How Task-Biased is Capital-Embodied Innovation?*

Hyejin Park†, Younghun Shim‡

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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, this paper shows that CEI is biased toward abstract and non-routine occupations. Furthermore, the results highlight the heterogeneous effects of CEI across the capital-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 61% less biased towards abstract-task occupations without CEI. The degree of job polarization 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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†Université de Montréal; Email Address: hyejin.park@umontreal.ca
‡University of Chicago; Email Address: yhshim@uchicago.edu

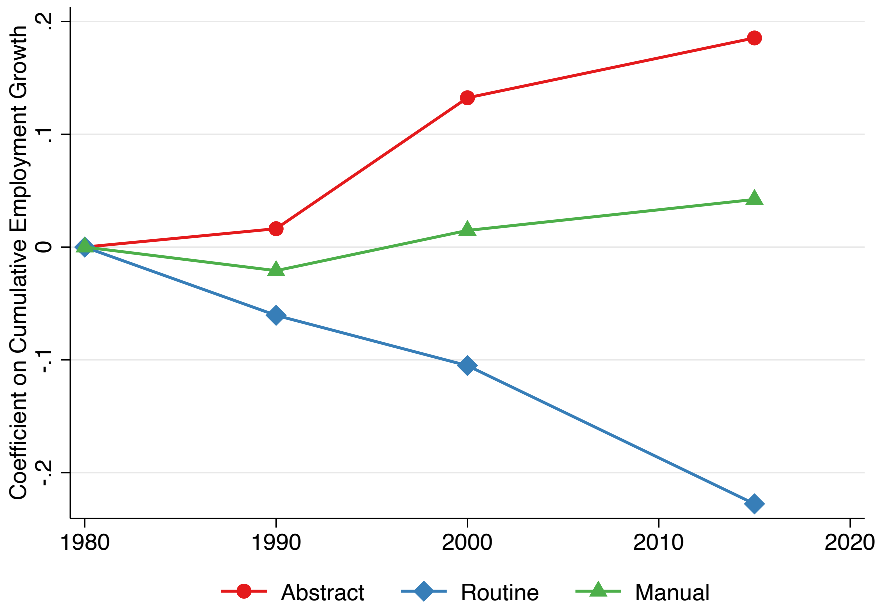
1 Introduction

Labor markets in developed economies have shown secular trends since the late 20th century. One of the labor market trends that drew the most attention in economics is the task-biased nature; employment share decreases for occupations that involve more routine tasks, which *can be accomplished with explicitly programmed rules* (Autor et al., 2003), but employment share increases for more abstract tasks that require *managerial, interactive, and formal reasoning requirements* (Autor and Dorn, 2013). To show this trend, Figure 1 plots the OLS coefficient of task scores on cumulative log employment growth since 1980 at the occupation level. In 2000, one standard deviation higher routine task score predicts 10 percent smaller employment growth while one standard deviation higher abstract task score predicts 13 percent larger employment growth. The coefficient estimates become further larger in 2015, implying that the task-biased labor market changes are accumulated over time.

Previous studies have found the source of this biased labor market change on the demand side. The measured productivity in the aggregate production function decreases (increases) disproportionately more for occupations with routine (abstract) task components, which is called task-biased technical change. The literature often emphasizes the role of new technologies in task-biased technical changes and focuses on a few episodes of new technologies, such as computerization (Autor et al., 2003) and automation (Acemoglu and Restrepo, 2018).

This paper also explores the technological origin of labor market changes but considers more comprehensive technologies than new robots and computers. Specifically, this paper constructs a measure of capital-embodied innovation (CEI) using patent data and associates the measure with the task content of labor market changes. The measure is calculated as the number of patents matched to a capital good variety through a text-based matching between the abstracts of patents from the United States Patent and Trademark Office (USPTO) and that of capital goods from Wikipedia. Using the heterogeneous capital mix for different occupations from the Occupational Information Network (O*NET), heterogeneous exposures to CEI

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. Each observation is weighted by its employment in 1980.

are measured at the occupation level. This measure is then used in an estimated model of the occupational labor market to study how the task-biased nature of labor market changes would have looked without CEI.

This paper contributes to the literature by studying whether occupational heterogeneity of capital deepening can constitute task-biased labor market changes. Specifically, our approach complements a recent paper by Caunedo et al. (2021), which stresses the role of declines in capital prices. They also use the mapping between capital goods and occupations from O*NET to measure yearly series of capital stock and prices across different occupations with the fixed asset series of NIPA. From this data, they study how decreases in capital prices affect the labor demand at the occupation level. They discover that the heterogeneous reductions in capital prices, as well as the heterogeneous elasticity of substitution with capital, generate the vast majority of labor market polarization during the last few decades.

This paper studies a related but more fundamental source of capital deepening: innovation. Reductions in capital prices can come from many different sources, such as CEI, trade, and changes in market structure. A measure of CEI helps to quantify the contribution of technological factors to price changes and capital deepening. Identifying specific sources of capital deepening and biased technical changes is important for policy evaluations. If decreases in the price of capital result from innovations and innovations of capital goods used by skilled, high-wage, and abstract-task occupations respond more elastically to innovation subsidies, innovation policies lead to unequal consequences in the labor market.

Moreover, CEI can capture changes in measured productivity of quality-adjusted capital stock in the production function, which also contributes to capital deepening. Robot innovations, for example, not only lower the price of robots but also make it possible for robots to perform more complex and diverse tasks. Then, the demand for robots increases more than the price reduction implies. If adopting new robots increase coordination and management costs at factories, then the demand for robots increases less than the price reduction implies. The measure of CEI developed in this paper gives a comprehensive view of the source of capital deepening.

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. One occupation can have both substitutable and complementary capital goods.

In order to address this issue, this paper proposes a novel way to categorize capital-occupation relations based on the substitutability between capital and labor inputs. It is argued that what determines substitutability is the degree of similarity between the functions of capital goods and occupational tasks. Practically, if the Wikipedia description of a capital good is similar to the task description of an occupation from O*NET, the capital-occupation pair is classified as task-substituting. In other cases, capital is defined as task-complementing for labor inputs. These two capital categories have different elasticities of substitution with occupational labor inputs. Moreover, CEI has different impacts on occupational labor demand depending on the category of the capital good.

This paper builds a static general equilibrium model with the occupational labor market to quantify the importance of CEI on changes in the labor market between 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. Task-substituting and task-complementing capitals are allowed to have different elasticity of substitution with labor in the production function specification.

Parameters of the model are estimated using the Generalized Method of Moments (GMM). A potential endogeneity problem is that occupation-specific productivity and supply shocks can be correlated with patent activities. To tackle this problem, this paper constructs shift-share instruments using citation shares of patent classes across different academic fields and growth rates of academic publications that generate knowledge spillover to patents. To create a plausibly exogenous variation in CEI measures, only academic publications from European institutions are used to calculate the growth rates of academic publications.

The estimated model is used to evaluate the impact of CEI on various labor market trends. Specifically, CEI measures are fixed at their 1980s levels to calculate the counterfactual equilibrium with only changes in the demand and supply residuals from the estimated model. The counterfactual equilibrium is compared to the actual data in the late 2010s in terms of task-biased labor market changes and job polarization.

The 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 find that CEI is task-biased in two senses. First, 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.

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 61% less biased towards abstract occupations without CEI. The routine-biased employment changes would have been smaller by 31%, and the degree of job polarization 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 CEI, this paper studies 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). This paper contrarily focuses 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 across different occupations. 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, patents are matched with capital goods used by occupations to measure capital-embodied innovation. By doing so, the innovation measure also includes new technologies that do not overlap with occupational tasks but are still used by occupational workers in the form of better and cheaper capital. Furthermore, new technologies have heterogeneous effects depending on whether the capital containing the new technology has similar functions as occupational tasks.

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 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.

[1]The tasks are differentiated across occupations.

In this economy, CEI affects relative labor demand in three channels. First, CEI changes the user costs of capital bundles. CEI can lower the price of capital bundles and increase the depreciation rate of existing capital. Thus, it is ambiguous whether CEI increases or decreases user costs of capital. Second, CEI changes the productivity of capital bundles in the production function, which is not captured in user costs of capital. Third, CEI directly affects the relative demand for occupational task inputs. Innovation can increase the range in which occupational labor inputs are used in the production function, which is not captured by changes in user costs and productivity of capital. The third channel also captures the misspecification of the nested CES production function.

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_{jio} of type j which is used by occupation o in industry i as follows:

$$k_{jio} = Z \cdot \min\{x_{jio1}/\kappa_{jio1}, \ldots, x_{jioN}/\kappa_{jioN}\}\,, \tag{1}$$

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

Non-arbitrage condition is given as $\sum_n q_n \kappa_{jion} = Q_{jio} Z$, where Q_{jio} is the price of capital bundle and q_n is the price of capital good n. The user cost of the capital bundle is given by the zero profit condition:

$$
\begin{aligned}
r_{jio} &= \sum \delta_{in} \frac{x_{jion} q_n}{k_{jio}} \\
&= \sum \delta_{in} \frac{x_{jion} q_n}{k_{jio} Q_{jio}} Q_{jio} \\
&\equiv \bar{\delta}_{io} Q_{jio},
\end{aligned}
\tag{2}
$$

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.

$$
P_{jio} = \sum_{n=1}^{N} \frac{x_{jion}}{k_{ion}} \#\text{Patent}_n = \sum_{n=1}^{N} \kappa_{jion} \#\text{Patent}_n \,, \tag{3}
$$

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, the technology base index P_{jio} is defined 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_{jio}, as well as the productivity of the capital bundle, z_{jio} as follows:

$$
\log r_{jio} = -\gamma_j^1 \log P_{jio} + \log \omega_{jio1}, \tag{4}
$$

$$
\log z_{jio} = \gamma_j^2 \log P_{jio} - \log \omega_{jio2}, \tag{5}
$$

where ω_{jio1} and ω_{jio2} are components of capital price and productivity that are not explained by CEI. A positive γ_j^1 implies that the user cost of capital bundle is lower with CEI-j. This happens when the price of capital gets cheaper. On the other hand, γ_j^1 can be negative if deprecation rates for existing capital increase sharply with CEI. For example, the innovation in computer technology made the price of computer service much cheaper than before. At the same time, existing computer stocks depreciate at a faster rate.

A positive (negative) γ_j^2 implies that the productivity of quality-adjusted capital stock increases (decreases) with CEI-j. The productivity of quality-adjusted capital stock does not necessarily increase with CEI like user costs of capital. 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.

2.3 Labor Demand

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

$$\mathbf{Y} = \prod_i Y_i^{\alpha_i}. \tag{6}$$

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

$$Y_i = \left(\sum_o \mu_{io} y_{io}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{7}$$

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

$$y_{io} = \left(z_{cio}^{\frac{\rho_c-1}{\rho_c}} k_{cio}^{\frac{\rho_c-1}{\rho_c}} + \left(z_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}} \right)^{\frac{\rho_s}{\rho_s-1}\frac{\rho_c-1}{\rho_c}} \right)^{\frac{\rho_c}{\rho_c-1}}, \tag{8}$$

where k_{cio} is task-complementing capital, z_{cio} is its productivity, k_{sio} is task-substituting capital, z_{sio} is its productivity, and l_{io} is the labor. Following in Krusell et al. (2000), the nested CES structure allows 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.

A representative firm chooses labor and capital inputs to maximize profit. When firms solve the problem, input ratios between occupational labor and capital are determined with relative input prices as follows:

$$\frac{r_{sio}}{w_o} = z_{sio}^{\frac{\rho_s-1}{\rho_s}} \left(\frac{k_{sio}}{l_{io}}\right)^{-\frac{1}{\rho_s}}, \tag{9}$$

$$\frac{r_{cio}}{w_o} = \left(z_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_s-\rho_c}{(\rho_s-1)\rho_c}} z_{cio}^{\frac{\rho_c-1}{\rho_c}} k_{cio}^{\frac{-1}{\rho_c}} l_{io}^{\frac{1}{\rho_s}}. \tag{10}$$

Θ_{io} is defined as the output of the inner CES composite per worker as below:

$$\begin{aligned}\Theta_{io} &:= \left(z_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_s}{\rho_s-1}} / l_{io} \\ &= \left(z_{sio}^{\frac{\rho_s-1}{\rho_s}} \left(\frac{k_{sio}}{l_{io}}\right)^{\frac{\rho_s-1}{\rho_s}} + 1\right)^{\frac{\rho_s}{\rho_s-1}}.\end{aligned} \tag{11}$$

Plugging the optimal input ratio from Equation (9) into Equation (11), along with Equation (4), the following equation is derived.

$$\begin{aligned}\Theta_{io} &= \left(z_{sio}^{\rho_s-1} \left(\frac{r_{sio}}{w_o}\right)^{1-\rho_s} + 1\right)^{\frac{\rho_s}{\rho_s-1}} \\ &= \left(P_{sio}^{\tilde{\gamma}_s(\rho_s-1)} \left(\frac{\tilde{\omega}_{sio}}{w_o}\right)^{1-\rho_s} + 1\right)^{\frac{\rho_s}{\rho_s-1}}.\end{aligned} \tag{12}$$

In this equation, $\tilde{\gamma}_s$ is the sum of γ_s^1 and γ_s^2, and $\tilde{\omega}_{sio}$ is the sum of ω_{sio1} and ω_{sio2}. If $\tilde{\gamma}_s > 0$ and $\rho_s > 1$, Θ_{io} increases in P_{sio} unambiguously. In words, $\tilde{\gamma}_s = \gamma_s^1 + \gamma_s^2 > 0$ 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. Lastly, the following equation arrives after Equation (11) and (12) are plugged into Equation (10):

$$\begin{aligned}\frac{r_{cio}}{w_o} &= \Theta_{io}^{\frac{\rho_s-\rho_c}{\rho_s\rho_c}} z_{cio}^{\frac{\rho_c-1}{\rho_c}} \left(\frac{k_{cio}}{l_{io}}\right)^{-\frac{1}{\rho_c}} \\ &= \left(P_{sio}^{\tilde{\gamma}_s(\rho_s-1)} \left(\frac{\tilde{\omega}_{sio}}{w_o}\right)^{1-\rho_s} + 1\right)^{\frac{\rho_s-\rho_c}{(\rho_s-1)\rho_c}} z_{cio}^{\frac{\rho_c-1}{\rho_c}} \left(\frac{k_{cio}}{l_{io}}\right)^{-\frac{1}{\rho_c}}.\end{aligned} \tag{13}$$

Equation (13) 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, 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.

$\tilde{y}_{io} := y_{io}/l_{io}$ is defined as as the output per worker. Using the expressions of optimal input ratios, Equation (8) is further written as follows.

$$\begin{aligned}\tilde{y}_{io} &= \Theta_{io}^{\frac{\rho_s-\rho_c}{\rho_s}} \left(z_{cio}^{\rho_c-1} \left(\frac{r_{cio}}{w_o}\right)^{1-\rho_c} + \Theta_{io}^{\frac{\rho_c-1}{\rho_s}}\right)^{\frac{\rho_c}{\rho_c-1}} \\ &= \Theta_{io}^{\frac{\rho_s-\rho_c}{\rho_s}} \left(P_{cio}^{\tilde{\gamma}_c(\rho_c-1)} \left(\frac{\tilde{\omega}_{cio}}{w_o}\right)^{1-\rho_c} + \Theta_{io}^{\frac{\rho_c-1}{\rho_s}}\right)^{\frac{\rho_c}{\rho_c-1}}.\end{aligned} \tag{14}$$

Derivation is in Equation (32) in Appendix A.1. $\tilde{y}_{io}$ 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 $\tilde{\omega}_{cio}$ is the sum of ω_{cio1} and ω_{cio2}. If $\tilde{\gamma}_c > 0$ and $\rho_c > 1$, $\tilde{y}_{io}$ 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, when we solve the representative firm's problem, the labor demand across occupations within an industry is given by

$$\frac{w_o}{w_p} = \frac{\mu_{io}}{\mu_{ip}} \left(\frac{y_{io}}{y_{ip}}\right)^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \frac{\left(z_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_c-\rho_s}{(\rho_s-1)\rho_c}}}{\left(z_{sip}^{\frac{\rho_s-1}{\rho_s}} k_{sip}^{\frac{\rho_s-1}{\rho_s}} + l_{ip}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{\rho_c-\rho_s}{(\rho_s-1)\rho_c}}} \left(\frac{l_{io}}{l_{ip}}\right)^{-\frac{1}{\rho_s}} \tag{15}$$

$$= \frac{\mu_{io}}{\mu_{ip}} \left(\frac{\tilde{y}_{io}}{\tilde{y}_{ip}}\right)^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \frac{\Theta_{io}^{\frac{\rho_c-\rho_s}{\rho_s\rho_c}}}{\Theta_{ip}^{\frac{\rho_c-\rho_s}{\rho_s\rho_c}}} \left(\frac{l_{io}}{l_{ip}}\right)^{-\frac{1}{\sigma}} . \tag{16}$$

Derivation is in Equation (33) in Appendix A.1. Equation (16) 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-embodied productivity changes.

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

$$\log\mu_{io} = \gamma_s^3 \log P_{sio} + \gamma_c^3 \log P_{cio} + \log\omega_{io3} , \tag{17}$$

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 $\mathbf{L}$ 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:

$$o^* = \underset{o}{\operatorname{argmax}} \left\{ \log w_o + \log \xi_o + \nu_{io} \right\}. \tag{18}$$

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

$$\frac{L_o}{\mathbf{L}} = \frac{\exp(\beta \log w_o + \beta \xi_o)}{\sum_p \exp(\beta \log w_p + \beta \xi_p)}. \tag{19}$$

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, a list of capital goods used at the occupation level comes from "Tools" data in O*NET.[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. There are 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).

Patent data from the United States Patent and Trademark Office (USPTO) are

[2] Version 25.0 updated in August 2020 is used for the exercise.
[3] Median is 29, and the standard deviation is 36.4.

used to measure innovation.[4] It has the universe of patents registered in the U.S. The exercise uses 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. Samples are restricted to utility patents and design patents are excluded to focus on quality improvement. As a result, the data contains 6.1 million patents from 1970 to 2015.

Microdata from the Census Bureau is used to construct employment by occupation, industry, and year. Microdata is downloaded from the Integrated Public Use Microdata Series (IPUMS). For occupational employment at the industry level, this exercise uses Decennial Census of 1980 and the American Community Survey (ACS) from 2015 to 2019 for observations in 1980, and 2015, respectively.[5] Employment is measured by the number of people with the occupation and the industry codes. Each observation is weighted by individual sampling weights from the Census Bureau. Decennial Census and the ACS are also used to construct immigrant supply shock measures in Section 3.4.2.

Occupational mean wage comes from the microdata for the Annual Social and Economic Supplement of the Current Population Survey. The 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. The occupation code last year as surveyed by the CPS are used. Since this is the wage of the last year, five-year observations from 1971 to 1975 are used to measure the average wage of 1970. Wages from different years are adjusted with the CPI to the base year[6]. In order to address heterogeneous labor market productivity across workers with different characteristics, wages are residualized using the Mincerian regression controlling for age (each age enters as dummies), education level, sex, race, industry, and time fixed effects.

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

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

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

The exercise includes only workers younger than 65 years old and older than 24 years old. To calculate the mean wage at the occupation level, only samples with 40 weeks of work or more in the previous year are considered. Samples are dropped if they have zero or missing labor income. Observations are excluded from samples if the nominal hourly wage is lower than 50% of the federal minimum wage of the corresponding year.

The occupation and industry codes are harmonized using the OCC1990 and the IND1990 variables provided by the IPUMS. The 2010 Standard Occupational Classification Code (SOC Code) on O*NET data is 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).

Capital stocks and user costs of capital at the occupation and industry level are imputed in a similar to Caunedo et al. (2021). The quantity of capital stock is measured by the fixed-cost capital estimates in the 2012 US dollar from the BEA at the industry level over different capital goods categories. Calculation of depreciation rates uses current-cost capital stock and capital depreciation series. For details on the imputation process, see Appendix A.2.

Lastly, the task scores and the offshorability of tasks at the occupation level are 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 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

Capitals for each occupation are categorized into two groups: task-substituting capital and task-complementing capital. The description of capital goods are compared to the tasks of the occupation. The capital is considered 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.

This paper uses "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, Wikipedia pages of capital goods are used.[9] Wikipedia has a broad coverage of products, and its articles usually include a technical description, which makes it easy to match with patents. The title of a capital good is searched using Wikipedia API and download the entire text of the corresponding article.[10] Among 4,180 capital goods, Wikipedia pages for 1,825 capital goods are found.

[7] Version of 25.0, updated in August 2020, is used.

[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/, The data on 02/28/2021 downloaded.

This paper calculates text similarity to match different texts following the literature, such as Argente et al. (2020) and Kogan et al. (2019). Specifically, the similarity is calculated between all the tools used by occupation with all the tasks in our data. As a result, similarity scores are calculated at the capital-task level. Then, for each capital-occupation pair, the similarity from the task level is aggregated to the occupation level with a uniform weight. As a result, similarity score is calculated at the tool-occupation level.

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

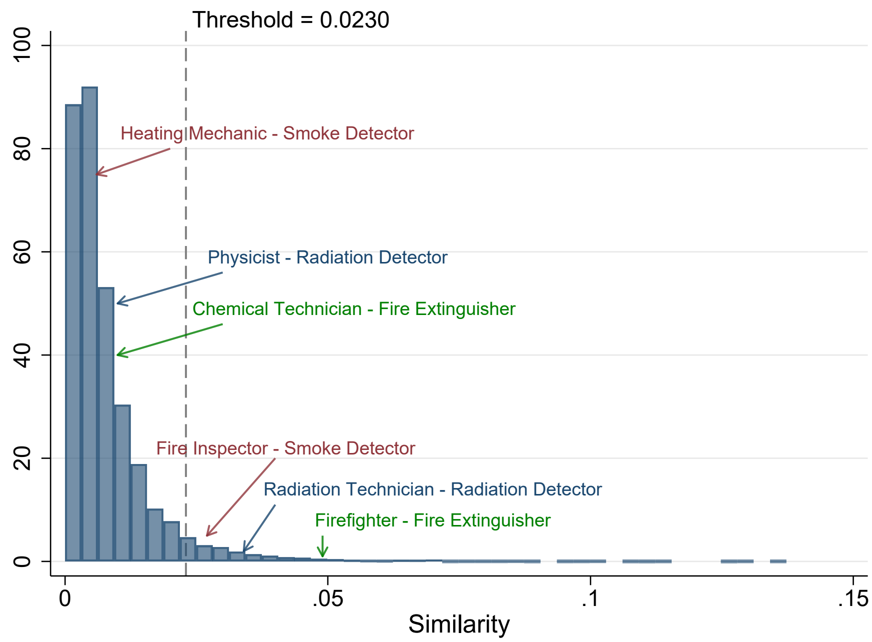
Next, the pairwise similarity is calculated between tasks and capital goods. Specifically, each text is vectorized to compute cosine similarity. This cosine similarity represents the share of overlapped single words or bigrams between two texts.[12] To incorporate the fact that the importance of words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

$$
\begin{aligned}
&\omega_{ij} = TF_{ij} \cdot IDF_i, \\
&TF_{ij} = \frac{f_{ij}}{\sum_i f_{ij}}, \\
&IDF_i = \log\left(\frac{J}{\sum_j \mathbb{1}\{i \in j\}}\right),
\end{aligned}
\tag{20}
$$

[11]The spacy package in python is used for this. 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: the graph shows density of similarity between capital goods and occupation tasks. The text similarity between description of capital goods and each task of occupation is calculated and aggregated 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 overlapping words. A capital good is considered task-substituting to the occupation if the similarity is more than the 95th percentile and the remaining capital goods as task-complementing[13]. Figure 2 also describes several examples of capital-

[13]The 95th percentile is 0.023 and close to the threshold used to match Wikipedia articles to patents below. This high threshold ensures that the two different types of capital have opposite effects on

occupation pairs. In this graph, smoke detectors are task-complementing for heating technicians but task-substituting for fire inspectors.

3.3 Construction of CEI Measure

The measure of the capital embodied innovation is calculated from patent data. To be specific, the text similarity is computed between patent texts and the descriptions of capital goods to count the number of patents corresponding to each capital good. Then, the average number of patents per capital good is calculated at the occupation and capital group level. Since capital goods are categorized into two groups, two measures of innovation are constructed for each occupation: innovation on task-complementing capital and task-substituting capital.

The same procedure in the previous section is followed 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, patents are assigned 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, multiple matching or non-matching is allowed depending on the similarity score. At most five capital goods are linked to each patent. The matching is made only if the similarity score is higher than 0.025.[14] 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.

the reduced form. The qualitative results are robust for reduced-form exercises. See Appendix A.5 for more discussion.

[14] It is the same as Argente et al. (2020). The reduced form exercises are conducted with various thresholds, but the result roughly stays the same.

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.

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, the measure of innovation of capital goods is aggregated at the occupation level. Note that one occupation uses multiple capital goods. The average number of patents is first calculated for each occupation and capital group in the fixed asset series by BEA. The number of patents are summed 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

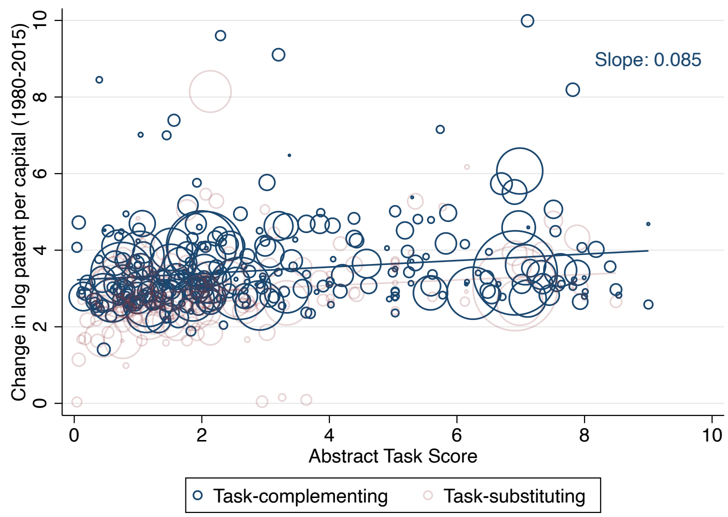
Table 2: Example of Patent Counts at the Occupation Level

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

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.

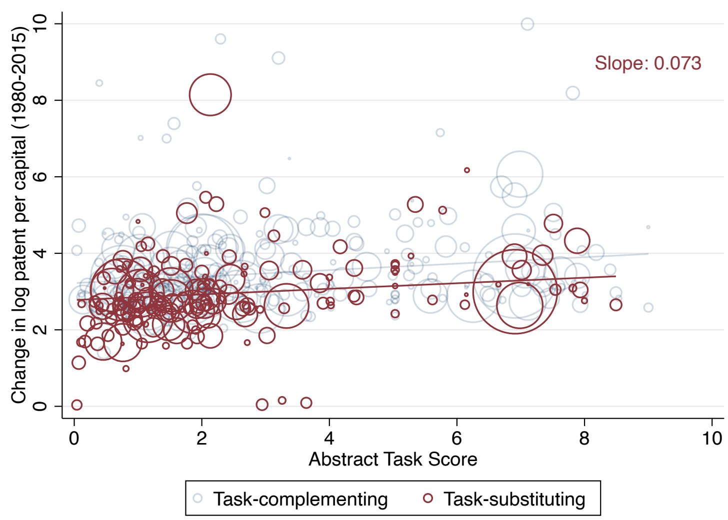
Figures 3 and 4 show the scatter plots between CEI measures and abstract task scores of each occupation. The CEI measures at the occupation level are calculated across different industries weighted by the 1980 employment share across industries. The size of the circle corresponds to the aggregate employment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



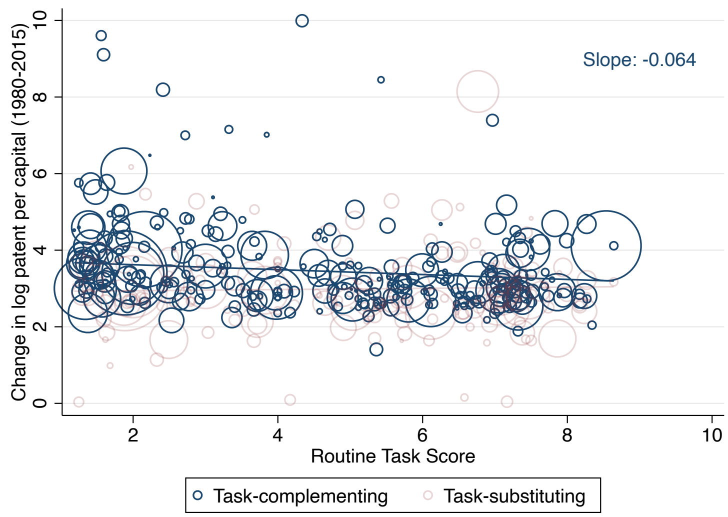
Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to employment size of each occupation in the 1980 Decennial Census. Task scores are from Autor and Dorn (2013).

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 employment size of each occupation in the 1980 Decennial Census. Task scores are from Autor and Dorn (2013).

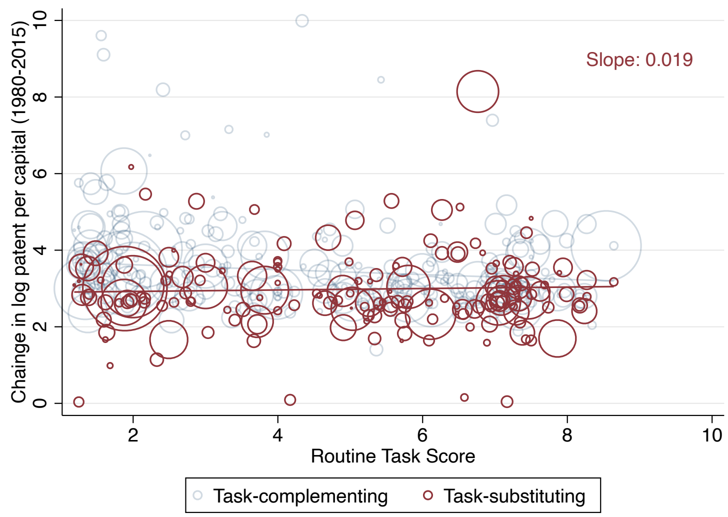
Figure 5: Routine Task Score and CEI-c



Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the employment of each occupation in the 1980 Decennial Census. Task scores are from 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. If CEI-c and CEI-s have opposite effects on occupational labor demand, the bias of CEI-c across routine task scores determines the biased changes in occupational labor demand. To summarize, innovations in 1980-2015 are more directed towards capital goods used by abstract and nonroutine occupations. But the bias of innovation is stronger for task-complementing capital.

Figure 6: Routine Task Score and CEI-s

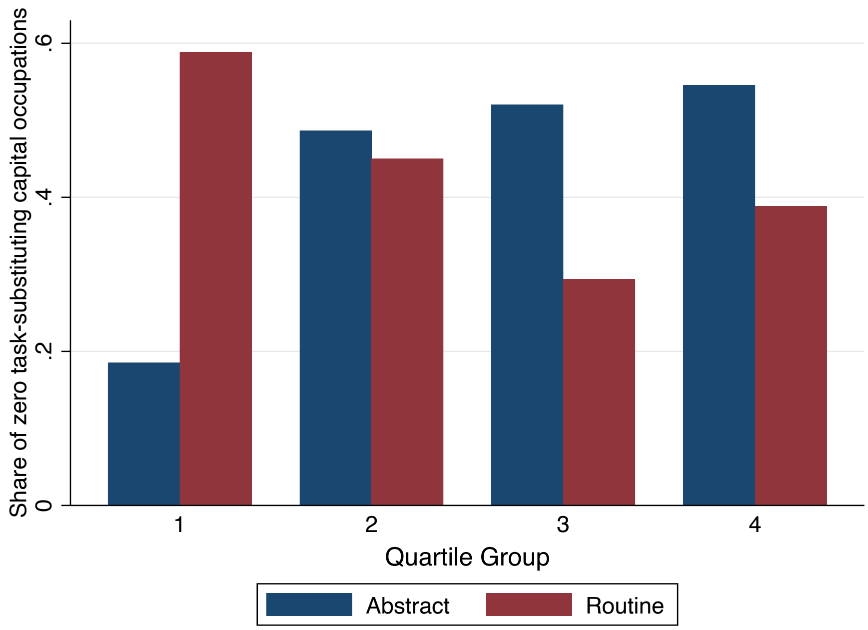


Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the employment of each occupation in the 1980 Decennial Census. Task scores are from Autor and Dorn (2013).

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 57% of workers in the last quartile of abstract task scores do not have any task-substituting capital, while this share is only about 19 % for the first quartile. As for routine task scores, more routine occupations are more likely to have at least one task-substituting capital good.

See Appendix A.3 for more properties of imputed capital stocks and their intensity across task groups and over time. Appendix A.3 shows that more routine 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.

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.

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

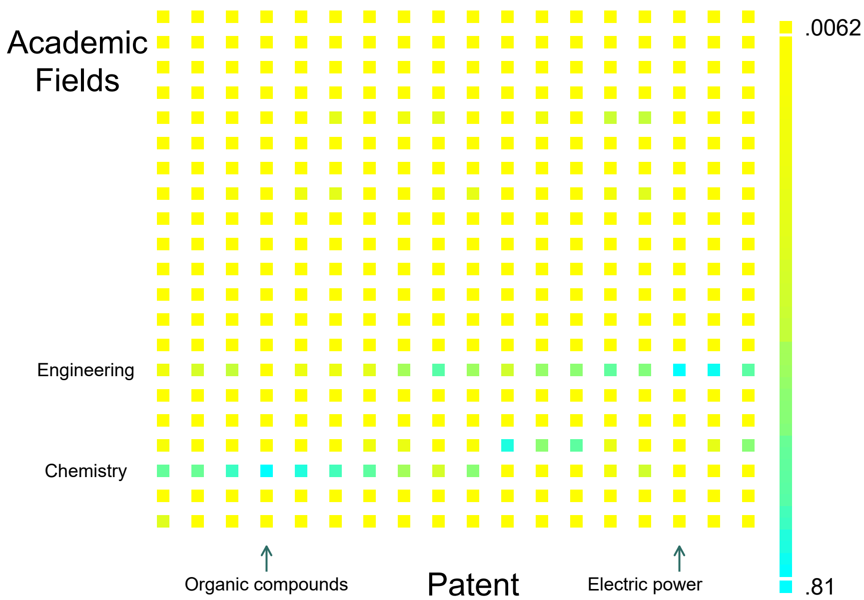
To measure the knowledge diffusion from academic publications to patents, data on citations made by patents to academic publications are used following the innovation literature (Jaffe et al., 1993; Arora et al., 2021). Specifically, if a patent cites an academic paper, this is interpreted as the patent receiving 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. Data on academic papers come from the Web of Science Field, which has 251 different classifications. For patents, IPC 3-digit is used, which has 387 classes. The number of citations from each patent class to science fields are divided by the total number of citations to science as below:

$$\alpha_{nm} = \frac{c_{nm}}{\sum_m c_{nm}}, \tag{21}$$

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.

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

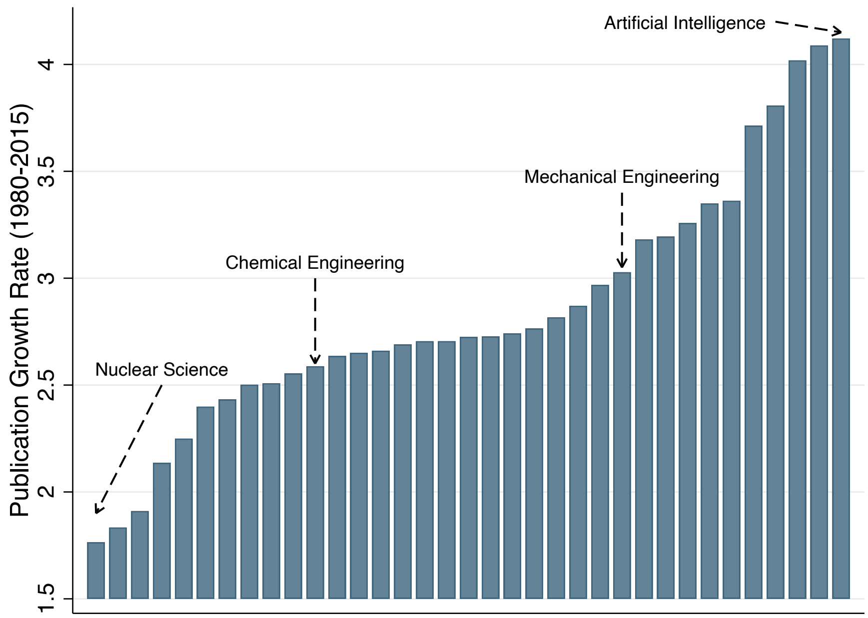


Notes: The graph shows α_{nm}, which is the share of citations from patent technology classes n to academic fields m. The graph also plots IPC 3-digit patent technology classes on the X-axis and plot Web of Science academic publication fields on the Y-axis. The graph only contains the IPC classes that have more than 50,000 citations to science in the entire period. The share of citations are calculated 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.

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, the upstream measure for each technology class are calculated and aggre-

Figure 9: Growth Rate of Publications over Academic Fields



Notes: The graph shows growth rates of publications between 1980–2015 over different Web of Science fields. The graph includes only fields that have more than 1,000 citations from patents. Publication data comes from MAG and includes publications associated only with European institutions.

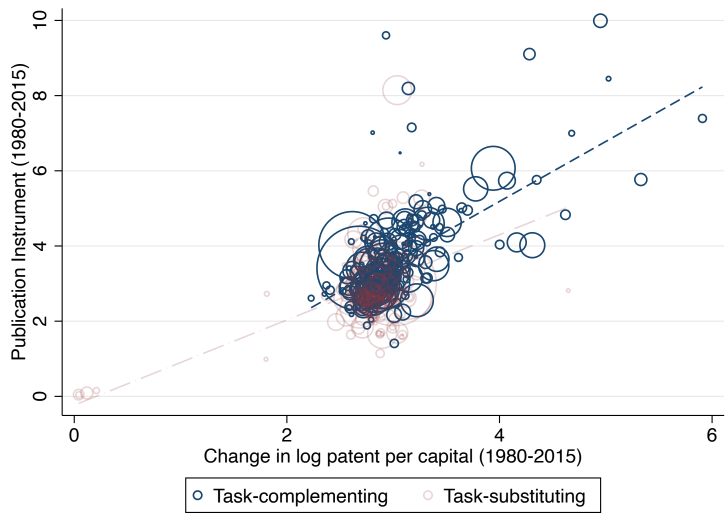
gated into the occupation level as below:

$$\text{Upstream}_{jio} = \Delta \log \left(\sum_n s_{nio} \sum_m \alpha_{nm} \mathcal{P}_m \right), \tag{22}$$

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 $j = C, S$. The instrument variable takes difference-in-logs at the occupation by industry level. Upstream shocks are calculated separately for CEI-s and CEI-c.

For the growth rate of publications, papers associated only with European institutions are collected across different fields in MAG to calculate the growth rate

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 employment of each occupation in the 1980 Decennial Census. Task scores are from Autor and Dorn (2013).

between 1970 and 2015. Only papers from European institutions are included because firms finance academic projects and increase academic publications in some fields. Figure 9 shows the distribution of the growth rate of publications[15]. The top five fields in terms of growth rate are artificial intelligence, information systems, hardware, software engineering, and control systems.

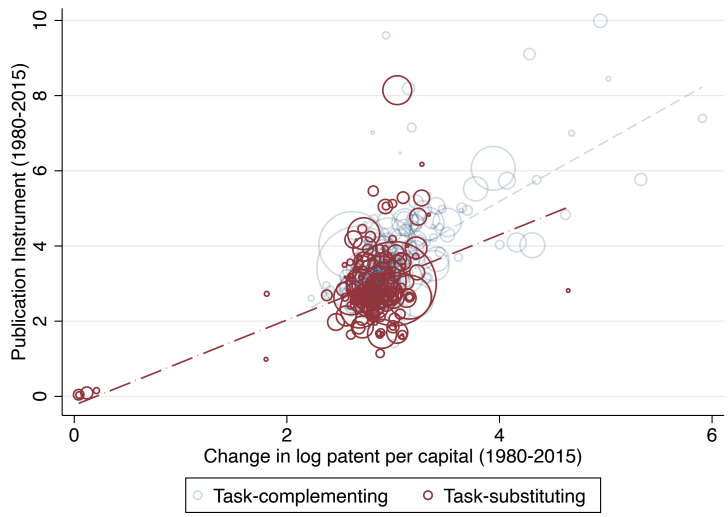
Figures 10 and 11 show scatter plots between CEI measures and the resulting academic publication instruments at the occupation level. The publication instruments are strongly positively associated with the actual CEI measures.

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. An independent supply shifter is calculated using trends in Latin American immigra-

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

Figure 11: CEI-s and Publication Instrument

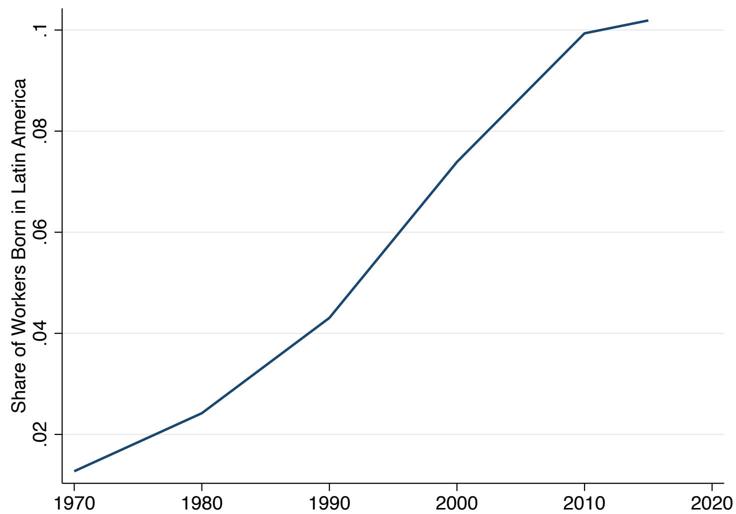


Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the employment of each occupation in the 1980 Decennial Census. Task scores are from Autor and Dorn (2013).

tion 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 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 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 Latin America

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.

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

The heterogeneous exposure to immigration shock is computed 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, the number of workers in 1980 is denoted by $l_o^{c,2015}$ and $L^{c,2015}$. Then, the Bartik immigration shock is defined as in the following equation.

$$z_o = \sum_c \frac{l_o^{c,1980}}{l_c^{1980}} \log \left(\frac{L^{c,2015} - l_o^{c,2015}}{L^{c,1980} - l_o^{c,1980}} \right). \tag{23}$$

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: The graph shows 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, parameters are sequentially estimated with the Generalized Method of Moments (GMM) using first order conditions. First, the elasticity of substitution for the inner CES composite is estimated from Equation (9). Then, the elasticity of substitution for the outer CES composite between the inner composite and task-complementing capital is estimated from Equation (10). Lastly, the elasticity of substitution across different occupational inputs is estimated using Equation (16). The elasticity of occupation labor can be estimated separately.

Variables are differenced between 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.

First, Combining Equation (4) and (9), we can get the following equation:

$$\Delta \log \left(\frac{\omega_{sio}}{w_o} \right) = \gamma_s \Delta \log P_{sio} - \frac{1}{\rho_s} \Delta \log \left(\frac{k_{sio}}{l_{io}} \right). \tag{24}$$

In this equation, $\gamma_s := \gamma_s^1 + \frac{\rho_{s-1}}{\rho_s}\gamma_s^2$ and $\omega_{sio} := \omega_{sio1}\omega_{sio2}^{\frac{\rho_{s-1}}{\rho_s}}$. We further assume that $\Delta \log \omega_{sio}$ can be expressed as follows:

$$\Delta \log \omega_{sio} = \alpha_s X_o + \phi_{si} + \epsilon_{sio}\,, \tag{25}$$

where ϕ_{si} is the industry-specific productivity shock for task-substituting capital. X_o includes the offshorability index and the task scores at the occupation level. It is also assumed that, for selected instrumental variables Z_{sio}, $\mathbb{E}(Z_{sio}\epsilon_{sio})$. Then, the GMM objective function is given by

$$\begin{aligned} &(\hat{\rho}_s, \hat{\gamma}_s) \\ &= \underset{\rho_s, \gamma_s}{\operatorname{argmin}} \sum_o k_{io}^{1980} \Big(\Delta \log \left(\frac{1}{w_o} \right) + \frac{1}{\rho_s} \Delta \log \left(\frac{k_{sio}}{l_{io}} \right) - \gamma_s \Delta \log P_{sio} - \alpha_s X_o - \phi_{si} \Big) Z_{sio}\,, \end{aligned} \tag{26}$$

where $k_{io}^{1980} = k_{sio}^{1980} + k_{cio}^{1980}$ is the total value of capital used by occupation o in industry i in 1980[16]. 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 con-

[16] Initial capital value measured in 2012 dollar at the occupation $\times$ industry level, as opposed to initial employment, as weights for the GMM condition. This is to give more weight to capital-intensive occupation $\times$ industry observations for .

trolling 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_{sio}, is isomorphic to an increase in the productivity of capital, $z_{sio}^{\frac{\rho_s-1}{\rho_s}}$. Thus, the effect of CEI-s on Equation refeq: focs through reductions in user costs of capital is not separately identified from the effect of CEI-s through improvements of productivity for capital. Thus, Equation (4) is estimated with the imputed user costs of capital to estimate γ_s^1. Then, the estimate of γ_s^2 is calculated from the estimate of γ_s. The residuals give $\hat{z}_{sio}$, estimates for z_{sio}. Then, $\hat{\Theta}_{io}$ is computed with the parameter estimates, $\hat{z}_{sio}$, and observed input price ratios.

Parameters in Equation (13) are also estimated with the GMM. We combine Equation (4) and (13) to get the following equation:

$$\Delta \log \left(\frac{\omega_{cio}}{w_o}\right) = \frac{\rho_s - \rho_c}{\rho_s \rho_c} \Delta \log \Theta_{io} + \gamma_c \Delta \log P_{cio} - \frac{1}{\rho_c} \Delta \log \left(\frac{k_{cio}}{l_{io}}\right). \tag{27}$$

In this equation, $\gamma_c := \gamma_c^1 + \frac{\rho_c - 1}{\rho_c} \gamma_c^2$ and $\omega_{cio} := \omega_{cio1} \omega_{cio2}^{\frac{\rho_c-1}{\rho_c}}$. ω_{cio} is assumed to have the following parametric form.

$$\Delta \log \omega_{cio} = \alpha_c X_o + \phi_{ci} + \mathbf{1}_{o \in \mathcal{G}^{-s}} \kappa_{ci} + \epsilon_{cio}\,, \tag{28}$$

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_{ci} addresses the mean difference between occupations with and without task-substituting capital within each industry. The estimation assumes orthogonality condition $\mathbb{E}(Z_{cio}\epsilon_{cio}) = 0$. Then, the GMM estimator is defined as

$$\begin{aligned}(\hat{\rho}_c, \hat{\gamma}_c) = \underset{\rho_c, \gamma_c}{\operatorname{argmin}} \sum_o k_{io}^{1980} \Big(& \Delta \log \left(\frac{1}{w_o}\right) + \frac{1}{\rho_c} \Delta \log \left(\frac{k_{cio}}{l_{io}}\right) \\ & - \frac{\rho_s - \rho_c}{\rho_s \rho_c} \Delta \Theta_{io} - \gamma_c \Delta \log P_{cio} - \alpha_c X_o - \phi_{ci} - \mathbf{1}_{o \in \mathcal{G}^{-s}} \kappa_{ci} \Big) Z_{cio}.\end{aligned} \tag{29}$$

Again, the parameter estimate are used to calculate estimates for z_{cio}. $\tilde{y}_{io}$ can be formulated 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. The estimate for γ_c^1 is used from the instrumented regression of capital cost on the task-complementing CEI measure to separate the estimate of γ_c^2.

Lastly, Equation (16) is used to estimate the across-occupation elasticity σ. The demand shock for occupational tasks μ_{io} is assumed to take the following form.

$$\Delta \log \mu_{io} = \tilde{\alpha} X_o + \psi_i + \mathbf{1}_{o \in \mathcal{G}^{-s}} \tilde{\kappa}_i + \gamma_s^3 \Delta \log P_{sio} + \gamma_c^3 \Delta \log P_{cio} + \varepsilon_{io}. \tag{30}$$

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

$$\begin{aligned}(\hat{\sigma}, \hat{\gamma}_s^3, \hat{\gamma}_c^3) = \underset{\sigma, \gamma_s^3, \gamma_c^3}{\operatorname{argmin}} \sum_o l_{io}^{1980} \Big(\Delta \log w_o + \frac{1}{\sigma} \Delta \log l_{io} - \frac{\rho_c - \rho_s}{\rho_c \rho_s} \Delta \log \Theta_{io} \qquad (31) \\ - \left(\frac{1}{\rho_c} - \frac{1}{\sigma} \right) \Delta \log \tilde{y}_{io} - \tilde{\alpha} X_o - \tilde{\psi}_i - \mathbf{1}_{o \in \mathcal{G}^{-s}} \tilde{\kappa}_i - \gamma_s^3 \Delta \log P_{sio} - \gamma_c^3 \Delta \log P_{cio} \Big) Z_{io}^l \,,\end{aligned}$$

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 (16) 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 elasticity of supply is calibrated at 2.5, average of the labor supply elasticity in the 1980s and the 2000s from Grigsby (2022)[17]. Grigsby (2022) accounts for heterogeneous skills and productivity across different demographic groups to estimate

[17] In the 1980s and the 2000s, the elasticity of labor supply is 1.67 and 3.44, respectively.

Table 3: Parameter Estimates - First Order Conditions

	ρ_s	γ_s	ρ_c	γ_c	σ
Estimate	10.040	0.047	5.682	-0.031	9.136
N	6675	-	11455	-	11455

Note: ρ_s (ρ_c) is the elasticity of substitution between task-substituting (task-complementing) capital and labor. σ is the elasticity of substitution between occupational inputs. γ_s (γ_c) is the coefficient of CEI-s (-c) on capital-labor substitution equation.

elasticity of labor supply. Unlike Grigsby (2022) who covers yearly adjustments for occupation choice, the estimation in this section with differenced variables deals with changes in occupation choice over 35 years. Thus, the calibrated elasticity of 2.5 is likely to be a lower bound, and the counterfactual exercise below is likely to understate the effect of demand-side changes.

3.6 Estimation Results

Tables 3 and 4 show the estimation results. In Table 3, the estimate for ρ_s is larger than the estimate for σ, which is larger than ρ_c. 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 productivity or a decrease in the price of task-substituting capital reduces relative labor demand. On the other hand, an increase in productivity or a decrease in the price of task-complementing capital raises relative labor demand. Estimates of elasticities are overall higher than the estimates in Caunedo et al. (2021) because this paper covers labor market adjustments over 35 years.

Because user costs of capital and relative productivity of capital both enter Equations (9) and (10), only a linear combination of γ_j^1 and γ_j^2 ($j = s, c$) is identified in the GMM estimation using first order conditions. $\gamma_s = \gamma_s^1 + \frac{\rho_s - 1}{\rho_s}\gamma_s^2$ is positive while $\gamma_c = \gamma_c^1 + \frac{\rho_c - 1}{\rho_c}\gamma_c^2$ is negative. The negative estimate for γ_s implies that production of occupational inputs becomes more capital-intensive with CEI-s, and the opposite

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	0.302	-0.283	-0.036	-0.139	2.867	0.025
N	6655	-	-	11455	-	-

Note: γ_s^1 (γ_c^1) is the coefficient of CEI-s (CEI-c) on user costs of capital. γ_s^2 (γ_c^2) is the coef. of CEI-s (CEI-c) on relative productivity of capital. γ_s^3 (γ_c^3) is the coefficient of CEI-s (CEI-c) on demand shifter for occupational inputs.

holds for CEI-c.

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. γ_j^1 ($j = s, c$), the effect of CEI on user cost of capital, can be estimated from a separate estimation between CEI measure and user costs of capital using publication instruments. Then, γ_j^2 ($j = s, c$) is recovered from $\gamma_j = \gamma_j^1 + \frac{\rho_j - 1}{\rho_j}\gamma_j^2$ ($j = s, c$).

The estimate for γ_s^1 is significantly positive while γ_c^1 is estimated negative. Both CEI-s and CEI-c reduce the quality-adjusted price of capital, which lowers user costs of capital. However, both types of CEI also increase depreciation rates of existing capital stocks, raising user costs. The price effect dominates for task-substituting capital whereas the depreciation rate effect dominates for task-complementing capital. This is why labor intensity increases with CEI-c relative to task-complementing capital in the estimation of Equation (10), captured by negative γ_c.

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 productivity of capital in the capital-labor substitution equations, after taking their effect on user costs into account. Thus, CEI-s reduces the productivity of task-substituting capital relative to labor inputs whereas CEI-c raises the productivity of task-complementing capital. This positive effect of CEI-c cancels out the negative effect of CEI-c on the user cost 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 (16), 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 the condition, $\hat{\rho}_s > \hat{\sigma} > \hat{\rho}_c$, implies that CEI-s (CEI-c) reduces (raises) relative labor demand. These results are consistent with reduced-form findings in Appendix A.4.

4 Counterfactuals

The counterfactual exercise aims to address the following question: what happens to the labor market and its summary statistics without CEI? To address this question, a counterfactual equilibrium is calculated 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, the statistics that summarize changes in the labor market are calculated and compared to the actual counterparts.

To see what task-biased labor market changes would look like without CEI between 1980 and 2015, the auxiliary linear regression in the introduction is used to measure the task bias 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, the changes in employment and wage between 1980 and 2015 are regressed on task scores.

Table 5 shows the task bias results after running the regression equation of employment and wage changes in logs on task scores at the occupation level. Notice 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 12 and 9 percentage points higher employment and wage growth rates, respectively. Without CEI more biased towards abstract occupations, however, this task bias is attenuated. Without the effect of CEI, one standard deviation higher abstract task score predicts about 5 and 6 percentage points higher employment and wage growth rates. Put differently, CEI makes 61% and 31% of abstract-task bias

Table 5: Counterfactual - Task-Biasedness

	Abstract Score		Routine Score	
	Employment	Wage	Employment	Wage
Without CEI	0.047	0.064	-0.114	-0.041
Actual Change	0.120	0.093	-0.166	-0.062

Notes: the table shows coefficient estimates of task scores on employment and wage growth between 1980 and 2015 from a univariate OLS regression at the occupation level. Industry×occupation-level counterfactual employment is aggregated to occupation level. Task scores are normalized to have a unit standard deviation. Each observation is weighted by its employment in 1980.

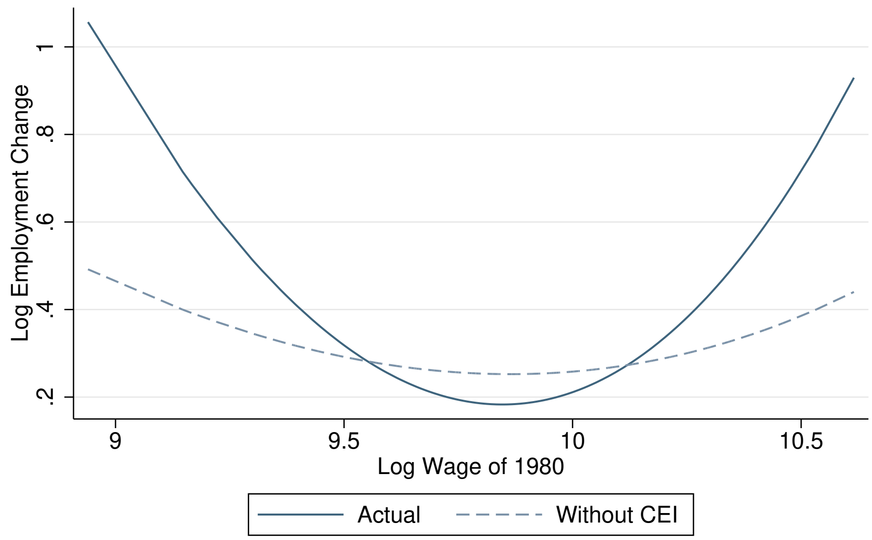
in employment and wage growth rates, respectively. CEI also contributed to the routine-biased labor market changes. CEI contributes to about 31% (33%) of employment (wage) growth biased against routine occupations.

Lastly, the effect of CEI on job polarization between 1980 and 2015 is shown 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 Autor and Dorn (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-wage occupations. Both CEI-c and CEI-s are lower for middle-wage occupations. However, because the effect of CEI-c dominates, the employment growth is smaller for middle-wage occupations.

5 Conclusion

This paper develops a measure of capital-embodied innovations (CEI) from patent data, using a text-based matching algorithm between patent descriptions and Wikipedia articles of capital goods. Occupation-level differences in the use of capital goods

Figure 14: Counterfactual - Jop Polarization



Notes: This graph shows 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 weighted by their employment in 1980.

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.

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

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A Appendix

A.1 Model Derivation

Derivation of Equation (14)

$$\tilde{y}_{io} := \left(z_{cio}^{\frac{\rho_c - 1}{\rho_c}} k_{cio}^{\frac{\rho_c - 1}{\rho_c}} + \left(z_{sio}^{\frac{\rho_s - 1}{\rho_s}} k_{sio}^{\frac{\rho_s - 1}{\rho_s}} + l_{io}^{\frac{\rho_s - 1}{\rho_s}} \right)^{\frac{\rho_s}{\rho_s - 1} \frac{\rho_c - 1}{\rho_c}} \right)^{\frac{\rho_c}{\rho_c - 1}} / l_{io}$$

$$= \left(z_{cio}^{\frac{\rho_c - 1}{\rho_c}} \left(\frac{k_{cio}}{l_{io}} \right)^{\frac{\rho_c - 1}{\rho_c}} + \left(z_{sio}^{\frac{\rho_s - 1}{\rho_s}} \left(\frac{k_{cio}}{l_{io}} \right)^{\frac{\rho_s - 1}{\rho_s}} + 1 \right)^{\frac{\rho_s}{\rho_s - 1} \frac{\rho_c - 1}{\rho_c}} \right)^{\frac{\rho_c}{\rho_c - 1}}$$

From Equation (13), $z_{cio}^{\frac{\rho_c - 1}{\rho_c}} \left(\frac{k_{cio}}{l_{io}} \right)^{\frac{\rho_c - 1}{\rho_c}} = \Theta_{io}^{\frac{(\rho_s - \rho_c)(\rho_c - 1)}{\rho_s \rho_c}} z_c^{\rho_c - 1} \left(\frac{r_{cio}}{w_{io}} \right)^{1 - \rho_c},$

From Equation (11), $\left(z_{sio}^{\frac{\rho_s - 1}{\rho_s}} \left(\frac{k_{cio}}{l_{io}} \right)^{\frac{\rho_s - 1}{\rho_s}} + 1 \right)^{\frac{\rho_s}{\rho_s - 1}} = \Theta_{io},$

$$\tilde{y}_{io} = \left(\Theta_{io}^{\frac{(\rho_s - \rho_c)(\rho_c - 1)}{\rho_s \rho_c}} z_c^{\rho_c - 1} \left(\frac{r_{cio}}{w_{io}} \right)^{1 - \rho_c} + \Theta_{io}^{\frac{\rho_c - 1}{\rho_c}} \right)^{\frac{\rho_c}{\rho_c - 1}}$$

$$= \Theta^{\frac{\rho_s - \rho_c}{\rho_s}} \left(z_c^{\rho_c - 1} \left(\frac{r_{cio}}{w_{io}} \right)^{1 - \rho_c} + \Theta_{io}^{\frac{\rho_c - 1}{\rho_s}} \right)^{\frac{\rho_c}{\rho_c - 1}}$$

From Equation (4), $r_{cio} = P_{cio}^{-\gamma_c^1} \cdot \omega_{cio1}, \quad z_{cio} = P_{cio}^{\gamma_c^2} / \omega_{cio2},$

$$= \Theta_{io}^{\frac{\rho_s - \rho_c}{\rho_s}} \left(P_{cio}^{\tilde{\gamma}_c (\rho_c - 1)} \left(\frac{\tilde{\omega}_{cio}}{w_o} \right)^{1 - \rho_c} + \Theta_{io}^{\frac{\rho_c - 1}{\rho_s}} \right)^{\frac{\rho_c}{\rho_c - 1}}. \tag{32}$$

Derivation of Equation (15) A representative firm maximize the industrial outputs by choosing labor and capital. When we take the first order condition with respect to l_{io}, we get the following equation:

$$w_o = \mu_{io} y_{io}^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \left(z_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}} \right)^{\frac{\rho_c-\rho_s}{(\rho_s-1)\rho_c}} l_{io}^{-\frac{1}{\rho_s}}$$

From Equation (11), $\left(z_{sio}^{\frac{\rho_s-1}{\rho_s}} k_{sio}^{\frac{\rho_s-1}{\rho_s}} + l_{io}^{\frac{\rho_s-1}{\rho_s}} \right)^{\frac{\rho_c-\rho_s}{(\rho_s-1)\rho_c}} = \Theta_{io}^{\frac{\rho_c-\rho_s}{\rho_c\rho_s}} l_{io}^{\frac{\rho_c-\rho_s}{\rho_c\rho_s}}$

$$w_o = \mu_{io} y_{io}^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \Theta_{io}^{\frac{\rho_c-\rho_s}{\rho_c\rho_s}} l_{io}^{-\frac{1}{\rho_c}} = \mu_{io} \tilde{y}_{io}^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \Theta_{io}^{\frac{\rho_c-\rho_s}{\rho_c\rho_s}} l_{io}^{-\frac{1}{\sigma}}$$

$$= \frac{\mu_{io}}{\mu_{ip}} \left(\frac{\tilde{y}_{io}}{\tilde{y}_{ip}} \right)^{-\frac{1}{\sigma}+\frac{1}{\rho_c}} \frac{\Theta_{io}^{\frac{\rho_c-\rho_s}{\rho_s\rho_c}}}{\Theta_{ip}^{\frac{\rho_c-\rho_s}{\rho_s\rho_c}}} \left(\frac{l_{io}}{l_{ip}} \right)^{-\frac{1}{\sigma}}. \tag{33}$$

A.2 Imputation of Capital Stock and User Cost of Capital

Occupation-specific capital stock are imputed using procedures similar to to Caunedo et al. (2021). Each occupation has a set of capital goods in UNSPSC codes. These UNSPSC codes are converted to the NIPA capital types using the crosswalk table in Aum (2017). The 2012 fixed-price capital stock series is used to measure the quantity of capital bundles normalized in 2012. For the price of capital bundle, the price deflator is calculated between current-cost and fixed-cost capital stock from the BEA. Depreciation rates are computed 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, current-cost shares are used to calculate the cost-weighted average of depreciation rates.

The capital intensity of an occupation o for the NIPA capital type n is first defined 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 n is imputed as

$$x_{sion} = \frac{l_{io}\#Capital_o^{n,s}}{\sum_p l_{ip}\#Capital_p^{n,s} + \sum_p l_{ip}\#Capital_p^{n,c}} K_i^n \tag{34}$$
$$x_{cion} = \frac{l_{io}\#Capital_o^{n,c}}{\sum_p l_{ip}\#Capital_p^{n,s} + \sum_p l_{ip}\#Capital_p^{n,c}} K_i^n$$

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.

$$k_{sio} = \sum_n x_{sion} \tag{35}$$
$$k_{cio} = \sum_n x_{cion}$$

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

$$r_{sion} = \mathbf{r} + \sum_n \frac{q_{sion} x_{sion}}{Q_{sio} k_{sio}} \delta_{in} \tag{36}$$
$$r_{cion} = \mathbf{r} + \sum_n \frac{q_{cion} x_{cion}}{Q_{cio} k_{cio}} \delta_{in}$$

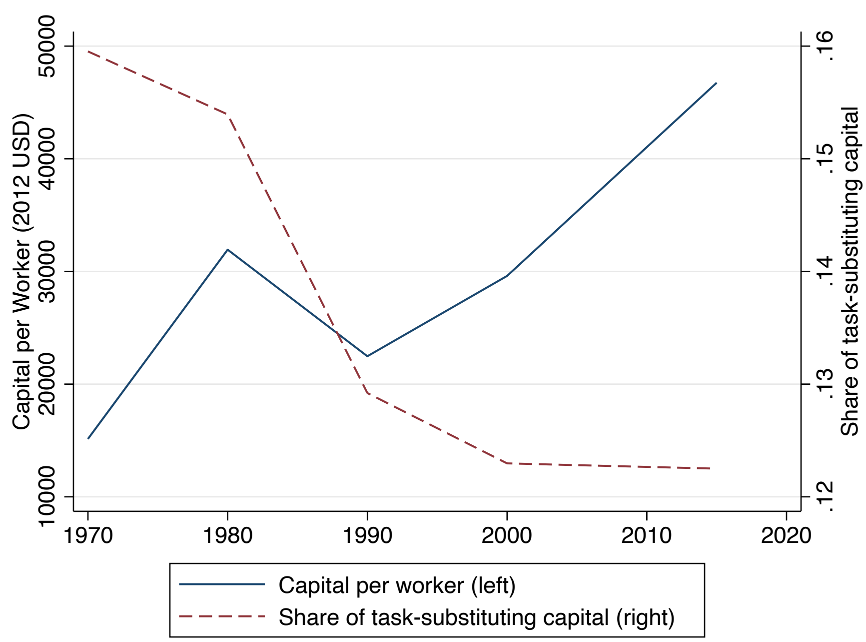
where $\mathbf{r}$ is the real interest rate and δ_{in} is the depreciation rate of capital good type. δ_{in} is imputed as the ratio between current-cost depreciated capital stock in a year to the average current-cost capital between the year and the year forward. q_{sion} is the price deflator between the current-cost stock of capital and the fixed-cost stock of capital measured in 2012 prices. Q_{sio} is defined by the non-arbitrage condition $\sum_n q_{jion} \kappa_{jion} = Q_{jio} Z$ where the factor-neutral conversion rate Z is normalized to one. $\mathbf{r}$ is set at 3% in a year.

A.3 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 15 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 is working with capital equivalent to 1,500 US dollars while an average worker in 2015 works with capital equivalent to 4,700 US dollars. The share of task-substituting capital is slowly decreasing, not increasing, over time. Task-substituting capital accounts 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.

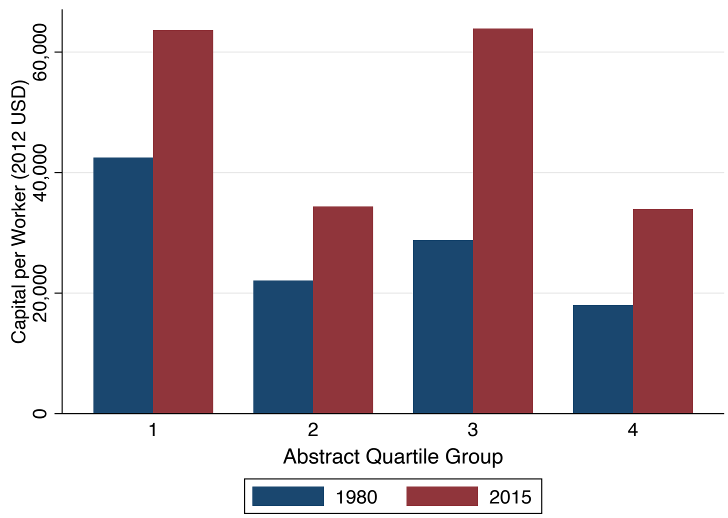
Figure 15: Capital per Worker over Time



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.

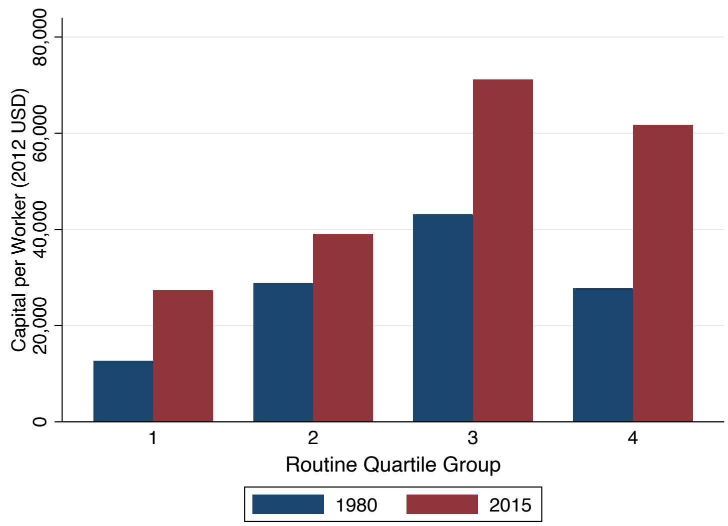
Next, Figures 16 and 17 show the average capital per worker in 1980 and 2015 over abstract and routine task score quartile groups. Less abstract and more routine occupations are more capital-intensive. However, the increment in capital stock per worker is more pronounced for more abstract and more routine task occupations. Later, it is shown 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 16: 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.

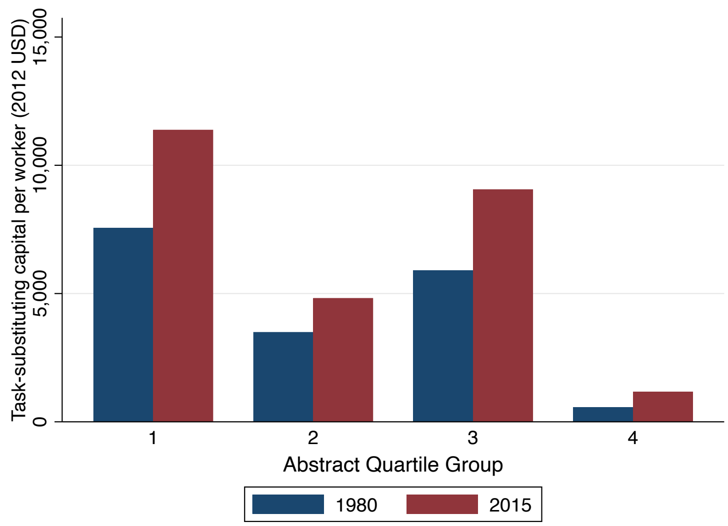
Figure 17: Capital per worker across routine task score quartile



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.

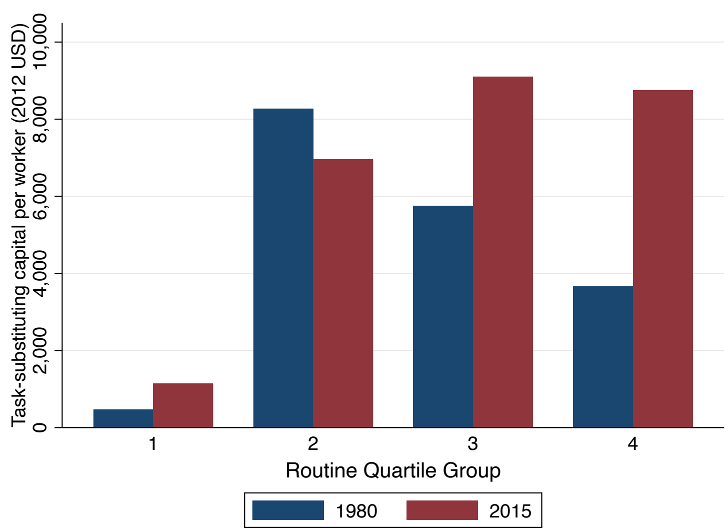
Figures 18 and 19 show the changes in task-substituting capital per worker. Again, less abstract occupations are more intensive in task-substituting capitals. However, the increase in task-substituting capital is now much dampened and less biased towards less abstract occupations. If occupations are 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 18: 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.

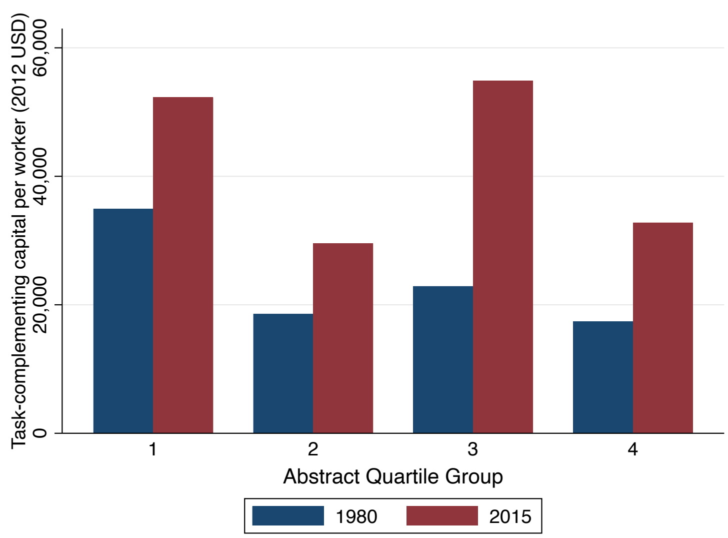
Figure 19: Task-Substituting Capital per Worker across Routine Task Score Quartile



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.

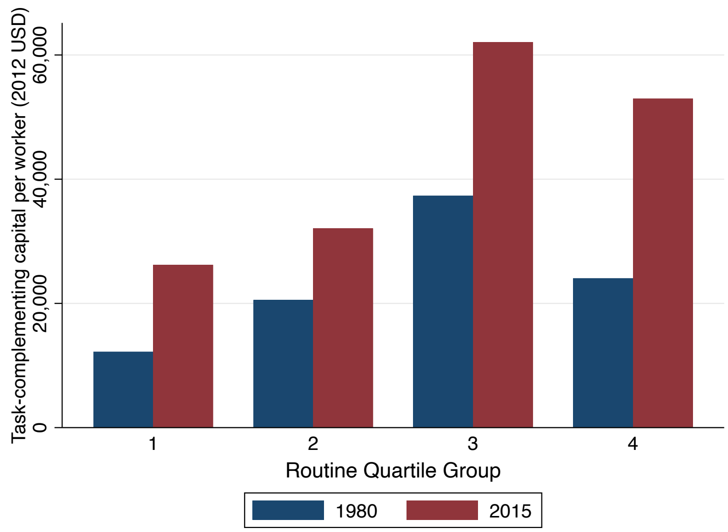
Figures 20 and 21 display the task-complementing capital stocks across abstract and routine task score quartiles, respectively. In 1980, more abstract task occupations were less intensive in task-complementing capital, but in 2015 their capital intensity is much more similar to less abstract occupations than before. In other words, the growth of task-complementing capital is more pronounced for more abstract task occupations. In Figure 20, 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 16 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 21, 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 19.

Figure 20: 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 21: Task-Complementing Capital per Worker across Routine Task Score Quartile

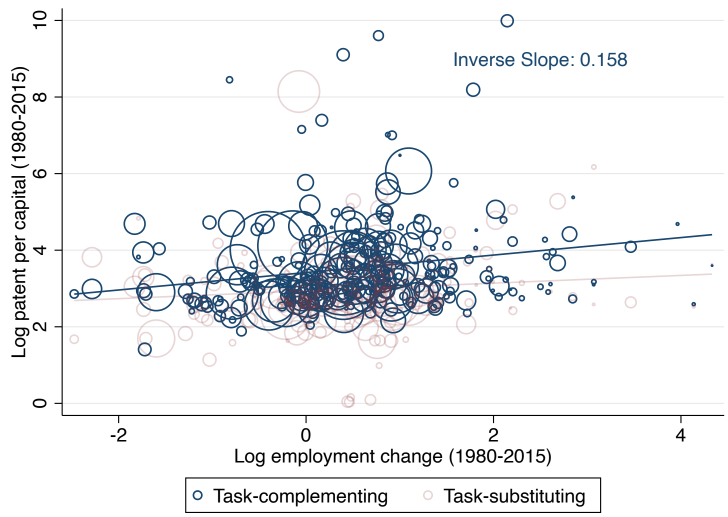


Notes: Quartile groups are made with the task scores from Autor and Dorn (2013) at the occupation level. Each occupation is weighted by the number of workers in 1980.

A.4 Reduced-Form Results

This appendix shows 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 22: Employment Change and CEI-c



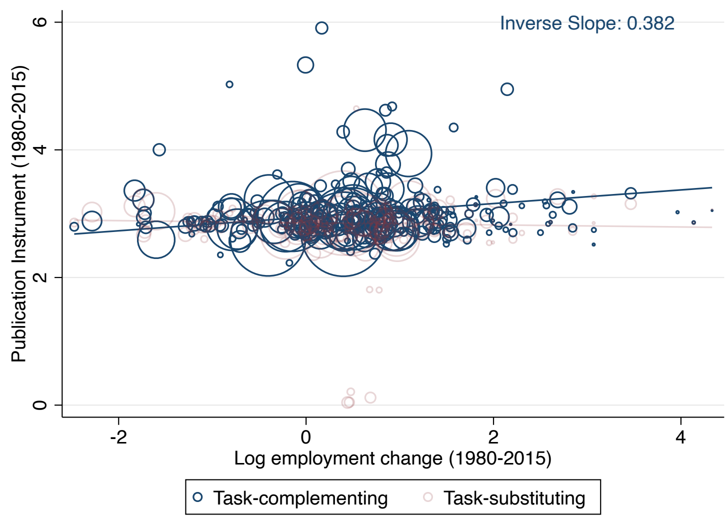
Notes: Each circle corresponds to an occupation code in OCC1990, and the size of a circle corresponds to the employment of each occupation in the 1980 Decennial Census. Task scores are from Autor and Dorn (2013).

Figure 23: Employment Change and CEI-s

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

Figures 22 and 23 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 24: 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 employment of each occupation in the 1980 Decennial Census. Task scores are from Autor and Dorn (2013).

Figure 25: 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 employment of each occupation in the 1980 Decennial Census. Task scores are from 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, Figures 24 and 25 show occupation-level scatter plots between employment changes and academic publication instruments. The instrument for task-complementing CEI increases with log employment change. On the other hand, the instrument for task-substituting CEI now decreases with log employment change. The upward bias of the OLS coefficient relative to the IV one suggests that the positive shocks to industry-level demand and capital productivity can increase demand for labor inputs and innovation for capital goods.

Table 6: Reduced-Form Results: Employment Change

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.154	0.242	0.131	0.237	
	(0.010)	(0.020)	(0.010)	(0.019)	
CEI-S	-0.048	-0.114	-0.029	-0.151	
	(0.010)	(0.030)	(0.010)	(0.032)	
Immigration			2.422	2.334	2.060
			(0.173)	(0.199)	(0.186)
Offshorability			0.028	0.047	0.057
			(0.009)	(0.011)	(0.009)
Routine			-0.008	-0.001	-0.026
			(0.004)	(0.004)	(0.004)
Abstract			0.094	0.093	0.101
			(0.005)	(0.005)	(0.004)
Manual			0.091	0.090	0.085
			(0.009)	(0.009)	(0.009)
First Stage F	-	656.4	-	570.2	-
N	11455	11455	11455	11455	11743

Table 6 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 7: Reduced-Form Results: Wage

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.002	-0.004	-0.008	0.002	
	(0.001)	(0.002)	(0.001)	(0.002)	
CEI-S	-0.014	-0.015	-0.012	-0.026	
	(0.001)	(0.003)	(0.001)	(0.003)	
Immigration			-0.242	-0.259	-0.194
			(0.019)	(0.022)	(0.018)
Offshorability			-0.013	-0.011	-0.015
			(0.001)	(0.001)	(0.001)
Routine			-0.011	-0.010	-0.011
			(0.000)	(0.000)	(0.000)
Abstract			0.007	0.007	0.007
			(0.000)	(0.001)	(0.000)
Manual			0.006	0.005	0.006
			(0.001)	(0.001)	(0.001)
First Stage F	-	656.4	-	570.2	-
N	11455	11455	11455	11455	11763

Table 7 shows the linear regression results on the wage instead. The results of wage changes trace out the results of employment growth with a smaller magnitude.

A.5 Different Thresholds

In Section 3.2, the threshold is set 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. This appendix shows the reduced-form results in Section A.4 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. The 80th, the 90th, the 94th, and the 96th percentile of the capital-occupation similarity distribution are tested for thresholds and repeat the reduced-form regression exercise.

Table 8: Employment Change with 80th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.147	0.253	0.171	0.277	
	(0.010)	(0.019)	(0.010)	(0.017)	
CEI-S	0.011	0.444	0.039	0.382	
	(0.011)	(0.022)	(0.011)	(0.023)	
Immigration			3.504	4.574	3.051
			(0.156)	(0.173)	(0.155)
Offshorability			0.011	-0.039	0.033
			(0.010)	(0.011)	(0.010)
Routine			0.018	-0.003	0.001
			(0.004)	(0.005)	(0.004)
Abstract			0.117	0.099	0.130
			(0.005)	(0.005)	(0.005)
Manual			0.119	0.098	0.107
			(0.009)	(0.010)	(0.009)
First Stage F	-	2001.7	-	1949.0	-
N	11430	11430	11418	11418	11751

Table 9: Employment Change with 90th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.130	0.331	0.161	0.318	
	(0.010)	(0.018)	(0.010)	(0.017)	
CEI-S	-0.022	-0.025	0.016	-0.019	
	(0.009)	(0.023)	(0.009)	(0.024)	
Immigration			3.403	3.652	3.009
			(0.158)	(0.178)	(0.156)
Offshorability			0.014	0.018	0.034
			(0.010)	(0.011)	(0.010)
Routine			0.013	0.023	0.000
			(0.004)	(0.004)	(0.004)
Abstract			0.119	0.114	0.130
			(0.005)	(0.005)	(0.005)
Manual			0.111	0.115	0.103
			(0.009)	(0.009)	(0.009)
First Stage F	-	1068.5	-	929.5	-
N	11440	11440	11428	11428	11751

Table 10: Employment Change with 94th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.142	0.190	0.121	0.200	
	(0.010)	(0.019)	(0.010)	(0.018)	
CEI-S	-0.031	-0.008	-0.019	-0.045	
	(0.009)	(0.024)	(0.009)	(0.025)	
Immigration			2.691	2.796	2.543
			(0.150)	(0.159)	(0.149)
Offshorability			0.017	0.022	0.026
			(0.009)	(0.011)	(0.009)
Routine			-0.008	-0.004	-0.019
			(0.004)	(0.004)	(0.004)
Abstract			0.096	0.094	0.104
			(0.005)	(0.005)	(0.005)
Manual			0.082	0.083	0.079
			(0.009)	(0.009)	(0.009)
First Stage F	-	931.5	-	844.6	-
N	11452	11452	11440	11440	11751

Table 11: Employment Change with 96th Percentile Threshold

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS
CEI-C	0.156	0.242	0.129	0.238	
	(0.010)	(0.019)	(0.010)	(0.019)	
CEI-S	-0.054	-0.131	-0.019	-0.111	
	(0.010)	(0.030)	(0.010)	(0.032)	
Immigration			2.675	2.697	2.473
			(0.174)	(0.199)	(0.173)
Offshorability			0.020	0.029	0.032
			(0.009)	(0.011)	(0.009)
Routine			-0.008	-0.005	-0.019
			(0.004)	(0.004)	(0.004)
Abstract			0.094	0.090	0.104
			(0.005)	(0.005)	(0.005)
Manual			0.096	0.094	0.091
			(0.009)	(0.009)	(0.009)
First Stage F	-	695.3	-	575.5	-
N	11455	11455	11443	11443	11751

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.6 Computers and Robots

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

Table 12: Share of Computer and Robot in CEI measures

	Mean	Sd	Median
Computer - complementing	0.25	0.30	0.10
Computer - substituting	0.03	0.15	0.00
Robot - complementing	0.00	0.01	0.00
Robot - substituting	0.01	0.07	0.00

Table 12 shows the share of computers and robots in CEI measures at the occupation level. A capital good is considered a computer if the commodity title has the words "computer" or "laptop". On the other hand, a capital good is considered a robot if the title has the words "automatic", "robot", or "drone". Computers account for 25% of task-complementing capital and 3% of substituting capital. Robots account for less than 0% of task-complementing capital and 1% of task-substituting capital.

Because robots account for a tiny fraction of capital goods, the counterfactual exercise is repeated only after excluding computers but not robots. The counterfactual patent measure now fixes the level of innovation for computers at its level in 2015 and changes only residual CEI to the level in 1980.

Table 13: Counterfactual Results Without Computer-Embodied Innovation

	Abstract Score		Routine Score	
	Employment	Wage	Employment	Wage
Without CEI	0.057	0.068	-0.116	-0.041
Actual Change	0.120	0.093	-0.166	-0.062

Table 13 exhibits the results. Even without changes in CEI on computers, the residual changes in CEI results in significant changes in abstract-biased employment growth. Compared to the results in Table 5, the residual CEI still replicates 86% ((0.12 - 0.057)/(0.12-0.047)) of abstract-biased employment changes. In other words, computer-related CEI generates 14% of the effect of CEI on abstract-biased employment growth. This value is lower than the share of computers in capital goods because computers are used for almost all occupations. The effect of computers on task-biased technological change comes from the heterogeneous intensity of computers in capital bundles. On the other hand, for routine task scores, excluding CEI on computers has a negligible effect on employment and wage changes. This results from routine-task input production intensive in machinery.

A.7 Counterfactual Details

The counterfactual exercise aims to derive the counterfactual equilibrium without CEI in 1980-2015. Demand-side variables such as ω_{io}^s, ω_{io}^c, μ_{io}, α_i, r_{io}^s, and r_{io}^c are fixed at their levels in 2015, change P_{io}^s and P_{io}^c at their levels in 1980. The total employment $\mathbf{L}$ is also fixed at its level in 2015. In order to run the counterfactual equilibrium, the two following equations are additionally needed.

$$1 = \frac{\alpha_i \mu_{io}}{\alpha_j \mu_{jo}} \left(\frac{Y_i}{Y_j}\right)^{\frac{1}{\sigma}-1} \left(\frac{y_{io}}{y_{jo}}\right)^{\frac{1}{\rho_c}-\frac{1}{\sigma}} \left(\frac{\Theta_{io}}{\Theta_{jo}}\right)^{\frac{\rho_c-\rho_s}{\rho_s \rho_c}} \left(\frac{l_{io}}{l_{jo}}\right)^{-\frac{1}{\rho_c}} \tag{37}$$

$$Y_i = l_{io} \left(\sum_o \mu_{io} \left(\frac{l_{io}}{l_{i0}}\right)^{\frac{\sigma-1}{\sigma}} \tilde{y}_{io}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = l_{i0} \tilde{Y}_i \tag{38}$$

Equation (37) is given by the first order conditions with respect to l_{io} and l_{jo}, respectively. Equation (38) expresses industrial outputs as a linear function of l_{io}, labor input of a reference occupation 0, and $\tilde{Y}_i$ that only depends on the ratio of labor inputs relative to a reference occupation 0. The manager (OCC1990 = 22) is used as the reference occupation.

By combining Equations (37) and (38), the following equation is derived.

$$1 = \frac{\alpha_i \mu_{io}}{\alpha_j \mu_{jo}} \left(\frac{\tilde{Y}_i}{\tilde{Y}_j}\right)^{\frac{1}{\sigma}-1} \left(\frac{\tilde{y}_{io}}{\tilde{y}_{jo}}\right)^{\frac{1}{\rho_c}-\frac{1}{\sigma}} \left(\frac{\Theta_{io}}{\Theta_{jo}}\right)^{\frac{\rho_c-\rho_s}{(\rho_s-1)\rho_c}} \left(\frac{l_{io}}{l_{jo}}\right)^{-1} \tag{39}$$