, when an unobserved demand shock hits the IT sector, the value of innovation in the IT sector will increase. This leads to an increase in innovation incentives on capital used in the IT sector, such as computers. Then, our CEI measure can be correlated with this unobserved demand shock correlated with wage and employment growth rates.

On the other hand, innovation activities can also be affected by labor supply shocks. More labor supplies in an occupation can imply that the return to capital innovation becomes smaller with substitution towards cheaper labor inputs. For example, if immigrants are more likely to work in consumer service sectors and more immigrants arrive, firms in consumer service sectors are less incentivized to invest in labor-saving capital technology. In this case, the coefficient of CEI measures on employment can be underestimated. Whether the OLS overestimates or underestimates the true coefficient is an empirical question.

To avoid this problem, academic publication shock is used as an instrument for patents. Inventors use knowledge from academic publications when they innovate and apply for a patent. For example, innovation in the computer sector builds on the knowledge produced in the electronic engineering field. Therefore, the increase in the number of papers in electronic engineering is positively correlated with innovation in the computer sector but not necessarily with demand shocks for IT workers.

To measure knowledge diffusion from academic publications to patents, we use citation data from patents to academic publications following the literature (Arora et al., 2021). Specifically, a large number of citations from patents within a technology class to papers in a specific academic field suggests that the academic field serves as an upstream source of knowledge for that technology class. Citation data is sourced from data provided by Marx and Fuegi (2020), who show that 17.6% of USPTO patents cite at least one academic paper, with an average of two academic citations per patent.

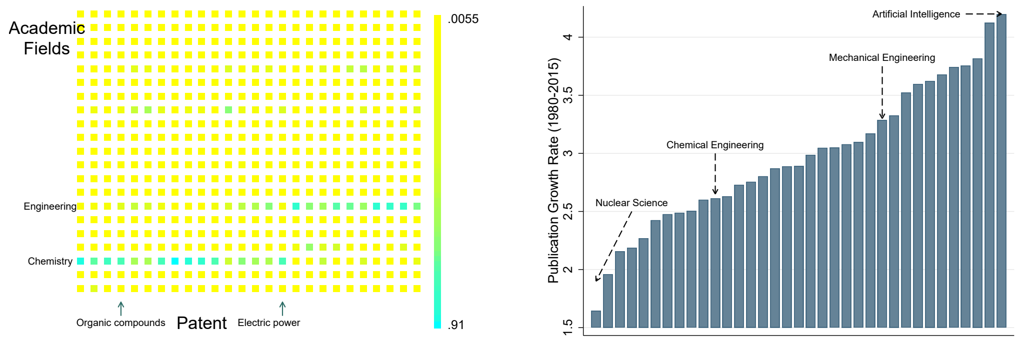
We construct the upstreamness of an academic field m to patent class n by using citations made from 1970 to 1980. For the academic field, the Web of Science Field is used, encompassing 251 distinct fields. For patents, 3-digit IPC patent classes, comprising 387 classes, are used. The upstreamness α_{nm} is calculated as below:

$$\alpha_{nm} = \frac{c_{nm}}{\sum_m c_{nm}} \,,$$

where c_{nm} is the number of citations from patent class n to academic field m in 1970–1980. The left panel of Figure A2 plots α_{nm}, showing the variation of citation share over patent classes. Engineering and chemistry are the fields that receive the most citations from patents.

Next, the upstream measure for each technology class is calculated and aggregated into the occupation-industry level as below:

$$\text{Upstream}_{io}^{j} = \Delta \log \left(\sum_n s_{nio} \sum_m \alpha_{nm} \mathcal{P}_m \right) \,,$$



A. Share of Citations B. Growth Rate of Publications

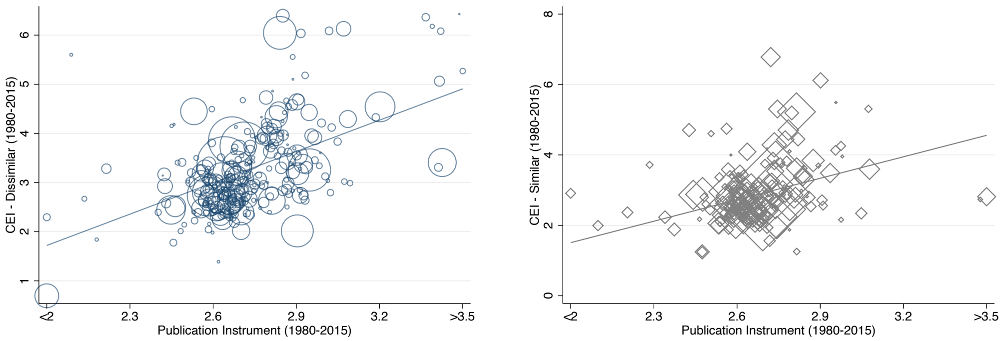
Figure A2: Citation Share and Publication Growth Rate

Notes. Panel A plots the share of citations from patent technology classes (row) to academic fields (column) in 1970–1980. The graph only contains the IPC classes that have more than 50,000 citations to science in the entire period. When the color gets closer to blue, it has a higher citation share. Panel B displays the growth rates of publications between 1980–2015 in different academic fields. Publication data comes from MAG and includes publications associated only with European institutions.

where $\mathcal{P}_m$ is the number of publications in field m, and s_{nio} is the stock-adjusted share of patent class n in capital goods used for occupation o and industry i for capital type $j \in \{d, s\}$. The instrument variable takes difference-in-logs at the occupation by industry level.

For the growth rate of publications, we source data from the Microsoft Academic Graph (MAG, Sinha et al. (2015)). Only papers affiliated with European institutions are counted to avoid the potential bias from US patenting firms also supporting academic projects, which could inflate the publication counts in the US. The right panel of Figure A2 displays the growth rate distribution of publications. The fields with the highest growth rates include artificial intelligence, information systems, hardware, software engineering, and control systems.

Figure A3 displays the scatter plots between CEI measures and the re-



A. CEI-d B. CEI-s

Figure A3: CEI and Publication Instrument

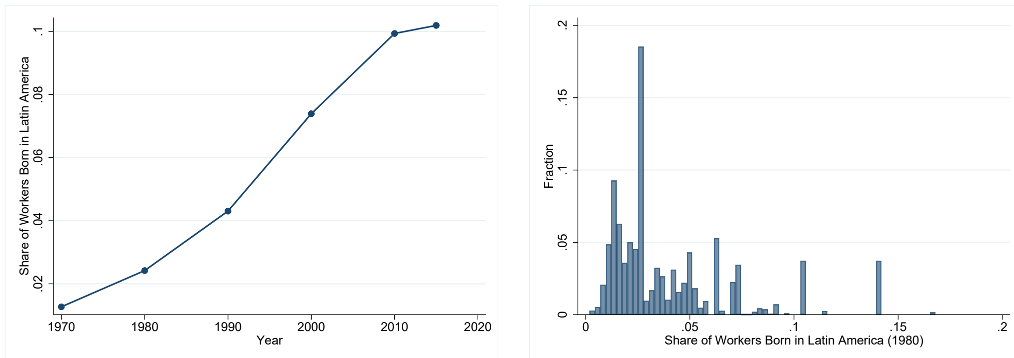
Notes. Panel A plots CEI-d and Panel B plots CEI-s over the publication instrument. Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the employment of each occupation in the 1980 Decennial Census.

sulting academic publication instruments at the occupation level. The publication instruments are strongly positively associated with the actual CEI measures.

C.2 Immigration Shock

In order to identify the elasticity of substitution in the production function separately from the effects of CEI measures, an exogenous supply shifter is needed. This shifter is calculated using trends in Latin American immigration and heterogeneous exposures to Latin American Immigration. From 1980 to 2015, the population of Latin American-born workers in the U.S. surged eightfold, while the number of U.S.-born workers doubled. As a result, the share of workers born in Latin America in total US employment increased from 2.3% in 1980 to almost 10% in 2015, as shown in Panel A of Figure A4.

Immigrants from Latin America are likely to have comparative advan-



A. Over Time B. Across Occupations (1980)

Figure A4: Share of Workers Born in Latin America

Notes. Panel A plots the share of workers in the U.S. who were born in Latin America over the years. Panel B plots the share of workers born in Latin America in 1980 at the occupation level and draws the histogram of the observations. Each occupation is weighted by the number of workers in 1980.

tages different from those of US-born workers, influencing their choice of occupation differently. Panel B of Figure A4 shows the histogram of the share of workers from Latin America in 1980 across different occupations, with the weight of each occupation based on its employment numbers that year. The proportion of Latin American workers significantly differs among occupations. For instance, in 1980, 13.5% of farm workers were from Latin America, whereas less than 0.2% of speech therapists were born in the region. Consequently, a surge in Latin American immigration would disproportionately affect the labor supply in certain occupations, such as farm workers.

We group Latin American countries into three groups: Mexico (G_1), other Central American countries (G_2), and Southern American countries (G_3). For each group, the heterogeneous exposure to immigration shock is computed based on the share of workers from Latin America in 1980. The

Bartik immigration shock for each country group G and occupation o is defined as in the following equation.

$$z_{Latin,G} = \sum_{c \in G} \frac{l_o^{c,1980}}{l_c^{1980}} \log \left(\frac{L^{c,2015} - l_o^{c,2015}}{L^{c,1980} - l_o^{c,1980}} \right).$$

Here, $l_o^{c,t}$ is the number of workers from country c in occupation o at period t, and $L^{c,1980} = \sum_o l_o^{c,1980}$ is the total number of workers in country c. Workers in occupation o are subtracted from calculating the supply shock to rule out the effect of occupation-level shocks associated with more immigration from country group c.

D Reduced-Form Results

Table A4 shows reduced-form estimates from the linear regression of wage and employment changes between 1980 and 2015 on CEI measures. Samples include occupations without task-similar capital with their CEI-s measures fixed at zero. All regressions include a Bartik-type demand shifter that predicts wage increases at the occupation level with the average of industry-level wage increases weighted by the industrial composition of each occupation. Also, regressions control for industry-fixed effects. These fixed effects are estimated separately for occupations with and without task-similar capital. Wage and employment changes are normalized with cross-sectional mean and standard deviation.

Panel A of Table A4 shows the results on wage changes. CEI-s have overall negative effects on wages, whereas CEI-d has overall positive effects, especially when we use publication IV. The OLS estimates of CEI-s are larger than the IV estimates, which is consistent with patenting incentives that are more responsive to demand shocks for occupational tasks. As for CEI-d, the OLS estimates are smaller than the IV estimates from columns (3) to (4). This is consistent with innovation activities increasing elastically to shocks biased to capital at the occupation level. Estimation results of employment changes in Panel B overall trace out the wage results.

Table A4: Reduced-Form Results: Baseline

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Panel A. Wage			
CEI-s	-0.013	-0.085	0.015	-0.090
	(0.011)	(0.031)	(0.011)	(0.030)
CEI-d	0.084	0.058	-0.079	0.037
	(0.010)	(0.027)	(0.009)	(0.024)
	Panel B. Employment			
CEI-s	0.117	-0.423	0.087	-0.529
	(0.012)	(0.038)	(0.012)	(0.041)
CEI-d	0.107	0.550	0.046	0.508
	(0.010)	(0.032)	(0.010)	(0.032)
First Stage F	-	619.5	-	675.7
Controls			✓	✓
N	10880	10880	10880	10880

Notes. This table shows coefficient estimates from linear regression of wage and employment changes between 1980 and 2015. Occupations without task-similar capital are included with CEI-s measures fixed at zero. All regressions include Bartik demand shifter based on industry-level wage changes and separate industry fixed effects for occupations with and without task-similar capital. All observations are weighted with 1980 employment. Columns with controls mean that the linear regression includes the occupational offshorability index, as well as the routine, manual, and abstract task scores from Autor and Dorn (2013). Columns (1) and (3) estimates with the OLS, and columns (2) and (4) instruments CEI measures with publication instruments in Appendix C.

D.1 Different Thresholds

The baseline threshold is set at the 90th percentile of the task-capital similarity score distribution to distinguish the task-similar and task-dissimilar capital goods. This threshold successfully gives opposite signs to CEI-s and CEI-d measures in the reduced-form regression. Table A5 and A6 show reduced-form results with different thresholds for task-similar capital. Intuitively, if the similarity increases substitutability with labor, a higher threshold reduces the average substitutability of task-similar capital and increases the reduced-form coefficient on employment growth. Indeed, the coefficients for CEI-s are lower with a higher threshold, and the coefficients for CEI-d are smaller in Table A5 with the 95th percentile as thresholds for task-similar capital.

Table A6 shows the reduced-form results with the 75th percentile as the threshold for the task-similar capital. If we include capital goods that are marginally less similar to occupational tasks as task-similar capital, the coefficient estimates of CEI-s become higher compared to the baseline case in Table A4. The coefficient estimates for CEI-s and CEI-d for wage in column (4) even switch the sign.

Table A5: Reduced-Form Results with 95th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Panel A. Wage			
CEI-s	0.142	-0.023	0.058	-0.097
	(0.010)	(0.021)	(0.010)	(0.023)
CEI-d	0.065	0.018	-0.062	0.011
	(0.009)	(0.025)	(0.009)	(0.023)
	Panel B. Employment			
CEI-s	0.031	-0.135	-0.087	-0.254
	(0.011)	(0.023)	(0.012)	(0.026)
CEI-d	0.103	0.335	0.027	0.262
	(0.010)	(0.026)	(0.010)	(0.026)
First Stage F	-	927.7	-	968.7
Controls			✓	✓
N	10889	10889	10889	10889

Notes. This table shows coefficient estimates from linear regression of wage and employment changes between 1980 and 2015 on CEI measures redefined with the 95th percentile of task-capital similarity score as thresholds for similar-dissimilar distinction. Occupations without task-similar capital are included with CEI-s measures fixed at zero. All regressions include Bartik demand shifter based on industry-level wage changes and separate industry fixed effects for occupations with and without task-similar capital. All observations are weighted with 1980 employment. Columns with controls mean that the linear regression includes the occupational offshorability index, as well as the routine, manual, and abstract task scores from Autor and Dorn (2013). Columns (1) and (3) estimates with the OLS, and columns (2) and (4) instruments CEI measures with publication instruments in Appendix C.

Table A6: Reduced-Form Results with 75th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Panel A. Wage			
CEI-s	-0.011	-0.005	-0.074	0.010
	(0.010)	(0.026)	(0.009)	(0.023)
CEI-d	0.071	-0.152	-0.017	-0.008
	(0.010)	(0.029)	(0.009)	(0.024)
	Panel B. Employment			
CEI-s	0.119	-0.191	0.073	-0.281
	(0.011)	(0.030)	(0.011)	(0.033)
CEI-d	0.039	0.521	0.018	0.546
	(0.011)	(0.034)	(0.011)	(0.034)
First Stage F	-	762.3	-	799.5
Controls			✓	✓
N	10753	10753	10753	10753

Notes. This table shows coefficient estimates from linear regression of wage and employment changes between 1980 and 2015 on CEI measures redefined with the 75th percentile of task-capital similarity score as thresholds for similar-dissimilar distinction. Occupations without task-similar capital are included with CEI-s measures fixed at zero. All regressions include Bartik demand shifter based on industry-level wage changes and separate industry fixed effects for occupations with and without task-similar capital. All observations are weighted with 1980 employment. Columns with controls mean that the linear regression includes the occupational offshorability index, as well as the routine, manual, and abstract task scores from Autor and Dorn (2013). Columns (1) and (3) estimates with the OLS, and columns (2) and (4) instruments CEI measures with publication instruments in Appendix C.

D.2 Patent Citations

Table A7 exhibits the reduced-form coefficients of CEI measures redefined with the number of citations on patents associated with occupations. The signs of coefficients, as well as the magnitudes, do not change significantly with citation-based measures of CEI.

D.3 Market Valuations of Patents

Table A8 shows the reduced-form coefficient estimates of CEI measures redefined with market valuations of patents calculated as in Kogan et al. (2017). The signs of coefficients, as well as the magnitudes, do not change significantly with citation-based measures of CEI.

Table A7: Reduced-Form Results with Patent Citations

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Panel A. Wage			
CEI-s	0.010	-0.080	0.035	-0.085
	(0.011)	(0.029)	(0.010)	(0.028)
CEI-d	0.091	0.057	-0.074	0.036
	(0.009)	(0.026)	(0.009)	(0.024)
	Panel B. Employment			
CEI-s	0.103	-0.403	0.070	-0.501
	(0.011)	(0.035)	(0.012)	(0.038)
CEI-d	0.107	0.542	0.045	0.503
	(0.010)	(0.032)	(0.010)	(0.031)
First Stage F	-	621.7	-	677.3
Controls			✓	✓
N	10880	10880	10880	10880

Notes. This table shows coefficient estimates from linear regression of wage and employment changes between 1980 and 2015 on CEI measures redefined with citation-weighted number of patents. Occupations without task-similar capital are included with CEI-s measures fixed at zero. All regressions include Bartik demand shifter based on industry-level wage changes and separate industry fixed effects for occupations with and without task-similar capital. All observations are weighted with 1980 employment. Columns with controls mean that the linear regression includes the occupational offshorability index, as well as the routine, manual, and abstract task scores from Autor and Dorn (2013). Columns (1) and (3) estimates with the OLS, and columns (2) and (4) instruments CEI measures with publication instruments in Appendix C.

Table A8: Reduced-Form Results with Patent Valuations

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Panel A. Wage			
CEI-s	-0.029	-0.069	-0.031	-0.076
	(0.008)	(0.026)	(0.007)	(0.026)
CEI-d	0.103	0.061	-0.054	0.044
	(0.008)	(0.025)	(0.007)	(0.022)
	Panel B. Employment			
CEI-s	0.113	-0.339	0.083	-0.440
	(0.008)	(0.033)	(0.009)	(0.037)
CEI-d	0.128	0.530	0.079	0.512
	(0.008)	(0.031)	(0.008)	(0.031)
First Stage F	-	383.0	-	390.8
Controls			✓	✓
N	10820	10820	10820	10820

Notes. This table shows coefficient estimates from linear regression of wage and employment changes between 1980 and 2015 on CEI measures redefined with market values of patents computed as in Kogan et al. (2017). Occupations without task-similar capital are included with CEI-s measures fixed at zero. All regressions include Bartik demand shifter based on industry-level wage changes and separate industry fixed effects for occupations with and without task-similar capital. All observations are weighted with 1980 employment. Columns with controls mean that the linear regression includes the occupational offshorability index, as well as the routine, manual, and abstract task scores from Autor and Dorn (2013). Columns (1) and (3) estimates with the OLS, and columns (2) and (4) instruments CEI measures with publication instruments in Appendix C.

E Computers and Robots

Computers and robots have been considered the most important technological changes in the labor market. This section shows the importance of computers and robots to generate labor market changes.

Table A9: Share of Computer and Robot in CEI measures

	Mean	SD.	Median
Computer - dissimilar	0.08	0.12	0.03
Computer - similar	0.05	0.19	0.00
Robot - dissimilar	0.00	0.03	0.00
Robot - similar	0.01	0.07	0.00

Notes. This table displays the summary statistics of the share of computer and robot patents at the occupation-industry level.

Table A9 shows the share of computers and robots in CEI measures at the occupation-industry level. A capital good is considered a computer if the commodity title has the words "computer" or "laptop." On the other hand, a capital good is considered a robot if the title has the words "automatic", "robot," or "drone." Computers account for 8% of task-dissimilar capital and 5% of task-similar capital, on average. Robots account for 0% of task-dissimilar capital and around 1% of task-similar capital.

In Appendix F.3, we repeat the counterfactual exercise after setting only innovations unrelated to computers fixed at the level in 1980 and show that computer-related CEI accounts for about 40% of the baseline counterfactual results. Since robots account for a negligible fraction of capital inputs, counterfactual equilibrium remains quantitatively unchanged after setting only innovations unrelated to robots fixed at the level in 1980.

F Counterfactual Appendix

F.1 Counterfactual Details

The counterfactual exercise aims to derive the counterfactual equilibrium without CEI in 1980-2015. Residual terms in demand-side equations, such as ω_{jio1}, ω_{jio2}, ω_{io3}, and α_i, are fixed at their levels in 2015. We only allow P_{sio} and P_{dio} to be at their levels in 1980. The total employment $\mathbf{L}$ is also fixed at its level in 2015. The two following equations are additionally needed to run the counterfactual equilibrium.

$$1 = \frac{\alpha_i \mu_{io}}{\alpha_j \mu_{jo}} \left(\frac{Y_i}{Y_j}\right)^{\frac{1}{\sigma}-1} \left(\frac{y_{io}}{y_{jo}}\right)^{\frac{1}{\rho_d}-\frac{1}{\sigma}} \left(\frac{\tilde{\Theta}_{io}}{\tilde{\Theta}_{jo}}\right)^{\frac{\rho_d-\rho_s}{\rho_s\rho_d}} \left(\frac{l_{io}}{l_{jo}}\right)^{-\frac{1}{\rho_d}} \tag{A8}$$

$$Y_i = l_{io} \left(\sum_o \mu_{io} \left(\frac{l_{io}}{l_{i0}}\right)^{\frac{\sigma-1}{\sigma}} \tilde{y}_{io}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = l_{i0}\tilde{Y}_i \tag{A9}$$

Equation (A8) is derived from the first order conditions of cost minimization with respect to l_{io} and l_{jo}, respectively. Equation (A9) expresses industrial outputs as a linear function of l_{io}, labor input of a reference occupation 0, and $\tilde{Y}_i$ that only depends on the ratio of labor inputs relative to a reference occupation 0. The manager (OCC1990 = 22) is used as the reference occupation.

By combining Equations (A8) and (A9), the following equation is derived.

$$1 = \frac{\alpha_i \mu_{io}}{\alpha_j \mu_{jo}} \left(\frac{\tilde{Y}_i}{\tilde{Y}_j}\right)^{\frac{1}{\sigma}-1} \left(\frac{\tilde{y}_{io}}{\tilde{y}_{jo}}\right)^{\frac{1}{\rho_d}-\frac{1}{\sigma}} \left(\frac{\tilde{\Theta}_{io}}{\tilde{\Theta}_{jo}}\right)^{\frac{\rho_d-\rho_s}{(\rho_s-1)\rho_d}} \left(\frac{l_{io}}{l_{jo}}\right)^{-1} \tag{A10}$$

We use this equation to pin down the industry-level employment of an occupation.

F.2 Counterfactual without User Cost Changes

This appendix shows how user cost changes alone contribute to labor market trends heterogeneous for different occupations using the structural model estimated in section 4. User cost changes heterogeneous across occupations cannot generate much of the heterogeneous labor market changes observed in the data. Table A10 summarizes the changes of user costs for similar and dissimilar capital over occupation groups made from occupational wage level in 1980. After adjustments of inflation, all occupation groups have declines in user costs of capital. However, especially high-wage occupations experience larger reduction in user costs of both similar and dissimilar capital.

Table A11 summarizes labor market polarization in a counterfactual equilibrium with changes in user costs but without CEI. The impact of user cost changes is small because user costs decreased similarly between 1980 and 2015 across occupation groups. Still, changes in user costs contribute to demand reallocation between low- and middle-wage occupations. Low-wage occupations experience smaller reductions in user costs of dissimilar capital, which reduces their relative labor demand. This force is counteracted by their smaller reductions in user costs of similar capital, and the effect of similar capital dominates. The demand is mostly reallocated from middle-wage occupations that are more intensive in similar capital than high-wage occupations.

Panel B of Table A11 decomposes the effects of user cost changes in similar and dissimilar capital. With changes in user costs of task-similar capital, labor demand is larger for middle-wage occupations but smaller for low-wage occupations. As for dissimilar capital, the reduction of user costs mostly boosts labor demand for high-wage occupations at the expense of middle-wage occupations.

Table A12 compares the task bias of labor market changes in the counterfactual equilibrium without changes in user costs. The effect of user costs on task-biased labor market changes is small, although the coefficient of abstract and routine task scores on wage changes is smaller in magnitude. With the non-linearity of the demand system, employment change is slightly more biased toward abstract occupations and more biased against routine occupations without user cost changes.

Table A10: User Cost Changes

	1Q	2Q	3Q	4Q	5Q
User Cost Change (Similar)	-0.544	-0.602	-1.284	-0.834	-1.224
User Cost Change (Dissimilar)	-0.496	-0.597	-1.016	-1.576	-1.100

Notes. This table summarizes the changes in user costs of similar and dissimilar capital used by occupations in the first (1Q), second (2Q), third (3Q), fourth (4Q), and fifth (5Q) quintiles of wage level in 1980. The changes in user costs adjust the changes in price level measured by CPI between January 1980 and January 2015.

Table A11: Polarization without User Cost Changes

	Wage			Employment		
	1Q	2Q-4Q	5Q	1Q	2Q-4Q	5Q
Actual Change	-0.085	-0.489	0.574	0.194	-0.656	0.462
	Panel A. Varying Supply Elasticity					
Without Δ User Cost (β=0.3)	-0.107	-0.465	0.572	0.192	-0.656	0.464
Without Δ User Cost (β=1)	-0.101	-0.471	0.572	0.191	-0.658	0.467
	Panel B. Similar vs. Dissimilar User Costs					
Without Δ User Cost (Similar)	-0.131	-0.441	0.572	0.188	-0.648	0.460
Without Δ User Cost (Dissimilar)	-0.091	-0.471	0.562	0.194	-0.659	0.465

Notes. This table shows the actual and the counterfactual growth rates of wage and employment growth of occupations grouped by their wages in 1980. The counterfactual equilibrium fixes the user costs of all capital inputs at their levels of 1980. The wage and employment changes are subtracted from the mean and divided by the standard deviation of occupation-level changes in each case. Columns under 1Q and 5Q denote occupations with 1980 wage levels in the first and the fifth quintiles, respectively. Columns under 2Q-4Q denote occupations between the two quintiles. Panel A summarizes counterfactual equilibria with patent measures fixed at their 1980 level for supply elasticity $\beta = 0.3$ and $\beta = 1$. Panel B fixes patent measures of either similar or dissimilar capital to the 1980 level. Panel B assumes $\beta = 0.3$.

F.3 Counterfactual with Computer-Embodied CEI

Table A13 summarizes the share of computers in similar and dissimilar capital stock and CEI measures. Over time, the share of computer stock increased in dissimilar capital, and the increase is larger for middle-wage occupations. Because computers are innovation-intensive capital goods, the share of computer-related patents in CEI measure is high even in 1980, and the share does not have a noticeable change over time and is relatively uniform across occupation groups.

Next, Table A14 shows counterfactual changes in employment and wage growth when only patents unrelated to computers are fixed at their level of 1980 to calculate CEI measures. CEI measures include the actual values for computer-related patents in 2015. The results imply a modest role of computers in generating labor market polarization. Compared to Table 6, the wage growth of high-wage occupations in the fifth quintile increases by 0.1 and 0.04 when $\beta = 0.3$ and $\beta = 1$, respectively. This comes from computers being used widely as dissimilar capital in all occupations and the intensity of computers in CEI being mostly uniform.

Lastly, Table A15 displays the coefficient estimates of task scores on wage and employment changes in a counterfactual equilibrium where only the number of patents unrelated to computers is fixed at the level of 1980. Consistent with Table A14, even when computer-related patents increase over time, labor market changes would have been less biased toward abstract and against routine occupations, and the change in wage growth coefficient is 40% of the change in Table 7. Thus, the contribution of computer-related innovations is limited.

Table A12: Task-Biased Labor Market Changes without Changes in User Costs

	Abstract		Routine	
	Wage	Employment	Wage	Employment
Actual Change	0.472	0.195	-0.322	-0.257
Without Δ User Cost (β=0.3)	0.464	0.196	-0.317	-0.258
Without Δ User Cost (β=1)	0.466	0.197	-0.320	-0.260

Notes. This table shows the actual and the counterfactual regression coefficients of occupation-level wage and employment growth rates on occupational task scores from Autor and Dorn (2013) as in Equation (19). The counterfactual equilibrium fixes the user costs of all capital inputs at their levels of 1980. Columns $\beta = 0.3$ and $\beta = 1$ set the elasticity of occupational labor supply at 0.3 and 1, respectively.

Table A13: Computer Intensity over 1980 Wage

	Similar			Dissimilar		
	1Q	2Q-4Q	5Q	1Q	2Q-4Q	5Q
	Panel A. Stock Intensity					
1980	0.000	0.031	0.005	0.011	0.066	0.039
2015	0.030	0.044	0.023	0.145	0.263	0.165
	Panel B. CEI Intensity					
1980	0.538	0.494	0.533	0.527	0.516	0.493
2015	0.562	0.492	0.501	0.632	0.619	0.598

Notes. This table summarizes the share of computers in similar and dissimilar capital over occupational wage level in 1980. The columns labeled 1Q and 5Q represent the occupations in the first and fifth quintiles, respectively, while the columns under 2Q-4Q cover occupations within the second to fourth quintiles.

Table A14: Polarization without Computer-based CEI

	Wage			Employment		
	1Q	2Q-4Q	5Q	1Q	2Q-4Q	5Q
Actual Change	-0.085	-0.489	0.574	0.194	-0.656	0.462
Without CEI (β=0.3)	-0.059	-0.171	0.230	0.194	-0.631	0.437
Without CEI (β=1)	0.016	-0.257	0.241	0.216	-0.601	0.385

Notes. This table shows the actual and the counterfactual growth rates of wage and employment growth of occupations grouped by their wages in 1980. The counterfactual equilibrium uses CEI measures that fix only patents unrelated to computers at their levels of 1980. The wage and employment changes are subtracted from the mean and divided by the standard deviation of occupation-level changes in each case. Columns under 1Q and 5Q denote occupations with 1980 wage levels in the first and the fifth quintiles, respectively. Columns under 2Q-4Q denote occupations between the two quintiles. Columns 'Without CEI ($\beta = 0.3$)' and 'Without CEI ($\beta = 1$)' set the elasticity of occupational labor supply at 0.3 and 1, respectively.

Table A15: Polarization without Computer-based CEI

	Abstract		Routine	
	Wage	Employment	Wage	Employment
Actual Change	0.472	0.195	-0.322	-0.257
Without CEI (β=0.3)	0.213	0.178	-0.232	-0.253
Without CEI (β=1)	0.224	0.146	-0.235	-0.248

Notes. This table shows the actual and the counterfactual regression coefficients of occupation-level wage and employment growth rates on occupational task scores from Autor and Dorn (2013) as in Equation (19). The counterfactual equilibrium uses CEI measures that fix only patents unrelated to computers at their levels of 1980. Columns 'Without CEI ($\beta = 0.3$)' and 'Without CEI ($\beta = 1$)' set the elasticity of occupational labor supply at 0.3 and 1, respectively.