Occupational exposure to capital-embodied technology *

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Abstract

What is the effect of technological change on income inequality? A vast literature suggests that skill-biased technological change (SBTC) is a mayor driver of income inequality. However, SBTC is a black box, much like total factor productivity (TFP) is to growth theory. To make progress on the effect of technology on inequality we need measurement. Theoretically, SBTC can be driven by capital-embodied technological change to the extent that capital and skills are complementary. In this paper, we explore the relationship between technological advancement and inequality by building measures of capital-embodied technological change *at the occupation level*. We document substantial heterogeneity in the degree of capital-skill complementarity across occupations. Importantly, we show that the role assigned to SBTC for the raise in employment in skill intensive occupations over the last 35 years is almost exclusively accounted for capital-embodied technological change. Finally, we show that the raise in the skill-premia over the same period is accounted for the dynamics of the capital labor ratio and factor complementarity in two occupations: technicians and low-skill services.

JEL codes: O13, O47, Q10.
Keywords: skill-biased technical change, inequality, capital-embodied technology adoption.

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1 Introduction

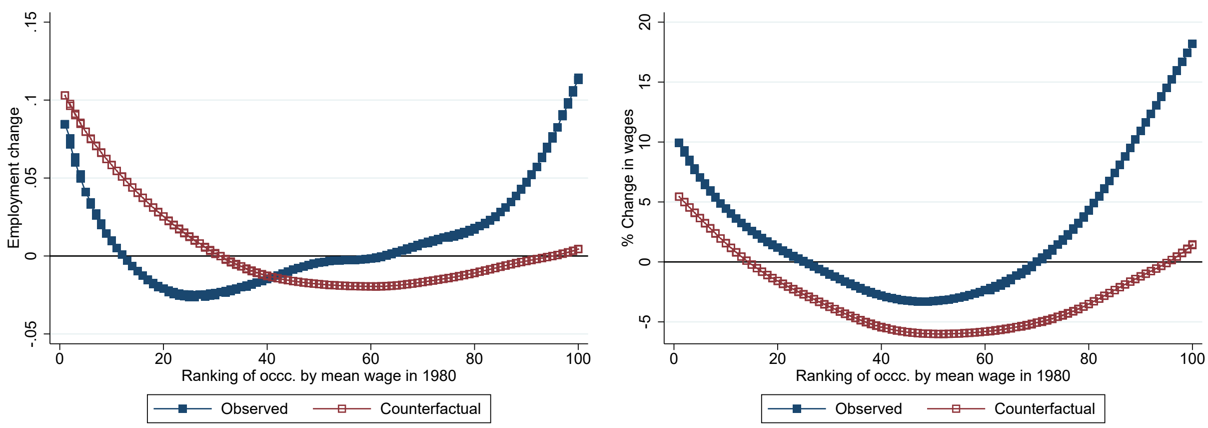
Inequality has been on the rise in Western societies, over the last half century. The bias of technological change toward skill has been isolated as a key driver of this raise. Katz & Murphy (1992) were the first to highlight the need for a bias toward skill in technical change to reconcile the increase in skill supply and the skill-premia observed in the US over the last 30 years. A lot of attention has then been given to the link between the bias of technology and inequality. Despite this, the literature has been mostly silent as of how skill-biased technical change operates. Krusell, Ohanian, Rios-Rull & Violante (2000, KORV) showed that capital-skill complementarities combined with technological change in equipment is a plausible and quantitatively relevant mechanism to explain the dynamics of the skill-premium in the US. In this paper, we zoom in on this mechanism and study the role of occupational heterogeneity in capital-skill complementarity in presence of technological change in equipment for labor market outcomes in the US.

Patterns of the skill-premium are mostly explained by within occupation inequality, rather than disparities across occupations (Roys & Taber, 2018). This suggests, prima facie, that skill-biased technical change has been different across occupations. This heterogeneity is also consistent with the non-monotonicity in employment and wage changes across occupations as documented in Autor & Dorn (2013). Through the lens of the mechanism proposed by KORV, either the rate of embodiment of technology differs for capital used in distinct occupations, or for a given rate of embodiment, the capital-skill complementarity is different across occupations, or both. Understanding the source of these disparities is first order in assessing the possible trade-offs between long-run growth through improvements in technology, and income inequality. This paper advances the frontier by constructing quality-adjusted stocks of capital by occupation, for major NIPA equipment categories. These stocks allow us to measure the rate of embodiment per bundle of capital equipment, in each occupation, which is our measure of occupational exposure to technical change. In addition, data on stock of equipment at the occupation level allows us to estimate occupation-specific elasticities of substitution between equipment and labor, of different types.

With these measures at hand we shed new light on the heterogeneous dynamics of employment across occupations with different skill requirements. We first construct a reduced form exercise in the spirit of Autor & Dorn (2013) and reweight the employment distribution across occupations imposing no employment change in occupations above the median of the distribution of changes in our measure of occupational capital per worker (see Panel (a) in Figure **??**). Consistent with skill-biased technical change being driven by capital-embodied technology adoption, we find that there would have been no gains in employment for occupations with high skill requirements absent capital-embodied technical change. In the same spirit, we also study the heterogeneous dynamics of wage changes across occupations, i.e. wage polarization. If we shut down wage gains in occupations that experienced large changes in capital per worker, we find that wages gains would be lower throughout the occupation spectrum, and that they would have been particularly lower for occupations with high-skill requirements (see Panel (b) in Figure **??**).

Figure 1: Exposure to CETC and labor market

(a) Employment polarization　　　　(b) Wage polarization



While both these counterfactuals provide motivating evidence for the role of heterogeneous exposure of capital-embodied technical change, they do not provide definitive evidence. To the extent that the occupational exposure may be correlated with other features of the occupation, labor market dynamics, etc., the role of capital-embodied technical change would likely be overstated. To properly assess its role for labor outcomes and inequality, we build a novel structural model. The model formalizes mechanisms through which technology changes the nature of the tasks that are being accomplished by an occupation. First, new capital can replace workers. Second, it can increase the demands for workers of particular skills and third, it may generate new tasks. We model these ideas in the context of a task model Acemoglu & Autor (2011). We split the space of tasks in three regions: an automation region, where capital and low-skill labor are substitutes (as in Acemoglu & Restrepo, 2018 and Martinez, 2018), a standarization region, where capital and workers have unitary elasticity, but where tasks can be performed either by low or high skill workers (as in Katz & Murphy, 1992 and Acemoglu, Gancia & Zilibotti, 2011); and a complex tasks region, where capital and high skill workers are complementary and low skill workers are not used. This region corresponds to new tasks created by technological progress (as in Kaboski, 2009). The set of tasks, as well as the set of automatable and standarizable tasks changes in time at an exogenous rate. Which tasks are effectively automated or standarized depends on the equilibrium costs of capital, low and high skill labor, and the rate of arrival of standardization opportunities relative to the shift in the set of tasks to be performed.

To illustrate the predictions of the model for our exercise we focus on the evolution of the skill-premium. The tractability of the model allow us to describe it in close form. The expression for the skill premium is a generalization of the standard one in Katz & Murphy (1992) to allow for heterogeneity in task and worker productivity, and importantly, to allow for heterogeneity in the elasticity of substitution between capital and skills. The equilibrium skill-premium depends on the effective task productivity which is a function of the endogenous assignment of heterogeneous workers to tasks, and the aggregate supply of low and skill workers. In addition, the equilibrium skill-premium depends on the capital-labor ratio of the occupations where capital and skills are complementary.[1] This result is novel, both to the labor literature that has extensively used version of the task model where capital is either omitted or assumed perfect substitutable to labor; and to the macro literature pioneered by KORV, where the relevant elasticity is that of some aggregate production function.

To bring the predictions of the model to the data, we need to construct a mapping between the tasks in the model, and the occupations in the data. To do it, we estimate the elasticity of substitution between capital and labor and rank occupations by their degree of complementarity to their corresponding quality-adjusted bundle of capital. To fix ideas, we focus on results that aggregate occupations at the 1-digit level. We find that technicians and low-skill services are the occupations most complementary to capital, while agriculture and mining are among the ones with highest rates of substitution. Hence, we map information on labor shares and capital-labor ratios from technicians and low-skill services to complex tasks. If we feed the path of capital-labor ratios in this occupations into a regression of aggregate skill-premium, controlling by the relative supply of skill, we find that we can explain most of the dynamic typically associated to the "trend" in technology, or skill-biased technical change (see Figure **??**).

In the next section we explain how we construct measure of capital at the occupation level. Then we lay out the model and main results. We are still in the process of properly calibrating the economy and we hope to have a full battery of quantitative results by the time of the conference.

[1] Of course this capital-labor ratio is in turn endogenous to the relative supply of workers and high skill workers, making the skill premia a highly non-linear function of the factor supplies and task and worker productivity.

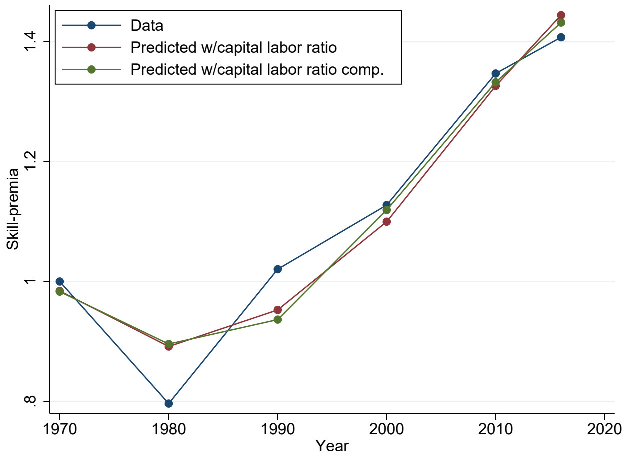


Figure 2: Evolution of the skill premia, data in blue, standard approach with aggregate capital-labor ratios as in KORV in red, using only capital-labor ratios in low-skill services and technicians in green.

2 An index of occupation's capital requirements

2.1 Data description

In order to build measures of capital requirements at the occupation level, we combine four different data sources: O*net data on the use of tools as described in the Tools and Technology supplement; NIPA series of investment for 16 equipment categories; quality-adjusted series for the price of equipment updated from Cummings and Violante (2002) by DiCecio; and employment measures by education level and occupation from Ipums-USA for the years 1950-2016. We describe each data source in the Appendix 1. We classify industries into agriculture, manufacturing, low-skill services, and high skill services. Our classification of low- and high-skill services follows **?** for 2-digit industry codes. They define high-skill service industries as those that pay a higher share of labor compensation to college graduates than all service industries do on average, over the period 1998-015. [2]

*From O*net tools to occupation's quality-adjusted capital stocks*

[2] This classification is also consistent with using the years of education of workers employed in the industry at our baseline year (1979). For example, the classification is practically the same if we consider the industries were average years of education were 13 or higher in 1979 as high-skilled.

We first use O*net data to estimate the number of tools by equipment used for each one of the 775 occupations as defined by the O*net-soc code. Second, we collapse this information by estimating the average tool use for each of the 440 occupations according to the American Community Survey (ACS) 2010 occupation code using the crosswalk provided by I-PUMS. Third, based on occupation data, we assign the number of tools in each equipment used at work by each individual from 1960 onwards. This measure is fixed for all years. Fourth, we estimate the quality-adjusted stock of capital of the entire US economy following permanent inventory method and deflating series of investment with quality-adjusted prices. Fifth, the quality-adjusted stock of capital of a given equipment is assigned to a worker using the fraction of total tools in the economy for a given equipment category that is used by the worker. Finally, we estimate the capital assigned to a worker (which is the same for all workers in a given occupation for a given year) as the sum of the quality-adjusted stock of capital of each equipment type that was assigned in the previous step.

Measure of the capital stock at the occupation level

Let T_{oe} be the total tools used by a worker in occupation o in equipment e (fixed across years), N_o^t is the total number of workers in occupation o at time t, then NT_e^t is the total tools in the economy in equipment e at time t defined by

$$NT_e^t = \sum_o T_{oe} * N_o^t.$$

Let $K_{e,t}$ be the nominal value of total stock of capital of equipment e at time t and p_e^t be the price of equipment e at time t relative to consumption, that is:

$$p_e^t = p_c^t / pi_e,$$

where p_c is consumer price index and pi_e^t is the price of investment in equipment e controlling for quality at time t. We deflate investment series from NIPA by the relative price of investment to consumption and build capital stocks following the law of motion

$$K_e^t + 1 = K_e^t(1 - \delta_e) + i_e^t * p_e^t$$

where the depreciation rates are consistent with those reported in BEA (see Table **??**).

To make the analysis more tractable, we split the space of capital stocks between those with high rates of capital embodiment, or large decays in the price of investment relative to consumption (HCETC), and those with low rate of embodiment, or small movements in the relative price of investment to consumption (LCETC). In addition, because an extensive literature focuses on the role of computers for labor market outcomes (Beaudry et.al. 2008, Burstein, et.al. 2018, Aum et.al. 2018 and Atalay et.al. 2018) we also single it out from HCETC equipment to make comparisons easier. Table **??** make the classification explicit and shows the dynamic of prices and stocks.

The value of the stock of capital in occupation o at time t in equipment e is equal to:

$$K_o e^t = \frac{T_{oe} * N_o^t}{NT_e^t} * K_e^t$$

And in per capita terms:

$$parisoneak_o e^t = \frac{T_{oe}}{NT_e^t} * K_e^t * p_e^t$$

That is the total stock of capital in a given equipment assigned to a worker in a given occupation is the quality-adjusted stock of capital multiplied by the fraction of tools used by each worker in that equipment.

The total stock of capital per worker is defined as the sum of the stock of capital in all equipment and it is defined as

$$k_o^t = \sum^{o} \frac{T_{oe}}{NT_e^t} * K_e^t * p_e^t \tag{1}$$

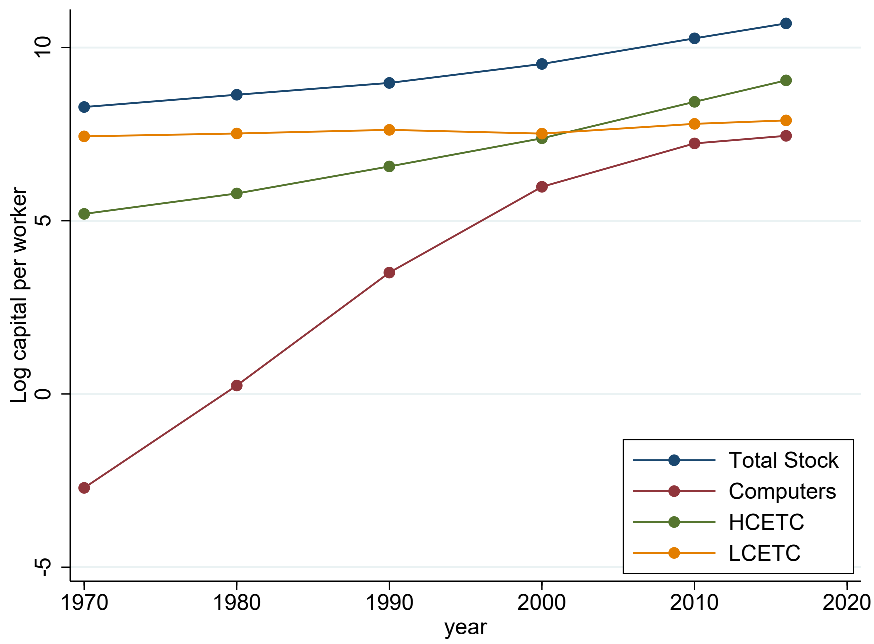
Table ?? displays the composition of the stock by 1-digit occupations at different points in time.[3] At the same time, Table ?? show summary statistics on how capital of different type correlate with labor market outcomes at the occupation level.

Next, we describe the series of capital stock for broad equipment categories and aggregated up to 1-digit occupation categories across time (see Figure ??). Two features stand-out. First, capital intensity in computers has increased the most, consistently with a large decline in their relative price, but the aggregate dynamic of the capital-labor ratio tracks closely that of the stock of HCETC equipment. Second, the dispersion in capital intensity across occupations have been declining, and the occupations where capital intensity raised the most are managers, sales and administrative services.

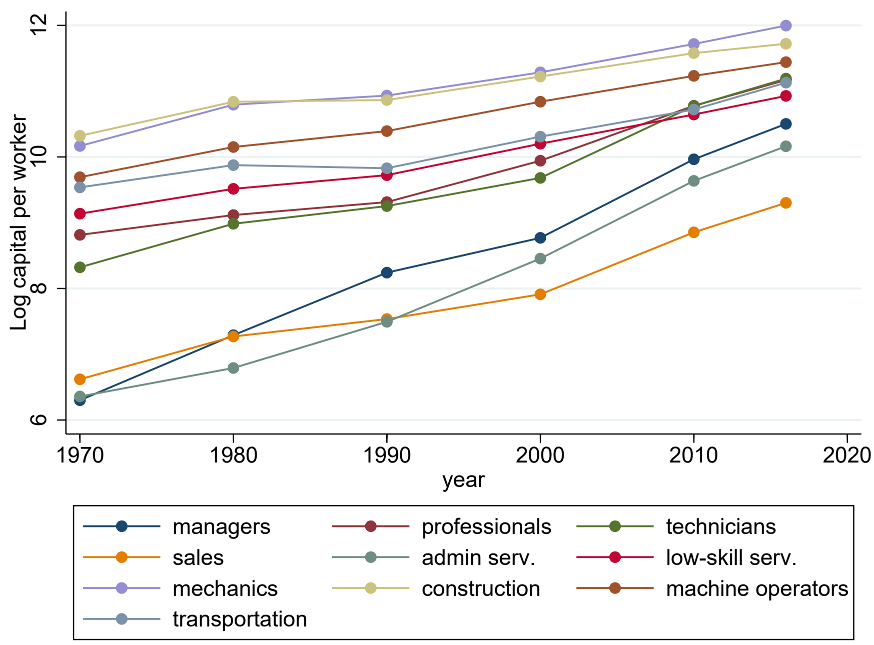
[3] This classification can be done at the level of 300 occupations but we choose higher aggregation here to ease the exposition.

Figure 3: Capital per worker by type and occupation

(a) Stock by equipment type



(b) Stock by occupation



3 A model of occupational exposure to CETC

The environment that we present next combines and expands the frameworks presented in Acemoglu, Gancia and Zillibotti (1998), Kaboski (2009), Acemoglu and Restrepo (2018) and Martinez (2008) The economy is populated by workers of heterogeneous skill, for simplicity, we assume two skill levels, high H and low L. We assume there is a continuum of tasks. [4] of support LI_t, I_t available at time t in the economy. This support riases exogenously at some rate γ and we assume that new tasks require high-skill workers and capital to be completed. Each task maps to task-specific productivity level, $a(i)$ and a production technology that we describe below.The space of tasks available at a point in time is distributed in 3 regions: (i) The interval $(0, A_t]$ are tasks that are automated, that is, tasks that could be potentially done entirely with a piece of equipment; (ii) The interval $(A_t, S_t]$ characterizes standardized tasks, that is, tasks that in the past were performed by high-skilled workers, but that can now be produced with low skill-workers; (iii) The interval $(S_t, I_t]$ characterizes new tasks, that can only be performed with high-skill workers. In equilibrium, whether a task is automated, standardized or not depends relative prices of capital and labor, as well as the relative price of high and low skill workers and their comparative advantage in producing a given task, as indexed by their productivity z. We assume that low-skill workers have a comparative advantage in engaging in low-index tasks, and than worker productivity increases in the task index, i.e.

$$z(0, L) > z(0, H) \quad \text{and } z_1(i, L) < z_1(i, H) \text{ both larger than zero.}$$

The set of tasks that are effectively automated are denoted by the interval, $(0, A_t^*]$, the set of tasks that are effectively standarized are $(A_t, S_t^*]$.

[4] I am using tasks and occupations interchangeably but in the next iteration we may need to think carefully about what each of them mean and how to twickle the model to better match the data. Most of the papers in the literature start with task as primitives and then build up empirical measures to match to occupations

The production technologies in these three regions are

$$y(i) = a_k(i)k(i) + l(i,L)a(i) \qquad \text{if } i \in (0, A_t]$$

$$y(i) = a(i)k(i)^{\alpha}(\sum_{e=L,H} l(i,e)z(i,e))^{1-\alpha} \qquad \text{if } i \in (A_t, S_t]$$

$$y(i) = a(i)(k(i)^{\rho} + (l(i,H)z(i,H))^{\rho})^{\frac{1}{\rho}} \qquad \text{if } i \in (S_t, I_t]$$

for $\rho < 1$

A few characteristics deserve further discussion. First, capital and labor are perfect substitutes in task that have potential for automatization. Second, standardized tasks can be completed with high or low-skill workers. Finally, capital-skill complementarities are stronger in new tasks, than they are in standardized tasks.

Total output in the economy is characterized by a constant returns aggregator as

$$Y_t = (\int_0^{A_t} y_t(i)^{\frac{\sigma-1}{\sigma}} di)^{\frac{\sigma}{\sigma-1}}$$

with σ being the elasticity of substitution across output from different tasks. If $p(i)$ is the shadow value associated to goods produced in task i, then the inverse demand function is

$$p(i) = (\frac{Y_t}{y_t(i)})^{\frac{1}{\sigma}}$$

Before characterizing factor allocations and the distribution of task we make the following assumptions on labor returns. **Assumption 1***workers in automatable tasks are paid a common wage, independent of the efficiency of workers in the task.* The latter is analogous to a minimum wage for workers in automatable tasks, $(0, A_t]$. It is analogous to assuming that worker efficiency doesn't matter in automatable tasks (with a production function $z(i,L)(\frac{a_k(i)}{z(i,L)}k(i) + l(i,L))$), and that the shifter $z_{i,L}$ is just the Hicks neutral productivity shifter of the task while $a_k(i)/z_{i,L}$ is the efficiency of capital normalized by such a shifter.

Assumption 2*workers in standardizable tasks and complex tasks are paid relative to their efficiency units.*

Endogenous distribution of tasks:

With these technologies, we can determine the optimal thresholds A_t^* and S_t^* as a function of parameters and factor prices. In particular, tasks will be automated if the costs of the capital composite assigned to a task, $k(i)$, is lower than the labor cost, i.e.

$$r(i) \leq \frac{a_k(i)}{a(i)} w(L) \text{ with equality at } i = A_t^\star \tag{2}$$

Second, tasks will be standardized (in the sense that they will be completed by low-skill labor and capital, whenever their cost per efficiency unit is lower than the cost of high-skill labor.

$$w(L) \leq w(H) \tag{3}$$

So that the solution is bang-bang. Either all occupations are standardized, or they are not. $S^\star$ corresponds to a corner solution equal to either S_t or A_t, respectively. We are currently working on a version that gets around this bang-bang solution by assuming that the arrival of "standarization" opportunities for these tasks come at random, η, as in Acemoglu, Gancia & Zilibotti (2011). When the standarization opportunity arrives a non-trivial game between an incumbent (that uses high skilled workers, and an entrant, that can use low-skill workers). To the extent that $w_L < w_h$ the equilibrium will display standarization and because arrivals are stochastic, this won't necessarily be associated with a threshold, but rather a measure/distribution of tasks standardized within the interval (A_t, S_t)

Labor allocations:

To solve for the optimal labor allocation to each of the regions we combine optimality conditions for inputs with the inverse demand function derived above.

In particular, for tasks in the $(A_t^*, A_t]$ region (if not empty),

$$p(i) = \frac{w(L)}{a(i)} \quad \text{and} \quad \frac{y(i)}{y(i')} = (\frac{p(i')}{p(i)})^{\sigma}$$

which implies

$$\frac{y(i)}{y(i')} = (\frac{a(i)}{a(i')})^{\sigma}$$

Using the definition of output, we can further solve for relative labor demands,

$$\frac{l(i,L)}{l(i',L)} = (\frac{a(i)}{a(i')})^{\sigma-1} \tag{4}$$

We can follow the same procedure to solve for the labor allocation in tasks that are standarizable. In particular,

$$\frac{l(i,s)}{l(i',s)} = \frac{z(i',s)}{z(i,s)}(\frac{a(i)}{a(i')})^{\sigma-1} \tag{5}$$

Among complex tasks, the allocation is again

$$\frac{l(i,H)}{l(i',H)} = \frac{z(i',H)}{z(i,H)}(\frac{a(i)}{a(i')})^{\sigma-1} \tag{6}$$

Capital allocations:

The capital allocation to automatable tasks follows from the optimality condition in production and the optimal output demand for each task.

$$p(i) = \frac{r}{a_k(i)} \quad \text{and} \quad \frac{y(i)}{y(i')} = (\frac{p(i')}{p(i)})^{\sigma}$$

which implies

$$\frac{y(i)}{y(i')} = (\frac{a_k(i)}{a_k(i')})^{\sigma}$$

Using the definition of output,

$$\frac{k(i)}{k(i')} = (\frac{a_k(i)}{a_k(i')})^{\sigma-1} \tag{7}$$

The allocations of capital among standardizable and complex tasks follows for the optimal labor allocation and the equality in capital-labor ratios (where labor is measured in efficiency units) across tasks. Then,

$$\frac{k(i)}{k(i')} = (\frac{a(i)}{a(i')})^{\sigma-1} \tag{8}$$

So far we have characterized the relative allocation of capital and labor to different tasks. To further characterize factor levels and factor prices, we need to solve for the labor and capital demands at the thresholds.

Levels: By definition, the labor market clearing condition for high skill workers requires,

$$\overline{l(H)} = \int_{S_t^\star}^{S_t} l(i,H)di + \int_{S_t}^{I_t} l(i,H)di$$

where $S_t^\star$ is either the standardization threshold, so that all those tasks are completed by low-skill workers; or the automation threshold, so that those tasks are completed by high-skill workers.

We can solve for employment at the standardization threshold by rewriting the above condition as

$$\overline{l(H)} = l(S_t,H)(\int_{S_t^\star}^{S_t} \frac{l(i,H)}{l(S_t,H)}di + \int_{S_t}^{I_t} \frac{l(i,H)}{l(S_t,H)}di)$$

We can solve for employment at the standardization threshold by rewriting the above condition as

$$l(S_t,H) = \frac{\overline{l(H)}}{(\int_{S_t^\star}^{I_t} \frac{z(S_t,H)}{z(i,H)}(\frac{a(i)}{a(S_t)})^{\sigma-1})} \tag{9}$$

Following the same procedure, we can solve for low-skill labor at the automation threshold as

$$l(A_t, L) = \frac{\overline{l(L)}}{\int_{A_t^\star}^{A_t} (\frac{a(i)}{a(A_t)})^{\sigma-1} + \int_{A_t}^{S_t^\star} \frac{z(A_t,L)}{z(i,L)} (\frac{a(i)}{a(A_t)})^{\sigma-1}}$$

To compute the equilibrium allocation of capital at the thresholds, we can use the market clearing condition and the condition for automation (as long as it is interior) and we have a continuum of tasks, so that at the margin, the task has measure zero (when computing this, we may need to use a different condition, see below).

The market clearing condition of capital implies,

$$K = k(A_t^\star) \int_0^{A_t^\star} (\frac{a_k(i)}{a_k(A_t^\star)})^{\sigma-1} + k(S_t) \int_{S_t^\star}^{I_t} (\frac{a(i)}{a(S_t)})^{\sigma-1} \tag{10}$$

The optimality conditions for capital and labor demands at the automation threshold are

$$K = k(A_t^\star) \int_0^{A_t^\star} (\frac{a_k(i)}{a_k(A_t^\star)})^{\sigma-1} + k(S_t) \int_{S_t^\star}^{I_t} (\frac{a(i)}{a(S_t)})^{\sigma-1} \tag{11}$$

$$r = p(A_t^\star) a_k(A_t^\star) = (\frac{Y_t}{a_k(A_t^\star) k(A_t^\star)})^{\frac{1}{\sigma}} a_k(A_t^\star)$$

$$w(L) = p(A_t^\star) a(A_t^\star) = (\frac{Y_t}{a(A_t^\star) l(A_t^\star, L)})^{\frac{1}{\sigma}} a(A_t^\star)$$

which combined with equation **??** requires

$$\frac{l(A_t^\star, L)}{k(A_t^\star)} = \frac{a_k(A_t^\star)}{a(A_t^\star)}$$

Given $l(A_t^\star, L)$ we can pin down $k(A_t^\star)$ as

$$k(A_t^\star) = \frac{l(A_t^\star, L)}{l(A_t, L)} l(A_t, L) (\frac{a_k(A_t^\star)}{a(A_t^\star)})^{-1}$$

$$k(A_t^\star) = (\frac{a(A_t^\star)}{a(A_t)})^{\sigma-1} (\frac{a_k(A_t^\star)}{a(A_t^\star)})^{-1} \frac{\overline{l(L)}}{\int\limits_{A_t^\star}^{A_t} (\frac{a(i)}{a(A_t)})^{\sigma-1} + \int\limits_{A_t}^{S_t^\star} \frac{z(A_t,L)}{z(i,L)} (\frac{a(i)}{a(A_t)})^{\sigma-1}}$$

We can replace this expression in the market clearing condition to solve for $k(S_t)$

$$k(S_t) = (K - (\frac{a_k(A_t^\star)}{a(A_t^\star)})^{\sigma} \overline{l(L)} \frac{\int\limits_0^{A_t^\star} (a_k(i))^{\sigma-1}}{\int\limits_{A_t^\star}^{A_t} (a(i))^{\sigma-1} + \int\limits_{A_t}^{S_t^\star} \frac{z(A_t,L)}{z(i,L)} (a(i))^{\sigma-1}}) (\int\limits_{S_t^\star}^{I_t} (\frac{a(i)}{a(S_t)})^{\sigma-1})^{-1} \tag{12}$$

prices

With allocations fully characterized it is easy to describe equilibrium prices. In particular, given the optimality conditions for labor, we can solve

$$w_H = a(S_t)(1 + (\frac{k(S_t)}{z(S_t, H), l(S_t, H)})^{\rho})^{\frac{1}{\rho}-1} (\frac{Y_t}{y(S_t)})^{\frac{1}{\sigma}}$$

$$w_L = a(A_t)(\frac{Y_t}{y(A_t)})^{\frac{1}{\sigma}}$$

So that the skill-premia (in efficiency units) is

$$\frac{w_H}{w_L} = (\frac{a(S_t)}{a(A_t)})^{1-\frac{1}{\sigma}} (\frac{l(A_t, L)}{l(S_t, H) z(S_t, H)})^{\frac{1}{\sigma}} (1 + (\frac{k(S_t)}{z(S_t, H), l(S_t, H)})^{\rho})^{\frac{1}{\rho}(1-\frac{1}{\sigma})-1}$$

Using the optimal labor demand at the threshold we obtain the equilibrium expression of the skill-premia as in the canonical task model.

$$\frac{w_H}{w_L} = (\frac{l(\overline{L})}{l(\overline{H})})^{\frac{1}{\sigma}} (\frac{\int_{S_t^\star}^{I_t} (\frac{a(i)}{z(i,H)})^{\sigma-1}}{\int_{A_t^\star}^{A_t} (a(i))^{\sigma-1}})^{\frac{1}{\sigma}} (1 + (\frac{k(S_t)}{z(S_t,H), l(S_t,H)})^{\rho})^{\frac{1}{\rho}(1-\frac{1}{\sigma})-1} \tag{13}$$

A couple of features stand out from equation **??**. First, if the productivity in all automatable tasks is identical, $a(A_t) = a_A$ and the productivity in all standarizable tasks is the same, and in addition, there is no heterogeneity in labor productivity for standarizable tasks, then the first two terms of the equation above reduces to the skill-premia in the canonical model. Second, different patterns of elasticity between capital and labor enter into the equilibrium skill premia through GE effects.

We can log-linearize the equation above to obtain the standard skill-premia equation as in Katz and Murphy plus a term of the form,

$$(\frac{1}{\rho}(1 - \frac{1}{\sigma}) - 1) \frac{(\frac{k(S_t)}{z(S_t,H), l(S_t,H)})^{\rho}}{1 + (\frac{k(S_t)}{z(S_t,H), l(S_t,H)})^{\rho}} \rho \Delta (\frac{k(S_t)}{z(S_t,H), l(S_t,H)})$$

which is a function of the change in the capital labor ratio at the top of the skill distribution. In reality, one can show that the equilibrium capital-labor ratio at the threshold S_t is a complicated, but known function of the productivity across tasks and the supply of capital and labor in the economy as summarized by the level equations, **??** and **??**. In other words, technology and the supply of capital and skills enter non-linearly into the skill premium. Importantly from an empirical point of view, the predictions of the model can be directly tested in the data. With measures of capital-labor ratios in tasks where high-skill workers are the main labor input in production, we can run a regression as Katz & Murphy (1992), adjusted. The theory predicts that as capital deepening happens, i.e. $\frac{k}{l}$ raises, the impact on the skill premium depends on the elasticity of substitution between capital and labor, and the elasticity of substition across tasks. In particular, if capital and labor are complementary, $\rho < 0$, and output across tasks are substitutes, the skill premia raises in capital deepening. If instead output across tasks are complements (as it is the estimated parameters in many version of the standard task model), then the impact on the skill premia depends on the value of $\frac{\sigma-1}{\rho\sigma}$. If the latter is lower than one, which is likely to happen when capital and labor are very complementary, then the skill-premia raises again in capital deepening. If the opposite is true (for example, because capital and skill are not very complementary, then the skill premia falls in capital deepening.

4 Bringing the model to the data

The first issue to solve in bringing a tasks model to the data is that we need a mapping between tasks and occupations. To do it, we classify occupations depending on the elasticity of substitution between capital and labor.

Consider the problem of a firm that produces output for task i with a CES technology

$$y(i) = (a(i)k(i)^{\rho_i} + z(i)(l(i))^{\rho_i})^{\frac{1}{\rho_i}}$$

Note that this technology embeds the one used in each subspace of the task space describe before.

The optimality conditions are such that

$$ln(\frac{r}{w}) = ln(\frac{a}{z}) + (\rho_i - 1)ln(\frac{k}{l})$$

where w is residual wage after controlling for experience and worker characteristics. These controls are necessary because we were to run this structural regression using time-series data at the occupation level, we would be likely facing selection issues on the type of workers allocated to each of those occupations. We also show results when we do not include these controls.

We estimate the above regression for each of our 300+ occupations and then compute averages when aggregating up to 1-digit occupation categories. Table **??** shows the result of this estimation. We find that for Technicians and Low-skill services occupations capital and labor are complementary, whereas for Agriculture and Mining, those inputs are substitutes. We also find substantial variation in elasticities across occupations and many of them lie around a unitary elasticity. Then we recompute these elasticities by equipment category, assuming that the only type of capital used in production in those occupations is the type under consideration. We find that while Computers and LCETC equipment tend to be substitutes to labor, HCETC is broadly complementary to labor across occupation categories.

Table 1: Elasticities for different equipment at the 1-digit occupation level

Group by 1-digit occuaption	Elasticities					Employment share	
	All equipment		Computers	HCETC	LCETC	1980	2016
	Average wage	Predicted wage					
Managers	1.22	1.17	2.62	1.00	8.33	0.17	0.19
Professionals	0.98	0.99	-	0.80	12.20	0.14	0.21
Technicians	0.99	0.93	-4.90	0.76	8.40	0.04	0.04
Sales	1.03	1.01	2.17	1.10	33.33	0.08	0.09
Administrative Ser.	1.03	1.01	8.13	1.05	40.00	0.17	0.13
Low-Skilled Ser.	1.02	0.94	6.62	0.93	-	0.13	0.17
Agriculture	3.61	4.33	4.33	1.25	4.72	0.01	0.01
Mechanics	2.50	2.08	10.87	1.04	16.39	0.04	0.03
Construction	1.55	1.40	2.46	1.28	2.78	0.04	0.03
Mining	1.32	1.32	-3.22	0.86	8.62	0.02	0.01
Machine operators	1.56	1.20	4.12	2.02	4.76	0.11	0.05
Transportation	1.00	0.99	2.12	0.90	6.49	0.04	0.03
All	**1.10**	**1.14**	**7.30**	**0.95**	**13.89**	**1.00**	**1.00**

4.1 Calibration

Under construction

5 Conclusions

To be completed

6 Appendix

6.1 Data description and sources

Quality-adjusted prices by equipment

We use quality-adjusted price series to construct series of the relative price of investment to consumption. As in Greenwood, et.al. (1997), changes in this relative price can be interpreted as a measure of investment-specific technological change, i.e. technical change embodied in capital. We use and updated version of the constant-quality price indexes for capital goods estimated by Cummings and Violante (2002) over the period 1947-2016 for each equipment type, as updated in DiCecio (2008).

Stocks of equipment controlling for quality.

We build a measure of aggregate capital stocks for each equipment type following the permanent inventory method. Let K_e^t be the stock of equipment of type e at time t, and let δ_e be the equipment-specific depreciation rate, I_e^t be the nominal value of investment in equipment e at time t, and p_e^t be the quality-adjusted price of investment. Then, the stock of capital, controlling for changes in quality evolves according to:

$$K_e^{t+1} = K_e^t(1-\delta_e) + \frac{I_e^t}{p_e^t}.$$

Investment data corresponds to the detailed Investment in Private Nonresidential Fixed Assets NIPA table. This table contains detailed data on investment by equipment and sector.

Depreciation rates come from Table 3 U.S. Bureau of Economic Analysis (BEA). When the depreciation rate is reported at a more disaggregated level than the equipment category in NIPA, we average them out. We impose the same depreciation for Autos than for local and interurban passenger transit since the depreciation rate is missing for Autos. Table **??** shows the depreciation rate by equipment that we use. We estimate the initial capital taking the net stock of private fixed equipment valued at current prices in 1947 divided by price in 1947 (the first years of our price series). We took the simplifying assumption that initial capital in 1947 was of the same quality than investment. This implies an upward bias in our initial stock. As usual when constructing series via permanent invetory method, the initial stock of capital becomes unimportant once we focus onto enough periods into the future. [5]

We group the different equipment types following the classification from Table **??** and Table **??**.

*O*net data on tools used in each occupation*

We use data from the Tools and Technology module in O*net to estimate the number of tools for different type of equipment in each occupation. The module contains detailed data on the tools used for each of the 775 occupations classified by O*net-soc code. We follow Sangin Aum (2017) in classifying each of the tools into a family of commodities that we match with the NIPA classification of equipment according to Table 1. More than 4000 tools are then classified into 24 families of commodities according to NIPA codes.

Then, we use the occupation crosswalk from the US Census Bureau to end up with tool data for 440 occupations as classified by the Census in 2010. For each one of these occupations, we estimate the number of tools used in each type of equipment to create a measure of use intensity by equipment type as described in the body of the paper.

Census Data from I-pums

Data of workers' wages and employment status stems from Ipums-USA for 10-year census over the period 1950-2000 and the American Community Survey for 2000, 2010, and 2016. We follow Acemoglu and Autor (2011) procedures for data cleaning and sample selection. To estimate wages, we only consider income from wages; we trim the bottom and top 1.

[5] By 1980 the estimated capital stock is practically the same when we consider the initial capital to be 0 or to be of the same quality than investment (see Appendix Table **??**). The true initial capital is clearly between these two values, so that it is not relevant fro the series 1980-2016.

6.1.1 Tables

Table 2: Commodity family of tools and Nipa category

Family code	Family Name and Nipa equipment categories
4	**Computers and peripheral equipment**
43210000	Computer Equipment and Accessories
5	**Communication equipment**
43190000	Communications Devices and Accessories
43200000	Information tech. or broadcasting or telecomm.
43220000	Data Voice or Multimedia Network Equipment
45110000	Audio and visual presentation and composing
46170000	Security surveillance and detection
55110000	Electronic reference material
55120000	Signage and accessories
6	**Medical Instruments**
42150000	Dental equipment and supplies
42160000	Dialysis equipment and supplies
42170000	Emergency and field medical services products
42180000	Patient exam and monitoring products
42190000	Medical facility products
42200000	Medical diagnostic imaging and nuclear medicine
42210000	Independent living aids for the physically challenged
42220000	Intravenous and arterial administration products
42230000	Clinical nutrition
42240000	Orthopedic and prosthetic and sports medicine
42250000	Physical and occupational therapy and rehabilitation
42260000	Postmortem and mortuary equipment and supplies
42270000	Respiratory and anesthesia and resuscitation
42280000	Medical sterilization products
42290000	Surgical products
42300000	Medical training and education supplies
42310000	Wound care products
9	**Non-Medical Instruments**
41100000	Laboratory and scientific equipment
41110000	Measuring and observing and testing instruments
41120000	Laboratory supplies and fixtures
10	**Photocopy and related Equipment**
45100000	Printing and publishing equipment
45120000	Photographic or filming or video equipment
45140000	Photographic filmmaking supplies
11	**Office & accounting equipment**
44100000	Office machines and their supplies and accessories
44110000	Office and desk accessories
44120000	Office supplies
13	**Fabricated metal products**
27110000	Hand tools
27120000	Hydraulic machinery and equipment
27140000	Automotive specialty tools
31150000	Rope and chain and cable and wire and strap
31160000	Hardware
31170000	Bearings and bushings and wheels and gears
31180000	Packings glands boots and covers
40140000	Fluid and gas distribution
40170000	Pipe piping and pipe fittings
14	**Engines & turbines**
26100000	Power sources
26110000	Batteries and generators and kinetic power
26130000	Power generation
26140000	Atomic and nuclear energy machinery
17	**Metalworking machinery**
23240000	Metal cutting machinery and accessories
23250000	Metal forming machinery and accessories
23280000	Metal treatment machinery
18	**Special industry machinery, n.e.c.**
23100000	Raw materials processing machinery
23120000	Textile and fabric machinery and accessories
23130000	Lapidary machinery and equipment
23140000	Leatherworking repairing machinery and equipment
23150000	Industrial process machinery and equipment
23180000	Industrial food and beverage equipment
23190000	Mixers and their parts and accessories
23210000	Electronic manufacturing machinery and equipment
23220000	Chicken processing machinery and equipment
23230000	Sawmilling and lumber processing machinery
23260000	Rapid prototyping machinery and accessories
32110000	Discrete semiconductor devices
19	**General industrial eq.**
23110000	Petroleum processing machinery
23160000	Foundry machines and equipment and supplies
23200000	Mass transfer equipment
23270000	Welding and soldering and brazing machinery
23290000	Industrial machine tools
24100000	Material handling machinery and equipment
24110000	Containers and storage
24130000	Industrial refrigeration
24140000	Packing supplies
27130000	Pneumatic machinery and equipment
31140000	Moldings
40100000	Heating and ventilation and air circulation
40150000	Industrial pumps and compressors
40160000	Industrial filtering and purification

Table 2: Commodity family of tools and Nipa category (continue)

Family code	Family Name and Nipa equipment categories
4	**Computers and peripheral equipment**
20	**Electrical transmission, and industrial apparatus**
26120000	Electrical wire and cable and harness
31250000	Pneumatic and hydraulic and electric control systems
32100000	Printed circuits and integrated circuits
32120000	Passive discrete components
26	**Aircrafts**
25130000	Aircraft
25200000	Aerospace systems and components and equipment
27	**Ships & boats**
25110000	Marine transport
28	**Railroad equipment**
25120000	Railway and tramway machinery and equipment
29	**Other equipment**
32140000	Electron tube devices and accessories
42120000	Veterinary equipment and supplies
49120000	Camping and outdoor equipment and accessories
53100000	Clothing
53110000	Footwear
53120000	Luggage and handbags and packs and cases
53130000	Personal care products
53140000	Sewing supplies and accessories
54100000	Jewelry
54110000	Timepieces
30	**Furniture & fixtures**
30160000	Interior finishing materials
30170000	Doors and windows and glass
30180000	Plumbing fixtures
56100000	Accommodation furniture
56110000	Commercial and industrial furniture
56120000	Classroom and instructional furniture and fixtures
56130000	Merchandising furniture and accessories
33	**Agric. machinery**
21100000	Agricultural and forestry and landscape
21110000	Fishing and aquaculture equipment
36	**Construction machinery**
22100000	Heavy construction machinery and equipment
30120000	Roads and landscape
30190000	Construction and maintenance support equipment
30240000	Portable Structure Building Components
13	**Fabricated metal products**
39	**Mining & oilfield machinery**
20100000	Mining and quarrying machinery and equipment
20110000	Well drilling and operation equipment
20120000	Oil and gas drilling and exploration equipment
20140000	Oil and gas operating and production equipment
40	**Service industry machinery**
31240000	Industrial optics
47110000	Industrial laundry and dry cleaning equipment
47120000	Janitorial equipment
48100000	Institutional food services equipment
48110000	Vending machines
48120000	Gambling or wagering equipment
49130000	Fishing and hunting equipment
49140000	Watersports equipment
49150000	Winter sports equipment
49160000	Field and court sports equipment
49170000	Gymnastics and boxing equipment
49180000	Target and table games and equipment
49200000	Fitness equipment
49210000	Other sports
49220000	Sports equipment and accessories
49240000	Recreation and playground and swimming and spa
60100000	Teaching aids and materials and accessories
60120000	Arts and crafts equipment and accessories
60130000	Musical Instruments and parts and accessories
60140000	Toys and games
41	**Electrical equipment, n.e.c.**
32130000	Electronic hardware and component
32150000	Automation control devices
39120000	Electrical equipment and components and supplies
39130000	Electrical wire management devices
52140000	Domestic appliances
52150000	Domestic kitchenware and kitchen supplies
52160000	Consumer electronics
99	**Software**
43230000	Software
2225	**Trucks and Cars**
25100000	Motor vehicles
25170000	Transportation components and systems
25180000	Vehicle bodies and trailers
25190000	Transportation services equipment

Table 3: Equipment assignment by CETC

Nipa Line	**Equipment**	**% Changes in prices** 1950-2016	**% Changes in prices** 1980-2016	**% Changes in K** 1950-2016	**% Changes in K** 1980-2016
4	i) Computers	-100	-100	–	**211632**
	ii) High–CETC			**1210**	**2387**
5	Communication equipment	-99	-98	1071392	20283
26	Aircraft	-97	-93	725095	5241
6	Medical equipment and instruments	-70	-72	305188	4089
9	Nonmedical instruments	-70	-72	56126	1968
10	Photocopy and related equipment	-70	-72	33425	204
40	Service industry machinery	-64	-45	8537	826
18	Special industry machinery, n.e.c.	-44	-37	6145	762
14	Engines and turbines	-41	-27	10751	634
	iii) Low-CETC			**286**	**162**
20	Electrical transmission and apparatus	24	23	5163	433
2225	Autos & trucks	21	27	4745	462
11	Office and accounting equipment	87	55	563	19
13	Fabricated metal products	68	78	2662	172
27	Ships and boats	111	92	668	122
29	Other nonresidential equipment	127	138	8022	693
19	General industrial	233	149	2094	313
41	Electrical equipment, n.e.c.	231	189	3253	240
39	Mining and oilfield machinery	297	222	1993	305
28	Railroad equipment	344	249	216	83
17	Metalworking machinery	416	280	1063	115
30	Furniture and fixtures	373	285	1678	273
33	Agricultural machinery	587	446	433	44
36	Construction machinery	587	446	1208	130

Table 4: Depreciation rates by detailed equipment

Equipment code	**Detailed equipment**	**Nipa aggregate category**	**Depreciation rates**
EI11	Nuclear fuel	13	0.000
EI12	Other fabricated metals	13	0.092
EI21	Steam engines	14	0.052
EI22	Internal combustion engines	14	0.206
EI30	Metalworking machinery	17	0.123
EI40	Special industrial machinery	18	0.103
EI50	General industrial equipment	19	0.107
EI60	Electric transmission and distribution	20	0.050
EO11	Household furniture	30	0.138
EO12	Other furniture	30	0.118
EO21	Farm tractors	33	0.145
EO22	Construction tractors	33	0.163
EO30	Other agricultural machinery	33	0.118
EO40	Other construction machinery	36	0.155
EO50	Mining and oilfield machinery	39	0.150
EO60	Service industry machinery	40	0.158
EO72	Other electrical	41	0.183
EO80	Other	29	0.147
EP12	Office and accounting equipment	11	0.180
EP1A	Mainframes	4	0.312
EP1B	PCs	4	0.312
EP1C	DASDs	4	0.312
EP1D	Printers	4	0.312
EP1E	Terminals	4	0.312
EP1F	Tape drives	4	0.312
EP1G	Storage devices	4	0.312
EP1H	System integrators	4	0.312
EP20	Communications	5	0.130
EP31	Photocopy and related equipment	10	0.180
EP34	Nonelectro medical instruments	6	0.135
EP35	Electro medical instruments	6	0.135
EP36	Nonmedical instruments	9	0.135
ET11	Light trucks (including utility vehicles)	22	0.148
ET12	Other trucks, buses and truck trailers	22	0.192
ET20	Autos	25	0.148
ET30	Aircraft	26	0.096
ET40	Ships and boats	27	0.061
ET50	Railroad equipment	28	0.059

Table 5: Importance of initial capital on our capital embodiment measure

	Capital embodiment in 1960			Capital embodiment in 1980		
	Capital in 1947			Capital in 1947		
	0 (1)	$\frac{K_e^{1947}}{P_e^{1947}}$ (2)	(1)/(2)	0 (1)	$\frac{K_e^{1947}}{P_e^{1947}}$ (2)	(1)/(2)
Aggregate Equipment						
Computers and peripheral equipment	0	0	1.00	3	3	1.00
Communication equipment	5	5	0.90	83	84	0.99
Medical equipment and instruments	7	8	0.90	190	191	1.00
Nonmedical instruments	16	18	0.90	166	168	0.99
Photocopy and related equipment	6	6	0.91	236	236	1.00
Office and accounting equipment	172	189	0.91	652	668	0.98
Fabricated metal products	204	245	0.83	1286	1327	0.97
Engines and turbines	47	55	0.86	280	288	0.97
Metalworking machinery	634	790	0.80	2880	3036	0.95
Special industry machinery, n.e.c.	132	168	0.79	820	856	0.96
General industrial equipment	616	814	0.76	3197	3396	0.94
Electrical transmission and distribution	224	280	0.80	1246	1302	0.96
Autos & trucks	974	1083	0.90	5425	5534	0.98
Aircraft	2	2	0.87	104	104	1.00
Ships and boats	102	179	0.57	505	581	0.87
Railroad equipment	488	884	0.55	1539	1935	0.80
Furniture and fixtures	510	637	0.80	2299	2425	0.95
Agricultural machinery	1378	1665	0.83	5335	5622	0.95
Construction machinery	535	624	0.86	2676	2764	0.97
Mining and oilfield machinery	211	257	0.82	893	939	0.95
Service industry machinery	77	86	0.89	515	524	0.98
Electrical equipment, n.e.c.	31	36	0.86	212	217	0.98
Other nonresidential equipment	160	187	0.86	1160	1186	0.98

Table 6: Example of tool intensity in some occupations

	Computers	**Communication**	**Instruments (medical)**	**Instruments (non-med.)**	**Photocopy**	**Office**	**Other**	**Service industry machinery**	**Electrical**	**Autos and trucks**
Engineers, nec	**31**	3	16	246	5	3	1	2	4	0
Broadcast Technicians	17	**46**	0	22	14	1	0	0	47	2
Dentists	6	0	**172**	3	1	0	0	0	0	0
Biological Scientists	12	1	9	**177**	3	1	0	3	2	2
Printing Machine Op.	4	1	0	6	**33**	7	0	0	0	0
Administrative support	30	12	0	3	2	**31**	0	0	0	0
Hairdressers	2	0	0	0	0	1	**24**	0	4	0
Childcare Workers	5	3	5	0	0	1	0	**6**	10	2
Postsecondary Teachers	19	22	8	10	6	6	0	4	**17**	1
Automotive Mechanics	15	2	0	89	0	0	0	4	1	**31**

Table 7: Capital stock at the 1-digit occupation level

Group by 1-digit occuaption	Relative K		Share in 1980			Share in 2016		
	1980	2016	Computers	HCETC	LCETC	Computers	HCETC	LCETC
Managers	0.8	1.0	0.16	0.26	0.58	0.23	0.60	0.18
Professionals	0.9	1.1	0.00	0.36	0.64	0.07	0.66	0.27
Technicians	1.8	1.9	0.00	0.47	0.52	0.08	0.66	0.27
Sales	0.1	0.2	0.01	0.29	0.70	0.20	0.62	0.17
Administrative Services	0.2	0.5	0.03	0.32	0.65	0.18	0.60	0.23
Low-Skilled Services	1.0	0.9	0.00	0.26	0.73	0.04	0.47	0.49
Agriculture	8.6	3.4	0.00	0.02	0.98	0.00	0.10	0.90
Mechanics and repairers	2.5	2.2	0.00	0.05	0.95	0.01	0.20	0.79
Construction	2.4	1.6	0.00	0.08	0.92	0.02	0.20	0.79
Mining and precision workers	2.0	1.4	0.00	0.12	0.88	0.01	0.35	0.64
Machine operators	1.2	1.2	0.00	0.20	0.80	0.01	0.35	0.64
Transportation	1.5	1.0	0.00	0.02	0.98	0.03	0.27	0.71
All	**1.0**	**1.0**	**0.03**	**0.26**	**0.71**	**0.11**	**0.54**	**0.35**

Table 8: CETC and changes in the labor market 1980-2016

	Average wage change (1)	Total employment change (2)	Share of high-educated: Average change (3)	Share of high-educated: Relative to total (4)
Panel A: Total occupations				
Total occupations	1.30	0.00	9.34	1.00
Panel B: Classification of occupations by CECT				
Bottom third	-11.92	-5.01	4.89	0.52
Middle-third	-0.26	1.82	9.64	1.03
Upper-third	16.09	3.19	13.50	1.44
Panel C: Classification of occupations by higher share of equipment used				
Computer-intensive (34)	11.34	-3.18	13.58	1.45
High-CETC-intensive (98)	9.86	10.05	12.39	1.33
Low-CETC-intisive(195)	-7.78	-6.87	6.04	0.65
Panel D: Classification of occupations by use of computer				
Bottom third	-9.56	-5.84	5.34	0.57
Middle-third	5.04	3.45	9.22	0.99
Upper-third	8.43	2.39	13.47	1.44
Panel E: Classification of occupations by use of High-CETC				
Bottom third	-5.59	-5.44	7.12	0.76
Middle-third	-3.18	-0.87	8.24	0.88
Upper-third	12.68	6.30	12.66	1.36
Panel F: Classification of occupations by use of Low-CETC				
Bottom third	14.50	3.51	12.91	1.38
Middle-third	-1.09	2.08	9.43	1.01
Upper-third	-9.49	-5.59	5.69	0.61