How Task-Biased is Capital-Embodied Innovation?*

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Abstract

This paper develops a measure of Capital-Embodied Innovation (CEI). The measure counts the number of patents applied to capital goods by matching patent documents with Wikipedia articles on capital goods. Using occupation-level variations on the sets of capital goods from O*NET, we document that CEI is biased toward abstract and non-routine occupations. Furthermore, we highlight the heterogeneous effects of CEI across the capital good-occupation relationship. When the capital good performs a similar function as the occupational task (task-substituting capital), the CEI reduces the relative demand for labor. In case the capital good performs a different function than the occupation tasks (task-complementing capital), the CEI raises relative demand for labor. Abstract occupations have disproportionately more CEI on task-complementing capital than non-abstract occupations. A model-based counterfactual implies that the employment growth between the 1980s and the 2010s would be 70% less biased towards abstract task occupations without CEI. The degree of job polarization and occupational wage inequality would have also been lower without CEI.

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

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1 Introduction

Labor markets in developed economies have marked distinctive secular trends since the late 20th century. Many important trends in the labor market happen across different groups of workers (Goldin and Katz, 2007; Autor et al., 2008). Skilled and educated workers are earning more labor income than unskilled and uneducated workers, and this wage gap is increasing over time (Acemoglu and Autor, 2011; Katz and Autor, 1999). At the same time, jobs are more polarized than before; i.e. low- and high-wage occupations grow relative to middle-wage occupations (Autor et al., 2006; Goos et al., 2014). Occupational wage differentials are also widening over time.

These changes are attributed to the shifts in relative labor demand for a certain group of workers (Hornstein et al., 2005). Along with some aggregate production function in mind, the force behind these phenomena is often called biased technical changes. Whether the changes are skill-biased or task-biased, measured productivity in aggregate production has changed to favor a group of workers over others. Supply-related components, such as increases in college education, attenuated wage increase pressure for more skilled occupations with higher income but were not enough to muzzle the demand force (Goldin and Katz, 2010).

In this project, we explore the technological origins of labor market changes. Specifically, we construct a measure of capital-embodied innovation using patent data. This measure covers a broader set of capital goods than computers and robots. The measure is made by a text-based matching algorithm between the description of patents from the United States Patent and Trademark Office (USPTO) and that of capital goods from Wikipedia. We then connect capital goods to occupations using tool-occupation mapping from O*NET. The mapping specifies which capital goods are used by each occupation. Finally, we calculate the number of patents applied to each occupation through the capital used in performing occupational tasks. The changes in the number of patents over time are our measures of CEI. Variations in the sets of capital goods used by occupations are a useful source for the identification of the effect of the CEI.

We associate this measure with labor market changes at the occupation level and use it to evaluate the importance of technological factors for labor market trends between 1980 and 2015. Specifically, we focus on whether the CEI constitutes task-biased technical changes.

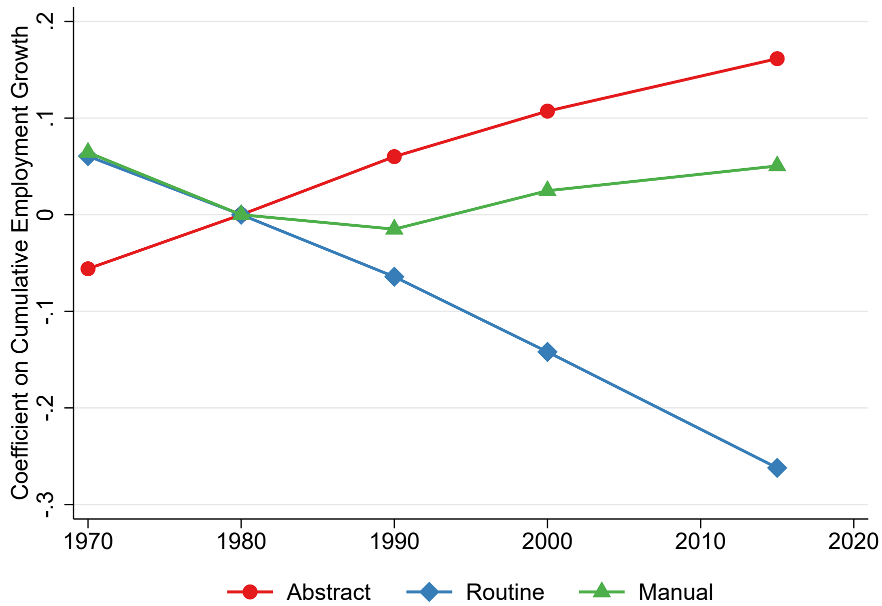
For this exercise, we use the abstract, routine, and manual task scores at the occupation level constructed by Autor and Dorn (2013). The occupation-level employment growth in the United States has been biased towards abstract occupations and against routine occupations. Figure 1 plots the OLS coefficient of task scores on cumulative log employment growth since 1980 at the occupation level. In 2015, for example, one standard deviation higher routine task score predicts 26 percent smaller employment growth while one standard deviation higher abstract task score predicts 17 percent larger employment growth. We show how CEI has affected this measured task-biasedness of labor market trends.

The key issue in identifying the effect of CEI on labor demand is that capital goods often have different substitutability with labor. Even the same capital good has a different relationship with various occupations. Robots, for example, are substitutes for manufacturing workers but are complements to robot engineers. Likewise, computers, as noticed by Autor et al. (2003), are substituting routine occupations disproportionately more.

Thus, we start by categorizing capital-labor relations. In doing so, we argue that what matters in shaping the substitutability is the degree of similarity between the functions of capital goods and the occupational tasks. If the Wikipedia description of a capital good is similar to the task description of an occupation from O*NET, we classify the capital-occupation pair as task-substituting. In other cases, we call that the capital is task-complementing for labor inputs. We distinguish these different types of capital in the model as well as in the data.

We build a general equilibrium model with labor markets at the occupation level to quantify the importance of CEI on changes in the labor market between

Figure 1: Coefficient of Task Scores on Cumulative Employment Growth Over Time



Notes: The Y axis is the coefficient estimate of task scores on cumulative employment growth from 1980 observations from a univariate OLS regression at the occupation level. Task scores are normalized to have a unit standard deviation.

the early 1980s and the late 2010s. Production takes occupational task composites, which require occupational labor inputs along with task-substituting and task-complementing capital goods. We allow task-substituting and task-complementing capital goods to have different elasticity of substitution with labor in the production function specification.

We then estimate parameters using the Generalized Method of Moments (GMM). A potential endogeneity problem is that the occupation-specific productivity and supply shocks can be correlated with the patent activities. To tackle this problem, we use the growth rates of academic publications that generate knowledge spillover to a certain technology fields of patents as our instrument variables. We use citations from patent to academic publications to identify the relevant academic papers for each technology fields, which creates a plausibly exogenous variation in CEI measures.

We use the estimated model to evaluate the impact of CEI on various labor market trends. Specifically, we fix the level of capital efficiency at the level of the 1980s and calculate the counterfactual equilibrium with only changes in the demand and supply residuals from the estimated model. We then compare the counterfactual equilibrium to the actual data in the late 2010s. We compute what happens to the task-biased labor market changes, job polarization, and occupational wage differentials without the CEI.

Our estimation results show that the elasticity of substitution between labor and task-substituting capital is larger than the cross-elasticity between occupational inputs. Moreover, the elasticity of substitution between labor and task-complementing capital is smaller than the elasticity of substitution across different occupational tasks. In this case, the CEI on task-substituting capital (CEI-s) reduces relative labor demand, and the CEI on task-complementing capital (CEI-c) raises relative labor demand.

From the estimated model, we discover that the CEI is task-biased in two senses. First, the CEI is higher for abstract and non-routine occupations, regardless of the capital type. This raises relative labor demand for abstract and non-routine occupations because CEI-c has a stronger effect on relative labor demand. Furthermore, routine and non-abstract occupations are more intensive in task-substituting capital, which reduces relative labor demand. Thus, a uniform CEI on task-substituting capital reduces labor demand for routine and non-abstract occupations.

Indeed, the counterfactual exercise reveals that the labor market would have experienced smaller task-biased changes without CEI, especially toward abstract occupations. The employment growth would have been 70% less biased towards abstract occupations without CEI. Moreover, jobs would have been less polarized in 1980-2015, and the rises in wage inequality across occupations would have been smaller without CEI.

Related Literature

This paper first contributes to the literature on secular shifts in labor demand by offering a framework to understand the forces behind the changes in labor demand. Overall, the labor demand has shifted to more educated and skilled workers with higher wages, as in Katz and Autor (1999) and Acemoglu and Autor (2011). At the same time, middle-wage occupations are losing their importance relative to high- and low-wage occupations in the United States. This so-called job polarization was first documented by Autor et al. (2006) in the United States and later shown to be a pervasive phenomenon in European countries by Goos et al. (2014). Using the CEI, we study whether a technological factor can explain secular trends in labor market demand.

Two economic forces are emphasized in explaining the source of these labor market trends: technological improvements and globalization. First, new technologies are considered more complementary to skilled workers and non-routine occupations (Nelson and Phelps, 1966; Krusell et al., 2000; Autor et al., 2003). Second, trade and outsourcing with developing countries disproportionately increase supplies for unskilled workers and low-wage occupations, reducing their relative productivity in the aggregate production function of developed countries (Acemoglu, 2003; Dix-Carneiro and Kovak, 2015; Burstein and Vogel, 2017). While the trade hypothesis can be easily tested and quantified using trade data, studies that emphasize the role of technological factors have a hard time testing their hypothesis.

This paper speaks to the first literature that studies technological factors behind labor market changes. Previous studies often focus on a few episodes of technological changes, such as computerization by Autor et al. (2003) and automation by Acemoglu and Restrepo (2020). They measure exposures to technological changes and associate these exposures with outcome variables in the labor market. Autor et al. (2003) use worker-level computer adoption dummies from the U.S. Current Population Survey to measure computerization. Acemoglu and Restrepo (2020) use the data about the number of robots from the International Federation of Robotics to measure the automation of industry and exposure of local labor markets to robots. Recent papers study the effect of adopting artificial intelligence in the workplace, such as Webb (2019). The CEI measure developed in this project covers more extensive technology improvements by including a broader set of capital.

This paper joins the recent literature on the aggregate production function with occupational inputs such as Caunedo et al. (2021). The structure is comparable to the task-based approaches which became increasingly popular after the 2000s. Since the seminal work by Autor et al. (2003), the unit of analysis for the impact of technical changes on the labor market has been a task, which is often categorized as routine, cognitive, abstract, or manual. Technical changes in computerization or robotization are regarded as increases in the capital that substitutes labor inputs in cognitive and manual tasks. These task-based approaches offer a powerful framework for the analysis of labor-substituting technologies both empirically and theoretically (David, 2013; Acemoglu and Restrepo, 2018; Cortes et al., 2017). We contrarily focus on broader technologies that can both increase and decrease labor demand, and the unit of analysis is occupation-specific tasks. Occupation is a more informative unit of analysis in this case because of variations in capital goods used in each occupation. As long as some capital goods have more technical changes than others and those capital goods are used by only a subset of occupations, the differences in wage or employment changes can be regressed on those innovations in capital goods even when both occupations have non-routine and abstract tasks.

Lastly, this paper is related to a growing literature that applies textual analysis to patent data (Kelly et al., 2021; Argente et al., 2020; Zhestkova, 2021; Bloom et al., 2021). Webb (2019) and Kogan et al. (2019) are the most relevant papers to this paper. Webb (2019) studies innovations in AI and robots, and Kogan et al. (2019) study a broader set of technologies and their effects on the labor market. While these papers match patents with the occupation's task descriptions to measure the exposure to technologies, we match patents with capital goods used by occupations to measure capital-embodied innovation. Furthermore, we study the heterogeneity of technologies by classifying them into task-complementing and task-substituting.

The remainder of the paper is organized as follows. Section 2 explains the empirical framework. Section 3 describes the data used for the analysis, estimation strategy, and estimation results. Section 4 presents the results from counterfactual exercises. Section 5 concludes.

2 Empirical Framework

2.1 Overview

The economy is static and consists of firms and workers. Final goods are produced with industrial outputs. Firm in each industry combines occupational-level task inputs to make industrial outputs. Occupation-level task inputs are made with capital goods and labor[1]. For example, an aerospace company combines tasks from aerospace engineers, engine mechanics, and janitors to produce its goods. The production of engine mechanics' task inputs requires not only engine mechanics but also services from capital goods such as pressure indicators and wire cutters.

Two types of capital goods enter the production of an occupational task depending on its relationship with the occupational task. First, task-substituting capital goods perform similar functions as occupational tasks. Second, task-complementing capital goods perform functions that are distinct from occupational tasks. One capital good can be task-substituting for an occupation but task-complementing for another. For engine mechanics that perform the maintenance of an engine, the engine test stand is a task-substituting capital good. For aerospace engineers that develop new aircraft, the engine test stand is a task-complementing capital good.

The labor market is distinguished by occupations but not by industries. Thus, the wage is equalized for an occupation across industries, and workers are indifferent across industries. Workers choose one occupation that gives them the highest utility after taking wages and idiosyncratic utility into account. Firms from different industries come to the labor market and hire workers of different occupations at a

[1] The tasks are differentiated across occupations.

set of competitive prices that clears all occupation-level labor markets.

Capital goods are elastically supplied at fixed user costs. Different occupations require different bundles of capital goods with different user costs. Also, different industries require different intensities of capital goods even for a given occupation. Thus, the user costs of capital goods differ across occupations and industries. CEI affects the price of capital bundles, the productivity of capital bundles in the production function, and the relative demand for occupational task inputs.

2.2 Production of Capital

Competitive capital good producers combine different capital goods to make occupation and industry specific bundles of task-complementing and task-substituting capital. Different capital goods are combined with Leontief technology to produce capital bundle, k_{io}^{j} of type j which is used by occupation o in industry i as follows:

$$k_{io}^{j} = Z \cdot \min\{x_{io1}^{j}/\kappa_{io1}^{j}, \ldots, x_{ioN}^{j}/\kappa_{ioN}^{j}\}\,, \tag{1}$$

where Z is the factor-neutral conversion rate between capital inputs and capital bundle, x_{ion}^{j} is the amount of capital goods used, and κ_{ion}^{j} is the fixed-cost share of capital good n in the composition of capital type j. $\sum_n \kappa_{ion}^{j} = 1$. j takes two values, s and c. $j = s$ denotes task-substituting capital and $j = c$ denotes task-complementing capital.

We have non-arbitrage condition given as $\sum_n q_n \kappa_{ion}^{j} = Q_{io}^{j} Z$, where Q_{io}^{j} is the price of capital bundle and q_n is the price of capital input n. The user cost of the capital bundle is given by the zero profit condition:

$$\begin{aligned} r^j_{io} &= \sum \delta_{in} \frac{x^j_{ion} q_n}{k^j_{io}} \\ &= \sum \delta_{in} \frac{x^j_{ion} q_n}{k^j_{io} Q^j_{io}} Q^j_{io} \\ &\equiv \bar{\delta}_{io} Q^j_{io}, \end{aligned} \tag{2}$$

where δ_{in} is the depreciation rate of capital good n in industry i. The user cost of capital bundle is the product between capital bundle price and the average user cost of individual capital goods weighted by their cost shares, $\bar{\delta}_{io}$.

The technology base for the capital bundle is an arithmetic average of knowledge base for individual capital goods.

$$P^j_{io} = \sum_{n=1}^{N} \frac{x^j_{ion}}{k_{ion}} \#\text{Patent}_n = \sum_{n=1}^{N} \kappa^j_{ion} \#\text{Patent}_n \,, \tag{3}$$

where $\#\text{Patent}_n$ is a measure of capital-embodied knowledge base for capital good n and defined in Section 3.1 as the average number of patents applied to capital type n. From now on, we call the change in technology base index P^j_{io} as CEI-j ($j = s$ or c; s for task-substituting capital and c for task-complementing capital). This expression for technology base enters the price of capital bundles, r^j_{io}, as well as the productivity of the capital bundle, z^j_{io} as follows:

$$\begin{aligned} \log r^j_{io} &= -\gamma^1_j \log P^j_{io} + \log \omega^j_{io1}, \\ \log z^j_{io} &= \gamma^2_j \log P^j_{io} - \log \omega^j_{io2} \,, \end{aligned} \tag{4}$$

where ω^j_{io1} and ω^j_{io2} are components of capital price and productivity that are not explained by CEI. A positive γ^1_j implies that the user cost of capital bundle gets cheaper with CEI-j. For example, the innovation in computer technology made the price of computer service much cheaper than before. Also, a positive (negative) γ^2_j implies that the productivity of quality-adjusted capital stock increases (decreases) with CEI-j. Unlike the effect of CEI on the price of capital bundle, the productivity of quality-adjusted capital stock does not necessarily increase with the CEI. A smaller computer reduces the maintenance cost of computer system. At the same time, a more sophisticated computer technology implies that firms have to offer training to workers to cope with a new technology. Indeed, γ_s^2 is estimated negative while γ_c^2 is estimated positive in Section 3.6.

2.3 Labor Demand

Aggregate output is a Cobb-Douglas composite of industrial outputs as

$$\mathbf{Y} = \prod_i Y_i^{\alpha_i}. \tag{5}$$

Industrial outputs are made of occupational inputs with a constant elasticity of substitution.

$$Y_i = \left(\sum_o \mu_{io} y_{io}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where μ_{io} is the occupation demand shifter. Occupational inputs y_{io} is defined as

$$y_{io} = \left(z_{io}^{c\,\frac{\rho_c-1}{\rho_c}} k_{io}^{c\,\frac{\rho_c-1}{\rho_c}} + \left(z_{io}^{s\,\frac{\rho_s-1}{\rho_s}} k_{io}^{s\,\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}} \right)^{\frac{\rho_s}{\rho_s-1}\frac{\rho_c-1}{\rho_c}} \right)^{\frac{\rho_c}{\rho_c-1}}, \tag{7}$$

where k_{io}^c is task-complementing capital, z_{io}^c is its productivity, k_{io}^s is task-substituting capital, z_{io}^s is its productivity, and l_{io} is the labor. Following in Krusell et al. (2000), we assume the nested CES structure to specify different substitutability between production inputs. ρ_s governs the elasticity of substitution between task-substituting capital and labor, while ρ_c governs the elasticity of substitution between task-complementing capital and labor. The nested CES structure implies that the elasticity of substitution between task-complementing capital and task-substituting capital is also ρ_c.

Input ratios between occupational labor and capital are determined with relative input prices as follows:

$$\frac{r^s_{io}}{w_o} = z_{io}^{s\,\frac{\rho_s-1}{\rho_s}} \left(\frac{k^s_{io}}{l_{io}}\right)^{-\frac{1}{\rho_s}}, \tag{8}$$

$$\frac{r^c_{io}}{w_o} = \left(z_{io}^{s\,\frac{\rho_s-1}{\rho_s}} k_{io}^{s\,\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_s-\rho_c}{(\rho_s-1)\rho_c}} z_{io}^{c\,\frac{\rho_c-1}{\rho_c}} k_{io}^{c\,\frac{-1}{\rho_c}} l_{io}^{\frac{1}{\rho_s}}. \tag{9}$$

After plugging the optimal input ratio from Equation (8) into Equation (9), we get the following equation.

$$\frac{r^c_{io}}{w_o} = \Theta_{io}^{\frac{\rho_s-\rho_c}{\rho_s\rho_c}} z_{io}^{c\,\frac{\rho_c-1}{\rho_c}} \left(\frac{k^c_{io}}{l_{io}}\right)^{\frac{-1}{\rho_c}}, \tag{10}$$

$$\begin{aligned} \Theta_{io} &= \left(z_{io}^{s(\rho_s-1)} \left(\frac{r^s_{io}}{w_o}\right)^{1-\rho_s} + 1\right) \\ &= \left(P_{io}^{s\tilde{\gamma}_s(\rho_s-1)} \left(\frac{\tilde{\omega}_{io}}{w_o}\right)^{1-\rho_s} + 1\right)^{\frac{\rho_s}{\rho_s-1}}. \end{aligned} \tag{11}$$

Equation (11) defines the marginal product of labor for the inner CES composite after the inner maximization. In this equation, $\tilde{\gamma}_s$ is the sum of γ^1_s and γ^2_s, and $\tilde{\omega}^s_{io}$ is the sum of ω^s_{io1} and ω^s_{io2}. If $\gamma_s > 0$, Θ_{io} increases in P_{io} unambiguously. In words, $\tilde{\gamma}_s = \gamma^1_s + \gamma^2_s > 0$ implies that the price of capital per productivity unit is cheaper with more CEI. Then, the same labor input can produce more inner composites for occupational task input production.

Equation (10) expresses how the input ratio between task-complementing capital and labor is determined *after* inner optimization. Whether CEI-s raises or reduces labor intensity relative to task-complementing capital depends on the sign of $\rho_s - \rho_c$. CEI-s stimulates substitution towards task-substituting capital and reduce relative labor demand for a given demand for inner CES composite. On the other hand, the CEI-s lowers shadow price of the inner CES composite and increases overall demand for the inner composite. If $\rho_s > \rho_c$, the former effect dominates, and vice versa.

Further plugging in the optimal input ratio into Equation (7), we derive the marginal product of labor for the occupational input after inner and the outer CES optimization.

$$\begin{aligned}\tilde{y}_{io} &= \Theta_{io}^{\frac{\rho_s-\rho_c}{\rho_s}} \left(z_{io}^{c\frac{\rho_c-1}{\rho_c}} \left(\frac{r_{io}^c}{w_o} \right)^{1-\rho_c} + \Theta_{io}^{\frac{\rho_c-1}{\rho_s}} \right)^{\frac{\rho_c}{\rho_c-1}} \\ &= \Theta_{io}^{\frac{\rho_s-\rho_c}{\rho_s}} \left(P_o^{c\tilde{\gamma}_c(\rho_c-1)} \left(\frac{\tilde{\omega}_{io}^c}{w_o} \right)^{1-\rho_c} + \Theta_{io}^{\frac{\rho_c-1}{\rho_s}} \right). \qquad (12)\end{aligned}$$

The occupational input is simply $y_{io} = \tilde{y}_{io} l_{io}$, and $\tilde{y}_{io}$ depends only on the input prices but not input quantities. Again, $\tilde{\gamma}_c$ is the sum of γ_c^1 and γ_c^2, and $\tilde{\omega}_{io}^c$ is the sum of ω_{io1}^c and ω_{io2}^c. If $\tilde{\gamma}_c > 0$, $\tilde{y}_{io}$ increases with CEI-c. $\tilde{y}_{io}$ also increases with Θ_{io} unambiguously for fixed prices. Importantly, $d \log \tilde{y}_{io} / d \log \Theta_{io} < 1$.

Lastly, the labor demand across occupations within an industry is given by

$$\begin{aligned}\frac{w_o}{w_p} &= \frac{\mu_{io}}{\mu_{ip}} \left(\frac{y_{io}}{y_{ip}} \right)^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \frac{\left(z_{io}^{s\frac{\rho_s-1}{\rho_s}} k_{io}^{s\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}} \right)^{\frac{\rho_a-\rho_s}{(\rho_s-1)\rho_a}}}{\left(z_{ip}^{s\frac{\rho_s-1}{\rho_s}} k_{ip}^{s\frac{\rho_s-1}{\rho_s}} + l_{ip}^{\frac{\rho_s-1}{\rho_s}} \right)^{\frac{\rho_a-\rho_s}{(\rho_s-1)\rho_a}}} \left(\frac{l_{io}}{l_{ip}} \right)^{\frac{-1}{\rho_s}} \qquad (13) \\ &= \frac{\mu_{io}}{\mu_{ip}} \left(\frac{\tilde{y}_{io}}{\tilde{y}_{ip}} \right)^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \frac{\Theta_{io}^{\frac{\rho_c-\rho_s}{\rho_s\rho_c}}}{\Theta_{ip}^{\frac{\rho_c-\rho_s}{\rho_s\rho_c}}} \left(\frac{l_{io}}{l_{ip}} \right)^{\frac{-1}{\sigma}}. \qquad (14)\end{aligned}$$

Equation (14) shows that the increase in $\tilde{y}_{io}$ from CEI-c increases relative labor demand for o if $\sigma > \rho_c$, as in Caunedo et al. (2021). If $\sigma > \rho_c$, the demand for the occupational inputs increases more elastically than the substitution toward task-complementing capital, increasing relative labor demand. An increase in Θ_{io} from CEI-s raises both $\tilde{y}_{io}$ and Θ_{io}. Since $d \log \tilde{y}_{io} / d \log \Theta_{io} < 1$, $\rho_s > \sigma$ implies that CEI-s reduces relative labor demand. Thus, the estimated values of elasticities determine how labor demand responds to capital-augmenting productivity changes.

P_{io}^s directly affects labor demand across occupations by changing μ_{io} as

$$\log \mu_{io} = \gamma_s^3 \log P_{io}^s + \gamma_c^3 \log P_{io}^c + \log \omega_{io3}\,, \tag{15}$$

where ω_{io3} is the unexplained component of the occupation demand shifters. A positive γ_j^3 implies that the occupational task inputs become more valuable in the production with more CEI than the decrease in the production cost predicts and vice versa.

2.4 Labor Supply and Equilibrium

The supply side follows the standard discrete choice model pioneered by McFadden (1973). The economy has an exogeneously given **L** amount of ex ante homogeneous workers indexed by $i \in [0, \mathbf{L}]$. Worker i observes wage of each occupation determined in the market, w_o, occupation-specific utility ξ_o, and idiosyncratic utility realized for each occupation ν_{io}. The worker chooses an occupation that gives the highest utility. Workers have the same wage and utility component across industries for a given occupation. Thus, they are indifferent across industries after choosing an occupation. The occupation choice problem can be written as the follows:

$$o^* = \underset{o}{\operatorname{argmax}} \left\{ \log w_o + \log \xi_o + \nu_{io} \right\}. \tag{16}$$

Assuming that ν_{io} follows an i.i.d. Type 1 Extreme Value Distribution with scale parameter $1/\beta$, we can get the following iso-elastic labor supply function.

$$\frac{L_o}{\mathbf{L}} = \frac{\exp(\beta \log w_o + \beta \xi_o)}{\sum_p \exp(\beta \log w_p + \beta \xi_p)}. \tag{17}$$

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

3 Estimation

3.1 Data

First, we collect a list of capital goods used by occupations. We use "tools used" data in O*NET, where we can see a list of capital goods used by different occupations.[2] O*NET collects capital goods such as machines or equipment that are essential to perform their occupation roles (Dierdorff et al., 2006). For example, aerospace engineers use capital goods such as lasers, and construction laborers use asphalt saws. We have 775 occupations, and each of them has 39 capital goods on average.[3] There are 4,180 unique capital goods in the data. Capital goods have their title and United Nations Standard Products and Services Code (UNSPSC).

We use patent data from the United States Patent and Trademark Office (USPTO).[4] It has the universe of patents registered in the U.S. We use application year, technology classes, type of patents, title, and abstract of patents. Application year instead of grant year is used since the application year is closer to the actual innovation year. We restrict our samples to utility patents and exclude design patents to focus on quality improvement. As a result, we have 6.1 million utility patents from 1970 to 2015.

Data from the Census Bureau is used to construct mean wage and employment level by occupation, industry, and year. We use the Decennial Census 1970, the Decennial Census 1980, and the American Community Survey (ACS) from 2015 to 2019 for observations in 1970, 1980, and 2015, respectively.[5] Mean wage is measured by the average weekly wage earnings and computed as the annual labor income divided by the number of weeks worked last year. Employment size at the occupation level is the number of people with the occupation code[6]. We focus on workers

[2]We use version 25.0, updated in August 2020.

[3]Median is 29, and the standard deviation is 36.4.

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

[5]We use the ACS samples from multiple surveys to increase the size of the samples used in each occupation and skilled labor cell.

[6]The labor income variables are measured based on the previous year of the survey. Unlike the

younger than 65 years old and older than 24 years old. Among them, only samples with 40 weeks of work or more in the previous year are considered in constructing the employment and the mean wage. We drop samples with zero or missing labor income. Each observation is weighted by the individual sampling weight offered by the Census Bureau. The occupation and industry codes are harmonized using the OCC1990 and the IND1990 variables provided by the Integrated Public Use Microdata Series (IPUMS).

The 2010 Standard Occupational Classification Code (SOC Code) on O*NET data is converted 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 variables. Then, the NAICS variable is aggregated to the 63 NAICS industries in National Income and Product Accounts (NIPA) by the Bureau of Economic Analysis (BEA).

We follow the steps in Caunedo et al. (2021) in imputing capital stocks and user costs of capital at the occupation by industry level. We use the fixed-cost capital estimates in the 2012 US dollar and implied depreciation rates from the BEA at the industry level over different capital good types. For details on the imputation process, see Appendix A.1.

Lastly, we borrow the task scores and the offshorability of tasks at the occupation level from Autor and Dorn (2013). They follow Autor et al. (2003) to measure routine, abstract, and manual task scores from job task requirements from the Dictionary of Occupational Titles by the US Department of Labor. Specifically, the abstract task score is measured as an arithmetic average of the DCP (direction, control, and planning of activities) and GED-MATH (quantitative reasoning requirements). The routine task score is computed as an arithmetic average of STS (adaptability to work

Current Population Survey, the occupation codes are surveyed only as of the time of the survey, not as of the previous year. Thus, we are using the current occupation code as a proxy to the last year's occupation code. In the Current Population Survey samples with the same sample selection, only 7 and 10 percent of workers change their occupation code between the previous year and the March of 1980 and 2015, respectively. We do not use the CPS because of its small sample size.

requiring set limits, tolerances, or standards) and FINGDEX (finger dexterity). The manual task score comes from EYEHAND (eye, hand, foot coordination) from Autor et al. (2003). Offshorability index is an average between Face-to-face Contact and On-Site Job variables constructed from O*NET by Firpo et al. (2011).

3.2 Task-Complementing and Task-Substituting Capital

We classify capitals into two groups: task-substituting capital and task-complementing capital. We compare the description of capital goods and the tasks of the occupation and consider the capital as task-substituting if they are similar and task-complementing if they are not similar. The basic idea is that if the function of the capital is similar to the tasks of the occupation, the capital goods can substitute labor. On the other hand, if the function of the capital is not similar to the task of occupation, but the occupation still uses the capital, it is less likely to substitute labor. A capital good can be task-substituting to one occupation but task-complementing to another occupation because different occupations have different tasks.

We use "Task Statements" data that has a list of tasks of the occupation from O*NET.[7] Each occupation has 22.9 tasks on average.[8] For example, an aerospace engineer has tasks such as "Evaluate product data or design from inspections or reports for conformance to engineering principles, customer requirements, environmental regulations, or quality standards".

For descriptions of capital goods, we use their Wikipedia pages.[9] Wikipedia has a broad coverage of products, and its articles usually include a technical description, which makes it easy to match with patents. We search the title of a capital good using Wikipedia API and download the entire text of the corresponding article.[10] Among 4,180 capital goods, we could find Wikipedia pages for 1,825 capital goods.

[7] We use a version of 25.0, updated in August 2020.

[8] Median is 23 and the standard deviation is 6.45

[9] O*NET provides only the title of the capital goods, not a description.

[10] wikipediaapi package in Python, https://pypi.org/project/wikipedia/, We downloaded the data on 02/28/2021

We calculate text similarity between two texts following the literature, such as Argente et al. (2020) and Kogan et al. (2019). Specifically, we calculate the similarity between all the tools used by occupation with all the tasks in our data. As a result, we have similarity scores at the tool-task level. Then, for each tool-occupation pair, we aggregate the similarity from the task level to the occupation level with a uniform weight. As a result, we get the similarity score at the tool-occupation level.

Before matching the two texts, we follow the common procedure in natural language processing literature to clean the texts. First, we remove "Stopwords". "Stopwords" are the most common words in English and do not have important meanings. For example, "is", "where", and "have" are classified as "stopwords". We remove them to avoid matching two texts just because they share a lot of the function words but do not share meaningful words. Then, we lemmatize words to convert words into their standard form.[11] For example, we change "generating" or "generated" to "generate". Lemmatizing helps us to match words that have the same meaning but in different forms.

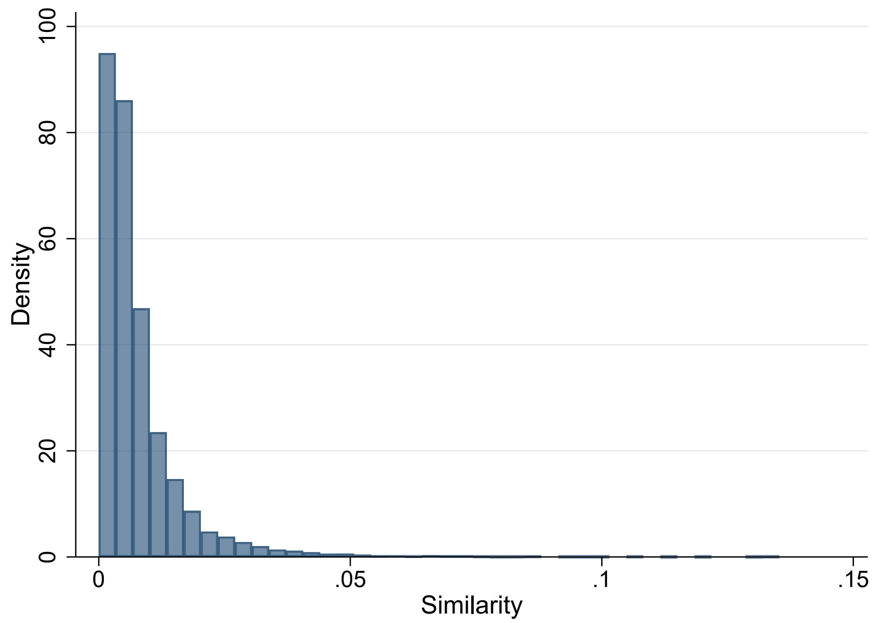
Next, we calculate the pairwise similarity between tasks and capital goods. Specifically, we vectorize each text and compute cosine similarity. This cosine similarity represents the share of overlapped single words or bigrams between two texts.[12] We also consider the fact that the importance of words would be smaller if they are used commonly. We use the term frequency-inverse document frequency (TF-IDF) to appropriately weigh words. ω_{ij} which is the weight of words i in document j, is as below.

$$\begin{aligned} \omega_{ij} &= TF_{ij} \cdot IDF_i, \\ TF_{ij} &= \frac{f_{ij}}{\sum_i f_{ij}}, \\ IDF_i &= \log\left(\frac{J}{\sum_j \mathbb{1}\{i \in j\}}\right), \end{aligned} \tag{18}$$

[11]We use the spacy package in python. https://spacy.io/

[12]Bigrams is a combination of two words such as "combustion engine", "air fuel".

Figure 2: Distribution of Similarity of Capital-Occupation Pairs



Notes: We plot the density of similarity between capital goods and occupation tasks. We first calculate text similarity between description of capital goods and each task of occupation, and aggregate at the capital-occupation level.

where J is the number of total documents. Therefore, IDF_{ij} is higher when the bigram frequently appears in the document but is lower when it appears in other documents as well. This transformation helps us to match two texts that have meaningful common words. The final similarity is between 0 to 1 by construction. If the score is 0, there is no common word, and if the score is 1, the two texts are identical.

Figure 2 shows the distribution of similarity between capital goods and occupations. The distribution is right-skewed as a lot of capital-occupation pairs do not have overlapped words. We consider a capital good as task-substituting to the occupation if the similarity is more than the 95th percentile and the remaining capital goods as augmenting. This high threshold ensures that the two different types of capital have opposite effects on the reduced form. The qualitative results are robust for reduced-form exercises. See Appendix A.4 for more discussion.

Table 1: The number of patent matched to each capital good

	Mean	Sd	Median	1Q.	3Q.	N.	Matching rate (%)
Patent (1970s)	39.53	94.94	7.92	2.00	30.65	1,802	23.83%
Patent (1980s)	81.93	190.84	17.18	4.23	66.00	1,802	23.87%
Patent (1990s)	152.86	410.81	30.70	8.67	115.23	1,802	23.49%
Patent (2000s)	264.11	806.38	43.90	13.67	175.75	1,802	23.00%

Notes: Matching rate is the number of matched patent divided by the number of total patents in a given period.

3.3 Construction of CEI Measure

We measure the capital embodied technological change using patent data. To be specific, we calculate the text similarity between patent texts and the descriptions of capital goods and count the number of patents corresponding to each capital good. Then, we calculate the average number of patents per capital good at the occupation and capital group level. Since we classify the capital goods of the occupations into two groups, we have two measures of innovation for each occupation: innovation on task-complementing capital and task-substituting capital.

We follow the same procedure in the previous section to calculate text similarity between the patent and capital. The title and the abstract of patents are used for this exercise. Using the computed similarity, we assign patents to capital. Some innovations might not be relevant to any of the capital in the data, and some innovations might be relevant to many capital goods. Therefore, we allow multiple matching or non-matching depending on the similarity score. We keep at most five capital goods for each patent and keep the matching if the similarity score is higher than 0.025.[13] As a result, 27% of patents are matched with at least one capital good. Table 1 shows the summary statistics of patents for each capital good. Example 1 shows an example of sample paragraphs of matched patents and capital goods. Blue words are the common bigrams in both texts.

[13]It is the same as Argente et al. (2020). We conducted the same exercises with flexible thresholds, but the result roughly stays the same.

EXAMPLE 1

Patent: System and method for detecting deterioration of oxygen sensor
feedback type air-fuel ratio control system control air-fuel ratio air-fuel mixture fed internal combustion engine accordance information signal issued first oxygen sensor installed exhaust line engine exhaust line catalytic converter position downstream first oxygen sensor provided system control system detects deterioration first oxygen sensor

Wikipedia: Oxygen sensor
oxygen sensor lambda sensor lambda refers air-fuel equivalence ratio usually denoted electronic device measure proportion oxygen gas liquid analysed common application measure exhaust gas concentration oxygen internal combustion engine automobile vehicle order calculate required dynamically adjust air-fuel ratio catalytic converter work optimally.

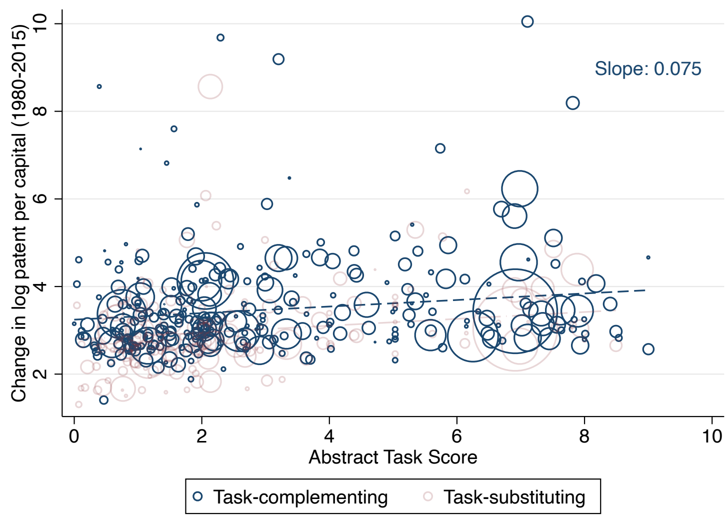
Next, we aggregate the measure of innovation of capital goods at the occupation level. Note that one occupation uses multiple capital goods. We calculate the average number of patents for each occupation and capital group. We sum the number of patents within the occupation for task-substituting and task-complementing and divide by the number of capital goods that have Wikipedia articles in each category because not all capital goods have Wikipedia articles. Table 2 shows an example where engine mechanics have the innovation on task-substituting capital goods equal to (15+10)/2 = 12.25, and the innovation on task-complementing capital goods equal to (10+5)/2 = 7.5.

Figures 3 and 4 show the scatter plots between CEI measures and abstract task scores of each occupation. The CEI measures at the occupation level are calculated across different industries weighted by the 1980 wage bill share across industries. The size of the circle corresponds to the aggregate wage bill in 1980. Note that the occupation with no task-substituting capital does not appear in the scatter plot for CEI-

Table 2: Example of counting patents at occupation level

Occupation	Capital Goods	Type	Patents
Engine Mechanics	Pressure Indicator	substituting	15
Engine Mechanics	Engine test stand	substituting	10
Engine Mechanics	Screwdriver	augmenting	10
Engine Mechanics	Wire cutter	augmenting	5

Figure 3: Abstract task score and CEI-c



Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

s. Both CEI-c and CEI-s measures, the numbers of patents per task-complementing and task-substituting capital good variety respectively, are biased towards occupations with higher abstract task scores.

Figure 4: Abstract task score and CEI-s

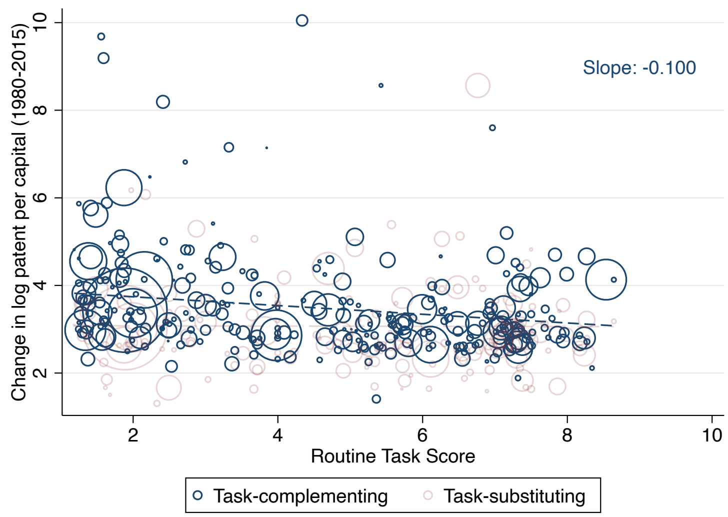
Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

For the biasedness of CEI around routine task scores, see Figures 5 and 6. The CEI of task-complementing capital is smaller for routine occupations. However, the CEI of task-substituting capital is overall unbiased over routine task scores. To sum up, innovations in 1980-2015 are more directed towards capital goods used by abstract and nonroutine occupations. But the biasedness of innovation is stronger for task-complementing capital.

Occupations with high abstract task scores are less likely to have task-substituting capital. Figure 7 shows the fraction of workers with zero task-substituting capital in 1980. About two-thirds of workers in the third quartile of abstract task scores do not have any task-substituting capital, while this share is only about 15 % for the first quartile. For the routine task scores, the share of workers with zero task-substituting capital is more balanced across quartile groups.

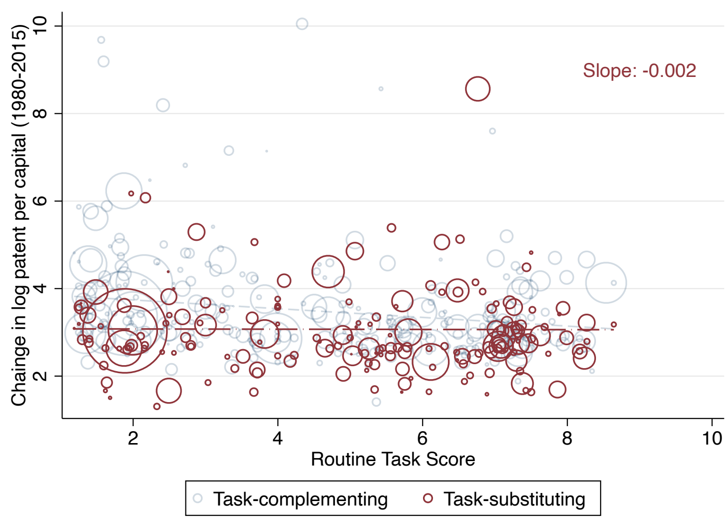
See Appendix A.2 for more properties of imputed capital stocks and their intensity across task groups and over time. Appendix A.2 shows that more rou-

Figure 5: Routine task score and CEI-c



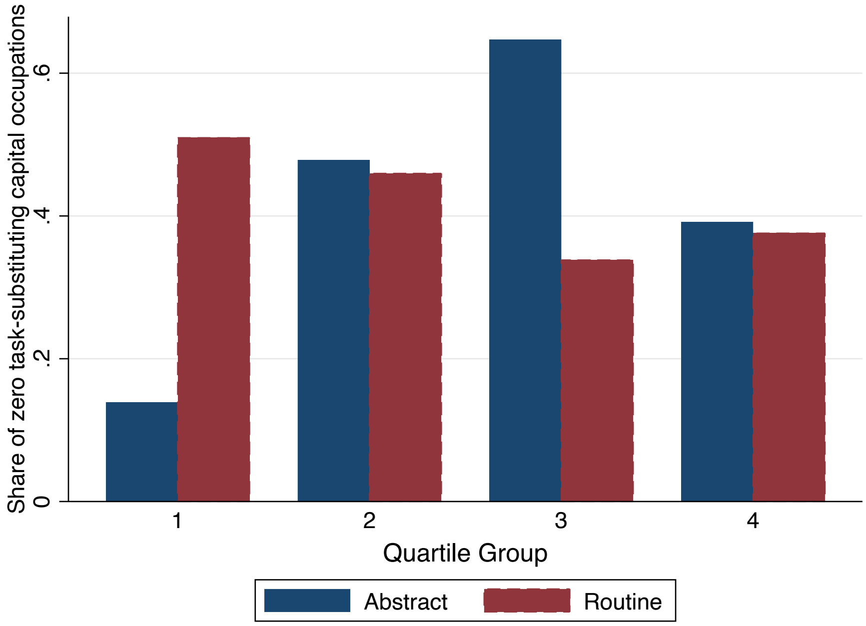
Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

Figure 6: Routine task score and CEI-s



Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

Figure 7: Share of occupations with zero task-substituting capital across task group



Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

tine and abstract occupations had a larger increase in capital stock per worker. Moreover, abstract occupations experienced a disproportionately large increase in task-complementing capital stocks, while routine occupations experienced more balanced increases between task-complementing and task-substituting capital stocks.

3.4 Instrumental Variables

3.4.1 Academic Paper Shock

A simple OLS regression of labor market variables on innovation yields a biased estimate if technical changes are directed by labor demand shocks (Acemoglu, 2002). For example, when there is another demand shock for IT sector workers, the value of innovation in the IT sector will increase, which leads to the increase in the innovation incentive on capital goods in the IT sector, such as a computer. Then, the CEI measure can be correlated with this unobserved demand shock which is correlated with wage and employment growth rates.

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, we use academic publication shocks as instruments for patents. We exploit the fact that 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 the knowledge diffusion from academic publications to patents, we use patent citations to academic publications following the innovation literature (Jaffe et al., 1993; Arora et al., 2021). Specifically, if a patent cites an academic paper, we assume that the patent receives knowledge diffusion from the academic paper. Thus, the upstream academic publications affect innovation activities in downstream patent fields.

Marx and Fuegi (2020) provide citation data from patents to academic papers in Microsoft Academic Graph (MAG hereafter, Sinha et al. (2015)), and 27% of USPTO patents cite academic papers. For academic papers, we use the Web of Science field, which has 251 different classifications. For patents, we use IPC 3-digit, which has 387 classes. We then count the number of citations from each patent class to science fields and divide it by the total number of citations to science as below:

$$\alpha_{nm} = \frac{c_{nm}}{\sum_m c_{nm}}, \tag{19}$$

where c_{nm} is the number of citations from patent class n to academic field m. α_{nm} indicates the degree of dependence of class n on field m.

Different patent classes have different shares of citations to different academic fields. For instance, there have been 42,938 citations from patents in electric power to papers in engineering, which accounts for 81% of the total citations made by electric power patents. Figure 8 plots α_{nm} within a selected sample. Engineering and chemistry are the fields that receive the most citations from patents.

Next, we construct the upstream measure for each technology class and aggregate it into the occupation level as below:

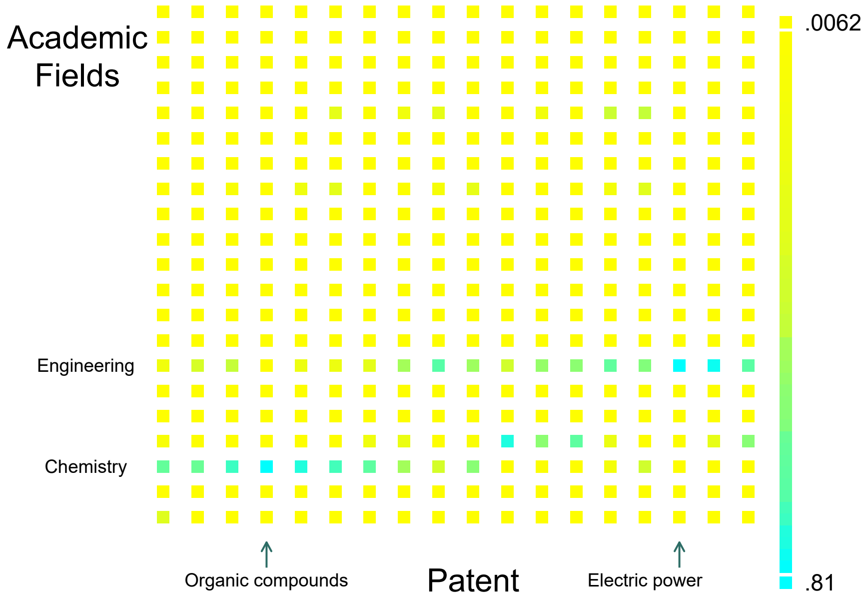
$$\text{Upstream}_{io}^{j} = \Delta \log \left(\sum_n s_{nio} \sum_m \alpha_{nm} \mathcal{P}_m \right), \tag{20}$$

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 $j = C, S$. We take the difference in logs to measure the upstream shock at the occupation level. Upstream shocks are calculated separately for CEI-s and CEI-c.

For the growth rate of publications, we collect all non-U.S. papers across different fields in MAG and calculate the growth rate between 1970 and 2015. We exclude academic papers with any affiliation from the U.S. because firms finance academic projects and increase academic publications in some fields. Figure 9 shows the distribution of the growth rate of publications[14]. The top five fields in terms of growth rate are artificial intelligence, information systems, hardware, software engineering, and control systems.

[14]The average is 2.84, the median is 2.74, and the standard deviation is 0.60.

Figure 8: Share of Citation from Patent Technology Classes to Academic Fields



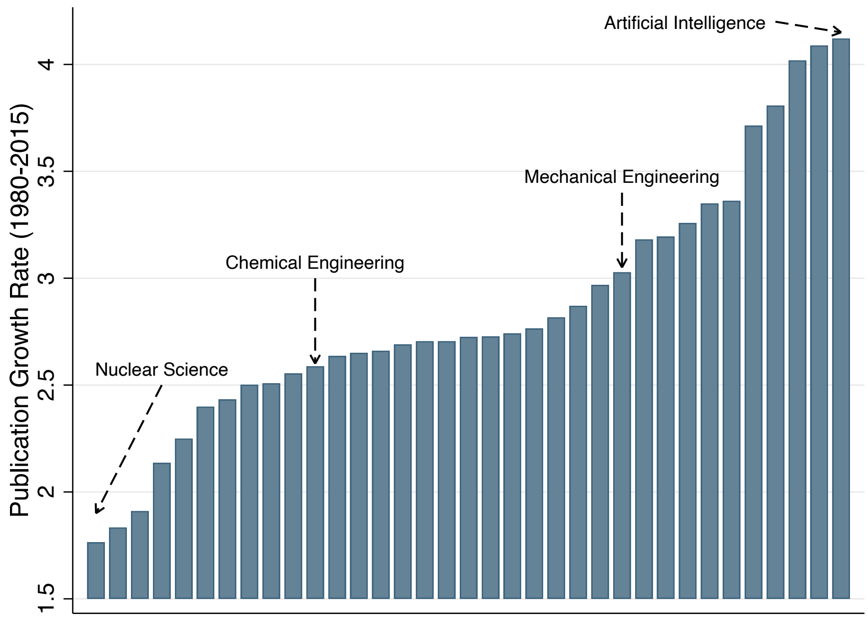
Notes: We plot α_{nm}, which is the share of citations from patent technology classes n to academic fields m. We plot IPC 3-digit patent technology classes on the X-axis and plot Web of Science academic publication fields on the Y-axis. We keep the IPC classes that have more than 50,000 citations to science in the entire period. We calculate the share of citations as the number of citations from the patent class to the academic field divided by the sum of all citations from the patent class to all papers in science. When the color gets closer to blue, it has a higher citation share.

Figures 10 and 11 show scatter plots between CEI measures and the resulting academic publication instruments at the occupation level. The publication instruments are strongly positively associated with the actual CEI measures.

3.4.2 Immigration Shock

In order to identify the elasticity of substitution in the production function separate from the effects of CEI measures, a separate supply shifter is needed. We construct an independent supply shifter using trends in Latin American immigration and heterogeneous exposures to Latin American Immigration. The number of workers born in Latin America grew by more than 8 times, from 1.4 million to 12

Figure 9: Growth Rate of Publications over Academic Fields

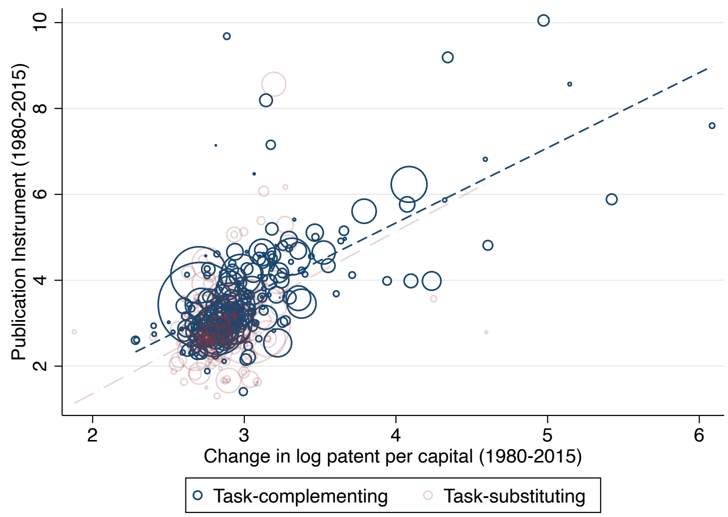


Notes: We plot the growth rate of publications between 1980–2015 over different Web of Science fields. We include fields that have more than 1,000 citations from patents. Publication data is from MAG. We count publications outside the U.S.

million, between 1980 and 2015, compared to the number of workers born in the U.S. which grew only by slightly more than twice from 61.8 million to 125 million in the same period. As a result, the share of workers born in Latin America in total US employment increased from 2.3 percent in 1980 to almost 10 percent in 2015 in Figure 12.

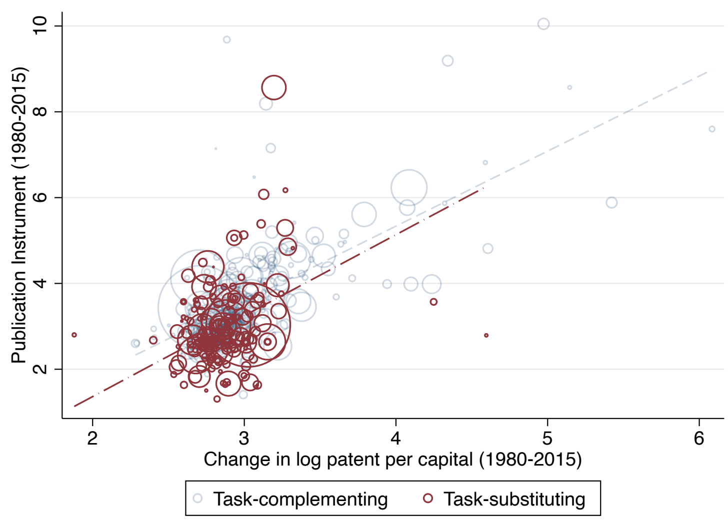
The immigrants from Latin America are likely to have comparative advantages different from workers born in the U.S. Thus, their occupation choice is different from the occupation choice of workers born elsewhere. Figure 13 shows the histogram of the share of workers from Latin America in 1980 across different occupations. Each occupation is weighted by their employment size in 1980. The share of workers from Latin America varies across occupations. For example, in 1980, 13.5 percent of farm workers are from Latin America while less than 0.2 percent of speech therapists are born in Latin America. Then, a surge in immigration from

Figure 10: CEI-c and Publication Instrument



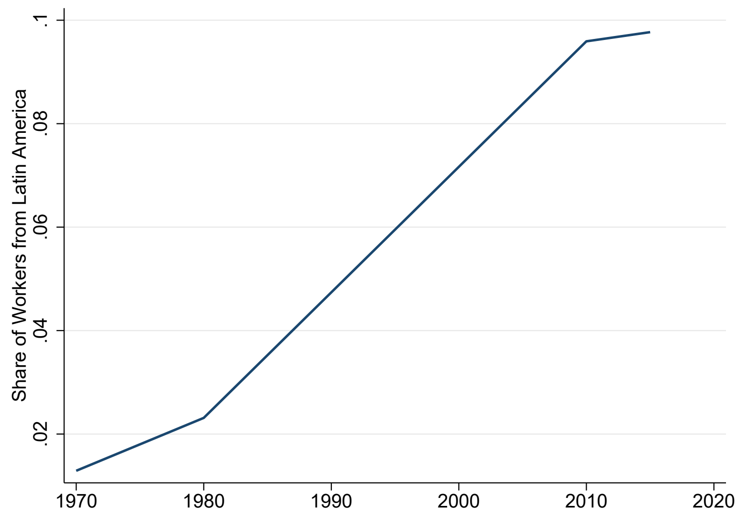
Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

Figure 11: CEI-s and Publication Instrument



Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

Figure 12: Share of Workers Born in Latin America over Time



Notes: This figure plots the share of workers in the U.S. who were born in Latin America over years.

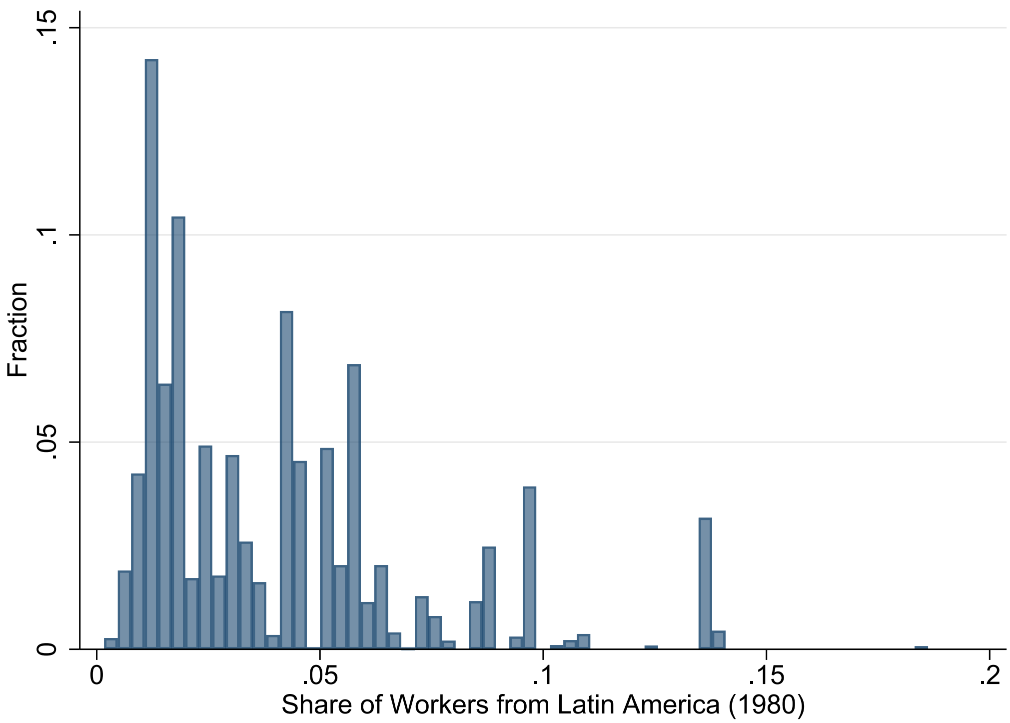
Latin America would have a disproportionately large impact on the labor supply of farm workers.

We measure the heterogeneous exposure to immigration shock based on the share of workers from Latin America in 1980. Specifically, let $l_o^{c,1980}$ denote the number of workers from Latin American country c in 1980 at occupation o and l_o^{1980} denote the total number of workers in 1980 at occupation o. Then, the total number of workers born in Latin American country c in the labor market is $L^{c,1980} = \sum_o l_o^{c,1980}$. Likewise, we can calculate the number of workers in 1980 as $l_o^{c,2015}$ and $L^{c,2015}$. Then, the Bartik immigration shock is defined as in the following equation.

$$z_o = \sum_c \frac{l_o^{c,1980}}{l_c^{1980}} \log \left(\frac{L^{c,2015} - l_o^{c,2015}}{L^{c,1980} - l_o^{c,1980}} \right). \tag{21}$$

Workers in occupation o are subtracted out from calculating the supply shock to rule out the effect of occupation-level shocks associated with more immigration from country group c.

Figure 13: Histogram of Share of Workers Born in Latin America in 1980



Notes: We calculate the share of workers born in Latin America in 1980 at the occupation level and draw the histogram of the observations. Each occupation is weighted by the numbers of workers in 1980.

3.5 Estimation Strategy

Due to the nested CES structure, we can sequentially estimate the parameters. We first estimate the elasticity of substitution for the inner CES composite between occupational labor and task-substituting capital. Then, we estimate the elasticity of substitution for the outer CES composite between the inner composite and task-complementing capital. Lastly, we estimate the elasticity of substitution across different occupational inputs. The elasticity of occupation labor can be estimated separately.

We take the difference between variables in 1980 and 2015 to estimate the model parameters. In the context of measuring capital productivity changes with the text-matching procedure, log-differencing removes time-invariant measurement errors associated with text-matching errors. For example, if the Wikipedia articles about lasers are easier to be matched 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 matching errors.

We estimate parameters in Equation (8) with the Generalized Method of Moments (GMM). We first express Equation (8) as follows:

$$\Delta \log \left(\frac{\omega_{io}^s}{w_o} \right) = \gamma_s \Delta \log P_{io}^s - \frac{1}{\rho_s} \Delta \log \left(\frac{k_{io}^s}{l_{io}} \right). \tag{22}$$

In this equation, $\gamma_s = \gamma_s^1 + \frac{\rho_{s-1}}{\rho_s} \gamma_s^2$ and $\omega_{io}^s = \omega_{io1}^s \omega_{io2}^{s \frac{\rho_{s-1}}{\rho_s}}$. We further assume that $\Delta \log \omega_{io}^s$ can be expressed as follows:

$$\Delta \log \omega_{io}^s = \alpha^s X_o + \phi_i^s + \epsilon_{io}^s , \tag{23}$$

where ϕ_i^s is the industry-specific productivity shock for task-substituting capital. X_o includes the offshorability index and the task scores at the occupation level. We further assume that, for selected instrumental variables Z_{io}^s, $\mathbb{E}(Z_{io}^s \epsilon_{io}^s)$. Then, the GMM objective function is given

$$\begin{aligned} &(\hat{\rho}_s, \hat{\gamma}_s) \qquad (24) \\ &= \underset{\rho_s, \gamma_s}{\operatorname{argmin}} \sum_o wb_{io}^{1980} \Big(\Delta \log \left(\frac{1}{w_o} \right) + \frac{1}{\rho_s} \Delta \log \left(\frac{k_{io}^s}{l_{io}} \right) - \gamma_s \Delta \log P_{io}^s - \alpha^s X_o - \phi_i^s \Big) Z_{io}^s , \end{aligned}$$

where wb_{io}^{1980} is the wage bill of occupation o in industry i in 1980. The set of instrumental variables include the immigration shock, the academic publication shock for task-substituting capital, and X_o. The parameters in this objectives are just identified with the number of GMM restrictions equal to the number of parameters. The identification assumption for γ_s is that, after controlling for the offshorability and the task scores, the non-US publication shock is orthogonal to productivity and depreciation shocks.

In the first order condition, a decrease in user costs of capital, r^s_{io}, is isomorphic to an increase in the productivity of capital, $z_{io}^{\frac{\rho_s-1}{\rho_s}}$. Thus, we can not differentiate the effect of CEI-s through reductions in user costs of capital and improvements of productivity for capital. Thus, we regress Equation 5 with imputed user costs of capital to estimate γ^1_s and get the estimate of γ^2_s from the estimate of γ_s. The residuals give $\hat{z}^s_{io}$, estimates for z^s_{io}. Then, we can define $\hat{\Theta}_{io}$ with parameter estimates, $\hat{z}^s_{io}$, and observed input price ratios.

Parameters in Equation (10) are also estimated with the GMM. We express Equation (10) as follows:

$$\Delta \log\left(\frac{\omega^c_{io}}{w_o}\right) = \frac{\rho_s-\rho_c}{\rho_s\rho_c}\Delta\log\Theta_{io} + \gamma_c\Delta\log P^c_{io} - \frac{1}{\rho_c}\Delta\log\left(\frac{k^c_{io}}{l_{io}}\right). \tag{25}$$

In this equation, $\gamma_c = \gamma^1_c + \frac{\rho_c-1}{\rho_c}\gamma^2_c$ and $\omega^c_{io} = \omega^c_{io1}\omega_{io2}^{c^{\frac{\rho_c-1}{\rho_c}}}$. We further assume a functional form of ω^c_{io} as

$$\Delta\log\omega^c_{io} = \alpha^c X_o + \phi^c_i + \mathbf{1}^{-s}_o\kappa^c_i + \epsilon^c_{io}\,, \tag{26}$$

where the indicator $\mathbf{1}_{o\in\mathcal{G}^{-s}}$ takes value one if the occupation does not have any task-substituting capital. In this case, the marginal product of labor for the inner composite, Θ_{io}, becomes automatically one. κ^c_i addresses the mean difference between occupations with and without task-substituting capital within each industry. We use the orthogonality condition $\mathbb{E}(Z^c_{io}\epsilon^c_{io}) = 0$. Then, the GMM estimator is defined as

$$\begin{aligned}(\hat{\rho}_c,\hat{\gamma}_c) = \underset{\rho_c,\gamma_c}{\operatorname{argmin}}\sum_o wb^{1980}_{io}\Big(\Delta\log\left(\frac{1}{w_o}\right) + \frac{1}{\rho_c}\Delta\log\left(\frac{k^c_{io}}{l_{io}}\right) \\ - \frac{\rho_s-\rho_c}{\rho_s\rho_c}\Delta\Theta_{io} - \gamma_c\Delta\log P^c_{io} - \alpha^c X_o - \phi^c_i - \mathbf{1}^{-s}_o\kappa^c_i\Big)Z^c_{io}.\end{aligned} \tag{27}$$

Again, the parameter estimate are used to calculate estimates for z^c_{io}. We can formulate $\tilde{y}_{io}$ from the estimates and the observables. The instrumental variables for this estimation include the immigration shock, the academic publication shock for task-complementing capital, and X_o. As in the case of task-substituting capital, only $\gamma_c = \gamma_c^1 + \frac{\rho_{c-1}}{\rho_c}\gamma_c^2$ are identified. We use estimates for γ_c^1 from the instrumented regression of capital cost on the task-complementing CEI measure to separate the estimate of γ_c^2.

Lastly, Equation (14) is used to estimate the across-occupation elasticity σ. The demand shock for occupational tasks μ_{io} is assumed to take the following form.

$$\Delta \log \mu_{io} = \tilde{\alpha} X_o + \psi_i + \mathbf{1}_o^{-s} \tilde{\kappa}_i + \gamma_s^3 \Delta \log P_{io}^s + \gamma_c^3 \Delta \log P_{io}^c + \varepsilon_{io}. \tag{28}$$

We use the condition that $\mathbb{E}(Z_{io}^l \varepsilon_{io}) = 0$. Then, the GMM objective can be expressed as:

$$\begin{aligned}(\hat{\sigma}, \hat{\gamma}_s^3, \hat{\gamma}_c^3) = &\underset{\sigma,\gamma_s^3,\gamma_c^3}{\operatorname{argmin}} \sum_o wb_{io}^{1980} \Big(\Delta \log w_o + \frac{1}{\sigma} \Delta \log l_{io} - \frac{\rho_c - \rho_s}{\rho_c \rho_s} \Delta \log \Theta_{io} \\ &- \left(\frac{1}{\rho_c} - \frac{1}{\sigma} \right) \Delta \log \tilde{y}_{io} - \tilde{\alpha} X_o - \tilde{\psi}_i - \mathbf{1}_o^{-s} \tilde{\kappa}_i - \gamma_s^3 \Delta \log P_{io}^s - \gamma_c^3 \Delta \log P_{io}^c \Big) Z_{io}^l ,\end{aligned} \tag{29}$$

where $\tilde{\psi}_i$ is the industry-specific productivity shocks for task composites (ψ) plus industry-level normalizing factor. The normalization is needed because Equation (14) identifies the amount of labor input relative to a baseline occupation in the industry. This equation also takes the mean difference of $\Delta \log \mu_{io}$ between occupations with and without without task-substituting capital within industries. The instrumental variables Z_{io}^l include the immigration shock, publication instruments, and X_o.

The supply elasticity can be estimated in a separate block. We assume that the occupation-level labor supply shock, $\Delta \log \xi_o$, is orthogonal to a demand shifter Z_o^s; i.e. $\mathbb{E}(Z_o^s \Delta \log \xi_{io}) = 0$. The GMM objective can be expressed as the following:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_o wb_o^{1980} \left(\Delta \log L_o - \beta \Delta \log w_o \right) Z_{io}^s. \tag{30}$$

The instrumental variable for this equation is the Bartik demand shock from industry-

Table 3: Parameter Estimates - First Order Conditions

	ρ_s	γ_s	ρ_c	γ_c	σ	β
Estimate	8.290	0.043	1.554	0.075	2.456	6.270

Table 4: Parameter Estimates - Effects of CEI

	γ_s^1	γ_s^2	γ_s^3	γ_c^1	γ_c^2	γ_c^3
Estimate	0.093	-0.057	-0.079	0.038	0.032	0.057

level employment.[15]

.

3.6 Estimation Results

Tables 3 and 4 shows the estimation results. In Table 3, the estimate for ρ^s is larger than the estimate for σ, which is larger than ρ^s. As discussed in Section 2.3, these values imply that the scale effect is smaller than the substitution effect for task-substituting capital, but the reverse is true for task-complementing capital. As a result, an increase in the productivity or a decrease in the price of task-substituting capital reduces relative labor demand. On the other hand, an increase in the productivity or a decrease in the price of task-complementing capital raises relative labor demand. The supply equation estimation shows that, over the 35 year horizon, occupation labor supply is very elastic with respect to a change in wage. A 10 percent point increase in wage is associated with a 6.3 percent point increase in occupational labor supply.

Table 4 presents the estimation results for the coefficient of CEI measures on capital user costs, capital productivity, and the residual demand for occupational task input. Estimates for γ_s^1 and γ_c^2 are significantly positive. Thus, both CEI-s and CEI-c

[15]We first calculate the industry-level demand shocks for occupation o in industry i by $\Delta \log(\sum_{p \neq o} l_{ip})$. Then, we take the average across industries weighted by the employment level in 1980 for each occupation.

are associated with a large reduction in the user cost of capital, raising capital intensity in occupational task production. The estimate for γ_c^2 is negative, but the estimate for γ_c^2 is positive. γ_s^2 and γ_c^2 govern how CEI-s and CEI-c affect the measured productivity of capital, after taking their effect on capital cost into account. Thus, CEI-s reduces measured productivity of task-substituting capital relative to labor inputs whereas CEI-c raises measured productivity of task-complementing capital.

Nonetheless, $\gamma_s^1 + \gamma_s^2$ and $\gamma_c^1 + \gamma_c^2$ are both positive. As a result, in Equation (14), the marginal product of labor for the inner composite, Θ_{io}, increases with CEI-s, and the marginal product of labor for the occupational task input, $\tilde{y}_{io}$, increases with CEI-c. Combining these results with $\hat{\rho}_s > \hat{\sigma} > \hat{\rho}_c$ implies that CEI-s (CEI-c) reduces (raises) relative labor demand. These results are consistent with reduced-form findings in Appendix A.3.

4 Counterfactuals

We aim to address the following question: what happens to the labor market and its summary statistics without CEI? To address this question, we calculate a counterfactual equilibrium with the CEI measures fixed at the level of 1980. Other demand and supply shocks stay at their levels of 2015. Using the counterfactual labor market outcomes, we replicate the statistics that summarize changes in the labor market.

We study how task-biased labor market changes are without the CEI between 1980 and 2015. We use an auxiliary linear regression equation to measure the task-biasedness of labor market changes. The estimate for the coefficient of task score on labor market changes summarizes how biased changes in the labor market were over abstract and routine task scores. Specifically, we address changes in employment and wage between 1980 and 2015 over task scores.

Table 5 shows the task-biasedness results after running the regression equation of employment and wage changes in logs on task scores at the occupation level. No-

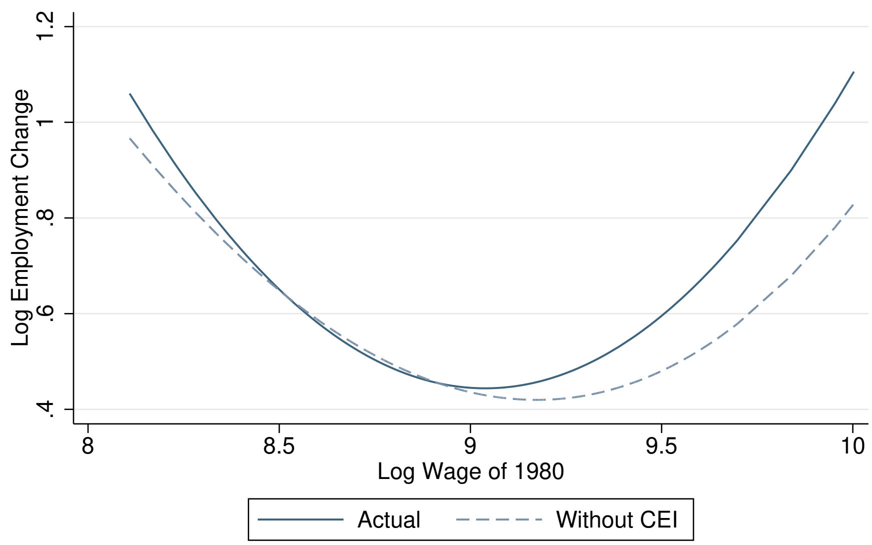
Table 5: Counterfactual - Task-biasedness

	Abstract Score		Routine Score	
	Employment	Wage	Employment	Wage
Without CEI	0.039	0.093	-0.126	-0.033
Actual Change	0.130	0.107	-0.169	-0.040

tice that the task scores are normalized to have a unit standard deviation. In this period, if an occupation has one standard deviation higher score of abstract tasks, the occupation has 13 and 11 percentage points higher employment and wage growth rates, respectively. Without the CEI that was more biased towards abstract occupations, however, this task-biasedness is attenuated. Without the capital-augmenting effect of the CEI, one standard deviation higher abstract task score predicts about 4 and 9 percentage points higher employment and wage growth rates. Put differently, the CEI makes 70% and 13% of task-biasedness in employment and wage growth rates. As for routine task scores, the effect of the CEI is smaller. The CEI contributes to about 25% of employment growth biased against routine occupations. With an elastic labor supply, wage responses to demand-side changes are small.

Then, we elaborate on the effect of CEI on job polarization between 1980 and 2015 in Figure 14. The curve depicts a fractional polynomial prediction of employment change between 1980 and 2015 against the log weekly wage in 1980. As in David (2013), employment growth at the occupation level takes a U-shape form over the log wage level in 1980. In relative terms, the importance of middle-wage occupations becomes smaller than that of high- and low-wage occupations. The counterfactual equilibrium without CEI features a smaller increase in employment for the high-wage and low- occupations. For low-income occupations, the effect of CEI is minimal because more demand for occupational service counteracts relatively stronger substitution towards task-substituting capital. Unlike the computerization and the automation literature that highlights the effect of capital on low- and middle-skill occupations, the CEI in this paper emphasizes the role of capital in the rise of high-skill occupations.

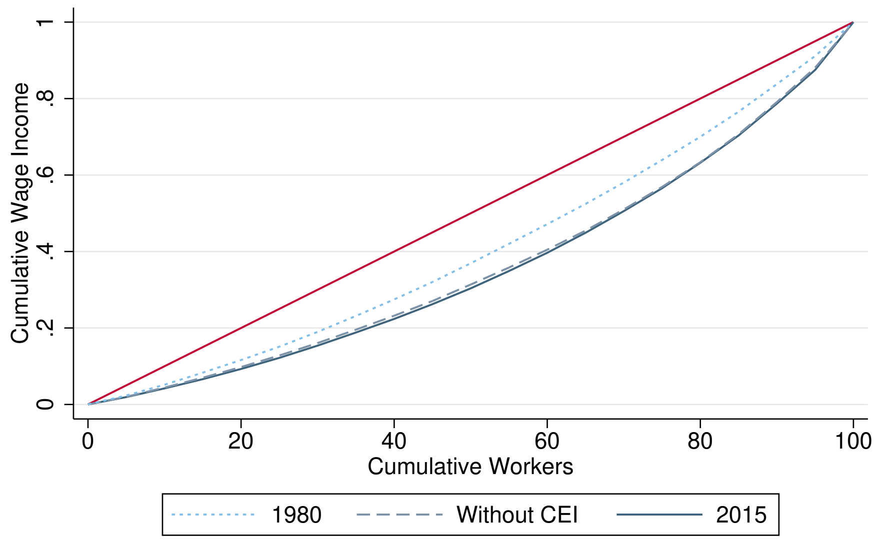
Figure 14: Counterfactual - Jop Polarization



Notes: We show the fitted line of log employment change between 1980 and 2015 across the average wage in 1980 at the occupation level. The observations are fitted with a quadratic fractional polynomial.

Lastly, we analyze how wage inequality measures would have behaved without the CEI. We draw the Lorenz curve with occupation-level wage differences in Figure 15 and calculate Gini coefficients and standard dispersion of log wage incomes in Table 6. All measures indicate that the wage income distribution would have been less unequal without CEI. As discussed in Section 3.1, task-complementing CEI is more biased toward abstract-task and high-wage occupations. Because the scale effect dominates the within-substitution effect between task-complementing capital and labor inputs, CEI contributes to a relative demand increase for abstract-task and high-wage occupations.

Figure 15: Counterfacutal - Lorenz Curve



Notes: We use employment and average wage at the occupation level to draw the Lorenz curve.

Table 6: Counterfactual - Wage Inequality

	1980	Without CEI	2015
Gini Coefficient	0.185	0.267	0.278
Dispersion of Log Wage	0.339	0.465	0.487

5 Conclusion

We develop a measure of capital-embodied innovations (CEI) from patent data. We use a text-based matching algorithm between patent descriptions and Wikipedia articles of capital goods. Occupation-level differences in the use of capital goods give useful cross-sectional variations to identify the impact of CEI on labor market outcomes. This is a novel way of using patent data to measure technological changes from the adopters' perspectives as opposed to the innovators' perspectives.

We also make an important distinction between capital goods that substitute labor inputs and capital goods that complement labor inputs in making occupational services. If the function of capital goods is similar to the tasks of occupation, the CEI on these capital goods spurs substitution towards capital goods and lowers relative labor demand for the occupation. On the other hand, if the function of capital goods is different from the tasks but still performing the task requires the capital goods, the CEI on the capital goods increases the relative labor demand for the occupation. This distinction implies that the effect of CEI on the labor market outcomes depends heavily on the direction of CEI.

With the CEI measure on patents, we could isolate technological factors from others, such as trade and outsourcing, for the labor market changes. Identifying a specific source of declines in capital price is important in projecting the future. If the price declines come from technological changes, as opposed to one-time changes in trade or market regime, the labor market changes caused by price declines will continue in the future. Thus, a long-term policy design is needed to reduce structural unemployment and lower labor market inequality. Our result implies that the CEI has been an important source of labor market changes and is likely to continue in the future.

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A Appendix

A.1 Imputation of Capital Stock and User Cost of Capital

We impute occupation-specific capital stock using procedures similar to to Caunedo et al. (2021). Each occupation has a set of capital goods in UNSPSC codes. We convert these UNSPSC codes to the NIPA capital types using the crosswalk table in Aum (2017). We use the 2012 fixed-price capital stock series to measure the quantity of capital bundles normalized in 2012. For the price of capital bundle, we use the price deflator between current-cost and fixed-cost capital stock from the BEA. We calculate depreciation rates from depreciated capital stock data from the BEA. Specifically, the depreciation rate is the ratio of depreciated capital stock in a year to the simple average between the capital stock evaluated at the end of the year and the capital stock evaluated at the end of the previous year. Lastly, we use current-cost shares to calculate the cost-weighted average of depreciation rates.

We first define the capital intensity of an occupation o for the NIPA capital type n by the number of UNSPSC codes in the "Tools used" dataset that are mapped into n. Let $\#Capital_o^{n,s}$ ($\#Capital_o^{n,c}$) denote the number of task-substituting (task-complementing) 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 type n is imputed as

$$\begin{aligned} x_{ion}^s &= \frac{l_{io}\#Capital_o^{n,s}}{\sum_p l_{ip}\#Capital_p^{n,s} + \sum_p l_{ip}\#Capital_p^{n,c}} K_i^n \\ x_{ion}^c &= \frac{l_{io}\#Capital_o^{n,c}}{\sum_p l_{ip}\#Capital_p^{n,s} + \sum_p l_{ip}\#Capital_p^{n,c}} K_i^n \end{aligned} \tag{31}$$

Thus, capital stocks are prorated across occupations with intensity-weighted number of workers. The final capital stock is given as the sum across all capital types.

$$k_{io}^s = \sum_n x_{ion}^s \tag{32}$$
$$k_{io}^c = \sum_n x_{ion}^c$$

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

$$r_{ion}^s = \mathbf{r} + \sum_n \frac{q_{ion}^s x_{ion}^s}{Q_{io}^s k_{io}^s} \delta_{in} \tag{33}$$
$$r_{ion}^c = \mathbf{r} + \sum_n \frac{q_{ion}^c x_{ion}^c}{Q_{io}^c k_{io}^c} \delta_{in}$$

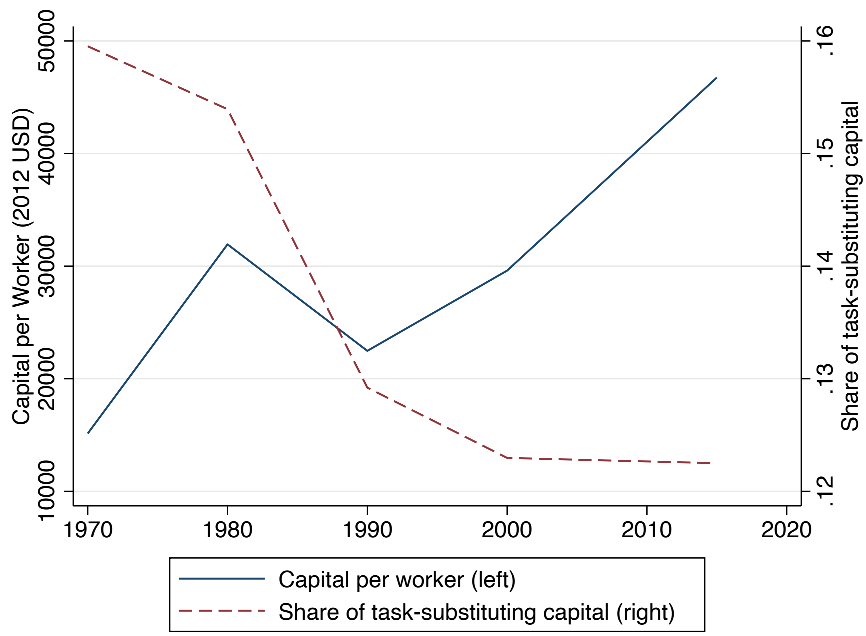
where $\mathbf{r}$ is the real interest rate and δ_{in} is the depreciation rate of capital good type. We impute δ_{in} by the ratio between current-cost depreciated capital stock in a year to the average current-cost capital between the year and the year forward. We set $\mathbf{r} = 3\%$ for a year.

A.2 Capital Stock per Worker over Time and Task Scores

This appendix shows the properties of imputed capital stock over time and in relation to the task scores of occupations.

Figure 16 shows the average fixed-cost capital stock in 2012 prices per worker and the share of task-substituting capital over time. An average U.S. worker becomes more intensive in capital evaluated in 2012 prices, over time. An average worker in 1970 was working with capital equivalent to 1,500 US dollars while an average worker in 2015 works with capital equivalent to 4,500 US dollars. The share of task-substituting capital is slowly decreasing, not increasing, over time. Task-substituting capital accounted for 16% of total capital in 1970 but accounts for 12% of total capital in 2015. This is consistent with the fact that the labor market in the U.S. shifts more towards occupations that are less substitutable with capital.

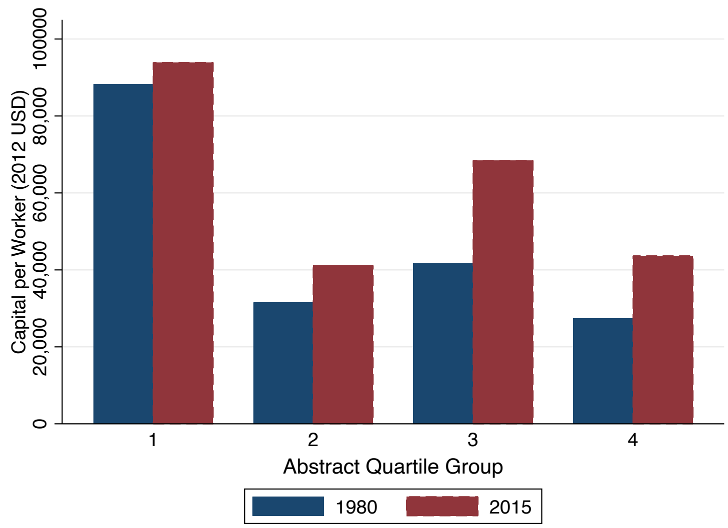
Figure 16: Capital per Worker over Time



Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

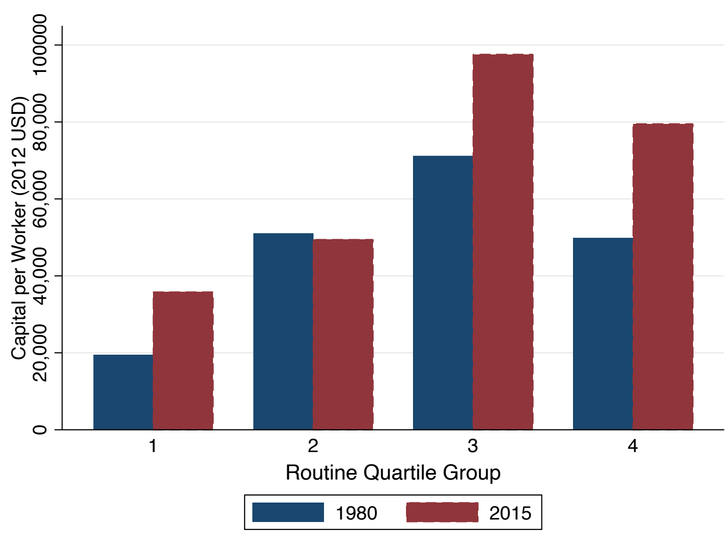
Next, Figures 17 and 18 show the average capital per worker in 1980 and 2015 over abstract and routine task score quartile groups. Less abstract and more routine occupations are more capital-intensive. However, the increment in capital stock per worker is more pronounced for more abstract and more routine task occupations. Later, we will show that the increment in the capital stock of more abstract task occupations is more tilted toward task-complementing occupations while the increment of routine occupations is more balanced between task-substituting and task-complementing capital.

Figure 17: Capital per worker across abstract task score quartile



Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

Figure 18: Capital per worker across routine task score quartile

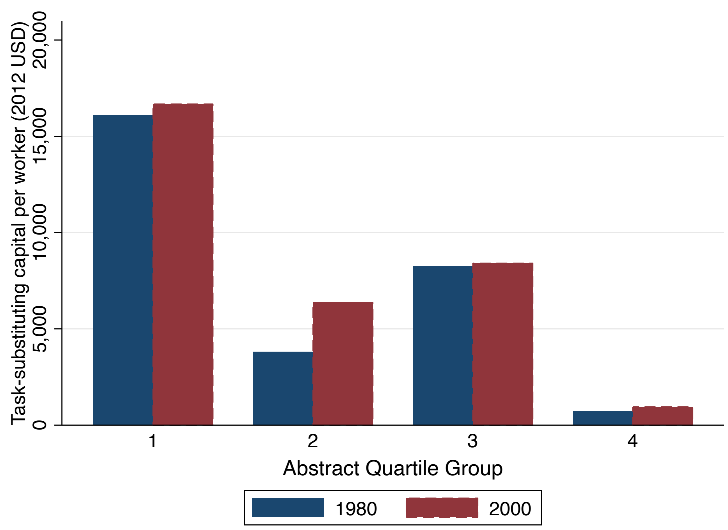


Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

Figures 19 and 20 show the changes in task-substituting capital per worker.

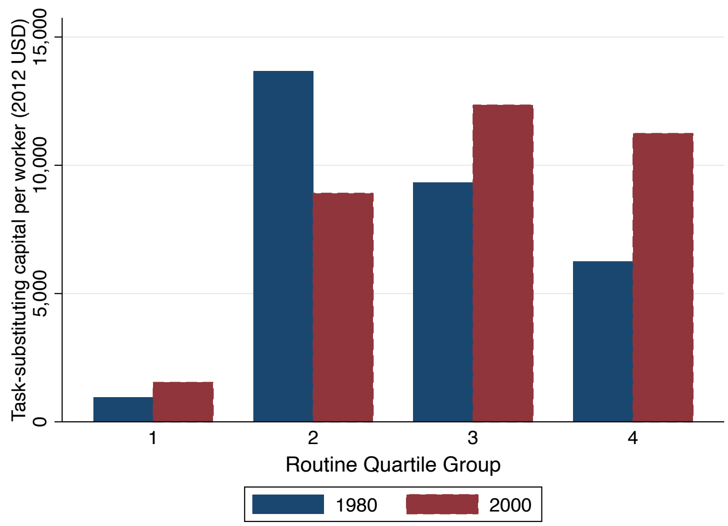
Again, less abstract occupations are more intensive in task-substituting capitals. However, the increase in task-substituting capital is now much dampened and less biased towards less abstract occupations. If occupations are categorized around routine task scores, on the other hand, the intensity in task-substituting capital increases only among the third and the third quartile of the routine scores. Thus, a uniform increase in CEI-s would have a disproportionately large effect on routine occupations.

Figure 19: Task-substituting capital per worker across abstract task score quartile



Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

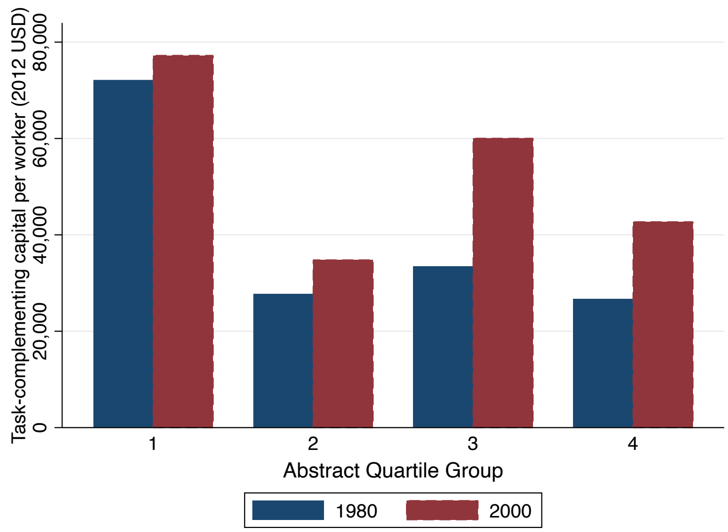
Figure 20: Task-substituting capital per worker across routine task score quartile



Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

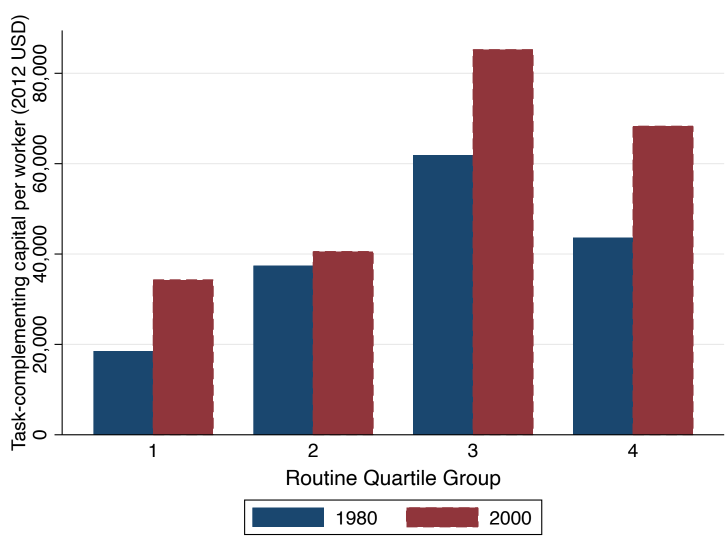
Figures 21 and 22 display the task-complementing capital stocks across abstract and routine task score quartiles, respectively. In 1980, more abstract task occupations were less intensive in task-complementing capital, but in 2015 their capital intensity is much more similar to less abstract occupations than before. In other words, the growth of task-complementing capital is more pronounced for more abstract task occupations. In Figure 21, the third and the fourth quartile of the abstract task scores had a little or negative increase in task-substituting capital. Thus, the increase in overall capital intensity for the third and the fourth quartile groups in Figure 17 entirely results from an increase in task-complementing capital stock. For more routine occupations, however, the increase in capital stock happens for both task-complementing and task-substituting capital. In Figure 22, the third and the fourth quartile groups of routine task scores experience a large increase in the task-complementing capital stock per worker as well as the increase in task-substituting capital in Figure 20.

Figure 21: Task-complementing capital per worker across abstract task score quartile



Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

Figure 22: Task-complementing capital per worker across routine task score quartile



Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

A.3 Reduced-Form Results

We show the correlation between employment changes and the CEI measures at the occupation level. Again, the CEI measures at the occupation level are calculated across different industries weighted by employment share in 1980. Occupation-level employment is calculated by aggregating occupation employment across industries.

Figure 23: Employment Change and CEI-c

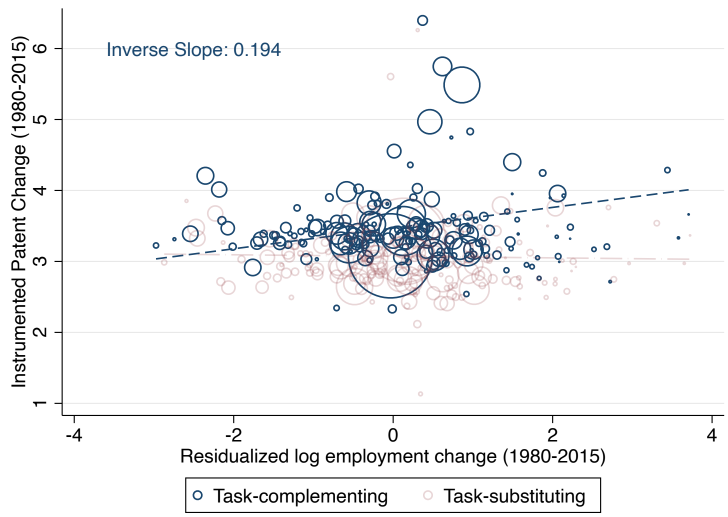
Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

Figure 24: Employment Change and CEI-s

Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

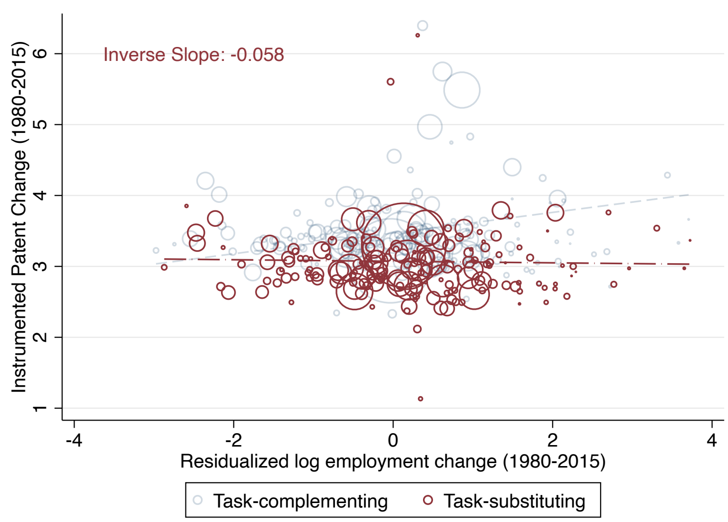
Figures 23 and 24 show the scatter plot between log employment change at the occupation level in 1980-2015 and CEI measures. Both CEI measures are positively correlated with employment changes, but the coefficient of task-complementing capital innovation is larger than that of task-substituting capital innovation. An 1 log point increase in patent per task-complementing capital is associated with a 0.2 log point additional increase in employment. On the other hand, the same increase in patent per task-substituting capital is associated with an 0.1 log point increase in employment.

Figure 25: Employment Change and Instrument for CEI-c



Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

Figure 26: Employment Change and Instrument for CEI-s



Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the wage bill of each occupation in the 1980 Decennial Census. Task scores are calculated by Autor and Dorn (2013).

As pointed out in Section 3.4.1, the OLS estimates for CEI measures can be biased if occupational task demand shocks and supply shocks affect innovation decisions for capital goods. Running an OLS regression without controlling for the other types of CEI makes a biased estimate since the two CEI measures as well as the CEI instruments are positively correlated.

To solve these issues, I use the CEI measures instrumented with academic publication shocks in Figures 25 and 26. Moreover, I regress the employment change onto the other CEI instruments and use the residualized employment changes. The scatter plot shows that, after controlling for the other CEI, the instrumented task-complementing CEI increases with log employment change. On the other hand, the instrumented task-substituting CEI now decreases with log employment change.

Table 7: Reduced-Form Results: Employment Change

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.165	0.219	0.155	0.217	
	(0.009)	(0.016)	(0.010)	(0.016)	
CEI-S	-0.028	-0.108	-0.020	-0.205	
	(0.012)	(0.032)	(0.012)	(0.037)	
Immigration			2.070	1.883	1.802
			(0.171)	(0.188)	(0.172)
Offshorability			0.035	0.062	0.043
			(0.010)	(0.011)	(0.010)
Routine			-0.031	-0.025	-0.048
			(0.004)	(0.004)	(0.004)
Abstract			0.067	0.071	0.074
			(0.004)	(0.004)	(0.004)
Manual			0.081	0.083	0.080
			(0.009)	(0.009)	(0.009)
First Stage F	-	753.8	-	605.0	-
N	10719	10719	10719	10719	11000

Table 7 summarizes coefficient estimates from the linear regression of employment changes on CEI measures and covariates. All specifications include industry dummies and industry dummies interacted with an indicator of occupations without task-substituting capital. Across all specifications, the coefficient of CEI on task-complementing capital is positive and statistically significant on changes in log employment. The linearized effect of CEI-c is robust to controlling for immigration shocks, offshorability index, and task scores at the occupation level. The OLS estimate is smaller than the IV estimates. This is consistent with a story that patenting incentives are higher with negative labor supply shock, which lowers employment growth.

For CEI on task-substituting capital, the linearized effect is negative and statistically significant for IVs for employment changes, even after controlling for other occupation-level characteristics. The OLS estimates are larger than the IV estimates, implying that patenting incentives are more responsive to demand shocks for occupational tasks.

Table 8: Reduced-Form Results: Wage Bill Change

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.191	0.207	0.168	0.194	
	(0.010)	(0.016)	(0.010)	(0.016)	
CEI-S	0.014	-0.025	0.001	-0.211	
	(0.012)	(0.033)	(0.012)	(0.038)	
Immigration			1.631	1.309	1.293
			(0.175)	(0.193)	(0.177)
Offshorability			0.040	0.070	0.052
			(0.010)	(0.011)	(0.010)
Routine			-0.030	-0.026	-0.048
			(0.004)	(0.005)	(0.004)
Abstract			0.091	0.096	0.099
			(0.004)	(0.005)	(0.004)
Manual			0.076	0.076	0.074
			(0.009)	(0.009)	(0.009)
First Stage F	-	753.8	-	605.0	-
N	10719	10719	10719	10719	11000

Table 8 shows the linear regression results on the wage bill instead. The change in wage bill is a better measure of changes in effective units of labor input if workers are heterogeneous in their productivity. The results of wage bill changes trace out the results of employment changes.

A.4 Different Thresholds

In Section 3.2, we set the threshold at the 95th percentile of the similarity score distribution for all the pairs between capital goods and occupation. This threshold successfully gives opposite signs to CEI-s and CEI-c measures in the reduced-form regression. Here we show the reduced-form results in Section A.3 after setting different thresholds for task-substituting capital. Intuitively, if the similarity increases with substitutability to labor, a lower threshold reduces the average substitutability of task-substituting capital and increases the reduced-form coefficient on employment growth. We test with the 80th, the 90th, the 94th, and the 96th percentile for thresholds and repeat the reduced-form regression exercise.

Table 9: Employment Change with 80th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.170	0.189	0.173	0.209	
	(0.009)	(0.015)	(0.010)	(0.014)	
CEI-S	-0.002	0.125	0.008	0.095	
	(0.010)	(0.017)	(0.011)	(0.018)	
Immigration			2.326	2.581	2.009
			(0.164)	(0.168)	(0.166)
Offshorability			0.041	0.025	0.049
			(0.010)	(0.010)	(0.010)
Routine			-0.018	-0.024	-0.040
			(0.005)	(0.005)	(0.004)
Abstract			0.081	0.074	0.090
			(0.004)	(0.005)	(0.004)
Manual			0.106	0.099	0.093
			(0.009)	(0.009)	(0.009)
First Stage F	-	2861.7	-	2795.2	-
N	10696	10696	10696	10696	11000

Table 10: Employment Change with 90th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.151	0.241	0.162	0.246	
	(0.009)	(0.015)	(0.010)	(0.015)	
CEI-S	0.001	0.056	0.032	0.018	
	(0.010)	(0.021)	(0.011)	(0.023)	
Immigration			2.393	2.556	1.968
			(0.169)	(0.179)	(0.168)
Offshorability			0.027	0.029	0.047
			(0.010)	(0.011)	(0.010)
Routine			-0.021	-0.015	-0.037
			(0.004)	(0.004)	(0.004)
Abstract			0.083	0.081	0.092
			(0.004)	(0.004)	(0.004)
Manual			0.094	0.100	0.090
			(0.009)	(0.009)	(0.009)
First Stage F	-	1715.5	-	1455.8	-
N	10706	10706	10706	10706	11000

Table 11: Employment Change with 94th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.163	0.213	0.155	0.221	
	(0.009)	(0.016)	(0.010)	(0.016)	
CEI-S	-0.004	0.015	0.002	-0.033	
	(0.011)	(0.022)	(0.011)	(0.024)	
Immigration			2.035	2.123	1.746
			(0.166)	(0.172)	(0.167)
Offshorability			0.033	0.040	0.044
			(0.010)	(0.011)	(0.010)
Routine			-0.032	-0.028	-0.049
			(0.004)	(0.004)	(0.004)
Abstract			0.066	0.066	0.074
			(0.004)	(0.004)	(0.004)
Manual			0.083	0.086	0.080
			(0.009)	(0.009)	(0.009)
First Stage F	-	1449.1	-	1306.1	-
N	10717	10717	10717	10717	11000

Table 12: Employment Change with 96th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.163	0.216	0.151	0.216	
	(0.009)	(0.016)	(0.010)	(0.016)	
CEI-S	-0.028	-0.129	-0.009	-0.176	
	(0.012)	(0.034)	(0.012)	(0.038)	
Immigration			2.225	2.112	1.951
			(0.171)	(0.186)	(0.172)
Offshorability			0.031	0.045	0.043
			(0.010)	(0.010)	(0.010)
Routine			-0.032	-0.030	-0.048
			(0.004)	(0.004)	(0.004)
Abstract			0.067	0.065	0.076
			(0.004)	(0.004)	(0.004)
Manual			0.088	0.084	0.087
			(0.009)	(0.009)	(0.009)
First Stage F	-	752.8	-	628.7	-
N	10719	10719	10719	10719	11000

When the threshold is too low at the 80th or the 90th percentile, the CEI measure on task-substituting capital has a positive coefficient in column (4). Still, the CEI measure on task-substituting capital has a significantly smaller coefficient than the CEI measure on task-complementing capital in all cases. The reduced-form coefficient of the CEI-s becomes negative at the 94 percentile threshold. After the 95th percentile, column (4) of each table exhibits significantly negative coefficients of the CEI-s on employment growth.

A.5 Counterfactual Details

We aim to derive the counterfactual equilibrium without the CEI in 1980-2015. We fix ω^s_{io}, ω^c_{io}, μ_{io}, α_i, r^s_{io}, and r^c_{io} at their levels in 2015, change P^s_{io} and P^c_{io} at their levels in 1980. We also fix the total employment $\mathbf{L}$ at its level in 2015. In order to run the counterfactual equilibrium, we need the two following equations.

$$1 = \frac{\alpha_i \mu_{io}}{\alpha_j \mu_{jo}} \left(\frac{Y_i}{Y_j}\right)^{\frac{1}{\sigma}-1} \left(\frac{y_{io}}{y_{jo}}\right)^{\frac{1}{\rho_a}-\frac{1}{\sigma}} \left(\frac{\Theta_{io}}{\Theta_{jo}}\right)^{\frac{\rho_a-\rho_s}{\rho_s\rho_a}} \left(\frac{l_{io}}{l_{jo}}\right)^{-\frac{1}{\rho_a}} \tag{34}$$

$$Y_i = l_{io}\left(\sum_o \mu_{io}\left(\frac{l_{io}}{l_{i0}}\right)^{\frac{\sigma-1}{\sigma}} \tilde{y}_{io}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = l_{i0}\tilde{Y}_i \tag{35}$$

Equation (34) is given by the first order conditions with respect to l_{io} and l_{jo}, respectively. Equation (35) 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. We use the manager (OCC1990 = 22) as our reference occupation.

By combining Equations (34) and (35), we get the following equation.

$$1 = \frac{\alpha_i \mu_{io}}{\alpha_j \mu_{jo}} \left(\frac{\tilde{Y}_i}{\tilde{Y}_j}\right)^{\frac{1}{\sigma}-1} \left(\frac{\tilde{y}_{io}}{\tilde{y}_{jo}}\right)^{\frac{1}{\rho_a}-\frac{1}{\sigma}} \left(\frac{\Theta_{io}}{\Theta_{jo}}\right)^{\frac{\rho_a-\rho_s}{(\rho_s-1)\rho_a}} \left(\frac{l_{io}}{l_{jo}}\right)^{-1} \tag{36}$$

The counterfactual equilibrium is calculated with the following steps.

1. Start with an arbitrary wage for each occupation w_o. We normalize w_o with the wage of managers. The initial wage was set following occupational wage in 1980.

2. Calculate labor supply at the occupation level given prices from Equation (17).

3. Compute the input ratios between task-substituting capital and labor by Equation (8) and get Θ_{io}.

4. Compute the input ratios between task-substituting capital and labor by Equation (10) and get $\tilde{y}_{io}$.

5. Get l_{io}/l_{i0} using Equation (14). Then we can derive $\tilde{Y}_i$.

6. Use Equation (36) to prorate L_0, the labor supply of managers given in step 2. This gives l_{io} and Y_i up to a constant .
7. Use Equation (34) to update the relative wage.
8. Go back to step 2. Iterate until they converge.