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Abstract

Over the past four decades in the US, routine employment has declined sharply while college attainment has risen steadily. I develop a quantitative model in which workers choose whether to attend college and whether to work in abstract or routine occupations. The calibrated model implies that computerization raises the return to educational skill within routine work, raising the within-occupation college share faster in routine jobs than in abstract jobs. I test this implication in the data by estimating how baseline task content predicts subsequent educational upgrading across occupations. The regression evidence confirms faster college-share growth in more routine-taskintensive occupations. Quantitatively, the model attributes about one half of the aggregate increase in the college share over 1980-2019 to computerization.

Keywords: investment specific technological change; computerization; occupational choice; schooling choice
JEL classification: E24, J24, O33, I21

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1 Introduction

Over the past four decades, computer technology has advanced rapidly. A large task-based literature, beginning with Autor et al. (2003), argues that automation associated with computerization reduces demand for routine-task-intensive work because computer capital substitutes for labor in routine tasks. A central lesson from this literature is that computerization reshapes occupational demand by changing the task content of jobs. Over the same period, however, educational attainment rose sharply. This raises a natural question: how does computerization interact with workers' education decisions and, in turn, the educational composition of employment across occupations?

A useful benchmark for occupational sorting is the classic self-selection framework of Roy (1951), in which individuals choose occupations based on innate comparative advantage. Yet, in practice, occupational sorting is inseparable from educational attainment and skill gained through education: abstract occupations employ a large share of college graduates, while routine and manual occupations employ far fewer. This gap suggests that a complete account of occupational change should incorporate education choices and allow technology to affect the relative value of education across occupations.

This paper studies how computerization shapes educational upgrading across occupations, with a particular focus on routine work. While computerization is often associated with a shrinking share of routine employment, its implications for the *educational composition* of routine employment are theoretically ambiguous. On the one hand, automation may replace rule-based tasks and raise the value of skills that are complementary to new technologies, increasing the college share within routine occupations. On the other hand, if computerization substitutes for tasks that previously required formal education, routine occupations could become less education-intensive. Which force dominates is an empirical question, and answering it is essential for interpreting long-run labor-market change.

To interpret how computerization reshapes educational attainment across occupations, I build a task-based quantitative general equilibrium model in which individuals jointly choose whether to attend college and whether to work in abstract or routine occupations, delivering a unified account of occupational reallocation and within-occupation educational upgrading. Occupations differ in their task requirements, and ICT (or computer) capital enters production alongside abstract tasks, routine tasks, and tasks learned through college education. How ICT capital reshapes the relative demand for these inputs is governed by a set of substitution parameters determined in the quantitative analysis. The model is calibrated by matching the US economy in 1980 and the subsequent long-run movements in employment shares and wage premia. Feeding in the observed decline in the relative price of ICT capital, the model delivers a sharp implication for occupational outcomes: computerization raises the return to skills attained through education within routine work, raising the within-occupation college share faster in routine occupations than in abstract occupations. The calibrated model also implies that computerization accounts for about one half of the aggregate rise in the college share over 1980–2019.

I then compare the predictions of the model to the data. Using U.S. data from 1980 to 2019, I document a systematic pattern of educational upgrading across occupations: routine-task-intensive occupations experience faster growth in the college share. In particular, occupations with higher baseline routine intensity exhibit larger increases in college attainment over time. The regression-implied and model-implied magnitudes align closely, providing quantitative support for the proposed mechanism. The result is robust to an alternative classification of occupations that groups abstract and manual occupations into a single non-routine occupational category (Appendix A.1).

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 develops the model and discusses its key mechanisms. Section 4 presents the quantitative analysis and its main occupational implications. Section 5 provides empirical evidence from cross-occupation regressions and compares it with the model's prediction. Section 6 evaluates the robustness of the benchmark calibration targets and shows that augmenting the model with a parsimonious non-ICT factor can also match the unconditional rise in college attainment across occupations without materially affecting the benchmark wage moments. Section 7 concludes.

2 Literature Review

Roy (1951)'s framework of self-selection and earnings has been widely applied. In his model, agents choose occupations according to comparative advantage, and subsequent work has progressively enriched the choice environment by incorporating schooling decisions and dynamic human-capital formation. Willis and Rosen (1979) extend the Roy framework to allow agents to choose educational attainment, while Willis (1987) introduces multi-dimensional skills that are valued differently across occupations. Moving beyond static selection, Keane and Wolpin (1997) and Heckman et al. (1998) develop dynamic settings in which agents accumulate human capital through schooling and on-the-job training, thereby linking early-life educational choices to later occupational outcomes. My model builds on this tradition by endogenizing both educational attainment and occupational choice, but it differs from much of the earlier selection literature in that the key driver of occupational reallocation and skill upgrading is a task-based technological change associated with computerization rather than purely exogenous changes in the wage structure.

In this sense, my model is closely related to Lee (2005), who develops a dynamic general equilibrium overlapping generations model of career decisions that allows agents to choose educational attainment and occupations and uses the Mincer (1974) wage function to value schooling and on-the-job training. This paper shares with Lee (2005) the framework of a life-cycle general equilibrium environment in which educational and occupational choices are jointly determined, but departs from his approach by explicitly modeling task demand shifts induced by computerization and by focusing on how such shifts reshape the educational composition of workers within broad occupational groups. In particular, instead of treating the return to schooling as an outcome summarized by a wage equation, my framework emphasizes the mechanisms through which technology changes the relative value of distinct skill components across occupations and over time, thereby delivering sharp predictions for educational upgrading within occupations.

My model is constructed based on the ideas of routine-biased technological change (RBTC; Autor et al. (2003)), and thus the task-based occupational framework of Autor and Dorn (2013) is a key feature of the analysis. The RBTC literature highlights that computer technologies substitute for routine tasks while complementing non-routine analytic and interactive tasks, generating job polarization and shifts in occupational demand. I incorporate this task-based structure into a quantitative general equilibrium model with endogenous education, which allows the model to connect the decline of routine task demand to changes in the educational composition of employment. In this regard, the paper is closely related to the work of vom Lehn (2020), who evaluates polarization in a neoclassical dynamic general equilibrium framework by modeling technological progress as a decline in the price of machines that are substitutable with routine tasks. Building on vom Lehn (2020), I add an explicit choice of educational attainment and skill acquired through schooling, which is essential for explaining my empirical finding that routine-task-intensive occupations exhibit faster growth in the college share. The paper is also related to the work of Cortes et al. (2017), who analyze occupational choice jointly with extensive-margin labor supply decisions. My focus is complementary in that I emphasize education-driven skill acquisition and its interaction with task-biased technological change as the central mechanism behind the evolving composition of routine employment.

A further motivation for my framework is the growing evidence that task content changes substantially not only among occupations but also within narrowly defined occupations over time. Consoli et al. (2023) provide direct evidence of within-occupation task reorientation by combining DOT and O*NET information, showing that within-occupation changes account for a sizeable fraction of the long-run decline in routine-task use. Ross (2017) likewise provides panel data evidence that task orientation evolves meaningfully both across and within occupations and that these changes are systematically related to wage outcomes. Atalay et al. (2020) complement these approaches by constructing task measures from the text of job advertisements and showing that a substantial portion of the long-run transformation away from routine tasks occurs within narrowly defined job titles. Together, these papers strengthen the empirical foundation for treating within-occupation shifts in task content as quantitatively important, and they motivate modeling skill requirements as evolving even for narrowly defined occupations, rather than being fixed over time.

Importantly, there is also evidence that within-occupation task reorientation is linked to computerization. Using German data with direct information on workplace technology adoption, Spitz-Oener (2006) documents that rising computer use is associated with declining routine task inputs and rising non-routine analytic and interactive tasks within occupations, accompanied by increasing educational demands. Similarly, using U.S. vacancy postings, Hershbein and Kahn (2018) show that skill requirements increased disproportionately in local labor markets that experienced larger downturns, consistent with firms accelerating routine-biased technological change, and that these upskilling effects were especially pronounced in routine-cognitive occupations. Moreover, focusing on office and administrative support jobs, Dillender and Forsythe (2022) show that software adoption in office and administrative support occupations, a major group of routine jobs, is associated with a sizable increase in the college share. Taken together, these findings provide a concrete empirical channel connecting computerization to within-occupation skill upgrading, and they motivate interpreting the heterogeneous growth of college attainment across occupations documented in this paper through the lens of technology-driven shifts in task demands.

While the central idea of my research follows RBTC, it also contributes to the broader discussion on skill-biased technological change (SBTC; Katz and Murphy (1992)) and the evolution of skill premia. Because agents in my model choose whether to enter college (be skilled workers) or start working after high school graduation (be unskilled workers), the framework can jointly account for changes in the college premium and occupation-specific premia in a general equilibrium setting. In this sense, my model is related to the capital-skill complementarity mechanism in Krusell et al. (2000) and subsequent quantitative studies with endogenous educational choice (e.g. Lee and Wolpin, 2010). The analysis is also closely connected to the long-run "race" between education and technology emphasized by Goldin and Katz (2008), in which the evolution of wage differentials reflects the interaction of secular skill demand growth with fluctuations in the growth rate of educational attainment. Although SBTC is not the central focus of this paper, incorporating educational choice helps constrain the model's predictions for how college attainment evolves across occupations, which is essential for interpreting the empirical patterns documented in this study.

Several papers quantify how SBTC affects educational attainment and aggregate schooling outcomes. He (2012) uses movements in the relative price of capital goods as a source of SBTC and quantifies the contribution of SBTC to the rise in college enrollment, while Restuccia and Vandenbroucke (2014) introduce schooling-level specific productivity parameters to study the evolution of average years of schooling under persistent skill-biased shifts. My model is closer to He (2012) in its emphasis on capital-skill complementarity and in using relative price movements as a key driver, but it differs in that the technological change is determined by the relative price of computer capital and is explicitly linked to task substitution and complementarity across occupations. As a result, the model is able to speak directly to how educational attainment changes differ systematically across occupations with different task intensities, which is central to my empirical analysis.

My quantitative result that routine-task-intensive occupations experience faster growth in the share of college graduates is related to existing evidence on the changing allocation of highly educated workers. In particular, Beaudry et al. (2016) document a "great reversal" in the demand for skill and cognitive tasks around 2000 and argue that high-skilled workers moved down the occupational ladder, increasingly performing jobs traditionally performed by less educated workers. This mechanism could be viewed as an alternative interpretation of rising college shares in routine occupations, and it provides an important benchmark for assessing whether upgrading reflects changing task requirements, reallocation of educated workers across the occupational ladder, or both. The present paper contributes to this debate by offering a structural framework in which task-biased technological change and education choices jointly determine occupational allocation, thereby providing strict quantitative predictions for the extent of within-occupation educational upgrading attributable to computerization.

Finally, my model is related to quantitative general equilibrium studies that combine task-based production with multi-dimensional skills and education choices, such as Barany et al. (2020), who develop and estimate a multi-sector general equilibrium model with sector-occupation choices over the life cycle and heterogeneous skill endowments that can be enhanced through schooling and experience. While Barany et al. (2020) share with my approach the emphasis on multi-dimensional skills and a structural general equilibrium framework, their analysis is broader and not designed to target within-occupation education upgrading among routine workers. Nevertheless, they document joint long-run trends in education and occupational polarization, including the evolving allocation of highly educated workers across routine and non-routine occupation groups. To the best of my knowledge, this paper is the first to construct a quantitative model that is explicitly designed to explain the growing importance of college graduates within routine-task-intensive occupations and to evaluate the contribution of computerization to that change.

3 Model

This section presents a tractable general equilibrium model with two occupations (abstract and routine) and two skill components that are valued differently across occupations: abstract jobs combine abstract skill and educational skill, while routine jobs combine routine skill and educational skill.[1] A distinctive feature of the model is that it can accommodate not only reallocation *between* occupations, but also changes in the skill composition *within* occupations. This modeling choice is motivated by evidence that task and skill requirements evolve substantially within occupations over time (Ross, 2017; Atalay et al., 2020), and that such within-occupation reorientation is systematically related to computerization (Spitz-Oener, 2006).

The central mechanism is straightforward: a decline in the relative price of computer capital induces firms to substitute computer capital for routine skill in the production of routine occupational services. Because routine production also relies on educational skill, this substitution can shift skill demands within routine jobs and alter the relative payoff to college education. The model generates implications about educational upgrading across occupations that I evaluate in the empirical analysis.

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[1] The main analysis abstracts from (non-routine) manual occupations to keep the model tractable and to sharpen the contrast between abstract and routine occupations when analyzing endogenous college choice and educational upgrading. A large literature on job polarization emphasizes that computerization reduces routine employment and that adjustment can also involve growth in manual jobs; Appendix A.1 shows that the main qualitative results are robust when manual occupations are grouped together with abstract occupations as a broader non-routine category.

3.1 Technology

Aggregate output Y_t is produced using abstract and routine occupational services, $Z_{a,t}$ and $Z_{r,t}$, through a CES aggregator:

$$Y_t = \left[\nu Z_{a,t}^{\frac{\sigma-1}{\sigma}} + (1-\nu) Z_{r,t}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

The model abstracts from manual occupations to focus on the abstract–routine margin.

Abstract occupational services combine abstract skill input $N_{a,t}$ and educational skill input $N_{e_a,t}$:

$$Z_{a,t} = \left[\mu_a N_{e_a,t}^{\frac{\rho_a-1}{\rho_a}} + (1-\mu_a) N_{a,t}^{\frac{\rho_a-1}{\rho_a}} \right]^{\frac{\rho_a}{\rho_a-1}}.$$

Routine occupational services combine educational skill input $N_{e_r,t}$ with a composite of routine skill input $N_{r,t}$ and computer capital K_t:

$$Z_{r,t} = \left[\mu_r N_{e_r,t}^{\frac{\rho_r-1}{\rho_r}} + (1-\mu_r) \left\{ \eta N_{r,t}^{\frac{\kappa-1}{\kappa}} + (1-\eta) K_t^{\frac{\kappa-1}{\kappa}} \right\}^{\frac{\kappa}{\kappa-1}\cdot\frac{\rho_r-1}{\rho_r}} \right]^{\frac{\rho_r}{\rho_r-1}}.$$

Here $N_{j,t}$ denotes efficiency units of skill input $j \in \{a, r, e_a, e_r\}$. I distinguish educational skill used in abstract and routine jobs because the relative importance and equilibrium price of educational skill can differ across occupations.[2]

This structure captures within-occupation changes in skill demands in a parsimonious way. As computer capital becomes cheaper, firms substitute K_t for routine skill $N_{r,t}$. Be-

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[2] There are three possible ways to nest routine skill input, educational input, and ICT capital in a CES aggregator, but I adopt the present nesting for a practical reason. If routine skill and educational inputs are nested first, a decline in the ICT price affects college and non-college workers symmetrically, so the model does not generate an increase in the college share. If, instead, educational input and ICT capital are nested first, the implied elasticity of substitution between routine input and the ICT–education composite becomes negative, which is not economically meaningful.

cause routine services $Z_{r,t}$ still require educational skill $N_{e_r,t}$, this substitution changes the relative marginal product of educational skill within routine jobs and can raise the skill price $w_{e_r,t}$ relative to $w_{r,t}$, generating incentives for educational upgrading in routine occupations.

I assume a representative competitive firm that takes skill prices $w_{a,t}, w_{r,t}, w_{e_a,t}, w_{e_r,t}$ and the rental rate of computer capital r_t as given. The firm chooses inputs to maximize profits:

$$\Pi_t = \max_{N_{a,t}, N_{e_a,t}, N_{r,t}, N_{e_r,t}, K_t} Y_t - w_{a,t}N_{a,t} - w_{e_a,t}N_{e_a,t} - w_{r,t}N_{r,t} - w_{e_r,t}N_{e_r,t} - r_t K_t. \tag{2}$$

Computer capital is supplied perfectly elastically at rental rate r_t. The accumulation of computer capital is given by

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

where I_t is investment in computer capital and q_t is the relative price of computer capital in terms of the consumption good. I assume full depreciation within a period, which provides a convenient approximation given the rapid obsolescence of computer capital.[3] The price q_t is exogenous, and a decline in q_t represents embodied technological progress in producing computer capital, following Greenwood et al. (1997). The quantitative analysis studies the effects of changes in q_t.

Under full depreciation and absent adjustment costs, the no-arbitrage condition implies

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

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[3] One model period corresponds to four years. Empirically, depreciation rates for computer capital are above 20% per year, so treating computer capital as fully depreciating within a period is a reasonable approximation for the purposes of the quantitative exercise.

where r_t^f is the risk-free rate.

3.2 Households

I consider an environment with heterogeneous workers, each identified by a vector of innate abilities, $\boldsymbol{u_0} = (u_{a0}, u_{r0}, u_{e0})$.[4] One unit of each skill can yield one unit of each task input. I assume that the set of innate skills $\boldsymbol{u_0}$ 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

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

which means that u_{r0} is independent of the other two skills, and u_{a0} and u_{e0} are correlated according to parameter ρ_u.[5] The average of the variable's natural logarithm can be normalized to zero without loss of generality.

There are two types of educational levels (high school graduates and college graduates) and two occupations (abstract and routine), resulting in $2 \times 2 = 4$ types of workers in this model. Conditional on occupational choice, agents supply the relevant skill inputs inelastically: abstract workers supply abstract skill and educational skill, while routine workers supply routine skill and educational skill. Educational skill is used in both occupations. Earnings are the sum of skill-specific payments for the inputs supplied.[6]

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

[5] I discuss the similarity between abstract skill and educational skill in Appendix A.4.

[6] As is well understood, representing earnings as an additive function of multiple skill components is not empirically innocuous (e.g. Heckman and Scheinkman, 1987; Autor and Handel, 2013). A particular

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. Agents can change occupations costlessly at the beginning of each working period. When $t = n$, agents retire. After retiring, their earnings fall to zero, and they have to rely entirely on their savings.

In this model, the advantage of entering college is that each agent can increase their educational skill u_e by a constant factor of γ. On the other hand, the disadvantage is that they lose the opportunity to earn income and receive on-the-job training while in college. 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 a 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 working one period increases all skills at a constant rate g.

I normalize the total population to one and consider a stationary environment in which cohort sizes are constant over time.

Each agent has a log utility over consumption. Let AC, AH, RC, and RH denote abstract college, abstract high school, routine college, and routine high school occupation-education combinations, respectively. Then, the problem for households in the i-th gen-

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concern in multisector characteristics models is the restrictive hypothesis that a given skill is priced uniformly across occupations, which would make that skill enter earnings as a common occupation-invariant shifter. This concern does not apply here because the model allows the price of educational skill to be occupation-specific (i.e., $w_{e_a,t} \neq w_{e_r,t}$), so educational skill does not enter as a common occupation-invariant earnings shifter.

eration is given by:

$$
\begin{aligned}
&\max_{\{c_t^i\},\{b_{t+1}^i\}} \sum_{t=0}^{T} \beta^t \log(c_t^i) \quad s.t. \\
&\qquad (t=0) \\
&\qquad c_0^i + b_1^i = 0 \quad if \quad \text{AC or RC} \\
&\qquad c_0^i + b_1^i = u_{a0} w_{a,0} + u_{e0} w_{e_a,0} \quad if \quad \text{AH} \\
&\qquad c_0^i + b_1^i = u_{r0} w_{r,0} + u_{e0} w_{e_r,0} \quad if \quad \text{RH} \\
&\qquad (t \in [1,n]) \\
&\qquad c_t^i + b_{t+1}^i = g^{t-1}(u_{a0} w_{a,t} + \gamma u_{e0} w_{e_a,t}) + r_t^f b_t^i \quad if \quad \text{AC} \\
&\qquad c_t^i + b_{t+1}^i = g^{t}(u_{a0} w_{a,t} + u_{e0} w_{e_a,t}) + r_t^f b_t^i \quad if \quad \text{A}H \\
&\qquad c_t^i + b_{t+1}^i = g^{t-1}(u_{r0} w_{r,t} + \gamma u_{e0} w_{e_r,t}) + r_t^f b_t^i \quad if \quad \text{RC} \\
&\qquad c_t^i + b_{t+1}^i = g^{t}(u_{r0} w_{r,t} + u_{e0} w_{e_r,t}) + r_t^f b_t^i \quad if \quad \text{R}H \\
&\qquad (t \in [n+1, T-1]) \\
&\qquad c_t^i + b_{t+1}^i = r_t^f b_t^i \\
&\qquad (t = T) \\
&\qquad c_t^i = r_t^f b_t^i .
\end{aligned}
$$

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 an abstract occupation or routine occupation $j \in \{A, R\}$ at the beginning of every period t according to:

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

where

$$W_{A,t}(u_a, u_r, u_e) = u_a w_{a,t} + u_e w_{e_a,t}, \tag{3}$$

$$W_{R,t}(u_a, u_r, u_e) = u_r w_{r,t} + u_e w_{e_r,t}. \tag{4}$$

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. A change in q_t motivates some workers to change their occupations because each unit return to skill also changes.

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

$$\operatorname*{arg\,max}_{k \in \{H,C\}} V_{k,0}(u_a, u_r, u_e),$$

where

$$V_{C,0}(u_a, u_r, u_e) = \sum_{s=1}^{n} \left(\frac{g^{s-1}}{\prod_{i=1}^{s} r_i^f} \right) \max_{j \in \{A,R\}} W_{j,s}(u_a, u_r, \gamma u_e), \tag{5}$$

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

I illustrate the choice problem at time $t = 0$ in a steady state, where q_t is constant, graphically in Figure 1. The horizontal axis is the distribution of u_e/u_r, and the vertical axis is the distribution of u_a/u_r. Here, I define $\Lambda \equiv (1/r^f) \sum_{s=1}^{n} (g/r^f)^{s-1}$ as the sum of growth-adjusted discount factors. In this representation, agents with higher abstract skills relative to routine skills tend to choose abstract occupation, 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 the occupation that gives higher wages to educational skills. If $w_{e_a} = w_{e_r}$, then the occupational choice between routine

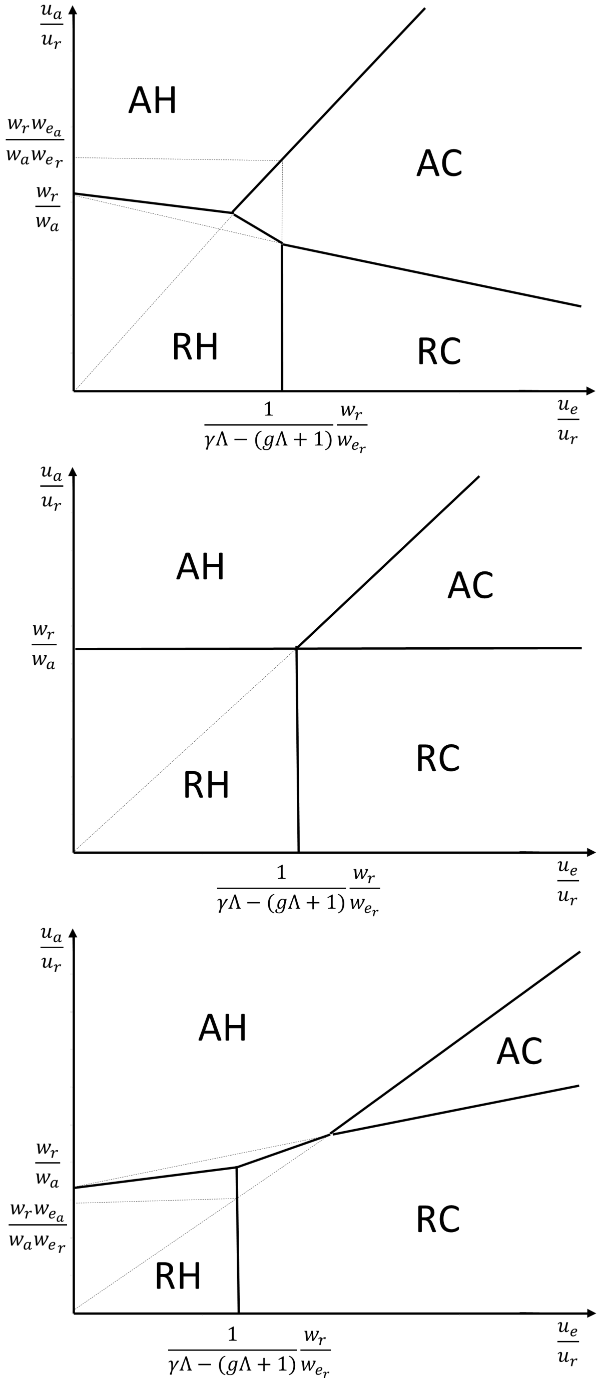

Figure 1: Choice of occupations and educational attainment in steady state (top panel: $w_{e_a} > w_{e_r}$, middle panel: $w_{e_a} = w_{e_r}$, bottom panel: $w_{e_a} < w_{e_r}$).

and abstract does not depend on u_e.

3.3 Equilibrium

A competitive equilibrium for the model economy with heterogeneous workers is a sequence of allocations $(c_t^i(\boldsymbol{u}), b_{t+1}^i(\boldsymbol{u}), N_{a,t}, N_{e_a,t}, N_{r,t}, N_{e_r,t}, K_t)$ and prices $(w_{a,t}, w_{e_a,t}, w_{r,t}, w_{e_r,t}, r_t, r_t^f)$ such that: (i) for each cohort i and ability vector $\boldsymbol{u}$, $(c_t^i(\boldsymbol{u}), b_{t+1}^i(\boldsymbol{u}))$ solves the household's problem given prices; (ii) $(N_{a,t}, N_{e_a,t}, N_{r,t}, N_{e_r,t}, K_t)$ solves the firm's problem given prices; and (iii) goods, labor-skill, and capital markets clear in every period.

The market-clearing conditions are:

$$Y_t = \int_{\boldsymbol{u}} \sum_{i=t-T}^{t} c_t^i(\boldsymbol{u})\phi(\boldsymbol{u})\mathrm{d}\boldsymbol{u} + I_t \tag{7}$$

$$N_{a,t} = \int_{\boldsymbol{u}} \sum_{i=t-n}^{t} g^{i-t+n} u_a(\boldsymbol{u})\phi_t^i(\boldsymbol{u}, \mathrm{A}H)\mathrm{d}\boldsymbol{u} + \int_{\boldsymbol{u}} \sum_{i=t-n}^{t-1} g^{i-t+n} u_a(\boldsymbol{u})\phi_t^i(\boldsymbol{u}, \mathrm{AC})\mathrm{d}\boldsymbol{u} \tag{8}$$

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

$$N_{r,t} = \int_{\boldsymbol{u}} \sum_{i=t-n}^{t} g^{i-t+n} u_r(\boldsymbol{u})\phi_t^i(\boldsymbol{u}, \mathrm{R}H)\mathrm{d}\boldsymbol{u} + \int_{\boldsymbol{u}} \sum_{i=t-n}^{t-1} g^{i-t+n} u_r(\boldsymbol{u})\phi_t^i(\boldsymbol{u}, \mathrm{RC})\mathrm{d}\boldsymbol{u} \tag{10}$$

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

$$K_t = \frac{1}{q_{t-1}} \int_{\boldsymbol{u}} \sum_{i=t-T}^{t} b_t^i(\boldsymbol{u})\phi_t^i(\boldsymbol{u})\mathrm{d}\boldsymbol{u}. \tag{12}$$

In these expressions, $\phi(\boldsymbol{u})$ denotes the density of innate abilities, which is assumed to be identical across cohorts. Let $\phi_t^i(\boldsymbol{u}, \mathrm{s})$ denote the density at time t of agents in cohort i with innate ability $\boldsymbol{u}$ who are of type $\mathrm{s} \in \{\mathrm{A}H, AC, RH, RC\}$.[7]

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[7] The cohort index i is redundant for $\phi(\boldsymbol{u})$ because the distribution of innate abilities is invariant across cohorts. By contrast, $\phi_t^i(\boldsymbol{u}, \mathrm{s})$ generally depends on both i and t because education and occupation choices map the same innate ability $\boldsymbol{u}$ into different types over the life cycle and across cohorts as equilibrium prices

3.4 Properties of the model

The key parameters governing the model's comparative statics are κ, ρ_r, and σ, which determine the elasticities of substitution across the relevant input bundles. These parameters control how changes in the rental rate of computer capital r_t translate into shifts in relative task demands and, through occupational and education choices, into changes in the composition of workers across $\{AC, AH, RC, RH\}$. In particular, κ and ρ_r govern how a change in r_t affects the relative demand for routine skill versus educational skill within routine jobs, which is a central incentive in choosing between RC and RH. The parameter σ governs substitution between abstract and routine occupational services and therefore matters for occupational reallocation. By contrast, the choice between AC and AH is not directly affected by computer capital in production, although it can respond indirectly through general-equilibrium movements in $(w_{a,t}, w_{e_a,t})$. The following propositions summarize the key comparative statics on the production side:

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

Proof. See Appendix A.3.1. □

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

Proof. See Appendix A.3.2. □

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change.

If the model were restricted to the routine occupation (i.e., the choice between RC and RH), Proposition 1 would translate directly into a within-routine force toward educational upgrading: as r_t falls under $\kappa > \rho_r$, the firm substitutes computer capital for routine skill, raising the relative marginal product of educational skill in routine production and thereby increasing the college share, since the education choice is monotone in the relative payoff to educational skill in this one-occupation environment. With the abstract occupation available, however, this demand-side shift need not imply that the equilibrium college share *within* the routine occupation rises. The reason is that the same change in r_t can also affect equilibrium wages in the abstract occupation, and the resulting change in the relative attractiveness of abstract jobs can differ between workers who would be RH and those who would be RC in the initial equilibrium. As a result, occupational switching toward abstract jobs can offset or even dominate the within-routine upgrading effect, so the routine-occupation college share need not increase monotonically with a decline in r_t.

Proposition 2 provides a clean implication for occupational reallocation: when $\kappa > \rho_r > \sigma$, a decline in the rental rate of computer capital increases the demand for abstract workers relative to routine workers and therefore raises the equilibrium share of employment in the abstract occupation.

4 Quantitative analysis

In this section, I conduct a quantitative analysis using the model described in the previous section. I quantify the implications of computer-specific technological progress by taking as given the observed decline in the relative price of ICT capital and computing the deterministic (perfect-foresight) transition implied by the model. In particular, I show how computerization affects the equilibrium college share and how the response differs between abstract and routine occupations.

4.1 Relative price of computer capital

The model's sole exogenous driving force is computer-specific technological change, captured by q_t. This can be interpreted as the relative price of computers. To measure the price of computers, I use the definition by Eden and Gaggl (2018).[8] I construct the price indexes directly from the BEA's fixed asset accounts. Figure 2 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 quantitative analysis, the entire future path of $\{q_t\}$ is announced in period 0 (1980), and the economy follows a deterministic perfect-foresight transition thereafter. To align the annual series with the model's four-year period, I use the observations for 1980, 1984, 1988, and so on. I assume that the relative price of computers remains constant after period 10 (i.e., after 2020), so there is no further news about q_t beyond that horizon.

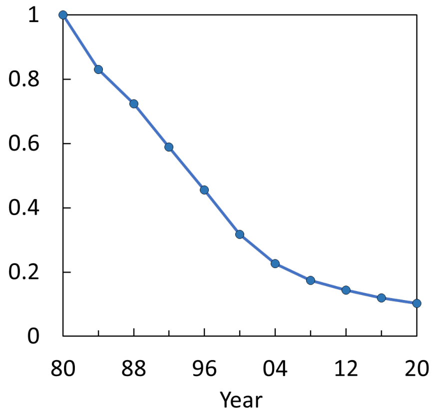

Figure 2: Relative price of computer (1980 = 1)

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[8] Eden and Gaggl (2018) use the BEA's detailed fixed asset accounts, and 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, PCs and peripherals (1RGPC), software and accessories (1RGCS), calculators, typewriters, other information equipment (1RGCA), or telephone and fax machines (1OD50) within consumer durables. See the Appendix A.6.1 for complete lists of the detailed assets.

4.2 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 from the calibration.[9] After excluding manual occupations, I re-normalize the abstract and routine groups so that their employment shares sum to one.

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. I set the elasticity of substitution between abstract skill and educational skill to $\rho_a = 100$, implying that these two inputs are (approximately) perfect substitutes in the production of abstract occupational services. I discuss this point more in Appendix A.4. The quantitative results are essentially insensitive to ρ_a because computerization affects the aggregate demand for abstract occupational services $Z_{a,t}$ through the higher-level nesting structure.

I calibrate the remaining 14 parameters using two approaches. First, the value of 5 parameters are directly imposed based on readily available information. The other 9 parameters are selected to fit the model. I select 6 targets from data in 1980, 2 targets based on the elasticities of substitution in Eden and Gaggl (2018), and 4 targets from the change in data from 1980 to 2019.

We begin with the 5 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. In determining n and T, 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 that $g = 1.05$. Finally, to determine ρ_u, I use the correlation between average years of schooling and abstract task measure by occupation,

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[9] For data source, see Appendix A.6.2 and A.6.3.

Table 1: 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	0.976	Share of abstract workers in 1980
μ_a	0.644	Share of college graduates in abstract occupation in 1980
μ_r	0.286	Share of college graduates in routine occupation in 1980
η	0.576	Labor share in 1980
γ	1.36	College premium in 1980
σ_u	1.0425	Variance of earnings in 1980
		Match the change in value from 1980 to 2019
σ	0.092	2 elasticities of substitution in Eden and Gaggl (2018)
ρ_r	0.80	and
κ	2.29	Changes in 4 kinds of values from 1980 to 2019

which implies that $\rho_u = 0.74$.

The remaining 9 parameters are determined in three steps. First, I use the share of abstract workers, the share of college graduates in abstract and routine occupations, the labor share, the variance of earnings, and the college premium in 1980 to fix the initial steady state in 1980. Unless otherwise noted, all moments are computed for ages 27–58.[10]

Second, I select certain 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.[11] Because the model features multiple skill inputs within each oc-

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[10] Throughout this paper, the college premium is measured as the ratio of unconditional average wages of college to non-college workers, and the abstract job premium is measured analogously as the ratio of unconditional average wages of abstract to routine workers. I do not adjust these premia for workforce composition beyond the grouping implicit in each definition (e.g., differences in the mix of education or occupations within the broad groups).

[11] Many papers compute these elasticities, but the values in Eden and Gaggl (2018) are the most suitable for this paper because (i) I use the exact definition of computer capital that they use, (ii) the estimation period they use (1967-2013) is close to this paper's period of interest (1980-2019), and (iii) the elasticities are

cupation and nests ICT capital differently, the two empirical elasticity targets in Eden and Gaggl (2018) do not map one-to-one to any of the model substitution parameters (σ, ρ_r, κ). Instead, I identify (σ, ρ_r, κ) by matching model-implied elasticities computed from the relationship between relative factor income shares and relative factor quantities along the transition. More specifically, I derive the model-implied elasticites apparent values in the following steps: (i) compute the income share of and number of workers in groups 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, and 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 $\ln(S_K/S_a)/\ln(K/L_a)$ is equal to 0.299 (corresponding to the elasticity of substitution $= 1.427$ between non-routine and computer capital) and $\ln(S_K/S_r)/\ln(K/L_r)$ is equal to 0.484 (corresponding to the elasticity of substitution $= 1.940$ between routine and computer capital).

Lastly, I fix the remaining degree of freedom using the change in real computer capital per capita, the change in the routine workers' share, the change in the college premium, and the change in the abstract job premium from 1980 to 2019.[12] Since these four long-run change moments over-identify the remaining single free parameter, I choose the parameter to minimize a loss function defined as the sum of absolute percentage deviations between the model and the data across these four moments.

Table 1 shows the calibration results. Most of the model's parameter values are jointly

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computed purely from the empirical data.

[12] I use 2019 as the end year to avoid distortions associated with the COVID-19 pandemic in 2020. Because the model is solved only at four-year intervals starting in 1980, the model-implied value for 2019 is obtained by linear interpolation between the model-implied values in 2016 and 2020, i.e., $Value_{2019} = (1/4) \times Value_{2016} + (3/4) \times Value_{2020}$. Unless otherwise noted, I apply the same interpolation throughout the paper.

determined, but I present a list of correspondence as some data targets play a much more central role in identifying a given parameter. Note that the calibration results show that $\kappa > \rho_r > \sigma$, so we can apply Propositions 1 and 2.

4.3 Results

I begin by evaluating the model's fit to the calibration targets. Figures 3 and 4 report the four long-run change moments targeted over 1980–2019: the routine employment share, real ICT capital per worker, the college wage premium, and the abstract job premium (all normalized to one in 1980).[13] The model tracks these long-run movements well. This fit is especially noteworthy given the limited degrees of freedom: the calibration uses 12 targets for 9 parameters, with six 1980 moments and two substitution elasticities imposed exactly, leaving a single remaining free parameter. I choose this one remaining parameter to minimize the sum of absolute percentage deviations from the four long-run change moments, so the model is able to jointly replicate multiple long-run changes with essentially one degree of freedom.

Next, I examine the decomposition of the model's changes in the college premium and the abstract job premium. While the aggregate changes in these premia are calibration targets, the model is not calibrated to match their internal decompositions across the four worker groups. Let $CP_t \equiv w_{C,t}/w_{H,t}$ denote the college premium, where $w_{C,t}$ and $w_{H,t}$ are the unconditional average wages of college and non-college workers, and define the normalized change $\Delta CP_t \equiv (w_{C,t}/w_{C,0})/(w_{H,t}/w_{H,0})$. Using $w_{j,t}$ and $L_{j,t}$ for the average wage and employment of group $j \in \{AC, RC, AH, RH\}$, a first-order approximation

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[13] The empirical series are constructed from IPUMS-USA. Because the IPUMS variable on weeks worked last year is unavailable for 2009–2018 in the data used to compute wage here, I measure long-run changes using the years 1980, 1990, 2000, 2008, and 2019.

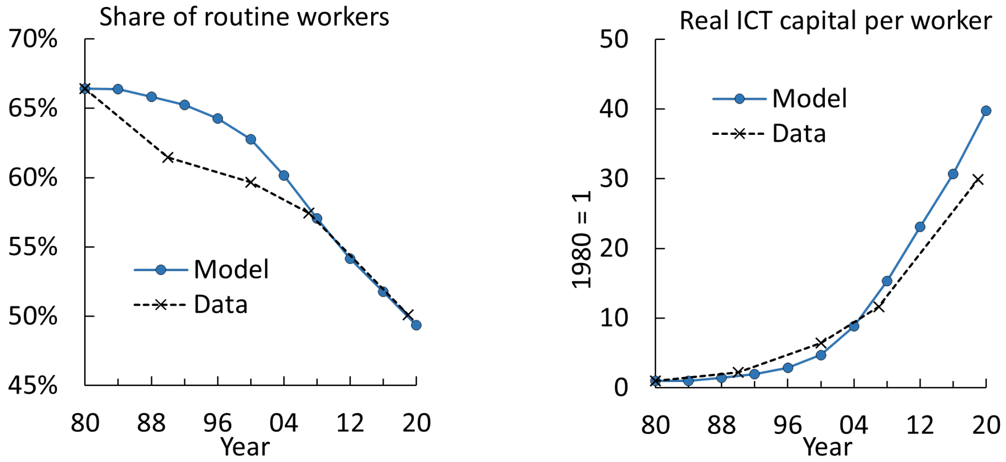

Figure 3: Left panel: share of workers in routine occupation. Right panel: real ICT capital per worker (1980 = 1).

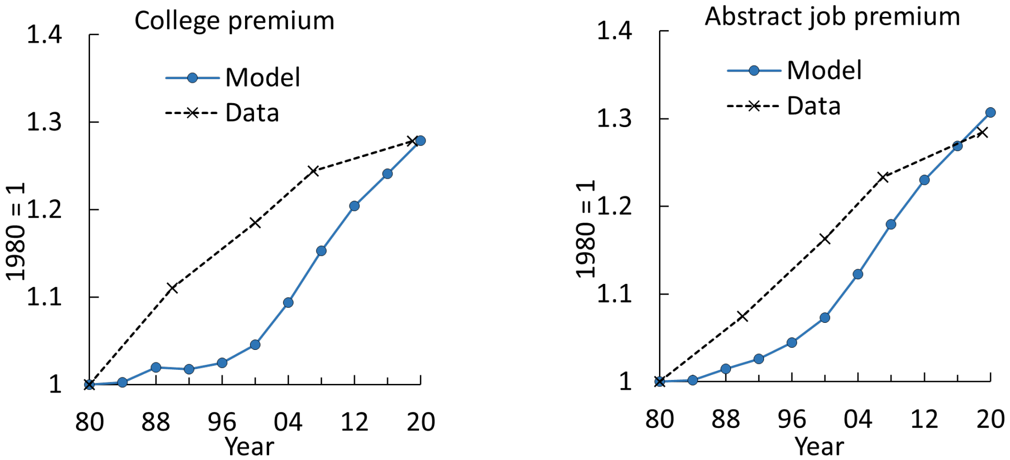

Figure 4: Left panel: college premium (1980 = 1). Right panel: abstract job premium (1980 = 1).

yields

$$\begin{aligned}
\Delta CP_t &\equiv \left(\frac{w_{C,t}}{w_{C,0}}\right) \Big/ \left(\frac{w_{H,t}}{w_{H,0}}\right) \\
&= \left(1 + \frac{L_{RC,t}}{L_{C,t}}\frac{\Delta w_{RC,t}}{w_{C,0}} + \frac{L_{AC,t}}{L_{C,t}}\frac{\Delta w_{AC,t}}{w_{C,0}} + \tilde{\Delta}_{C,t}\right) \Big/ \left(1 + \frac{L_{RH,t}}{L_{H,t}}\frac{\Delta w_{RH,t}}{w_{H,0}} + \frac{L_{AH,t}}{L_{H,t}}\frac{\Delta w_{AH,t}}{w_{H,0}} + \tilde{\Delta}_{H,t}\right) \\
&\simeq 1 + \frac{L_{RC,t}}{L_{C,t}}\frac{\Delta w_{RC,t}}{w_{C,0}} + \frac{L_{AC,t}}{L_{C,t}}\frac{\Delta w_{AC,t}}{w_{C,0}} - \frac{L_{RH,t}}{L_{H,t}}\frac{\Delta w_{RH,t}}{w_{H,0}} - \frac{L_{AH,t}}{L_{H,t}}\frac{\Delta w_{AH,t}}{w_{H,0}}, \qquad (13)
\end{aligned}$$

where $\Delta w_{j,t} \equiv w_{j,t} - w_{j,0}$ and the terms $\tilde{\Delta}_{C,t}$ and $\tilde{\Delta}_{H,t}$ capture composition effects:

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

These terms are typically small because they are products of changes in employment shares and baseline wage gaps. The approximation in (13) therefore provides a transparent breakdown of the change in the college premium into the contributions of wage changes for the four groups. I apply an analogous decomposition to the abstract job premium. Figure 5 reports the results. The model-generated decompositions are economically sensible and closely aligned with the data: *AC* (abstract college) is the largest contributor, and all four components contribute in the same direction as in the empirical decomposition, with no large discrepancies in their relative magnitudes.

I now turn to the implications for educational attainment, which is the main aim of this model. The left panel of Figure 6 reports the model-implied change in the aggregate college share attributable to computerization. By construction, the model focuses on the computerization channel and abstracts from other forces that can raise college attainment over time (e.g., changes in the quality of schooling, demographic shifts, or other secular trends). Within this accounting framework, the model implies that computerization explains nearly half (49.8%) of the increase in the aggregate college share over 1980–2019.

The right panel of Figure 6 then reports how this aggregate change differs across oc-

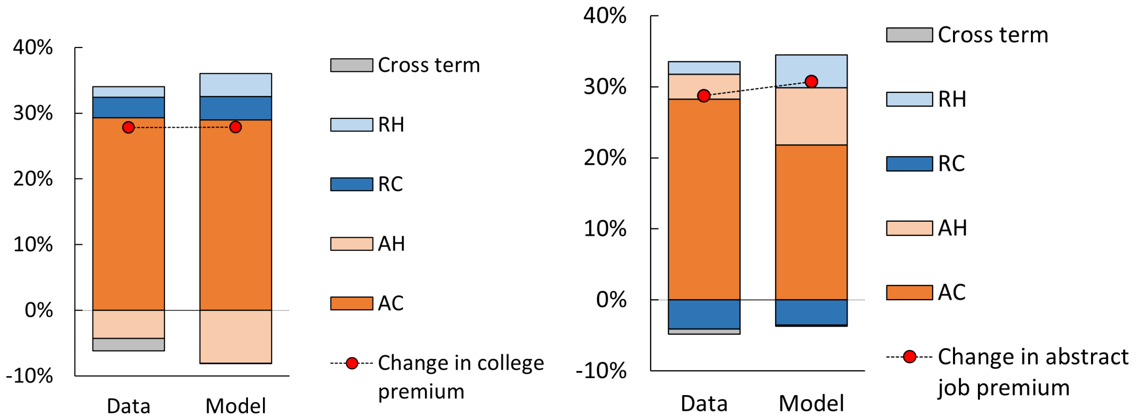

Figure 5: Breakdown of change in college premium (left panel) and abstract job premium (right panel).

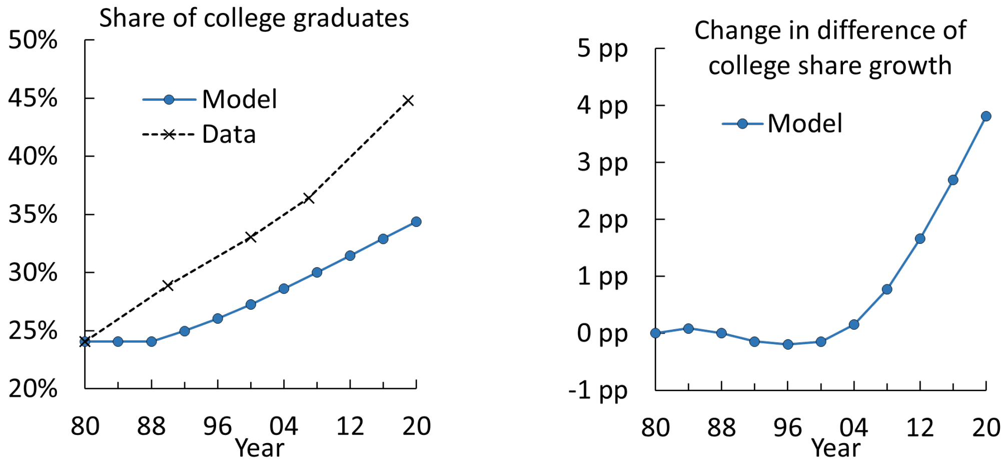

Figure 6: Left panel: total change in the aggregate college share due to computerization. Right panel: change in the difference of college graduates' share between routine and abstract occupations.

cupations. It plots the change in the routine–abstract gap in within-occupation college shares, normalized to zero in 1980:

$$\Delta \text{Gap}_t \equiv (C\_share_{r,t} - C\_share_{a,t}) - (C\_share_{r,1980} - C\_share_{a,1980}),$$

where $C\_share_{j,t}$ denotes the share of college graduates within occupation $j \in \{r, a\}$ in year t. A positive value means that the routine occupation has experienced faster growth in its within-occupation college share than the abstract occupation since 1980. Conversely, a negative value would indicate faster upgrading within the abstract occupation. Normalizing the series to zero in 1980 ensures that the figure highlights differential *changes* over time rather than level differences in college shares across occupations. The model implies faster within-occupation educational upgrading in routine occupations than in abstract occupations. This prediction is not something one can simply take for granted — one might instead expect the college share of routine work to shrink without substantial within-occupation upgrading. The next section therefore asks directly whether the data exhibit this pattern.

5 Empirical Facts

The quantitative analysis in Section 4 delivers a sharp qualitative implication: computerization can raise the return to educational skill within routine work, so occupations that are more routine-task intensive should experience faster growth in college attainment. This section provides empirical evidence consistent with that implication by exploiting cross-occupation variation in baseline task content.

5.1 Regression analysis

I construct occupation-level task measures following Autor et al. (2003), based on DOT 1977 task descriptors. I assign each non-farm occupation in the Autor and Dorn (2013) classification (323 detailed categories) three task measures—abstract, routine, and manual—and treat these values as fixed at their DOT 1977 levels. These baseline task measures provide a pre-determined characterization of each occupation's task content that I use to explain subsequent educational upgrading.

Using these measures, I estimate how baseline routine intensity predicts subsequent educational upgrading across occupations. For each occupation k, I use the change in the college share between 1980 and 2019 as the dependent variable and regress it on baseline task measures.[14] Specifically, the main specification takes the form

$$\Delta C_k = \alpha + \boldsymbol{\beta}' \boldsymbol{T}_k + \delta' X_k + \varepsilon_k,$$

where $\boldsymbol{T}_k$ denotes the vector of task measures or related indices assigned to each occupation k, and X_k collects control variables. In the baseline specification, X_k includes the initial college share and its square. I estimate the regression by weighted least squares (WLS), using the occupation's employment share as the weight. The motivation is that college-share changes for small occupations are measured with more sampling noise and can be disproportionately volatile; WLS downweights these noisy changes and focuses identification on occupations with economically meaningful size.

Table 2 reports the baseline results. I restrict the sample to ages 27–34, so that occupation-level college shares reflect relatively recent schooling decisions, making cross-occupation changes in educational attainment easier to detect.[15] The estimates in column (1) imply

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[14] I classify workers as college if they have a bachelor's degree or higher; all others are non-college. Therefore, non-college includes high school dropouts, high school graduates, and some college.

[15] Appendix A.2 reports results for additional age groups.

that occupations with higher routine intensity at DOT 1977 experienced faster growth in the college share over 1980–2019, and the routine coefficient is larger than the abstract coefficient in magnitude. I also control for the initial college share and its square in column (2) to capture non-linearities in the mechanical relationship between the initial level and subsequent changes in educational attainment. This control is motivated by a simple threshold interpretation: if college entry is characterized by a cutoff rule in educational skill, then a common shift in the cutoff generates larger changes in the college share when the density of educational skill is higher around the initial cutoff, which can vary systematically with the initial share. With these controls, the identification is cleaner: by absorbing systematic differences linked to the initial college share, the estimates isolate the role of baseline task content more transparently. The routine-intensity coefficient remains positive and significant and increases in magnitude relative to the baseline specification. Throughout the paper, I treat column (2) as the baseline specification: it controls for baseline differences in the initial college share while retaining the three task measures as the main explanatory variables.

Columns (3) and (4) use an alternative measure of routine exposure, routine task intensity, proposed by Autor and Dorn (2013):

$$RTI_k = \ln(r_k) - \ln(m_k) - \ln(a_k), \tag{14}$$

where r_k, m_k, and a_k are the routine, manual, and abstract task measures of occupation k, respectively. The results are similar: more routine-intensive occupations exhibit faster growth in college attainment. Columns (5) and (6) show that the positive relationship is also present in parsimonious specifications that include only the routine measure (with and without initial college share controls).

The finding is robust across a range of alternative choices. The qualitative implication is similar when I use years of schooling as the dependent variable (Appendix Table 6),

Table 2: 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)
Constant	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. The dependent variable is the change in the college graduate share of occupation *k* between 1980 and 2019, computed for workers aged 27–34. "College" denotes BA or higher (non-college includes high school dropouts, high school graduates, and some college). Columns (1)-(2) use the three DOT-1977 task measures (abstract, routine, manual) assigned to occupation *k*; columns (3)-(4) use routine task intensity (RTI) defined in Autor and Dorn (2013); columns (5)-(6) use only the routine task measure. Even-numbered columns additionally include a set of baseline controls (including the initial college share and its square). All specifications include a constant. Estimates are weighted least squares with weights given by occupation employment shares (baseline), and standard errors are reported in parentheses.

use an hours-worked-based measure of labor input rather than headcounts, restrict the sample to men, use OLS instead of WLS, and split the sample into two sub-periods (Appendix Table 8). Moreover, when I apply the same regression design to the pre-computer era (1950–1980), I do not find a positive association between routine intensity and subsequent educational upgrading (Appendix Table 9). Taken together, the evidence indicates that routine-task-intensive occupations experienced systematically faster educational upgrading over the last four decades, consistent with the model mechanism that computerization raises the relative value of educational skill within routine work.

5.2 Bridging the model and the data

This subsection evaluates the prediction that computerization raises the relative value of educational skill within routine work in the data by constructing an empirical counterpart from the regression estimates in Section 5.1 combined with baseline task content aggregated to the model's broad occupation groups. I then compare the model-implied and regression-implied magnitudes and assess how closely they align.

For comparability with the model-based objects, I use the specification estimated on workers aged 27–58 (Appendix Table 7) and extract the estimated coefficients on the baseline task measures. I then aggregate DOT-1977 task measures to the model's broad occupation groups (abstract and routine) by taking employment-share-weighted averages across the detailed occupations belonging to each group. Table 3 reports these weighted-average task measures for the abstract and routine groups.

Table 3: Task measures in abstract and routine occupations

	Abstract task	Routine task	Manual task
Routine occupation	2.129	5.177	1.217
Abstract occupation	5.556	3.246	0.951

Let $\widehat{\boldsymbol{\beta}}$ denote the vector of estimated coefficients on the task measures from the 27–58 age group regression, and let $\bar{\boldsymbol{T}}_r$ and $\bar{\boldsymbol{T}}_a$ denote the employment-share-weighted average task vectors for the routine and abstract groups. The regression-implied difference in educational upgrading between the two broad occupations is then

$$\widehat{\Delta}\Big(C\_share_r - C\_share_a\Big) \equiv \widehat{\boldsymbol{\beta}}'\left(\bar{\boldsymbol{T}}_r - \bar{\boldsymbol{T}}_a\right).$$

Intuitively, this calculation combines (i) how baseline task content predicts subsequent growth in the college share across detailed occupations with (ii) how baseline task content differs, on average, between the routine and abstract groups.[16]

Table 3 shows that the routine group is substantially more routine-task-intensive and less abstract-task-intensive than the abstract group. Given the estimated task coefficients, these baseline differences translate into a regression-implied prediction that the routine occupation experiences faster college-share growth than the abstract occupation, in line with the model's occupational implication.

Figure 7 compares this empirical counterpart to the model-implied change in the routine–abstract difference in college shares along the computerization-driven transition. The model series is presented in the right-hand-side panel of Figure 6. Both series are normalized to zero in 1980. The figure provides strong quantitative support for the model mechanism: the model-implied routine–abstract differential in college-share growth closely matches its regression-implied empirical counterpart, not only in sign but also in magnitude.

To further assess how this occupational pattern varies across the life cycle, Table 4 reports the routine–abstract difference in college-share growth over 1980–2019 by age group

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[16] Throughout the comparison in this subsection, I isolate the task-content channel by evaluating the regression prediction at a common set of baseline controls X (so that $X_r = X_a$). Hence, differences between routine and abstract occupations are driven solely by baseline task content, $\widehat{\boldsymbol{\beta}}'\left(\bar{\boldsymbol{T}}_r - \bar{\boldsymbol{T}}_a\right)$. Section 6 discusses the overall predicted change in the aggregate college share, allowing baseline controls to vary across occupations, rather than holding them fixed as in this subsection's task-content comparison.

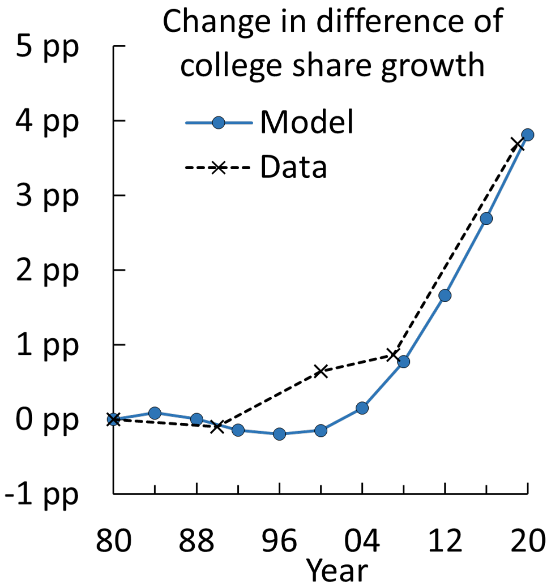

Figure 7: Model versus regression-implied change in the routine–abstract difference in college shares (normalized to zero in 1980; ages 27–58 for the empirical counterpart).

in the data and in the model. The data show a declining pattern by age group, consistent with the idea that the occupational upgrading pattern is more pronounced for younger cohorts. The model reproduces this qualitative age gradient, although it tends to generate larger changes for the youngest group.

Table 4: Routine–abstract differential in college-share growth by age (1980–2019)

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 are constructed from the baseline regression specification estimated separately by age group (Appendix Table 7) combined with employment-share-weighted task measures for the routine and abstract groups in Table 3. Model values for 2019 are obtained by linear interpolation between the model-implied values in 2016 and 2020, i.e., $Values_{2019} = (1/4) \times Values_{2016} + (3/4) \times Values_{2020}$.

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6 Discussion

The benchmark quantitative analysis attributes the observed changes in wages, occupational shares, and educational attainment to computerization by feeding in the decline in the relative price of ICT capital. By construction, it abstracts from other long-run forces that may also have increased college attainment. This discussion section has two goals. First, I verify the appropriateness of the benchmark calibration targets by showing that plausible non-ICT factors that raise college attainment have limited effects on the key moments used in the calibration (e.g., the college premium and the abstract job premium). Second, I show that augmenting the model with a parsimonious non-ICT force allows the model to jointly reproduce the unconditional rise in the aggregate college share and the unconditional college-share increases within both routine and abstract occupations, while preserving the model's computerization-driven occupational implication.

6.1 Non-ICT forces and calibration targets

The benchmark calibration in Section 4 uses long-run changes in wage premia and employment shares (e.g., the college premium, the abstract job premium, and the share of routine workers) to pin down the substitution parameters that govern how ICT capital reshapes labor demand. A potential concern is that other long-run forces that raise college attainment may also partly affect the moments used as calibration targets, which may distort the model implications.

This subsection addresses this concern directly by considering three non-ICT factors emphasized in the literature: (i) longer life expectancy and a higher retirement age (LE), (ii) an increase in the quality of college education (CQ), and (iii) a decline in the effective cost of college (Cost). For comparison, I also report the ICT-price (computerization) force used in the main analysis (SBTC in the sense of an embodied ICT-capital price decline). For each factor, I compute steady-state implications and summarize the induced changes in key aggregates, including the wage premia and occupational shares used as calibration targets. For LE, I calibrate the magnitude of the shock using the observed increases in life expectancy and retirement age over the last four decades (approximately 4 years and 2 years, respectively). For CQ and Cost, I scale the shock sizes so that each generates the same steady-state increase in the aggregate college share as the LE shock, thereby facilitating a transparent comparison across channels.[17]

Figures 8 and 9 report the results. The key takeaway is that non-ICT forces that raise the college share (LE, CQ, Cost) have only limited effects on the wage premia and occupational-share moments targeted in the benchmark calibration, especially relative to the ICT/SBTC-type factor. Put differently, these non-ICT channels can generate sizable changes in educational attainment while leaving the benchmark target moments largely unchanged. This pattern supports the benchmark identification strategy: the targeted moments are informative about the computerization mechanism and are comparatively insensitive to alternative drivers of college attainment.

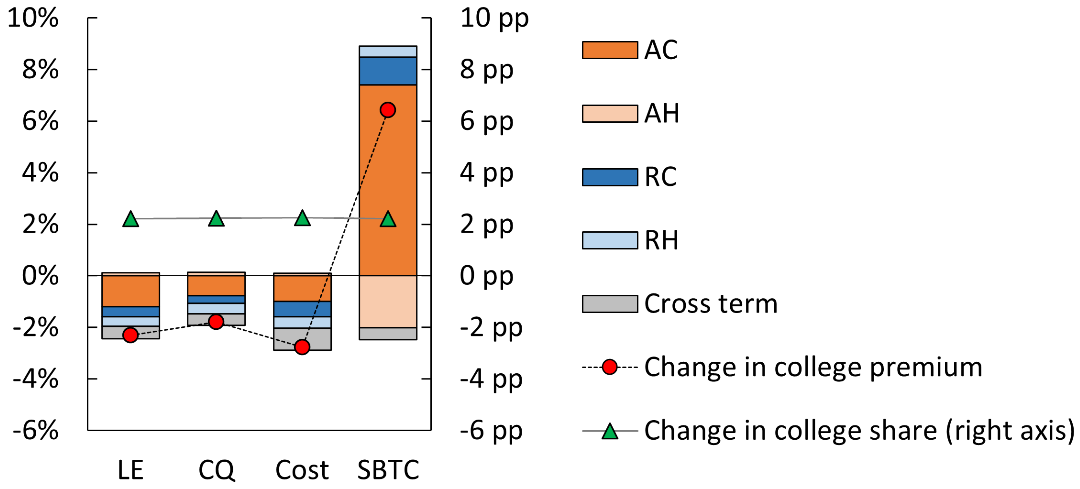

Figure 8: The effects of four kinds of shocks on key moments (LE: life expectancy and retirement age; CQ: college quality; Cost: college cost; SBTC: skill-biased technical change).

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[17] Appendix A.5 provides details on the motivation for the shocks, their implementation, and the steady-state calculations.

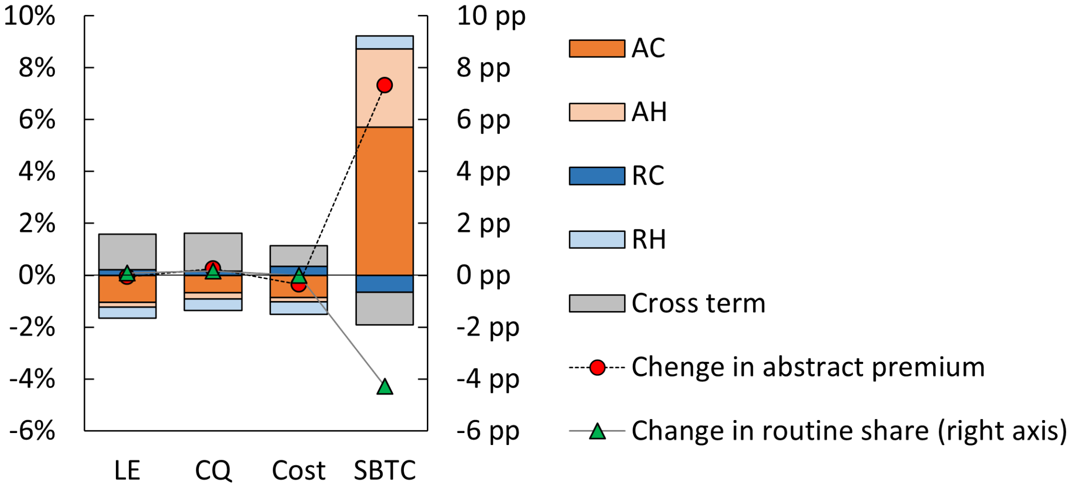

Figure 9: The effects of four shocks on key moments (LE: life expectancy and retirement age; CQ: college quality; Cost: college cost; SBTC: skill-biased technical change).

6.2 Reconciling unconditional college-share growth across occupations

In the empirical analysis, I control for the initial college share in 1980 to account for the initial level of college attainment when considering subsequent changes. This choice sharpens identification of the task-content channel by netting out systematic differences associated with initial college shares. At the same time, it implies that the benchmark regression-based comparison abstracts from forces operating through the initial-share channel. In the data, the unconditional college-share growth is larger in abstract occupations than in routine occupations, consistent with the baseline regression result and the fact that abstract occupations start from a higher college share in 1980.

a mechanical, non-linear relationship between the initial level and subsequent changes in the college share. This control is useful when the goal is to identify how baseline task content predicts *differential* upgrading across occupations, holding the initial level fixed. However, it also implies that the benchmark regression-based comparison abstracts from forces that operate through the initial college-share channel. In the data, unconditional college-share growth is larger in abstract occupations than in routine occupations, consistent with the fact that abstract occupations start from a higher college share in 1980.

This subsection shows that introducing a parsimonious non-ICT force can reconcile these unconditional patterns while leaving the benchmark wage moments and the computerization mechanism largely intact. As shown by the steady-state evidence in Section 6.1, alternative non-ICT forces (e.g., changes in life expectancy, college costs, and college quality) have qualitatively similar effects on the unconditional college share and benchmark moments. Given these similarities, I use a gradual improvement in the quality of college education as a representative non-ICT shock, captured by an exogenous trend in the college-quality parameter γ. Specifically, I let γ grow at a constant gross rate g_γ along the transition while keeping the ICT price path $\{q_t\}$ and all other parameters at their benchmark values. I then choose g_γ to match the observed *unconditional* increase in the aggregate college share over 1980–2019.[18]

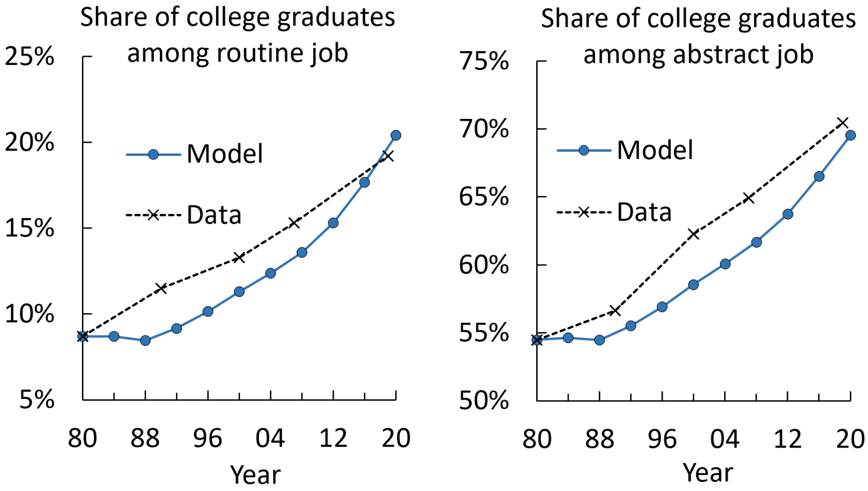

Figure 10: Transition paths under the augmented model with college-quality growth. Left panel: college share within routine occupations. Right panel: college share within abstract occupations.

Figure 10 reports the resulting paths of within-occupation college shares in the routine and abstract groups. The augmented model reproduces the unconditional rise in college

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[18] Appendix A.5 details the implementation, including the mapping from annual data to the model frequency and the calibration of g_γ.

attainment within both occupations at empirically plausible magnitudes, without directly targeting these within-occupation series. Appendix Figures 15 and 16 summarize the key moments. Consistent with Figures 8 and 9, introducing college-quality growth has little effect on the wage premia and other moments used to identify the benchmark substitution parameters. Thus, the benchmark calibration remains well grounded, while the augmented model can also match the unconditional increases in educational attainment across occupations.

7 Conclusion

Over the past four decades, the US has experienced a sharp decline in routine employment alongside a steady rise in college attainment. While each trend has been studied extensively, much less is known about how computerization may have jointly shaped occupational structure and educational upgrading within occupations.

This paper provides two complementary pieces of evidence. First, I develop and calibrate a quantitative model in which individuals choose whether to attend college and whether to work in abstract or routine occupations. Feeding the observed decline in the relative price of ICT capital into the model generates a sharp occupational implication: computerization raises the return to educational skill within routine work, so the within-occupation college share rises faster in routine occupations than in abstract occupations. The calibrated model also implies that computerization accounts for about one half of the aggregate increase in the college share over 1980–2019.

Second, I evaluate the model's occupational implications in the data. Using cross-occupation variation in baseline task content, I estimate the relationship between task measures and subsequent changes in college attainment. The regression evidence implies systematically faster growth in the college share in occupations that are more routine-task-intensive. Aggregating these estimated effects across occupations to the model's broad occupation groups yields an empirical counterpart that closely matches the model-implied routine–abstract pattern.

The quantitative model and the empirical evidence suggest that the consequences of computerization extend beyond reallocation across occupations: they also operate through systematic within-occupation upgrading, especially in routine occupations. This perspective helps reconcile declining routine employment with rising education levels and highlights that changes in the educational composition of routine jobs are a central part of how technology reshapes the labor market.

An important limitation is that the model treats the mapping from college attendance to educational skill in reduced form. Incorporating endogenous human-capital investment—allowing schooling and on-the-job learning to respond to changing incentives—would provide a richer account of heterogeneity in college quality, training, and wage dynamics. I leave this extension for future research.

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A Appendix

A.1 Robustness to Alternative Occupational Grouping: Non-routine = Abstract + Manual

This appendix reports robustness checks based on an alternative classification that groups *abstract* and *manual* occupations together as *non-routine* employment. The calibration and simulation procedures are identical to the benchmark analysis, except that the economy is partitioned into routine and non-routine occupations when constructing the empirical counterparts and model objects.

Table 5 shows the calibrated parameters. The alternative classification requires a definition of a non-routine skill measure only to calibrate ρ_u, but there is no consensus mapping from the underlying task measures to a single non-routine index. As a simple proxy, I define non-routine skill as the maximum of the abstract and manual task measures.

Table 5: Calibrated parameters for the alternative specification

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	0.63	Correlation between average years of schooling and non-routine skill
		Match the value in 1980 to the data
ν	0.953	Share of abstract workers in 1980
μ_a	0.584	Share of college graduates in non-routine occupation in 1980
μ_r	0.286	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	1.0238	Variance of earnings in 1980
		Match the change in value from 1980 to 2019
σ	0.171	2 elasticities of substitution in Eden and Gaggl (2018)
ρ_r	0.77	and
κ	2.39	Changes in 4 kinds of values from 1980 to 2019

Figures 11–13 show that the main quantitative results are largely unchanged under this alternative grouping. Here, NC and NH are non-routine college and non-routine

high school, respectively. The model continues to match the broad long-run movements in the routine employment share, real ICT capital per worker, and the non-routine job premium. The fit for the college premium is somewhat weaker than in the benchmark classification, but the overall dynamics remain comparable.

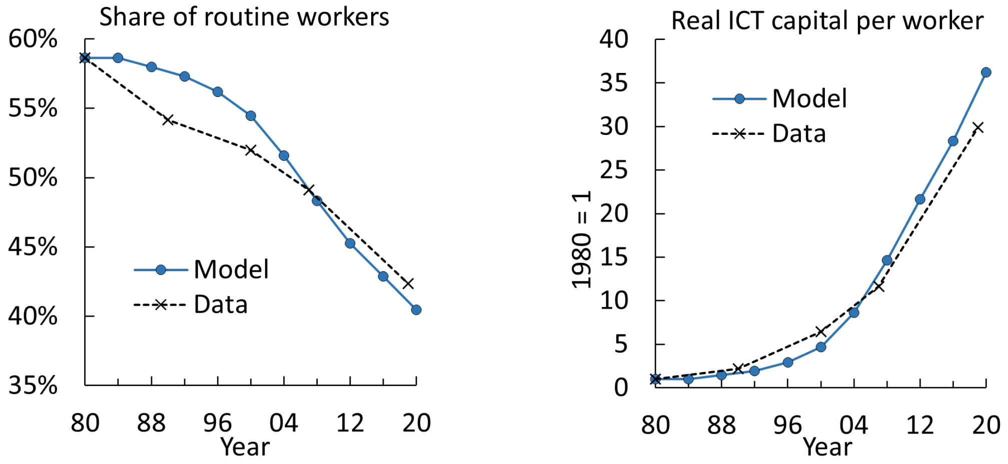

Figure 11: Left panel: share of workers in routine occupation. Right panel: real ICT capital per worker (1980 = 1).

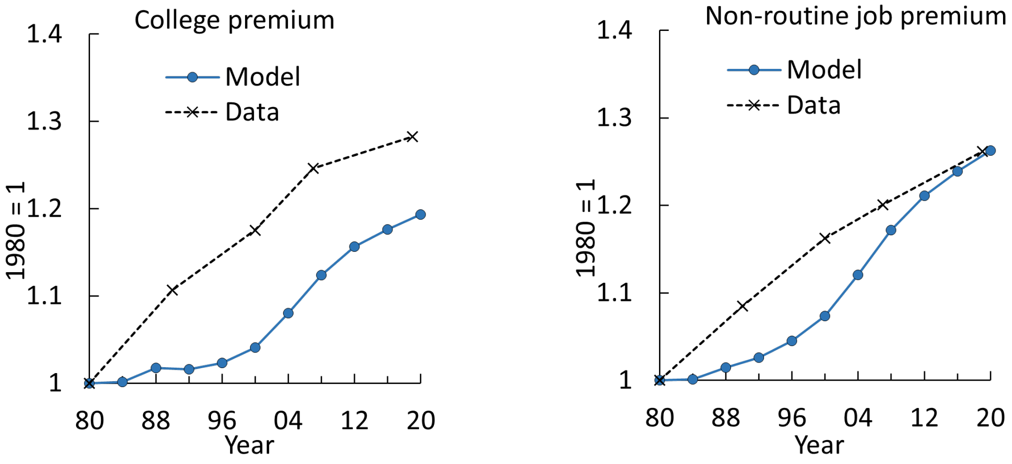

Figure 12: Left panel: college premium (1980 = 1). Right panel: non-routine job premium (1980 = 1).

Most importantly, the model's key occupational implication continues to hold: the within-occupation college share rises faster in routine work than in non-routine work, so the routine–non-routine difference in college shares increases along the computerization-driven transition (right panel of Figure 14).[19] Likewise, the model continues to predict a substantial role for computerization in aggregate educational upgrading. In the routine–non-routine classification, computerization accounts for 47.0% of the increase in the aggregate college share over 1980–2019 (left panel of Figure 14), which is very close to the benchmark estimate.

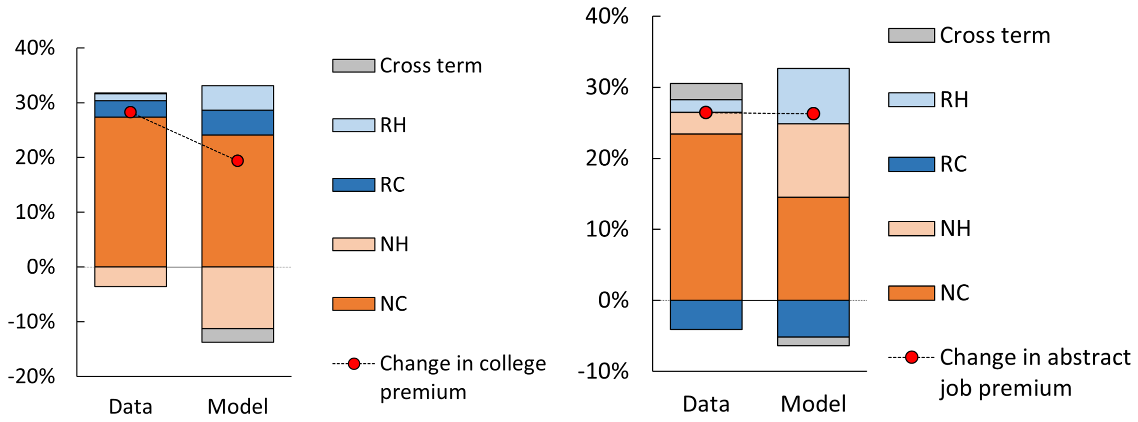

Figure 13: Breakdown of change in college premium (left panel) and abstract job premium (right panel).

Overall, reclassifying non-routine employment in this way does not materially alter the paper's quantitative conclusions: the mechanism that links computerization to faster educational upgrading within routine work remains intact, and the implied contribution of computerization to the rise in college attainment is quantitatively similar to the benchmark case.

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[19] Table 3 reports task measures for the abstract and routine groups only. For the alternative non-routine classification used in this appendix, I construct the corresponding task measures. The resulting abstract, routine, and manual task measures for non-routine occupations are 4.367, 3.081, and 1.190, respectively.

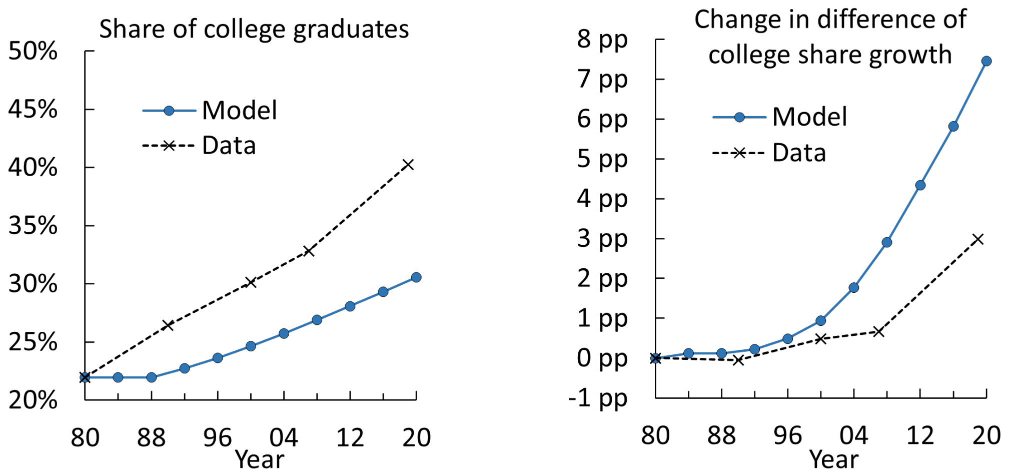

Figure 14: Left panel: total change in the aggregate college share due to computerization. Right panel: change in the difference of college graduates' share between routine and non-routine occupations.

A.2 Other regression results

Table 6: 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)
Constant	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 7: 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)
Constant	-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 8: 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)
Constant	-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 9: 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)
Constant	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 2.

A.3 Proof of propositions

A.3.1 Proposition 1

Proof. Given the production function (Equation (1)), solving the profit maximization problem 2 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

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

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

A.3.2 Proposition 2

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

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

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

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

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

Therefore, $\frac{\partial \frac{Z_a}{N_{e_r}}}{\partial r} < 0$ 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.4 Interpreting educational skill and its relation to abstract skill

While the task-based literature typically characterizes occupations using abstract, routine, and manual content, it is less common to model schooling as generating a separate skill input that enters production alongside these task components. This appendix clarifies how to interpret *educational skill* in the model and how its proximity to abstract skill is governed by the model parameters.

The model treats college as raising a productive skill component (educational skill) and abstracts from signaling (e.g. Spence, 1973), consistent with the human-capital view (e.g. Schultz, 1961; Becker, 1964; Mincer, 1974). In the task-based literature, occupations are typically summarized by abstract, routine, and manual content. It is therefore not standard to introduce schooling as an additional skill input that enters production alongside these task components. I do so for identification and interpretation: the mechanism of interest requires a skill that (i) is valued in both occupations and (ii) can be priced differently across occupations, so that computerization can alter the payoff to college *within* routine work.

A natural interpretation is that educational skill overlaps with abstract capability but is not identical to it. Empirically, what college raises is cognitive/math skills (e.g. Murnane et al., 1995), crystallized intelligence and technical comprehension (Carlsson et al., 2015), and more broadly, partly unobserved components such as motivation or ability to learn (Taber, 2001). These dimensions plausibly relate to abstract task content (the DOT abstract measure used here is built from Mathematics and managerial/planning responsibility), yet they need not coincide one-for-one with abstract skill as modeled in production. The model therefore keeps educational skill distinct while allowing it to be closely related to abstract skill.

Two parameters summarize this relation. On the demand side, ρ_a controls the elasticity of substitution between abstract and educational inputs in abstract production. In the quantitative implementation, I set ρ_a to a high value (e.g., $\rho_a = 100$), treating the two inputs as close substitutes. The main results are insensitive to this choice because the computerization shock operates primarily through the ICT–routine-skill nest and affects abstract production mainly through the aggregate demand for abstract occupational services Z_a. On the supply side, ρ_u governs the correlation between innate abstract ability and innate educational ability. I identify ρ_u using the empirical association between schooling and abstract-task intensity across occupations. While this target is not a one-to-one mapping, it provides a transparent way to pin down how aligned the two latent ability dimensions are in the data.

A.5 Non-ICT shocks: motivation and implementation

This appendix provides additional details for the discussion in Section 6. It explains why the three non-ICT factors—life expectancy and retirement age (LE), college quality (CQ), and college cost (Cost)—are considered, how each shock is implemented in the model, and how the steady-state comparisons in Figures 8 and 9 are constructed. It also reports additional transition-path results that are omitted from the main text.

The choice of non-ICT shocks

A large literature attributes the long-run rise in college attainment to multiple forces beyond computerization. First, a longer expected working life—arising from higher life expectancy and later retirement—raises the horizon over which education pays off, potentially increasing schooling (e.g. Oster et al., 2013; Manuelli et al., 2012). Second, the benefit of college may rise because the productivity of college education improves over time (e.g., through better curricula, pedagogy, or complementarities with workplace technologies) (e.g. Card and Krueger, 1992). Third, the effective cost of college may fall due to changes in direct costs (tuition, financial aid) and/or indirect barriers to attendance (e.g. Castro and Coen-Pirani, 2016). These channels are conceptually distinct from the computerization force emphasized in the main analysis. The purpose of the exercise is not to build a fully unified model of all drivers, but to verify that reasonable non-ICT forces that raise college attainment do not mechanically overturn the benchmark calibration results.

Shock implementation and steady-state comparison

I implement the four shocks as parameter changes that shift the steady state:

1. **LE (life expectancy and retirement age).** I increase life expectancy T and the length of working life n. Since one model period corresponds to four years, I approximate a 4-year increase in life expectancy by increasing T by one model period, and a 2-year increase in retirement age by increasing n by half a model period. Operationally, I first compute the steady state under a two-period increase in T and a one-period increase in n, and then scale the resulting changes by one-half to match a 4-year and 2-year increases, respectively.

2. **CQ (college quality).** I increase γ, the parameter capturing the productivity of college education in the model. This raises the return to acquiring educational skill and increases the steady-state college share.

3. **Cost (effective cost of college).** I introduce a parameter ϕ that shifts the effective cost of college. This parameter captures not only the direct costs of college but also any indirect costs stemming from social norms or biases. A reduction in ϕ lowers

the hurdle for college entry and increases the steady-state college share.[20]

4. **SBTC / ICT price (computerization).** I implement computerization as a decline in the relative price of ICT capital q (equivalently, embodied technological progress in ICT capital). This is the force used in the benchmark quantitative analysis.

For each shock, I compute the steady state and record changes in key moments, including the college premium, the abstract job premium, and the share of routine workers, as reported in Figures 8 and 9. For LE, the shock size is determined by observed changes in life expectancy and retirement age. For CQ and Cost, I scale the shock sizes so that each generates the same steady-state increase in the aggregate college share as the LE shock. This normalization ensures that differences across panels can be interpreted as differences in how strongly each channel moves the benchmark target moments *per comparable increase in college attainment*.

Additional transition-path results under college-quality growth

Section 6.2 augments the benchmark transition by allowing college quality to grow at a constant rate: $\gamma_{t+1} = g_\gamma \gamma_t$. I choose g_γ to match the unconditional rise in the aggregate college share over 1980–2019, holding fixed the ICT price path and all other parameters. Figure 15 reports the full set of transition paths. Figure 16 reports the corresponding decompositions of changes in the college premium and the abstract job premium. These decompositions are not targeted and are included as additional diagnostics.

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[20] Because the benchmark analysis abstracts from college attendance costs, a reduction in ϕ effectively acts as a subsidy.

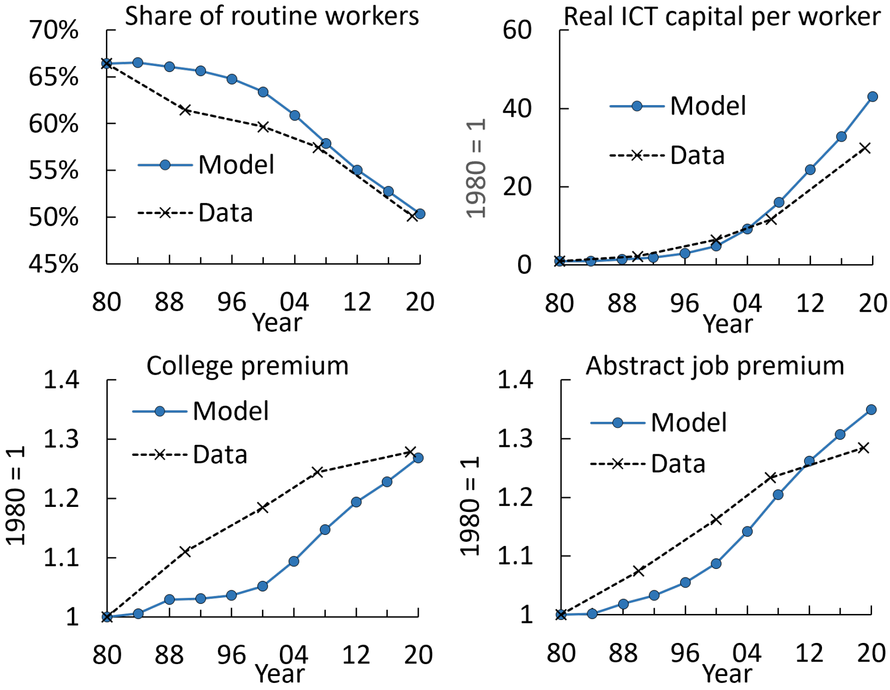

Figure 15: Transition paths under the augmented model with college-quality growth. From upper left to lower right: (i) share of routine workers, (ii) real computer capital per capita, (iii) college premium, and (iv) abstract job premium.

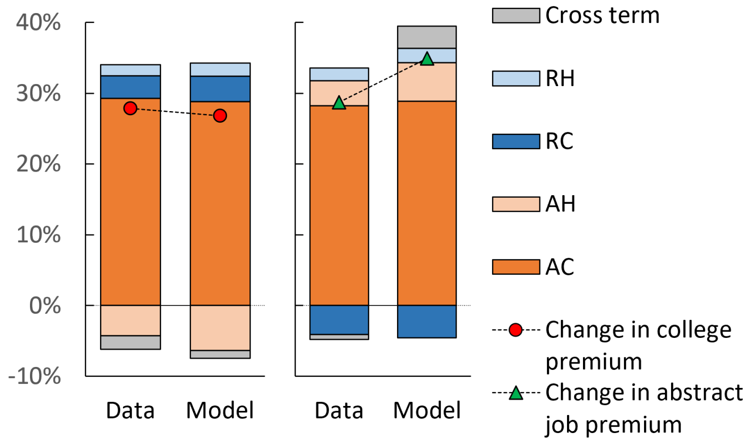

Figure 16: Decomposition of changes in the college premium (left panel) and the abstract job premium (right panel) under the augmented model with college-quality growth.

A.6 Data appendix

A.6.1 Computer capital

Computer capital is constructed from the BEA detailed fixed asset accounts and consumer durables data. Table 10 lists the BEA asset codes and titles classified as ICT capital following Eden and Gaggl (2018).

Table 10: 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 codes assigned by BEA.

A.6.2 IPUMS-USA

I compute the college share, years of schooling, the routine employment share, and group-specific wages using IPUMS-USA (Ruggles et al., 2023). I use the years 1950, 1980, 1990, 2000, 2007, and 2019. The IPUMS series is available at 10-year intervals before 2000, and the weeks-worked variable is unavailable for 2008–2018 in the data used here. Table 11 lists the variables.

Table 11: 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

A.6.3 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. Because the crosswalk for the 2019 occupation-code scheme is not provided there, I construct the required correspondence table (Table 12). I include an occupation in the sample if its employment weight is non-zero.

Table 12: Occupation categories and skill measures

Occ	Occupation Groups and	ACS 2019	Occ	Skill Measures		
Code	Occupation Titles	Codes	Groups	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					

Occ Code	Occupation Groups and Occupation Titles	ACS 2019 Codes	Occ Groups	Skill Measures Abstract	 Routine	 Manual
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
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

Occ Code	Occupation Groups and Occupation Titles	ACS 2019 Codes	Occ Groups	Skill Measures		
				Abstract	Routine	Manual
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					
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					

Occ Code	Occupation Groups and Occupation Titles	ACS 2019 Codes	Occ Groups	Skill Measures Abstract	 Routine	 Manual
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
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

Occ	Occupation Groups and	ACS 2019	Occ	Skill Measures		
Code	Occupation Titles	Codes	Groups	Abstract	Routine	Manual
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
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

Occ Code	Occupation Groups and Occupation Titles	ACS 2019 Codes	Occ Groups	Skill Measures Abstract	 Routine	 Manual
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
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

Occ	Occupation Groups and	ACS 2019	Occ	Skill Measures		
Code	Occupation Titles	Codes	Groups	Abstract	Routine	Manual
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
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

Occ Code	Occupation Groups and Occupation Titles	ACS 2019 Codes	Occ Groups	Skill Measures Abstract	Routine	Manual
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).