The Effect of Computerization on Occupational Choice and Educational Attainment*

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Abstract

In the US, the share of routine workers has significantly decreased, while educational attainment has witnessed an upward trend over the past decades. This study examines these trends simultaneously, showing that routine-intensive occupations have increased the share of college graduates more rapidly than others over the last 40 years. Based on this empirical fact, I develop a model to analyze the influence of computerization on both occupational choice and educational attainment. This model not only explains the empirical consequence but also estimates that around 50% of the growth in the share of college graduates can be attributed to computerization.

Keywords: investment specific technological change, automation, occupational choice, schooling choice.

JEL Codes: E24, J24, O33, I21.

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1 Introduction

For the last 40 years, we have witnessed rapid growth in computer technology. Autor et al. (2003) and the subsequent literature suggest that the progress in automation due to computer technology yields a decline in the share of workers in the routine occupation because this technology substitutes for labor in routine tasks. One common way to characterize the effect of computerization on occupational choice is based on Roy (1951)'s model, introducing heterogeneity in a couple of abilities. An agent chooses an occupation j if the expected earnings of the occupation j, usually defined as the product of the unit wage w_j and the ability to perform the occupation u_j, is the highest among the set of occupations.

Importantly, agents choose their occupations based only on their innate ability in such a model. However, there is a huge gap in educational attainment between abstract, routine and manual workers. Abstract workers are more likely to be college graduates than routine and manual workers, so there will be some relationship between occupational choice and educational attainment.

As is well known, the United States is experiencing growing educational attainment. Average years of schooling and the share of college graduates have been increasing. Some fraction of this trend will be due to the change in direct or indirect costs/benefits of college education, and it will change the share of college graduates throughout the occupations. However, some factors may have different effects on the college graduates' share among occupations. For example, some occupations may recently need more skills that can be trained through a college education.

Concerning the effect of computerization on routine workers' educational attainment, there will be two conflicting paths. One possibility is that routine workers may be required to have more skills that can be trained by education (hereafter, educational skill) because computer capital can do some simple tasks. In this case, the educational attainment of routine workers will increase. Alternatively, routine workers may have needed

sophisticated and well-educated skills before the age of computerization, but they may be required to have skills unrelated to education recently because computer capital can do the task instead. In this case, the educational attainment of routine workers will decrease.

In this paper, I reveal that the change in educational attainment is related to occupational choice. Then, I give a model that explains this relationship and conduct a quantitative analysis. In Section 3, I analyze the relationship between occupational choice and educational attainment in two ways. First, I compute the change in abstract, routine, and manual task inputs for college graduates and non-college graduates.[1] I find that routine task inputs have been decreasing distinctly for non-college graduates, while that is not true for college graduates. Second, I conduct some regression analysis. I find that occupations with higher routine intensity tend to gain educational attainment more rapidly in the recent 40 years. In Section 4, I give a model that can explain this trend. I consider a general equilibrium model where agents choose whether to go to college or not and whether to work in the abstract or routine occupation. Also, I show some properties of the model. In Section 5, I conduct quantitative analysis. I calibrate some parameters to fit the data in 1980 and the change in the share of routine workers and see if the quantitative results fit the empirical fact. This model matches the empirical facts that routine-task-intensive occupations experience higher educational attainment than others. Also, I find that around 50% of the increase in the share of college graduates is due to computerization. In Section 6, I focus on two things to reinforce the results in Section 5. First, I discuss what educational skill is. Second, I consider other drivers of increasing educational attainment and assess their effects. In Section 7, I summarize the results.

[1]Non-college graduates include high school dropouts, high school graduates, and some college.

2 Literature Review

In the context of self-selection, Roy (1951)'s framework of self-selection and earnings is widely applied. In his model, agents choose occupations according to comparative advantage. Willis and Rosen (1978) extend this model to include schooling choice. Also, Willis (1987) allows multi-dimensional skills, which are occupation-specific and are perfect substitutes over workers within occupations. In Keane and Wolpin (1997) and Heckman et al. (1998), agents accumulate their human capital through both schooling and on-the-job training. In this sense, my model is closely related to Lee (2005). Lee develops a dynamic general equilibrium overlapping generations model of career decisions to estimate skill prices, allowing agents to choose educational attainment and occupations. In Lee's model, the values of schooling and on-the-job training are measured directly by Mincer (1974) wage function, without assuming implicit skill sets to enhance.

Also, my model is constructed based on the thoughts on routine-biased technological change (RBTC; Autor et al. (2003)), and so the occupational tasks framework of Autor and Dorn (2013) is a key feature of my model. In particular, it is closely related to vom Lehn (2020), who studies technological change and job polarization in a neoclassical framework. Roughly speaking, I add a skill acquired by education and a choice problem of educational attainment to vom Lehn (2020)'s model. It is also related to Cortes et al. (2017), who discuss the choice problem of occupations and whether to work or not simultaneously.

While the main context of my research follows RBTC, it also contributes to the discussion on skill-biased technological change (SBTC; Katz and Murphy (1992)). Since agents can choose whether to enter college (be skilled workers) or to start working soon after high school graduation (be unskilled workers), this model can compute the change in college premium (or skill premium) as well as abstract job premium. In this sense, my model represents capital-skill complementarity as in Krusell et al. (2000) or subsequent papers that allow an endogenous choice of education (e.g. Lee and Wolpin, 2010).

Some papers discuss the change in educational attainment due to skill-biased technical change. For instance, He (2012) uses the relative price of capital goods as a whole as a shock as a source of SBTC and shows that about 35% of the increase in the college enrollment rate for the period 1951-2000 can be explained by SBTC. Also, Restuccia and Vandenbroucke (2014) introduce schooling-level specific productivity parameters and see the effect of constant changes of these parameters on the average years of schooling. They show that SBTC accounts for almost 100% of the increase in average years of schooling between 1940 and 2000 in the baseline model and 38% if they use the most conservative scenario. My model is more similar to He (2012) regarding capital-skill complementarity, while I use the relative price of computer capital as a shock.

Additionally, in my model, each occupation requires two types of skills, and the relative significance of these skills can vary. In this regard, this research is connected to the works of Ross (2017) and Atalay et al. (2020). They investigate the evolution of task requirements within occupations by analyzing the differences between the Dictionary of Occupational Titles (DOT) and O*NET (Ross, 2017) or between newspaper advertisements (Atalay et al., 2020).

Lastly, my empirical result, which shows the growing importance of college graduates among routine workers, is related to some existing findings (e.g. Barany et al., 2020). However, as far as I know, it is the first paper that constructs a model to explain this result.

3 Empirical Facts

3.1 Share of routine task by educational attainments

I begin with the well-known fact that the share of routine tasks has declined for the last 40 years. I consider three skills: abstract, routine, and manual skills. To measure the degree of intensity of these three skills, I use the skill measures constructed by Autor et al.

(2003) based on DOT 1977 task measures.[2] Also, I use the occupational classification developed by Autor and Dorn (2013) and divide non-farm occupations into 323 occupation categories. Then, I apply these three task values to each occupation.

Figure 1 illustrates the extent to which changes in the task inputs from 1980 to 2019 due to changes in the occupational share, keeping task values constant for each occupation. Each value is a weighted average of task values using the share of workers as a weight. I set each task variable equal to 1 in 1980. As is evident in the figure, the share of workers employed in occupations intensive in routine tasks has declined substantially. By contrast, the share of workers employed in occupations that intensively use abstract tasks has increased during the last four decades. Computerization is widely recognized as the primary factor contributing to this phenomenon.

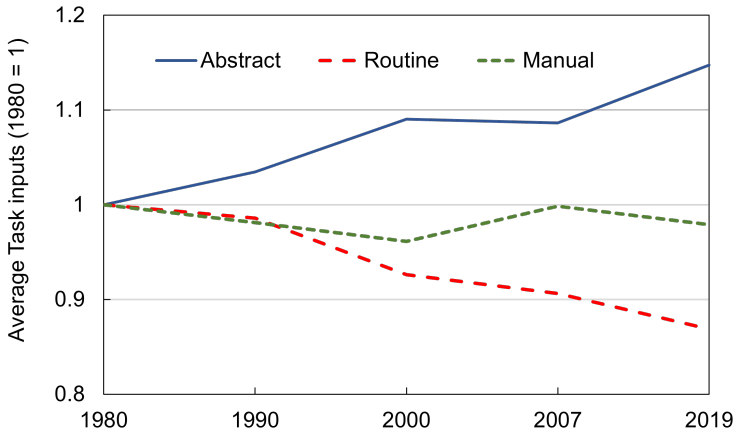


Figure 1: Changes in three types of task inputs

However, when dividing it into two educational levels, we can find a clear difference between them. Figure 2 illustrates the same changes as Figure 1 but is restricted only to college or non-college graduates. We can see the decline in the routine tasks in the left panel of Figure 2, which restricts data to non-college graduates. However, we cannot see the decline in routine tasks for college graduates in the right panel of Figure 2. Therefore,

[2]The data is available on the author's homepage.

there have been more educated workers in routine-intensive occupations recently.

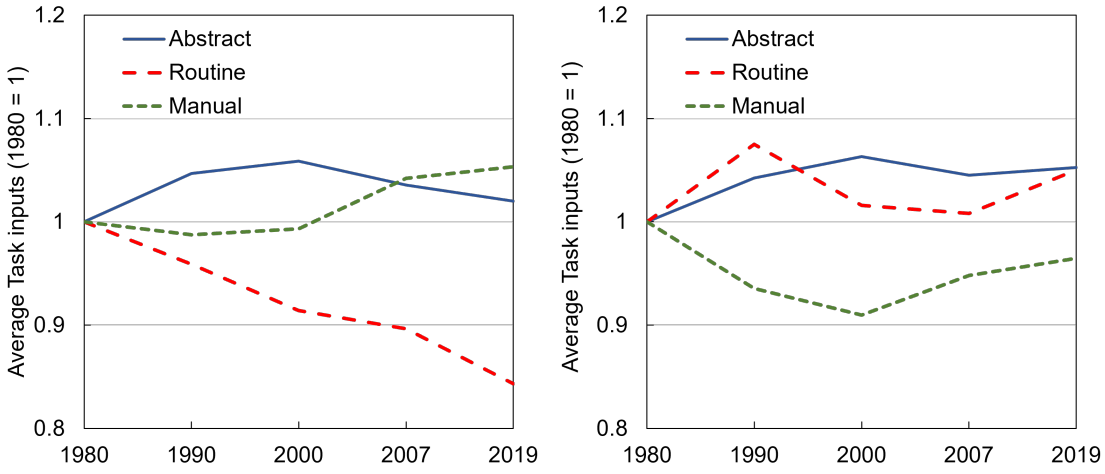


Figure 2: Changes in three types of task inputs by educational attainment (left: non-college graduates, right: college graduates)

Note that these graphs fix the task level for each occupation at the 1977 DOT level. The actual task level may change, so it does not necessarily imply that the routine skill itself gains importance among college graduates. Instead, some other skills that college graduates have more than non-college graduates may gain importance among routine occupations.[3]

3.2 Regression analysis

Next, I conduct regressions to detect the effect of routine intensity on the change in educational attainment. I put the difference in the share of college graduates from 1980 to 2019 as a dependent variable and three types of skills as explanatory variables. Then, I conduct weighted least squares (WLS) regressions using employment share as a weight. I use WLS regressions because the changes in the share of college graduates for minor occupations, where we find small samples, are more volatile. Also, I restrict data to the

[3] Ross (2017) and Atalay et al. (2020) detect the change in each skill over time.

age between 27 and 34 to focus on the choice problem of whether to go to college or not.[4]

Table 1 shows the results of the regression analysis. The first column simply regresses all three (abstract, routine, and manual) task measures on the change in college graduates' share. The result shows that routine task measure in 1980 positively affects the change in college graduates' share, and the effect is larger than that of abstract skill.

Table 1: Effect of routine intensity on the change in college graduates' share

	(1)	(2)	(3)	(4)	(5)	(6)
Abstract skill	0.0075***	-0.0076**				
	(0.0026)	(0.0034)				
Routine skill	0.0096***	0.0141***			0.0088***	0.0147***
	(0.0022)	(0.0034)			(0.0023)	(0.0021)
Manual skill	-0.0202***	-0.0125***				
	(0.0042)	(0.0038)				
Routine task intensity			0.0170***	0.0199***		
			(0.0027)	(0.0025)		
Initial share		0.7444***		0.6334***		0.6982***
		(0.0887)		(0.0637)		(0.0666)
(Initial share)^2		-0.7278***		-0.6423***		-0.7061***
		(0.0855)		(0.0707)		(0.0727)
Trend	0.0612***	-0.0146	0.0804***	0.0009	0.0631***	-0.0464***
	(0.0169)	(0.0181)	(0.0065)	(0.0101)	(0.0115)	(0.0029)
Observations	323	323	323	323	323	323

Note: ***, **, and * denote significance at the 1, 5 and 10 percent levels. Each task measure is computed by using DOT 1977. Initial share is the share of college graduates in 1980.

I also conduct a regression by controlling the initial share of college graduates and the square of it in the second column.[5] This result implies that routine task measure

[4] I demonstrate the results for the other age groups in Appendix A.1.

[5] According to the empirical data, occupations with initially higher college graduates' share tend to gain more share of college graduates for recent 40 years, which implies that the change in the share of college graduates will be dependent on the initial level. We can interpret this tendency with a simple model: assume that agents with more educational skills than a certain value $\bar{e}_j$ choose to enter college, where j is their chosen occupation. In this setting, the share of college graduates in occupation j is $1 - \Phi(\bar{e}_j)$, where $\Phi(e)$ is the CDF of the distribution of educational skill e. As such, the marginal change of college graduates' share in a parallel shift of the threshold is $-\frac{\mathrm{d}}{\mathrm{d}e}\left(1 - \Phi(e)\right)|_{e=\bar{e}_j} = \phi(\bar{e}_j)$, and so depends on the initial share $\bar{e}_j$.

enhances educational attainment for the last 40 years while non-routine (abstract and manual) occupations rather discourage college education. I will use this result in the quantitative analysis in Section 5.

The third and fourth columns show the relationship between college education and routine skill, using another measure: routine task intensity. Routine task intensity for occupation k (RTI_k) is a measure proposed by Autor and Dorn (2013) and defined by

$$RTI_k = \ln(r_k) - \ln(m_k) - \ln(a_k), \tag{1}$$

where r_k, m_k, and a_k are the routine, manual, and abstract task measures in occupation k, respectively. I can get similar results when I use routine task intensity as an explanatory variable.

The regressions in the fifth and sixth columns use only the routine task measure as an explanatory variable. I get similar results as well.

Importantly, the main implication does not change when using years of schooling as a dependent variable (Table 5), using the hour-worked-based labor force instead of the number of workers, restricting only men, conducting OLS instead of WLS, or dividing the period into two sub-periods (Table 7). Moreover, applying the analysis to the change between 1950-1980, before the computer era, we cannot observe a positive contribution of routine skill or routine task intensity. See Appendix A.1 for these results. Therefore, it is a robust trend that routine-intensive occupations have experienced an increasing educational level more than others during the last four decades.

4 Model

In this section, I give a model that can explain the relationship between the change in the share of college graduates and the routine task intensity. The hypothesis is that routine tasks are replaced by computer capital, and therefore routine workers need to have

less routine skill and more other skills such as manipulating computer capital, reporting and fixing errors with computers, or explaining some outcome. More people will attend college if the latter skills are trained through a college education.

I consider a general equilibrium model that has the potential to explain the behavior. Then, I show some properties of the model.

4.1 Technology

Output Y_t is produced by a CES production function using inputs by abstract occupation $Z_{a,t}$ and routine occupation $Z_{r,t}$. This model is abstract from manual occupation to focus on the difference in educational attainment between abstract and routine occupations. These two kinds of inputs further consist of computer capital and three types of task inputs: (i) routine task, (ii) abstract task, and (iii) task that can be trained by education (hereafter, educational task):

$$
\begin{aligned}
Y_t &= \left[\nu Z_{a,t}^{\frac{\sigma-1}{\sigma}} + (1-\nu) Z_{r,t}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \qquad (2) \\
Z_{a,t} &= \left[\mu_a N_{e_a,t}^{\frac{\rho_a-1}{\rho_a}} + (1-\mu_a) N_{a,t}^{\frac{\rho_a-1}{\rho_a}} \right]^{\frac{\rho_a}{\rho_a-1}} \\
Z_{r,t} &= \left[\mu_r N_{e_r,t}^{\frac{\rho_r-1}{\rho_r}} + (1-\mu_r) \left\{ \eta N_{r,t}^{\frac{\kappa-1}{\kappa}} + (1-\eta) K_t^{\frac{\kappa-1}{\kappa}} \right\}^{\frac{\kappa}{\kappa-1}\frac{\rho_r-1}{\rho_r}} \right]^{\frac{\rho_r}{\rho_r-1}},
\end{aligned}
$$

where $N_{j,t}$ is efficiency units of labor in each task j , $j \in \{a, r, e_a, e_r\}$, and K_t is computer capital. Since the educational task is used in both abstract and routine occupations, it needs subscripts.

Regarding the input by abstract workers $Z_{a,t}$, it is produced by a CES aggregate of total abstract task inputs $N_{a,t}$ and total educational task inputs $N_{e_a,t}$. On the other hand, the input by routine workers $Z_{r,t}$ is a CES aggregate of total routine task inputs $N_{r,t}$, total

educational task inputs, and computer capital K_t.[6][7] Here, I implicitly assume that the relative importance of tasks can vary within occupations since each task demand can change differently.[8]

I assume that a representative firm produces aggregate output that behaves competitively, paying skill prices $w_{j,t}$ for efficiency units of task input j and renting computer capital K_t, which is supplied perfectly elastically at market price r_t. Note that the importance of the educational task can be different between abstract and routine occupations, so we need subscript a or r to describe the unit wage for the educational task as is the case with the task input.

The firm's problem is given by:

$$\Pi_t = \max_{N_{a,t}, N_{a_e,t}, N_{r,t}, N_{e_r,t}, K_t} Y_t - w_{a,t}N_{r,t} - w_{a_r,t}N_{e_a,t} - w_{r,t}N_{r,t} - w_{e_r,t}N_{e,t} - r_t K_t. \tag{3}$$

Also, I assume that the capital accumulation process is given by

$$K_{t+1} = \frac{I_t}{q_t},$$

where I_t is the investment in computer capital, and q_t is the relative price of computers to consumption goods. I assume a perfect depreciation, but this assumption is not far from reality since the depreciation rate of computer capital is above 20% per year, and one period is four years long in this model. Also, I assume q_t is exogenous, so the decrease in

[6]There are three ways of nesting routine task, educational task, and computer capital within a CSE function, but I choose this way of nesting for a practical reason. If nesting the routine and educational tasks first, then this model will not increase the share of college graduates because the declining price evenly affects high school graduates and college graduates. If nesting educational task and computer capital first, then the elasticity of substitution ρ_r is negative when calibrating parameters, which does not make sense.

[7]This model is abstract from other capital stocks for simplicity.

[8]Some papers analyze the possibility of changing tasks within occupations. See Ross (2017) and Atalay et al. (2020).

q_t represents increased technological progress.[9] In quantitative analysis, we see the effect of the change in this q_t.

It is easy to derive the relationship between q_t and r_t from the Euler equation:

$$r_t = r_t^f q_{t-1},$$

where r_t^f is the risk-free rate.

4.2 Households

I consider an environment with heterogeneous workers, each identifiable by their vector of innate abilities, $\boldsymbol{u_0} = (u_{a0}, u_{r0}, u_{e0})$.[10] One unit of each skill can yield one unit of each task input. I assume that the set of innate skills $\boldsymbol{u_0} = (u_{a0}, u_{r0}, u_{e0})$ is log-normally distributed:

$$\boldsymbol{u_0} \equiv \exp(X) \;\; with \;\; X \sim N(0, \sigma_u^2 \Sigma),$$

where the correlation matrix Σ is

$$\Sigma = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & \rho_u \\ 0 & \rho_u & 1 \end{bmatrix},$$

which means that u_{r0} is independent of the other two skills, and u_{a0} and u_{e0} are correlated with parameter ρ_u. The average of the variable's natural logarithm can be normalized to zero without loss of generality.

[9] This inclusion of technological progress follows Greenwood et al. (1997), who introduce the factor q to represent the current state of the technology for producing equipment.

[10] In this paper, I use the terms "ability" and "skill" interchangeably.

There are two types of educational levels (high school graduates and college graduates) and two occupations (abstract and routine), so there are $2 \times 2 = 4$ types of workers in this model. If agents choose to work in the abstract occupation, then they supply their abstract and educational skills inelastically. On the other hand, they supply their routine and educational skills inelastically if they choose to work in the routine occupation. Note that educational skill is used in both occupations. The earnings are the sum of earnings for every task they supply.[11]

In this model, agents live for fixed $T + 1$ periods, each equivalent to 4 years. The model starts with high school graduation. Each agent chooses whether to go to college or start working at period 0 ($t = 0$) based on their skill level $\boldsymbol{u_0}$. Agents who choose to go to college will start working at $t = 1$. When they start working, they choose either abstract or routine occupations. Still, they can change their occupations even after choosing their initial jobs. When $t = n$, agents are retired. After retiring, they do not get earnings, and their source of money is just savings.

In this model, the advantage of entering college is that each agent can increase their educational skill u_e by a factor of a constant rate γ. On the other hand, the disadvantage is that they lose the opportunity to get earnings and on-the-job training during the college education. Therefore, agents enter college if the marginal return to college is larger than the marginal cost and do not enter college if not. This parameter γ governs the quality of college education, so the change of γ will increase the share of college graduates. However, I fix γ at a constant value in the main analysis to extract the effect of computerization. After entering firms, agents can increase their skills through on-the-job training. I assume that one-period working increase all the skills at a constant rate g.

[11] As is well understood, Roy (1951)'s self-selection framework, assuming the earnings as the sum of each return to skill, is not empirically straightforward (e.g. Heckman and Honore, 1990; Heckman and Scheinkman, 1987; Autor and Handel, 2013). However, my model allows educational skills to have different values between occupations (i.e., w_{e_r} is not necessarily equal to w_{e_a}), which is not denied in these papers.

I assume that the population is fixed, so the number of agents in every generation is also fixed at a certain constant level. Let the total population be 1. Then, the number of agents in one generation is $1/(T+1)$, and the number of total workers is $(n+1-P_e^i)/(T+1)$, where P_e^i is the share of agents who go to colleges among i-th generation.

Each agent has a log preference over consumption. Let AC, AH, RC, and RH denote abstract college, abstract high school, routine college, and routine high school, respectively. Then, the problem for households in the i-th generation is given by:

$$\max_{\{c_t^i\},\{b_{t+1}^i\}} \sum_{t=0}^{T} \beta^t \log(c_t^i) \quad s.t.$$

$$(t=0)$$

$$c_t^i + b_{t+1}^i = 0 \quad if \quad \text{AC or RC}$$

$$c_t^i + b_{t+1}^i = u_{r0} w_{a,t} + u_{e0} w_{e_a,t} \quad if \quad \text{A}H$$

$$c_t^i + b_{t+1}^i = u_{r0} w_{r,t} + u_{e0} w_{e_r,t} \quad if \quad \text{R}H$$

$$(t \in [1,n])$$

$$c_t^i + b_{t+1}^i = g^{t-1}(u_{a0} w_{a,t} + \gamma u_{e0} w_{e_a,t}) + r_t^f b_t^i \quad if \quad \text{AC}$$

$$c_t^i + b_{t+1}^i = g^{t}(u_{a0} w_{a,t} + u_{e0} w_{e_a,t}) + r_t^f b_t^i \quad if \quad \text{A}H$$

$$c_t^i + b_{t+1}^i = g^{t-1}(u_{r0} w_{r,t} + \gamma u_{e0} w_{e_r,t}) + r_t^f b_t^i \quad if \quad \text{RC}$$

$$c_t^i + b_{t+1}^i = g^{t}(u_{r0} w_{r,t} + u_{e0} w_{e_r,t}) + r_t^f b_t^i \quad if \quad \text{R}H$$

$$(t \in [n+1, T-1])$$

$$c_t^i + b_{t+1}^i = r_t^f b_t^i$$

$$(t=T)$$

$$c_t^i = r_t^f b_t^i$$

Each agent with a set of skills (u_a, u_r, u_e) and educational attainment $k \in \{C, H\}$ chooses whether to work in abstract occupation or routine occupation $j \in \{A, R\}$ at the

beginning of every period t according to:

$$\arg\max_{j\in\{A,R\}} W_{jk,t}(u_a, u_r, u_e),$$

where

$$W_{Ak,t}(u_a, u_r, u_e) = u_a w_{a,t} + u_e w_{e_a,t}, \tag{4}$$

$$W_{Rk,t}(u_a, u_r, u_e) = u_r w_{r,t} + u_e w_{e_r,t}. \tag{5}$$

Note that agents can change their occupations freely. However, agents will not change their occupations regardless of this assumption if the economy is in a steady state. The change in q_t motivates some workers to change their occupations because each unit return to skill also changes.

Given the future earnings, each agent chooses whether to go to college or not $k \in \{C, H\}$ at $t = 0$ according to:

$$\arg\max_{j\in\{H,C\}} V_{k,0}(u_a, u_r, u_e),$$

where

$$V_{C,0}(u_a, u_r, u_e) = \frac{1}{g}\sum_{s=1}^{n}\left(\frac{g^s}{\prod_{i=1}^{s} r_i^f}\right)\max_{j\in\{A,R\}} W_{jk,s}(u_a, u_r, \gamma u_e), \tag{6}$$

$$V_{H,0}(u_a, u_r, u_e) = \sum_{s=0}^{n}\left(\frac{g^s}{\prod_{i=1}^{s} r_i^f}\right)\max_{j\in\{A,R\}} W_{jk,s}(u_a, u_r, u_e). \tag{7}$$

I illustrate the choice problem at time $t = 0$ in a steady state, where q_t is constant, graphically in Figure 3. The horizontal axis is the distribution of u_e/u_r, and the vertical axis is the distribution of u_a/u_r. I define $\Lambda \equiv (1/r^f)\sum_{s=1}^{n}(g/r^f)^{s-1}$. Not surprisingly, agents with higher abstract skills relative to routine skills tend to choose abstract occu-

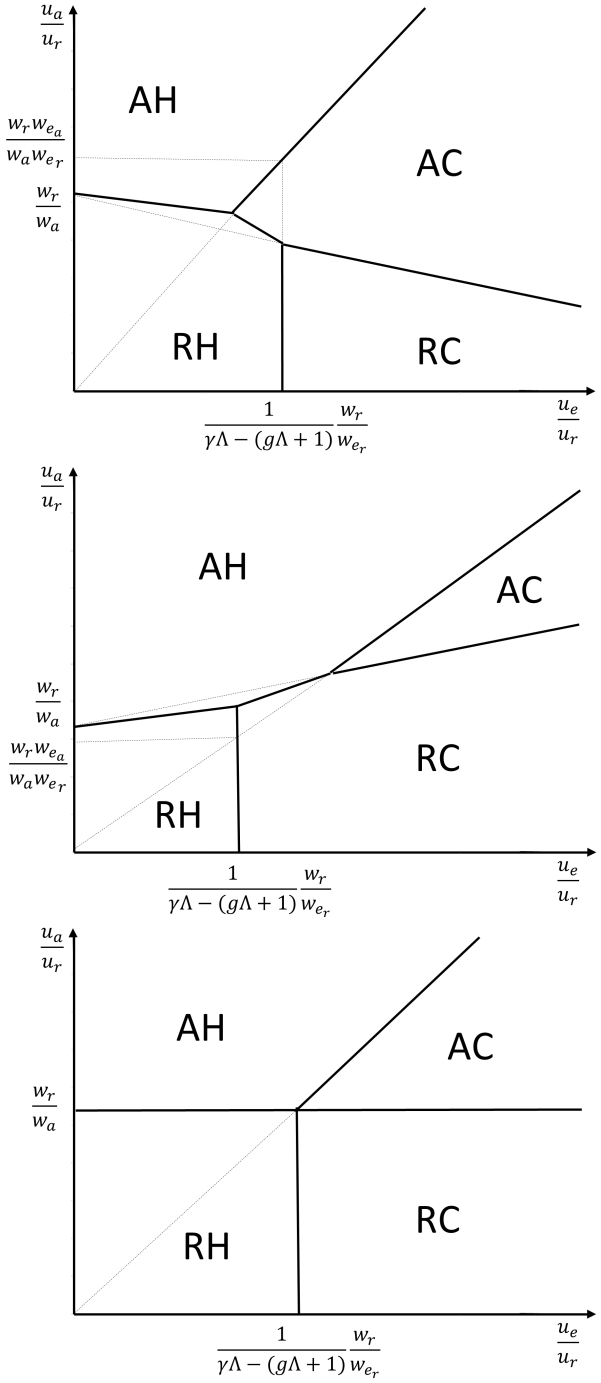


Figure 3: Choice of occupations and educational attainments in a steady state (top: when $w_{e_a} > w_{e_r}$, middle: when $w_{e_a} < w_{e_r}$, bottom: when $w_{e_a} = w_{e_r}$).

pation, and agents with relatively high educational skills tend to choose to go to college. Also, if $w_{e_a} \neq w_{e_r}$, then agents with relatively high educational skills tend to enroll in an occupation that gives higher wages to educational skills. If $w_{e_a} = w_{e_r}$, then the occupational choice between routine and abstract does not depend on u_e.

4.3 Equilibrium

The competitive equilibrium for the model economy with heterogeneous workers is given by a set of allocations $(c_t^i(\boldsymbol{u}), b_{t+1}^i(\boldsymbol{u}), N_{a,t}, N_{e_a,t}, N_{r,t}, N_{e_r,t}, K_t)$, such that: (i) $(c_t^i(\boldsymbol{u}), b_{t+1}^i(\boldsymbol{u}))$ solves the household problem, taking $(w_{a,t}, w_{e_a,t}, w_{r,t}, w_{e_r,t}, r_t, r_t^f)$ as given; (ii) $(N_{a,t}, N_{e_a,t}, N_{r,t}, N_{e_r,t}, K_t)$ solve the firm problem, taking $(w_{a,t}, w_{e_a,t}, w_{r,t}, w_{e_r,t}, r_t, r_t^f)$ as given; and (iii) labor, capital and output markets clear.

Concerning market clearing conditions, the following equations hold:

$$Y_t = \int_{\boldsymbol{u}} \sum_{i=t-T}^{t} c_t^i(\boldsymbol{u})\phi(\boldsymbol{u})\mathrm{d}\boldsymbol{u} + I_t \tag{8}$$

$$N_{a,t} = \int_{\boldsymbol{u}} \sum_{i=t-n}^{t} g^{i-t+n} u_a(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{A}H)\mathrm{d}\boldsymbol{u} + \int_{\boldsymbol{u}} \sum_{i=t-n}^{t-1} g^{i-t+n} u_a(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{AC})\mathrm{d}\boldsymbol{u} \tag{9}$$

$$N_{e_a,t} = \int_{\boldsymbol{u}} \sum_{i=t-n}^{t} g^{i-t+n} u_e(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{A}H)\mathrm{d}\boldsymbol{u} + \int_{\boldsymbol{u}} \sum_{i=t-n}^{t-1} g^{i-t+n} \gamma u_e(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{AC})\mathrm{d}\boldsymbol{u} \tag{10}$$

$$N_{r,t} = \int_{\boldsymbol{u}} \sum_{i=t-n}^{t} g^{i-t+n} u_r(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{R}H)\mathrm{d}\boldsymbol{u} + \int_{\boldsymbol{u}} \sum_{i=t-n}^{t-1} g^{i-t+n} u_r(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{RC})\mathrm{d}\boldsymbol{u} \tag{11}$$

$$N_{e_r,t} = \int_{\boldsymbol{u}} \sum_{i=t-n}^{t} g^{i-t+n} u_e(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{R}H)\mathrm{d}\boldsymbol{u} + \int_{\boldsymbol{u}} \sum_{i=t-n}^{t-1} g^{i-t+n} \gamma u_e(\boldsymbol{u})\phi(\boldsymbol{u}, \mathrm{RC})\mathrm{d}\boldsymbol{u} \tag{12}$$

$$K_t = \frac{1}{q_{t-1}} \int_{\boldsymbol{u}} \sum_{i=t-T}^{t} b_t^i(\boldsymbol{u})\phi(\boldsymbol{u})\mathrm{d}\boldsymbol{u}. \tag{13}$$

4.4 Properties of the model

The most critical parameters of this production function are κ, ρ_r, and σ, which represent the elasticities of substitution between task bundles. These parameters govern how a change in the rental rate computers affects the demand for each task, and so the share of workers in each group {AC, AH, RC, RH}. Especially, κ and ρ_r are essential for the effect of the computer price on the choice problem between RC and RH. σ also has a vital role in choosing occupations. On the other hand, the choice between AC and AH is not affected by the computer price. We can derive the following propositions:

Proposition 1. The demand for the educational task in the routine occupation relative to routine task $N_{e_r,t}/N_{r,t}$ is decreasing in the rental rate of computers r_t if the elasticity of substitution between the routine task and computer capital is larger than the elasticity of substitution between the educational task and the bundle of routine task and computer capital, i.e., $\kappa > \rho_r$.

Proof. See Appendix A.2.1. □

Proposition 2. The demand for abstract workers relative to routine workers is decreasing in the rental rate of computers r_t if (i) the elasticity of substitution between the routine task and computer capital is larger than the elasticity of substitution between the educational task and the bundle of routine task and computer capital, i.e., $\kappa > \rho_r$, and (ii) the elasticity of substitution between the educational task and the bundle of routine task and computer capital is larger than the elasticity of substitution between the abstract occupation and routine occupation, i.e., $\rho_r > \sigma$.

Proof. See Appendix A.2.2. □

If this model focused on the choice problem between only RC and RH, it would be immediate to conclude that the decline in the computer price increases the share of college graduates if $\rho_r > \sigma$, using Proposition 1. However, the dynamics become more

complicated when adding the options of AC and AH. For example, the share of college graduates within the routine occupation does not necessarily increase even if the condition in Proposition 1 holds. It is because initial RC workers could be more likely to move to the abstract occupation than RH workers.

The aggregate share of college graduates is very likely to, but not for sure, increase in response to the decline in the computer price if the conditions hold. Even if the outflow from RC to abstract is more significant than RH, RC tends to move to AC, and RH tends to move to RH because of the similarity of skill sets, as is clear from Figure 3. As such, the aggregate share of college graduates changes little due to this outflow. It means the flow from RH to RC matters for the aggregate share of college graduates.

On the other hand, Proposition 2 simply implies that the share of abstract occupation will increase as the computer price decreases if $\kappa > \rho_r > \sigma$.

5 Quantitative analysis

In this section, I conduct a quantitative analysis with the model described in the previous section. My main goal here is to reveal that the model can explain the rapid increase in college graduates' share in routine occupation. For this sake, I calibrate parameters first and compare the result with the empirical regression result I show in Section 3.2.

5.1 Relative price of computer capital

The model's sole exogenous driving force is computer-specific technological change q_t. We can interpret it as the relative price of computers. To measure the price of computers, I use the definition by Eden and Gaggl (2018).[12] I measure the price indexes directly from

[12]They use the BEA's detailed fixed asset accounts, and they consider an asset to be ICT if the BEA classifies it as software (classification codes starting with RD2 and RD4) or as equipment related to computers (classifications codes starting with EP and EN) within non-residential assets, and PCs and periph-

the BEA's fixed asset accounts. Figure 4 shows the path of price q_t relative to the GDP deflator. The price is normalized to 1 in 1980. This figure reveals that the relative price of computers (or ICTs) has fallen substantially. In the analysis, agents realize all the future

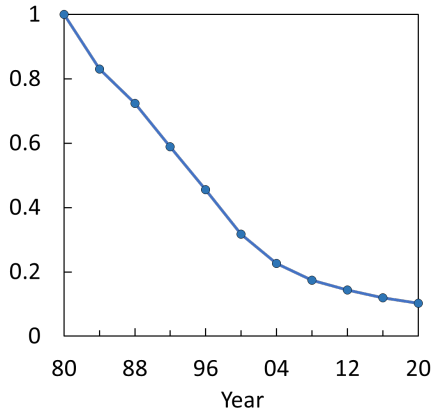


Figure 4: Relative price of computer (1980 = 1)

paths of the relative computer price in period 0 (in 1980). I assume the relative computer price is constant after period 10 (after 2020). As such, the shock occurs only in 1980, and there is no uncertainty after 1980.

5.2 Calibration

We need broad occupation categories to calibrate parameters since there are only two kinds of occupations (abstract and routine) in this model. As such, I compile 323 detailed occupation categories into three broad categories: abstract, routine, and manual occupations in line with the definition by Autor and Dorn (2013), and omit manual occupation.[13]

There are 15 parameters in this model: $\nu, \mu_a, \mu_r, \eta, \sigma, \kappa, \rho_a, \rho_r, \beta, n, T, g, \gamma, \sigma_u$, and ρ_u. Among them, I set the elasticity parameter between abstract and educational tasks $\rho_a =$

erals (1RGPC), software and accessories (1RGCS), calculators, typewriters, other information equipment (1RGCA), telephone and fax machines (1OD50) within consumer durables. See the Appendix A.3.1 for complete lists of the detailed assets.

[13]For data source, see Appendix A.3.2 and A.3.3.

100, which means that the output by abstract occupation is (almost) a linear combination of these two tasks, which means they provide the same output. I discuss it more in Section 6.1. However, this parameter ρ_a can be selected arbitrarily because the outcome is almost insensitive to it. It is because, by the construction of the production function, the change in the computer capital has an effect on abstract occupation as a whole (Z_a).

For the rest 14 parameters, I calibrate them in two ways. First, 5 parameters are directly imposed based on readily available information. The remaining 9 parameters are selected to fit the model. I pick up 5 targets from data in 1980, 4 targets from the change in data from 1980 to 2019, and 2 targets from the elasticities of substitution by Eden and Gaggl (2018). In this step, I select the parameters to (i) perfectly match the data in 1980 and elasticities of substitution and then (ii) maximize the model's fit concerning some changes for the last 40 years.

Table 2: Calibrated parameters

Parameters	Values	Targets
		Assumption or other available information
β	0.85	Discounting 0.96 for each year ($0.96^4 \simeq 0.85$)
n	10	Working from 19 to 62
T	13	Life expectancy = 74
g	1.05	Ratio of average earnings at 27-30 to average lifetime earnings
ρ_u	0.74	Correlation between average years of schooling and abstract skill
		Match the value in 1980 to the data
ν	0.989	Share of abstract workers in 1980
μ_a	0.689	Share of college graduates in abstract occupation in 1980
μ_r	0.332	Share of college graduates in routine occupation in 1980
η	0.536	Labor share in 1980
γ	1.36	College premium in 1980
σ_u	1.0316	Variance of earnings in 1980
		Match the change in value from 1980 to 2019
σ	0.087	2 elasticities of substitution in Eden and Gaggl (2018)
ρ_r	0.80	and
κ	2.39	Changes in 4 kinds of values from 1980 to 2019

Let's start with the parameters that are directly imposed: β, n, T, g, and ρ_u. Since the length of one period is 4 years, I set $\beta = 0.85 \simeq 0.96^4$, where 0.96 is the standard value. Regarding the life cycle, it is reasonable to assume that high school graduates work from

19 to 62 and college graduates work from 23 to 62. Life expectancy in 1980 was around 74. As such, I set $n = 10$ and $T = 13$. The average earnings ratio at 27-30 years old to average lifetime earnings implies $g = 1.05$. Also, I use the correlation between average years of schooling and abstract task measure by occupation, which implies $\rho_u = 0.74$.

There are three steps to fix the rest of the 10 parameters. First, I use the share of abstract workers, the share of college graduates in abstract and routine occupations, labor share, the variance of earnings, and college premium in 1980 to fix the initial steady state in 1980.

Second, I select some parameters to match the model outcome with the two types of elasticity of substitution in Eden and Gaggl (2018). They empirically compute the elasticity between non-routine workers and computer capital and between routine workers and computer capital.[14] However, I cannot directly apply their values to elasticity parameters as this model has a different structure. Instead, I compute apparent values of corresponding elasticities implied by my model and compare them with the values in Eden and Gaggl (2018). In detail, I derive the apparent values in the following steps: (i) compute income share and workers in AC, AH, RC, and RH, respectively, and the amount of computer capital from period 0 to 10 (corresponding to 1980-2020), (ii) aggregate AC and AH for abstract occupation, and RC and RH for routine occupation, and (iii) compute the average $\ln(S_K/S_a)/\ln(K/L_a)$ and $\ln(S_K/S_r)/\ln(K/L_r)$, where K is computer capital, L_a and L_r are the number of abstract and routine workers, S_K, S_a and S_r are the income shares of K, L_a and L_r, respectively. Eden and Gaggl (2018) estimate that the former one is equal to 0.299 (corresponding to the elasticity of substitution $= 1.427$ between non-routine and computer capital) and the latter one is equal to 0.484 (corresponding to the elasticity of substitution $= 1.940$ between routine and computer capital).

[14] Many papers compute those elasticities, but the values in Eden and Gaggl (2018) is the most suitable for this paper because (i) I use the exact definition of computer capital as theirs, (ii) the estimation period they use (1967-2013) is close to this paper's aim (1980-2019), and (iii) the elasticities are computed purely from the empirical data.

Lastly, I fix the other parameters, using the change in real computer capital per capita, routine workers' share, college premium, and abstract job premium from 1980 to 2019. Since there are more targets than parameters, I chose parameters to maximize the fit.

Table 2 shows the calibration results. Most of the model's parameter values are jointly determined, but I make a list of correspondence as some data targets play a much more central role in identifying a parameter. Note that the calibration results show $\kappa > \rho_r > \sigma$, so we can apply Propositions 1 and 2.

5.3 Results

First, let's see the model fit of targeted values. Figure 5 and 6 are the values where the changes from 1980 to 2019 are targeted. This model tracks the change over the last 40 years well. Note that I use 12 targets to fit 9 parameters, and 8 of 12 targets are imposed to fit perfectly. As such, there is only one degree of freedom to fit these four changes, so the fittings are good. However, the model results underestimate some values between 1980 and 2020. It means those values change more drastically in early periods than the model implies.

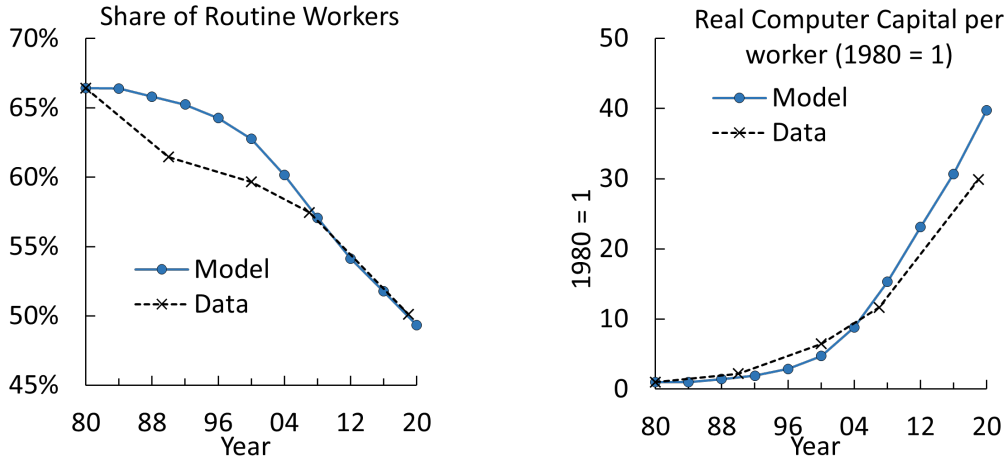


Figure 5: Left: share of workers in routine occupation, right: real computer capital per worker (1980 = 1)

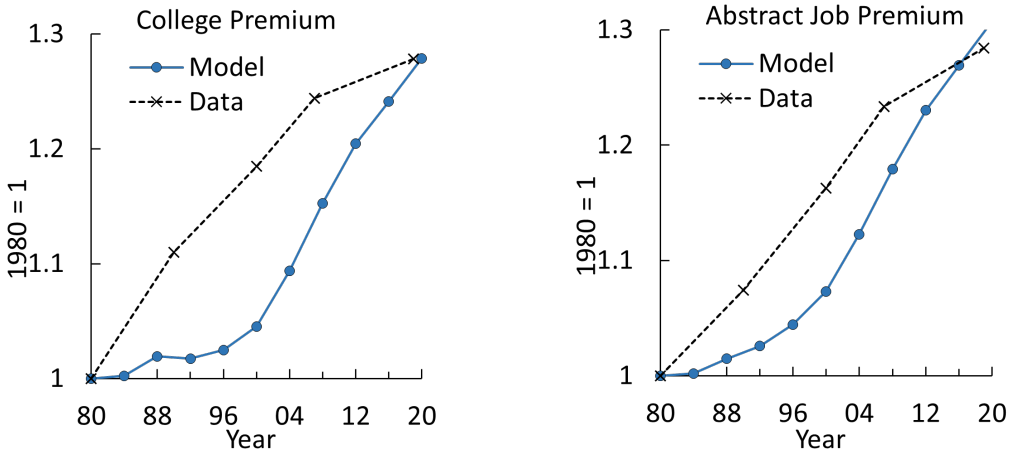


Figure 6: Left: college premium (1980=1), right: abstract job premium (1980 = 1)

Next, I show two main results in this paper. They are in Figure 7. The left one is the change in the difference in college graduates' share between routine and abstract occupations, and it is normalized to 0 in 1980. i.e., I compute

$$(C_share_{r,t} - C_share_{a,t}) - (C_share_{r,1980} - C_share_{a,1980}),$$

where $C_share_{j,t}$ is the share of college graduates within occupation $j \in \{r, a\}$ in year t.

Table 3: Task measures in abstract and routine occupations

	Abstract task	Routine task	Manual task
Routine occupation	2.066	5.241	1.227
Abstract occupation	4.372	3.184	1.210

The empirical data on the figure is given in the following way: (i) conduct a regression in the empirical analysis section for ages between 27-58 (the rightmost column of Table 6 for the change from 1980 to 2019) (ii) compute the weighted average of abstract, routine, and manual task measures in both abstract and routine occupations (Table 3), (iii) match the coefficients in (i) with task measures in (ii), and (iv) compute the aggregate effect of the three task measures. Since the routine task measure is larger and the abstract

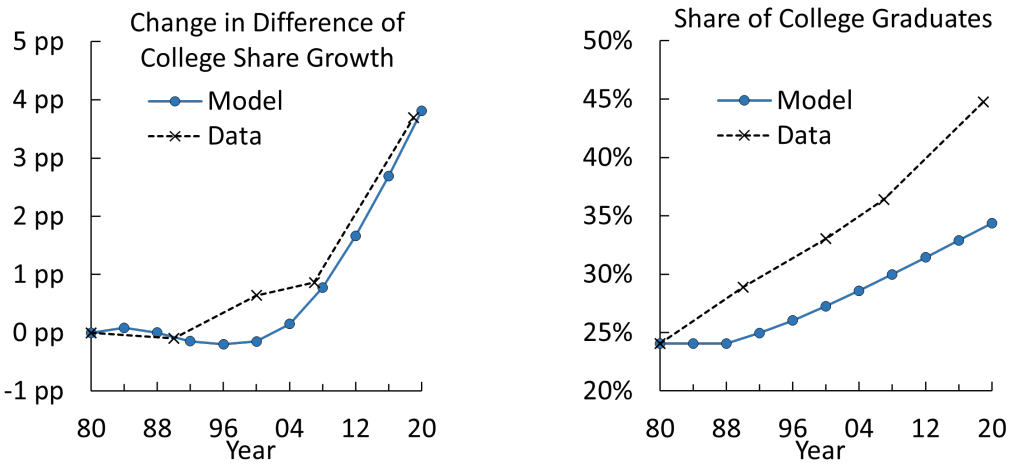


Figure 7: Left: change in the difference of college graduates' share between routine and abstract occupations, right: the total change in share of college graduates due to computerization

task measure is smaller in the routine occupation than in the abstract occupation, the regression analysis implies that routine occupation has experienced a higher gain in college graduates' share due to computerization.

The result shows that the model describes the relatively rapid increase in college graduates' share in routine occupation very well. This figure shows the case of ages between 27-58, but I show the change from 1980 to 2019 for four age groups (27-34, 35-42, 43-50, 51-58) in Table 4. It tracks a decreasing pattern of change by age group, though the values in the model are more drastic than the data.

Table 4: Change in the difference of college graduates' share by age group

Age group	27-34	35-42	43-50	51-58
Data	4.62%pt	3.56%pt	3.14%pt	1.26%pt
Model	10.59%pt	3.71%pt	0.53%pt	0.40%pt

Note: Data is computed using Table 4 and the result of regressions in Table 6.

The right graph in Figure 7 is a total change in the share of college graduates. The value in the model does not match the data well, but I do not intend to match them. This

underestimation will be reasonable because I take only the effect of computerization into account. I do not consider, for example, an improvement in the quality of education, an increasing population, and a longer life expectancy. This figure shows that almost half (49.8%) of the increase in college graduates' share is due to computerization.

Lastly, let's see breakdowns of the changes in college premium and abstract job premium for the last 40 years. While the aggregate changes in these two premiums are the targets, I did not target the breakdowns of them. The breakdown of the change in college premium from period 0 to t, ΔCp_t, is given by

$$\begin{aligned}
\Delta Cp_t &= \left(\frac{w_{C,t}}{w_{C,0}}\right) \Big/ \left(\frac{w_{H,t}}{w_{H,0}}\right) \\
&= \left(1 + \frac{L_{RC,t}}{L_{C,t}}\frac{\Delta w_{RC}}{w_{C,0}} + \frac{L_{AC,t}}{L_{C,t}}\frac{\Delta w_{AC}}{w_{C,0}} + \tilde{\Delta}_C\right) \Big/ \left(1 + \frac{L_{RH,t}}{L_{H,t}}\frac{\Delta w_{RH}}{w_{H,0}} + \frac{L_{AH,t}}{L_{H,t}}\frac{\Delta w_{AH}}{w_{H,0}} + \tilde{\Delta}_H\right) \\
&\simeq 1 + \frac{L_{RC,t}}{L_{C,t}}\frac{\Delta w_{RC}}{w_{C,0}} + \frac{L_{AC,t}}{L_{C,t}}\frac{\Delta w_{AC}}{w_{C,0}} - \frac{L_{RH,t}}{L_{H,t}}\frac{\Delta w_{RH}}{w_{H,0}} - \frac{L_{AH,t}}{L_{H,t}}\frac{\Delta w_{AH}}{w_{H,0}}, \qquad (14)
\end{aligned}$$

where $w_{j,t}$ and $L_{j,t}$ are wage and the number of workers of group j at time t, $\tilde{\Delta}_C$ and $\tilde{\Delta}_H$ are terms defined by

$$\begin{aligned}
\tilde{\Delta}_C &= \left(\frac{L_{RC,t}}{L_{C,t}} - \frac{L_{RC,0}}{L_{C,0}}\right)\left(\frac{w_{RC,0} - w_{AC,0}}{w_{C,0}}\right), \\
\tilde{\Delta}_H &= \left(\frac{L_{RH,t}}{L_{H,t}} - \frac{L_{RH,0}}{L_{H,0}}\right)\left(\frac{w_{RH,0} - w_{AH,0}}{w_{H,0}}\right),
\end{aligned}$$

which are negligible because they are the product of two different terms. I assume $\Delta w_j / w_{j,0} << 1$ in the approximation in Equation (14). Therefore, the increases in Δw_{RC} and Δw_{AC} contribute positively, and the increases in Δw_{RH} and Δw_{AH} contribute negatively. This decomposition corresponds to four counterfactual analyses of what would happen if only one of the four groups changed its wage. I use a similar breakdown for the abstract job premium. Figures 8 is the results. Those two figures adequately illustrate the wage dynamics; AC (abstract college) is the most significant contributor, and the signs of all four groups match the data.

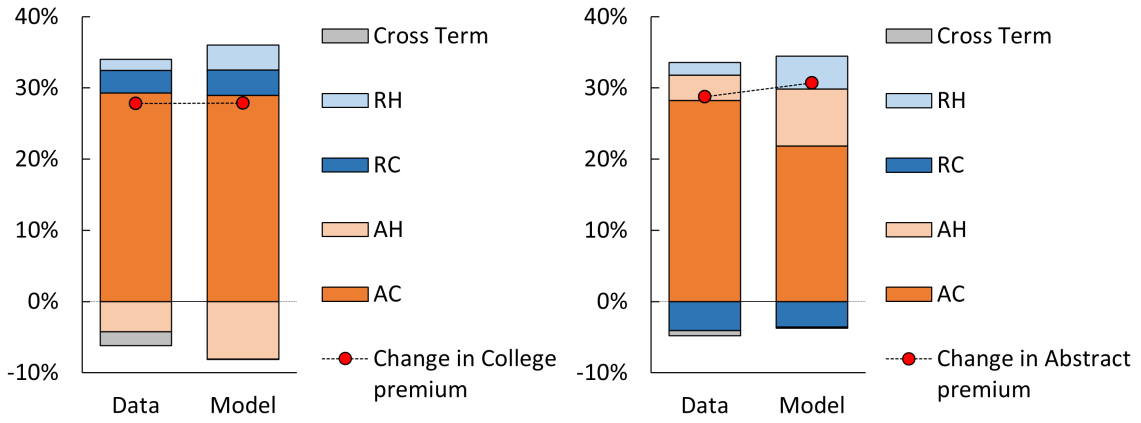


Figure 8: Breakdown of change in college premium (left) and abstract job premium (right)

6 Discussion

6.1 College education and educational skill

There is a wealth of research on the benefits of a college education. Mainly, the advantage is divided into two factors: productivity enhancement (i.e., college education increases some kinds of skill) (e.g. Schultz, 1961; Becker, 1964; Mincer, 1974) and signaling (i.e., a worker signals to firms that he has higher innate ability than a high school graduate) (e.g. Spence, 1973). This paper only considers the productivity enhancement effect.

Regarding productivity enhancement, there are no common beliefs about what kind of skills college students accumulate. I list three main arguments below:

1. Cognitive (math) skill (e.g. Murnane et al., 1995)

2. Crystallized intelligence (synonym and technical comprehension) (Carlsson et al., 2015)

3. Unobserved ability (possibly motivation or ability to learn) (Taber, 2001)

To see the list, skills acquired by college education, or educational skills, are similar to abstract skills.[15] In the model in Section 4, I treat educational skills as different from

[15] Abstract task measure consists of two variables in DOT: (i) Mathematics and (ii) Adaptability to ac-

abstract skills. However, there are two parameters to decide the similarity between these skills: elasticity of substitution between abstract task and educational task ρ_a and correlation between innate abstract ability and innate educational ability ρ_u. The former tracks the similarity from the demand side's perspective and the latter from the supply side.

Regarding ρ_a, the assumption $\rho_a = 100$ will not be far from reality though results are insensitive to ρ_a. $\rho_a = 100$ means that the output by abstract occupation is almost a linear combination of abstract and educational skill input, so these two skills are perfect substitutes.

On the other hand, ρ_u affects results. The value is selected using the correlation between the average years of schooling and the abstract task measure by occupation. While this target is not a one-to-one correspondence with ρ_u, it should be a good measure that implies a similarity between abstract and educational skills regarding each agent's innate skill set. It will be simpler to assume that there are no correlations between any innate skills, but the positive ρ_u will make the model more reasonable. In summary, the educational skill will be similar to (but not the same as) abstract skill, and I reflect this similarity on the model by the parameters ρ_u and ρ_a.

6.2 Other channels to increase educational attainment

The only driving force in the main model is the price of computer capital, so the other structural changes are not considered. However, this model would be far from reality if the other factors had a significant role. Since the model explains only 50% of the change in the share of college graduates, the remaining 50% of the change will be due to other factors. Therefore, I conduct further analysis to fill the gap by adding another driving force to the model in this section.

To begin, let's see the reasons for increasing educational attainment. Previous literature exhibits the following reasons:

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cepting responsibility for the direction, control, or planning of an activity.

1. Longer life expectancy and retirement age (e.g. Oster et al., 2013; Manuelli et al., 2012)

2. Change in the benefit of education (e.g. Card and Krueger, 1992)

3. Change in the cost of education (e.g. Castro and Coen-Pirani, 2016)

4. Skill-biased technical change (SBTC) (e.g. Restuccia and Vandenbroucke, 2014; He, 2012)

The third factor will include not only direct cost such as tuition, but also indirect cost such as barriers for women to attend college, for instance. The fourth factor corresponds to the main analysis in this paper.

Then, I simulate the effect of these four factors by comparing the steady states. Specifically, I changed the following parameters: (i) T (life expectancy) and n (retirement age), (ii) γ (quality of college), (iii) ϕ (cost of college; newly introduced parameter), and (iv) q (relative price of computer capital or SBTC).

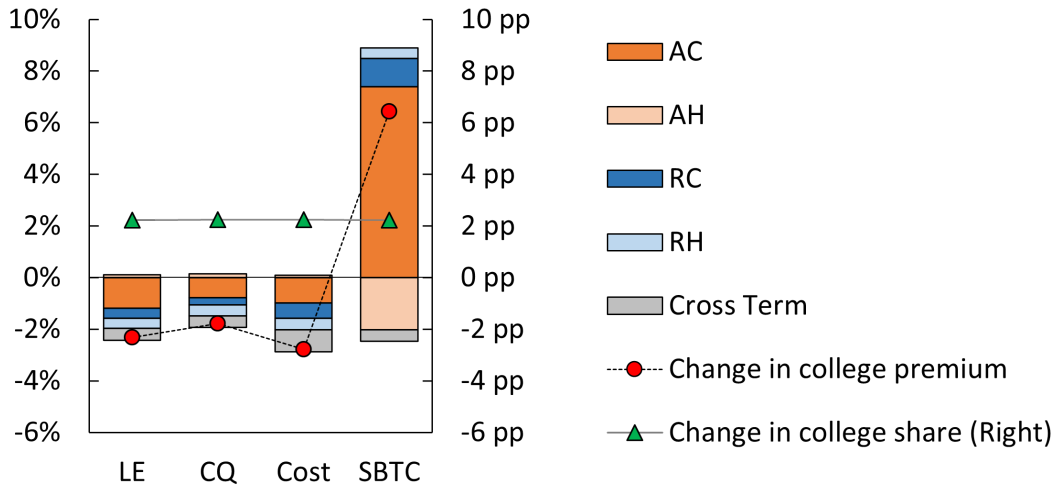


Figure 9: The effect of four kinds of shocks (LE: life expectancy and retirement age, CQ: college quality, Cost: college cost, SBTC: skill-biased technical change)

Among the first three factors, only the first one has a criterion of how large the shock is. Life expectancy has increased by around 4 years, and retirement age has increased

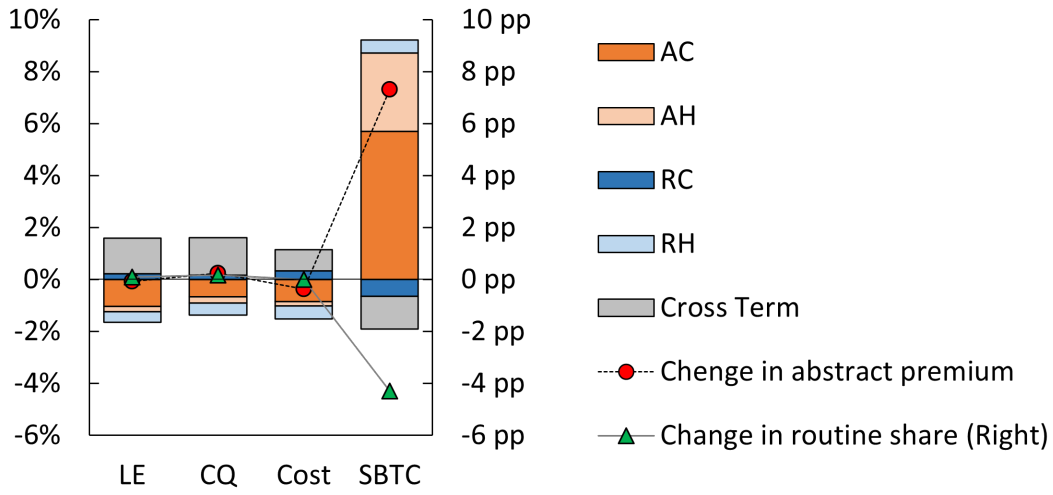


Figure 10: The effect of four kinds of shocks (LE: life expectancy and retirement age, CQ: college quality, Cost: college cost, SBTC: skill-biased technical change)

by around 2 years over the last 40 years. Therefore, I first see the effect of this change, and then I give shocks for the other factors to have the same effect on the share of college graduates.[16] The results are in Figure 9 and Figure 10. According to these figures, the first three shocks share similarities but differ significantly from the last one in magnitude.

Therefore, I pick up the change in college quality as a representative shock that affects the share of college graduates and include it in the transitional dynamics in the benchmark quantitative analysis. In detail, I allow the quality of college education γ to change over time at a constant rate. Let the rate of the improvement of γ be g_γ. I calibrate this parameter to match the actual change in the share of college graduates for the last 40 years. I leave the other parameters unchanged. Then, I get $g_\gamma = 1.011$, which means the quality of college education improves by 1.1% every period (every four years).[17] The results are shown in Figure 11 and Figure 12.

Notably, the first four graphs in Figure 11 change little from the main results. Since I

[16] For the first one, as one period is 4 years long in this model, I compute the case of two periods' increase in life expectancy and one period's increase in retirement age and halve the results.

[17] I assume γ is constant ($g_\gamma = 1$) in the initial steady state and after period 10, which corresponds to 2020.

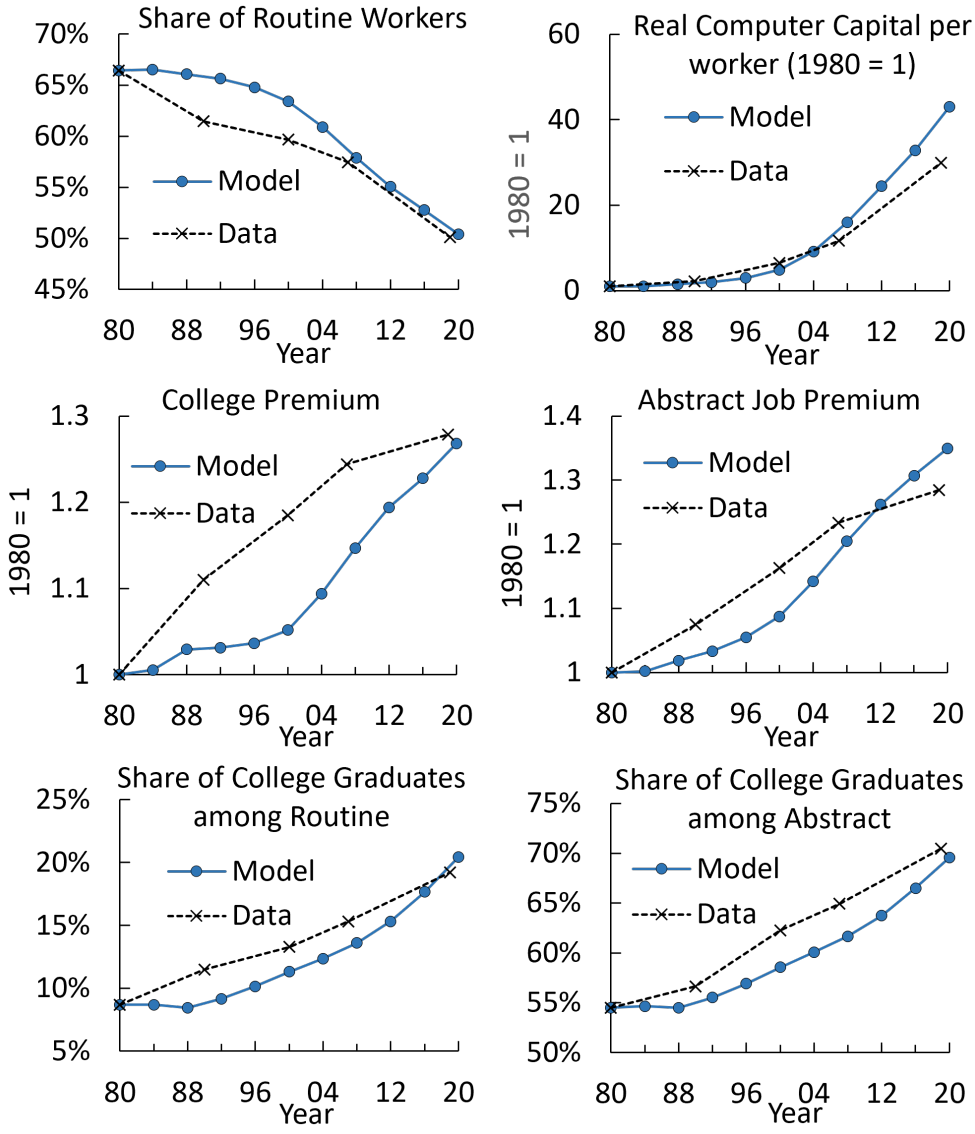


Figure 11: From the upper left to lower right, (i) share of routine workers, (ii) real computer capital per capita, (iii) college premium, (iv) abstract job premium, (v) share of college graduates among routine occupation, and (vi) share of college graduates among abstract occupation.

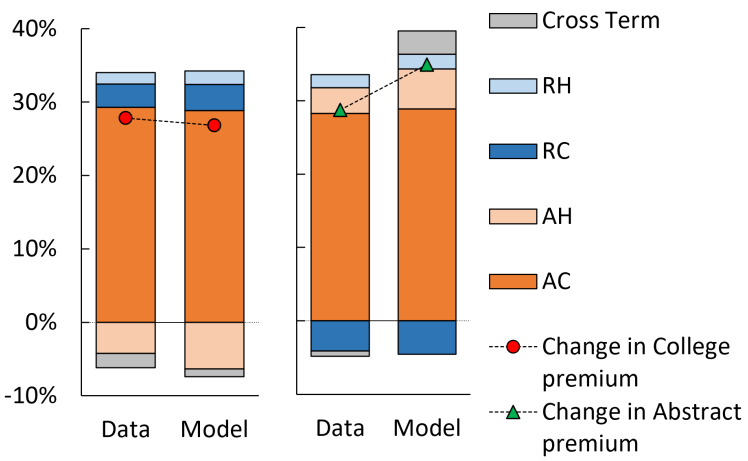


Figure 12: Left: breakdown of change in college premium, right: breakdown of change in abstract job premium

do not re-calibrate the parameters, the fact implies that g_γ little affects these values. g_γ also has little effect on the targeted apparent elasticities of substitution (computer capital - abstract task: 1.427 $\rightarrow$ 1.435, computer capital - routine task: 1.940 $\rightarrow$ 1.943).

Therefore, I can conclude from the results that g_γ affects mainly the share of college graduates, leaving the other values unchanged, so the results in Section 5 are reliable even if the increase in educational attainment is somewhat driven by some other factors.

Additionally, I get two welcome results. First, the latter two graphs in Figure 11 show that the model tracks the actual change in college graduates' share for each occupation well. While I target the aggregate change in college graduates' share, these two values are not targeted. Second, Figure 12 illustrates that the breakdowns of both college premium and abstract job premium rather fit better than those in the main model. All four groups' contributions to each premium match the data well.

7 Conclusion

The United States has experienced a significant decline in the share of routine workers and growing educational attainment for the last 40 years. There is much research about

either of these two trends, but little research focuses on their relationship.

In this paper, I empirically show that educational attainment is not independent of occupational choice. Specifically, I show that routine-intensive occupations have experienced a higher increase in educational attainment over the last 40 years.

To simulate this empirical fact, I construct a model where agents choose (i) whether to go to college or not and (ii) whether to work in the abstract or routine occupation. Based on a common belief that computerization (or computer capital) affects the share of routine workers, I assume the change in the price of computer capital is only the driving force of the economy. This model tracks the declining share of routine workers, the accumulation of computer capital, the change in college premium, and the change in abstract job premium well.

I draw three main quantitative conclusions. First, this model explains that routine occupation has experienced higher educational attainment over the last 40 years, as the empirical analysis implies. Second, around 50% of the increase in the share of college graduates is due to computerization. Third, the wage dynamics can be explained by this model, and other factors that contribute to increasing educational attainment do not significantly affect these dynamics.

While this paper demonstrates many aspects of the occupational and educational choice problem, this model reveals little information on the human capital accumulation process because the parameters for human capital accumulation are exogenously given. Endogenous investment choice in human capital will show the difference in the quality of college education and on-the-job training among agents, providing more information on the wage structure. I leave this exploration for future research.

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A Appendix

A.1 Other regression results

Table 5: The effect of routine skill intensity on the change in years of schooling

	(1)	(2)	(3)	(4)	(5)	(6)
Abstract skill	-0.0818***	-0.0291*				
	(0.0123)	(0.0152)				
Routine skill	0.0360***	0.0204*			0.0553***	0.0276**
	(0.0108)	(0.0106)			(0.0111)	(0.0107)
Manual skill	-0.0736***	-0.0843***				
	(0.0202)	(0.0194)				
Routine task intensity			0.0942***	0.0717***		
			(0.0131)	(0.0125)		
Initial years of schooling		-0.1128***		-0.1139***		-0.1192***
		(0.0195)		(0.0139)		(0.0149)
Trend	0.7724***	2.1996***	0.4644***	2.0218***	0.3401***	2.0615***
	(0.0818)	(0.2592)	(0.0314)	(0.1924)	(0.0559)	(0.2212)
Observations	323	323	323	323	323	323

Note: ***, **, and * denote significance at the 1, 5 and 10 percent levels. Each task measure is computed by using DOT 1977. Initial years of schooling is the average years of schooling in 1980.

Table 6: The effect of routine skill intensity on the change in the share of college graduates by age group

	Age 27-34 (Benchmark)	Age 35-42	Age 43-50	Age 51-58	Age 27-58
Abstract skill	-0.0076**	-0.01***	-0.0113***	-0.0065***	-0.0083***
	(0.0034)	(0.0029)	(0.0027)	(0.0025)	(0.0026)
Routine skill	0.0141***	0.006***	0.0033*	-0.0003	0.0054***
	(0.0022)	(0.0019)	(0.0017)	(0.0016)	(0.0017)
Manual skill	-0.0125***	-0.01***	-0.0081**	-0.0036	-0.0078**
	(0.0039)	(0.0034)	(0.0032)	(0.0029)	(0.0031)
Initial share	0.7444***	0.953***	1.1089***	0.9926***	0.8887***
	(0.0887)	(0.0789)	(0.0757)	(0.0744)	(0.0718)
(Initial share)^2	-0.7278***	-1.0087***	-1.2023***	-1.1132***	-0.9308***
	(0.0855)	(0.0783)	(0.0771)	(0.0779)	(0.0716)
Trend	-0.0146	0.0568***	0.0727***	0.0727***	0.0375***
	(0.0181)	(0.0149)	(0.0129)	(0.0115)	(0.0132)
Observations	323	323	323	323	323

Note: ***, **, and * denote significance at the 1, 5 and 10 percent levels. Initial share is the share of college graduates in 1980.

Table 7: The effect of routine skill intensity on the change in the share of college graduates

	Benchmark	OLS	Only men	Hour worked	1980-2000	2000-2019
Abstract skill	-0.0076**	0.0003	-0.001	-0.0079**	-0.0003	-0.0055**
	(0.0034)	(0.004)	(0.0031)	(0.0033)	(0.002)	(0.0023)
Routine skill	0.0141***	0.0061**	0.0045*	0.0139***	0.0045***	0.0082***
	(0.0022)	(0.0027)	(0.0024)	(0.0022)	(0.0013)	(0.0016)
Manual skill	-0.0125***	-0.0109***	0.0016	-0.01**	-0.001	-0.009***
	(0.0039)	(0.0042)	(0.0038)	(0.0039)	(0.0024)	(0.0029)
Initial share	0.7444***	0.6055***	0.3759***	0.7708***	0.2512***	0.4804***
	(0.0887)	(0.0942)	(0.0842)	(0.089)	(0.0537)	(0.0578)
(Initial share)^2	-0.7278***	-0.6245***	-0.3539***	-0.7476***	-0.2057***	-0.4919***
	(0.0855)	(0.0936)	(0.0793)	(0.0854)	(0.0518)	(0.0556)
Trend	-0.0146	0.0108	-0.02	-0.0221	-0.0335***	0.0165
	(0.0181)	(0.0204)	(0.0197)	(0.0188)	(0.011)	(0.0132)
Observations	323	323	323	323	323	323

Note: ***, **, and * denote significance at the 1, 5 and 10 percent levels. Initial share is the share of college graduates in 1980 for the first five regressions and in 2000 for the rightmost regression.

Table 8: The effect of routine skill intensity on the change in the share of college graduates from 1950 to 1980

	(1)	(2)	(3)	(4)	(5)	(6)
Abstract skill	0.0165***	0.0138***				
	(0.0025)	(0.0029)				
Routine skill	-0.0161***	-0.0167***			-0.017***	-0.0163***
	(0.0019)	(0.0017)			(0.0022)	(0.0019)
Manual skill	-0.0246***	-0.0184***				
	(0.0036)	(0.0033)				
Routine task intensity			-0.0039	-0.0073**		
			(0.0033)	(0.0028)		
Initial share		0.5481***		0.9786***		0.9175***
		(0.0888)		(0.0873)		(0.0792)
(Initial share)^2		-0.8058***		-1.2335***		-1.1828***
		(0.106)		(0.1135)		(0.1021)
Trend	0.1717***	0.1533***	0.1116***	0.0697***	0.1837***	0.1385***
	(0.0138)	(0.0128)	(0.0072)	(0.0077)	(0.0115)	(0.011)
Observations	186	186	186	186	186	186

Note: ***, **, and * denote significance at the 1, 5 and 10 percent levels. Each task measure is computed by using DOT 1977. Initial years of schooling is the average years of schooling in 1950. Column (1)-(6) corresponds to the columns in Table 1.

A.2 Proof of propositions

A.2.1 Proposition 1

Proof. Given the production function 2, solving the profit maximization problem 3 gives the following expressions:

$$
\begin{aligned}
r &= \frac{\partial Y}{\partial K} = \frac{\partial Y}{\partial Z_r}\frac{\partial Z_r}{\partial X}\frac{\partial X}{\partial K} \\
&= (1-\nu)\left(\frac{Y}{Z_r}\right)^{\frac{1}{\sigma}} \cdot (1-\mu_r)\left(\frac{Z_r}{X}\right)^{\frac{1}{\rho_r}} \cdot (1-\eta)\left(\frac{X}{K}\right)^{\frac{1}{\kappa}},
\end{aligned}
$$

$$
\begin{aligned}
w_r &= \frac{\partial Y}{\partial N_r} = \frac{\partial Y}{\partial Z_r}\frac{\partial Z_r}{\partial X}\frac{\partial X}{\partial N_r} \\
&= (1-\nu)\left(\frac{Y}{Z_r}\right)^{\frac{1}{\sigma}} \cdot (1-\mu_r)\left(\frac{Z_r}{X}\right)^{\frac{1}{\rho_r}} \cdot \eta\left(\frac{X}{N_r}\right)^{\frac{1}{\kappa}},
\end{aligned}
$$

$$
\begin{aligned}
w_{e_r} &= \frac{\partial Y}{\partial N_{e_r}} = \frac{\partial Y}{\partial Z_r}\frac{\partial Z_r}{\partial N_{e_r}} \\
&= (1-\nu)\left(\frac{Y}{Z_r}\right)^{\frac{1}{\sigma}} \cdot \mu_r\left(\frac{Z_r}{N_{e_r}}\right)^{\frac{1}{\rho_r}},
\end{aligned}
$$

where $X = \left[\eta N_r^{\frac{\kappa}{\kappa-1}} + (1-\eta)K^{\frac{\kappa}{\kappa-1}}\right]^{\frac{\kappa-1}{\kappa}}$. Algebraic manipulation using the above three equations yields the expression for N_{e_r}/N_r:

$$
\begin{aligned}
\frac{N_{e_r}}{N_r} &= \left(\frac{w_X}{w_{e_r}}\right)^{\rho_r}\left(\frac{\mu_r}{1-\mu_r}\right)^{\rho_r}\left(\frac{w_r}{w_X}\right)^{\kappa}\left(\frac{1}{\eta}\right)^{\kappa} \\
&= (w_X)^{\rho_r-\kappa}\left(\frac{1}{w_{e_r}}\right)^{\rho_r}\left(\frac{\mu_r}{1-\mu_r}\right)^{\rho_r}(w_r)^{\kappa}\left(\frac{1}{\eta}\right)^{\kappa},
\end{aligned}
$$

where $w_X = \left[\eta^\kappa w_r^{1-\kappa} + (1-\eta)^\kappa r^{1-\kappa}\right]^{\frac{1}{1-\kappa}}$ is the marginal cost of a bundle of routine task and computer capital. Accordingly, the marginal change of N_{e_r}/N_r in terms of r is

$$\begin{aligned}\frac{\partial \frac{N_{e_r}}{N_r}}{\partial r} &= -(\kappa-\rho_r)\,(w_X)^{\rho_r-\kappa-1}\left(\frac{1}{w_{e_r}}\right)^{\rho_r}\left(\frac{\mu_r}{1-\mu_r}\right)^{\rho_r}(w_r)^\kappa\left(\frac{1}{\eta}\right)^\kappa\frac{\partial w_X}{\partial r}\\ &= -(\kappa-\rho_r)\,(w_X)^{\rho_r-\kappa-1}\left(\frac{1}{w_{e_r}}\right)^{\rho_r}\left(\frac{\mu_r}{1-\mu_r}\right)^{\rho_r}(w_r)^\kappa\left(\frac{1-\eta}{\eta}\right)^\kappa\left(\frac{w_X}{r}\right)^\kappa.\end{aligned}$$

Therefore, $\frac{\partial \frac{N_{e_r}}{N_r}}{\partial r} < 0$ if $\kappa > \rho_r$. □

A.2.2 Proposition 2

Proof. Similar to the proof of Proposition 1, we can derive Z_a/N_{e_r} and Z_a/N_r:

$$\begin{aligned}\frac{Z_a}{N_{e_r}} &= \left(\frac{w_{Z_r}}{w_{Z_a}}\right)^\sigma\left(\frac{\nu}{1-\nu}\right)^\sigma\left(\frac{w_{e_r}}{w_{Z_r}}\right)^{\rho_r}\left(\frac{1}{\mu_r}\right)^{\rho_r}\\ &= (w_{Z_r})^{\sigma-\rho_r}\left(\frac{1}{w_{Z_a}}\right)^\sigma\left(\frac{\nu}{1-\nu}\right)^\sigma(w_{e_r})^{\rho_r}\left(\frac{1}{\mu_r}\right)^{\rho_r},\end{aligned}$$

$$\begin{aligned}\frac{Z_a}{N_r} &= \left(\frac{w_{Z_r}}{w_{Z_a}}\right)^\sigma\left(\frac{\nu}{1-\nu}\right)^\sigma\left(\frac{w_X}{w_{Z_r}}\right)^{\rho_r}\left(\frac{1}{1-\mu_r}\right)^{\rho_r}\left(\frac{w_r}{w_X}\right)^\kappa\left(\frac{1}{\eta}\right)^\kappa\\ &= (w_{Z_r})^{\sigma-\rho_r}(w_X)^{\rho_r-\kappa}\left(\frac{1}{w_{Z_a}}\right)^\sigma\left(\frac{\nu}{1-\nu}\right)^\sigma\left(\frac{1}{1-\mu_r}\right)^{\rho_r}(w_r)^\kappa\left(\frac{1}{\eta}\right)^\kappa,\end{aligned}$$

where $w_{Z_a} = \left[\mu_a{}^{\rho_a} w_{e_a}^{1-\rho_a} + (1-\mu_a)^{\rho_a} w_a^{1-\rho_a}\right]^{\frac{1}{1-\rho_a}}$ and $w_{Z_r} = \left[\mu_r{}^{\rho_r} w_{e_r}^{1-\rho_r} + (1-\mu_r)^{\rho_r} w_X^{1-\rho_r}\right]^{\frac{1}{1-\rho_r}}$ are the marginal costs of abstract routine input, respectively.

Accordingly, the marginal change of Z_a/N_{e_r} and Z_a/N_r in terms of r is

$$\begin{aligned}\frac{\partial \frac{Z_a}{N_{e_r}}}{\partial r} &= -(\rho_r-\sigma)\,(w_{Z_r})^{\sigma-\rho_r-1}\left(\frac{1}{w_{Z_a}}\right)^\sigma\left(\frac{\nu}{1-\nu}\right)^\sigma(w_{e_r})^{\rho_r}\left(\frac{1-\mu_r}{\mu_r}\right)^{\rho_r}(1-\eta)^\kappa\left(\frac{w_{Z_r}}{w_X}\right)^{\rho_r}\left(\frac{w_X}{r}\right)^\kappa,\\ \frac{\partial \frac{Z_a}{N_r}}{\partial r} &= -(\rho_r-\sigma)\,(w_{Z_r})^{\sigma-\rho_r-1}(w_X)^{\rho_r-\kappa}\left(\frac{1}{w_{Z_a}}\right)^\sigma\left(\frac{\nu}{1-\nu}\right)^\sigma(w_r)^\kappa\left(\frac{1-\eta}{\eta}\right)^\kappa\left(\frac{w_{Z_r}}{w_X}\right)^{\rho_r}\left(\frac{w_X}{r}\right)^\kappa\\ &\quad -(\kappa-\rho_r)\,(w_{Z_r})^{\sigma-\rho_r}(w_X)^{\rho_r-\kappa-1}\left(\frac{1}{w_{Z_a}}\right)^\sigma\left(\frac{\nu}{1-\nu}\right)^\sigma\left(\frac{1}{1-\mu_r}\right)^{\rho_r}(w_r)^\kappa\left(\frac{1-\eta}{\eta}\right)^\kappa\left(\frac{w_X}{r}\right)^\kappa.\end{aligned}$$

Therefore, $\frac{\partial \frac{Z_a}{Ne_r}}{\partial r} < 0$ and $\frac{\partial \frac{Z_a}{N_r}}{\partial r} < 0$ if $\kappa > \rho_r > \sigma$.

Since routine workers' input is a function of N_{e_r} and N_r, we can define it as a function of these two tasks, $f(N_{e_r}, N_r)$. Note that it is different from Z_r since Z_r includes computer capital. Since $\partial f(N_{e_r}, N_r)/\partial Ne_r$ and $\partial f(N_{e_r}, N_r)/\partial Nr$ are larger than zero by construction, the demand for abstract workers relative to routine workers is a decreasing function of r. □

A.3 Data appendix

A.3.1 Computer capital

Computer capital comes from BEA Detailed Data for Fixed Assets and Consumer Durable Goods. In Table 9, I list codes and titles of computer capital defined by Eden and Gaggl (2018).

A.3.2 IPUMS-USA

I compute the share of college graduates, years of schooling, the share of routine workers, and the wages by group using IPUMS-USA (Ruggles et al., 2023). I use the data in 1950, 1980, 1990, 2000, 2007 and 2019. The data are available every 10 years before 2000 and weeks worked is unavailable between 2008 and 2018, weeks worked is unavailable. The list of variables are in Table 10.

A.3.3 Classification of occupations

I use the occupation classification constructed by Autor and Dorn (2013). We can find the classification and skill measures on the author's website. Since the occupation codes correspondence of 2019 criteria is unavailable there, I make the correspondence table in Table 11. I use occupations in the list as the sample if they have non-zero weights.

Table 9: Detailed list of computer capital

Codes	Computer Capital
Equipments	
EP1A	Mainframes
EP1B	PCs
EP1C	DASDs
EP1D	Printers
EP1E	Terminals
EP1F	Tape drives
EP1G	Storage devices
EP1H	System integrators
EP20	Communications
EP34	Nonelectro medical instruments
EP35	Electro medical instruments
EP36	Nonmedical instruments
EP31	Photocopy and related equipment
EP12	Office and accounting equipment
Intellectual Property Products	
ENS1	Prepackaged software
ENS2	Custom software
ENS3	Own account software
RD21	Computers and peripheral equipment manufacturing
RD22	Communications equipment manufacturing
RD23	Semiconductor and other component manufacturing
RD24	Navigational and other instruments manufacturing
RD25	Other computer and electronic manufacturing, n.e.c.
RD40	Software publishers
Consumer Durables	
1RGPC	Prepackaged software
1RGCS	Custom software
1RGCA	Own account software
1OD50	Computers and peripheral equipment manufacturing

Note: Codes are fixed assets code assigned by BEA.

Table 10: IPUMS-USA variables

Variables	Label
YEAR	Census year
PERWT	Person weight
SEX	Sex
AGE	Age
EDUC	(general) Educational attainment [general version]
EDUCD	(detailed) Educational attainment [detailed version]
OCC	Occupation
WKSWORK1	Weeks worked last year
UHRSWORK	Usual hours worked per week
INCWAGE	Wage and salary income

Table 11: Occupation categories and skill measures

Occ Code	Occupation Groups and Occupation Titles	ACS 2019 Codes	Occ Groups	Skill Measures		
				Abstract	Routine	Manual
	Managerial and Professional Specialty Occupations					
	Executive, Administrative, and Managerial Occupations					
4	Chief executives, public administrators, and legislators	10	Abstract	5.56	1.93	0.58
7	Financial managers	120	Abstract	7.45	2.10	0.04
8	Human resources and labor relations managers	135-137	Abstract	5.86	1.82	0.24
13	Managers and specialists in marketing, advert., PR	41, 51-52, 60, 2825	Abstract	6.97	1.38	0.08
14	Managers in education and related fields	230	Abstract	6.90	1.48	0.18
15	Managers of medicine and health occupations	350	Abstract	7.82	2.41	0.36
18	Managers of properties and real estate	410	Abstract	5.19	1.84	1.29
19	Funeral directors	4465	Abstract	7.64	1.25	0.00
22	Managers and administrators, n.e.c.	20, 101-102, 110, 140, 220, 300, 310, 335, 340, 360, 420, 440, 600, 725	Abstract	6.91	1.89	0.47
	Management Related Occupations					
23	Accountants and auditors	800, 930	Abstract	7.62	5.99	0.02
24	Insurance underwriters	860	Abstract	2.96	2.81	0.02
25	Other financial specialists	820, 830, 845, 850, 910, 940, 960	Abstract	7.15	3.10	0.07
26	Management analysts	710	Abstract	7.11	4.34	0.69
27	Personnel, HR, training, and labor rel. specialists	630, 640, 650	Abstract	5.83	1.81	0.24
28	Purchasing agents and buyers of farm products	510	Abstract	4.94	1.99	0.00
29	Buyers, wholesale and retail trade	520	Abstract	6.48	1.35	0.05
33	Purchasing managers, agents, and buyers, n.e.c.	150, 530	Abstract	6.54	1.61	0.11
34	Business and promotion agents	500	Abstract	6.33	1.74	0.79
35	Construction inspectors	6660	Abstract	2.96	5.55	3.32
36	Inspectors and compliance officers, outside	565, 900	Abstract	3.43	4.89	1.28
37	Management support occupations	425, 735, 750	Abstract	6.16	1.97	0.56
	Professional Specialty Occupations					
43	Architects	1305-1306	Abstract	5.23	3.31	0.10
44	Aerospace engineers	1320	Abstract	8.40	6.08	1.26
45	Metallurgical and materials engineers	1450	Abstract	8.54	7.22	0.87
47	Petroleum, mining, and geological engineers	1520	Abstract	8.01	6.02	0.43
48	Chemical engineers	1350	Abstract	9.00	6.66	0.30
53	Civil engineers	1360	Abstract	8.18	7.35	2.21
55	Electrical engineers	1400	Abstract	7.34	6.48	2.92
56	Industrial engineers	1430	Abstract	7.57	5.19	0.99
57	Mechanical engineers	1460	Abstract	7.93	7.26	0.27
59	Engineers and other professionals, n.e.c.	1340, 1420, 1440, 1530	Abstract	7.02	5.72	1.03
64	Computer systems analysts and computer scientists	1005-1007, 1031-1032, 1050, 1065, 1105-1106, 1108	Abstract	5.35	2.88	1.39
65	Operations and systems researchers and analysts	700, 705, 1220	Abstract	5.39	2.78	1.12
66	Actuaries	1200	Abstract	7.99	5.53	0.00
68	Mathematicians and statisticians	1240	Abstract	5.30	3.10	0.22
69	Physicists and astronomists	1700	Abstract	5.28	6.83	0.24
73	Chemists	1720	Abstract	8.49	7.10	0.36

Occ Code	Occupation Groups and Occupation Titles	ACS 2019 Codes	Occ Groups	Skill Measures		
				Abstract	Routine	Manual
74	Atmospheric and space scientists	1710	Abstract	7.12	1.25	0.00
75	Geologists	1745, 1750	Abstract	5.78	6.52	2.01
76	Physical scientists, n.e.c.	1760	Abstract	9.00	6.25	0.00
77	Agricultural and food scientists	1600	Abstract	6.65	5.27	1.04
78	Biological scientists	1610	Abstract	7.82	7.69	0.94
79	Foresters and conservation scientists	1640	Abstract	4.06	2.04	2.91
83	Medical scientists	1650	Abstract	7.84	7.79	1.04
84	Physicians	3100	Abstract	7.89	4.69	1.76
85	Dentists	3010	Abstract	4.17	4.09	2.33
86	Veterinarians	3250	Abstract	2.86	7.13	0.25
87	Optometrists	3040	Abstract	4.00	2.50	0.00
88	Podiatrists	3120	Abstract	4.72	2.49	0.28
89	Other health and therapy occupations	3000, 3261, 3270	Abstract	8.00	3.75	2.50
95	Registered nurses	3255-3256, 3258	Abstract	3.33	7.04	2.39
96	Pharmacists	3050	Abstract	4.43	7.99	0.00
97	Dieticians and nutritionists	3030	Abstract	7.96	1.55	0.00
98	Respiratory therapists	3020	Abstract	5.03	4.00	1.05
99	Occupational therapists	3150	Abstract	5.03	4.00	1.05
103	Physical therapists	3160	Abstract	5.03	4.00	1.05
104	Speech therapists	3140, 3230	Abstract	5.03	4.00	1.05
105	Therapists, n.e.c.	3200, 3210, 3245	Abstract	5.03	4.00	1.05
106	Physicians' assistants	3110	Abstract	5.03	4.00	1.05
154	Subject instructors, college	2205	Abstract	7.32	1.54	0.27
155	Kindergarten and earlier school teachers	2300	Abstract	3.64	1.83	2.63
156	Primary school teachers	2310	Abstract	2.59	1.34	2.28
157	Secondary school teachers	2320	Abstract	7.11	1.57	0.76
158	Special education teachers	2330	Abstract	5.52	3.74	1.70
159	Teachers, n.e.c.	2350, 2360, 2555,	Abstract	5.59	3.41	1.93
163	Vocational and educational counselors	2001-2006	Abstract	4.62	1.36	0.18
164	Librarians	2435	Abstract	3.02	1.64	0.39
165	Archivists and curators	2400	Abstract	4.90	1.89	1.93
166	Economists, market and survey researchers	1800	Abstract	5.25	3.23	0.18
167	Psychologists	1821, 1822, 1825,	Abstract	5.03	1.81	0.08
169	Social scientists and sociologists, n.e.c.	1860	Abstract	5.29	1.42	1.00
173	Urban and regional planners	1840	Abstract	3.37	2.23	0.00
174	Social workers	2011, 2012, 2013, 2014	Abstract	6.70	1.41	0.10
176	Clergy and religious workers	2040, 2050, 2060,	Abstract	3.41	1.31	0.08
177	Welfare service workers	2015, 2016, 2025,	Abstract	4.99	1.64	0.88
178	Lawyers and judges	2100, 2105	Abstract	3.32	1.41	0.00
183	Writers and authors	2850	Abstract	1.92	1.25	0.00
184	Technical writers	2840	Abstract	3.86	2.42	0.87
185	Designers	2631-2636, 2640	Abstract	4.20	4.57	0.47
186	Musicians and composers	2751, 2752, 2755,	Abstract	2.61	3.21	3.83
187	Actors, directors, and producers	2700, 2710	Abstract	5.62	2.11	1.52
188	Painters, sculptors, craft-artists, and print-makers	2600	Abstract	2.23	5.57	0.20
189	Photographers	2910	Abstract	1.85	7.35	0.18
193	Dancers	2740	Abstract	1.00	7.50	10.0
194	Art/entertainment performers and related occs	2770, 2861, 2862, 2865	Abstract	3.64	2.73	1.03
195	Editors and reporters	2810, 2830, 2920,	Abstract	4.39	1.88	0.04
198	Announcers	2805	Abstract	1.87	4.35	0.00
199	Athletes, sports instructors, and officials	2721, 2722, 2723,	Abstract	5.59	3.51	5.85
	Technical, Sales, and Administrative Support Occupations					
	Technicians and Related Support Occupations					

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203	Clinical laboratory technologies and technicians	3300	Abstract	3.06	7.94	0.52
204	Dental hygienists	3310	Abstract	2.00	8.64	0.21
205	Health record technologists and technicians	3515	Abstract	3.46	4.65	0.00
206	Radiologic technologists and technicians	3321-3324, 3330	Abstract	3.13	7.44	2.44
207	Licensed practical nurses	3500	Abstract	1.60	4.90	2.47
208	Health technologists and technicians, n.e.c.	3401, 3402, 3545, 3550	Abstract	2.43	6.49	1.53
214	Engineering technicians	1551, 1555	Abstract	3.58	7.26	1.20
217	Drafters	1541, 1545	Abstract	3.85	8.27	0.12
218	Surveryors, cartographers, mapping scientists/techs	1310, 1560	Abstract	7.54	7.28	4.16
223	Biological technicians	1900, 1910	Abstract	3.26	6.58	0.68
224	Chemical technicians	1920	Abstract	3.70	7.00	1.00
225	Other science technicians	1935	Abstract	4.01	6.30	0.75
226	Airplane pilots and navigators	9030	Abstract	3.64	4.17	5.02
227	Air traffic controllers	9040	Abstract	2.29	2.49	0.00
228	Broadcast equipment operators	2905	Abstract	2.66	3.23	0.43
229	Computer software developers	1010, 1021, 1022,	Abstract	7.51	5.06	0.69
233	Programmers of numerically controlled machine tools	7905	Abstract	6.15	5.55	0.47
234	Legal assistants and paralegals	2145, 2170, 2180,	Abstract	2.99	3.68	0.16
235	Technicians, n.e.c.	1970, 1980	Abstract	4.03	5.85	1.17
	Sales Occupations					
243	Sales supervisors and proprietors	4700, 4710	Routine	6.99	1.87	0.51
253	Insurance sales occupations	4810	Routine	3.20	3.24	0.01
254	Real estate sales occupations	810, 4920	Routine	2.12	1.32	0.05
255	Financial service sales occupations	4820	Routine	6.47	2.07	0.01
256	Advertising and related sales jobs	4800	Routine	3.20	1.59	0.00
258	Sales engineers	4930	Routine	5.74	3.32	0.47
274	Salespersons, n.e.c.	726, 4850, 4940, 4965	Routine	2.15	1.59	0.20
275	Retail salespersons and sales clerks	4740, 4750, 4760, 4840	Routine	2.06	2.15	0.45
276	Cashiers	4720	Routine	1.52	7.46	0.04
277	Door-to-door sales, street sales, and news vendors	4950	Routine	1.64	1.61	1.55
283	Sales demonstrators, promoters, and models	4900	Routine	1.96	2.34	0.70
	Administrative Support Occupations					
303	Office supervisors	5000	Routine	4.58	4.50	0.12
308	Computer and peripheral equipment operators		Routine	1.91	7.01	1.92
313	Secretaries and stenographers	5710, 5720, 5730, 5740	Routine	1.99	8.54	0.01
316	Interviewers, enumerators, and surveyors	5230, 5310, 5340,	Routine	1.77	6.09	0.08
317	Hotel clerks	5300	Routine	1.45	2.72	0.32
318	Transportation ticket and reservation agents	4830, 5410	Routine	2.06	2.17	0.12
319	Receptionists and other information clerks	5400	Routine	1.32	2.53	0.04
326	Correspondence and order clerks	5350	Routine	1.63	3.37	0.26
328	Human resources clerks, excl payroll and timekeeping	5360	Routine	1.81	6.12	0.08
329	Library assistants	2440, 5320	Routine	0.53	3.03	1.90
335	File clerks	5260	Routine	0.76	6.93	0.05
336	Records clerks	5420	Routine	1.80	5.87	0.09
337	Bookkeepers and accounting and auditing clerks	5120	Routine	2.91	7.32	0.02
338	Payroll and timekeeping clerks	5140	Routine	2.05	7.96	0.00
344	Billing clerks and related financial records processing	5110	Routine	1.95	7.04	0.07
346	Mail and paper handlers	5560	Routine	0.98	4.72	0.58
347	Office machine operators, n.e.c.	5900	Routine	0.74	4.58	0.33
348	Telephone operators	5010, 5020	Routine	1.08	2.68	0.03
349	Other telecom operators	5040	Routine	1.91	5.26	0.00

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354	Postal clerks, exluding mail carriers	5540	Routine	1.27	3.27	0.02
355	Mail carriers for postal service	5550	Routine	1.07	1.27	0.29
356	Mail clerks, outside of post office	5850	Routine	1.01	4.72	0.06
357	Messengers	5510	Routine	0.39	1.81	0.47
359	Dispatchers	5521, 5522	Routine	4.39	2.73	0.04
364	Shipping and receiving clerks	5500, 5610	Routine	2.54	5.26	0.20
365	Stock and inventory clerks	5150	Routine	1.93	4.65	0.39
366	Meter readers	5530	Routine	1.00	5.00	0.00
368	Weighers, measurers, and checkers	5630	Routine	1.41	5.59	0.19
373	Material recording, sched., prod., plan., expediting cl.	160, 5600	Routine	2.99	4.89	0.18
375	Insurance adjusters, examiners, and investigators	540, 5840	Routine	2.21	1.61	0.03
376	Customer service reps, invest., adjusters, excl. insur.	5240, 5330	Routine	2.28	3.14	0.10
377	Eligibility clerks for government prog., social welfare	5250	Routine	1.73	6.31	0.08
378	Bill and account collectors	5100	Routine	2.29	1.56	0.00
379	General office clerks	5860	Routine	2.13	6.76	0.06
383	Bank tellers	5160	Routine	2.34	8.34	0.00
384	Proofreaders	5910	Routine	0.39	5.43	0.00
385	Data entry keyers	5810	Routine	1.78	7.16	0.24
386	Statistical clerks	5920	Routine	1.85	6.13	0.08
387	Teacher's aides	2545	Routine	2.62	1.36	0.26
389	Administrative support jobs, n.e.c.	5165, 5220, 5940,	Routine	1.77	6.27	0.08
	Service Occupations					
	Housekeeping and Cleaning Occupations					
405	Housekeepers, maids, butlers, and cleaners	4230	Manual	0.69	1.40	2.21
408	Laundry and dry cleaning workers	8300	Manual	0.31	2.66	0.50
	Protective Service Occupations					
415	Supervisors of guards	3725	Manual	2.18	1.75	0.36
417	Fire fighting, fire prevention, and fire inspection occs	3720, 3740, 3750,	Manual	2.07	1.55	6.17
418	Police and detectives, public service	3710, 3820, 3840, 3870	Manual	1.66	1.28	3.80
423	Sheriffs, bailiffs, correctional institution officers	3700, 3801, 3802,	Manual	0.74	1.32	1.94
425	Crossing guards	3940	Manual	0.48	1.19	2.43
426	Guards and police, except public service	3910, 3930	Manual	0.64	1.37	0.30
427	Protective service, n.e.c.	3900, 3945, 3946, 3960	Manual	2.07	2.56	1.78
	Other Service Occupations					
433	Supervisors of food preparation and service	4010	Manual	2.44	3.66	0.65
434	Bartenders	4040	Manual	1.16	1.30	0.09
435	Waiters and waitresses	4110	Manual	1.13	1.38	2.30
436	Cooks	4000, 4020	Manual	1.86	5.03	0.09
439	Food preparation workers	4030	Manual	0.60	2.40	1.47
444	Miscellanious food preparation and service workers	4055, 4120, 4130, 4140, 4150, 4160	Manual	0.44	1.92	1.61
445	Dental Assistants	3640	Manual	2.00	7.52	0.03
447	Health and nursing aides	3601-3603, 3605, 3610, 3620, 3630, 3645-3649, 3655	Manual	1.52	3.00	2.15
448	Supervisors of cleaning and building service	4200	Manual	1.92	3.31	2.10
450	Superv. of landscaping, lawn service, groundskeeping	4210	Manual	3.80	3.61	1.82
451	Gardeners and groundskeepers	4251, 4252, 4255,	Manual	1.24	3.72	2.73
453	Janitors	4220	Manual	1.03	3.82	2.36
455	Pest control occupations	4240	Manual	0.99	3.30	2.33

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457	Barbers	4500	Manual	1.56	6.97	0.02
458	Hairdressers and cosmetologists	4510, 4521, 4522, 4525	Manual	2.45	3.65	0.11
459	Recreation facility attendants	4330, 4400, 4435,	Manual	2.13	2.45	1.78
461	Guidesxxx	4540	Manual	0.81	1.68	1.09
462	Ushers	4420	Manual	0.77	1.94	0.85
464	Baggage porters, bellhops and concierges	4530	Manual	1.56	1.71	2.15
466	Recreation and fitness workers	4621, 4622	Manual	6.50	1.81	1.84
467	Motion picture projectionists		Manual	1.00	7.50	0.00
468	Child care workers	4600, 4640	Manual	1.67	1.30	0.31
469	Personal service occupations, n.e.c.	4461, 4655	Manual	2.71	1.62	0.99
470	Supervisors of personal service jobs, n.e.c.		Manual	2.91	2.65	1.41
471	Public transportation attendants and inspectors	9050, 9410, 9415,	Manual	1.70	1.40	4.65
472	Animal caretakers, except farm	4340, 4350	Manual	0.74	4.92	1.52
	Precision Production, Craft, and Repair Occupations					
	Mechanics and Repairers					
503	Supervisors of mechanics and repairers	7000	Routine	4.05	5.52	1.66
505	Automobile mechanics and repairers	7200	Routine	2.04	7.12	2.31
507	Bus, truck, and stationary engine mechanics	7210	Routine	2.04	7.11	2.28
508	Aircraft mechanics	7140	Routine	2.95	7.17	2.15
509	Small engine repairers	7240	Routine	2.08	7.32	0.92
514	Auto body repairers	7150, 7160	Routine	1.40	6.91	0.39
516	Heavy equipement and farm equipment mechanics	7220, 7260	Routine	2.04	7.05	2.13
518	Industrial machinery repairers	7330	Routine	2.13	7.38	1.81
519	Machinery maintenance occupations	7350	Routine	0.12	2.80	0.36
523	Repairers of industrial electrical equipment	7100, 7120	Routine	2.28	7.36	0.58
525	Repairers of data processing equipment	7010	Routine	3.20	7.69	0.30
526	Repairers of household appliances and power tools	7320	Routine	1.65	6.36	1.07
527	Telecom and line installers and repairers	7020, 7420	Routine	2.42	7.62	4.08
533	Repairers of electrical equipment, n.e.c.	7030	Routine	2.67	7.02	1.33
534	Heating, air conditioning, and refrigeration mechanics	7315	Routine	2.02	7.15	2.20
535	Precision makers, repairers, and smiths	7430, 8750	Routine	1.79	8.17	0.13
536	Locksmiths and safe repairers	7540	Routine	2.05	7.29	1.03
539	Repairers of mechanical controls and valves	7300	Routine	1.69	6.47	1.09
543	Elevator installers and repairers	6700	Routine	2.14	7.36	2.05
544	Millwrights	7360	Routine	1.75	7.20	4.09
549	Mechanics and repairers, n.e.c.	7340, 7510, 7560, 7640	Routine	2.10	7.30	1.84
	Construction Trades					
558	Supervisors of construction work	6200	Routine	5.58	3.97	1.42
563	Masons, tilers, and carpet installers	6220, 6240	Routine	1.54	7.06	2.75
567	Carpenters	6230	Routine	2.19	7.38	4.51
573	Drywall installers	6330	Routine	1.06	7.50	2.73
575	Electricians	6355, 7130	Routine	3.07	7.34	2.47
577	Electric power installers and repairers	7040, 7410	Routine	2.75	6.95	4.34
579	Painters, construction and maintenance	6410	Routine	1.38	7.32	2.54
583	Paperhangers		Routine	1.09	7.50	2.71
584	Plasterers	6460	Routine	1.32	7.27	4.80
585	Plumbers, pipe fitters, and steamfitters	6441, 6442	Routine	2.18	7.33	2.55
588	Concrete and cement workers	6250	Routine	1.00	6.14	2.62
589	Glaziers	6360	Routine	1.22	6.84	2.10
593	Insulation workers	6400, 6720	Routine	1.91	6.66	2.63
594	Paving, surfacing, and tamping equipment operators		Routine	0.55	6.52	4.99

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595	Roofers and slaters	6515	Routine	1.18	7.39	4.95
597	Structural metal workers	6530, 7740	Routine	1.25	6.95	4.81
598	Drillers of earth	6825	Routine	1.12	5.23	3.61
599	Misc. construction and related occupations	6710, 6540, 6765,	Routine	1.34	5.66	2.49
	Extractive Occupations					
614	Drillers of oil wells	6800	Routine	0.91	4.83	2.92
615	Explosives workers	6835	Routine	2.54	5.40	2.54
616	Miners	6850	Routine	0.71	4.55	2.36
617	Other mining occupations	6950	Routine	0.70	4.54	2.34
	Precision Production Occupations					
628	Production supervisors or foremen	7700	Routine	6.25	3.98	0.88
634	Tool and die makers and die setters	8130	Routine	2.65	8.17	0.08
637	Machinists	8030	Routine	2.68	8.24	0.47
643	Boilermakers	6210	Routine	2.91	7.26	0.00
644	Precision grinders and fitters		Routine	0.88	6.83	0.10
645	Patternmakers and model makers	8100	Routine	2.77	7.65	0.05
649	Engravers	8910	Routine	1.12	7.89	0.70
653	Other metal and plastic workers	6520	Routine	2.95	7.44	2.32
657	Cabinetmakers and bench carpeters	8500	Routine	2.65	7.17	2.40
658	Furniture/wood finishers, other prec. wood workers	8510	Routine	0.71	5.63	0.15
666	Dressmakers, seamstresses, and tailors	8350	Routine	1.36	7.74	2.04
668	Upholsterers	8450	Routine	1.83	7.32	0.26
669	Shoemakers, other prec. apparel and fabric workers	8335	Routine	1.44	6.89	2.99
675	Hand molders and shapers, except jewelers	8920	Routine	0.95	5.40	0.93
677	Optical goods workers	3520	Routine	2.32	7.16	0.12
678	Dental laboratory and medical applicance technicians	3421-3424, 3430, 8760	Routine	2.29	8.27	1.79
679	Bookbinders	8256	Routine	0.95	6.35	1.83
684	Other precision and craft workers	8000, 8025, 8225,	Routine	1.61	6.54	0.41
686	Butchers and meat cutters	7810	Routine	1.49	6.55	0.00
687	Bakers	7800	Routine	1.26	6.78	0.14
688	Batch food makersxxx	7840	Routine	0.86	5.11	0.99
694	Water and sewage treatment plant operators	8620	Routine	2.69	6.09	1.16
695	Power plant operators	8600	Routine	4.02	5.45	1.74
696	Plant and system operators, stationary engineers	8610	Routine	1.93	5.75	1.34
699	Other plant and system operators	8630	Routine	1.20	5.20	1.87
	Operators, Fabricators, and Laborers					
	Machine Operators, Assemblers, and Inspectors					
703	Lathe, milling, and turning machine operatives		Routine	1.79	7.24	0.54
706	Punching and stamping press operatives	7950	Routine	0.84	5.55	2.42
707	Rollers, roll hands, and finishers of metal		Routine	1.83	4.58	0.53
708	Drilling and boring machine operators		Routine	1.50	6.87	0.32
709	Grinding, abrading, buffing, and polishing workers		Routine	0.76	6.56	0.19
713	Forge and hammer operators	7925	Routine	1.19	5.84	2.25
719	Molders and casting machine operators		Routine	0.96	5.34	0.89
723	Metal platers		Routine	1.63	6.56	0.18
724	Heat treating equipment operators		Routine	1.59	6.43	1.03
727	Sawing machine operators and sawyers	8530	Routine	0.58	5.25	2.36
729	Nail, tacking, shaping and joining mach ops (wood)	8540	Routine	0.64	5.02	1.27
733	Other woodworking machine operators	8555	Routine	0.89	5.36	1.03
734	Printing machine operators, n.e.c.	8255	Routine	1.44	6.90	0.62

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736	Typesetters and compositors	8250	Routine	1.34	7.51	0.57
738	Winding and twisting textile and apparel operatives		Routine	0.17	5.34	1.09
739	Knitters, loopers, and toppers textile operatives		Routine	0.11	7.43	0.54
743	Textile cutting and dyeing machine operators	8365	Routine	0.76	5.71	1.06
744	Textile sewing machine operators	8320	Routine	0.45	7.86	3.29
745	Shoemaking machine operators		Routine	0.42	5.95	2.13
747	Clothing pressing machine operators	8310	Routine	0.07	2.33	1.73
749	Miscellanious textile machine operators	8465	Routine	0.46	5.36	0.80
753	Cementing and gluing machne operators	8850	Routine	0.86	5.11	0.99
754	Packers, fillers, and wrappers	8800	Routine	0.37	3.67	1.18
755	Extruding and forming machine operators	8720	Routine	0.82	4.98	0.96
756	Mixing and blending machine operators	8650	Routine	0.69	5.79	0.59
757	Separating, filtering, and clarifying machine operators	8640	Routine	0.87	5.18	1.14
763	Food roasting and baking machine operators	7830	Routine	1.19	6.48	0.29
764	Washing, cleaning, and pickling machine operators		Routine	0.82	4.89	0.96
765	Paper folding machine operators	8930	Routine	0.86	5.11	0.99
766	Furnance, kiln, and oven operators, apart from food	8040, 8730	Routine	1.93	5.75	1.34
769	Slicing, cutting, crushing and grinding machine	7850, 8710	Routine	0.73	5.56	1.02
774	Photographic process workers	8830	Routine	1.05	6.73	0.35
779	Machine operators, n.e.c.	7855, 8940, 8990,	Routine	1.16	6.11	1.89
785	Assemblers of electrical equipment	7720, 7730, 7750,	Routine	0.59	5.80	0.57
789	Painting and decoration occupations	8810	Routine	2.56	7.12	3.06
799	Production checkers, graders, and sorters in manufacturing	8740	Routine	1.39	6.27	0.64
	Transportation and Material Moving Occupations					
803	Supervisors of motor vehicle transportation	9005	Routine	6.71	3.66	0.86
804	Truck, delivery, and tractor drivers	9130, 9600	Routine	0.75	2.00	4.66
808	Bus drivers	9121, 9122	Routine	1.04	1.28	4.95
809	Taxi cab drivers and chauffeurs	9110, 9141, 9142, 9150	Routine	0.97	1.38	4.84
813	Parking lot attendants	9350	Routine	0.00	1.25	5.00
823	Railroad conductors and yardmasters	9240	Routine	6.12	2.80	3.71
824	Locomotive operators: engineers and firemen	9210	Routine	3.90	1.98	2.76
825	Railroad brake, coupler, and switch operators	9265	Routine	0.99	2.03	3.47
829	Ship crews and marine engineers	9300, 9310	Routine	3.29	4.23	4.72
834	Miscellanious transportation occupations	9430	Routine	0.48	1.19	2.43
844	Operating engineers of construction equipment	6305	Routine	0.81	6.72	4.90
848	Crane, derrick, winch, hoist, longshore operators	9510, 9570	Routine	0.21	5.72	3.97
853	Excavating and loading machine operators		Routine	0.83	6.56	4.78
859	Stevedores and misc. material moving occupations	9650, 9760	Routine	1.49	3.52	2.21
865	Helpers, constructions	7610	Routine	0.88	2.92	1.19
866	Helpers, surveyors	6600	Routine	1.07	5.08	2.51
869	Construction laborers	6260, 6730	Routine	0.99	4.90	2.54
873	Production helpers	8950	Routine	0.65	4.77	0.82
875	Garbage and recyclable material collectors	9720	Routine	0.04	1.25	2.87
878	Machine feeders and offbearers	9630	Routine	0.35	3.41	1.54
885	Garage and service station related occupations	9365	Routine	0.94	1.59	0.19
887	Vehicle washers and equipment cleaners	9610	Routine	0.32	2.16	0.66
888	Packers and packagers by hand	9640, 9645	Routine	0.14	2.77	0.57
889	Laborers, freight, stock, and material handlers, n.e.c.	6740, 9620	Routine	0.76	2.49	1.45

Note: Occ Code (Occ 1990dd Code), occupation groups, and skill measures are constructed by Autor and Dorn (2013). The correspondences between Occ 1990dd and each year's occupation classification, which are not shown here, are also constructed by Autor and Dorn (2013).