Optimal Skill Mixing Under Technological Advancements *

Elmer Zongyang Li†

May, 2023

Abstract

Using worker survey and online job posting data, I document that the U.S. economy has seen a substantial increase in the mixing of skill requirements from 2005-2018, both for incumbent jobs and newly posted vacancies. American workers increasingly work in occupations that demand mixtures of analytical, computer, and interpersonal skills rather than specializing in one of them, even in granular occupations. This change occurred primarily within the low- to medium-wage occupations, and the return to working in occupations or studying college majors with more mixed skills has also increased. To understand the sources of these shifts, I build a directed search model with multi-dimensional skills in which firms optimally choose occupations' skill intensities before matched with a worker, delivering endogenous specialization in skill demand. Counterfactual analysis shows that rises in skill complementarity in production and declines in occupation design cost account for the majority of skill changes and corresponding wage and employment dynamics in this period.

Keywords: skill demand, technological changes, occupations, search model, worker training
JEL Codes: J21, J23, J24, J31, E24

*I am extremely grateful for Philipp Kircher, Julieta Caunedo, Michael Lovenheim, and Mathieu Taschereau-Dumouchel for their guidance and continuous support. Special thanks to Sergio Ocampo Díaz for his suggestions and Carter Braxton for providing the data. I also want to thank Maria Fitzpatrick, Fatih Guvenen, Nir Jaimovich, Joseba Martinez, Simon Mongey, Pascual Restrepo, Evan Riehl, Seth Sanders, and Michael Waldman for their inspiring comments. Also thanks to numerous seminar participants. All errors are my own.

†Li: Department of Economics, Cornell University, 109 Tower Road, 404 Uris Hall, Ithaca, New York 14853-2501 (e-mail: zl685@cornell.edu).

I Introduction

The nature of work in the United States has changed dramatically in recent decades. As technology advances, do employers increasingly require a broader range of skills, or *mix* their demand of different skills, and if so, how should workers face this change? A vast literature documents the decline in the demand for "routine" tasks and related worker skills due to technological shifts (i.e., Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011) and the rising importance of social skills (Cortes, Jaimovich, and Siu 2021; Deming 2017). This evidence points toward changes in the mixtures of skills that appear in occupations as employers adopt new technologies. The degree of skill mixing among occupations has important and distinct implications: if occupations demand more of a particular skill, evidencing specialization in skill demand, then it benefits workers to become experts; if, however, occupations mix their use of different skills, evidencing "skill mixing," multidisciplinary schooling and training is more advantageous.

Using both worker survey and job posting data, I document that from 2005 to 2018, occupations in the United States increasingly demand mixtures of different skills. The main dataset that this study employs—Occupational Information Network (O*NET)—contains surveys of incumbent workers of their current jobs and provides the importance of different skill requirements. I show that longitudinal variation in skill demand can be credibly analyzed using O*NET by considering longer time spans and focusing on constantly updated occupations. A second dataset, Lightcast (formerly Burning Glass), offers real-time skill demand from millions of online job vacancies and supplements O*NET data by measuring the extensive margin share of jobs requiring certain skills. To evaluate the degree of skill mixing of each occupation, I calculate the cosine similarity between an occupation's skill vector and the unit vector on which skills along several domains are equally important; therefore, this "mixing index" increases as an occupation's demand for different skills gets closer.

Leveraging O*NET dataset, I find that even at 7-digit occupation level, there is a sizable increase in the degree of skill mixing, particularly for analytical, computer, and interpersonal skills that are considered to be non-routine. Compared to their distributions in 2005, the skill mixing indexes of these skills have increased by 9 percentiles on average for the whole econonmy, and by 4 percentiles for occupations that are constantly updated every 6 years. The growth of skill mixing is even starker in higher level 4-digit occupations, by 14 and 11 percentiles respectively. Such increases persists within gender, industry, and occupation groups, are unaffected by controls of workers' labor supply, and are robust to alternative measures of skills and indexes of mixing. Lightcast data further confirms the trend of skill mixing: the share of online posted jobs demand a mixture of the non-routine skills have increased by 4.6 percentiles in 2018 compared to its distribution in 2005.

Two facts stand out for the phenomenon of skill mixing. First, a shift-share decomposition shows that skill mixing has occurred primarily within-occupation, with worker reallocation playing a minor role. For example, for the 14 percentile increase in the mixing of the analytical, computer, and interpersonal skills in the full O*NET data, within-occupation increase contributed 9.5 percentiles; in Lightcast data, 4.4 percentiles of the 4.7 percentile increase in the mixing of the four skills are attributable to within-occupation increases. Thus, the intensive margin shift in occupational skill requirements drives skill mixing, distinguishing it from other labor market changes for which worker reshuffling plays a key role, or the change is mainly across-occupation.[1] Second, the greatest increase in the mixing of the four non-routine skill appear among service and white-collar occupations, while for routine skill, mixing happened at a higher level for blue-collar occupations. Thus, low- to medium-wage occupations are the main drivers of skill mixing. While both gender experiences increases in skill mixing, male workers are more likely see a higher rise in skill mixing in higher-wage occupations.

The trend of skill mixing has distributional implications for the labor market. One of the key structural changes in the U.S. labor market post-1980 is job polarization (Acemoglu and Autor 2011; Goos, Manning, and Salomons 2014), which persists during 2005-2018 as observed in the data. It appears that skill mixing is important in accouting for these distributional dynamics. For occupations within similar wage ranks in 2005, those that have become more skill-mixed witness a higher increase in employment share

[1] For example, in Autor and Dorn (2013), the polarization of the labor market is attributed to the substitution of medium-skill workers in routine jobs and their flow into service jobs; in Deming (2017) across-occupation employment shift drives the rising importance of social skills.

and wage growth. Almost the entirety of employment and wage growth is accounted for by occupations that have become more skill-mixed during this period. Skill mixing provides a novel and multi-dimensional perspective of these changes.

To evaluate the impact of skill mixing on workers' labor market outcomes, I estimate the wage returns to skill mixing combining the National Longitudinal Survey of Youth 1979 and 1997 (NLSY 79 & 97), taking advantage of the rich information on participant's abilities employment and educational histories. I find a significant return to skill mixing for both occupational choices and worker skills. To assess the wage premium, I run a regression with multiple skills and their interactions on both the occupation and worker sides with two-way fixed effects in the spirit of Abowd, Kramarz, and Margolis (1999) (hereafter AKM). My preferred specifications indicate that workers switching to occupations that are one standard deviation more mixed of analytical and computer, as well as analytical and interpersonal skills gain a 1.3 to 2.7 percent wage premium; meanwhile, worker who are more mixed of these skills earn 2.8 to 4.4 percent more. Further, leveraging the education information in NLSY, I calculate the skill content and degree of mixing for each college major. I find that workers switching to a college major a standard deviation of more mixed of analytical and computer or of mechanical and interpersonal skills earn 5 percent more.

The rich empirical findings on skill mixing pose challenges in understanding their driving forces. In what follows, I attempt to provide an overarching framework to investigate the mechanisms. For this purpose, I build a directed search model with several novel features. First, both firms and workers are represented by multi-dimensional skills, allowing more nuanced interactions and dependencies between various skills in the labor market. Second, firms must make decisions about occupation design before meeting workers, a process that involves a rental cost payable upon meeting as in Acemoglu (1999).[2] This endogenous occupation design is crucial in simulating the

[2] The endogenous choices of the intensity of inputs were first studied in the appropriate technology literature (Atkinson and Stiglitz 1969; Basu and Weil 1998; Acemoglu and Zilibotti 2001; Jones 2005; Caselli and Coleman 2006; León-Ledesma and Satchi 2019). Several studies in the labor literature allow firms to adjust labor usage besides the quantity margin. In Lazear (2009), firms choose the weight on the skills workers supplied, and in Eeckhout and Kircher (2018), firms trade-off between more versus higher quality workers.

dynamic choices of skill mixing based on firms' anticipation of the skill distribution in the labor market. Third, the model incorporates non-linear production and rental cost technologies, departing from the common assumption of linear production functions in standard search models. This non-linearity, crucially, allows the model to capture the varying degrees of skill complementarity in production and the increasing marginal costs of combining skills in occupations. Despite the rich setup, the model remains tractable satisfying Block Recursivity as in Menzio and Shi (2011).

The model provides clear insights into changes in skill mixing, wages, and employment that are tied closely to the empirical observations. The key insight is that when skills become more complementary in production, or less costly to combine, it is more profitable for firms to mix different skills rather than to specialize in one. This is reflected in the job design where occupations requiring mixed skills become more prevalent. Furthermore, the model predicts that such changes in the production and cost environment will lead to an increase in the output of worker-firm matches, thereby raising wages and improving job finding probabilities for workers. These predictions provide a robust theoretical foundation for understanding the empirical trends.

I quantitatively evaluate the model to assess the relative importance of various factors that contribute to the observed skill mixing, and to investigate the implications for wages and employment. Using two periods of NLSY data, I calibrate the model parameters using Simulated Methods of Moments (SMM). The estimation results provide some key statistics on the elasticity of substitution in production and the cost structure. I find that under the multi-dimensional matching framework, skills are substitutable in production; in designing occupations, firms face increasing marginal cost. Moreover, sizable technology shifts have occurred: from the early 2000s to the late-2010s, skills have become more complementary in production, and firm faces lower cost in designing occupation, incentivizing skill mixing. Meanwhile, workers with higher analytical, computer, or interpersonal skills are more productive than those with expertise in routine skill, exacerbating the mixing of the former skills.

Finally, I conduct counterfactual analyses to gauge the relative significance of each channel in the model in explaining the shifts in the extent of skill mixing and explore implications for wage and employment distributions. I find that shifts in the complementarity of skills in production and the decline in occupation design costs are the main drivers and account near entirety of skill mixing, with marginal contributions of skill supply variation. For both the wage and employment dynamics, the increase in skill complementarity in production and the differential increases in skill efficiency play a pivotal role in accounting for the observed rise in dispersion of high-skill relative to low-skill occupations, and the rise in occupation rental cost actually contributes negatively. For employment distribution changes, the variation in skill supply also plays an important role.

The rest of the paper is organized as follows. The ensuing section connects this paper to a broader set of literature and discusses the contributions. Section III presents the main empirical findings about skill mixing and many of its features. In section IV, I show the returns to mixing both at the occupation and worker levels. Section V presents a directed search model with occupation design to study the skill mixing problem and derives comparative statistics. Estimation of the model parameters and counterfactual analysis are discussed in Section VI. Section VII concludes.

II Literature Review

I study labor market dynamics emphasizing *skill mixtures* and explore new theoretical perspectives to explain them. The empirical objective aligns with the literature investigating the long-term trend of skill demand and biased technological changes (i.e., Tinbergen 1974, 1975; Katz and Murphy 1992; Autor, Katz, and Krueger 1998; Autor, Levy, and Murnane 2003; Goldin and Katz 2010; Acemoglu and Autor 2011; Autor and Dorn 2013). My finding that the intensive margin within-occupation changes drive skill mixing is consistent with other studies that find the major role played by within-occupation variation for aggregate job attributes (Autor and Handel 2013; Atalay et al. 2020; Freeman, Ganguli, and Handel 2020; Cortes, Jaimovich, and Siu 2021).[3] Different from these studies, I focus

[3]Cortes, Jaimovich, and Siu (2021) discovered that from 1980 to post-2010, high-paying occupations in the United States require more social skills. Using worker-reported job tasks, Autor and Handel (2013) found that there is significant within-occupation variation in task requirements. Extracting task information

on the changes in the mixing of different skills and model incomplete specialization in skill demand.

Theoretically, I build a directed search model with multi-dimensional skills and endogeneous occupation design, follwing the recent literature on directed search (i.e., Menzio and Shi 2010, 2011; Schaal 2017; Braxton and Taska 2023). Two main contributions of the paper are: First, I allow firms to have endogenous skill demand in the spirit of Acemoglu (1999), which delivers the comparative statics regarding skill mixing. Second, I model skills in a multi-dimensioinal environment with non-linearity that departs from most search models, but allows to analyze complementarity and increasing cost in occupation design.

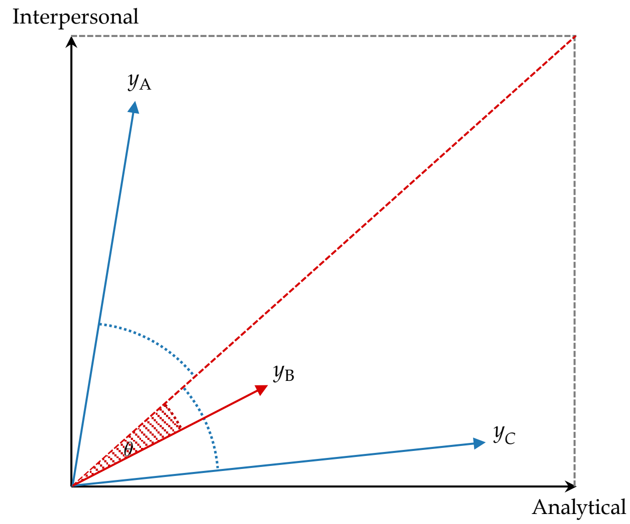
A burgeoning literature explores the multidimensional matching of workers and firms that features two-sided heterogeneity and skill transferability (i.e., Yamaguchi 2012; Lindenlaub 2017; Lise and Postel-Vinay 2020). The focus of the literature has been the assortativeness of the matching between workers and firms and the adjustment of worker skills.[4] I instead focus on firms' trade-off in different skill demands and how it responds to changes in technology or skill supply.

Quantitatively, I provide model-based identifications of the elasticity of substitution parameters among a number of different skills and the relevant cost parameters under a tractable general equilibrium model of the labor market with endogenous skill intensities. Meanwhile, These results contribute to the recent work on task-based models that has typically assumed exogenously the elasticity of substitution among different types of skills (i.e., Autor, Levy, and Murnane 2003; Autor and Dorn 2013), and also relates to studies on the elasticity of substitution among different types of workers (Johnson 1997; Heckman, Lochner, and Taber 1998; Krusell et al. 2000).

from job ads, Atalay et al. (2020) revealed that the major change in job content during 1950-2000 occurred within-occupation, a pattern that is found to persist post-2000 by Freeman, Ganguli, and Handel (2020).

[4]Exceptions include Ocampo (2022), in which tasks are optimally combined, generating endogenous occupational heterogeneity.

Figure 1: Illustrating Skill mixing



Notes: This figure contrasts three occupations—A, B, and C—in the skill space of analytical and interpersonal skills. Each occupation is characterized by its skill vector (y_A, y_B, y_C), and also by the angle between the skill vector and the 45-degree line. The angle is used to measure skill mixing as it illustrates the trade-off between skills.

III Evidence of Skill Mixing

In this section, I first show that the degree of skill mixing in the multi-dimensional skill space can be measured using an angle-based index. I then apply O*NET and Lightcast data at different granularity to show the increase in skill mixing, the decomposition into within- and across-occupation changes, the underlying sources of variation as well as occupational heterogeneity. Lastly, I illustrate the importance of the mixing of different skills in terms of its distributional implications for employment and wage dynamics.

III.A Measures and Data

The Degree of Skill Mixing: An intuitive way to evaluate the degree of mixing of an occupation's skill demands is to check the angle difference between that occupation's skill vector and the unit vector on which different skill requirements are equivalent. In figure 1, both occupations A and C are more specialized as their skill vectors point away from the diagonal, whereas occupation B is considered more mixed with a smaller angle (θ).[5] I formalize the idea behind figure 1 by measuring skill mixing using cosine similarity.[6] Specifically:

Definition 1 (Degree of Skill Mixing of an occupation)**.** *The skill mixing index for an occupation j in a K-dimensional space characterized by the skill intensity vector $y_j = \{\alpha_{j1}, ..., \alpha_{jK}\} \in \Upsilon \subseteq \mathbb{R}^{K+}$ is the cosine similarity between its skill vector and the norm $\hat{v}$ in the skill space.*

$$Mix(y_j) = \frac{y_j \hat{v}}{||y_j|| \cdot ||\hat{v}||}, where\ \hat{v} = [1, 1, ..., 1]' \subseteq \mathbb{R}^{K+} \tag{1}$$

Data Construction: I compute the above index and assess the degree of skill mixing of occupations across years first using the Occupational Information Network (O*NET) that is developed by the North Carolina Department of Commerce and administered by the U.S. Department of Labor.

The purpose of O*NET is to replace the Dictionary of Occupational Titles (DOT) that has been used widely to analyze occupation skill requirements and work settings (i.e., Autor, Levy, and Murnane 2003), and is more comprehensive, contains around 270 descriptors about occupations that are grouped into 9 modules.[7] Initial versions of O*NET comprise legacy ratings of job analysts from DOT data. Starting in 2003, O*NET starts to collect responses from random samples of workers (job incumbents). For consistency, I only use descriptors from questionaries that are updated by workers.[8]

The key challenge of using O*NET comes from employing the longitudinal variation of occupation descriptors. Specifically, each version of O*NET contains around 970 7-digit occupations, but an average of 110 of targeted occupations are updated each year[9]. This creates a selection issue of occupations updated if one were to construct

[5]A nice feature of angle difference is that it doesn't depend on the length of the skill vector, only on the degree of skill mixing.

[6]Cosine similarity together with other measures, such as Euclidean distance and Manhattan distance, have been used to calculate the similarity between vectors (i.e., Xia, Zhang, and Li 2015). An angle-based measure is by no means the only measure of skill mixing, though it has the clearest graphical illustration of the trade-off among skills. Online Appendix A.2 discusses alternative measures.

[7]Online Appendix A.1 provides a more detailed description of O*NET and the descriptors used.

[8]Specifically, I use descriptors from Work Context, Work Activities, Knowledge, and Skills questionaries.

[9]The decision of occupation updating is based on analysts' evaluations of factors such as the size of employment, the demand for labor, and alterations in the type of work involved. See Council et al. (2010)

skill demand measures using the descriptor. Since, unlike previous studies that focus on worker reallocation across occupations, and therefore employ one year of O*NET, this paper intends to study the changing skill demand, and using the longitudinal variation is important.

I apply two approaches to analyze longitudinal variation in skill demand using O*NET data, following i.e., Ross (2017); Freeman, Ganguli, and Handel (2020). First, I focus on larger year intervals. For the analysis period from 2005 to 2018, in analyzing the overall trend, I focus on the difference in skill requirements between 2005 and 2018, for which most occupations have been updated twice over the years. In gaining more granular time patterns, I use 4-year intervals, so more than 50In addition, I use data from online job postings from Lightcast (formerly "Burning Glass Technologies"), a labor market analytics firm that collects and analyzes millions of job postings from across the internet. Lightcast provides detailed profiles of each job posting, including education requirements and thousands of codified skills extracted and standardized from the posting text. The key advantage is that it provides comprehensive and up-to-date information on labor market conditions, and many recent studies have used this dataset to analyze trends in job skill demand (see, i.e., Deming and Kahn (2018); Hershbein and Kahn (2018); Braxton and Taska (2023)). One needs to note though, that measurements of skills from Lightcast contain different information than those from O*NET: while O*NET asks about the level and importance, of the intensive margin, Lightcast collects information on whether a skill is required for a job, the extensive margin. Moreover, Ligthcast potentially misses jobs advertised through other channels, thus overrepresenting jobs or sectors that are more likely to advertise online, and online vacancies by nature overrepresent growing firms (Davis, Faberman, and Haltiwanger 2013). Here I use Lightcast as an additional source complementing the picture of changing skill mixing over time.

Skill Measures: From O*NET occupation descriptors, I obtain measures of skills by combining descriptors directly following Acemoglu and Autor (2011) as these have been widely used and are easily comparable to other studies. To have a feasible dimension of skills to understand their mixing, I collapse all the routine skills (routine cognitive and manual) into one, call them routine skills, and keep non-routine skills (non-routine analytical and interpersonal) separate.[10][11] To more closely capture the rise of computer technology post-2000, I construct a computer skill measure based on two components related to operating a computer.

The above four skill measures comprise most of the analysis in this paper. To give a fuller view of the changing skill demand, I also incorporate two additional skills that haven't been studied in previous papers: leadership and design, as a complementary to the analysis of the skill mixing of widely used measures. To further reduce noise in the skill measures, particularly in portraying a more granular longitudinal time pattern, I conduct principal component analysis (PCA) on the chosen descriptors following Guvenen et al. (2020) and Yamaguchi (2012), and the final skill measure is rescaled linearly to lie in [0,1].[12] Online Appendix Table A2 shows the detailed composing descriptors for each of the skill measures.

As a check of validity, online Appendix Table A3 shows that my constructed skills correlate highly with other similar skill measures used in the literature. In Online Appendix A.2, I build "broader" skill measures that each include more relevant descriptors, which are also highly correlated with the benchmark ones. Along with the discussion of my empirical results, I demonstrate their robustness to using alternative measures not applying PCA, normalizing by standard deviation, and using broader measures.

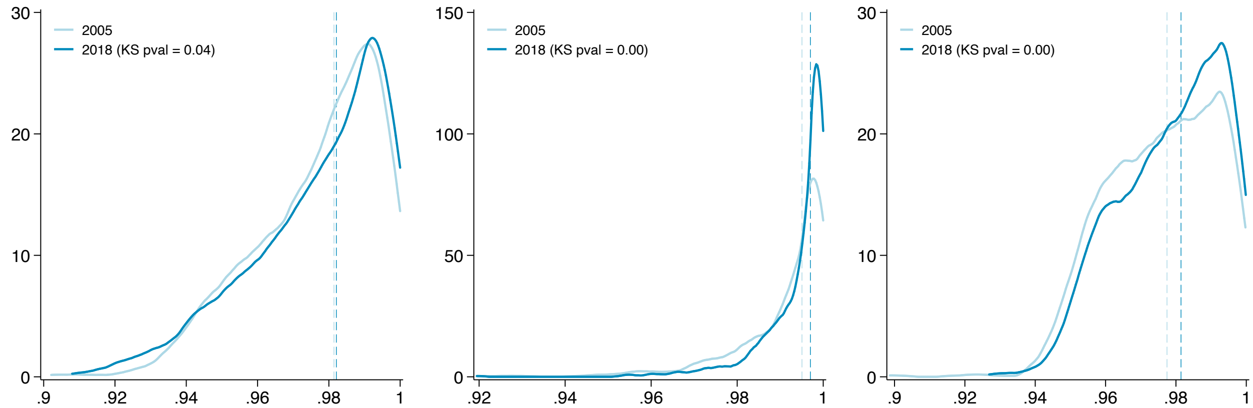
To measure skills from Ligthcast data, I directly use the measures from Braxton and Taska (2023), which follows Hershbein and Kahn (2018) in measure construction. Specifically, for the year 2007-2017 of Lightcast data that this study uses, a vacancy is defined to use the analytical skill if any of the codified skill requirements contain keywords

[10] I didn't use non-routine manual as part of the composing descriptors coming from surveys of job analysts exclusively, and for this study, I only use the descriptors that are updated by job incumbents for consistency purposes

[11] I omit the word "non-routine" when referring to specific non-routine skills and denote by analytical or interpersonal skills hereafter.

[12] Based on Definition 1, it is crucial that skill vectors are in the positive real space for an angle-based measure to be appropriate. In that regard, normalization by standard deviation won't work unless with additional re-normalization, and linear transformation to a positive interval appears most desirable as it also retains the cardinal information that is likely to be useful for an easily interpretable skill comparison (e.g., Autor and Handel (2013), Deming (2017), and Lise and Postel-Vinay (2020)). Alternative measures of skills and skill mixing are discussed in Online Appendixes A.2 and **??**.

Figure 2: Density for Skill Mixing Indexes (Cosine Distances), 2005 vs. 2018



(1) RNR Skills (2) Non-routine Skills (3) Other Non-routine

*Notes: These figures plot the kernel density of different skill mixing indexes in 2005 (light blue line) and 2018 (dark blue line). The x-axis displays the value of skill mixing indexes with a maximum of 1 by construction. "RNR" indicates routine and non-routine skills that are defined by Acemoglu and Autor (2011). "Other non-routine" include leadership and design skills. These plots are created using O*NET at 7-digit occupations without employment weighting.*

such as "research", "analy", and "decision". Similarly, a vacancy is defined to require interpersonal skill if the codified job skill contains keywords such as "communication" or "teamwork".[13] For each occupation, the share of posted vacancies that require a particular skill is then the measure of skill for that occupation, capturing the extensive margin of firm skill demand. In categorizing occupations for Lightcast data, I use a 4-digit consistent census occupation code developed by Autor and Dorn (2013) to match it with employment weight from ACS.

III.B Aggregate Trends

The degree of skill mixing in occupations has increased significantly from 2005 to 2018, and the rise is particularly sharp for non-routine skills. I start by showing this trend happens at even very granular occupations by checking 7-digit occupations in O*NET data in the year 2005 and 0218 respectively. Figure A2 depicts the density and median value of three skill mixing indexes, one for routine and non-routine (RNR) skills, another

[13]More specifically, the keywords used to capture analytical skill are: "research", "analy", "decision", "solving", "math", "statistic", and "thinking". The keywords used to capture interpersonal skills are "communication", "teamwork", "collaboration", "negotiation", and "presentation".

only for non-routine skills, and the last for the other non-routine skills. Since the indexes are unweighted by employment for these occupations, the shifting distribution reflects only occupations' skill mixing change, not subject to worker reallocation.

Panel (1) shows that the degree of skill mixing for RNR skills has seen a modest rightward shift over this period. The Kolmogorov-Smirnov (KS) test value shows that the difference in distribution is significant at 5 percent. However, the rightward shift of the density is even larger for the skill mixing index of nonroutine analytical, computer, and interpersonal skills (Panel 2), and for some other non-routine skills that include leadership and design skills (Panel 3). The density of the mixing index of these skills peaked at a higher value in 2018 relative to 2005, and the KS test is significant at a 1 percent level, implying that the occupations in the economy requiring a high level of mixing of has grown significantly.

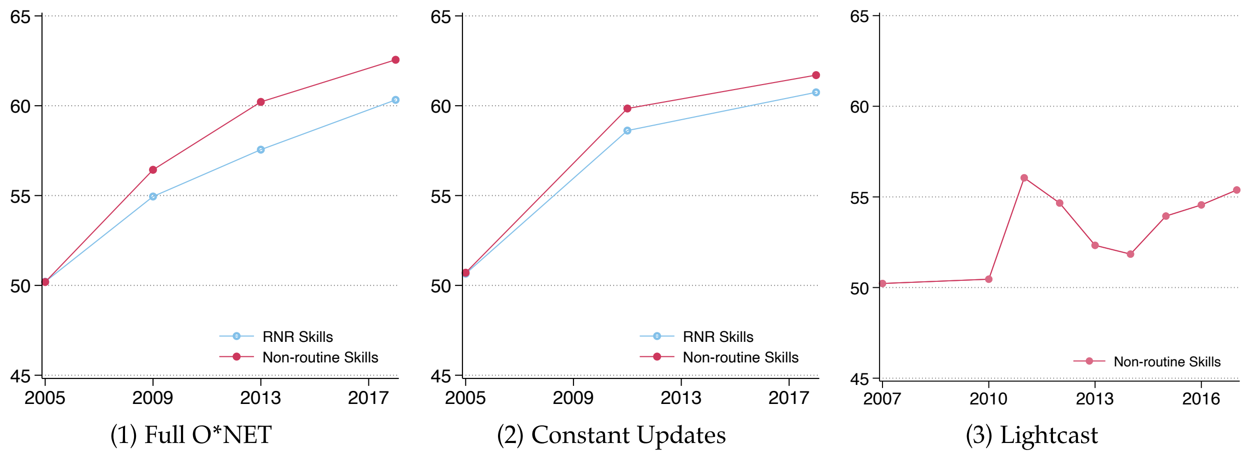
Further, the overall pattern of increasing skill mixing persists taking into account of changing composition of occupations in the labor force. In online **??**, I combine O*NET data with employment weight Occupational Employment and Wage Statistics (OEWS) at 6 digit level and show that the right shift of all the skill mixing index become more perceivable weighted by employment share across the years.[14] This implies that occupations that employ more workers have shown an even greater increase in the degree of skill mixing, and the overall share of employment in the economy requiring a high level of skill mixing has grown.

Alternative to using indexes to check the degree of skill mixing, one can non-parametrically plot the density of skill requirements in two-dimensional spaces. Online Appendix Figure A1 depicts the non-parametric plots of six skill pairs in 2005 and 2018 respectively and a similar increase of skill mixing occurred, particularly for non-routine skills.

Time Pattern: To more carefully examine the time profile of the changing skill mixing and understand the sources of variation, I combine the longitudinal variation in

[14]The OEWS uses 6-digit SOC codes, while O*NET uses 7-digit occupation codes that are based on 6-digit SOC. I match OEWS with O*NET at a 6-digit SOC level and distribute the employment weight evenly for 7-digit O*NET occupations within a 6-digit occupation.

Figure 3: Trend of Skill Mixing in the US Economy, 2005-2018



*Notes: These figures plot the employment-weighted skill mixing indexes in the U.S. economy from 2005-2018. The y-axis is the percentile of skill indexes in year 2005. By construction, each index has a mean of 50 percentiles in 2005; succeeding points are employment-weighted means mapped to its percentile in 2005. Panel (1) and (2) combine O*NET and ACS data with consistent 4-digit occupation codes from Autor and Price (2013) and developed by Deming (2017). The matching of different O*NET releases and ACS years are detailed in online Appendix Table 1. Panel (1) show the trend for the universe of occupations while Panel (2) only include 274 7-digit occupations that are constantly updated between 2005, 2011, and 2018. Panel (3) combines Lightcast job posting data and ACS with same occupation coding. Employment weights from ACS are the total hours of work aggregated to sex-education-industry-occupation cells.*

skill mixing from O*NET as well as with ACS to conduct further analysis. I show the trend pattern at 4-year intervals so that more than half of the occupations (about 60% of employment) are updated between observations. By construction, each index has a mean of 50 percentile in 2005; succeeding points are employment-weighted means of each index mapped to its percentile in 2005 (see Autor, Levy, and Murnane (2003) and Deming (2017) for other examples). I weight each skill requirement from O*NET data by the total hours of work in each sex-education-industry-occupation cell to implicitly control for changes in task inputs due to variations in gender, education, industry, and occupation mixes in the U.S. economy.

Figure 3 demonstrates that the degree of mixing of non-routine skills has risen sharply between 2015 and 2018. By 2018, the degree of mixing among non-routine skills or an average occupation in the economy is 12.6 percentile higher than its 2005 level. The degree of skill mixing of RNR has also increased to a slightly lesser extent, averaging 10.3 percentiles higher. Meanwhile, the degree of skill mixing for all the occupations in the

U.S. economy has steadily increased throughout the sample period from 2015 to 2018.

As mentioned, a potential concern of using O*NET data to obtain the longitudinal variation of skill demand is that the trend could be affected by the inconsistency in updating occupations. In Panel (2) of Figure 3, I compute these trends focusing only on 274 7-digit occupations that are constantly updated between 2005, 2011, and 2018, thus reflecting a consistent updating of skill demand among these occupations. The same qualitative pattern holds, that is, there has been a sharp increase in the degree of skill mixing, particularly of non-routine skills between 2005 and 2018. Nonetheless, for the constantly updated occupations, the shift is mostly pronounced before 2011.[15]

In Panel (3) of Figure 3, I complement the picture of changing degree of skill mixing using the Lightcast data through a similar paring with O*NET data, though starting in 2007, the first year when the company starts to collect job postings. Overall, firms are also more likely to post job requirements that contain more mixed-skill demands. By 2017, the degree of skill mixing in job postings averaged 5.1 percentiles higher. The time pattern of skill mixing among job postings appears to be more volatile, first peaking in 2011, then sliding down until 2014, before dramatically rising afterward until 2017. Despite the greater variance, the same qualitative pattern holds that occupations have a higher demand for the mixing of non-routine skills.[16]

Another concern is that the overall patterns shown so far are driven by the choice of skill measures or the choice of skill mixing index. I discuss alternative skill measures and mixing indexes and the robustness of these trend results in online Appendix A.1 and A.2. Online Appendix Figure A5 and A6 show the robustness of the trend using these alternative measures of skills, alternative indexes of skill mixing, as well as indexes for different skill pairs instead of high-dimensional indexes. Across these checks, the qualitative picture remains the same such that there has been a significant rise in the

[15]In online Appendix Figure A3, I show employment percentages and hourly wages across various job categories in the full and the sample for constantly updated occupations. The hourly wage rates across the categories seem fairly consistent between the full and selected samples with minor discrepancies, only that the selected sample has less presence of professionals and sales occupations.

[16]The higher degree of volatility is partly driven by the nature of the measure and the data. The measures of skills from job postings are whether firms require a particular skill in the text of job ads, naturally noisier than the question on level and importance from O*NET. Moreover, firm job posting is more influenced by firm entry and exit patterns

Table 1: Time Trend of Skill Mixing Indexes

	Skill Groups	6-digit Occupations			4-digit Occupations		
		total	within	across	total	within	across
Full O*NET	RNR Skills	6.78	4.93	1.85	12.23	9.26	2.97
	Non-routine Skills	9.21	5.62	3.59	14.07	9.53	4.54
Constant Updates	RNR Skills	5.59	6.73	-1.14	9.70	10.57	-0.87
	Non-routine Skills	4.05	5.33	-1.29	10.58	9.50	1.09
Lightcast	Non-routine Skills				4.66	4.37	0.28

Notes: This table shows the shift-share decomposition of changes in the average level of different mixing indexes between 2005-2018 in percentile units. Specifically, for a change in the percentile of a mixing index h over two periods t and τ*, its change* $\Delta T_{h\tau} = T_\tau - T_t$ *which can be decomposed to* $\Delta T_h = \sum_j \left(\Delta E_{j\tau}\alpha_{jh}\right) + \sum_j \left(E_j \Delta\alpha_{jh\tau}\right) = \Delta T_h^a + \Delta T_h^w$ *where* $E_{j\tau}$ *is employment weight in occupation j in year* τ*, and* $\alpha_{jh\tau}$ *is the level of mixing index h in occupation j in year* τ*,* $E_j = \frac{1}{2}(E_{jt} + E_{j\tau})$ *and* $\alpha_{jh} = \frac{1}{2}(\alpha_{jht} + \alpha_{jh\tau})$*.* ΔT_h^a *and* ΔT_h^w *then represent across-occupation and within-occupation change.*

degree of skill mixing, particularly for non-routine skills.

Decomposing the Sources: The longitudinal variation of skill mixing could be a result of either intensive margin skill mixing index changes within occupations or extensive margin employment shifts across occupations. If the former is a bigger driver of the increase in skill mixing, then it points out that demand-side dynamics play a more primary role. Equipped with the longitudinal variation in skill measures as well as changing occupational employment shares, I now perform the decomposition.

Table 1 shows the decomposition of the changes in the employment-weighted skill mixing indexes into within-occupation index shifts and across-occupation employment changes, at both 6-digit SOC and 4-digit census occupation levels. Across different datasets and skill groups, the within-occupation variation dominates across-occupation variation to account for the bulk of the increase in skill mixing. For example, for the 9.2 percentile increase in the mixing of non-routine skills in the full O*NET data, within occupation increase contributes 5.6 centiles while only 1.1 percentiles are due to worker reallocation; for the 4.7 percentile increase in the mixing of non-routine skills in Lightcast

Table 2: Time Trend of Skill Mixing Indexes

	RNR Skills	Non-routine Skills
Full O*NET	0.70***	0.71***
	[0.10]	[0.09]
Constant Updates	0.75***	0.65***
	[0.11]	[0.11]
Lightcast		0.33**
		[0.15]
Sex × Industry × Occ. FE	X	X
Exp. and edu. controls	X	X

*Notes: This table reports the results of regressing values of RNR skills and Non-routine skills on a time trend variable (year values) for the full ONET, Constant Updates, and Lightcast datasets combined with ACS. See online Appendix A.1 and A.5 for the data construction. The regressions include controls for sex—industry-occupation fixed effects, as well as 5-category (no high-school, high-school graduate, some college, college graduate, post-college) education fixed effects, polynomials of years of work experience up to power 4, and the interaction of experience polynomials and education fixed effects and gender. Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, and * p<0.1.*

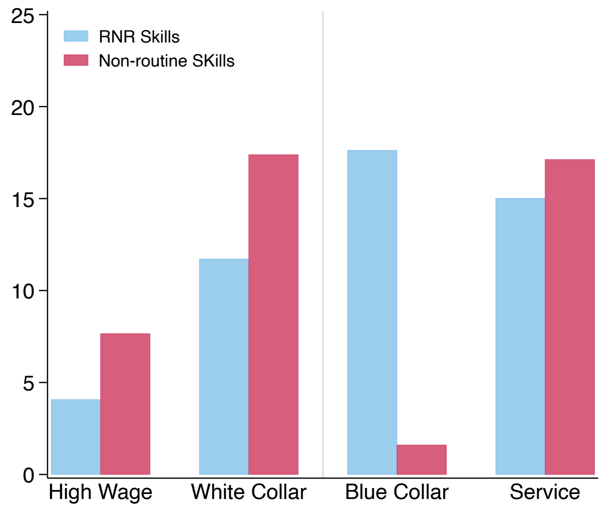
data, within occupation increase account for 4.4 percentiles.[17]

Interestingly, for the constantly updated occupations at 6 digits, worker reallocation contributes negatively to the increase in skill mixing using OEWS data. This pattern implies that for these very granular occupations that have been updated consistently, within-occupation variation more than accounts for the observed increase in skill mixing. At 4-digit occupations, worker reallocation does contribute positively to the increase in skill mixing among constantly updated occupations for non-routine skills but the magnitude is small relative to the within-occupation variation; for RNR skills, the contribution remains negative.

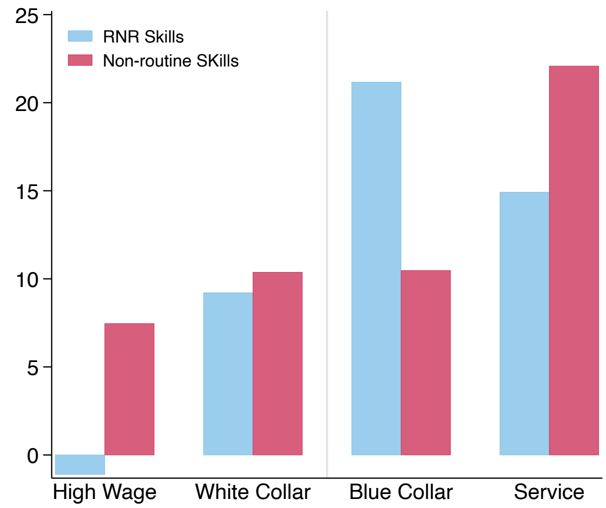
An alternative explanation of the employer-side shifts in accounting for skill mixing is that even within occupations, the supply of labor might have changed, due to, i.e., rising human capital, or labor force participation of females. To further shed light on the sources, Table 2 shows a regression of skill mixing indexes on linear time trend (years) across combinations of O*NET and Lightcast with ACS data. I further control the interaction of gender, industry, and occupation effects, and flexible polynomials and interactions of years of education and experiences. The table shows a universal increase in the degree of

[17] Online Appendix A4 shows the decomposition results using skill mixing indexes for different skill pairs and a similar result holds.

Figure 4: Skill Mixing Index Change by Occupation Groups and Gender, 2005-2018



(1) Male



(2) Female

*Notes: This figure plots the changes in skill mixing indexes across different occupation groups for male and female workforce. The units of the index changes are percentiles of their distributions in 2000. Workers are categorized into four occupation groups – High Skill, White Collar, Blue Collar, and Service following Acemoglu and Autor (2011). O*NET and ACS data are combined for these figures with consistent occupation codes Autor and Price (2013) and developed by Deming (2017).*

skill mixing in the magnitude of 0.65 to 0.75 percentile per annum using O*NET data, and 0.33 per annum using Lightcast data. Moreover, this increase persists within gender, industry, and occupation groups and is unaffected by controls of worker's labor supply, therefore highlighting that demand-side dynamics is playing a pivotal role in driving skill mixing.

III.C Skill Mixing Changes by Occupation

Beneath these general trends of skill mixing are differential patterns among occupations and gender groups. Figure 4 shows the changes in the skill mixing indexes from 2005-2018 for four major occupation categories that are grouped based on wage levels and represent all U.S. non-agriculture employment.[18] for male and female workforce respectively. The changes are in percentiles of their 2005's counterfactual distributions similar to what was used in Figure 3.

[18] The grouping is based on Acemoglu and Autor (2011).

First in terms of occupations, service, and while-collar occupations more than the others lead to the increase in mixing non-routine skills. For RNR skills, on the other hand, blue-collar jobs have seen the highest increase in mixing, followed by service. These results indicate that the bulk of skill mixing happens in lower-wage occupations, particularly the service sector. Now turning to gender differences, male workers saw a higher rise in skill mixing for both skill groups in white-collar and high-wage occupations, while female workers saw higher growth in lower-wage blue-collar, and service occupations.[19] This implies that male workers are more likely employed in higher-wage occupations that become more skill mixed, while female workers are more likely to be employed in lower-wage occupations that become more mixed in using skills.[20]

In the online Appendix Figure A4 I show the decomposition of skill mixing by industries, and a similar pattern holds. The private service sector followed by retail trade and construction leads others in the growth of skill mixing, while business and professional services have much less increases in skill mixing, particularly for RNR skills.[21] I also show the decomposition of occupations' changing mixing of individual skill pairs, which confirms that non-routine skill drives skill mixing in all occupations, while routine skills are only more mixed with other skills in blue collar and service occupations.

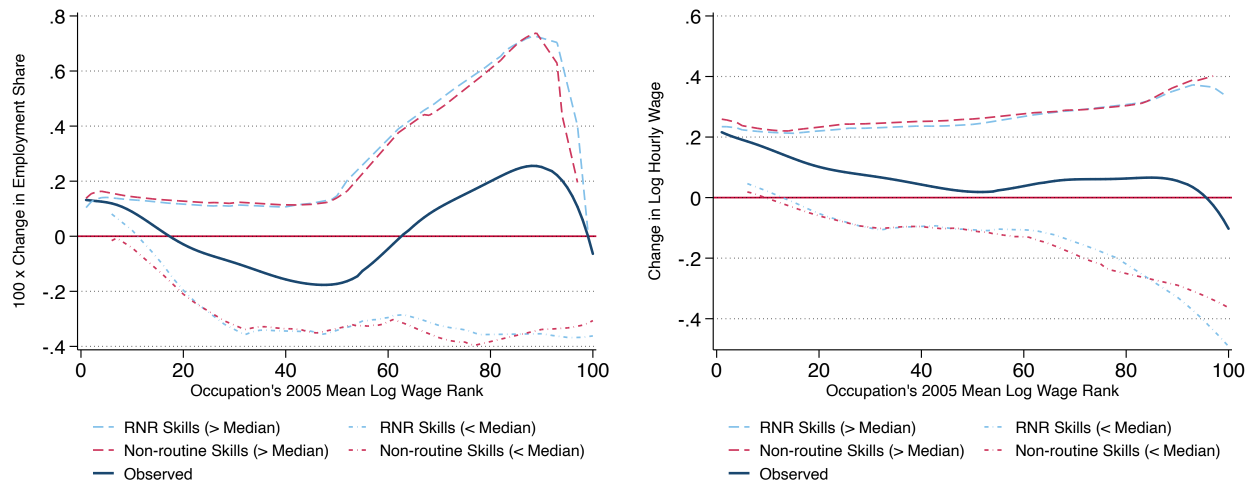
Distributional Implications: One of the key structural changes in the U.S. labor market post-1980 is the pronounced job polarization or hollowing out of middle-skill employment and wage growth, due potentially to the routine-biased technological change and offshoring (Acemoglu and Autor 2011; Goos, Manning, and Salomons 2014). To see how much skill mixing can relate to these distributional dynamics, Figure 5 depicts the smoothed observed changes in both the share of total hours worked and log wage in 2005-2018 for occupations ranked by their hourly wage percentiles in 2005. I reconstruct these smoothed employment/wage changes for two groups of occupations: those with

[19] The figure a separating line between these occupations to show this more clearly

[20] Though the discussion of gender gap is out of the scope of the analysis of this paper, part of the result could be driven that male workers are given more opportunities to work in mixed-skill occupations that are at the higher end of the wage distribution due to gender segregation (see Blau, Brummund, and Liu (2013)) on the trends in gender segregation.

[21] The sectors that have the least growth in skill mixing are public, education, and mining

Figure 5: Smoothed Employment and Wage Changes by Skill Percentile, 2005-2018



Notes: These figures plot the smoothed observed as well as counterfactual changes of employment share (Panel A) and hourly wage (Panel B) for occupations between 2005-2018. On the x-axis, occupations are ranked into 100 percentiles by the average log wages of workers in those occupations in 2000. The changes in the share of hours worked and percent wage growth are then calculated for each percentile, which fit into smoothed lines using cubit polynomial fit. Counterfactual lines are the smoothed employment/wage changes only for occupations with above-median increases in the skill mixing indexes.

above-median increases in skill mixing indexes and those below the median.

Figure 5 first confirms the inverted bell shape (polarization) of observed employment and to a lesser extent, the change of wage. It illustrates key differences for occupations that have become more skill mixed. For occupations within similar wage ranks in 2005, those that become more mixed in skill use have a higher increase in employment share and wage growth. In fact, almost the entirety of employment and wage growth is accounted for by occupations that have become more skill mixed during this period. Therefore, relating to polarization, the differential growth in employment and wage among occupations at the high and low end of 2005's wage distributions are totally accounted for by skill-mixing occupations during this period. Besides being an important phenomenon for labor market dynamics, skill mixing also provides a unified and multi-dimensional perspective of the changes.

IV Returns to Skill Mixing

In order to better understand the influence of skill mixing on workers' labor outcomes, this section will examine the wage returns associated with skill mixing in relation to occupational choices and inherent worker skills. Additionally, the return on investment for a college major with a more mixed skill set will be discussed.

IV.A Data and Measurement

To assess wage returns associated with skill mixing, I use the National Longitudinal Survey of Youth (NLSY) datasets from both 1979 and 1997 cohorts, which offer comprehensive records of the participant's employment and educational histories. I combine these two cohorts to increase the sample size, limiting to the period from 2005 to 2019 to align with the timing of my skill mixing measurements from O*NET as discussed in the previous section.[22] The NLSY data is connected with O*NET via the census occupation data in NLSY and the crosswalk formulated by Autor and Dorn (2013). My principal focus is the real log hourly wage, adjusted to 2013 dollars. As Altonji, Bharadwaj, and Lange (2012), I trim values of the real hourly wage below 3 or above 200. The results of wage returns are robust to considering alternative sample constructions, such as excluding respondents over the age of 55 or using the unprocessed real hourly wage. The key advantage of NLSY is that it is a worker-level panel, and also contains information on worker's pre-market abilities. This allows for the control of worker characteristics in assessing occupational wage returns to skill mixing and also facilitates the evaluation of return to a worker-level degree of skill mixing. The selected measures of worker abilities are chosen to align well with the skill measures in O*NET: the Armed Forces Qualifying Test (AFQT) scores represent analytical skill; the social skills measure developed by Deming (2017) is employed to represent interpersonal skill.[23]; routine skill is measured by the

[22]The NLSY 1979 and NLSY 1997 are nationally representative surveys of youth, capturing data from individuals aged 14 to 22 in 1979 and 12 to 16 in 1997 respectively. During my sample period, the median age is 37, and 91 percent of the sample aged below 50.

[23]I use the AFQT scores constructed by Altonji, Bharadwaj, and Lange (2012) that are consistent across NLSY waves and account for age-at-test, test format, and other peculiarities. For interpersonal skills, I use the social skill measure developed by Deming (2017) assessing extraversion, which is constructed based on

workers' Armed Services Vocational Aptitude Battery (ASVAB) mechanical orientation scores.[24] As NLSY offers scant information on workers' computer skills, I adopt the worker's occupation or college major's computer skill value in the year 2005 as a proxy for the worker's initial endowment of computer skill. Online Appendix Table **??** lists the corresponding measures.

Moreover, the college education information in NLSY allows me to evaluate the return to studying college majors with different degrees of skill mixing.[25] I calculate for workers who studied a particular major, the employment weighted average of skill intensities and skill mixing indexes of their occupations contained in O*NET, to be used as measures of skills and skill mixing for that major.[26] In Online Appendix Table A8, I list the top majors both in terms of the levels and changes in the degrees of skill mixing for different skill pairs. Agriculture and Natural Resources stand out as it is the highest in mixing all different skills. Two other majors: Architecture and Environmental Design and Mathematics are among the top majors in mixing analytical, computer, and interpersonal skills. Whereas Engineering and Law surpass other majors in becoming more mixed of routine skills and other skills.

IV.B Wage Returns

To test for the returns to skill mixing, I regress the log wage of worker i in occupation j on the levels of different skills k required by that occupation, as well as their degrees of

sociability in childhood and adulthood in NLSY79, and two questions from the Big 5 inventory in NLSY97 respectively

[24] ASVAB test scores are only available for the NLSY79 survey. For NLSY97, I impute their ASVAB scores using a regression model with indicators for gender and ethnicity, and fixed effects that include age, year, census division, metropolitan area, and urbanity.

[25] There are some inconsistencies in NLSY's field of study coding: NLSY79 uses its own major codes that contain 25 two-digit categories, while NLSY97 uses another set codes for years leading to 2010 and transfers to National Center for Education Statistics (NCES)'s 2010 College Course Map (CM10) for years after 2010. For consistency, I map the two different types of major codes in NLSY97 to the 25 two-digit major categories in NLSY79. Online Appendix Table A9 shows the crosswalk of different types of major field of study codes.

[26] I take the first field within a year as representing a worker's major field in the case of multiple fields.

mixing:

$$
ln(wage_{ijt}) = \sum_k \sum_{h \neq k} \left[\beta_k \text{skill}_{k,jt} + \beta_{kh} Mix(\{\text{skill}_{k,jt}, \text{skill}_{h,jt}\} \right] +
$$

$$
\sum_k \sum_{h \neq k} \left[\omega_k \text{skill}_{k,ijt} + \omega_{kh} Mix(\{\text{skill}_{k,ijt}, \text{skill}_{h,ijt}\}) \right] + \gamma X_{ijt} + \delta_j + \delta_t + \delta_i + \epsilon_{ijt} \tag{2}
$$

$$
\text{where skill}_k, \text{skill}_h \in \{\text{ananlytical, computer, mechanical, interpersonal}\}
$$

Conditional on skill levels, the coefficients on skill mixing indexes β_{kh} identify the returns to working in occupations more mixed of those skill combinations. To further examine the worker level returns to skill mixing, I add to the right-hand side the levels of the skills that workers have, and their degrees of mixing. The coefficients on worker-level mixing indexes ω_{kh} then identify the wage premium to the mixing of worker skills conditional on occupation skill requirements. Throughout all the specifications, I include ethnicity by gender, age, metropolitan status, individual year, years of education, census region, and urbanity fixed effects. I also include occupation fixed effect to control time-invariant differences across occupations and focus on how the changes in skill requirements within the occupation are affecting wage returns, consistent with the empirical finding that this margin is the main driver of skill mixing. To focus the discussion on the wage returns to skill mixing, I only present the results on the skill mixing index β_{kh} and ω_{kh}, and discuss the returns to individual skills and how they interact with skill mixing in online Appendix A.7.

Table 3: Return to Skill Mixing of Occupation and Worker Skills

Dependent: ln(hourly wage)	(1)	(2)	(3)	(4)
Occupation Skills				
Mix (analytical + computer)	0.007	0.011**	0.013***	0.011
	[0.005]	[0.005]	[0.005]	[0.008]
Mix (analytical + interpersonal)	0.016***	0.016***	0.015***	0.027***
	[0.005]	[0.005]	[0.004]	[0.007]
Mix (computer + routine)	-0.022**	-0.029***	-0.021***	-0.026**
	[0.009]	[0.009]	[0.008]	[0.012]
Mix (computer + interpersonal)	-0.008	-0.012**	-0.014***	-0.011
	[0.006]	[0.006]	[0.005]	[0.009]
Mix (routine + analytical)	-0.050***	-0.056***	-0.050***	-0.057***
	[0.008]	[0.009]	[0.008]	[0.012]
Mix (routine + interpersonal)	0.023***	0.029***	0.019**	0.023*
	[0.008]	[0.009]	[0.008]	[0.012]
Worker Skills				
Mix (afqt + computer)		0.044*		0.021*
		[0.023]		[0.013]
Mix (afqt + social)		0.028*		-0.081***
		[0.015]		[0.021]
Mix (computer + asvab mech)		0.013		-0.081***
		[0.025]		[0.027]
Mix (computer + social)		0.008		0.065***
		[0.013]		[0.020]
Mix (asvab mech + afqt)		0.001		0.115***
		[0.009]		[0.042]
Mix (asvab mech + social)		-0.040***		-0.064
		[0.011]		[0.044]
Ethnicity $\times$ Gender, Age, Region, Edu FE	X	X	X	X
Occupation FE	X	X	X	X
Worker FE			X	X
Observations	87,655	78,719	87,655	50,580
R-squared	0.426	0.439	0.758	0.762

*Notes: This table reports the result of estimating equation (2) using pooled NLSY79&97 data for employed workers from 2005-2019. Log hourly wages are the outcome variables and person-year is the unit of observation. The occupational skill and skill mixing measures come directly from O*NET and are merged to NLSY79&97 based on census occupation codes. The worker-level skill measures are constructed as in Table* **??** *and skill mixing indexes are then calculated accordingly. All measures of skill and skill mixing are normalized to have mean 0 and standard deviation 1. Ethnicity-by-gender, age, year, census region, urbanicity, and a 5-category (no high-school, high-school graduate, some college, college graduate, post-college) education fixed effects are included for all regressions, with additional fixed effects as indicated in the table. Standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10.*

Occupation and Worker Level Returns: Table 3 shows the wage returns to skill mixing at both the occupation and individual levels and indicates a positive premium of mixing non-routine skills. Column (1) shows that workers in occupations that become one standard deviation more mixed of analytical and interpersonal skills earn a wage gain of 1.6 percent per year, significant at the 1 percent level. Workers in occupations that become more mixed of analytical and computer skills also reap wage increases though not significant. Other the other hand, workers in occupations more mixed of routine and other skills saw a wage decline, except for routine and interpersonal, the mixing of which gives a 2.3 percent wage gain.

One potential concern is that workers sort into occupations in which their skills are rewarded higher, making it difficult to estimate the returns to the mixing of occupational skills across workers. In column (2), I further include worker abilities and their degree of mixing. Such a specification serves two purposes. On the one hand, the inclusion of additional worker characteristics improves the precision of the identified wage premiums at the occupation level; on the other, it sheds light on the return to skill mixing at the worker level conditional variations in the workers' occupations. The results indicate that on the occupational level, the wage premium for analytical and interpersonal, as well as routine and interpersonal skills persist, while for analytical and computer has become stronger, at 1.1 percent per year, and significant at 5 percent level. Turning to the worker side, workers that are a standard deviation more mixed of analytical and computer, as well as analytical and interpersonal also earn a wage premium of 3-4 percent, though is not very precisely estimated.

In column (3), I further restrict the analysis to within worker variation by adding worker fixed effects; along with the occupation fixed effects, this specification essentially resembles an AKM model.[27] The magnitudes of the returns to skill mixing shown in column (3) are similar to those in column (2). Workers who are in an occupation that are one standard deviation more mixed of analytical and computer as well as analytical and interpersonal skills see their wage increase by 1.3 and 1.5 percent respectively, and those

[27]Using within worker variation to study wage growth has been discussed and applied in i.e., Neal (1999); Gibbons et al. (2005); Lazear (2009) and Deming (2017). Choné and Kramarz (2021) found that under a worker assignment model with bundled skills, the implied wage equation also has an AKM form.

who are in occupations that are one standard deviation more mixed of mechanical and interpersonal skills earn 1.9 percent more. Contrarily, workers in occupations that are more mixed with the rest of the skill combinations are associated with a wage reduction of 1.4 to 5 percent.

In online Appendix Table A6, I show that the occupational level returns to skill mixing conditional on worker fixed effects is robust to alternative measures of skills and mixing. Across all these robustness checks, a similar qualitative pattern holds. Specifically, there is about a 1 to 2.5 percent wage premium for mixing analytical and computer as well as analytical and interpersonal skills and a 3 percent of a wage premium for mixing routine and interpersonal skills. The mixing of other skill combinations is associated with negative wage returns at the occupation level.

Returns to College Major's Skill Mixing: With the calibrated skill accumulation of workers, I test the return to obtaining a more mixing skill set in column (5), conditional on occupational skill requirements and worker fixed effects. Workers don't seem to earn a wage premium as they become more mixing of most skills in switching occupations, except for mechanical and interpersonal skills, the mixing of which brings a 10.8 percent return.[28] At the same time, the positive and significant returns to switching to an occupation more mixing of analytical and computer as well as analytical and interpersonal skills persist conditional time-varying worker characteristics, validating their robustness.

To focus on the role that schooling and college education play in workers' human capital formation and return to skill mixing, in column (6) I represent a worker's human capital by the skill content of a worker's accumulated education experience.[29] Such a designation necessarily restricts the analysis to those who have entered college and brings up selection concerns; however, controlling worker fixed effects and fixed and time-varying occupation attributes, the evidence will imply whether it is rewarding to

[28]This is consistent with the evidence in Autor and Dorn (2013) that low-skill service occupations attract workers from mid-skill routine occupations and are associated with a wage gain; the result here indicates that such transition is likely to be also accompanied by the mixing of mechanical and interpersonal skills on the workers' side.

[29]I apply rolling averages of skill and mixing measures of a worker's entire education history to represent that worker's education skill content, therefore, there is worker-level variation.

transition to a more mixing major conditional on one's job choices. The result in column (6) shows a positive return of around 5 percent to switching to a college major a standard deviation of more mixing of analytical and computer or of mechanical and interpersonal skills. The wage premium to skill mixing appears to be larger for college major choices relative to occupation choices.

V A Directed Search Model with Occupation Design

The rich empirical findings on skill mixing pose challenges in understanding their driving forces. In what follows, I attempt to provide an overarching framework to investigate the mechanisms. For this purpose, I build a directed search model with several unique features: First, both firms and workers are represented by multi-dimensional skills; Second, firms must make decisions about occupation design before meeting workers, a process that involves a rental cost payable upon meeting as in Acemoglu (1999); Third, the model incorporates non-linear production and rental cost technologies. Despite the rich setup, the model remains tractable satisfying Block Recursivity as in Menzio and Shi (2011). Under these specifications, the model offers clear insights regarding changes in skill mixing, wages, and employment that are linked to the empirical findings.

V.A Environment

Workers: Time is discrete. At each period t, there is a unit measure of heterogeneous workers that lives forever. Each worker is characterized by a vector of multi-dimensional skills $\mathbf{x}_t = \{x_t^1, ..., x_t^k, \ldots, x_t^K\} \in S \subset \mathbb{R}^K$, where K is the dimension of a closed skill space S. Workers are risk-neutral, have linear utilities equal to their consumption, and discount the future with a factor β.

Firms: On the other side of the market, there is an endogenous measure of risk-neutral firms each running one vacancy. Potential entrant firms pay a cost c to post their vacancies across different occupations $j = \{1, ..., J\}$, with $J \geq 2$. Each occupation is characterized in the same multi-dimensional skill space as workers' skills,

$\mathbf{y}_t = \{y_t^1, ..., y_t^k, \ldots, y_t^K\} \in S \subset \mathbb{R}^K$, which has the interpretation of a vector skill requirement or skill importance for each of the worker skills. Firms share workers' discount factor β. In the exposition below, I subsume time subscript in describing worker and firm characteristics.

The production function of each worker-firm pair takes a CES form of the skill inputs of workers and skill requirements of occupation j that the firm runs the job:

$$f(\mathbf{x}, \mathbf{y}) = \left[\sum_{k=1}^{K} (x^k y^k)^\sigma \right]^{\frac{1}{\sigma}}, \tag{3}$$

where the elasticity of substitution between the two skills is $\frac{1}{1-\sigma}$.[30] This production technology represents an extension of the production technology used in the multi-dimensional skill matching literature (i.e., Lise and Postel-Vinay 2020; Lindenlaub 2017; Ocampo 2022), where there is within-match complementarity between worker and firm attributes, but I also allow complementarity across skills regulated by σ. When multi-dimensional skill distributions of workers and firms are available, such a production technology gives a clearer portrayal of the interaction between skill demand and supply.

A unique feature of this model is that I allow firms to actively design the job before meeting the worker (Acemoglu (1999)), delivering a flexible degree of skill mixing. Specifically, firms with both filled and unfilled vacancies design their occupations by optimally choosing the occupational skill requirements $y(j)$ in each period, consistent with the empirical finding that both incumbent jobs and vacancies have changing degrees of skill mixing. Such a design choice captures the overall quality of the job and the optimal degree of skill mixing. Nonetheless, such a job design incurs a maintenance cost that has to be paid every period in the form of $C(\mathbf{y})$. This cost increases in the skill level that the firm chooses, and may represent the rental expenses of the necessary equipment to run an occupation. Moreover, ρ regulates the additional expenditure firm incurs when firms switch among skills and will affect firms' choices of skill intensities α_{jk} and hence the degree of skill mixing as well.

[30] Since labor is the only input in the model, it can be understood as "equipped" labor, and occupations' skill requirement or importance $\mathbf{y}$ takes a factor augmenting form.

Labor Market: There is a continuum of submarkets that are indexed by worker and occupation skill profiles $(\mathbf{x}, \mathbf{y})$, as well as the share of worker-firm output ω that firms promise to workers.[31] Workers with skill profile $\mathbf{x}_t$ direct their search towards different occupations and promised utilities, meeting one vacancy at a time. Matching between workers and firms is frictional and is regulated by a standard constant to scale matching function. Under this directed search environment, each submarket has a separate tightness (vacancy-unemployment ratio), denoted by $\theta_t(x, y, \omega)$. In each submarket, workers find job with probability $p(\theta_t(x, y, \omega))$, and firms fill the vacancy with probability $q(\theta_t(x, y, \omega)) = p(\theta_t(x, y, \omega))/\theta_t(x, y, \omega)$.

The timing of the model evolves as follows. At the beginning of each period, a fraction δ of worker-firm pairs separate exogenously. Before the labor market opens and unlike standard search models, firms will first need to design the occupations at this stage before they post vacancies across submarkets. The labor market then opens, and both unemployed and employed search for unfilled vacancies and form matches with firms under the constant return to scale matching technology. The labor market then closes, firms produce the output, pay the occupation maintenance cost, as well as the wage which is a share of output to workers. Unemployed workers receive a transfer with a value of b. Lastly, workers are able to be learning-by-doing, and their skills evolve according to the Markov process depending on their employed occupations.

Aggregate and Individual State: Despite the multi-dimensional skill setup, the model still achieves great analytical tractability by relieving the dependence on the entire distribution of workers across firms in characterizing agents' decisions.[32] The aggregate state,

[31]This arrangement can be considered as an employment contract simply specifies the output share ω promised to the worker contingent on the state for the current period, as well as the continuation value of the match in the subsequent period (see next section). The contract is assumed to be fully committed by both the workers and firms.

[32]Such a convenient feature was coined as "block recursive" in Menzio and Shi (2010) and Menzio and Shi (2011) for a broad range of directed search models (see the required conditions therein). Block recursivity allows not only analytical tractability but also enables standard numerical techniques to solve the model. The framework considered in this paper involves more heterogeneity and requires an additional degree of directness, as discussed.

which is the distribution of workers across employment status, skill profiles, occupational skill requirements, and promised utilities does not enter into agents' value functions. This is a result of two features of the model. First, as search is directed and workers choose the share of output firms offer, their promised life utility does not depend on their outside options, and workers do not need to forecast the wage depending on the entire distribution of employment. Second, there are separate markets for workers of different profiles, and workers search for jobs within their own submarket, in which firms carry different occupations. This additional degree of directedness implies that the market tightness of a submarket is independent of the worker distribution in other markets, relieving the burden of workers and firms to forecast other markets in making their decisions.[33]

Nonetheless, in the model, I allow workers to learn on the job, and their subsequent skill profiles are contingent upon their current employment status, as in Lise and Postel-Vinay (2020). More explicitly, the worker's skills $\mathbf{x}$ in the finite set S follow a Markov process: $\pi(\mathbf{x}'|\mathbf{x}, \mathbf{y})$, conditioned on their current skill level and employed occupation. Depending on the skill requirements of their present occupations, the skill profiles may undergo either an increase or a decrease. For those who are unemployed, they are classified such that their current occupation requires a zero level for all the skills in the worker's skill profile.

V.B Model Equilibrium

I shall now characterize the optimal strategies for workers' job search and firms' job creation and continuation. The value functions for workers are described at the point of the production stage when the labor market comes to a close, while for firms I also consider the job design stage before the labor market opens.

[33] Such additional directness implies that, i.e., computer scientists only confront other computer scientists in job search, while sales clerks only compete with other sales clerks. In reality, the degree of separability will depend on specific occupations and the overall economic condition. As reported by Osberg (1993), search directedness is procyclical and is higher when the market is tight. In bringing the model to the data, I use economic recovery periods and more coarse occupations to be consistent with the model.

Worker's Problem: Let $U_t(\mathbf{x})$ denote the value of being unemployed and searching for a worker $\mathbf{x}$ at time t. Similarly, let $W_t(\mathbf{x}, \mathbf{y}, \omega)$ be the total discounted returns from holding a job of skill requirements $\mathbf{y}$ and output share ω at time t. These values can be written as:

$$
\begin{aligned}
U_t(\mathbf{x}) = b + \beta E\Big\{ \max_{y', \omega'} \; & p(\theta_{t+1}(\mathbf{x}', y', \omega'))W_{t+1}(\mathbf{x}', y', \omega') \\
& + \big[(1 - p(\theta_{t+1}(\mathbf{x}', y', \omega'))\big] U_{t+1}(\mathbf{x}')\Big\} \\
W_t(\mathbf{x}, \mathbf{y}, \omega) = \omega f(\mathbf{x}, \mathbf{y}) + \delta U_{t+1}(\mathbf{x}') + \beta(1-\delta)E\Big\{ & \max_{\mathbf{y}', \tilde{\omega}'} \; p(\theta_{t+1}(\mathbf{x}', \mathbf{y}', \tilde{\omega}'))W_{t+1}(\mathbf{x}', \mathbf{y}', \tilde{\omega}') \\
& + \big[(1 - p(\theta_{t+1}(\mathbf{x}', \mathbf{y}', \tilde{\omega}'))\big] W_t(\mathbf{x}', \mathbf{y}, \omega)\Big\}
\end{aligned}
\tag{4}
$$

Unemployed workers gain a utility b through the current period's transfer. In the subsequent period, their skills may transition to $\mathbf{x}'$, which are likely to depreciate due to their unemployed status. Meanwhile, within the submarket that aligns with their skill profiles, workers engage in the search for vacancies that span a variety of occupations $\mathbf{y}$ and output shares ω, looking for the highest continuation value. In choosing $\mathbf{y}$ and ω, workers face the tradeoff between the value of employed and the success probability of a match $p(\theta_{t+1}(\mathbf{x}', y', \omega')$, both of which hinge on the occupation and output share that the workers target. Should the match prove successful, the workers enjoy the continued value that employment offers; otherwise, their status of unemployment persists.

Workers currently employed in a firm characterized by $(\mathbf{y}\omega)$ receive a wage equivalent to the share *omega* of the output from their match. When the subsequent period arrives, they face a probability *delta* of an exogenous separation, in which case they become unemployed with a value $U_{t+1}(\mathbf{x}')$ and engage in job search immediately. Employed workers perform on-the-job searches in their current match for new occupations and output shares $(\mathbf{y}', \tilde{\omega}')$, on the premise that there is a positive probability $p(\theta_{t+1}(\mathbf{x}', \mathbf{y}', \tilde{\omega}'))$ that the continuation value from the new match offers exceeds that of the original firm. In the absence of such possibilities or if the transition is not successful, the worker remains with the initial firm.

Firm's Problem: Consider a firm running occupation $\mathbf{y}$, offering output share ω, and employing worker $\mathbf{x}$. Let $J_t(\mathbf{x}, \mathbf{y}, \omega)$ denote the total discounted profits to this firm:

$$J_t(\mathbf{x}, \mathbf{y}, \omega) = (1-\omega) f(\mathbf{x}, \mathbf{y}) - C(\mathbf{y}) + \beta(1-\delta) E\Big\{(1 - p(\theta_{t+1}(\mathbf{x}', \mathbf{y}', \tilde{\omega}')) J_t(\mathbf{x}', \mathbf{y}, \omega)\Big\} \quad (5)$$

In the current period, firms receive a portion $(1-\omega)$ of the worker-firm output, after paying the workers their wages. In addition, firms also need to cover the occupation maintenance cost $C(\mathbf{y})$, which depends on the skill levels required by the occupation in which the firm is engaged. The labor market operates under free entry for firms, hence, maintaining a vacancy bears no value. In the case of exogenous separation, or with a probability $p(\theta_{t+1}(\mathbf{x}', \mathbf{y}', \tilde{\omega}'))$ that the worker finds another job at an optimal occupation $\mathbf{y}'$ and output share $\tilde{\omega}'$ through on-the-job search, the firm accrues no profits. In the case where the match persists, the firm continues to acquire discounted profits from the match.

$$c = \beta E\Big\{\max_{\mathbf{y}} q(\theta_t(\mathbf{x}, \mathbf{y}, \omega)) J_t(\mathbf{x}, \mathbf{y}, \omega)\Big\} \quad (6)$$

The free-entry condition further highlights firms' choice of optimal degree of skill mixing and the tradeoff that agents face in the model. Prior to the opening of the labor market in each period, incumbent and entrant firms re-design the occupation, taking into consideration the overall production technology and worker skills within their respective submarkets.[34] Given that the value of a vacancy is zero, firms will opt for an optimal skill mixing that equates the firm's anticipated discounted profits to the cost of vacancy posting as in equation (6). This condition implicitly pins down market tightness $\theta_t(\mathbf{x}, \mathbf{y}, \omega)$. If an occupation for a specific worker type becomes more profitable, the number of vacancies posted will increase, leading to a rise in market tightness but at the same time a reduction in the job-filling rate.

The free entry condition also reflects the tradeoff faced by workers. Since workers receive the remaining output claimed by the firms, in markets with higher job-finding

[34] Considering that incumbent firms and new entrants utilize identical production technologies and confront the same worker skills within each submarket, their choices align

probabilities (i.e., tighter markets), the value of employment is likely to be lower. Workers' job finding probability also feedback to firms' discounted profits through worker on-the-job search and the chance that the firm attracts other employed workers.

Skill Mixing, Wages and Employment: The multi-dimensional skill directed search model discussed above, coupled with endogenous occupation design, generates several predictions regarding changes in skill mixing, wages, and employment. These predictions are closely linked to the empirical findings presented in Sections III and IV. An important aspect of these predictions is the role played by the degree of skill complementarity in a production framework with indivisible skills.

The formal propositions and proofs of these outcomes are detailed in Online Appendix B.1. I provide a brief discussion here. Under a production technology as delineated in equation (3) and an occupational rental cost defined in (7), if skills demonstrate increased complementarity in production or if they possess a higher degree of increasing marginal costs, firms find it more profitable to utilize a mix of different skills instead of specializing in a single one. Additionally, the supply of skills by workers influences these outcomes. As workers supply a more diverse set of skills, it becomes more efficient to design jobs that require this mix of skills. Moreover, if skills become more complementary in production or less costly to combine, the output of the worker-firm match rises, leading to wage increases. Through the free entry condition specified in equation (6), this increased joint worker-firm value results in a tighter labor market and an elevated job-finding probability for workers. I quantitatively calibrate the model and test these predictions in the next section.

VI Quantitative Analysis

In this section, I calibrate the model to evaluate the quantitative importance of different factors contributing to the phenomenon of skill mixing, and explore implications for wages and employment. I first describe data construction and measurement, followed by a discussion of estimation protocol, moment selection, and parameters identified. I then perform counterfactual analyses and show that technological shifts embodied in the changes in complementarity of skills in production, the rental cost of occupation maintenance, as well as biases towards different worker skills have played a major role in driving the variation in skill mixing. I then show that these forces also account for a significant part of wage and employment shifts.

VI.A Measurement and Calibration

Data and Measurement: I apply the same combination of NLSY 79 & 97 along with O*NET data as in Section IV to calibrate the model. The datasets provide counterparts to the model variables such as worker skills ($\mathbf{x}$), occupational skill requirements ($\mathbf{y}$), unemployment rate, and wage levels. The model is calibrated to two periods of data from early 2000s to late 2010s seperately, which coincides with a substantial shift in skill mixing and abstracts from the financial recession. Specifically, the model is fitted to the data from 2005–2006 and 2016–2019 to ensure comparability of sample sizes across these two periods, and I restrict to those workers with wage, occupation, and ability information.[35] Finally, for both worker and job skill profiles, I consider the same set of skills (analytical, computer, interpersonal, routine) as in Section IV, only combining analytical and computer skills into one to have skill dimension of three to be feasible for quantitative analysis.

Considering the potential influence of skill supply variation on skill mixing, the model calibrates workers' skills to align with their choice of occupation and college major (if attended), as well as their employment status, following the approach of Lise and Postel-Vinay (2020). This introduces variation in worker skill supply *across* the two periods. Worker skills are adjusted upwards if the requirements of an occupation or a college major exceed their original skills, and downwards otherwise, or if the worker is unemployed. The speed of skill adjustment is asymmetric and skill-specific. The parameters governing the skill adjustment are provided in Online Appendix Table **??**.[36]

[35]NLSY 1997 was conducted annually during 2005-2006, but only biannually in 2016-2019, so does NLSY 1979 for the later period. The same sizes for the two selected periods are 30,654 and 43,340 respectively.

[36]Using the estimates from Lise and Postel-Vinay (2020) as in online Appendix Table **??**, a worker accumulates γ times the gap between the worker's skills and an occupation's requirements in each year,

Functional Forms: The model is parameterized as follows. The multi-dimensional skill production function is defined as in equation 3, which accommodates cross-skill complementarity controlled by σ and enables a sensible interaction between skill demand and supply, in line with the multi-dimensional matching literature (i.e.,Lise and Postel-Vinay 2020; Lindenlaub 2017; Ocampo 2022). I allow a flexible form of occupation rental cost $C(\mathbf{y})$ as in equation 7, where ρ regulates the degree of increasing or decreasing marginal cost of elevated skill requirements, and τ governs the overall cost of operating an occupation.

$$C(\mathbf{y}) = \tau[\sum_{k=1}^{K}(y^k)^\rho] \tag{7}$$

The matching function assumes a standard Cobb-Douglas form, $M(s, v) = \mu s^\eta v^{1-\eta}$, indicating that η is the elasticity of matches concerning total search effort, and μ is the matching efficiency. This function leads to the job finding rate being $p(\theta) = \mu\theta^{1-\eta}$ and the vacancy filling rate being $q(\theta) = \mu\theta^{-\eta}$.

Calibration Strategy: The calibration of parameters falls into two categories. For parameters that regulate the search environment, I follow closely the conventions of the search and matching literature. However, for those parameters linked to the technology for skills in production, I estimate them internally through Simulated Methods of Moments (SMM).

The model period is one quarter. Given that all agents are risk-neutral, the discount rate β is assigned a value of 0.99, corresponding to an annual interest rate of approximately 4 percent. The job separation rate δ is set at 10 percent per quarter, as in Shimer (2005). For employed workers, their bargaining power *omega* is set at 0.6, mirroring the labor share of GDP in 2005. For unemployed workers, the unemployment benefit b is set at 0.25 as in Braxton and Taska (2023), which equates to about 51 percent of worker

with the value of γ depending on learning or depreciation (upward or downward accumulation). Workers' skills can be lost when not employed but can't be lower than their initial endowments. Finally, for skill changes while in school, I specify that workers spend on average 3 years learning the skills of their majors.

Table 4: Moments and Model Match

	First Period		Second Period	
	Data	Model	Data	Model
Worker moments				
Relative wage of high type				
Analy/computer	1.23	1.18	0.92	0.97
Interpersonal	1.03	0.98	1.29	1.42
Routine	1.52	1.43	1.63	1.69
Unemploy. Rate	0.09	0.10	0.16	0.16
Occupation moments				
Relative wage of high skill	1.30	1.35	1.56	1.57
Employ. share (low skill)	0.43	0.43	0.37	0.34
Employ. share (high skill)	0.57	0.57	0.63	0.66
$100 \times$ Skill mixing (low skill)	97.54	98.36	98.96	98.75
$100 \times$ Skill mixing (high skill)	95.74	96.33	94.12	94.92

Notes: This table reports the average values of the targeted and non-targeted moments both in the data and through model simulation except. The data used for the moment calculation and for SMM estimation are two periods of pooled NLSY79&97 for employed workers: period 1 from 2005–2006 and period 2 from 2016–2019. Two types of moments are included: the worker moments include the relative wage of high type workers as well as the unemployment rate; the occupation moments include the relative wage of high skill occupations, the employment share and the skill mixing in low and high skill occupations.

consumption in the calibrated model. The elasticity of the matching function η is set at 0.5 as is standard, and the matching efficiency μ is set to 0.65, as in Mercan and Schoefer (2020). Therefore, the internally estimated parameters include: the elasticity among skills in production σ, the scale and elasticity parameter of occupation rental cost (τ, ϕ), and the vacancy posting cost.

Before describing the estimation protocol, I outline how to map occupations and workers in the model to the data and the choice of grid points. I classify occupations into high- and low-skill, as in Section IV, with the former group including high-wage and white-collar jobs, and the latter blue-collar and service jobs. The grid points for occupations' skill requirements $\mathbf{y}$ are set such that moving up one grid corresponds to 30 percent of the observed median value for each occupation. On the worker side, for each of the worker skill in $\mathbf{y}$, a worker belongs to the high type if the skill is above the average value among all workers; with three chosen skills, there are 8 worker types in the model. I internally estimate the relative efficiency of high-type worker relative to low-type for each skill ($\alpha_k, k = \{\text{analy/computer, interpersonal, routine}\}$). Since labor is the only input in production, these relative efficiencies represent the skill bias toward higher skill that leads to higher productivity (i.e., Katz and Murphy 1992; Autor, Katz, and Krueger 1998).

The SMM procedure starts with solving the steady state policy for the agents given the parameters of the model. A panel of workers, each with a lifespan of 40 quarters, is then simulated. These workers start as unemployed and draw their skill supply from the calibrated empirical distribution. As each model period concludes, the workers' skills evolve following a Markov process, $\pi(\mathbf{x}'|\mathbf{x}, \mathbf{y})$, where the skill adjustment probability is calibrated in line with Lise and Postel-Vinay (2020) (see online Appendix **??** for more details). Each iteration thus results in a distribution of employment statuses and corresponding labor market outcomes. The parameters are then estimated SMM, which minimizes the gap between simulated and empirical moments by searching over the parameter space and offers local identification. Online Appendix B.3 provides further details on the numerical implementation.

The estimation targets 9 moments as shown in Table **??** for the first period that include: i) the relative wage of the high-type worker for each skill; ii) the unemployment rate; iii) the relative wage of high-skill occupation; iv) the share of employment across occupations; and iv) the skill mixing indexes across occupations. For the second period, I leave the skill mixing indexes untargeted, which serves as model validation and will be the focus of counterfactual analysis. The model parameters are jointly identified from the moments. The relative wage and employment share contain information on the output, therefore production and occupation rental cost technology. The degree of skill mixing and its variation across occupations further disciplines the elasticates in firms' occupation design. Conditional on output, the relative wages of high-type workers identify the skill biases of different skills.[37] Finally, the unemployment rate disciplines the vacancy posting cost.

[37] As Diamond, McFadden, and Rodriguez (1978) shows, if there is only time series data on the ratio of different inputs and their marginal products, then the elasticity of substitution cannot be separately identified from the biased technical change. It is crucial that here I have multiple occupation as well as worker types in the model simulation and hence the across occupation and worker variation of skill inputs and their output.

Table 5: Parameter Estimates

	σ	τ	ϕ	α_a	α_p	α_r	c
First period	1.0	0.6	6.7	2.2	1.0	1.8	1.1
Second period	0.4	1.5	2.6	2.8	2.5	1.7	8.9

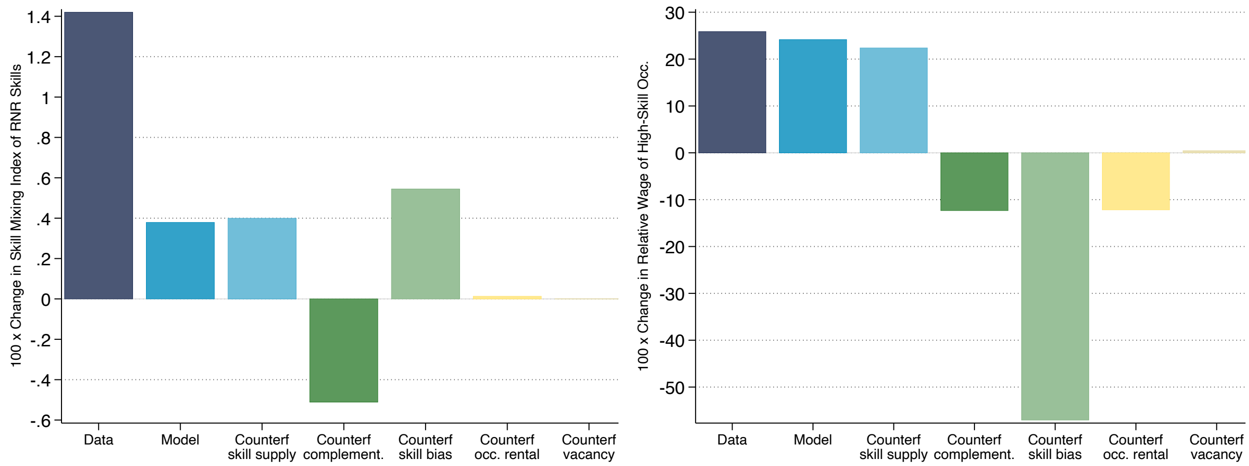
Notes: This table shows the estimated elasticity in production parameter (σ), the scale and degree of increasing marginal rental cost (τ and ρ), vacancy posting cost (c) as well as relative productivity of high-skill workers (α_k) in two periods using SMM. The data used for the moment calculation and for SMM estimation are two periods of pooled NLSY79&97 for employed workers: period 1 from 2005–2006 and period 2 from 2016–2019.

Table **??** shows that the model-predicted moments satisfactorily replicates key features of the data.

Estimation Results: Table **??** presents the identified parameters, indicating considerable technological shifts between the two periods. For the initial period, the estimated σ is close to 1, suggesting that skills are highly substitutable in production. Firms encounter rising marginal costs as they increase skill requirements ($\phi \geq 1$). When it comes to skill biases, workers with higher levels of analytical/computer or routine skills are approximately twice as productive as those with lower skill, while high interpersonal skill workers are not more productive.

In the second period, there is a significant rise in skill complementarity in production. As discussed in Section VI, this increased complementarity intensifies firms' incentives to mix skills. During this period, the occupation rental cost for firms rises, although the convexity in skill requirement choices has declined. Skill biases increase for both analytical and interpersonal skills, while for routine skills, it remains relatively unchanged. This suggests that wage premiums for routine experts are lower compared to other skills; it also implies that the incentive to mix routine with other skills in high-skill occupation declines. Since there is a sizable uptick in unemployment in the NLSY data across the two periods, the cost of posting vacancies also sees a considerable rise.

Figure 6: Model Counterfactual



Notes: The table shows the model generated increase in skill mixing in low-skill occupations (panel 1) and relative wage of high-skill occupation (panel 2). Different model channels are shut down sequentially by eliminating the relative caliberated values to highlight the contribution of each channel. The full model has all the model features. Worker skill supply variation across the periods are caliberated according to Table **??**. The values of skill complementarity, occupational rental cost, skill bias, and vacancy posting cost across two periods are shown in Table 5.

VI.B The Drivers of Skill Mixing and Implications for Wages and Employment

In this section, I employ the model to perform a counterfactual examination to assess the relative significance of each channel in the model in explaining the shifts in the extent of skill mixing. Additionally, I evaluate the influence of these elements on the changes in earnings and employment distribution. Specifically, I focus on the roles of skill supply variation, skill complementarity in production, occupation rental cost, skill bias of high-type workers, and vacancy posting cost in generating moment variations that align with the data. To gauge the significance of each of these elements, I sequentially suspend the shifts in parameter values associated with these channels and observe the impact on different outcomes.

Counterfactual Skill Mixing: I start by evaluating the contribution of different channels to the increase in skill mixing in low skill occupations, as depicted in the first panel of Figure 6. The counterfactual outcomes suggest that shifts in the complementarity of skills in production and the rise in occupational rental costs are the primary drivers of skill mixing. The full model with all features accounts for about 30 percent of the increase in skill mixing in low-skill occupations across the two periods. In the absence of worker skill supply variation across the periods, the counterfactual increase in the degree of skill mixing remains almost unchanged and only slightly increases, suggesting that the evolving skill mixtures provided by workers during this period did not significantly influence skill mixing and at most counteracts skill mixing to a minor extent.

Subsequently, I shut down the increase in complementarity of skills in production. Strikingly, the change in skill mixing becomes negative, with a magnitude as considerable as the positive increase in skill mixing in the full model. This denotes that skill complementarity is a dominating force driving the increase in skill mixing. Skill bias changes present a contrasting scenario. After its suspension, the degree of skill mixing shifts from negative to positive, and rises beyond even the level in the full model, indicating that the increase in skill bias favouring high-type workers actually lowers the increase in skill mixing. From the estimation results, it can be seen that the differential increase in skill efficiency for analytical/computer and interpersonal skill, along with the relative stability in the skill bias for routine skill, makes integrating these skills within the same occupation less desirable. Finally, occupational rental cost appears as another key factor leading to the increase in skill mixing – after it has been shut down, the degree of skill mixing decreases, with a magnitude greater than the full model. Vacancy posting cost seems to play a negligible role in driving skill mixing.

Wage and Employment Effects: I now examine how these model channels that affect skill mixing affect wage and employment distribution. The second panel of Figure 6 shows the changes in relative wage of high-skill with respective low-skill occupation from early 2000 to late 2010s, for which the model successfully generate the increase of about 25 percent that is consistent with data. Similar to the changes in skill mixing, the rise in skill complementarity in production plays a pivotal role in accounting for the observed rise in wage dispersion of high-skill relative to low-skill occupation, and the changes in worker skill supply and vacancy posting cost plays a negligible role. Absent the rise in skill complementarity in production, the relative wage premium of high-skill occupation would have decreased by more than 30 percent, leading the relative wage premium of high-skill occupation to a negative regions.

But unlike skill mixing, for the wage distribution dynamics, skill bias changes are the primary drivers, and the rise in occupation rental cost actually contribute negatively. Without skill bias changes, the high-skill occupation's wage premium would have declined by nearly 40 percent, and without occupation rental cost variation, the rise in high-skill occupation's wage premium would have been even higher. These results are intuitive: as skill biases increase the productivity of high-type workers, who tend to sort into high-skill occupations, the wage gain in those occupations would be higher, and firms in high-skill occupations would specific even higher skill requirements for these workers. Whereas the occupation rental cost makes it more expensive to increase the skill requirements, it reduces the high-skill occupations' wage premium.

In online Appendix 7, I examine the implication of these different channels for the employment gain in high-skill occupations, which present a similar picture to the wage premium, only that worker skill supply plays a important role for employment share increase in high-skill occupation.

VII Conclusion

Skills are inevitably embedded in workers and understanding the demand for skill *mixtures* is important in studying the dynamics of the labor market. I present a rich set of empirical findings on the phenomenon of "skill mixing", and show that between 2005-2018, there has been a sizable growth in the degree of mixing, particularly for analytical, computer, and interpersonal skills. To understand the heterogeneous within-occupation variation in skill mixing of different occupations, I provide an integrated explanation incorporating insights from the directed search and endogenous technological change literature. Bringing the model to the data, I estimate parameters that are important in understanding the interaction among skills and show that technological change is the main driver of skill mixing.

The phenomenon of skill mixing brings forth very different policy implications for worker training and college consulting. Using NLSY 79 and 97 combined with O*NET data, I show that workers in occupations that become more mixed of analytical, computer, and interpersonal skills earn a positive wage premium. Further, I calculated the degree of mixing for each college major and show that students who have studied a college major more mixed of analytical and interpersonal skills earn as much as 5 percent more. In sum, this paper's results suggest that in a world with an increasing trend of skill mixing with positive wage premiums due to technological advancements, educators and policymakers should consider providing more "mixed" skills to workers rather than focusing solely on nurturing expertise and specialization.

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Appendix for Online Publication

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A ADDITIONAL EMPIRICAL RESULTS

A.1 Data Construction

In this section, I give more details on data construction for the two primary datasets on job skill demand employed in Section III and IV, namely O*NET (Occupation Information Network) and Lightcast (previously known as "Burning Glass"). Specifically, I discuss strategies for leveraging the longitudinal information in these datasets with higher precision. I also present an overview of their inherent characteristics, advantages and disadvantages, and how they are cross-walked with other datasets used in the analysis.

O*NET: Administered by the U.S. Department of Labor, O*NET is a replacement to the Dictionary of Occupational Titles (DOT). It is more comprehensive and more frequently updated and has been used widely to analyze occupation skill requirements and work settings (i.e., Acemoglu and Autor 2011; Yamaguchi 2012; Autor and Price 2013).

Nonetheless, to use the longitudinal variation from O*NET, the key challenge concerns partial updating – each new version of O*NET only update an average of 110 of targeted occupations among the 970 7-digit occupations. Online Appendix Table A1 lists different versions of O*NET, the release year, and the year composition for 3 of the modules. Specifically, for each release of O*NET, I assign a "Considered Year" such that at least 55% to 60% of occupations are updated after that year.

Moreover, I use 4-year intervals. The last column of online Appendix Table A1 show the percent of occupations that are updated from the last considered year of data included in the analysis. On average, more than 50 percent of the occupations are updated across the succeeding years included in the analysis.

O*NET contains around 270 descriptors about occupations that are grouped into 9 modules: abilities, knowledge, skills, work context, work activities, experience/education requirement, job interest, work values, and work styles. For my main analysis, I only use descriptors from 3 modules: work context, work activities, and knowledge that are more interpretable as the skill requirements, and are consistently evaluated by incumbent workers for each new release. These descriptors come as importance, level, extent, and relevance. To interpret the skill measures as gauging the intensity, I use the importance information, similar to i.e., Acemoglu and Autor (2011) and Guvenen et al. (2020), but the level and importance pieces of information are highly correlated and don't affect the qualitative patterns of skill mixing shown in the paper.

In Section III, I show the longitudinal changes in skill mixing by combining O*NET and ACS datasets. O*NET uses SOC 2000 occupation classification for releases between 2000 and 2010 and SOC 2010 for years after 2010. To link O*NET and ACS, I first bridge SOC codes to the census' OCC 2000 and OCC 2010 codes respectively using crosswalks provided by the Analyst Resource Center and the Bureau of Labor Statistics. Then different years of OCC codes are homogenized using a balanced and consistent panel of occupation codes developed by Autor and Dorn (2013) and updated by Deming (2017). The same code is also used for combining all years of ACS and O*NET data.

Lightcast: Lightcast (formerly "Burning Glass Technologies") is an analytics software company that has developed a comprehensive and detailed dataset derived from online job postings, capturing real-time labor market information, reflecting the current demand for skills and occupations. One of the key advantages of Lightcast data is its extensive coverage and high-frequency updates. By examining over 40000 online job boards and company websites, it provides near universe of online posted vacancies; moreover, it provides a level of detail that is rarely matched by other sources of labor market data, such as job titles, employer information, and specific skill requirements. This allows for a very granular analysis of job skill requirements and labor market dynamics.across different industries and regions.

The information that Lightcast collected is then parseed and deduplicated into a systematic list of thousands of codified skills. Similar to Hershbein and Kahn (2018) and Braxton and Taska (2023), the dataset that this study uses defines different skills if the codified skills from Lightcast contains relevant key words. Specifically, the key words used to capture analytical skill are: "research", "analy", "decision", "solving", "math", "statistic", and "thinking". The key words used to capture interpersonal skill are "communication", "teamwork", "collaboration", "negotiation", and "presentation". For each occupation, the share of posted vacancies that require a particular skill is then the measure of skill for that occupation, capturing the extensive margin of firm skill demand.

However, like any data source, Lightcast data also has its limitations. For instance, it only covers online job postings, which may not represent the entire labor market, especially for low-skilled jobs or jobs in small firms that do not typically advertise online. It may also have a bias towards certain types of jobs or industries that use online job advertisements more frequently, and online vacancies by nature overrepresent growing firms (Davis, Faberman, and Haltiwanger 2013). One note of Lightcast data is that the measure of skill as introduced above focuses on the extensive margin – whether a job uses a skill or not – this is very different than the level and importance information that O*NET contains.

Table A1: O*NET Versions and Corresponding Years

	Released Year	Division	Work Context	Work Activities	Knowledge	Considered Year	Percent Updated
O*NET 13.0	2008	Post 2005	73.79%	73.79%	73.79%	2005	–
		Before 2005	26.21%	26.21%	26.21%		
O*NET 18.0	2013	Post 2009	57.15%	57.21%	57.21%	2009	59.8
		Before 2009	42.85%	42.79%	42.79%		
O*NET 22.0	2017	Post 2013	57.84%	57.67%	57.67%	2013	45.8
		Before 2013	42.16%	42.33%	42.33%		
O*NET 25.0	2022	Post 2018	54.52%	54.52%	54.52%	2018	64.2
		Before 2018	45.48%	45.48%	45.48%		

Notes: The table summarizes different versions of the O*NET (Occupational Information Network) database, along with their released year, year division for the 5 modules (work context, work activities, knowledge, skills, abilities), and the considered year for each version. The "Post" and "Before" rows indicate whether the data in each version was collected post or before a particular year. The "Considered Year" column represents the year considered to be corresponding to each release of O*NET based on the year division of data.

A.2 Details of Skill Measures

In this section I briefly discuss the choice of skill measures used in the main analysis. Specifically, I show the composition of descriptors of each skill used in the main analysis. I also discuss the composite skill measures' validity and correlation with other measures used in the literature.

Table A2: O*NET Skill Measures and Composing Descriptors

Non-routine Analytical

- Analyzing data/information
- Thinking creatively
- Interpreting information for others

Non-routine Interpersonal

- Establishing and maintaining personal relationships
- Guiding, directing and motivating subordinates
- Coaching/developing others

Computer

- Interacting With Computers
- Programming
- Computers and Electronics

Design

- Design
- Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment

Routine

- Importance of repeating the same tasks
- Importance of being exact or accurate
- Structured v. Unstructured work (reverse)
- Pace determined by speed of equipment
- Controlling machines and processes
- Spend time making repetitive motions

Leadership

- Making Decisions and Solving Problems
- Developing Objectives and Strategies
- Organizing, Planning, and Prioritizing Work
- Coordinating the Work and Activities of Others
- Developing and Building Teams
- Guiding, Directing, and Motivating Subordinates
- Provide Consultation and Advice to Others

Table A2 lists the O*NET descriptors for each of the constructed composite skill measures. The analytical measure corresponds to "non-routine cognitive analytic" and the interpersonal measure corresponds to "non-routine interpersonal" from Acemoglu and Autor (2011). I collapse Acemoglu and Autor (2011)'s "routine cognitive" (the first three items under Routine) and "routine manual" (the last three items under Routine) into a big routine skill, as occupations using these skills have been shown to have had similar labor market dynamics (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011). I didn't include the "non-routine manual" from Acemoglu and Autor (2011), since it involves descriptors from the “Abilities” module of O*NET that is evaluated solely by job analysts, and for consistency purposes I focus on occupation descriptors that are evaluated by incumbents workers.

Further, I include two additional composite skills that are be non-routine. First, I include a “leadership” composite skill that is comprised of descriptors of problem-solving, strategic thinking, teamwork, and communication. They all demand an ability to guide and manage teams, strategize and plan, solve problems, coordinate activities, and communicate effectively within a team or organizational context. Second, I include a “design” composite skill measure revolves around technical proficiency and creativity. The composing descriptors necessitate a strong understanding of design principles, the ability to draft and layout specifications for technical devices.

Table A3: Correlations Among Skill Measures

Skill Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) analytical	1.00								
(2) routine	-0.45	1.00							
(3) interpersonal	0.44	-0.49	1.00						
(4) computer	0.92	-0.27	0.25	1.00					
(5) math skill	0.50	-0.11	0.12	0.46	1.00				
(6) social skill	0.34	-0.54	0.61	0.24	0.09	1.00			
(7) analytical (broader)	0.84	-0.59	0.55	0.68	0.63	0.57	1.00		
(8) mechanical (broader)	-0.43	0.58	-0.24	-0.38	-0.11	-0.38	-0.49	1.00	
(9) interpersonal (broader)	0.10	-0.35	0.73	0.02	-0.09	0.70	0.28	-0.22	1.00

Notes: This table reports the correlation among different skill measures constructed using O*NET data from 2000-2020. The first four skills measures in rows (1) to (4) are the ones used in the main text and are constructed using the O*NET descriptors shown in Table A1. The next two measures in rows (5) to (6), math skill and social skill are constructed based on Deming (2017). Math skill is the average of 1) mathematical reasoning ability, 2) mathematics knowledge, and 3) mathematics skill. Social skill consists of the average of four variables, 1) social perceptiveness, 2) coordination, 3) persuasion, and 4) negotiation. Rows (7) to (9) contain the broader analytical, mechanical, and interpersonal skills constructed using factor analysis as discussed in online Appendix A.5 with their specific component variables.

Table A3 shows the correlation among the chosen skills used in the main analysis, as well as math skill and social skill are constructed based on Deming (2017), and broader skill measures skills constructed using factor analysis as discussed in online Appendix A.5. It reveals the analytical skill (row 1), exhibits a strong positive correlation with computer skills (0.92) and a moderate correlation with math skills (0.50). This pattern suggests that positions requiring analytical skills frequently necessitate computer and mathematical proficiency. Interpersonal skills (row 3) indicate a moderate-to-strong positive correlation with social skills (0.61) and broader interpersonal skills (0.73). This correlation suggests that occupations demanding interpersonal skill also emphasize social abilities. These results validate the interpretation of the analytical and interpersonal skills with strong positive correlation with math and social skills used in other studies.

On the other, a strong negative correlation exists between routine and interpersonal skills (-0.49) and between routine and interpersonal skills (-0.45), indicating that these skill sets rarely overlap in job requirements. The broader skill categories (rows 7 to 9) align well with their narrower counterparts, reinforcing the validity of these categorizations. In sum there exist specific, identifiable skills in the labor market, some of which are more align with each other, but they tend not to overlap, reflecting distinct competencies.

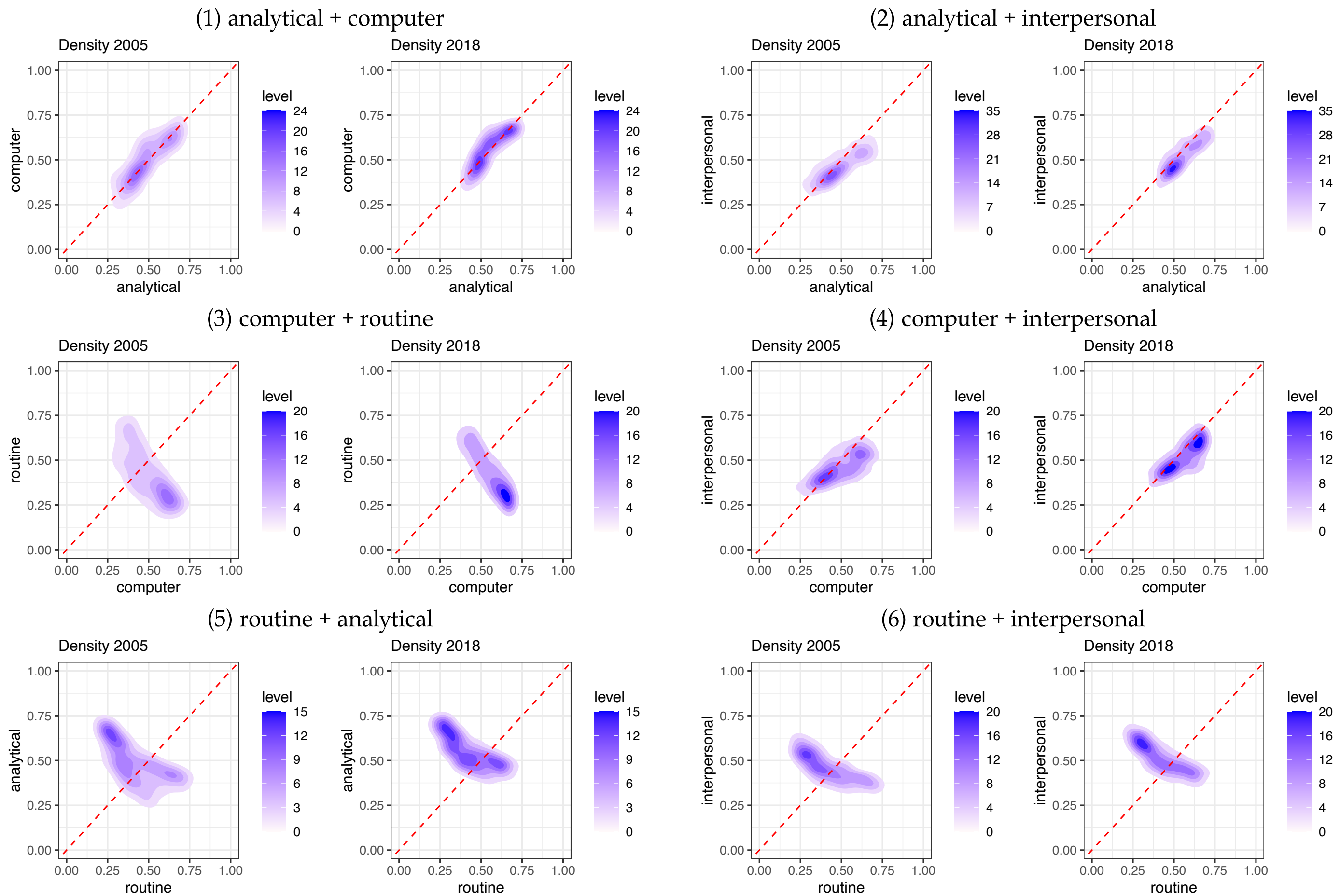
A.3 Alternative Non-parametric Examination of Trend

An intuitive alternative check of the changes in the degree of skill mixing across periods is to non-parametrically plot the density of skill intensities in different skill dimensions. Figure A1 depicts the density of skill requirements of six skill pairs out of the four constructed skills in 2005 and 2018 respectively using O*NET data combined with ACS. As in previous studies of job attributes, I aggregate the ACS to sex-education-industry cells that implicitly control for changes in task inputs due to variations in skill and industry mixes in the U.S. economy. Employment weights are obtained as the total hours of work aggregated to each cell. The ACS then supplies the O*NET data with employment across worker types to present an overarching picture of skill intensities in the economy.

From the figure, there is a clear shift towards mixed skill requirements in panel (1) pertaining to analytical and computer skills where these skills are positively correlated. Two salient changes happened in this period: first, the entire distribution of skill intensities moves near the 45-degree line; second, there is a significant increase in density around the 45-degree line. Both of these changes will lead to an increased degree of skill mixing, according to how it is defined based on the position of skill vectors relative to the 45-degree line. Such a change is also salient for other non-routine skill combinations: in the analytical and interpersonal skills space (panel 2), as well as in the computer and interpersonal skills space (panel 4).

On the other hand, one can scarcely observe changes towards mixing in the routine skill spaces, as shown in panel (3),(5) and (6). From these three plots, there is an increase in density towards the non-routine direction, losing density in routine skill, and the resulting change in relationship with the diagonal doesn't indicate a strengthening of mixing.

Figure A1: Non-parametric Depiction of Skill Intensities, 2005 vs. 2018

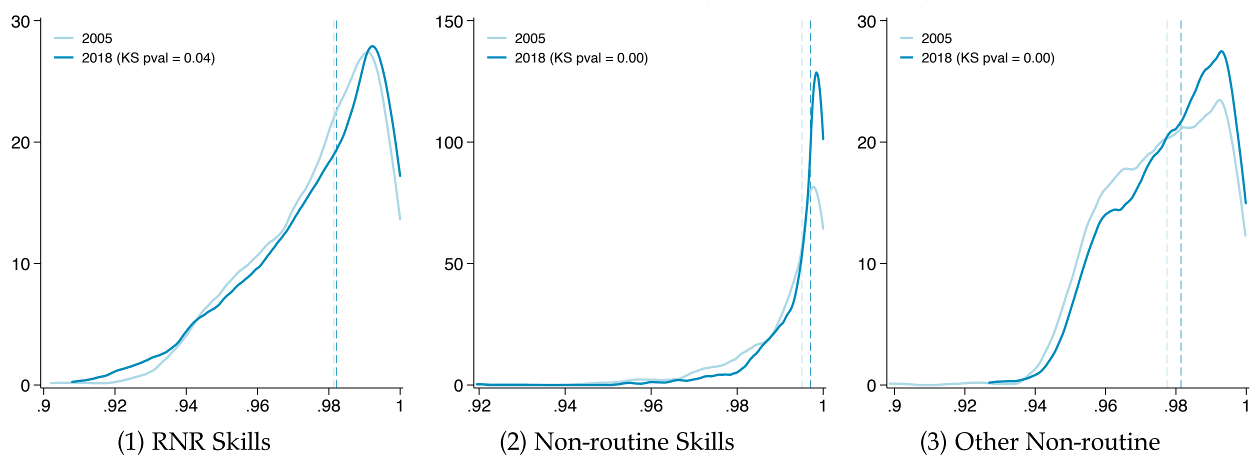


Notes: These density plots show the intensity of occupation skill requirements across the U.S. economy in 2005 (column 1) and 2018 (column 2) in six two-dimensional skill spaces, as illustrated in the six panels. Darker colors indicate higher density and the 45-degree line is also plotted. O*NET and ACS data are combined for the construction of these plots. The two datasets are merged using consistent occupation codes constructed by Autor and Price (2013) and further developed by Deming (2017). Skill measures are constructed using the O*NET descriptors shown in Table A1. All measures are normalized to [0,1].

A.4 Robustness of Trend Results to Different Weights and Groupings

In this section, I discuss the robustness of the trend results to different weighting, granularities, and groupings. In particular, I show the density results using weighted skill mixing indexes instead of unweighted in the main analysis; the trend of skill mixing using indexes for different skill pairs, instead of high-dimensional indexes; the heterogeneity of skill mixing increases across occupations using indexes for different skill pairs; and the differential changes in skill mixing across industries.

Figure A2: Density for Skill Mixing Indexes (Weighted Cosine Distances), 2005 vs. 2018



Notes: These figures plot the PDF of different mixing indexes in 2005 (light blue line) and 2018 (dark blue line). The x-axis displays the value of mixing indexes with a maximum of 1 by construction. These plots are created using O*NET and ACS data merged with occupation codes constructed by Autor and Price (2013) and developed by Deming (2017).

On concern of analysis of skill mixing shown in A2 is that as it shows the changes in the density of skill mixing indexes without weighting, it might not accurately represent the overall picture of mixing in the whole economy. In **??**, I weight the skill mixing indexes using employment weight at 6-digit SOC level occupation from OEWS. The results show a similar message that there is sizable increase in skill mixing particularly for non-routine skills. The only difference is that with employment weighting, the increase in the skill mixing of RNR skill is more discernable. This implies relative higher weight of occupations intensive in RNR skills that also increase in skill mixing in these skills.

Next, I discuss the changes in skill mixing using indexes of different skill pairs instead of high-dimensional indexes. Figure A5 panel (1) shows the results. The figure shows similar results as the main analysis: there is a stronger increase in skill mixing among non-routine skills. For the skill combinations involving routine skills, the change in skill mixing is negligible.

In Table A4, I show the decomposition results of the changes in the skill mixing indexes for different skill pairs across different datasets. A similar pattern as the main analysis in 1, that is within-occupatoin variation surpassed across-occupation variation in accounting for the increase for skill mixing. This is particularly true using constantly updated occupations at 6-digit occupatoin level for non-routine skill pairs, and also quite apparent in the Lightcast data. The only slight difference is that for full O*NET data at 6-digit level, across-occupatoin variation do contribute to a comparable amount to the change in skill mixing for skill pairs with routine skill.

Additionally, in Figure A3, I show employment percentages and hourly wages across various job categories in the full and the sample for constantly updated occupation. This information gives the occupational structure and return for these two samples. It can be seen that while professionals make up a smaller percentage in the selected sample, they exhibit a higher average wage, suggesting a focus on higher-earning professionals in the selected sample. Conversely, the sales category shows a drastic reduction in the selected sample, indicating its limited representation. The hourly wage rates across the categories seem fairly consistent between the full and selected samples, with minor discrepancies.

Table A4: Decomposition of Mixing Indexes' Changes by Skill Pairs

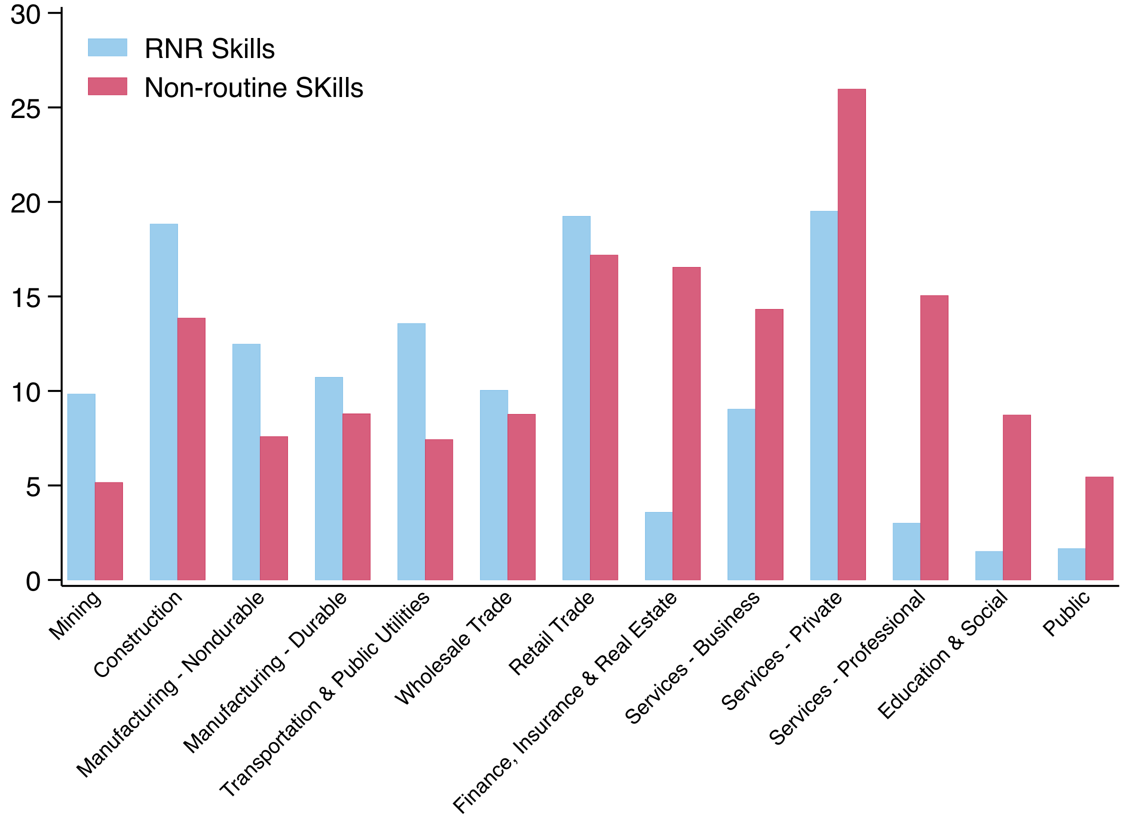
	Skill Groups	6-digit Occupations			4-digit Occupations		
		total	within	across	total	within	across
Full O*NET	analytical + computer	10.52	6.40	4.12	10.49	6.60	3.89
	analytical + interpersonal	5.36	2.90	2.46	8.17	4.08	4.09
	computer + routine	4.38	2.41	1.97	5.16	2.94	2.22
	computer + interpersonal	7.23	3.60	3.63	11.81	7.51	4.30
	routine + analytical	4.00	2.29	1.71	4.23	3.16	1.07
	routine + interpersonal	1.93	0.12	1.81	2.35	1.08	1.26
Constant Updates	analytical + computer	5.59	6.03	-0.44	6.42	5.89	0.53
	analytical + interpersonal	3.53	4.58	-1.05	4.00	3.00	1.00
	computer + routine	2.88	3.69	-0.81	0.52	1.93	-1.42
	computer + interpersonal	0.78	1.86	-1.09	6.86	5.93	0.93
	routine + analytical	2.04	2.13	-0.09	1.48	3.60	-2.12
	routine + interpersonal	0.81	0.82	-0.01	-0.33	1.47	-1.80
Lightcast	analytical + computer				12.64	11.74	0.90
	analytical + interpersonal				2.51	2.20	0.31
	computer + interpersonal				-4.18	-3.79	-0.39

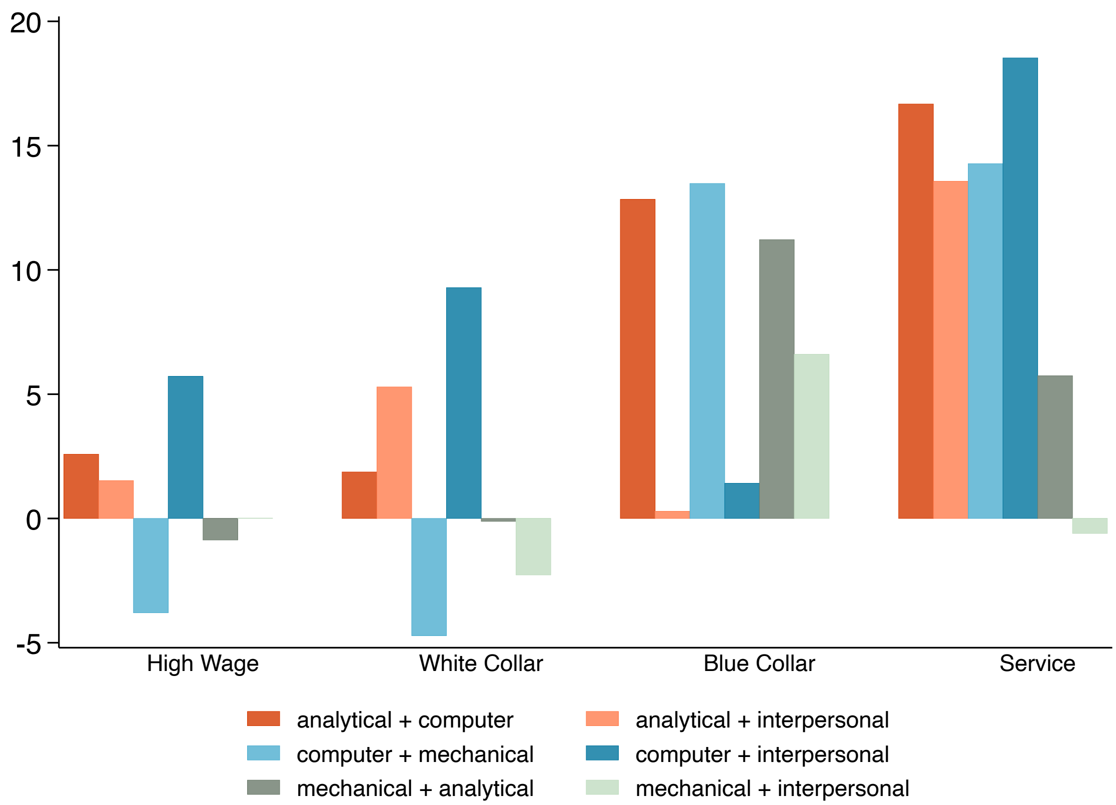
Notes: This table shows the shift-share decomposition of changes in the average level of different mixing indexes between 2005-2018 in percentile units. Specifically, for a change in the percentile of a mixing index h over two periods t and τ, its change $\Delta T_{h\tau} = T_\tau - T_t$ which can be decomposed to $\Delta T_h = \sum_j \left(\Delta E_{j\tau}\alpha_{jh}\right) + \sum_j \left(E_j \Delta\alpha_{jh\tau}\right) = \Delta T_h^a + \Delta T_h^w$ where $E_{j\tau}$ is employment weight in occupation j in year τ, and $\alpha_{jh\tau}$ is the level of mixing index h in occupation j in year τ, $E_j = \frac{1}{2}(E_{jt} + E_{j\tau})$ and $\alpha_{jh} = \frac{1}{2}(\alpha_{jht} + \alpha_{jh\tau})$. ΔT_h^a and ΔT_h^w then represent across-occupation and within-occupation change.

Figure A3: Mixing Index Change by Industry and Occupation Groups, 2005-2018

Now, I turn to discuss the robustness of the occupation heterogeneity in skill mixing changes. Figure A3 a detailed overview of the changes in different skill categories across various occupational classifications.

Figure A4: Mixing Index Change by Industry and Occupation Groups, 2005-2018





A.5 Robustness of Trend Results to Measures of Skills

In this section, I discuss the robustness of the trend results to using alternative measures of skills. Specifically, I present alternative trend results using different ways of processing skill descriptors from O*NET, such not using PCA, and standardizing rather than rescaling. I also show the robustness using broader skill measures than those applied in the main analysis.

Alternative Construction of Skills: Since O*NET contains a large number of descriptors, many of which capture the same dimensions of skill requirements, it becomes standard practice to first abstract useful information from the descriptors to construct lower-dimensional measures of skills. The first approach, as in Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011) and Deming (2017), takes the average of a subset of variables and assumes that such average represents a particular broader skill intensity and not others. The other approach, as in Lise and Postel-Vinay (2020), applies PCA to the entire set of variables, which assumes that each of the variables contains information about underlying components that are orthogonally distributed. Both approaches impose different assumptions, with the first one giving more easily interpretable skill groups while the second being more data-driven. A third approach, as in Yamaguchi (2012), first picks descriptors that are ex-ante most easily interpretable with respect to each skill dimension, and then conducts PCA on those descriptors to abstract the most relevant variation. The main body of the paper adopts the third approach; here I show robustness checks using alternative skill measures.

Online Appendix Figure A5 presents the trend results using skill measures constructed by taking an average of the descriptors without imposing PCA (panel 2) and using skill measures normalized by standard deviation rather than linearly scaled to $[0, 1]$ (panel 3). Normalizing by standard deviation necessarily creates negative values for the skills; since the mixing index is defined based on positive real values, having these negative values invalidates the mixing index in measuring skill mixing. One solution is to add a positive number to the skill measures. As any number chosen is essentially arbitrary, here I added the negative of the smallest value such that the re-scaled measure lies exactly above 0. For both of these robustness exercises, the main message is similar to the main text: there is a significant increase in mixing for non-routine skills, and less so for RNR skills.

Skill Measures: Another concern is that by using skill measures from Acemoglu and Autor (2011), each of which is constructed from a few descriptors, the resulting skill measures could be relatively “narrow” and don’t provide a comprehensive depiction of the skill spaces. To alleviate this concern, I construct skill measures using a broader set of descriptors, similar to that of Lise and Postel-Vinay (2020). I first select descriptors from abilities, knowledge, skills, and work activities files that are more relevant for job skill demand, leaving me with around 163 descriptors. I then combine each year’s O*NET data with ACS and conduct PCA on the merged data from the year 2005-2018.

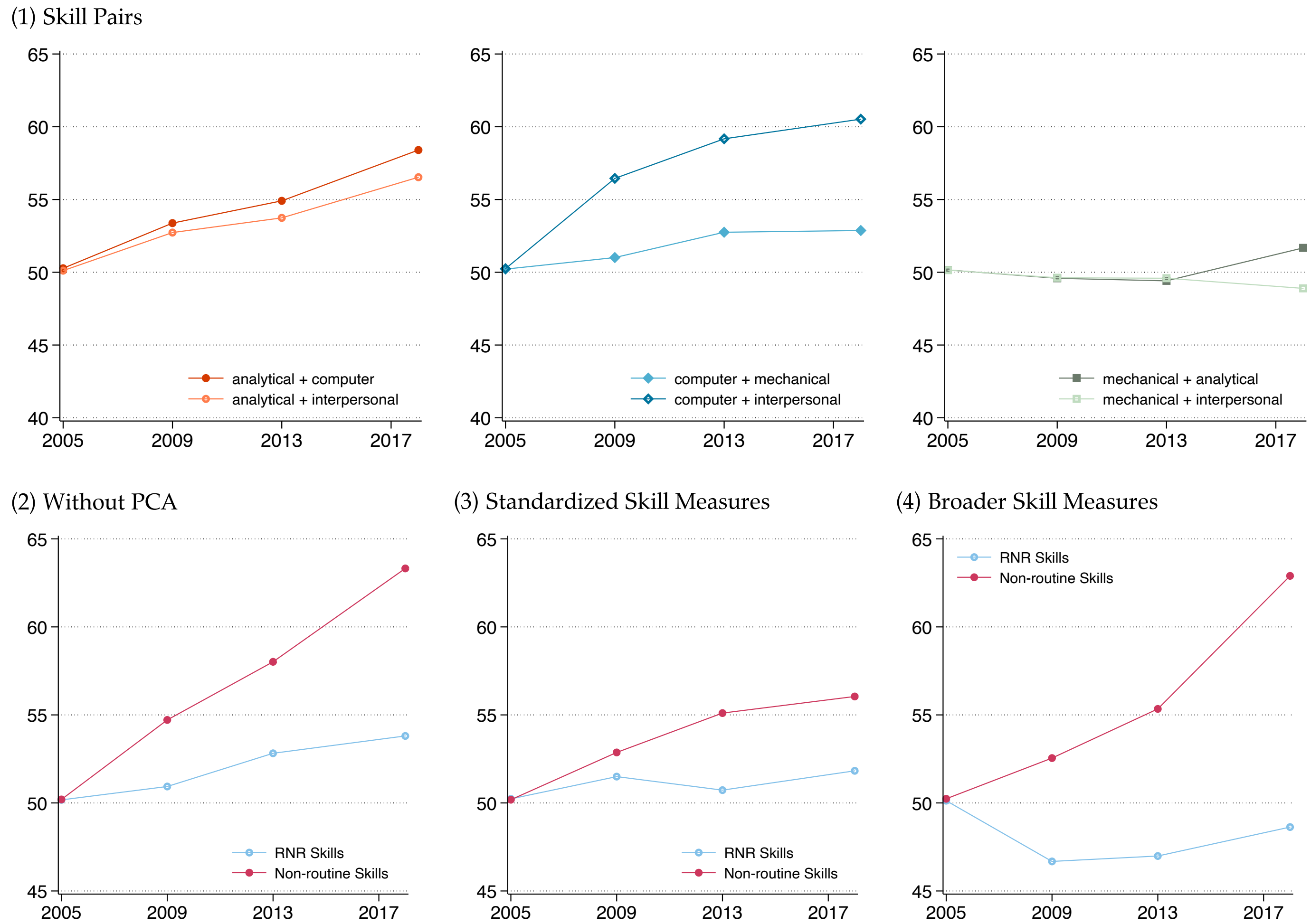
The result from this approach supports the choice of analytical, routine, and interpersonal skills in the main text The first three factors out of PCA explain around 60% of the variation across all the descriptors for years. The first factor has a strong positive association with reason and math skills, such as "Deductive Reasoning", "Inductive Reasoning" and "Mathematics", while the second factor relates more to motor coordination and mechanical work, such as "Multi-limb Coordination", "Mechanical" and "Equipment Maintenance". The third factor is clearly more associated with interacting with other people, such as "Selling or Influencing Others" and "Resolving Conflicts and Negotiating with Others". I interpret the second factor as "mechanical" rather than routine for the broader skill measures.

After conducting PCA, one could directly extract the factors imposing the assumptions that these factors are orthogonal to each other. While this is obviously quite convenient, it nevertheless creates the challenge of interpretability, since each of the factors has been constructed such that it is positively or negatively correlated with all of the 163 descriptors, and the assumption of orthogonality appears strong if the underlying skills are complementary in production across occupations. To take a fine balance between comprehensibility and interpretability, I adopt an approach similar to the measurement validation literature (Costello and Osborne 2005; Thompson and Daniel 1996), where I first conduct PCA/factor analysis to reveal the underlying dimensionality and structure of the measure (as has been done in the previous step). Guided by the factor loadings, I then hand-pick the skill descriptors into three broad groups “analytical”, “mechanical” and “interpersonal” without imposing the orthogonality assumption.

Online Appendix Table A5 illustrates the selected descriptors for each of the composite skill measures. These descriptors are broadly in line with Acemoglu and Autor (2011) but have several distinctions. First, the descriptors coming from factor analysis lean more toward reasoning, comprehension, and expression. Second, the mechanical skill used in the main text is the average of two ASVAB test scores that are constructed by the weighted average of 26 O*NET descriptors. The ASVAB “Mechanical Comprehension” tests contestants’ “understanding of the principles of mechanical devices, structural support, and properties of materials” and the ASVAB Electronics Information tests contestants’ “understanding of electrical current, circuits, devices, and systems”, both stressing one’s knowledge basis. On the other hand, the descriptors chosen by conducting PCA relate more to physical control, coordination, and machine operation aspects rather than mental perception. Third, the descriptor choices for interpersonal skill from factor analysis also emphasize interactions with others as in Acemoglu and Autor (2011) but are more comprehensive.

Online Appendix Figure A5 panel (4) illustrates the trend results using these broader skill measures. The message on the growth of skill mixing remains the same as the main text, that is there is strong growth of skill mixing for non-routine skills. Nontheless, for RNR skills, the degree of skill mixing has decreased using the broader measures.

Figure A5: Trend of Skill Mixing with Alternative Skill Measures



Notes: These three panels plot the employment-weighted mixing indexes of different skills in the U.S. economy from 2005-2018 using O*NET and ACS data. Panel (1) shows the changes in skill mixing indexes of 6 skill pairs of the 4 skills. In panel (2) mixing indexes are calculated using skill measures without using PCA, and in panel (3), skill measures are normalized to have mean 0 and standard deviation 1. Panel (4) shows the changes in mixing indexes using broader skill measures as described in Online Appendix A.

Table A5: Components of Broader Skill Measures

Analytical	**Mechanical**	**Interpersonal**
• Deductive Reasoning	• Multilimb Coordination	• Assisting and Caring for Others
• Inductive Reasoning	• Speed of Limb Movement	• Selling or Influencing Others
• Mathematical Reasoning	• Mechanical	• Resolving Conflicts and Negotiating
• Number Facility	• Performing General Physical Activities	• Coaching and Developing Others
• Mathematics	• Handling and Moving Objects	• Staffing Organizational Units
• Economics and Accounting	• Controlling Machines and Processes	• Service Orientation
• Reading Comprehension	• Operate Vehicles, Mechanized Devices or Equipmnt	• Administration and Management
• Writing	• Repairing and Maintaining Mechanical Equipment	• Customer and Personal Service
• Speaking	• Repairing and Maintaining Electronic Equipment	
• Oral Comprehension	• Installation	
• Written Comprehension	• Equipment Maintenance	
• Oral Expression	• Repairing	
• Written Expression	• Production and Processing	

Notes: This table lists the O*NET descriptor components for each of the constructed (broader) composite skill groups as discussed in online Appendix A.5.

A.6 Robustness of Trend Results to Measures of Skill Mixing

I introduce two additional measures and show the robustness of the trend results using these alternative mixing measures.

A first commonly used measure for concentration or specialization based on the share of a total quantity is the Herfindahl–Hirschman Index (HHI).[38] Equation (8) shows how to use inverse HHI to measure skill mixing for an occupation represented by $(\alpha_{ja}, \alpha_{js})$. Observe that this index is maximized when $\alpha_{ja} = \alpha_{js}$, exactly corresponding to the case when the skill vector lies on the unit vector and becomes most mixed. If one skill's intensity is greater than the other, the occupation becomes less mixed and this index becomes smaller. Similar to an angle-based mixing index, this measure is insensitive to the length of a skill vector, since each skill is normalized by the total quantity of skills in that occupation.

$$\left[\left(\frac{\alpha_{ja}}{\alpha_{ja}+\alpha_{js}}\right)^2 + \left(\frac{\alpha_{js}}{\alpha_{ja}+\alpha_{js}}\right)^2\right]^{-1} \tag{8}$$

$$-\frac{|\alpha_{ja}-\alpha_{js}|}{\alpha_{ja}+\alpha_{js}} \tag{9}$$

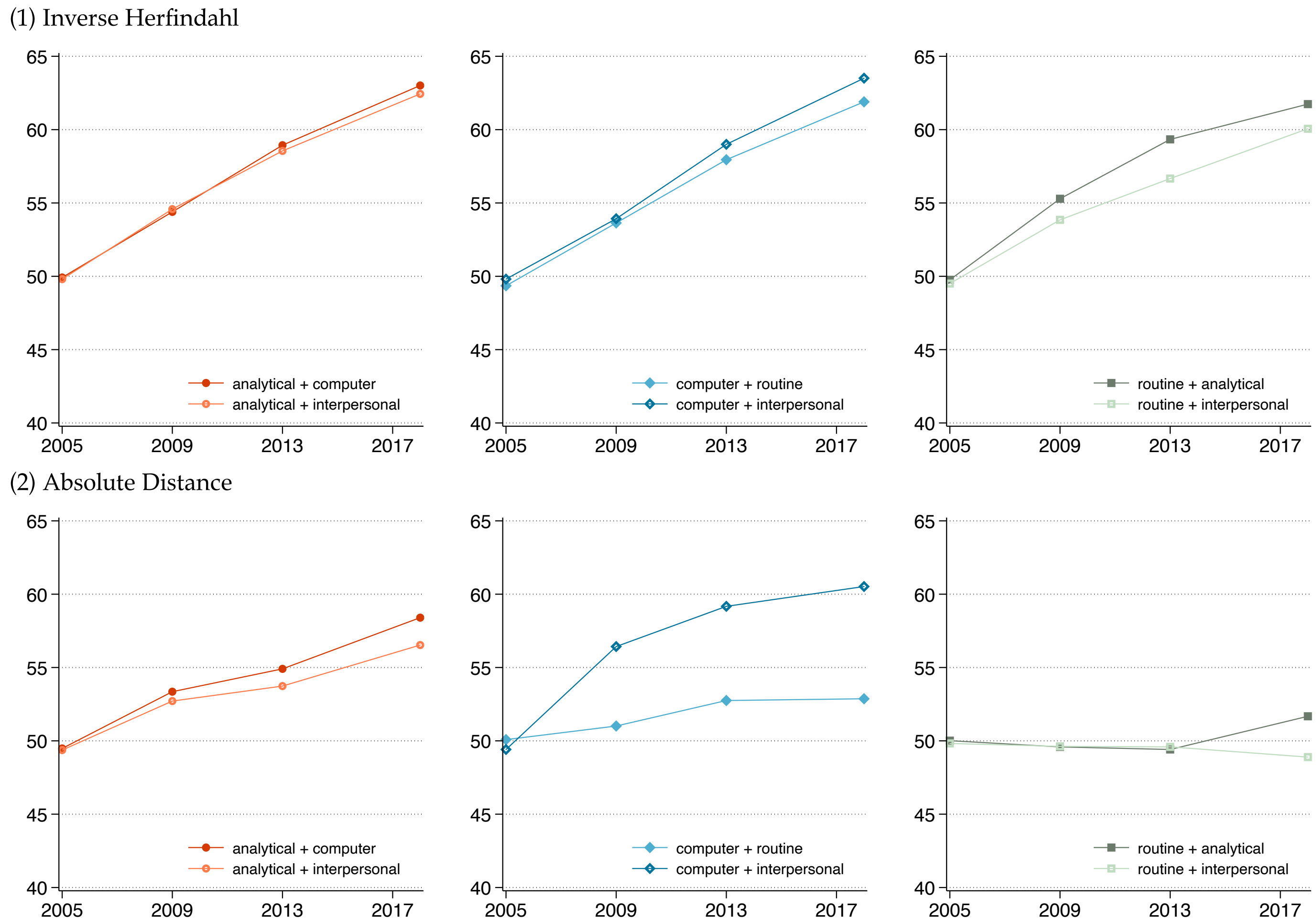
Under a similar vein, the degree of skill mixing could also be measured by normalizing the absolute distance between skill intensities for a skill vector: as this distance decreases, the overall skill portfolio becomes more balanced; normalization then eliminates the effect of the length of the skill vector. Equation (9) gives a particular specification of such a measure. As can be seen from this construction, as the absolute distance between skill intensities decreases and the degree of mixing increases, this measure also increases, though from the direction of $(-\infty, 0)$.

In Online Appendix Figure A6, I show the robustness of the trend results using these alternative measures in panels (1) and (2). Both measures deliver the same message as

[38] For applications in the labor literature, Ransom and Phipps (2017) and Jin (2017) use the inverse of HHI as the "variety index" to examine how diverse the jobs held for students who graduated from a certain major. Similar logic can be applied to the measurement of skill mixing: in the context of 2-dimensional skill space, the more "varied" skills an occupation uses essentially means that skills are more mixed.

the cosine mixing index in the main text, that is, there is a sizable increase in skill mixing, particularly for non-routine skills. The only difference is that for the HHI skill index, there is also comparable increase in skill mixing for RNR skills.

Figure A6: Trend of Skill Mixing with Alternative Indexes



Notes: These three panels plot the employment-weighted mixing indexes of different skills in the U.S. economy from 2005-2018 using O*NET and ACS data. In panels (1) and (2), mixing indexes are calculated using the Inverse Herfindahl index and Absolute Distance as discussed in online Appendix A.6.

A.7 Additional Results on Wage Returns

In this section, I provide more detailed results on wage returns, and provide robustness results to the main paper. I first check the returns to returns to individual skills and how they interact with skill mixing. Table 3 columns (1) and (2) show that by restricting to within-occupation variation, computer and interpersonal skills show a higher return, whereas analytical and mechanical skills' return decline.[39] Column (3) includes skill mixing measures and an important pattern appears: the coefficients for most individual skills become slightly more negative (except for computer skill), while the hybrid indexes of analytical paired with computer and interpersonal skills, as well as of mechanical and interpersonal skills show significant positive returns of 0.7 to 1.2 percent. This indicates that the mixing of skills earns separate and additional rewards beyond those predicted by individual skills.

[39]The insignificant or even negative return to analytical skill over time also finds support from the literature. Lise and Postel-Vinay (2020) shows a strong negative 14.4 percent return on cognitive skill using NLSY data with 3-digit occupation fixed effects. Deming (2017) found that the return to cognitive skills has declined across the NLSY79 and NLSY97 cohorts, similar to Castex and Kogan Dechter (2014).

Table A6: Return to Skill Mixing Full Table with Individual Skills

Dependent: ln(hourly wage)	(1)	(2)	(3)	(4)
Occupation Skills				
Analytical	-0.019**	-0.019**	-0.012	-0.033***
	[0.009]	[0.009]	[0.008]	[0.011]
Computer	-0.002	-0.008	-0.003	-0.017
	[0.010]	[0.011]	[0.009]	[0.013]
Interpersonal	-0.019**	-0.022**	-0.021***	-0.027**
	[0.009]	[0.009]	[0.008]	[0.011]
Routine	0.027***	0.035***	0.025***	0.047***
	[0.010]	[0.011]	[0.009]	[0.015]
Mix (analytical + computer)	0.007	0.011**	0.013***	0.012
	[0.005]	[0.005]	[0.005]	[0.008]
Mix (analytical + interpersonal)	0.016***	0.016***	0.015***	0.028***
	[0.005]	[0.005]	[0.004]	[0.007]
Mix (computer + routine)	-0.022**	-0.029***	-0.021***	-0.026**
	[0.009]	[0.009]	[0.008]	[0.012]
Mix (computer + interpersonal)	-0.008	-0.012**	-0.014***	-0.012
	[0.006]	[0.006]	[0.005]	[0.009]
Mix (routine + analytical)	-0.050***	-0.056***	-0.050***	-0.058***
	[0.008]	[0.009]	[0.008]	[0.012]
Mix (routine + interpersonal)	0.023***	0.029***	0.019**	0.023*
	[0.008]	[0.009]	[0.008]	[0.012]
Worker Skills				
Afqt (analytical)		0.065***		-0.038
		[0.012]		[0.023]
Computer		0.045***		0.017
		[0.006]		[0.023]
Social (interpersonal)		0.015***		-0.003
		[0.005]		[0.029]
ASVAB (routine)		-0.008		-0.012
		[0.016]		[0.022]
Mix (afqt + computer)		0.044*		0.017
		[0.023]		[0.013]
Mix (afqt + social)		0.028*		-0.075***
		[0.015]		[0.020]
Mix (computer + asvab mech)		0.013		-0.070***
		[0.025]		[0.026]
Mix (computer + social)		0.008		0.061***
		[0.013]		[0.019]
Mix (asvab mech + afqt)		0.001		0.096**
		[0.009]		[0.039]
Mix (asvab mech + social)		-0.040***		-0.045
		[0.011]		[0.042]
Ethnicity*Gender, Age/Year, Region, Edu FE	X	X	X	X
Occupation FE	X	X	X	X
Worker FE			X	X
Observations	87,655	78,719	87,655	50,580
R-squared	0.426	0.439	0.758	0.761

Notes: See Table 3 notes.

Table A7: Robustness Checks of Return to Skill Mixing

Dependent: ln(hourly wage)	(1)	(2)	(3)	(4)
Occupation Skills				
Analytical	-0.014*	-0.008	-0.009	-0.013
	[0.008]	[0.033]	[0.008]	[0.008]
Computer	-0.002	0.069**	0.002	-0.038***
	[0.009]	[0.027]	[0.009]	[0.010]
Interpersonal	-0.019**	-0.118***	-0.018**	-0.014*
	[0.008]	[0.030]	[0.008]	[0.008]
Routine	0.026***	0.091***	0.005	0.010
	[0.009]	[0.017]	[0.008]	[0.008]
Mix (analytical + computer)	0.007	-0.040	0.008*	0.020***
	[0.005]	[0.036]	[0.005]	[0.007]
Mix (analytical + interpersonal)	0.010**	0.156***	0.006	0.025***
	[0.004]	[0.042]	[0.004]	[0.005]
Mix (computer + routine)	-0.028***	-0.045***	-0.021**	-0.087***
	[0.007]	[0.015]	[0.008]	[0.013]
Mix (computer + interpersonal)	-0.011**	-0.019	-0.013***	-0.021***
	[0.005]	[0.033]	[0.005]	[0.008]
Mix (routine + analytical)	-0.033***	-0.080***	-0.041***	-0.041**
	[0.007]	[0.015]	[0.008]	[0.018]
Mix (routine + interpersonal)	0.010	0.033**	0.033***	0.026**
	[0.007]	[0.016]	[0.006]	[0.012]
Ethnicity × Gender, Age, Region, Edu FE	X	X	X	X
Occupation FE	X	X	X	X
Worker FE	X	X	X	X
Observations	87,655	87,655	87,655	87,655
R-squared	0.757	0.757	0.757	0.758

Notes: This table reports the robustness checks to the results in Table 3. Columns (1) and (2) use Absolute Distance and Inverse Herfindahl measures to construct mixing indexes (see online Appendix A.6 for details) and Columns (3) and (4) use standardized and broad measures of skills (see online Appendix A.5 for details). Log hourly wages are the outcome variables and person-year is the unit of observation. The occupational skill and skill mixing measures come directly from O*NET and are merged to NLSY79&97 based on census occupation codes. All measures of skill and skill mixing are normalized to have mean 0 and standard deviation 1. Ethnicity-by-gender, age, year, census region, urbanicity, and a 5-category (no high-school, high-school graduate, some college, college graduate, post-college) education fixed effects are included for all regressions, with additional fixed effects as indicated in the table. Standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Top College Majors in Skill Mixing

Mixing Index – Level	Mixing Index – Change
analytical + computer	
Physical Sciences	Agriculture and Natural Resources
Social Sciences	Mathematics
Area Studies	Letters
analytical + interpersonal	
Education	Mathematics
Military Sciences	Architecture and Environmental Design
Theology	Agriculture and Natural Resources
computer + routine	
Military Sciences	Agriculture and Natural Resources
Health Professions	Law
Mechanics	Engineering
computer + interpersonal	
Physical Sciences	Agriculture and Natural Resources
Education	Letters
Psychology	Architecture and Environmental Design
routine + analytical	
Mechanics	Agriculture and Natural Resources
Military Sciences	Area Studies
Transportation	Engineering
routine + interpersonal	
Mechanics	Law
Military Sciences	Theology
Transportation	Mathematics

Notes: This table lists the top 3 college majors for each mixing index both in terms of levels and in terms of changes from 2005 to 2019. To calculate the degree of skill mixing for college majors, I first map the occupation level degree of skill mixing contained in the O*NET data to NLSY, and then calculate for each college major's students, the employment weighted average of skill intensities and mixing indexes of their occupations. I use both NLSY79&97 to get the employment weight on occupations.

Table A9: Return to Skill Mixing Full Table with Individual Skills

NLSY97 Code (before 2010)	Major Field of Study	NLSY79 Code
0	None, no major yet (didn't/don't) have to declare yet;	.
1	Agriculture/Natural resources	1
2	Anthropology	22
3	Archaeology	22
4	Architecture/Environmental design	2
5	Area studies	3
6	Biological sciences	4
7	Business management	5
8	Communications	6
9	Computer/Information science	7
10	Criminology	22
11	Economics	22
12	Education	8
13	Engineering	9
14	English	15
15	Ethnic studies	3
16	Fine and applied arts	10
17	Foreign languages	11
18	History	22
19	Home economics	13
20	Interdisciplinary studies	49
21	Mathematics	17
22	Nursing	12
23	Other health professions	12
24	Philosophy	15
25	Physical sciences	19
26	Political science and government	21
27	Pre-dental	4
28	Pre-law	14
29	Pre-med	4
30	Pre-vet	4
31	Psychology	20
32	Sociology	22
33	Theology/religious studies	23
36	Nutrition/Dietetics	4
37	Hotel/Hospitality management	5
38	Other - Recoded to Liberal Arts and Sciences	49
39	Other - Recoded to Automobile/Automotive Mechanics Technology/Technician	24
40	Other - Recoded to Human Services, General	21
41	Other - Recoded to Social Work	21
42	Other - Recoded to Electrical/Electronics Maintenance and Repair Technology	24
43	Other - Recoded to Geography	22
44	Other - Recoded to International Relations & Affairs	21
45	Other - Recoded to transportation & materials moving	25
46	Other - Recoded to security and protective services	21
47	Other - Recoded to legal support services	14
48	Other - Recoded to other sciences/applied sciences	49
99	UNCODABLE	99

NLSY97 Code (CM10)	Major Field of Study	NLSY79 Code
1	Agriculture, agriculture operations, & related sciences	1
3	Natural resources and conservation	1
4	Architecture and related services	2
5	Area, ethnic, cultural, gender, and group studies	3
9	Communications, journalism, and related programs	6
10	Communications technologies/technicians & support services	6
11	Computer & information sciences & support services	7
12	Personal and culinary services	49
13	Education	8
14	Engineering	9
15	Engineering technologies & engineering-related fields	9
16	Foreign languages, literatures, and linguistics	11
19	Family and consumer sciences/human sciences	13
22	Legal professions and studies	14
23	English language and literature/letters	15
24	Liberal arts and sciences, general studies & humanities	49
25	Library science	16
26	Biological and biomedical sciences	4
27	Mathematics and statistics	17
28	Military science, leadership, and operational art	18
29	Military technologies and applied sciences	18
30	Multi/interdisciplinary studies	49
31	Parks, recreation, leisure, and fitness studies	21
32	Basic skills development/remedial education	8
33	Citizenship activities	21
34	Health-related knowledge and skills	12
35	Interpersonal and social skills	6
36	Leisure and recreational activities	49
37	Personal awareness and self-improvement	8
38	Philosophy and religious studies	15
39	Theology and religious vocations	23
40	Physical sciences	19
41	Science technologies/technicians	24
42	Psychology	20
43	Homeland security, law enforcement, firefighting, and related protective services	18
44	Public administration and social service professions	21
45	Social sciences	22
46	Construction trades	24
47	Mechanic and repair technologies/technicians	24
48	Precision production	24
49	Transportation and materials moving	25
50	Visual and performing arts	10
51	Health professions and related programs	12
52	Business, management, marketing, & related support services	5
53	High school/secondary programs and certificates	8
54	History	22
60	Residency programs	12
999	Uncodable	99

NLSY79 Code	Major Field of Study
0	None, General Studies
1	Agriculture and Natural Resources
2	Architecture and Environmental Design
3	Area Studies
4	Biological Sciences
5	Business and Management
6	Communications
7	Computer and Information Sciences
8	Education
9	Engineering
10	Fine and Applied Arts
11	Foreign Languages
12	Health Professions
13	Home Economics
14	Law
15	Letters
16	Library Science
17	Mathematics
18	Military Sciences
19	Physical Sciences
20	Psychology
21	Public Affairs and Services
22	Social Sciences
23	Theology
24	Mechanics
25	Transportation
49	Interdisciplinary Studies
99	Other

B THOERY AND QUANTITATIVE

B.1 Propositions and Proofs

Lemma 1. *An occupation* $\mathbf{y} = \{y^1, ..., y^k, \ldots, y^K\} \in S \subset \mathbb{R}^K$ *within a closed skill space* S *of dimension* K *is more mixed in skills based on Definition 1 if for any pair of skills* (j, k)*, the ratio of* $\frac{y_j}{y_k}$ *becomes closer to 1.*

Proof of Lemma 1: For the occupation $\mathbf{y}$ and we want to establish how the degree of skill mixing changes if the skill dimensions for j and k are to vary. The lemma can be simply proved by considering the skill mixing index for for this occupation. Let $y_k = ry_j$, the mixing index for $\mathbf{y}$ is:

$$\frac{y + ry + A}{\sqrt{K}\sqrt{y^2 + r^2y^2 + B}} = \frac{1 + r}{\sqrt{K}\sqrt{1 + r^2}},$$

where A and B are two constants that don't depend on y_k and y_j. The above equation is maximized at $r = 1$. This completes the proof.

Proposition 1 (Changes in Skill Mixing)**.** *Consider an occupation* $\mathbf{y}_t = \{y_t^1, ..., y_t^k, \ldots, y_t^K\} \in S \subset \mathbb{R}^K$ *within a closed skill space* S *of dimension* K*. Assume that firms operate the occupation with a production technology as described by equation (3) and under an occupational rental cost defined by equation (7). Under these conditions, occupation* $\mathbf{y}_t$ *will show an increased degree of skill mixing given the following conditions:*

(i) The skills within the vector $\mathbf{y}_t$ demonstrate an rise in complementarity in production (a decrease in σ), provided that σ does not undergo a change in sign.

(ii) The skills within the vector $\mathbf{y}_t$ exhibit an higher increasing marginal cost (an increase in ϕ), under the condition that $\phi > \sigma$.

Additionally, occupation $\mathbf{y}_t$ will exhibit a increased degree of skill mixing in the (y_t^k, y_t^h) dimension if the ratio between (x_t^k, x_t^h) approaches unity.

Proof of Proposition 1: Lemma 1 posits that an occupation $\mathbf{y}_t$ exhibits greater skill mixing if the ratio across all skill dimensions approximates 1. Therefore, establishing the influence of the ratio on the degree of skill mixing suffices. The initial step concentrates on any two skills within the vector (y_t^k, y_t^h).

The firm value function indicates that the firm re-optimizes the choice of $\mathbf{y}_t$ in each period. Consequently, within a given submarket at a particular time instance $(\mathbf{x}_t, \mathbf{y}_t)$, the firms' choices of $\mathbf{y}_t$ remain uninfluenced by the continuation value, rendering it a static problem. Time subscript is subsumed in the subsequent proof.

By deriving the first-order condition of firms' optimization problems in the submarket $(\mathbf{x}, \mathbf{y})$ and taking ratios, one obtains the following condition: $\frac{y_h}{y_k} = (\frac{x_h}{x_k})^{\frac{\sigma}{\rho-\sigma}}$. Therefore, the ratio of firms' optimal skill requirement choices for any two skills (y_h, y_k) is influenced by three variables: the elasticity parameter of substitution in production σ, the degree of increasing marginal occupational rental cost ρ, and the ratio of worker skills in the submarket (x_h, x_k).

From the equation, it is evident that as σ decreases, indicating an increase in skill complementarity in production, $\frac{y_h}{y_k}$ will converge to 1 for any two skills (y_h, y_k), under the assumption that σ does not change sign. Similarly, as ρ increases, $\frac{y_h}{y_k}$ will approximate 1 for any two skills (y_h, y_k), given that $\rho - \sigma$ does not change sign.

The influence of worker skill bias on the degree of skill mixing of $\mathbf{y}$ presents a more complex scenario, as a change in the ratio $\frac{x_h}{x_k}$ does not directly imply a change in the ratio of other skill pairs. Consequently, to gauge its impact on the degree of skill mixing, the focus must remain on the (y_h, y_k) dimension. For this specific dimension, if $\frac{x_h}{x_k}$ converges to 1, then $\frac{y_h}{y_k}$ also approaches 1.

Proposition 2 (Changes in Wage and Job Finding). *Consider an occupation* $\mathbf{y}_t \in S \subset \mathbb{R}^K$ *within a closed skill space S of dimension K. Assume that firms operate the occupation with a production technology as described by equation 3 and under an occupational rental cost defined by equation 7. Also, these firms offer a output share* ω *to workers and have value functions described by equation 5. Further, let worker value described by equation 4. Under these conditions, workers in occupation* $\mathbf{y}$ *will earn a higher wage and have a higher job finding probability under condition (i) and (ii) of Proposition 1*

Proof of Proposition 2:

Wages: To establish the change in wages, one need to show that the output of the worker-firm match increases as the elasticity parameter σ decreases and approaches 0 from 1, or if σ decreases in the negative range, consistent with skills becoming more complementary in production. At a particular output share rate ω, such value changes of σ will lead to higher wages.

Now, let's obtain the first derivative of ρ for the production function 3. WLOG, let's consider the case of two skills, and express y_1x_1 and y_2x_2 as m and n. The output of a worker-firm match can be expressed as $q = (m^\rho + n^\rho)^{1/\rho}$. We can take log of the production function $\ln(q) = \frac{1}{\rho}\ln(m^\rho + n^\rho)$ and then take logarithmic differentiation that gives the following:

$$\frac{1}{q}\frac{\partial q}{\partial \rho} = -\frac{1}{\rho^2}\ln(m^\rho + n^\rho) + \frac{1}{\rho}\frac{1}{m^\rho + n^\rho}(m^\rho \ln(m) + n^\rho \ln(n))$$

Solving for $\frac{\partial q}{\partial \rho}$ gives:

$$\frac{\partial q}{\partial \rho} = q[-\frac{1}{\rho^2}\ln(m^\rho + n^\rho) + \frac{1}{\rho}\frac{1}{m^\rho + n^\rho}(m^\rho \ln(m) + n^\rho \ln(n))]$$
$$\frac{\partial q}{\partial \rho} = q[-\frac{1}{\rho}\ln(q) + \frac{1}{\rho}q^{-\rho}(m^\rho \ln(m) + n^\rho \ln(n))]$$

In the case of the calibration of the model, since m, n, and y are all in the range of $[0,1]$, one can show that the above derivative is negative when $0 < \rho < 1$ or when $\rho < 0$.

With respect to (ii) of Proposition 1, it is easy to see that since for the analysis of this paper, both $(\mathbf{x}, \mathbf{y})$ are in the range $[0,1]$, therefoer the occupation rental cost is decreasing in ϕ, so wage should increase as occupation rental cost increases.

Employment: For job finding probability, it suffices to to show that $p(\theta_t(\mathbf{x}, \mathbf{y}, \omega))$ is increasing in σ and ϕ. This becomes simpler, since the above proof establishes that worker-firm output is increasing in both σ and ϕ, so does firm's value $J(\mathbf{x}, \mathbf{y}, \omega)$. By the free entry condition in equation (6), at a fixed vacancy posting cost, an increase in $J(\mathbf{x}, \mathbf{y}, \omega)$ implies a decrease in $q(\theta_t(\mathbf{x}, \mathbf{y}, \omega))$ and therefore implies an increase in $p(\theta_t(\mathbf{x}, \mathbf{y}, \omega))$ under constant return to scale matching technology.

B.2 Equilibrium Definition and Block Recursivity

In this section I define the recursive competitive equilibrium for the economy. Following Menzio and Shi (2011), I further show that the equilibrium is block recursive.

Definition 2 (Recursive Competitive Equilibrium)**.** *A recursive competitive equilibrium for this economy is a collection of household policy functions for occupation choices for both unemployed and employed workers $\{y'_U(\mathbf{x}), y'_W(\mathbf{x}, \mathbf{y}, \omega)\}$, occupation skill choices for both firms with incumben jobs and new vancancies $\{y'_J(\mathbf{x}, \mathbf{y}, \omega)\}$, labor market tightness $\theta_t(\mathbf{x}, \mathbf{y}, \omega)$, and a distribution of agents across the aggregate states, which include employment status, skill profiles, occupational skill requirements, and output share such that:*

1. *The worker's policy functions solve their respective dynamic programming problems as in equation (4)*
2. *Firms' policy functions solve their respective dynamic programming problems as in equation (5)*
3. *The labor market tightness in each submarket $(\mathbf{x}, \mathbf{y}, \omega)$ is consistent with free-entry condition in equation (6)*
4. *The distribution of agents across aggregate states is consistent with individual policy functions*

Next, I briefly discuss a key nature of the model, which is in equilibrium the distribution of workers across the aggregate states bears no influence on the decision-making problems of workers or firms. Therefore, the model's equilibrium satisfy Block Recursivity as in Menzio and Shi (2011).

Proposition 3 (Block Recursitivity of Equilibrium)**.** *Under the model specification of linear utility and invertible and constant returns to scale matching function, also assume that the set of occupation characteristics $\mathbf{y}$ has bounded support, then the recursive competitive equilibrium as defined in definition 2 is block recursive.*

Proof of Proposition 3: The proof establishes through backward induction as in Braxton and Taska (2021). At the terminal period $t = T$, for an employed worker, the continuation value is zero for $T + 1$ onward, so the worker's dynamic programming problem does not depend on the aggregate distribution across states, and is equal to the worker's share of output $W_T(\mathbf{x}, \mathbf{y}, \omega) = \omega f(\mathbf{x}, \mathbf{y})$.

Similarly, the firm's value function also remains independent of the aggregate distribution $J_T(\mathbf{x}, \mathbf{y}, \omega) = (1 - \omega) f(\mathbf{x}, \mathbf{y})$. As a result, through the free entry condition in equation (6), the market tightness $\theta_T(\mathbf{x}, \mathbf{y}, \omega)$ is also independent of the aggregate distribution.

Firms at $T - 1$ make occupation design choices $\mathbf{y}$ to solve the firm dynamic programming problem in equation (**??**); workers at $T - 1$ make labor market search choices over occupations $\mathbf{y}$ to solve the worker dynamic programming problem in equation (4); As long as $\mathbf{y}$ is within a bounded interval bounded interval, the extreme value theorem assures at least one solution to this problem. This process is repeated stepping back from $t = T - 1, ..., 1$, which completes the proof.

B.3 Algorithm and Solution Method

The quantitative method used for estimation is SMM. Given the parameters in the model that are internally estimated $\Theta = \{\sigma, \rho, \phi, c, \alpha_k\}$, each iteration of SMM first solves the steady state firm and worker policy function, after which a panel of worker is simulated to obtain the equilibrium distribution of labor market outcomes.

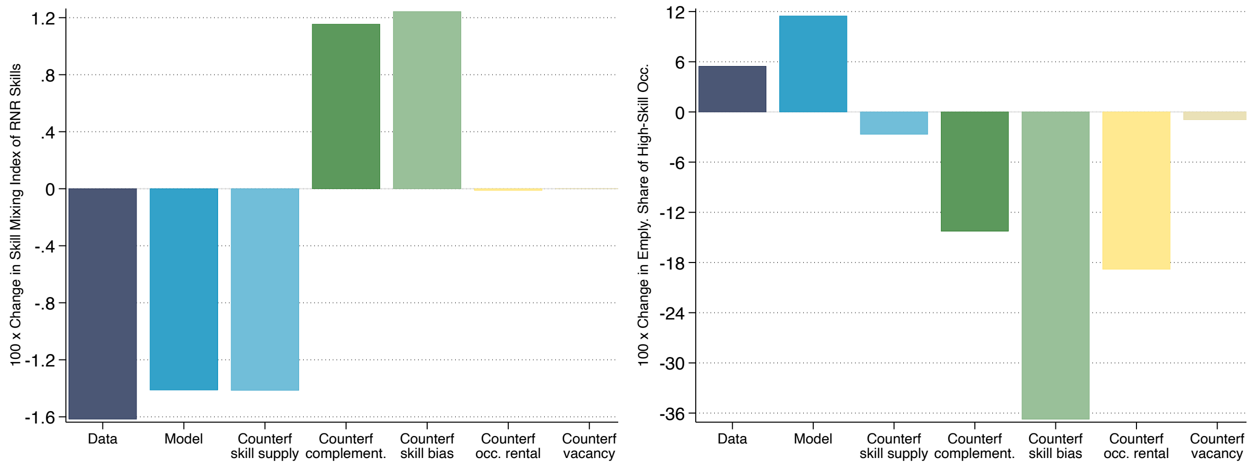
Specifically, to find the steady state policy of agents, I use value function iteration:

1. Fix the number of periods T
2. Starting from the terminal period T, solve the firm problem as in equation (4)
3. Use the free entry condition in equation (6) to obtain the market tightness $\theta_T(\mathbf{x}, \mathbf{y}, \omega)$
4. With the market tightness, solve the worker dynamic programming problem in equation (4)
5. Repeated stepping back from $t = T - 1, ..., 1$
6. Check if the difference in worker value $U_{t+1} - U_t$, $W_{t+1} - W_t$ and the firm value $J_{t+1} - J_t$ is less than a predetermined tolerance level. If yes stop, if not increase T and go back to first step

Next, I simulate 10,000 workers for $T(T > 200)$ periods, burning the first 40 periods to obtain distribution of labor market outcomes across different occupations and worker types. Finally, the SMM procedure minimizes the Euclidean distance between the model-implied moments and the same moments obtained from data.

B.4 Additional Counterfactual Results

Figure 7: Model Counterfactual



Notes: The table shows the model generated increase in skill mixing in high-skill occupations (panel 1) and relative employment of high-skill occupation (panel 2). Different model channels are shut down sequentially by eliminating the relative caliberated values to highlight the contribution of each channel. The full model has all the model features. Worker skill supply variation across the periods are caliberated according to Table **??**. The values of skill complementarity, occupational rental cost, skill bias, and vacancy posting cost across two periods are shown in Table 5.