Non-College Occupations, Workplace Routinization, and the Gender Gap in College Enrollment

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Abstract

Women used to lag behind men in college enrollment but now exceed them. This paper focuses on the role of non-college job prospects in explaining these trends. We first document that routine-biased technical change disproportionately displaced non-college occupations held by women. We next instrument for routinization to show that declining non-college job prospects for women increased female enrollment. Two stage least squares results show that a one percentage point rise in routinization increases female college enrollment by 0.6 percentage points, while the effect for male enrollment is not systematically significant. We next embed this instrumental variation into a dynamic model that links education and occupation choices. The model finds that routinization decreased returns to non-college occupations for women, leading them to shift to cognitive work and increasing their college premium. In contrast, non-college occupations for men were less susceptible to routinization. Altogether, our model estimates that workplace routinization accounted for 63% of the growth in female enrollment and 23% of the change in male enrollment between 1980 to 2000.

Keywords: human capital, college enrollment, gender, occupations, automation

JEL Classifications: I23, I24, I26, J16, J24, J23

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"Out of high school, men are more willing than women to enter a trade. For example, there are jobs open to become electricians, carpenters, plumbers and more...Many of my male peers entered a career right out of high school and they are successful and happy."
-Laura Thomas, Quinnipiac University, "Why the Future at U.S. Colleges is Female" (2021)

1 Introduction

In the United States, women used to lag behind men in college enrollment. As their work outcomes improved over time, social scientists predicted that the college gender gap would eventually close, and that men and women would attend college at roughly equivalent rates thereafter. Women indeed closed the gap in 1970-1980, as shown in Figure 1. Contrary to expectations, the gap then reversed: women are now attending college at increasingly higher rates relative to men. It remains an open puzzle as to why women exceed men in college enrollment, especially when male college graduates tend to work longer hours and earn higher median salaries than female college graduates. To reconcile this apparent contradiction, prior work has posited a greater *supply* of women prepared for college than men. It argues that men face greater obstacles to formal human capital investment because more of them struggle to pay attention, stay disciplined, and persevere through school (Becker et al., 2010; Bertrand and Pan, 2013; Goldin et al., 2006).

In contrast, this paper proposes that *demand* for a college degree is greater among women than men, given differences in job prospects with only a high school diploma ("non-college job prospects").[1] We observe that the non-college labor market is severely polarized by gender, in that almost all occupations are male- or female-dominated, and few are gender-equal. From this observation emerge two stylized facts. The first is that non-college occupations dominated by women tend to pay less than those dominated by men. The second is that many female-dominated occupations disappeared from the non-college labor market between 1970 and 2000. Together, these facts suggest that outside options to college-going were worse for women, but deteriorated even further over time. We posit that the widening disparity in non-college job prospects contributed to the widening of the reverse college gender gap.

To assess this hypothesis, we leverage *routinization* – automation's displacement of routine tasks – as a shifter of non-college job prospects. A burgeoning literature on routine-biased technical change has established that over time, automated devices such as answering

[1] To focus on the role of non-college job opportunities, this paper abstracts away from the myriad other explanations that could also contribute to the college gender gap, such as the marriage market premium from a college degree (see Ge, 2011 and Zhang, 2021) and the "motherhood wall" in more demanding occupations (for a recent review, see Juhn and McCue, 2017).

machines and computers increasingly substituted for human labor in performing routine tasks, eroding demand for workers in routine-intensive occupations (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Autor et al., 2003; Cortes et al., 2014; Cortes et al., 2017; Goos et al., 2009, 2014; Jaimovich and Siu, 2012; Spitz-Oener, 2006). A few papers note that routinization had especially severe impacts for the job prospects of women (Autor and Wasserman, 2013; Beaudry and Lewis, 2014; Black and Spitz-Oener, 2010). We further highlight that *non-college* women were the most vulnerable to displacement. In 1970, over 70% of non-college young female workers worked in "routinizable occupations" (defined more precisely below). When exploring the change in labor share from 1970 to 2000, we find that routinization lowered labor share *only* for non-college women, but not for college men, non-college men, or college women.

Following Autor and Dorn (2013), we measure local susceptibility to routinization using *routine task intensive (RTI) share*, the share of occupations that involve many routine tasks relative to other tasks. We use instrumental variation in routinization to overcome two challenges with causal inference. One is that RTI share in a local labor market could depend on the share of college and non-college workers, reflecting reverse causation. Another is that both RTI share and college enrollment rates could be correlated with unobserved factors, such as social norms regarding women's education, the ease of graduating high school, or opportunities to finance a college education. Both sources of endogeneity would bias our estimates of how routine non-college work opportunities impact college enrollment decisions.

Our instrument predicts a local labor market's displacement from routinization using job posting data on administrative activity. The intuition is that labor markets with high shares of industries intensive in administrative activity would experience more displacement in routine-intensive work over time. Time-series variation stems from within-occupation changes at the national level, which should not depend on changes in any particular commuting zone. Cross-sectional variation stems from 1950 industry composition, which pre-dates labor market and educational changes that occur during our analysis period of 1960-2000. Our identifying assumption is that within-occupation changes in administrative activity at the national level should only influence college enrollment in a commuting zone in ways reflected by routinization. We test these identifying assumptions in robustness checks, which verify that our results are not driven by other changes to the share of non-college workers or local shocks to markets from which the job postings originated. We also validate our results using alternative instruments, which exploit different sources of identifying variation to predict vulnerability to routinization.

Our first set of results comes from the two stage least squares (2SLS) regressions. The first stage regressions indicate that labor markets with higher shares of administrative industries in 1950 experienced greater routinization in 1960-2000. The second stage results demonstrate that routinization increased college enrollment among young women. We find that a 1 percentage point rise in routinization would increase the proportion of 18-25 year old women who attend college by 0.58-0.61 percentage points. Equivalently, moving from a commuting zone that experienced the 25th percentile of routinization to one that experienced the 75th percentile of routinization (a difference of 5.51 percentage points) leads to a 3.20-3.36 percentage point rise in female college-going. For men, who experienced less displacement in their non-college job prospects, coefficient estimates are directionally smaller and not systematically significant. We thus use routinization to establish that the deteriorating availability of non-college jobs increased college enrollment. Since women's non-college jobs were more vulnerable to routinization, female college enrollment grew at a faster rate relative to male enrollment.

To investigate the mechanism behind our 2SLS results, we develop a two-period Roy model with unobserved skill heterogeneity. In the model, forward-looking individuals choose their education level in the first period and their occupation in the second period. We allow men and women to have heterogeneous endowments in cognitive, manual, and administrative skills, which are measured by the Armed Services Vocational Aptitude Battery (ASVAB) from the National Longitudinal Survey of Youth 1979 (NLSY79). We estimate the model using maximum likelihood.

Our model allows skill prices to vary across genders and occupations. Gender differences in skill endowments and skill prices create different comparative advantages for men and women, leading to gender polarization among non-college occupations. In the presence of this polarization, changes in skill price due to routinization would have uneven impacts on the occupational returns of men versus women. To capture this gender asymmetric effect, we specify skill prices to be functions of predicted routinization generated from the first stage of our 2SLS approach. The structural model allows us to posit an explicit mechanism for the second stage relationship between routinization and enrollment, rather than assuming an *ad hoc* linear mapping as in most analyses using instrumental variables. By allowing individuals to have heterogeneous responses to local routinization levels, our model generates more precise predictions compared with a simple back-of-the-envelope calculation based on our 2SLS estimates.

Our model then explains the tight connection between the gender polarization of the non-college labor market and the reversal of the college gender gap. Men are more likely to sort into manual occupations given their higher mechanical skill, and women are more likely to sort into administrative occupations given their higher administrative skill. Since manual occupations pay more relative to administrative occupations, men enjoy a comparative advantage in non-college work overall. Women's comparative disadvantage, on the other hand, led them into administrative occupations that were more susceptible to displacement over time. As the labor market routinized, the price of administrative skill declined, impacting occupations predominantly held by non-college women. Skill returns for non-college men experienced smaller changes, since the occupations they held were harder to routinize. Consequently, routinization increased female college enrollment but had little impact on male college enrollment. Simulations from our model demonstrate that, as routine tasks became automated, the change in occupational returns increased female enrollment by 6.0 percentage points and male enrollment by 0.6 percentage points. This accounts for 63.2% of the change in college enrollment for women, but only 23.1% of the change in college enrollment for men.

Contributions to the literature. To our knowledge, this is the first paper that uses automation as a source of variation to investigate how the non-college labor market shaped the college gender gap over time. We use a new instrument to exploit the impact of automation on the demand for non-college workers in routine-intensive jobs. Prior work on the impact of labor market returns on the college gender gap has mostly relied on cross-sectional comparisons (Charles and Luoh, 2003; Dougherty, 2005; Jacob, 2002), occupational choice models (Olivieri, 2014), or general equilibrium models (Huang, 2014; Rendall, 2017). Relative to these approaches, our paper better accounts for potential sources of endogeneity, such as supply-side factors which could influence both non-college occupation share and college enrollment (e.g., social norms regarding women's work, ease of graduating high school, financial resources for pursuing college).

Second, we contribute to the literature on routine-biased technical change by quantifying automation's impact on the rise of female college-going. To our knowledge, this is the first paper to evaluate the causal impact of automation on the college gender gap. Most prior studies focus on the gender asymmetric impact of technological change on the labor market outcomes (Autor and Wasserman, 2013; Black and Spitz-Oener, 2010; Borghans et al., 2014; Cortes et al., 2021; Dillender and Forsythe, 2019; Juhn et al., 2014; Ngai and Petrongolo, 2017; Olivetti and Petrongolo, 2014, 2016; Yamaguchi, 2018). Our paper demonstrates substantial impacts on human capital acquisition, and therefore the skills that men versus women bring to the future workforce. Specifically, we show that routinization, a gender-neutral process, generates gender-asymmetric changes in college enrollment due to differences in skill endowments and skill prices. Our findings illuminate the role of technological change in shaping gender disparities in human capital. According to our simulation, changes in occupational returns from routinization can explain about 63% of the growth in female enrollment but only 23% of the change in male enrollment from 1980 to 2000.

Third, our paper uses a model-based approach to link gender-based occupation polarization with the college gender gap. Since most prior papers use job task requirements to indirectly infer gender differences in skill levels (Duran-Franch, 2020; Ngai and Petrongolo, 2017; Olivetti and Petrongolo, 2014; Rendall, 2017; Yamaguchi, 2018), they cannot disentangle the skill endowments of individuals from the skill returns of jobs. We overcome this limitation by separately measuring skill endowments and task requirements, which is necessary to determine how routinization changed the value of different skills. The closest frameworks to ours are Prada and Urzúa (2017) and Roys and Taber (2019), but our model deviates from them in two ways. We introduce instrumental variation from routinization to shift skill prices, following the spirit of Eisenhauer, Heckman, and Vytlacil (2015) and Heckman et al. (2018). This helps us separately identify skill prices and skill endowments, which are usually jointly determined in a classical Roy model. Furthermore, we study both male and female workers and focus on gender inequality as it pertains to college enrollment choices, whereas the other two papers only analyze male workers.

The paper is organized as follows. Section 2 describes stylized facts and data. Sections 3 and 4 describe our methodology and results from the 2SLS approach. Sections 5 and 6 describe our methodology and results from the structural model approach. We conclude in Section 7.

2 Data and Stylized Facts

We begin this section with an overview of our data. We then discuss the descriptive evidence that motivates our analytical approach. First, we present two stylized facts regarding the gender polarization among non-college occupations. Second, we describe our measure of routinization, followed by descriptive evidence that links routinization with the widening gender gap in non-college job prospects.

2.1 Data

We start our analysis with data from the U.S. decadal census for 1950-2000, which are collected by the U.S. Census Bureau and publicly provided by the Integrated Public Use Microdata Series (IPUMS; Ruggles et al., 2021). The census data for 1950, 1960, and 1970 include 1% of the entire U.S. population, while the census data for 1980, 1990, and 2000 include 5% of the population. Following Autor and Dorn (2013), we specify a local labor market as a commuting zone, which captures commuting patterns for work across counties. Commuting zones are defined across the entire contiguous United States, in contrast to other geographic constructs that are defined for only certain areas and therefore may under-represent certain industries (e.g., metropolitan statistical areas may underrepresent industries in rural areas such as agriculture or mining).[2]

The dependent variable is the college enrollment rate among 18-25 year olds. Individuals are considered college enrollees if they have ever enrolled in college. Since our paper investigates the decision to attend college among those prepared for college, we limit our analysis to those with a high school diploma or GED. We focus on college enrollment rather than college completion since our goal is to understand the impact of non-college job prospects on the *choice* to pursue higher education. College completion is influenced by a number of factors other than non-college job prospects, such as financial resources or academic ability, which complicate the task of isolating how non-college job opportunities change the demand for a college degree.

To measure the impact of routinization, we use data from Autor and Dorn (2013). We focus on measures of routine task intensive (RTI) share at the commuting zone level, described further in subsection 2.3.1. Our instrumental variable comes from job posting data from Atalay et al. (2020). We use the share of occupations that involve high levels of administrative activity, where administrative activity measures are constructed based on job postings from *The Boston Globe*, *The New York Times*, and *The Wall Street Journal* from 1950 to 2000.

Our structural model uses individual level data from the geocoded National Longitudinal Survey of Youth 1979 Cohort (NLSY79). The NLSY79 interviews the same 12,686 respondents annually from 1979-1994 and every two years from 1996 until present day. We construct a binary college attendance decision that equals 1 if years of education exceed 12 and 0 otherwise. We designate the individual's occupation choice to be the modal occupation between ages 25 to 35, and the occupation's monetary return as the individual's average annual earnings when she worked in this occupation. The final sample contains 8,540 individuals, with 4,217 men and 4,323 women. We provide further details and summary statistics in Appendix A.

Two advantages of the NLSY79 make it a good complement to the census data. First, the NLSY79 contains information on the respondent's county of residence at age 14 and traces each individual up to age 35, allowing us to account for potential composition effects due to migration. Second, the NLSY79 enables us to capture individual skill heterogeneity, as measured by test scores. Our primary skill measures come from the Armed Services

[2]Following Acemoglu and Autor (2011), we calculate labor supply weights by adjusting the sampling weight using the number of hours worked per week and the number of weeks worked per year.

Vocational Aptitude Battery (ASVAB), a set of tests designed by the U.S. Department of Defense to measure a wide array of cognitive and non-cognitive skills. These individual-level ability measures shed light on why men and women may have comparative advantages in different occupations, which is key to understanding gender differences in the college premium.

2.2 Gender polarization among non-college occupations

Our empirical approach is motivated by two stylized facts from the census data. To describe them, we classify occupations by gender and education. "Male-dominated" occupations are those with less than 30% women; "female-dominated" occupations comprise of more than 70% women; and "gender-equal" occupations comprise of 30-70% women. "Non-college occupations" have at least 50% high school graduates, and "college occupations" comprise of at least 50% college enrollees.

The first stylized fact is that female-dominated non-college occupations tend to earn lower pay than do male-dominated occupations. As shown in Figure 2a, there is a "missing quadrant" in the non-college labor market. Plenty of male-dominated occupations pay above the median income of all workers (including college graduates), indicating that men still have the potential to earn high pay even if they only possess a high school diploma. In contrast, female-dominated occupations pay below the 20th percentile, indicating female high school graduates tend not to hold the same high-paying occupations that male high school graduates do. Occupations such as miner, machinist, and truck driver are over 90% male and earn between the 40th to the 80th percentile of annual earnings. Occupations that are over 90% female, such as cashier, housekeeper, and cosmetologist, earn at or below the 10th percentile of annual earnings. Based on this descriptive evidence, a typical male high school graduate still has the potential for high earnings, whereas his female counterpart appears less likely to sort into occupations with high earnings potential. Indeed, field experiments by Carrell and Sacerdote (2017) find that college mentoring raised college-going for female high school students by much more than for male high school students. In follow-up surveys, male high school students cited their better non-college job prospects as one reason why they were less responsive to treatment.

College occupations display the opposite missing quadrant, as shown in Figure 2b. There is a dearth of low-paying occupations that are male-dominated, but plenty of low-paying occupations that are female-dominated. The evidence in Figure 2 is consistent with an underlying sorting mechanism for college enrollment, where few men enter low-paying college occupations given the availability of high-paying non-college occupations. On the other hand, it would be expected for many women to hold low-paying college occupations if their non-college job prospects were not particularly lucrative.[3]

The second stylized fact is that many female-dominated occupations disappeared from the non-college labor market over time. Figure 3a displays how non-college occupations vary by gender composition in 1970. Non-college occupations exhibited severe gender polarization. One third (34%) of non-college occupations were female-dominated; over half (53%) were male-dominated; and only 13% were gender-equal. By 2000, female-dominated occupations plummeted from 34% to 13%; male-dominated occupations rose even higher to 76%; and gender-equal occupations remained low at 12%. College occupations demonstrate the opposite trend, as shown in Figure 3b. The share of gender-equal occupations rose from 17% to 50%, while the share of male-dominated occupations dropped from 72% to 21%. The share of female-dominated occupations rose from only 12% to 29%. The descriptive evidence suggests that as female non-college job opportunities were declining, women were entering college occupations that were formerly male-dominated. Over time, men and women appeared more substitutable in college work, but non-college occupations remained polarized by gender. Guided by this evidence, we designate college occupations as "white-collar", female-dominated non-college occupations as "pink-collar", and male-dominated non-college occupations as "blue-collar".

When investigating this disappearance, we note that the occupations which experienced the greatest decline in female workers happened to be intensive in *routine* tasks. Table 1 depicts broad changes across one-digit occupational groups from 1960 to 2000. As a share of the 18-30 year old female workforce, workers in office and administrative support occupations declined from 45.2% in 1960 to 25.7% by 2000, an enormous decline of 19.6 percentage points. Most occupations in this category, such as secretary, clerical worker, stenographer, or typist, involved a great deal of repetitive tasks which were easy to codify using automated devices. The most routine-intensive of these occupations experienced the greatest displacement. From 1970 to 2000, the share of secretaries declined by 66% and the share of typists by 95%. The erosion of routine-intensive jobs appears to be larger for women than men. By way of comparison, the largest occupational decline in 18-30 year old men occurred in the production occupations, from 17.7% to 11.7% during 1960 to 2000. This decline of 6.0 percentage points is less than one-third of the decline experienced by women in office and administrative support occupations.

We next examine changes among non-college occupations based on their routinizability (defined in greater detail in Section 2.3.1). We plot the fraction of non-college occupations by

[3]In Section 5, we will show this sorting mechanism can arise naturally given different comparative advantages to non-college work for men versus women.

gender composition in Figure 4 for routinizable occupations (panel a) and non-routinizable occupations (panel b). The right side of Figure 4a shows that among all routinizable occupations, those that were female-dominated virtually all disappeared from the non-college labor market. In contrast, occupations that were 50% or more male increased in labor share between 1970 to 2000. Figure 4b shows that for non-routinizable occupations, there was little change in the distribution by gender composition during 1970-2000. Comparing panels (a) and (b), it appears that the decline in female-dominated occupations shown in Figure 3 is driven by routinizable occupations.

The evidence suggests that erosion of women's non-college job prospects could have been due to *routinization*, defined as automation substituting for human labor in the execution of routine tasks. The next section presents our method of measuring routinization.

2.3 Routinization and occupational composition

2.3.1 Measuring routinization

To explore how routinization impacted non-college job opportunities, we focus on the *routinization of the office* during 1960-2000 (Autor et al., 2003; Black and Spitz-Oener, 2010). Examples include the electric typewriter, the fax machine, the word processor, and the personal computer, which all substituted for human labor in the execution of routine tasks (Atlassian, 2022). Beyond the scope of this paper are other forms of automation which could impact college-going through alternative channels. For example, beginning in the 1990s, industrial roboticization substituted for manually intensive work and displaced the job prospects of men (Acemoglu et al., 2020; Acemoglu and Restrepo, 2019, 2020). Prior to the 1960s, improvements in household production technologies contributed to the mass entry of women into the labor force (Greenwood et al., 2005). Other forms of early automation include machinery which substituted for manual-intensive labor in agriculture and manufacturing prior to the 1950s (Adams, 2019; Atack et al., 2019; Autor, 2015).

Our measure of routinizability comes from an occupation's "routine task intensity" (RTI), a measure used in Autor and Dorn (2013). The RTI of occupation k is calculated using the logged index of its routine, manual, and abstract tasks:

$$RTI_k = \ln(routine_{k,1980}) - \ln(manual_{k,1980}) - \ln(abstract_{k,1980})$$

The RTI measure captures an occupation's routine content net of its manual and abstract content. "Routine," "manual," and "abstract" task content are compiled from census data and the Dictionary of Occupational Titles.[4] "Routine" tasks are defined as codifiable tasks that can be executed following an explicit set of rules. As technology progressed, automating devices replaced human labor in executing routine tasks, decreasing employer demand for workers who specialize in these tasks. For example, electric typewriters and carbon paper obviated the need for clerical workers to fill out forms one by one using pen and paper (Decker, 2016).

"Manual" tasks are defined as tasks requiring in-person execution, which tend to be physical or service-oriented tasks. Routinizability declines with manual job content, which involves the handling of objects across space, such as lifting materials or moving around. Operative, production, and service occupations were shielded from automation compared to clerical occupations, since they involved manual tasks that were difficult to automate. For example, it was difficult to program a machine to wait tables at a restaurant, a highly manual task which requires navigating around furniture and other moving bodies in unpredictable situations. Such technology only emerged after the 1990s (Acemoglu and Restrepo, 2020).

Lastly, "abstract" tasks involve complex mental processes that are not easily programmable, such as problem solving, management, and complex communication. If two occupations have the same routine and manual job content, the occupation with greater abstract content would have lower routinizability, since the execution of routine tasks would occur in conjunction with cognitively demanding tasks that could not be completed using automated devices. Prior work has also found that automation directly substituted for routine tasks while complementing abstract and manual tasks.[5]

Based on the definitions of routine, abstract, and manual task content, occupations high in RTI are vulnerable to routinization. In fact, the decline in female-dominated non-college occupations shown in Figure 4 was driven by occupations in the top third of RTI. Therefore, to measure the impact of routinization, we focus on "RTI share", or the share of high RTI occupations:

$$\text{RTI share}_{ct} = \frac{\sum_{k=1}^{K} \mathbf{1}(RTI_k > RTI_{1980}^{P66})L_{ckt}}{\sum_{k=1}^{L} L_{ckt}}$$

where L_{ckt} is the total number of workers 16-64 years of age in commuting zone c, occupation k, and year t. Occupation k is designated high-RTI if it exceeds the 66th percentile of routine

[4] We fix them to 1980 levels, which nets out within-occupation changes over time so that any change in RTI across labor markets will stem only from changes in occupational composition.

[5] Brynjolfsson and Hitt (2000) and Bresnahan et al. (2002) demonstrate that computers and routine tasks functioned as substitutes in production. On the other hand, by increasing the marginal productivity of abstract tasks, computers and similar automating devices raised labor demand for workers with abstract skills (Autor et al., 2003; Bresnahan et al., 2002; Brynjolfsson and Hitt, 2000; Spitz-Oener, 2006).

task intensity for all occupations in 1980: $RTI_k > RTI^{P66}_{1980}$.[6]

We then define our routinization measure as the change in RTI share for commuting zone c in year t:

$$\text{routinization}_{ct} = \text{RTI share}_{c,1950} - \text{RTI share}_{ct}$$

where t ranges from 1960 to 2000.

2.3.2 Linking routinization, job polarization, and college enrollment

Prior literature has established that the routine content of jobs declined over time because automation substituted for human labor in executing routine tasks (see Autor and Dorn, 2013; Goos et al., 2009). We find that among youth, these changes are borne by women. This result is consistent with related work showing that the decline in routine jobs is stronger for women than men (Autor and Wasserman, 2013; Black and Spitz-Oener, 2010). Figure 5 panel a graphs standardized routine task intensity (RTI) across all jobs held by 18-30 year old men and women. While the RTI of women's jobs was consistently higher than men's, it declined substantially from over 0.4 standard deviations in 1970 to 0.2 standard deviations by 2000. In contrast, the RTI of men's jobs held relatively steady at -0.2 standard deviations in 1970-2000. In Appendix Figure A.1, we investigate whether the gender difference in RTI is driven by changes in routine, manual, or abstract content over time. Aggregate trends show that only routine content could have driven these gender differences, since manual content barely changed and abstract content followed similar trends for men and women.

We next compare the labor share of routinizable occupations (high RTI) with non-routinizable occupations (low RTI). Panel b of Figure 5 breaks down automation susceptibility by gender. Among young women, the share of routinizable occupations peaked at 55.8% in 1970 and then plummeted by over 10 percentage points to 44.1% by 2000. The share of non-routinizable occupations, on the other hand, grew from 22.5% in 1970 to 32.3% in 2000. The differential trends between routinizable and non-routinizable occupations suggest that automation displaced certain jobs held by women. Remarkably, these divergent trajectories are not observed for men. Among young men, the labor shares of routinizable and non-routinizable jobs follow parallel trajectories: both grew about 3-5 percentage points from 1980 to 2000. Automation's displacement of routine-intensive jobs appears to have largely affected the jobs held by young women, without noticeably affecting the aggregate

[6] The impact of automation is better captured by the share of high RTI occupations than other measures, such as average RTI level, which would not capture the full extent of each local labor market that is vulnerable to automation. We set the threshold of RTI to be the 66th percentile of the 1980 occupational distribution following Autor and Dorn (2013). In robustness checks, we designate occupations as high-RTI if they are in the top half of routine task intensity, rather than the top third. This alternative definition does not appreciably change our results (see Table 5).

labor share of young men.

The natural next question is whether the decline among routinizable occupations affected the college-going margin for women. Panel c of Figure 5 depicts labor share by RTI and college status among all 18-30 year old women. For non-college women, there are stark differences in how labor share changed over time in routinizable versus non-routinizable jobs. First, the share of routinizable occupations reached almost one-third (31.8%) of all non-college working women 18-30 years old in 1970. From there, however, it plummeted to less than half this level by 2000, from 31.8% to 14.1%. In contrast, the share of non-routinizable jobs was quite small and constant at 5.4-7.3% over the same time period. The decline in routinizable labor share among non-college women mirrors the decline among all women in panel b, suggesting that automation's impact on women's jobs was concentrated in non-college jobs. Indeed, routinizable college jobs did not experience this same displacement. Panel c shows that for college women, the labor share of both routinizable and non-routinizable jobs followed parallel trajectories, increasing by 10-12 percentage points from 1970 to 2000.

Together, the three panels in Figure 5 indicate that the displacing impact of automation coincided with a decline in the routinizable jobs held by non-college women, but not men or college women. Our findings align with Black and Spitz-Oener (2010), who report a "strong decline in routine tasks experienced by women and almost not at all by men" for Western Germany (pg. 188). We extend on Black and Spitz-Oener (2010) by further isolating the decline to non-college women, which suggests women's outside options to college-going were disproportionately vulnerable to routinization. The gender asymmetries in impacts are natural in light of differential sorting into non-college occupations. Men's "blue-collar" jobs were highly manual, which made them difficult to displace even if they were intensive in routine tasks. Women's "pink-collar" jobs were less manual, since they involved operations such as bookkeeping and calculating, which were easy to automate (Autor et al., 2003; Black and Spitz-Oener, 2010).

3 Two Stage Least Squares Approach

The descriptive evidence we have shown so far does not necessarily establish the causal effect of routinization on women's college enrollment. Similarly, ordinary least squares (OLS) regressions may not be sufficient to isolate causal impacts. Table 2 presents positive OLS estimates between routinization and college enrollment, which suggest that labor markets which underwent greater routinization experienced growth in female enrollment ($p < 0.01$) and marginal growth in male enrollment ($p < 0.10$). Alternative explanations could be driving these estimates. For example, if more students graduated from college for other reasons, the college workforce would rise relative to the non-college workforce, mechanically decreasing the non-college labor share.

We therefore use an instrument to predict *displacement due to routinization* using the share of occupations that involve administrative support and clerical work.[7] The logic is that areas with historically high administrative shares would experience more task displacement as routinization took place. We calculate administrative share using data from Atalay et al. (2020), who extract information the skills and activities involved in an occupation based on job postings in *the Boston Globe*, *the New York Times*, and *the Wall Street Journal* during 1940-2000. They use textual machine learning approaches to map each job title in a posting to a code in the Census 2000 Occupation Index (Bureau, 2021). We then use their measures of job characteristics at the occupation code level to construct our instrument. Specifically, we use the frequency with which postings related to a census occupation code mention *administrative activity*, defined by the Occupational Information Network as "day-to-day administrative tasks such as maintaining information files and processing paperwork" (O*NET, 2022). Atalay et al. (2020) measure administrative activity based on the occurrence of the following keywords: "administrative," "paperwork," "filing," and "typing".[8]

To predict routinization at the commuting zone level, we fix industry shares in 1950 and interact them with "administrative share", the share of occupations with high administrative activity in each industry. The intuition is that commuting zones with high 1950 shares of administrative industries should experience greater routinization as these industries automate over time. Therefore, the administrative share IV is:

$$\text{admin share IV}_{ct} = \sum_{i=1}^{I} E_{i,c,1950} \frac{\sum_k L_{ikt} \mathbf{1}(\text{admin}_{kt} > \text{admin}_{1950}^{P66})}{\sum_k L_{ikt}}$$

where i indexes industry, k indexes occupation, t indexes year from 1960 to 2000, and c indexes commuting zone. $E_{i,c,1950}$ represents the share of industry i in commuting zone c in 1950. The expression $\frac{\sum_k L_{ikt} \mathbf{1}(\text{admin}_{kt} > \text{admin}_{1950}^{P66})}{\sum_k L_{ikt}}$ is the administrative share in industry i in year t. It is constructed using L_{ikt}, which represents the number of workers in occupation k, industry i, year t. The indicator $\mathbf{1}(\text{admin}_{kt} > \text{admin}_{1950}^{P66})$ equals 1 if occupation k in year t is

[7]Following the literature on skill-biased technical change (see Atalay et al., 2020; Autor et al., 2003), we treat administrative tasks as synonymous with clerical tasks, as opposed to managerial tasks.

[8]The administrative activity measure hones in on the subset of tasks that are most likely to be routinized, but may not fully capture the range of routine tasks affected. We prefer this conservative measure over measures that incorporate a larger range of tasks, which would risk violating the exclusion restriction by attributing too many task changes to automation. The risk of using too conservative a measure is that the relevance condition may not be satisfied. However, as the F-statistics in Table 3 will demonstrate, the first stage relationship between routinization and our instrument is quite strong. Moreover, we plot administrative activity and RTI share across occupations in Appendix Figure A.2. The raw data show a strong positive correlation, indicating that occupations high in administrative activity exhibited high routine task intensity.

in the top third of administrative activity, based on the occupation distribution in 1950.[9,10]

With this administrative share instrument, we then perform the following two stage least squares regression. The first stage regression captures the relationship between routinization and the instrument within commuting zone c and year t:

$$\text{routinization}_{ct} = \alpha_0 + \alpha_1 \text{admin share IV}_{ct} + \alpha_2 W_{ct} + \theta_c + \phi_t + u_{ct} \tag{1}$$

In our regression approach, our measure of routinization focuses on the RTI share among *non-college workers between 25 to 65 years old*. Focusing on the non-college RTI share enables us to directly measure how routinization changed the outside options to college-going.[11] Focusing on jobs held by 25-65 year olds fits our underlying premise that 18-25 year olds make their college-going decisions based on the job prospects of *those currently working*. Furthermore, excluding 18-25 year olds also avoids simultaneity concerns: if enrollment among 18-25 year olds rose for other reasons during this time, fewer workers would take routine task intensive jobs, and RTI share would mechanically decline.

We control for commuting zone-year level controls W_{ct}, commuting zone, census region, and year. The matrix of control variables W_{ct} includes the proportion of female, Black, and Hispanic residents. It also includes the proportion of people by 10-year age bin. Additional controls are discussed later in this section.

The intuition behind our first stage regression is that commuting zones starting out with high levels of administrative work should have undergone greater routinization. For example, the commuting zone around Republic city in the state of Washington had high 1950 shares of the legal services industry, which used to comprise of many administrative jobs that involved completing and filing forms. As the legal industry automated, the extent of routinization would be especially severe in Republic city compared to other labor markets. This would lead to a positive first stage coefficient between predicted administrative share, our instrument,

[9] Following the logic of Autor and Dorn (2013), we define "highly administrative occupation" based on whether the occupation is in the top third of the 1950 distribution. Fixing the occupational distribution to 1950 allows us to compare how administrative share changes over time for industries that traditionally involved intensive administrative activity.

[10] While $E_{i,c,1950}$ and L_{ikt} are constructed from the census, the indicator $\mathbf{1}(\text{admin}_{kt} > \text{admin}^{P66}_{1950})$ is constructed using job posting data from Atalay et al. (2020). Incorporating job posting data has two advantages. First, it better isolates labor demand changes than employment data from the census, which reflects the equilibrium outcome of both demand and supply forces. Second, our job posting data come from newspapers in Boston and New York City. Commuting zones in areas outside of these two cities would not directly depend on worker supply shocks that are specific to these cities.

[11] However, this measure is endogenous to supply-side considerations that influence educational choices, such as social norms regarding education or the ease of graduating from high school. In Section 4.1, we apply our 2SLS specification to routinization among both college and non-college workers and find no change in our results.

and routinization.

The second stage regression then uses the first stage linear prediction $\widehat{\text{routinization}}_{ct}$ to isolate the impact on college enrollment in commuting zone c, year t for gender g:

$$\text{college enrollment}^{g}_{ct} = \beta_0 + \beta_1 \widehat{\text{routinization}}_{ct} + \beta_2 W_{ct} + \theta_c + \phi_t + \epsilon^{g}_{ct} \qquad (2)$$

As with the first stage regression in Equation 1, the second stage regression controls for commuting zone-year characteristics W_{ct}, commuting zone dummies, and year dummies.[12]

Under the frameworks of Adao et al. (2019) and Borusyak et al. (2018), the shift-share approach is equivalent to a weighted instrumental variable regression in which industry-level shocks are the instrument and industry shares are the weights. The exclusion restriction is therefore that the administrative share at the national industry level can only affect college enrollment in ways reflected by routinization at the commuting zone level. This restriction is met if no commuting zone plays a large role in determining administrative share in an industry. Since our job posting data come from newspapers located in New York City and Boston, in robustness checks we exclude the commuting zones containing these cities to determine whether our 2SLS results are driven by local omitted variables correlated with both college enrollment and administrative work.

The general threat to the exclusion restriction is that industry-level changes in routine activity, measured by administrative occupation share, could be correlated with enrollment in ways not captured by commuting zone-level changes in RTI share. Using commuting zone dummies accounts for time-invariant omitted factors, but not changes across time correlated with both enrollment and labor market prospects. We next discuss plausible time-varying confounders that could generate the gender differences in college-going we report in Section 4. These confounders motivate the inclusion of certain controls into the W_{ct} matrix.[13]

One possibility is that non-automation factors could drive industry level changes correlated with both enrollment and routinization in a commuting zone. For instance, the decline in manufacturing over this period could change both college enrollment and the proportion of high-RTI occupations within an industry (see Autor et al., 2013). We therefore include in W_{ct} lagged shares of the largest industries: manufacturing, mining, and retail trade.[14]

[12]Note that while the reduced form and second stage effects on enrollment are gender-specific, we pool gender in estimating the first stage effect. This avoids the assumption that men and women operate in isolated markets and allows for correlation between impacts for men and women. For example, estimating the impact of routinization among men's jobs on male enrollment would ignore how changes in men's jobs could influence the decision to attend college for women. This would violate the exclusion restriction for instrumental variables analysis.

[13]In Section 4.1, we check that our results hold even when we do not use the control variables discussed below (Table 5).

[14]A trade-off exists between controlling for some industries versus all industries. Our identification relies

We also control for lagged service sector shares, given the Autor and Dorn (2013) finding that automation raised service sector employment. Using the lagged shares is preferable to current shares, since current shares may directly depend on college enrollment rates.

Supply-side factors could influence enrollment in ways correlated with the instrument. For example, high female labor force participation in a commuting zone may raise the share of industries that employ female high school graduates in 1950. More non-college jobs may be available to women in this commuting zone than in others, which would then increase their outside options to college-going, leading to lower growth in female enrollment in 1960-2000. We therefore control for both female and male labor force participation among 25-65 year olds. Since 25-65 year olds are beyond typical college age, their labor force participation should not directly depend on the college enrollment of 18-25 year olds.

Related concerns are serial correlation in RTI share, as well as persistence in other unobservable factors that could influence women's labor market prospects. For instance, commuting zones with more routine jobs in 1950 may have more favorable social norms regarding women's schooling in 1960-2000. In some specifications, we control for lagged RTI share to capture the effects of these and related social norms. Finally, as mentioned above, routinization changed both the returns to non-college work and college work. To separate the pull factor of rising college earnings from the push factor of declining non-college job opportunities, we control for median earnings in abstract-intensive occupations in certain specifications.

We use the standard error correction procedure of Adao et al. (AKM, 2019). AKM (2019) demonstrate that shift-share instruments introduce correlation across labor markets with similar industry shares, and that clustering standard errors at the local labor market level is insufficient to account for such correlation. To report the results of our weak instrument tests, we calculate Montiel Olea-Pflueger F-statistics, which are preferable to Kleibergen-Paap F-statistics in assessing instrument strength (Andrews et al., 2018; Andrews and Stock, 2018; Olea and Pflueger, 2013). Given recent literature on the limitations of using t-ratio based inference and first stage F-statistics to assess instrument strength (Lee et al., 2020), we report Anderson-Rubin weak instrument-robust confidence intervals.

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on industry-level shocks, so controlling for all industries would lead the industry dummies to absorb valuable identifying variation. We therefore only control for major industries that compose a large share of the overall labor force.

4 Two Stage Least Squares Results

We begin by investigating the first stage relationship between the instruments and routinization, presented in Table 3. As discussed in Section 3, we use various sets of controls to account for potential confounds. Column (1) controls for demographic characteristics at the commuting zone level, male and female labor force participation, the ten-year lagged service sector share, and the ten-year lagged shares of the industries with the highest labor shares in our data: manufacturing, retail, and mining. Adding to these controls, columns (2) and (4) include the median annual log earnings of occupations in the top third of abstract intensity. Columns (3) and (4) include the ten-year lag of RTI share.

Throughout this paper, we measure routinization as the percentage point reduction in RTI share from 1950 levels. We find that on average, a commuting zone with a 1 percentage point higher share of administrative industries in 1950 experienced 0.38-0.39 percentage points more routinization in 1960-2000 ($p < 0.01$). Coefficient estimates remain constant even when we control for median earnings in abstract-intensive work in columns (2) and (4), suggesting that the decline in RTI share is driven by declining routine task demand rather than growing returns to abstract-intensive work. Similarly, our estimates do not change when we control for lagged RTI share in columns (3) and (4), indicating that serial correlation in unobservables is unlikely to explain these relationships. Across all specifications, Montiel Olea-Pflueger F-statistics hover at 201.45-214.57. To visually assess fit, Appendix Figure A.3b plots the raw data against the linear prediction. The raw data exhibit a clear positive relationship between routinization and the administrative share IV, indicating that commuting zones with higher historical administrative industry shares experienced greater routinization.

Next, Table 4 reports the reduced form results for female enrollment (panel A) and male enrollment (panel B). Across all regressions, we find greater female enrollment rates among commuting zones with higher instrument values. This finding is consistent with the premise that women's non-college job opportunities diminished in labor markets more vulnerable to routinization. Commuting zones predicted to undergo 1 percentage point more routinization exhibit on average a 0.22-0.23 percentage point rise in female enrollment ($p < 0.01$). The coefficient for men is about 75% of the estimate for women and marginally significant at 0.17 percentage points ($p < 0.10$).

We next turn to the two stage least squares results in panels C-D of Table 4. By isolating variation in routinization based on changes in administrative activity over time, we aim to capture declines in employer demand for routine-intensive occupations. This then translates into fewer job options for high school graduates, since most routine-intensive occupations provided opportunities for non-college workers. Consistent with this story, panel C demonstrates that commuting zones that underwent more routinization experienced higher female enrollment rates. Our estimates indicate that a 1 percentage point rise in routinization led to a 0.58-0.61 percentage point rise in the proportion of 18-25 year old women enrolled in college ($p < 0.01$). Panel D shows that the corresponding estimate for male enrollment is 0.44 percentage points ($p < 0.10$). Another way to quantify our results is to compare a commuting zone which experienced the 75th percentile of routinization to one which experienced the 25th percentile of routinization. This difference, which amounts to a 5.51 percentage point gap in the extent of routinization, would have increased female enrollment by 3.18-3.33 percentage points and male enrollment by 2.40-2.44 percentage points.

Comparing across specifications, we find that including median earnings for cognitive occupations does not change our estimates. This is consistent with the evidence in Appendix Figure A.1 that abstract task content changed at similar rates for both men and women, and therefore cannot explain the gender differential in college enrollment trends. Adding lagged routine share also does not change point estimates across specifications, indicating that persistence in occupational composition across time is unlikely to drive our results.

Our Anderson-Rubin weak instrument-robust 95% confidence intervals exclude 0 for female enrollment but cannot reject the null hypothesis of no effect for male enrollment. The results establish a consistently significant negative relationship for women, but not for men. However, the coefficient estimates on male and female enrollment do not statistically differ. It is possible that the erosion of routine jobs also impacted male college-going, since some men worked in occupations vulnerable to automation. In addition to the few men who worked in secretarial and clerical occupations, high-RTI occupations that were dominated by men include shipping clerks, meter readers, security guards, machinists, and machinery repairers. Yet, even if a one percentage point reduction in RTI share generated equal responses for male and female enrollment, far more women worked in high-RTI jobs than men (around 70% of non-college women compared to 40% of non-college men during 1960-2000), so the aggregate change in non-college job prospects for women would still exceed that for men. We explore the implications of these estimates on aggregate trends in the college gender gap over time in Sections 5 and 6.

4.1 Additional specifications

We next address potential concerns regarding our main regression specification from Table 4 panels C and D. Table 5 summarizes results from our additional specifications. Column (1) excludes controls which may be correlated with omitted variables that influence routinization:

contemporaneous labor force participation, lagged service sector share, lagged major industry shares, and lagged routine share. Our point estimates change slightly, but not significantly. We find that greater routinization predicts greater college enrollment for women but not for men. In particular, a 1 percentage point reduction in the share of high RTI occupations from 1950 levels raises female enrollment by 0.5 percentage points ($p < 0.01$) but does not significantly change male enrollment.

Local shocks in Boston and New York. The content of job postings may be endogenous to the supply of skills in the local labor market. For example, if a commuting zone has a large share of college workers skilled in abstract tasks, employers may specify more abstract tasks and fewer routine or manual tasks in their job postings. The advantage of our approach is that we exploit trends in administrative activity over time in Boston and New York City, so local shocks from other commuting zones should not directly affect our job posting data. To ensure that local shocks in Boston and New York City are not driving our results, we exclude the commuting zones containing these two cities. The results are shown in column (2), Table 5. Our point estimates of 0.608 ($p < 0.01$) for female enrollment and 0.503 ($p < 0.10$) for male enrollment are similar to our main estimates.

Changes in abstract occupation share. In our main specifications, we instrument for routinization, which reflects the routine, manual, and abstract content of occupations in a commuting zone. We control for manual content, but allow abstract content to vary freely with routine content since prior work has found that routinization coupled the decline in routine content with a rise in abstract content over time (see Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002). However, this raises the question of whether our results are driven by deteriorating job prospects in routine-intensive occupations or by improving job prospects in abstract-intensive occupations. While we already control for abstract median earnings in Table 4, we go further by controlling for abstract occupation share in column (3) of Table 5. This additional control places severe restrictions on the variation we use, but better nets out the impact of non-automation forces that shift routine and abstract content simultaneously. Despite the stringency of this specification, estimates are similar to the main results, leading us to conclude that the response of female enrollment to changes in RTI share are not driven by improving returns to abstract-intensive occupations alone. We find point estimates of 0.628 ($p < 0.01$) for women in panel A and 0.441 ($p > 0.10$) for men in panel B.

Changes in the composition of non-college workers. Our sample period witnessed substantial growth in college enrollment due to many supply-side factors, such as greater high school completion rates, social norms encouraging college graduation, and more generous financing options for education. Our main specification uses routinization among non-college workers, but the rise in college enrollment over this period could change the composition of the non-college workforce and impact this measure through channels other than routinization. To address this concern, in an additional specification we use routinization among both non-college and college workers, which is less sensitive to college enrollment changes. Column (4) shows that this alternate measure does not appreciably change our main estimates, suggesting that changes in non-college worker share during our sample period did not drive our 2SLS estimates.

The administrative activities instrument and clerical requirements instrument. Lastly, we look to alternate methods of using the job posting data to predict routinization. First, throughout the paper we define administrative share based on the share of occupations in the top third of administrative activity in 1950. We chose the top third to be consistent with the RTI share measure from Autor and Dorn (2013), but note that our results could be driven by this arbitrary designation. In Table 5 column (5), we show that our results hold when we define administrative share based on occupations in the top *half* of administrative activity.

We also explore using instrumental variation from the average administrative activity of all occupations in an industry, rather than the share of highly administrative occupations. In column (6), we construct the "administrative activity instrument" using the predicted frequency of administrative activities. The units are the number of mentions of an administrative activity per job posting, rather than the share of occupations that require intensive amounts of administrative activity. In column (7), we construct a similar instrument called the "clerical requirements instrument", based on the number of times a clerical knowledge requirement is specified per job posting for an occupation. Estimated effects in specification (6) and (7) are comparable with the effects in our baseline results, although the results in column (7) are slightly higher than the main estimates. These comparisons indicate that our results do not depend on the particular structure of our administrative share instrument. Rather, we arrive at the same results using multiple methods of instrumenting for routinization.

Overall, the results indicate that the positive relationship between routinization and female enrollment is consistently significant across different forms of instrumental variation and different model specifications. In contrast, the impact on male enrollment is weak. Across all specifications in Table 5, Anderson-Rubin 95% confidence intervals are squarely positive for women but include 0 for men. We rule out a null effect in characterizing the relationship between routine intensive work and female college-going, but fail to reject the null hypothesis of no relationship between routine intensive work and male college-going.

5 Structural Model Approach

Our 2SLS results show that commuting zones with greater predicted routinization experienced higher levels of female college enrollment. We next propose the mechanism that can explain these findings. An augmented Roy model with latent skills delves into how individual choices can change based on non-college job prospects. Following the dynamic discrete choice literature (Eisenhauer, Heckman, and Mosso, 2015; Keane and Wolpin, 1997; Roys and Taber, 2019; Todd and Zhang, 2020), we explicitly model sequential education and occupation decisions. Our innovation is that we incorporate instrumental variation in routinization into occupation-specific skill prices.[15] By doing so, we leverage instrumental variation to exogenously shift skill prices and identify the causal effects of routinization at well-defined margins of the education and occupation choices. These estimates are then used to simulate how male and female enrollment would change based only on changes from routinization, enabling us to quantify the importance of routinization in explaining trends in the reverse college gender gap.

The model has two periods with transitions and nodes shown in Figure 6. Individuals are forward looking and sequentially choose their education D_i in period 1 and their occupation O_i in period 2. In the first period, individuals choose whether to attend college based on the flow utility of schooling and expected values from the second period. Initial skill endowments are unobserved by the econometrician but fully observed by each individual. Following Heckman et al. (2006) and Prada and Urzúa (2017), we identify workers' unobserved skills by constructing a measurement system based on individuals' test scores from the NLSY79. We use $\theta_i = [\theta_{ci}, \theta_{mi}, \theta_{ai}]$ to represent a vector of three-dimensional skill sets for individual i, where subscripts c, m, and a are used to denote cognitive, mechanical, and administrative skills, respectively. We allow for gender differences in skill distributions.

We demarcate three different occupation choices $O_i \in \{\text{White collar, Blue collar, Pink collar}\}$. White collar occupations ($O_i = 1$) refer to occupations dominated by college workers; blue collar occupations ($O_i = 2$) refer to occupations dominated by the male high school graduates; and pink collar occupations ($O_i = 3$) refer to occupations dominated by female high school graduates. This classification is derived from the contrast between the college and non-college labor markets shown in Figure 3, where gender polarization is severe in non-

[15]Eisenhauer, Heckman, and Vytlacil (2015) and Heckman et al. (2018) have also incorporated instruments into discrete choice models. However, the decision rules in their models are not fully dynamic.

college occupations but not in college occupations. Men and women appear to sort into similar jobs if they have a college degree, but different jobs if they only have high school diplomas. This classification enables our model to capture, for instance, the notion that blue collar jobs tend to be more brawn-intensive, leading to a comparative advantage for men due to their higher mechanical skill endowments. Lastly, we allow for home-staying as an outside option to working ($O_i = 4$).

Our specification is intentionally more parsimonious than typical life-cycle dynamic discrete choice models such as Keane and Wolpin (1997, 2001), Roys and Taber (2019), and Todd and Zhang (2020). It assumes that attending college is the only binary education choice, that occupation choices are made once and permanent, and that individuals cannot return to school after entering the labor market. Our model is intentionally simple so as to focus on the connection between college attendance decisions and the heterogeneous college wage premium across different occupations. This simplicity enables us to specify an explicit mechanism by which instrumental variation in routinization shifts skill prices.

5.1 Sequential schooling and occupation choices

The model is solved through backwards induction. In the second period, individual i with gender $g \in \{m, f\}$ chooses an occupation depending on perceived expected values across alternatives. Ex post, individual i who chooses occupation O_i given an education level D_i receives utility $U(O_i|D_i)$:

$$U(O_i|D_i) = \log Y(O_i|D_i) + \log P(O_i|D_i) + \epsilon_{O,D,i} \tag{3}$$

where $Y(O_i|D_i)$ denotes the monetary return from occupation O_i given an education level D_i, while $P(O_i|D_i)$ is the non-pecuniary utility of working in occupation O_i (e.g., job amenities, job flexibility, potential discrimination costs). The term $\epsilon_{O,D,i}$ is an idiosyncratic preference shock that follows the extreme value type I distribution.[16] Earnings in occupation O_i are expressed as

$$\log Y(O_i|D_i) = X_i^Y \beta^g_{O,X} + D_i \beta^g_{O,D} + \theta_i \beta^g_{O,\theta} + \theta_i D_i \beta^g_{O,D,\theta} + u^g_{O,i} \tag{4}$$

where X_i^Y is a vector of relevant observed variables, including cohort, region, and urban dummies. The subscript $g \in \{m, f\}$ denotes male and female, respectively. The college premium comes from both $D_i \beta^g_{O,D}$ and $\theta_i D_i \beta^g_{O,D,\theta}$, in which $\beta^g_{O,D}$ captures the common return to education while $\beta^g_{O,D,\theta}$ captures the component varying by skill level θ_i. Lastly, $u^g_{O,i}$ is

[16] Note that we can only identify differences among options, as opposed to their levels. We therefore normalize the value of the home-staying option to be 0 for identification purposes.

the random component, realized only after occupation O_i has been chosen. Analogously, the non-pecuniary utility $P(O_i|D_i)$ from entering occupation O_i has the following expression

$$\log P(O_i|D_i) = X_i^Y \alpha_{O,X}^g + D_i \alpha_{O,D}^g + \theta_i \alpha_{O,\theta}^g + \theta_i D_i \alpha_{O,D,\theta}^g \tag{5}$$

where $\alpha_{O,D}^g$ represents the non-pecuniary return to education shared by all workers and $\alpha_{O,D,\theta}^g$ captures the extra non-pecuniary education premium that varies by worker's skill level θ.

In the first period, individual i decides whether or not to attend college depending on the perceived value of the flow utility and expected value from the second period.

$$\begin{aligned} D_i &= \mathbf{1}[V_i^1 + \xi_{D,i}^g > V_i^0] \\ V_i^0 &= E_\epsilon[U(O_i|D_i = 0)] \\ V_i^1 &= X_i^D \lambda_X^g + \theta_i \lambda_\theta^g + \rho E_\epsilon[U(O_i|D_i = 1)] \end{aligned} \tag{6}$$

where D_i denotes a binary variable equal to 1 if the individual chooses to attend college and 0 otherwise. X_i^D captures a vector of characteristics commonly believed to be relevant factors for education choice.[17] The term $\theta_i \lambda_\theta^g$ captures the heterogeneous cost of attendance for individual i with skill θ_i and gender g.[18] The preference shock on education $\xi_{D,i}^g$ is assumed to be orthogonal to X_i^D and θ_i.

5.2 Incorporating routinization

One of the biggest challenges in the generalized Roy model is the identification of skill prices, as they are endogenous outcomes jointly determined by supply and demand. Existing literature addresses this challenge by either using general equilibrium models (Lee and Wolpin, 2006) or assuming exogenous skill demand functions (Roys and Taber, 2019). In contrast, we use the instrument for routinization defined in Section 3 to shift job prospects, specifically occupation-specific skill prices. Our framework allows routinization to impose different changes to skill returns based on pre-existing skill endowments, yielding different incentives to attend college. This setup, which is similar in spirit to Heckman et al. (2018), enables us to identify the heterogeneous causal impact of routinization at the individual level.

We incorporate routinization by specifying skill prices as functions of the first stage prediction of local routinization, estimated from Equation 1. In particular, we assume that the vector of pecuniary and non-pecuniary returns to skills are functions of $\widehat{routinization}_{c(i),t}^g$:

[17] Following Eisenhauer, Heckman, and Mosso (2015) and Prada and Urzúa (2017), X_i^D includes parental education, the number of siblings, an indicator variable for broken home, and family income at age 14.

[18] For identification purposes, we normalize the flow utility of not attending college to 0.

$$
\begin{aligned}
\beta^g_{O,\theta}(c,t) &= \beta^{g,0}_{O\theta} + \beta^{g,1}_{O,\theta}\widehat{routinization}^g_{c(i),t} \\
\beta^g_{O,D,\theta}(c,t) &= \beta^{g,0}_{O,D,\theta} + \beta^{g,1}_{O,D,\theta}\widehat{routinization}^g_{c(i),t} \\
\alpha^g_{O,\theta}(c,t) &= \alpha^{g,0}_{O,\theta} + \alpha^{g1}_{O,\theta}\widehat{routinization}^g_{c(i),t} \\
\alpha^g_{O,D,\theta}(c,t) &= \alpha^{g,0}_{O,D,\theta} + \alpha^{g,1}_{O,D,\theta}\widehat{routinization}^g_{c(i),t}
\end{aligned}
\tag{7}
$$

Here, $\widehat{routinization}^g_{c(i),t}$ is the first stage predicted level of routinization for individual i of gender g in commuting zone $c(i)$ and year t. Therefore, $\{\beta^g_{O,\theta}(c,t), \beta^g_{O,D,\theta}(c,t), \alpha^g_{O,D}(c,t), \alpha^g_{O,D,\theta}(c,t)\}$ is the skill price vector that individuals in commuting zone c would adopt when making their education choices at period t. Substituting Equation (7) into Equations (4) and (5) yields:

$$
\begin{gathered}
\log Y(O_i|D_i) = X_i^Y\beta^g_{O,X} + D_i\beta^g_{O,\theta} + \theta_i\beta^{g,0}_{O,\theta} + \theta_i D_i\beta^{g,0}_{O,D,\theta} \\
+\theta_i\beta^{g,1}_{O,D,\theta}\widehat{routinization}^g_{c(i),t} + \theta_i D_i\beta^{g,1}_{O,D,\theta}\widehat{routinization}^g_{c(i),t}
\end{gathered}
$$

$$
\begin{gathered}
\log P(O_i|D_i) = X_i^Y\alpha^g_{O,X} + D_i\alpha^g_{O,\theta} + \theta_i\alpha^{g,0}_{O,\theta} + \theta_i D_i\alpha^{g,0}_{O,D,\theta} + \\
+\theta_i\alpha^{g,1}_{O,D,\theta}\widehat{routinization}^g_{c(i),t} + \theta_i D_i\alpha^{g,1}_{O,D,\theta}\widehat{routinization}^g_{c(i),t}
\end{gathered}
$$

Based on the above equation, returns to different occupations depend on both individual characteristics (e.g., gender, education, and skill levels) as well as predicted routinization in the resident commuting zone. Therefore, identical workers in the same occupation may have different returns if they live in areas that experienced different amounts of routinization.

It is worth noting that we assume that routinization must only impact college-going in ways reflected by changes in skill prices. Our model effectively uses the change in skill price due to routinization as a sufficient statistic to capture the impact of routinization within different occupations.

5.3 Structural model estimation strategy

5.3.1 Latent abilities

We use the NLSY79's ASVAB tests to construct multi-dimensional skill profiles at the individual level. The ASVAB comprises nine subtests: arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge, numerical operations, coding speed, automotive and shop information, electronics information, and mechanical comprehension. Following Prada and Urzúa (2017), we perform Exploratory Factor Analysis (EFA) analysis on the NLSY79's ASVAB tests to construct multi-dimensional skill profiles at the individual level. The analysis suggests that two separate skills ("factors") are necessary to explain the variation in ASVAB scores. For both men and women, the first factor has the highest loadings for subtests designed to assess cognitive skill. However, there are gender differences in factor loadings for the second factor. For men, the loadings are statistically significant only for the three mechanical subtests: automotive and shop information, electronics information, and mechanical comprehension. For women, loadings for the second factor are statistically significant only for the two administrative subtests: coding speed and numerical operations. Figure 7 displays the estimated factor loadings.

Based on our results, we characterize each individual's skill set θ_i by three dimensions: the common first factor as cognitive ability $\theta_{c,i}$, men's second factor as mechanical skill $\theta_{m,i}$, and women's second factor as administrative skill $\theta_{a,i}$.[19] This particular skill structure sheds light on how men and women can have different comparative advantages in different occupations, leading to the occupational sorting shown in Figure 2. Men tend to have higher mechanical skill, which would give them a comparative advantage in manually intensive tasks. Women tend to have higher administrative skills, which provide a comparative advantage in routine office work. Appendix A provides more information on the EFA implementation.

Guided by the exploratory factor analysis, we specify the measurement equations for an individual i with latent skill vector $\theta_i = [\theta_{c,i}, \theta_{m,i}, \theta_{a,i}]$ as follows:

$$
\begin{aligned}
C_{j,i} &= \lambda_j^c \theta_{c,i} + e_{j,i}^c, j = 1, 2, ..., 4 \\
M_{j,i} &= \lambda_j^c \theta_{c,i} + \lambda_j^m \theta_{m,i} + e_{j,i}^m, j = 5, 6, 7 \\
A_{j,i} &= \lambda_j^c \theta_{c,i} + \lambda_j^a \theta_{a,i} + e_{j,i}^a, j = 8, 9
\end{aligned}
\tag{8}
$$

where $C_{j,i}$ denotes the four subtests exclusive for the cognitive ability measure, M_{ji} denotes the three mechanical subtests, and $A_{j,i}$ denotes the two administrative subtests.[20] We restrict the loading coefficients $\{\lambda_j^c, \lambda_j^m, \lambda_j^a\}$ to be gender neutral so that any gender differences in test scores reflect only gender differences in latent abilities. Lastly, to identify the system, we assume that all error terms $\{e_{1,i}^c, ..., e_4^c, e_{5,i}^m, e_{6,i}^m, e_{7,i}^m, e_{8,i}^a, e_{9,i}^a\}$ are mutually independent and uncorrelated with the skill vector θ_i.

It is worth noting that we allow latent abilities to be correlated with each other, as several test scores are relevant for multiple abilities. To identify the system, we follow Carneiro et al. (2003), Eisenhauer, Heckman, and Mosso (2015), Heckman et al. (2006), and Prada and Urzúa (2017) and assume that at least one measure in $M_{j,i}$ is exclusively driven by mechanical skill, and one measure in $A_{j,i}$ is exclusively driven by administrative skill, and a set of standard normalizations.[21] We refer interested readers to the aforementioned papers

[19] Our EFA results match with Prada and Urzúa (2017) regarding the definition of mechanical skills for men. However, the results on administrative skill for women are novel.

[20] In particular, $C_{j,i}$ ∈{arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge}, $M_{j,t}$ ∈{automotive and shop information, electronics information, and mechanical comprehension} and $A_{j,i}$ ∈{coding speed and numerical operations}.

[21] In practice, we assume the factor loadings of cognitive skill on automotive shop information test (λ_5^c)

or Appendix B for further details on identification.

5.3.2 The maximum likelihood function

The measurement equations are jointly estimated with the model using maximum likelihood. Let $\psi \in \Psi$ denote a vector of structural parameters and $\Omega_i = \{X_i, T_i, O_i, Y_i, D_i\}$ be the vector of observable characteristics of individual i, including exogenous control variables X_i, a college dummy D_i, occupations O_i, and annual earnings Y_i. Test scores T_i include cognitive test scores $C_{j,i}$, mechanical test scores $M_{j,i}$, and administrative test scores $A_{j,i}$. The likelihood function for individual i is given by

$$\begin{aligned}\ell_i(\Omega_i|\psi) = \int_\theta & \underbrace{\Pi_{j=1}^4 f_j(C_{j,i}|\theta_i;\psi)\Pi_{j=5}^7 f_j(M_{j,i}|\theta_i;\psi)\Pi_{j=8}^9 f_j(A_{j,i}|X_i,\theta_i;\psi)}_{\text{skill measurements}} \\ & \underbrace{\left(f_Y(Y_i|D_i,O_i,X_i,\theta_i;\psi)\right)^{I(O_i\neq 4)}}_{\text{wage outcomes}} \underbrace{\Pi_{k=1}^4 \left(\Pr(O_i|D_i,X_i,\theta_i;\psi)\right)^{I(O_i=k)}}_{\text{occupations}} \\ & \underbrace{\Pi_{l=0}^1 \left(\Pr(D_i|X_i,\theta_i;\psi)\right)^{I(D_i=l)}}_{\text{college}} dF_\theta(\theta;\psi)\end{aligned} \tag{9}$$

where $\Pr(.)$ represents the probability of occupation choice O_i or education choice D_i defined in Equations 3 and 6, $f_j(.)$ is the probability density function for test j defined by Equations 8, $f_Y(.)$ is the probability density function of earnings Y_i in Equation 4, and $F_\theta(.)$ is the joint cumulative distribution of the latent skill vector $\theta \in \Theta$. After taking the logarithm of Equation (9) and summing across all individuals, we obtain the sample log likelihood $\log L$:

$$\log L = \sum_{i=1}^{N} \log \ell_i(\Omega_i|\psi)$$

Lastly, we impose some distributional assumptions to complete our likelihood function. In particular, $\epsilon_{O,D,i}$ follows the standard Gumbel distribution while other error terms follow the normal distribution. For latent skills, we use mixtures of normal distributions, which provides minimal restrictions on the underlying distributions of $[\theta_c, \theta_m, \theta_a]$.[22] Following Prada and Urzúa (2017), we use mixtures of two normal distributions and assume $E[\theta_c] = E[\theta_m] = E[s] = 0$.[23] After plugging the distribution assumptions into Equation (9), $\Pr(O_i)$ will be

and on coding speed test (λ_9^c) are equal to 0. The loading of cognitive skill on mathematics knowledge (λ_2^c), the loading of mechanical skill on mathematics knowledge (λ_7^m) and the loading of administrative skill on numerical operations (λ_9^a) are standardized to 1.

[22] Ferguson (1983) argues that any probability distribution can be approximated arbitrarily well by a finite mixture of normal densities. Therefore, this distributional assumption should provide sufficient flexibility while imposing a minimal number of restrictions on the underlying distributions.

[23] However, the mean values for men and women may differ and do not necessarily equal 0.

a multinomial logit function and $\Pr(D_i)$ will be a probit function. We can then obtain the estimates $\hat{\psi}$ by maximizing the total likelihood function

$$\hat{\psi} = \text{argmax}_{\psi} \sum_{i=1}^{N} \log \ell_i(\Omega_i|\psi).$$

The standard errors are computed using the BHHH algorithm (Berndt et al., 1974).

6 Structural model results

6.1 Goodness of model fit

To assess model fit, we compare simulated occupation and education choices with those from the real data in Table 6. The upper panel shows that moments from the model simulation are close to the real data on occupational choice. The simulation replicates that the two most common choices for men are white and blue collar occupations, while the two most common choices for women are white and pink collar occupations. The middle panel shows that for average log wages, simulated wages are reasonably close to actual wages. The average wage is highest in white collar occupations and lowest in pink collar occupations, both for men and for women. The lower panel summarizes education choices. Although our model slightly overpredicts the overall college attendance rate, it captures the pattern that women attend college at much greater rates than men. The fraction of women enrolled in college is around 60%, while the fraction of men is around a half.

6.2 The relationship between skills, occupational sorting, and education decisions

Our model estimates reveal notable gender differences in skill profiles, depicted in Figure 8. First, Figure 8a demonstrates similar distributions of cognitive skill for men and women, although the variance is lower for women than men.[24] This provides further evidence that men and women are substitutable in white collar work, and can explain why the majority of college occupations were gender-equal in 2000 (see Figure 3b).

In contrast, there are substantial gender differences in mechanical and administrative skills. Figure 8b shows that the mechanical skill distribution for men is higher in mean and

[24]This result is consistent with Becker et al. (2010), who argue that the lower variance in skills among women contributes to why more women than men are prepared to attend college. Our paper argues that independent of any differences in the *supply* of students prepared for college, demand for a college degree is also higher among women than men.

variance than for women, and that mechanical skills for women appear to max out near the male mean. Figure 8c shows that women on average have higher administrative skills than do men. These differences in mechanical and administrative skill provide a basis for the gender polarization among non-college occupations shown in Figure 3. They also help substantiate related research claiming that gender-based occupational segregation arose from higher mechanical skill among men (Huang, 2014; Rendall, 2017; Welch, 2000).

Aside from the difference in skill profiles, women and men may also receive different returns for the same skill in the same occupation. Figure 9 plots the returns to different occupations by skill quintiles for men and women (left and right panels, respectively). Blue bars represent returns from blue-collar occupations, pink bars represent returns from pink-collar occupations, and white bars represent returns from white-collar occupations. Comparing the blue bars between the left and right panels reveals that men receive higher returns from blue-collar jobs than women do, even among those with the same level of mechanical skill. On the other hand, the pink bars show that women receive much higher rewards from pink collar jobs than men do among those with the same level of administrative skill. Lastly, the white bars show that average returns for white-collar jobs are similar between men and women.[25]

Second, Figure 9 shows that different occupations reward different skills. Returns to blue-collar occupations tend to increase with mechanical skill for men, possibly because manually intense jobs such as HVAC engineer, material mover, or equipment repairer tend to require a great degree of mechanical skill. Compensating wage differentials contribute to the high pay of these occupations, since they are manually challenging even if not cognitively intense. Returns to pink-collar occupations increase with administrative skill for women, possibly because office roles such as secretary or clerical worker reward the ability to file paperwork, coordinate others' schedules, and quickly enter strings of letters repeatedly into administrative forms. Returns to white-collar occupations increase with cognitive skill for both men and women, given that they tend to be intense in abstract tasks such as problem-solving, computation, and critical thinking.

Together, Figures 8 and 9 suggest that gender differences in skill endowments lead to comparative advantages at different occupations. This then creates gender differences in occupational sorting, as shown in Figure 10. Cognitive skill is positively correlated with

[25]It is unclear why returns differ between men and women who possess the same skill in the same occupation. We speculate that differences in skill returns could be due to occupational sorting. That is, controlling for mechanical skill, returns will be greater for men than women in blue-collar jobs since more men tend to sort into these jobs, making the non-pecuniary amenities of the job higher for men than women. For example, blue-collar jobs such as HVAC engineer, material mover, or equipment repairer have adapted to a majority male workforce, which may affect how comfortable women feel in these occupations regardless of mechanical ability.

white-collar work for both men and women. As cognitive skill increases, men shift from blue-collar occupations to white-collar occupations, while women shift from pink-collar occupations and home-staying to white-collar occupations. Mechanical skill is positively correlated with blue-collar occupations only for men. When moving up the quintiles of the mechanical skill distribution, men increasingly sort into blue-collar occupations and out of white-collar occupations. For women, high mechanical skill is positively associated with home-staying and negatively associated with white-collar occupations. Lastly, administrative skill is more relevant for women's occupation choices than men's. As administrative skill increases, the share of women entering pink-collar occupations grows while the share entering white-collar occupations declines. For men, on the other hand, administrative skill has little impact on the likelihood of sorting into any of the four occupational choices.

We then examine the correlation between skill endowment and college attendance in Figure 11. While cognitive skill predicts college-going for both men and women, it explains more of the variation in men's college-going. Women with low cognitive skill still attend college at high rates, while comparable men exhibit low attendance rates. The disparity is highest among individuals in the first and second quintiles of cognitive skill, but declines as cognitive skill increases. The patterns are consistent with the idea that women have worse outside options to attending college than men. Men with low cognitive skills still have the option of entering blue-collar work, which can pay well, especially for men with high mechanical skills. Therefore, the compensation from attending college must be sufficiently high to warrant giving up the high pay from a blue-collar job. In other words, college is worthwhile only for men whose cognitive skill is sufficiently high relative to their mechanical skill. In contrast, women's non-college work options tend to be less lucrative, making it worthwhile to attend college even if their cognitive ability was relatively low.

Figure 11 shows that as mechanical skill increases, enrollment declines for men but stays flat for women. The evidence suggests that mechanical skill presents a sharp trade-off between college and non-college work for men but not women. This interpretation is consistent with the prior result that higher mechanical skill plays a larger role in whether men enter blue collar work, which presents especially lucrative outside options to attending college. Lastly, as administrative skill increases, female enrollment slightly declines but male enrollment does not change. High administrative skill appears to present some trade-off between college and non-college work for women, in that returns to pink collar work rise for women with high administrative skill. However, this trade-off is not nearly as stark as the trade-off that mechanical skill presents for men.

The interactions between college attendance and skill endowments imply different levels of occupational polarization in the college and non-college labor markets, shown in Figure 12.

The non-college labor market exhibits severe gender polarization. Few non-college workers hold white collar occupations, given the complementarity between white collar occupations and college degrees. Instead, non-college men specialize in blue collar jobs given their higher mechanical skills, whereas non-college women specialize in pink collar jobs since they tend to have higher administrative skills. In contrast, the college labor market exhibits less gender polarization. Both male and female college graduates tend to hold white collar jobs due to strong complementarities between their cognitive skills and white collar work. Together, these results recreate the gender polarization in Figure 3 that motivated our study from the outset.

6.3 The effect of automation on occupation choice and college enrollment

We next use our estimated model to quantitatively assess how much of the gender gap is attributable to changes in automation between 1980 to 2000. We incorporate local variation in routinization to assess the impact on college-going based on the commuting zone of residence. We then simulate the counterfactual trajectory of occupation choices for the 1979 cohort assuming that automation was the *only* change from 1980 to 2000 that impacted skill prices. All other primitive parameters, including the utility value for home-staying, are kept constant.[26]

Table 7 reports our simulated college enrollment rates between 1980 to 2000. Although routinization increased the college attendance rate for both men and women, the growth rate for women is ten times as large. Female enrollment grew 6 percentage points, accounting for 63.2% of the observed 9.5 percentage point change between 1980 to 2000. In contrast, male enrollment grew by only 0.6 percentage points, accounting for 23.1% of the observed 2.6 percentage point change. The growth in college-going is driven by the decreasing returns to pink-collar occupations relative to white-collar occupations. Between 1980 to 2000, we simulate a rise of 18.5 percentage points in white-collar jobs, with the majority of this change driven by the shift out of pink-collar jobs (17.7 percentage points). The simulated change in occupation shares is consistent with the empirical fact that many female-dominated occupations disappeared from the non-college labor market over time, highlighted in Figure 3. By way of comparison, the share of men who left blue-collar occupations and entered white collar occupations was only one-tenth as large, at 1.2 and 1.8 percentage points respectively. Lastly, our simulation predicts a slight rise in the proportion of people that leave the labor

[26]However, labor force participation may still evolve over time if routinization changed the difference in utility from working versus not working.

force. This finding suggests that routinization decreased demand for certain workers, which aligns with prior findings of the negative impact of automation on labor force participation (Grigoli et al., 2020).

7 Conclusion

The college gender gap reversed in 1970-1980 when women exceeded men in college enrollment. This came as a surprise to social scientists, who anticipated that male and female enrollment rates would eventually converge. We argue that women's greater enrollment is partly attributable to their worse outside job options. We establish two stylized facts based on the premise that the non-college labor market is highly polarized by gender, in that most occupations were male- or female-dominated and few occupations were gender-equal. First, non-college occupations dominated by men tend to pay better than those dominated by women, suggesting that job opportunities may be worse for high school graduates if they are female. Second, this discrepancy grew over time as automation displaced routine-intensive occupations, which employed the majority of young, working non-college women.

Informed by these stylized facts, we instrument for routinization. Our instrument predicts the share of occupations intensive in administrative activity based on job posting data from major newspapers in 1950-2000. The intuition behind our instrument is that industries with higher administrative activity involve more routine tasks, and local labor markets with greater historic shares of these industries would experience more routinization over time. Consistent with this intuition, our first stage regressions show that local labor markets with higher predicted administrative shares in 1950 experienced greater routinization as workplaces automated. This decline led to significant enrollment growth among 18-25 year old women, but effects for men are directionally smaller and not systematically significant. We estimate that moving from a commuting zone which experienced the 25th percentile of routinization to one which experienced the 75th percentile of routinization corresponds to a 3.34 rise in female enrollment.

To investigate the mechanisms that explain these results at the individual level, we develop a two-period discrete choice model. The model embeds instrumental variation from the job posting data to examine how routinization affects the value of different skills. Using a maximum likelihood procedure, we find that gender differences in skills lead men to sort into manual-intensive work and women into routine-intensive work. The resulting gender polarization among non-college occupations translates to a comparative advantage for men in non-college work in general, given the greater pay in manual occupations relative to administrative occupations. Over time, automation decreased the value of administrative skill in routine-intensive work, lowering the opportunities for non-college women and exacerbating their comparative disadvantage in non-college work. The model argues 1) that women's college premium increased relative to men's over time and 2) that the *efficient* college enrollment rate for women is higher than for men given men's comparative advantage in non-college work.

Given prior research showing that boys face greater struggles in school (Becker et al., 2010; Bertrand and Pan, 2013; Cappelen et al., 2019; Goldin et al., 2006), popular media has framed the college gender gap as a problem rooted in men's "under-investment" in college. Our results indicate that men's relative "under-investment" is natural given that their job options are plentiful and lucrative even with only a high school diploma. Similarly, women's relative "over-investment" is a rational response to their bleak non-college job options. Given the gender-based sorting we document in the non-college labor market, we argue that it is efficient for a gender gap to exist.

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Table 1: Change in Occupation Groups, 1960-2000

	Share among 18-30 Year Old Workers							
	Females (%)				Males (%)			
	1960-2000	1960	1980	2000	1960-2000	1960	1980	2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Office and Administrative Support Occupations	-19.55	45.23	35.17	25.68	1.05	7.64	6.84	8.69
Production Occupations	-8.13	13.68	10.50	5.55	-6.01	17.73	17.73	11.72
Agriculture and Construction Occupations	-0.48	1.19	0.82	0.71	4.34	8.84	13.81	13.18
Installation, Maintenance, and Repair Workers	0.26	0.16	0.40	0.41	0.67	6.42	7.54	7.09
Transportation and Material Moving Occupations	1.11	0.86	2.81	1.97	-4.85	15.23	13.91	10.38
Computer, Mathematical, Engineering, and Science Occupations	2.30	1.06	2.41	3.36	1.13	6.29	5.91	7.42
Service (Food, Maintenance, Sales) Occupations	4.17	23.90	20.69	28.06	10.74	10.96	15.13	21.70
Healthcare and Protective Occupations	4.74	6.39	10.60	11.13	2.55	2.65	4.26	5.20
Community, Social Services, Education, Arts, Media Occupations	6.70	5.14	8.75	11.84	1.95	3.23	4.48	5.19
Management, Business, Science, Arts Occupations	9.21	2.05	7.85	11.26	0.36	9.05	10.39	9.42

Notes: Occupation groups as share of 18-30 year old workforce. Columns (1) and (5) report the change (in percentage points) from 1960 to 2000. Data from Census.

Table 2: OLS Regression of College Enrollment on Routinization

	College enrollment			
	(1)	(2)	(3)	(4)
	A. Women			
Routinization	0.416	0.448	0.431	0.467
	(0.096)***	(0.098)***	(0.094)***	(0.095)***
Observations	3610	3610	3610	3610
	B. Men			
Routinization	0.215	0.221	0.235	0.243
	(0.120)*	(0.122)*	(0.128)*	(0.130)*
Observations	3610	3610	3610	3610
Commuting zone FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Median cognitive earnings		✓		✓
Lagged RTI share			✓	✓

OLS regressions of enrollment on instruments at the commuting zone-year level. All regressions include demographic controls for the proportion of female, Black, and Hispanic residents and by 10-year age bin. All regressions also control for U.S. census division, year, commuting zone, labor force participation, manual occupation share, and 10-year lagged major industry shares: services, manufacturing, retail, and mining. Columns (2) and (4) add median annual log earnings for occupations in the top third of abstract-intensive tasks. Columns (3) and (4) additionally control for the 10-year lag of RTI share. Standard errors clustered at commuting zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: First Stage Regression of Routinization on Instruments

	Routinization			
	(1)	(2)	(3)	(4)
Administrative share IV	0.387	0.383	0.388	0.383
	(0.026)***	(0.027)***	(0.027)***	(0.027)***
F-statistic	214.572	204.993	204.654	201.452
Observations	3610	3610	3610	3610
Commuting zone FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Median cognitive earnings		✓		✓
Lagged RTI share			✓	✓

First stage regression of RTI share on instruments. All regressions include demographic controls for the proportion of female, Black, and Hispanic residents and by 10-year age bin. All regressions also control for U.S. census division, year, commuting zone, labor force participation, manual occupation share, and 10-year lagged major industry shares: services, manufacturing, retail, and mining. Columns (2) and (4) add median annual log earnings for occupations in the top third of abstract- intensive tasks. Columns (3) and (4) additionally control for the 10-year lag of the share of high-RTI occupations. Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of Adao et al. (2019). Olea-Pflueger F-statistics reported using AKM (2019) standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Reduced Form and Second Stage Regressions

	College enrollment			
	(1)	(2)	(3)	(4)
	A. Reduced form regression, women			
Administrative share IV	0.224	0.232	0.224	0.232
	(0.062)***	(0.062)***	(0.061)***	(0.061)***
Observations	3610	3610	3610	3610
	B. Reduced form regression, men			
Administrative share IV	0.169	0.170	0.169	0.170
	(0.092)*	(0.092)*	(0.091)*	(0.091)*
Observations	3610	3610	3610	3610
	C. Second stage regression, women			
Routinization	0.578	0.606	0.578	0.606
	(0.163)***	(0.166)***	(0.160)***	(0.161)***
	[0.258,0.898]	[0.281,0.931]	[0.265,0.891]	[0.291,0.922]
First Stage F-statistic	214.572	204.993	204.654	201.452
Observations	3610	3610	3610	3610
	D. Second stage regression, men			
Routinization	0.436	0.444	0.436	0.444
	(0.236)*	(0.238)*	(0.232)*	(0.234)*
	[-0.026,0.898]	[-0.022,0.910]	[-0.019,0.891]	[-0.015,0.904]
First Stage F-statistic	214.572	204.993	204.654	201.452
Observations	3610	3610	3610	3610
Commuting zone FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Median cognitive earnings		✓		✓
Lagged RTI share			✓	✓

This table presents the reduced form (panels A-B) and second stage (panels C-D) estimates. Panels A and C display the estimates for women, while panels B and D display the estimates for men. All regressions include demographic controls for the proportion of female, Black, and Hispanic residents and by 10-year age bin. All regressions also control for U.S. census division, year, commuting zone, labor force participation, manual occupation share, and 10-year lagged major industry shares: services, manufacturing, retail, and mining. Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of Adao et al. (2019). Montiel Olea-Pflueger first stage F-statistics reported using AKM (2019) standard errors. The second stage estimates include Anderson-Rubin (1949) weak instrument robust confidence intervals using the AKM (2019) correction procedure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Second Stage Regressions, Additional Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A: Female Enrollment			
Routinization	0.495	0.607	0.628	0.736	0.365	0.548	0.784
	(0.167)***	(0.158)***	(0.161)***	(0.242)***	(0.145)**	(0.145)***	(0.145)***
	[0.167,0.822]	[0.297,0.917]	[0.312,0.944]	[0.263,1.210]	[0.080,0.650]	[0.213,0.884]	[0.350,1.219]
F-statistic	137.280	205.558	182.001	51.040	203.540	161.233	111.715
Observations	3610	3600	3610	3610	3610	3610	3610
				B: Male Enrollment			
Routinization	0.315	0.503	0.441	0.540	0.254	0.432	0.616
	(0.266)	(0.234)**	(0.238)*	(0.315)*	(0.196)	(0.196)	(0.196)*
	[-0.207,0.838]	[0.044,0.961]	[-0.025,0.907]	[-0.077,1.157]	[-0.129,0.638]	[-0.101,0.964]	[-0.048,1.280]
F-statistic	137.280	205.558	182.001	51.040	203.540	161.233	111.715
Observations	3610	3600	3610	3610	3610	3610	3610
Minimum controls	✓						
Excluding Boston and NYC		✓					
Control for abstract occupation share			✓				
RTI share: non-college workers	✓	✓	✓		✓	✓	✓
RTI share: college and non-college workers				✓			
IV: Administrative Share (top third)		✓	✓	✓			
IV: Administrative Share (top half)					✓		
IV: Administrative Activities						✓	
IV: Clerical Requirements							✓

Two stage least squares regressions, additional specifications. Column (1) uses a minimum set of controls: total commuting zone population, year dummies, census region dummies, commuting zone dummies, manual occupation share, proportion by gender, race, and ten-year age bin. Columns (2)-(7) start from the basic specification of Table 4 Column (1). Column (2) excludes commuting zones that contain Boston and New York City. Column (3) additionally controls for abstract occupation share. Column (4) uses the routinization of all workers, rather than only non-college workers used in the main specification. The IV in column (5) uses the share of occupations in the top half of administrative activity, rather than the top third. Column (6) uses the administrative activities IV, and column (7) the clerical requirements IV. Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of Adao et al. (2019). Montiel Olea-Pflueger F-statistics reported using AKM (2019) standard errors. Anderson-Rubin (1949) confidence intervals reported using AKM (2019) correction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Goodness of Model Fit

	Women		Men	
	NLSY79	Sim	NLSY79	Sim
	(1)	(2)	(3)	(4)
Occupation choices				
White collar	0.409	0.407	0.369	0.384
Blue collar	0.055	0.056	0.509	0.497
Pink collar	0.337	0.328	0.059	0.050
Not working	0.199	0.209	0.064	0.069
Average log wages by occupation				
White collar	1.907	1.956	2.069	2.110
Blue collar	1.631	1.622	1.779	1.801
Pink collar	1.416	1.444	1.570	1.571
Education choices				
High school	0.395	0.368	0.517	0.504
College	0.605	0.632	0.483	0.496

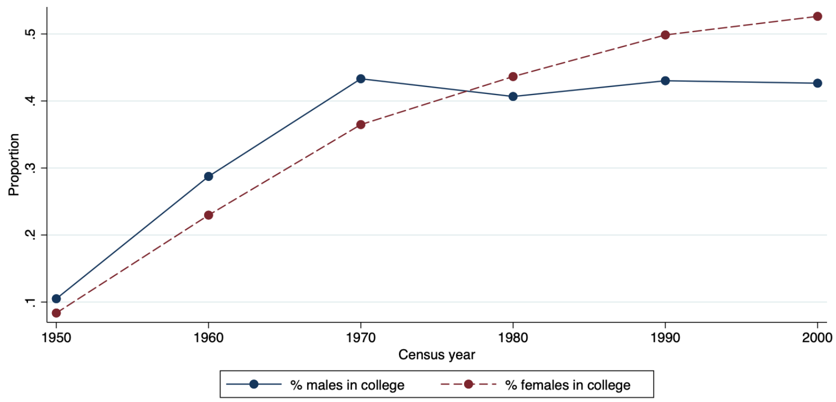
This table compares conditional moments from the model simulation with those from the NLSY79 data. Columns (1)-(2) compare moments for female workers and Columns (3)-(4) compare moments for male workers. The top panel displays occupation choices, the middle panel displays log average wages, and the bottom panel displays education choices.

Table 7: Simulated Changes in Occupation and Education due to Routinization

	Women				Men			
Year	1980	1990	2000	1980-2000	1980	1990	2000	1980-2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Occupation choices								
White collar	0.407	0.542	0.592	0.185	0.384	0.396	0.402	0.018
Blue collar	0.056	0.063	0.064	0.008	0.497	0.489	0.485	-0.012
Pink collar	0.328	0.194	0.151	-0.177	0.050	0.050	0.050	0.000
Not working	0.209	0.201	0.193	-0.016	0.069	0.065	0.063	-0.006
Education choices								
High school	0.368	0.322	0.308	-0.060	0.504	0.500	0.498	-0.006
College	0.632	0.678	0.692	0.060	0.496	0.500	0.502	0.006

This table presents simulated education and occupation choices for the NLSY79 cohort. Columns (1)-(3) report simulated choices for women based on changes in predicted RTI share over time. Column (4) reports the difference in simulated choices for women from 1980 to 2000. Columns (5)-(7) report simulated choices for men based on changes in predicted RTI share over time. Column (8) reports the difference in simulated choices for men from 1980 to 2000.

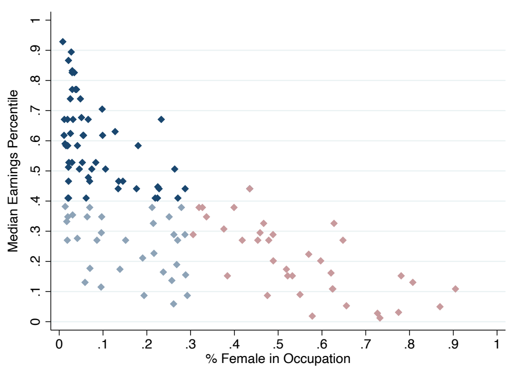
Figure 1: College Enrollment by Gender, 1950-2000



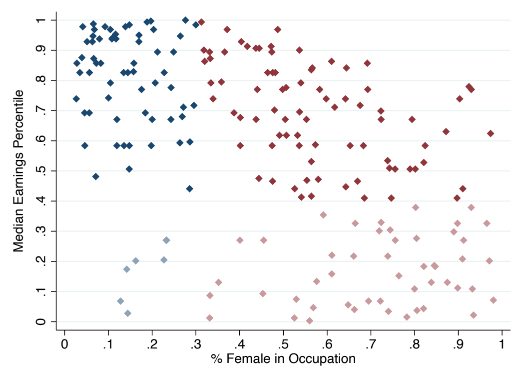
Proportion of 18-25 year olds ever enrolled in college. Solid lines represent male enrollment and dashed lines represent female enrollment. Data from the U.S. census.

Figure 2: Occupations by Gender Composition and Percentile Median Earnings, 2000

(a) Non-College Occupations



(b) College Occupations

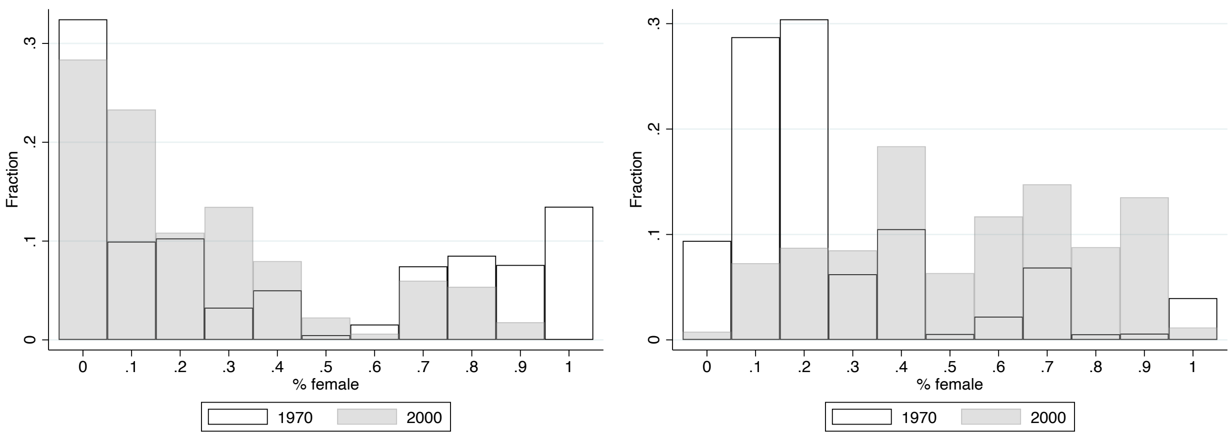


Occupations by proportion female and median annual earnings percentile in 2000. Panel a depicts occupations with 50% or fewer college graduates in 2000. Panel b depicts occupations with 50% or more college graduates in 2000. Navy markers indicate occupations where women comprise less than 30% of all workers, with dark navy markers representing occupations with earnings above the 40th percentile and light navy markers representing occupations with earnings below the 40th percentile. Maroon markers indicate occupations where women comprise 30% or more of all workers. Data from the U.S. census.

Figure 3: Occupational Dispersion by Gender Composition

(a) Non-College Occupations

(b) College Occupations

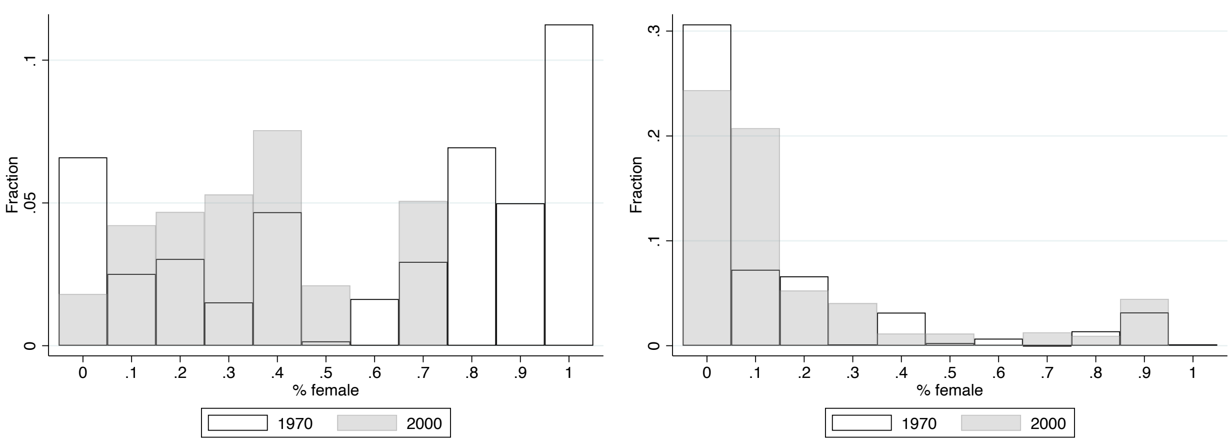


Distribution of occupations by proportion female in 1970 and 2000 for "non-college" occupations (a) and "college" occupations (b). "Non-college" occupations are those with 50% or fewer college graduates, while "college" occupations are those with over 50% college graduates. The designation of occupations as "college" or "non-college" changes each year based on the education composition of workers. Individuals aged 18-30 years old. Data from the U.S. census.

Figure 4: Occupational Dispersion by Gender Composition, Non-College Occupations

(a) Routinizable Occupations

(b) Non-Routinizable Occupations



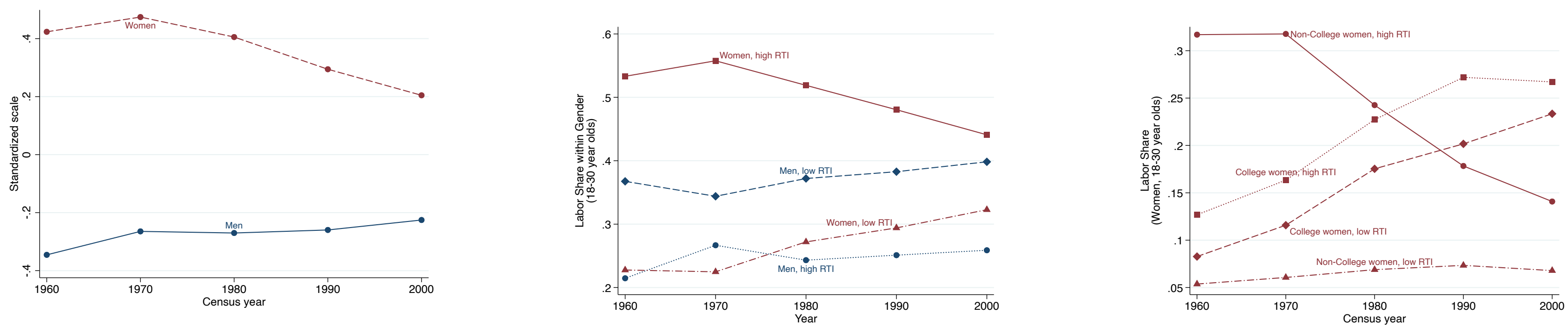
Distribution of occupations by proportion female in 1970 and 2000 for non-college occupations. Panel a shows routinizable occupations (top third of RTI), while panel b shows non-routinizable occupations (below the top 3rd of RTI). Individuals aged 18-30 years old. Data from the U.S. census and Autor and Dorn (2013).

Figure 5: Changes in Routine Task Intensity (RTI), 1960-2000

(a) RTI by Gender

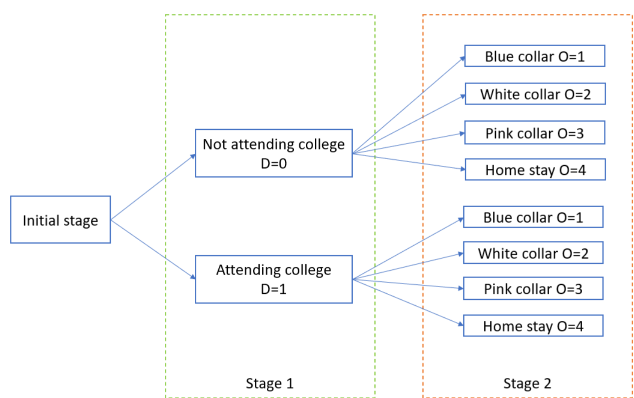
(b) Low vs. High-RTI Labor Share, By Gender

(c) Low vs. High-RTI Labor Share, By Education (Women)



Panel a plots standardized routine task intensity (RTI) of work held by men and women. Panels b and c plot labor share by high versus low RTI occupations. Panel b plots the labor share by RTI among women (red) and the labor share by RTI among men (blue). Panel c plots the labor share among women by RTI and education. Data from the U.S. census and Autor and Dorn (2013). 18-30 year olds.

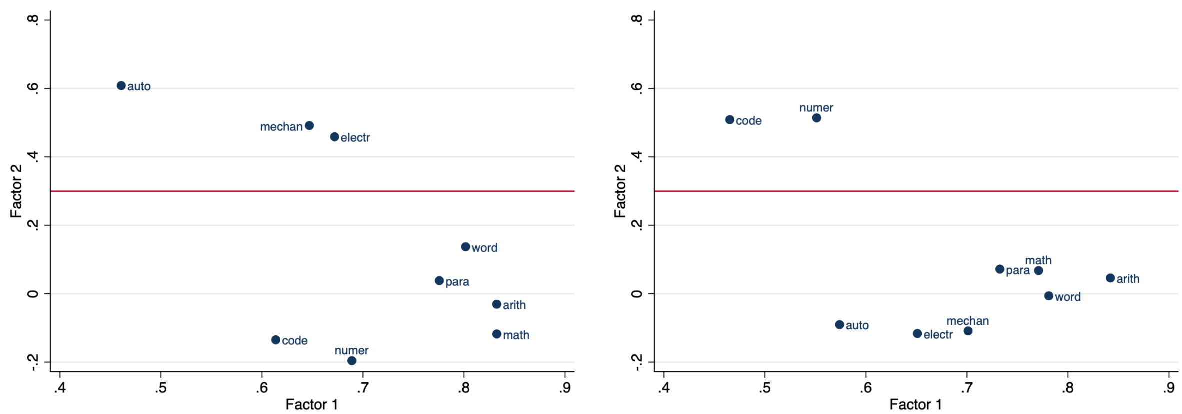
Figure 6: Two Period Dynamic Discrete Choice Model



Description of structural discrete choice model. In Stage 1, individuals decide whether or not to attend college. In Stage 2, they choose their occupation from four choices: blue collar, white collar, pink collar, or home staying. The model is solved via backward induction.

Figure 7: Factor Analysis Loadings

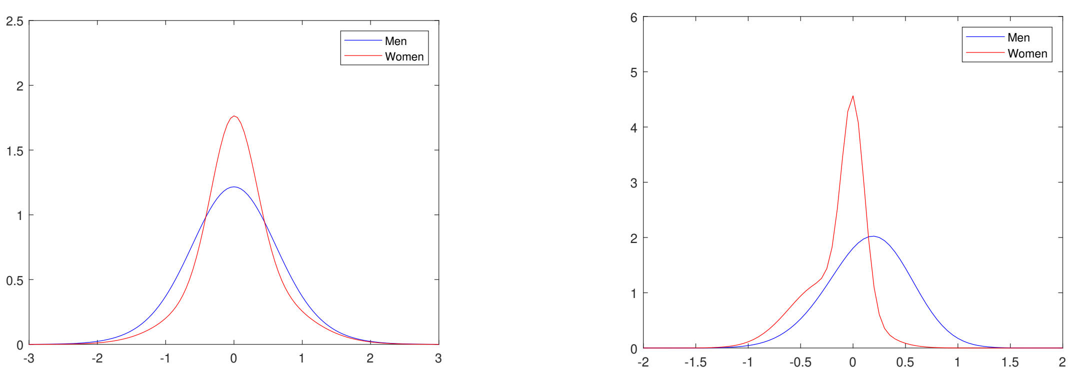
(a) Male (b) Female



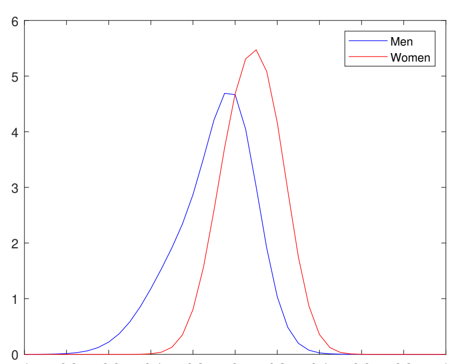
Loadings calculated from exploratory factor analysis (quartimax rotation). The red horizontal line marks the statistically significant threshold (see Diekhoff, 1992; Sheskin, 2004). arith = arithmetic reasoning; auto= automotive information and shop information; code = coding speed; electr = electronics information; math = mathematics knowledge; mechan = mechanical comprehension; numer = numerical operations; para = paragraph comprehension; word = word knowledge.

Figure 8: Distribution of Skills by Gender

(a) Cognitive Skill (b) Mechanical Skill

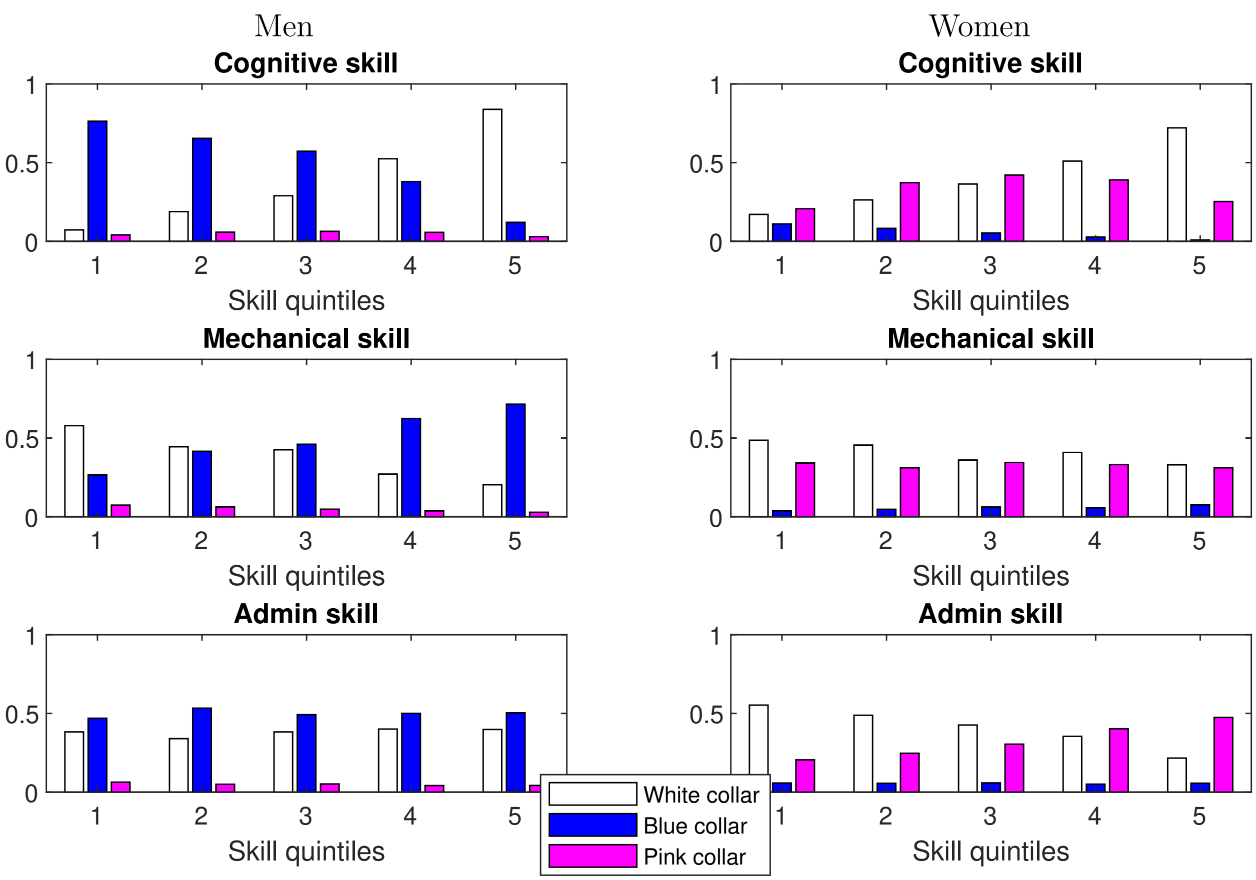


(c) Administrative Skill



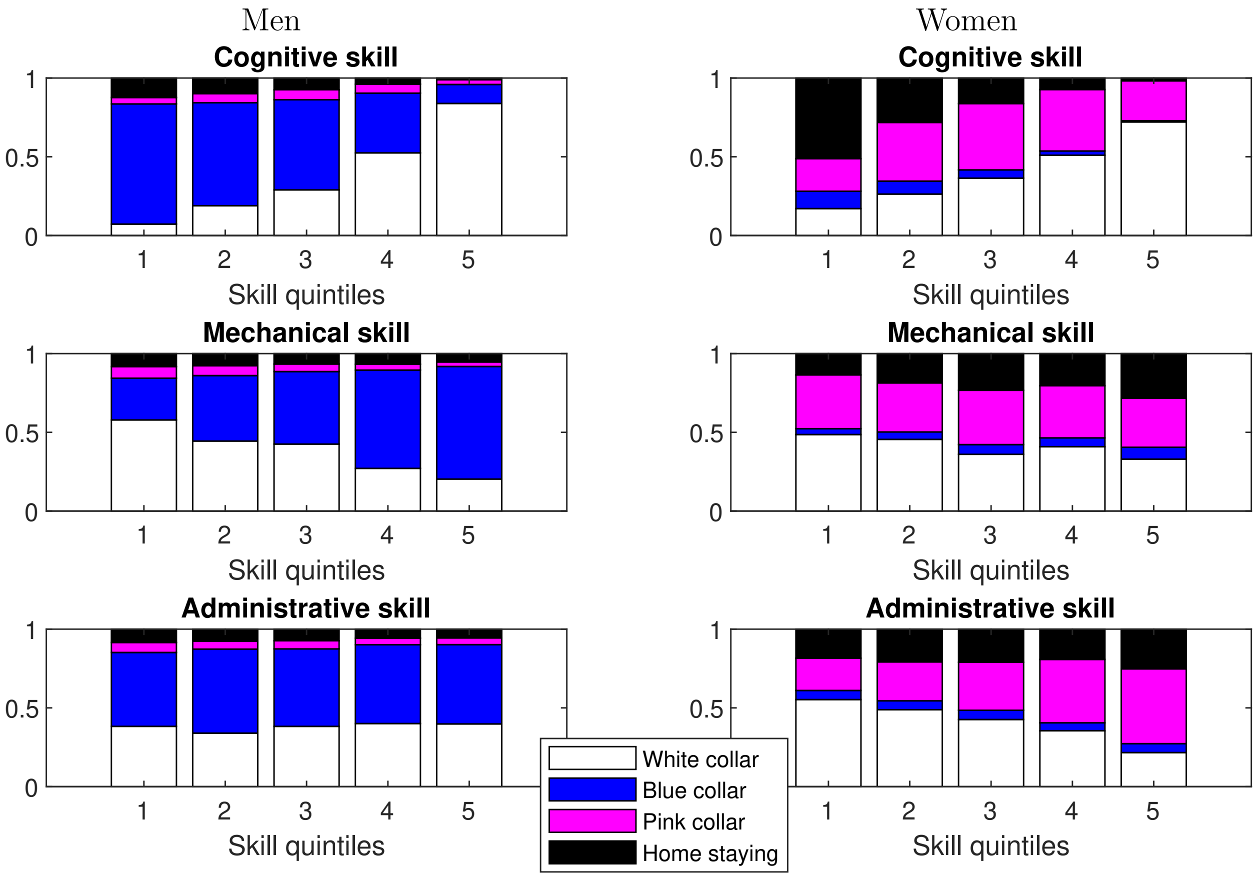
Distribution of skills by gender. The blue distribution is for men, and the red distribution is for women. Panel (a) presents the estimated distribution of cognitive skill, while panels (b) and (c) present analogous results for mechanical skill and administrative skill, respectively.

Figure 9: Occupational Returns by Skill Quintile and Gender



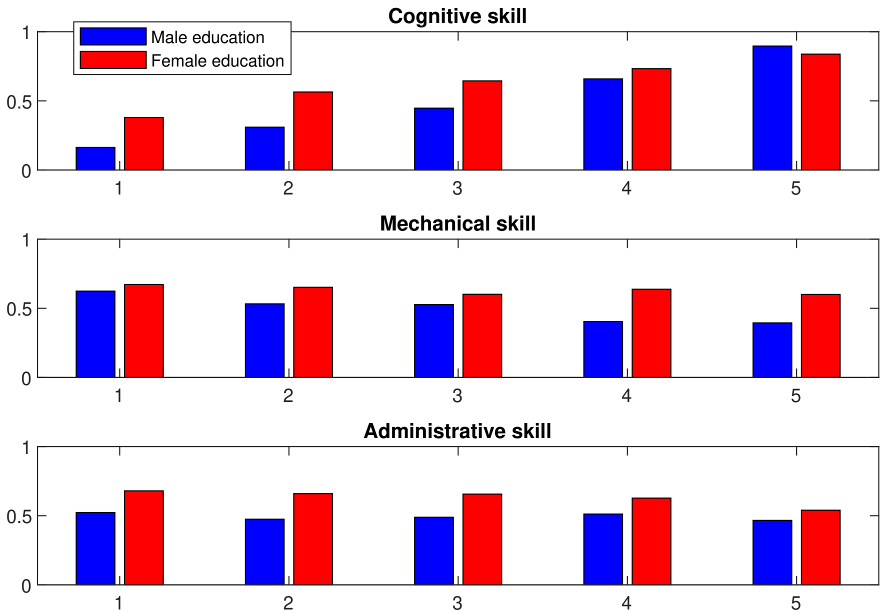
We simulate each individual 200 times based on the estimates of the model to calculate average returns to each occupations by skill quintiles and gender. Returns include both the wage return and non-pecuniary returns. The upper panels present the effect of cognitive skill by gender, integrating out the effect of the other two dimensions of ability. The middle panel and the lower panel present analogous results for mechanical skill and administrative skill, respectively.

Figure 10: Occupation Choice Distribution by Skill Quintile and Gender



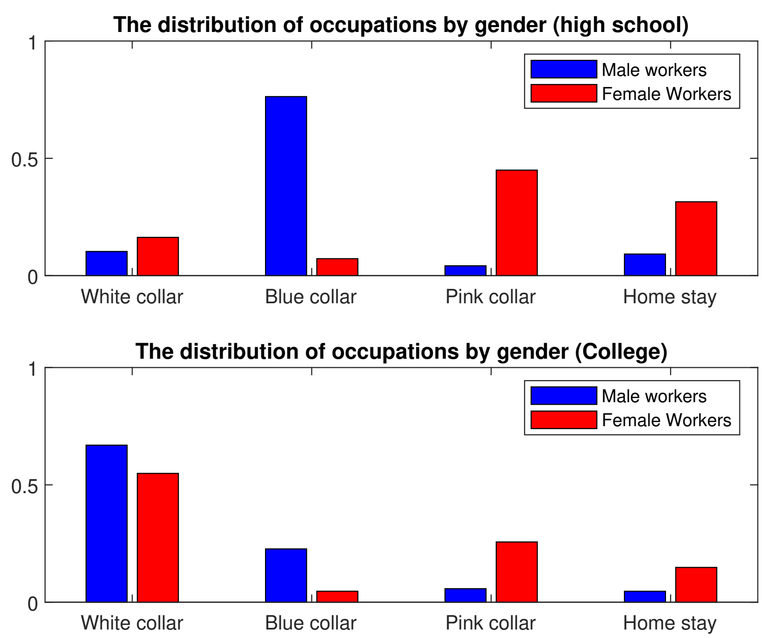
We simulate each individual 200 times based on the estimates of the model to calculate the distribution of occupation choices by skill quintiles and gender. The upper panels present the effect of cognitive skill by gender, integrating out the effect of the other two dimensions of skills, while the middle panel and the lower panel present analogous results for mechanical skill and administrative skill, respectively.

Figure 11: College Attendance Rates by Skill Quintiles



We simulate each individual 200 times based on the estimates of the model to calculate the college attendance rate by skill quintile and gender. The vertical axis is the fraction of workers in each skill group. The upper panels present the effect of cognitive skill, integrating out the effect of the other two dimensions of skills. The middle panel and lower panel present analogous results for mechanical skill and administrative skill, respectively.

Figure 12: Distribution of Occupations by Gender and Education



We simulate each individual 200 times based on the estimates of the model to calculate the occupation distribution by gender and education levels. The vertical axis is the fraction of workers in each occupation group. The upper panels present occupation distribution for college-goer, with blue bars for men and red bars for women. The lower panel present present occupation distribution for high school graduates, with blue bars for men and red bars for women.

Online Appendix - For Online Publication

A Data Appendix

A.1 Census microdata

Our first data sets come from the decennial census microdata from 1950 to 2000, which are conducted by the U.S. Census Bureau and made publicly available through the Integrated Public Use Microdata Series (IPUMS, Ruggles et al. (2021)). For enrollment, we only examine 18-25 year olds to ensure that we only detect changes in education among those closest to college enrollment age. Following Acemoglu and Autor (2011), we restrict the sample to full-time (at least 35 hours worked per week), full-year (at least 40 weeks worked per year) workers.

The college enrollment variable is constructed using the harmonized EDUCD variable. Individuals are coded as college enrollees if they report having at least some college education. They are coded as never having enrolled in college if their highest reported level of educational attainment was a high school diploma or equivalent. Those who did not report an education level were excluded from the analysis.

Annual earnings data is obtained from the variable INCWAGE, the pre-tax individual income from wages and salary. Annual earnings are only computed for workers who report working for wages or salary. We exclude individuals who report being self-employed or an unpaid family worker and individuals who report working no weeks in the previous year. Annual earnings are topcoded at the pre-determined Census topcode levels, which vary from year to year. They are bottom coded as the 1st percentile of reported earnings for each year. All earnings are inflated to 2008 dollars.

All regressions are conducted at the commuting zone-year level. We merge the census data to corresponding commuting zones using the crosswalks provided by Autor and Dorn (2013). Demographic characteristics, occupations, education, earnings, and work variables are collapsed to the commuting zone level using labor supply weights calculated following the method of Acemoglu and Autor (2011).

Appendix Table A.1 presents summary statistics by decade from 1960 to 2000. Each variable represents the average across commuting zones. Female enrollment increases steadily over the decades, while male enrollment quickly rises from 1960-1970, then declines in 1980 before rising again. The proportion of women in each commuting zone stays constant at 50-51%, and the proportion of blacks also hold constant at 8% over our analysis period. The share of Hispanics grows steadily over time, from 3% in 1960 to 8% in 2000.

A.2 Data from Autor and Dorn (2013)

To obtain information on work content, we merge the census data to the occupational task intensity data compiled by Autor and Dorn (2013) using the OCC1990 variable, which is harmonized across all years. Autor and Dorn (2013)'s Routine Task Intensity (RTI) measure is the primary measure we use to determine how routine-intensive an occupation is. Following Autor and Dorn (2013), we classify an occupation as highly routine-intensive occupation if its RTI measure falls in the top third of all RTI in 1980. Out of 330 total occupations, 113 occupations fit this criterion.

Our main analysis concerns RTI share, the proportion of jobs in a commuting zone that are highly routine intensive. Routinization, the main endogenous regressor in the two stage least squares approach, is the reduction in RTI share from 1950 base levels. We restrict the RTI share measure to only 25-65 year olds. If youth choose to enroll in college for reasons not captured by our data, that would mechanically lower labor share and bias the estimated causal relationship between labor share and college enrollment. We therefore exclude 18-25 year olds to avoid these simultaneity concerns. In our main specifications, we focus on the RTI share among non-college workers, since we aim to isolate the impact of routinization on non-college employment opportunities. Appendix Table A.1 summarizes this RTI share measure, averaged over all commuting zones. The RTI share among non-college workers rises from 1960 to 1980, from an average of 15.4% across all commuting zones to 21.5%. It falls from 1980 on, reaching 13.6% in 2000. These trends are roughly consistent with the change in RTI share depicted in Figure 5.

We also use Autor and Dorn (2013)'s measures on the manual and abstract task content of occupations as control variables in our two stage least squares (2SLS) approach. Specifically, we control for *predicted manual and abstract occupation share*, which are constructed in parallel ways. For both measures, we interact a commuting zone's 1950 industry composition with the share of occupations in the top third of manual or abstract content.

$$\text{manual occupation share}_{ct} = \sum_i E_{i,c,1950} \frac{\sum_k L_{i,k,1950} \mathbf{1}[\text{manual}_{k,1980} > \text{manual}^{P66}_{1980}]}{\sum_k L_{i,k,1950}}$$

$$\text{abstract occupation share}_{ct} = \sum_i E_{i,c,1950} \frac{\sum_k L_{i,k,1950} \mathbf{1}[\text{abstract}_{k,1980} > \text{abstract}^{P66}_{1980}]}{\sum_k L_{i,k,1950}}$$

where i indexes industry, c indexes commuting zone, and k indexes occupation. $E_{i,c,1950}$ is the share of industry i in commuting zone c in 1950. $L_{i,k,1950}$ is the number of workers in industry i, occupation k in 1950. We follow Autor and Dorn (2013) and define highly manual and highly abstract occupations based on the 1980 distribution, which was when RTI peaked in the census data. $\mathbf{1}[\text{manual}_{k,1980} > \text{manual}^{P66}_{1980}]$ equals 1 for occupations in the top third of manual content in 1980 and 0 otherwise. $\mathbf{1}[\text{abstract}_{k,1980} > \text{abstract}^{P66}_{1980}]$ equals 1 for occupations in the top third of abstract content in 1980 and 0 otherwise. We construct our controls for manual and abstract occupation share in this way since contemporaneous occupational shares may depend on employment shares and education decisions.

A.3 Data from Atalay et al. (2020)

Our instrumental variables come from Atalay et al. (2020). To extract occupational characteristics, Atalay et al. (2020) perform textual analysis on advertisements for job vacancies from *The Boston Globe*, *The New York Times*, and *The Wall Street Journal* from 1940 to 2000. For each occupation in each year, they characterize the work styles, knowledge requirements, and task content desired by employers based on measures used in the literature. They compile one set of measures to match information in the Occupational Information Network (O*NET), which describes the activities, tasks, and skills associated with thousands of jobs throughout the U.S. economy (see Occupational Information Network, 2022 and Hershbein and Kahn (2018)).

Using this set of measures, we construct our main instrumental variable, which predicts the administrative share in a commuting zone. We define administrative share as the proportion of jobs that are in the top third of administrative activity based on the 1950 occupational distribution, when administrative activity was at its highest. According to O*NET, administrative activity consists of "performing day-to-day administrative tasks such as maintaining information files and processing paperwork" (O*NET Work Activity 4Ac1; Occupational Information Network, 2022). Occupations that involve high amounts of administrative activity include receptionists, information clerks, secretaries, and administrative assistants. Atalay et al. (2020) compile an occupation-level measure of administrative activity based on mentions per job posting, using keywords such as "filing," "paperwork," "administrative," and "typing". Summary statistics in Appendix Table A.1 show that the administrative share instrument exhibits a sizable decline over time, from 0.298 in 1960 to 0.0775 in 2000. This is consistent with the decline in RTI share due to routinization during this time period.

We also use predicted administrative activity as a separate instrument. Rather than as a share, this instrument is measured as the frequency of keyword mentions ("administrative", "paperwork", "typing", and "filing") per job posting. We construct the administrative activity instrument as follows:

$$\text{administrative activity}_{ct} = \sum_i E_{i,c,1950} \sum_k \text{admin}_{i,k,t}$$

where $\text{admin}_{i,k,t}$ represents the average number of keywords for administrative activity per job posting associated with occupation k in industry i at year t. $E_{i,c,1950}$ is the share of industry i in commuting zone c in 1950.

Our last instrument is constructed from Atalay et al. (2020)'s data on *clerical requirements*, which corresponds to whether an occupation requires "knowledge of administrative and clerical procedures and systems such as word processing, managing files and records, stenography and transcription, designing forms, and other office procedures and terminology" (O*NET Knowledge Requirement 2C1b; Occupational Information Network, 2022). Examples of occupations high in clerical requirements are word processors, typists, secretaries, administrative assistants, and office clerks. Atalay et al. (2020) classify a job ad as specifying clerical requirements if it includes words such as "clerical," "secretarial," "stenography," or "typing".[27] It is constructed in a parallel form to the administrative activity

[27] The data set has a few other variables related to routine work, but they do not isolate routine tasks as cleanly as the administrative activity or clerical requirements variables. O*NET includes descriptions of whether an occupation requires *knowledge of administration and management* (O*NET Knowledge Requirement 2C1a). It involves overseeing, managing, and coordinating with others, which are considered abstract tasks that would make an occupation harder to automate. Atalay et al. (2020) also characterize occupations based on the task content classification of Spitz-Oener (2006). Specifically, Spitz-Oener (2006) found that *routine cognitive* tasks made an occupation more susceptible to automation, ceteris paribus. However, in the Atalay et al. (2020) data, an occupation's routine cognitive task content depends on ad words such as "correcting," "calculating," "measuring," "fixing," and "rectifying," which are quite vague and encompass a

instrument:

$$\text{clerical requirements}_{ct} = \sum_i E_{i,c,1950} \sum_k \text{clerreq}_{i,k,t}$$

where $\text{clerreq}_{i,k,t}$ represents the average number of keywords for clerical requirements per job posting associated with occupation k in industry i at year t. $E_{i,c,1950}$ is the share of industry i in commuting zone c in 1950.

A.4 National Longitudinal Survey of Youth 1979

The National Longitudinal Survey of Youth 1979 (NLSY79) surveys the same 12,686 from 1979 until present day. Surveys were conducted annually until 1994, and then once every two years. We restrict our sample to the 11,155 individuals who finished at least 12th grade or hold a GED degree. We then further drop individuals who were employed but did not have wage information between 25 to 35, leaving a sample size of 8,540. Finally, we exclude individuals who were missing ASVAB test scores or relevant family background information. Our final sample consists of 2,505 men and 2,490 women. Appendix Table A.3 presents summary statistics for key variables in the model.

A.4.1 Measuring skill heterogeneity

We use the NLSY79's Armed Services Vocational Aptitude Battery (ASVAB) test scores to construct multi-dimensional skill profiles at the individual level. In 1981, over 90% of NLSY79 respondents completed the ASVAB. The ASVAB is comprised of nine subtests: arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge, numerical operations, coding speed, automotive and shop information, electronics information, and mechanical comprehension. Some of these subtests are used to construct the Armed Forces Qualification Test (AFQT) score, a common measure of cognitive ability in the literature on skill returns.[28] Rather than use AFQT directly, we take a different approach by using exploratory factor analysis (EFA) on all nine subtests to construct multiple dimensions of skill. This technique is frequently used to avoid ambiguity in the number of latent factors and the underlying factor structure of a set of variables (Diekhoff, 1992).

Exploratory Factor Analysis (EFA) enables us to make use of the correlation structure in scores among the nine ASVAB subtests when constructing our skill measures. The analysis suggests that two separate skills ("factors") are necessary to explain the variation in ASVAB scores.[29] Figure 7 displays the estimated factor loadings. For both men and women, the first factor has significant loadings on all subtests. It is highest for arithmetic reasoning, word

greater variety of tasks than those that were routinized.

[28]Different studies use slightly different subtests to construct AFQT scores. Arithmetic reasoning, paragraph comprehension, and word knowledge are commonly used. However, mathematics knowledge, numerical operations and coding speed have also been adopted to construct the AFQT (see, among many others, Neal and Johnson, 1996; Cameron and Heckman, 1998; Heckman and Cameron, 2001; Ellwood, Kane, et al., 2000; Kautz and Heckman, 2014; Heckman et al., 2006).

[29]Our EFA approach follows that of Prada and Urzúa (2017), who also find that a two-factor structure was most appropriate for explaining the variance in ASVAB test scores for men.

knowledge, mathematics knowledge, and paragraph comprehension, which are designed to measure cognitive ability and comprise the main components of the AFQT.

There are gender differences in factor loadings for the second factor. For men, loadings are statistically significant only for the automotive and shop information, electronics information, and mechanical comprehension.[30] The United States Department of Defense designed these subtests to measure mechanical skill, since they evaluate the ability to solve simple mechanics problems and understand basic mechanics principles (Welsh et al., 1990). For women, loadings for the second factor are statistically significant only for coding speed and numerical operations. The Department of Defense classifies these subtests into the administrative qualification area, since they measure the ability to memorize strings of letters or perform quick arithmetic operations on the fly (ASVAB Prep Tests, 2022).

B Robustness Appendix

B.1 Two Stage Least Squares Approach: Additional Instruments

The administrative activity and clerical requirement instruments are constructed similarly and use similar identification assumptions. In both cases, we obtain variation at the commuting zone level by interacting the frequency of mentions in job postings with the industry share in 1950:

$$\mathrm{IV}_{ct} = \sum_{i=1}^{I} E_{i,c,1950} \sum_{k \in i} Z_{kt} \tag{10}$$

where Z_{kt} represents the number of mentions of administrative activity or clerical requirements per job posting for occupation k in year t. All other indices are defined as above.

The intuition is that commuting zones with high historic shares of industries intensive in administrative activity or clerical requirements would experience greater routinization over time. The identifying assumption for these instruments is similar to the identifying assumption for the administrative share instrument. The administrative activity or clerical requirements in an occupation at the national level should only influence enrollment in ways captured by RTI share at the commuting zone level. That is, local omitted variables that influence both RTI share and college enrollment should have negligible influence on the administrative activity or clerical requirements of an occupation at the national level.

Appendix Table A.2 shows the first stage regression estimates in columns (6) and (7). Point estimates are 3.217 for the administrative activities instrument and 1.460 for the clerical requirements instrument ($p < 0.01$). They are larger than the 0.315 to 0.389 estimated using the administrative share instrument, since the units are in terms of mentions per job posting rather than shares. Our estimates indicate that commuting zones predicted to have 1 more mention of administrative activity per 100 job postings in 1950 will experience 3.22 percentage points more routinization in future years. Commuting zones predicted to have 1 more mention of clerical requirements per 100 job postings in 1950 will experience 1.46 percentage points more routinization in future years. Montiel Olea-Pflueger F-statistics are

[30] Factor loadings exceeding 0.3 are considered statistically significant (see Diekhoff, 1992; Sheskin, 2004).

161.23 for the administrative activities instrument and 111.72 for the clerical requirements instrument.

B.2 Structural Model Identification

Our model identification strategy follows those formally laid out in Carneiro et al. (2003) and Prada and Urzúa (2017), so we only sketch out the main components below.

We first identify the loading factors that are exclusive to the cognitive skill measures

$$C_{j,i} = \lambda_j^c \theta_{c,i} + e_{j,i}^c, j = 1, 2, 3, 4$$

We normalize the loading associated with mathematics knowledge to 1 ($\lambda_2^c = 1$) to nonparametrically identify the other three loading factors $\{\lambda_1^c, \lambda_3^c, \lambda_4^c\}$. For example, $\lambda_1^c = \frac{Cov(C_j,C_1)}{Cov(C_j,C_2)} = \frac{\lambda_j^c \lambda_1^c var(\theta_c)}{\lambda_j^c \lambda_2^c var(\theta_c)} = \frac{\lambda_1^c}{\lambda_2^c}$ because λ_2^c has been normalized to be 1. We can then apply Klotarski's theorem to secure nonparametric identification of the distributions of θ_c and $e_{j,i}^c$, with $j = 1, 2, 3, 4$ (Carneiro et al., 2003).

We proceed to summarize how we identify the loading factors in the mechanical skill measures

$$M_{j,i} = \lambda_j^c \theta_{c,i} + \lambda_j^m \theta_{m,i} + e_{j,i}^m, j = 5, 6, 7$$

We specify a linear correlation between $\theta_{c,i}$ and $\theta_{m,i}$:

$$\theta_{m,i} = \alpha_1 \theta_{c,i} + \theta_{1,i}$$

where θ_1 is an additional factor, assumed to be independent of θ_c. The above mechanical skill measure equation can be written as

$$\begin{aligned} M_{j,i} &= \lambda_j^c \theta_{c,i} + \lambda_j^m \theta_{m,i} + e_{j,i}^m \\ &= \lambda_j^c \theta_{c,i} + \lambda_j^m (\alpha_1 \theta_{c,i} + \theta_{1,i}) + e_{j,i}^m \;\; j = 5, 6, 7 \\ &= \beta_j \theta_{c,i} + \lambda_j^m \theta_{1,i} + e_{j,i}^m \end{aligned}$$

where $\beta_j = \lambda_j^c + \lambda_j^m \alpha_1, j = 5, 6, 7$. Under this setup, we can decompose the identification strategy into three steps.

1. Once we identify the variance of cognitive skill $var(\theta_c)$ and the loading factors associated with the cognitive measures, we can recover β_j from $Cov(M_j, C_{j'}) = \lambda_{j'}^c \beta_j var(\theta_c)$.

2. We normalize mathematics knowledge: $\lambda_7^m = 1$. This secures the identification of the other factor loadings λ_5^m and λ_6^m in the mechanical test score system: $\lambda_5^m = \frac{cov(M_5,M_6)}{cov(M_6,M_7)}$ and $\lambda_6^m = \frac{cov(M_5,M_6)}{cov(M_5,M_7)}$. We can then apply Klotarski's theorem to nonparametrically identify the distributions of θ_1 and $e_{j,i}^m$, with $j = 5, 6, 7$.

3. To identify α_1, we assume the factor loading of cognitive skill on automotive shop information test is 0 ($\lambda_5^c = 0$). This implies that the cognitive factor θ_c affects the first mechanical test score M_5 only indirectly, through its correlation with the mechanical factor θ_m. We can then recover α_1 from the equation $\beta_5 = \lambda_5^m \alpha_1$.

Identification for the loading factors in the administrative skill equations follow a similar process. We first impose

$$\theta_{a,i} = \alpha_2 \theta_{c,i} + \theta_{2,i}$$

where θ_2 is an additional factor, assumed to be independent of θ_c. The administrative measure equations can be rewritten as follows:

$$\begin{aligned} A_{j,i} &= \lambda_j^c \theta_{c,i} + \lambda_j^a \theta_{a,i} + e_{j,i}^a \\ &= \lambda_j^c \theta_{c,i} + \lambda_j^a (\alpha_2 \theta_{c,i} + \theta_{2,i}) + e_{j,i}^a \;\; j = 8, 9 \\ &= \gamma_j \theta_{c,i} + \lambda_j^a \theta_{2,i} + e_{j,i}^a \end{aligned}$$

where $\gamma_j = \lambda_j^c + \lambda_j^m \alpha_2, j = 8, 9$. Finally, we impose the normalization assumptions $\lambda_9^c = 0, \lambda_9^a = 1$, where $j = 9$ denotes the numerical operations subtest.

C Additional Tables and Figures

Table A.1: Summary Statistics, U.S. Census Data

	1960	1970	1980	1990	2000	All years
Female enrollment	0.217	0.348	0.407	0.502	0.529	0.376
	(0.00306)	(0.00361)	(0.00348)	(0.00363)	(0.00341)	(0.00252)
Male enrollment	0.228	0.381	0.313	0.388	0.397	0.305
	(0.00377)	(0.00404)	(0.00337)	(0.00390)	(0.00363)	(0.00214)
RTI share	0.154	0.215	0.179	0.152	0.136	0.161
	(0.00136)	(0.00170)	(0.00153)	(0.00125)	(0.00117)	(0.000741)
Admin share IV	0.298	0.189	0.175	0.180	0.0775	0.228
	(0.00180)	(0.00133)	(0.00132)	(0.00105)	(0.000452)	(0.00189)
Population	565149.2	555278.7	310933.0	340498.1	386447.3	394666.5
	(82541.9)	(59610.9)	(31270.0)	(34956.9)	(39302.9)	(20208.0)
% female	0.502	0.510	0.511	0.511	0.506	0.505
	(0.000450)	(0.000360)	(0.000382)	(0.000366)	(0.000387)	(0.000193)
% black	0.0842	0.0801	0.0760	0.0769	0.0815	0.0808
	(0.00497)	(0.00425)	(0.00431)	(0.00430)	(0.00445)	(0.00187)
% Hispanic	0.0317	0.0326	0.0487	0.0575	0.0800	0.0460
	(0.00339)	(0.00310)	(0.00400)	(0.00437)	(0.00492)	(0.00159)
% ages 18-25	0.0858	0.114	0.129	0.0988	0.0969	0.105
	(0.000656)	(0.000679)	(0.000788)	(0.000834)	(0.000820)	(0.000359)
% ages 25-35	0.117	0.113	0.152	0.156	0.123	0.135
	(0.000528)	(0.000392)	(0.000628)	(0.000593)	(0.000609)	(0.000349)
% ages 35-45	0.123	0.107	0.106	0.143	0.154	0.128
	(0.000386)	(0.000288)	(0.000324)	(0.000469)	(0.000368)	(0.000312)
% ages 45-55	0.111	0.108	0.0961	0.0997	0.134	0.109
	(0.000362)	(0.000286)	(0.000265)	(0.000305)	(0.000417)	(0.000237)
% ages 55-65	0.0864	0.0942	0.0958	0.0892	0.0925	0.0903
	(0.000539)	(0.000395)	(0.000454)	(0.000382)	(0.000421)	(0.000204)
% ages 65 or older	0.0969	0.111	0.126	0.143	0.143	0.117
	(0.000943)	(0.000934)	(0.00110)	(0.00110)	(0.00106)	(0.000530)

Summary statistics for U.S. census sample, 1960-2000. The sample is restricted to individuals who have finished high school or hold a GED. All summary statistics represent the average across commuting zones. Standard errors in parentheses.

Table A.2: First Stage Regressions, Additional Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IV: Admin Share (top third)	0.355	0.389	0.382	0.315			
	(0.030)***	(0.027)***	(0.028)***	(0.044)***			
IV: Admin Share (top half)					0.350		
					(0.025)***		
IV: Admin Activities						3.217	
						(0.253)***	
IV: Clerical Requirements							1.460
							(0.138)***
F-statistic	137.280	205.558	182.001	51.040	203.540	161.233	111.715
Observations	3610	3600	3610	3610	3610	3610	3610
Minimum controls	✓						
Excluding Boston and NYC		✓					
Control for abstract occupation share			✓				
RTI share: non-college workers	✓	✓	✓		✓	✓	✓
RTI share: college and non-college workers				✓			
IV: Administrative Share (top third)		✓	✓	✓			
IV: Administrative Share (top half)					✓		
IV: Administrative Activities						✓	
IV: Clerical Requirements							✓

First stage regression of routinization on instruments, additional specifications. Column (1) uses a minimum set of controls: total commuting zone population, year dummies, census region dummies, commuting zone dummies, manual occupation share, proportion by gender, race, and ten-year age bin. Columns (2)-(7) start from the basic specification of Table 3 Column (1). Column (2) excludes commuting zones that contain Boston and New York City. Column (3) additionally controls for abstract occupation share. Column (4) uses the routinization of all workers, rather than only non-college workers used in the main specification. The IV in column (5) uses the share of occupations in the top half of administrative activity, rather than the top third. Column (6) uses the administrative activities IV, and column (7) the clerical requirements IV. Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of Adao et al. (2019). Montiel Olea-Pflueger F-statistics reported using AKM (2019) standard errors. Anderson-Rubin (1949) confidence intervals reported using AKM (2019) correction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Summary Statistics, NLSY79 Data

	Men		Women		Difference	
	Mean	Std. Dev.	Mean	Std. Dev.	Diff	P-value
College by age 25	0.485	0.500	0.609	0.488	-0.123	0.000
Cohort 1 (born 1957-1958)	0.267	0.442	0.254	0.435	0.013	0.300
Cohort 2 (born 1959-1960)	0.225	0.418	0.244	0.430	-0.019	0.105
Cohort 3 (born 1961-1962)	0.253	0.434	0.268	0.443	-0.015	0.222
Cohort 4 (born 1963-1964)	0.247	0.432	0.231	0.422	0.017	0.170
Father completed high school	0.269	0.443	0.269	0.444	-0.001	0.974
Mother completed high school	0.208	0.406	0.21	0.407	-0.003	0.831
Living in urban area at age 14	0.780	0.414	0.779	0.415	0.001	0.938
Living in the South at age 14	0.330	0.470	0.356	0.479	-0.027	0.045
Family income in 1979	11.31	0.935	11.31	0.895	-0.001	0.971
Number of siblings in 1979	3.40	2.394	3.51	2.442	-0.104	0.129
Occupation choices between 25 to 35						
White collar	0.074	0.262	0.441	0.497	-0.366	0.000
Blue collar	0.542	0.498	0.093	0.290	0.450	0.000
Pink collar	0.384	0.486	0.467	0.499	-0.083	0.000
Home staying	0.066	0.248	0.200	0.400	-0.134	0.000
Average annual earnings between 25 to 35						
White collar	23,579	15,904	15,233	8,969	8346	0.000
Blue collar	14,461	9,075	11,201	6,278	3260	0.000
Pink collar	11,138	7,694	8,119	5,319	3019	0.000

Summary statistics for the NLSY79 sample. The sample is restricted to individuals who have finished high school (12th grade) or hold a GED degree. Their occupation choice is defined as the modal occupation between ages 25 to 35. College by age 25 is a dummy variable that equals 1 if the individual's years of education exceeds 12 by age 25. The sample only includes individuals with complete family background information and test score information.

Table A.4: Estimates of Wage Coefficients by Occupation and Gender

	Men			Women		
	White	Blue	Pink	White	Blue	Pink
College	0.141	0.011	0.013	0.102	0.152	0.003
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
$\widehat{Routinization}$	-0.200	0.035	-0.212	-0.661	-0.455	1.381
	(0.007)	(0.008)	(0.018)	(0.009)	(0.017)	(0.017)
Cognitive	0.119	-0.037	0.105	0.119	0.259	-0.045
	(0.004)	(0.001)	(0.006)	(0.004)	(0.003)	(0.003)
Cognitive*college	0.062	-0.173	-0.032	0.007	-0.149	0.076
	(0.004)	(0.002)	(0.006)	(0.004)	(0.005)	(0.004)
Cognitive*$\widehat{Routinization}$	0.105	0.242	0.043	0.657	-0.414	-0.012
	(0.022)	(0.007)	(0.030)	(0.019)	(0.019)	(0.016)
Cognitive*college*$\widehat{Routinization}$	-0.006	-0.033	-0.008	-0.026	0.002	-0.008
	(0.022)	(0.010)	(0.032)	(0.020)	(0.029)	(0.018)
Manual	-0.037	0.088	-0.058	-0.123	-0.138	-0.103
	(0.003)	(0.003)	(0.009)	(0.007)	(0.019)	(0.009)
Manual*college	-0.001	0.126	0.008	0.083	-0.112	-0.286
	(0.003)	(0.002)	(0.007)	(0.007)	(0.029)	(0.011)
Manual*$\widehat{Routinization}$	-0.071	-0.191	-0.215	-0.561	0.320	0.375
	(0.019)	(0.013)	(0.048)	(0.035)	(0.106)	(0.046)
Manual*college*$\widehat{Routinization}$	-0.014	-0.004	0.022	-0.012	-0.041	-0.092
	(0.016)	(0.013)	(0.044)	(0.035)	(0.158)	(0.054)
Admin	0.246	0.128	0.216	-0.311	-0.094	0.131
	(0.014)	(0.008)	(0.025)	(0.023)	(0.043)	(0.015)
Admin*college	-0.103	0.065	-0.190	-0.182	0.072	-0.197
	(0.011)	(0.009)	(0.023)	(0.023)	(0.051)	(0.018)
Admin*$\widehat{Routinization}$	0.133	0.098	0.030	-0.144	0.273	0.251
	(0.078)	(0.041)	(0.142)	(0.134)	(0.238)	(0.081)
Admin*college*$\widehat{Routinization}$	0.031	-0.020	0.001	0.127	0.061	0.018
	(0.068)	(0.050)	(0.121)	(0.130)	(0.309)	(0.098)
Constant	1.940	1.776	1.655	1.892	1.657	1.057
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
Standard deviation	0.457	0.411	0.475	0.409	0.452	0.444
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)

Parameter estimates for the wage coefficients in Equation 4, reported by occupation and gender. Standard errors in parentheses.

Table A.5: Estimates for Utility Parameters by Occupation and Gender

	Men			Women		
	White	Blue	Pink	White	Blue	Pink
College	0.478	-0.904	0.419	0.890	-1.001	-0.493
	(0.011)	(0.009)	(0.020)	(0.012)	(0.016)	(0.011)
$\widehat{Routinization}$	0.148	0.535	0.167	-6.689	-3.194	5.267
	(0.204)	(0.164)	(0.276)	(0.198)	(0.355)	(0.188)
Cognitive	0.479	-0.053	0.335	1.162	0.573	0.398
	(0.052)	(0.024)	(0.063)	(0.041)	(0.057)	(0.022)
Cognitive*college	0.531	0.987	0.564	0.560	-0.350	-0.288
	(0.057)	(0.031)	(0.089)	(0.042)	(0.080)	(0.031)
Cognitive*$\widehat{Routinization}$	-0.839	0.838	-0.449	-8.097	-2.628	9.567
	(0.289)	(0.127)	(0.347)	(0.222)	(0.308)	(0.111)
Cognitive*college*$\widehat{Routinization}$	0.030	-0.003	-0.012	3.976	-0.006	-4.103
	(0.312)	(0.164)	(0.484)	(0.229)	(0.428)	(0.159)
Manual	-0.001	0.497	-0.175	-0.726	-0.186	-0.629
	(0.059)	(0.035)	(0.095)	(0.081)	(0.155)	(0.063)
Manual*college	-1.094	-0.413	-0.217	0.154	1.596	0.537
	(0.062)	(0.039)	(0.123)	(0.076)	(0.219)	(0.080)
Manual*$\widehat{Routinization}$	-1.094	0.298	-0.608	1.193	0.559	-0.174
	(0.330)	(0.186)	(0.518)	(0.427)	(0.858)	(0.323)
Manual*college*$\widehat{Routinization}$	-0.005	0.013	0.016	-0.009	-0.023	0.000
	(0.345)	(0.202)	(0.664)	(0.407)	(1.179)	(0.413)
Admin	0.358	-0.073	0.015	0.735	-0.208	-0.087
	(0.220)	(0.134)	(0.306)	(0.262)	(0.450)	(0.190)
Admin*college	-0.508	0.109	-0.320	1.107	-0.674	0.212
	(0.176)	(0.125)	(0.242)	(0.211)	(0.405)	(0.128)
Admin*$\widehat{Routinization}$	0.041	0.117	-0.442	-4.632	-0.801	6.643
	(1.223)	(0.702)	(1.706)	(1.430)	(2.503)	(1.012)
Admin*college*$\widehat{Routinization}$	0.010	-0.010	-0.042	-0.612	-0.100	0.830
	(0.967)	(0.654)	(1.342)	(1.128)	(2.351)	(0.678)
Constant	-6.304	-4.497	-5.647	-5.377	-5.572	-4.852
	(0.037)	(0.031)	(0.047)	(0.039)	(0.066)	(0.036)

Parameter estimates for the non-pecuniary utility coefficients in Equation 5, reported by occupation and gender. Standard errors in parentheses.

Table A.6: Estimates for the Education Equation by Gender

	Men		Women	
	Estimate	Std. Error	Estimate	Std. Error
Cognitive	1.18	0.37	1.11	0.38
Manual	-0.39	0.39	-0.22	0.39
Admin	0.16	1.49	0.17	1.64
Cohort 2	-0.15	0.13	-0.20	0.12
Cohort 3	0.00	0.13	0.15	0.11
Cohort 4	-0.02	0.14	0.25	0.14
Father's education	0.85	0.17	0.34	0.15
Mother's education	0.25	0.13	0.80	0.29
Urban	0.39	0.13	0.19	0.11
South	0.38	0.14	0.21	0.13
Intact family	0.48	0.04	0.15	0.03
Number of siblings	-0.03	0.01	0.00	0.01
Constant	-5.28	0.67	-1.51	0.62
Standard deviation	0.85	0.19	0.71	0.41

Parameter estimates for the education decision in Equation 6 are reported in columns (1) and (3) for men and women, respectively. Columns (2) and (4) report the associated standard errors.

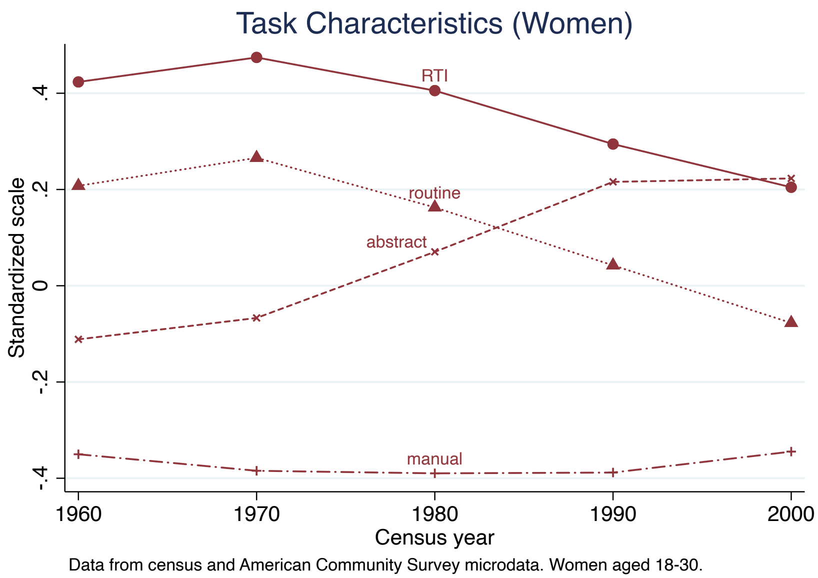
Table A.7: Parameters for Skill Distributions and Measurement Equations

	Skill distribution		Measurement equation			
	Men	Women	Loadings		Std. Dev.	
	(1)	(2)		(3)		(4)
μ_{cog}	-0.003	0.068	λ_1^m	1.552	$\sigma_{c,1}$	0.465
	(0.051)	(0.088)		(0.046)		(0.023)
μ_{manual}	0.296	-0.271	λ_2^c	0.565	$\sigma_{c,2}$	0.527
	(0.038)	(0.023)		(0.015)		(0.016)
μ_{admin}	-0.194	0.160	λ_2^m	0.929	$\sigma_{c,3}$	0.540
	(0.022)	(0.024)		(0.027)		(0.016)
$\sigma_{cog}^{(1)}$	0.800	0.745	λ_3^c	0.505	$\sigma_{c,4}$	0.479
	(0.090)	(0.126)		(0.016)		(0.016)
$\sigma_{manual}^{(1)}$	0.336	0.335	λ_4^c	1.064	$\sigma_{m,5}$	0.502
	(0.091)	(0.101)		(0.021)		(0.017)
$\sigma_{admin}^{(1)}$	0.191	0.111	λ_6^c	0.998	$\sigma_{m,6}$	0.557
	(0.084)	(0.143)		(0.020)		(0.016)
$\sigma_{cog}^{(2)}$	0.556	0.324	λ_7^c	0.936	$\sigma_{m,7}$	0.619
	(0.082)	(0.135)		(0.019)		(0.017)
$\sigma_{manual}^{(2)}$	0.398	0.108	λ_8^c	0.815	$\sigma_{a,8}$	0.699
	(0.091)	(0.121)		(0.024)		(0.028)
$\sigma_{admin}^{(2)}$	0.117	0.117	λ_9^a	0.945	$\sigma_{a,9}$	0.953
	(0.090)	(0.132)		(0.136)		(0.027)

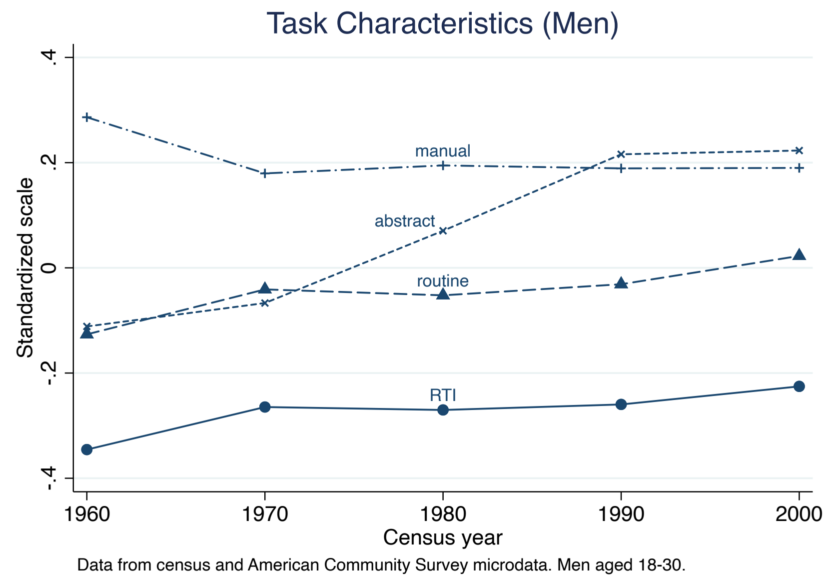
The left panel, "Skill distribution", reports the distribution of skills by gender. Each skill is a mixture of two normal distributions. μ_{cog} denotes the mean of the first normal distribution for cognitive skill. The mean of the second normal distribution is pre-determined to be 0. $\sigma_{cog}^{(1)}$ reports the standard deviation of the first normal distribution for cognitive skill and $\sigma_{cog}^{(2)}$ reports the standard deviation of the second normal distribution for cognitive skill. μ_{manual} denotes the mean of the first normal distribution for manual skill. The mean of the second normal distribution is pre-determined to be 0. $\sigma_{manual}^{(1)}$ reports the standard deviation of the first normal distribution for manual skill and $\sigma_{manual}^{(2)}$ reports the standard deviation of the second normal distribution for manual skill. μ_{admin} denotes the mean of the first normal distribution for administrative skill. The mean of the second normal distribution is pre-determined to be 0. $\sigma_{admin}^{(1)}$ reports the standard deviation of the first normal distribution for administrative skill and $\sigma_{admin}^{(2)}$ reports the standard deviation of the second normal distribution for administrative skill. The right panel, "Measurement Equation" reports the estimates of the loading factors associated with Equation 7 in column (3). It reports the standard deviation of the residual term in each test score measurement equation in column (4). Standard errors in parentheses.

Figure A.1: Routine Task Intensity (RTI) and Task Content

(a) Women

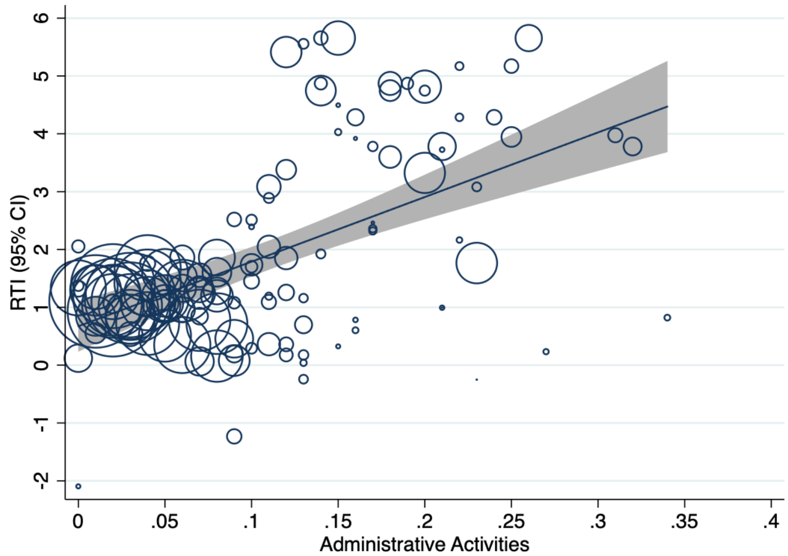


(b) Men



The figure decomposes RTI into its component task content measures in for women (panel a) and men (panel b). All variables are standardized. Data from the U.S. census and Autor and Dorn (2013).

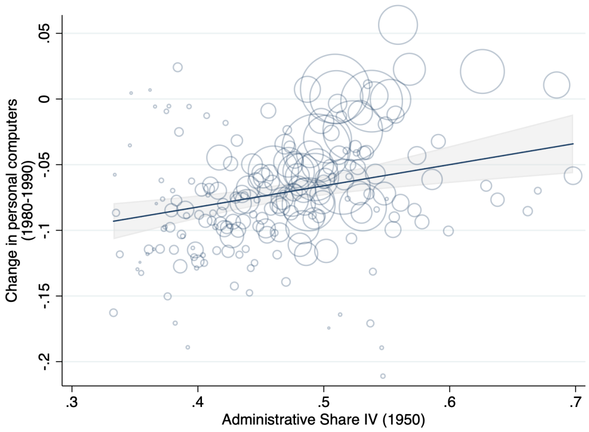
Figure A.2: Relationship between RTI and Administrative Activity across Occupations (all years)



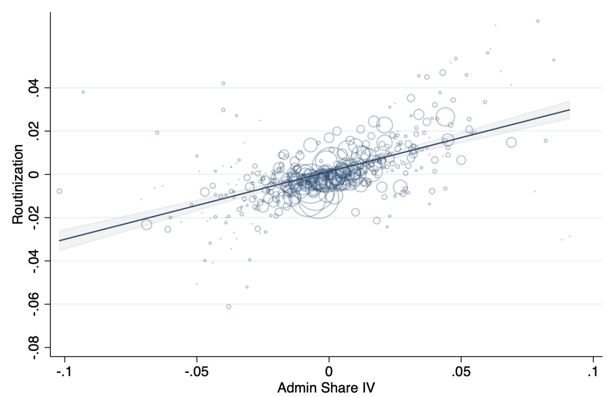
Raw correlation between routine task intensity (RTI) and administrative activity across occupations. RTI is measured in standard deviations. Administrative activity is measured in the number of keyword mentions per ad. Data from the U.S. census, Autor and Dorn (2013), and Atalay et al. (2020).

Figure A.3: Assessing Administrative Share Instrument

(a) Instrument Predicts Future Automation



(b) Instrument Predicts Routinization



Both panels assess the predictive power of the administrative share instrument. Panel (a) plots the instrument in 1950 against the change in personal computers in 1980-1990. Panel (b) depicts the first stage prediction. It depicts the residual plot of routinization and the administrative share instrument after partialling out the controls in Table 3, column (4). In both panels, the solid line represents the correlation estimated from an OLS regression using labor supply weights. The shaded gray area depicts 95% confidence intervals. Data from the U.S. census, Autor and Dorn (2013), and Atalay et al. (2020).