

The Link between Labor Market Dynamism and Job Polarization*

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JOB MARKET PAPER

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Abstract

Over the last two decades labor market dynamism, measured by flows of workers between employers, declined substantially in the US. During the same period employment polarized into low and high skill jobs. This paper shows that the two trends are linked. First, I provide a framework to study employment and worker flows, where skill intensity of jobs and workers' skills are complements. I analyze within this framework the effects of routine-biased technological change and the increasing supply of college graduates on labor market flows. When routine-biased technological change displaces mid-skill jobs, it lowers the opportunity to move up to better jobs for low-skilled workers. Similarly, high skilled workers have less opportunity to take stepping stone jobs and are more likely to start employment further up the job ladder, reducing the frequency of transitions between employers. The rising share of college graduates puts further pressure on labor markets by increasing competition for jobs from top to bottom. In equilibrium workers trade down to jobs with lower skill intensity to gain employment, but find it harder to move up as they are competing with more highly educated workers. I quantitatively assess whether such mechanisms contribute to the fall in labor market dynamism, by estimating the model using data on labor market flows. I find that routine-biased technological change accounts for 40% of the decline in job-to-job mobility.

Keywords: Job Polarization, Sorting, On-the-job Search, Skill Distributions, Job Competition

JEL Codes: E24, J62, J64, O33

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1 Introduction

In the last two decades the US labor market experienced a decline in labor market mobility and job polarization, that is a shift in employment away from mid skill jobs towards low and high skill jobs. While technology has been identified as an important driver of polarization in employment, the underlying causes for the decline in labor market mobility, as measured by job-finding rates on and off the job, are less clear.¹ In this paper, I argue that the recent decline in worker mobility is driven by the displacement of mid-skill jobs and further intensified by the increasing supply of college graduates. The displacement of mid-skill jobs leaves low skilled workers with less opportunity to move up the job ladder. Thus, they are moving less between jobs. High skilled workers are less likely to find a stepping stone job in the middle of skill distribution and start out employment directly in higher skill jobs. As they start out employment further up the job ladder, they also move less between jobs. Such changes in the demand for skills have been accompanied by a large increase in the number of college educated workers. Additional high skilled workers intensify competition for high skilled jobs and in response workers trade down to lower skill jobs, that is competition trickles down the job ladder and intensifies at all types of jobs. The trickle down of competition makes it harder for everyone to move up the job ladder, leading to a further decline in job-to-job mobility.

First, I propose a novel theoretic framework that links the allocation of employment across jobs with worker mobility. The model embeds production with heterogeneous occupations and workers into a directed search model of the labor market. The setup highlights that, when workers' have a comparative advantage in some jobs, the division of production into occupations will depend both upon the relative productivity of occupations and the supply of skills. Furthermore, as workers compete with each other for jobs, the incentives for job search depend not only upon the value of employment but also on the composition of the pool of applicants. Thus, the allocation of workers to jobs, their mobility between jobs and overall employment are determined jointly in equilibrium. To capture the key characteristics of the labor market the model incorporates search frictions, on-the-job search and endogenous termination of jobs. Furthermore, the model allows for two-sided heterogeneity and sorting. These features are essential to study labor market flows in the presence of rich heterogeneity and assortative matching, as observed in the data. The allocation of workers to jobs is not random, for example college graduates are more likely to work as managers, while high school graduates are more likely to work as waiters. Occupations with different levels of productivity coexist because they are imperfect substitutes. For instance, there are jobs as managers and waiters. In the model, the production of two waiters are perfect substitutes, but the output of waiters and managers are not. Thus, in equilibrium the relative

¹At the same time, the decline in worker mobility raised concerns about the limited opportunities workers have to move to better jobs. See Moscarini and Postel-Vinay (2016) and Abel, Florida, and Gabe (2018) for evidence of a “failing” job ladder in recent years. Closely related, there is also concern about whether college graduates are increasingly employed in jobs that do not require a college degree, see for example Abel and Deitz (2014) for a discussion of the employment of college graduates in recent years.

price of output across occupations adjusts to ensure that job posting in all occupations is optimal.

Then, I proceed by applying the framework to study the recent experiences in the US labor market. To provide a quantitative assessment of the importance of technology for the decline in job-finding rates I estimate the main model parameters using labor market flow rates, separately for the late 1990s and the most recent years. For the estimation I group jobs based on two criteria: (1) whether the job’s tasks are predominantly routine and (2) whether the job has mainly cognitive or manual skill requirements. Furthermore, I group workers based on their education level as a proxy for their skill level. Then, I fit the model to data on job-finding rates and vacancies. The model can capture well the observed distribution of job-finding rates by education-occupation group. Using the estimated parameters, I analyze to what extent routine-biased technological change explains the decline in job-to-job mobility. I find that by itself routine-biased technological change can explain approximately 40% of the overall decline.

Relation to Literature. First, this article builds upon and contributes to the literature on the recent decline of labor market mobility. Davis and Haltiwanger (2014) and Hyatt and Spletzer (2013) provide empirical evidence for a decline in labor market mobility and argue that while composition shifts in the labor force are important, they can only explain 30-40% of the decline in mobility. Furthermore, they provide evidence that shifts in employment across industries has not been a driver of the decline as workers reallocate towards industries with traditionally higher turnover. In this study, I build upon their evidence, but focus upon a novel explanation of the decline in mobility. That is, changes in composition of the supply of and demand for skills have far-reaching equilibrium effects on labor markets.

Cairo (2013) studies the effect of increasing training costs on turnover in a random search model with large firms. She finds that increasing training costs, acting as a fixed cost to hiring that is subsequently lost when separating, decreases turnover. By increasing the cost of match formation the willingness to sustain matches under bad conditions increases and thus turnover declines. Fujita (2015) argues that increasing “turbulence” - a higher rate of skill loss at separation from employment - can explain lower turnover. The logic behind his finding is very similar to Cairo (2013), but instead of an increase in the fixed cost of hiring there is an increase in the cost of separation. Both papers argue that their findings can explain a joint decline in job-finding and separation rates. In the descriptive analysis of labor market flows, however, I find that separations to non-employment conditional on a workers education level are increasing while job finding rates decline over the last two decades. This paper contributes to the findings of those papers by analyzing worker mobility in a framework with sorting and on-the-job search, two essential features of the data, and providing a rationale for declining worker mobility in the absence of changes in matching and separation of costs.

Engbom (2017) highlights aging and its interaction with firms hiring decisions and innovation as a force driving down labor demand and turnover. Mercan (2018) argues that the availability of information about workers has increased and thus allows tighter selection at the hiring stage, leading to fewer

job-to-job moves. While these papers address potential explanations for the decline in mobility and employment, they do not address the sorting of workers to jobs and whether the decline in mobility is related to changes in sorting patterns. One exception is recent work by Eeckhout and Weng (2018) who study mobility and sorting. They focus on changes in the complementarity between workers' unobserved skills and jobs technology, but I focus on changes in demand for and supply of skills. While these papers study related questions they focus on different mechanisms and the importance of each mechanism for the decline in mobility is still an open question. Thus I consider them complimentary to this paper. The main contribution of my paper is to analyze worker mobility in a setting where there is not only sorting, but also competition between workers leading to rich equilibrium interaction between worker mobility and the demand for and supply of skills.

Second, this study also contributes to the literature on models with search frictions and sorting in the labor market. Barnichon and Zylberberg (2018) consider a setup of the labor market with similar features as in this paper and analyze employment by education level of workers over the business cycle. They find that highly-educated workers are downgrading towards low-skill jobs in downturns, which leads to more unemployment for workers with less education as high-skilled workers are preferentially hired. This paper is based on a similar job competition mechanism and they provide outside evidence that the mechanism is relevant for the allocation of workers to jobs. Though related, they do not focus on the trend in worker mobility and its possible causes. Furthermore, they do not include on-the-job search, which is at the core of this paper. Lise and Robin (2017) also study sorting over the business cycle, but use a random search framework that, in contrast, does not feature explicit competition at the hiring stage. While, they address only business cycles and I focus on trend changes in the labor market, it is also the key mechanisms of how sorting happens in the labor market that are different. I focus on competition between applicants and directed search, while in their framework sorting is entirely based on matching sets. By allowing for competition between workers at the hiring stage, I can address to what extent high skilled workers crowd out lower skilled workers from particular jobs and employment.

Third, the current article is also closely related to the literature on technological change, job polarization and wage inequality. Following the contributions by Goos and Manning (2003) and Autor, Levy, and Murnane (2003) a large literature has analyzed how technology can explain job polarization and other labor market outcomes, for instance Acemoglu and Autor (2011), Goos, Manning, and Salomons (2014) and Stokey (2016). Cortes, Jaimovich, and Siu (2017) build on this literature and study a frictionless model of the labor market to analyze to what extent the declining labor force participation rate can be explained by technological factors. In this paper I proceed in a similar manner, but focus instead on the role of technology for job search both on and off the job. Beaudry, Green, and Sand (2016) and Aum (2017) provide evidence that the supply of educated workers outpaced the demand for skilled workers since 2000. In this paper I find a similar pattern and will take into account both shifts in demand for jobs and the supply of educated workers. Aum, Lee, and Shin (2018) argue that the negative effect of "routinization" on aggregate productivity growth was not visible due the rise in

productivity of the computer industry until the 1990s, which became a more important input across all industries over the same period. This is in line with the findings in Jaimovich and Siu (2012) and this paper, as the decline routine employment is concentrated in the period after 2000.

The remainder of the article is organized as follows. Section 2 provides a descriptive overview of the recent trends in worker mobility and employment. In Section 3 I lay out the theoretical framework. The structural estimation setup follows in Section 4, where I discuss identification and present the estimated parameters and model fit. In Section 5 I perform the decomposition of the decline in labor market flows using the estimated model. The last section offers concluding remarks.

2 Descriptive Evidence

Data Sources and Sample Selection

The CPS Basic Monthly files for the period 1994 to 2017 are the main source of data. The raw data are provided by Sarah, King, Rodgers, Ruggles, and Warren (2018). Occupations are categorized based on their cognitive requirements and routine task content following Autor et al. (2003), see table 1 for an overview. The grouping into routine vs. non-routine jobs captures to what extent occupations are exposed to displacement by automation technology. The differentiation along cognitive skill requirements allows to distinguish jobs with high vs low cognitive ability requirements. I connect the jobs cognitive skill requirement to workers by using education levels as a proxy for cognitive skills. In the main analysis I use three groups for education levels: (1) at most a high school degree (2) some college, but not a full four year degree and (3) a four year college degree or more. In order to exclude individuals in education and close to retirement, I restrict the sample to individuals of age 25-45. All calculations use CPS sample weights.

Decline in Worker Mobility and Job Polarization

In this section I present evidence for a trend decline in worker mobility and job polarization. Over the last two decades there was a substantial decline in job finding rates both on and off the job.

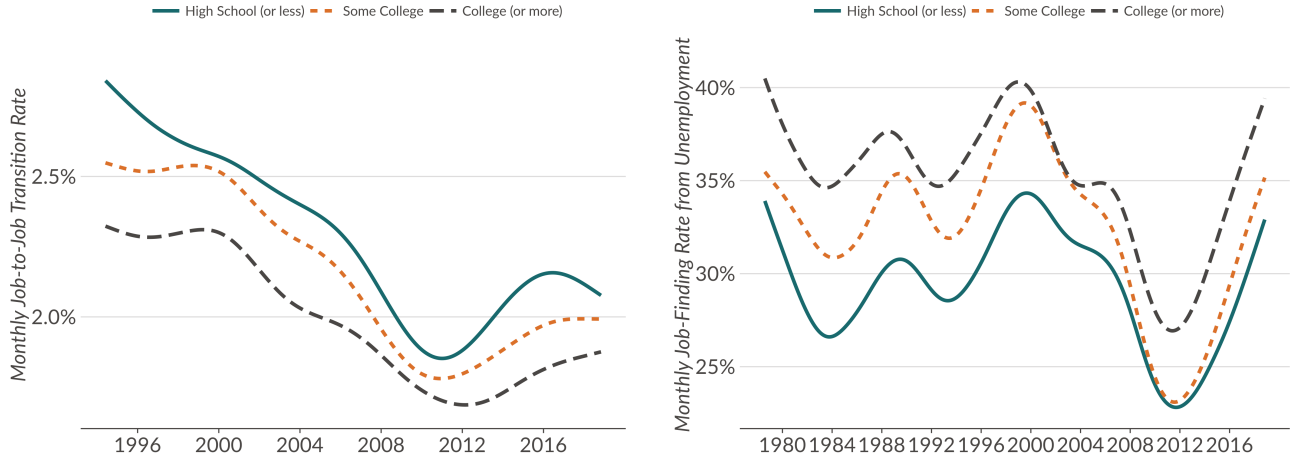
Figure 1 shows in panel 1a the job-to-job transition rate and in panel 1b the job finding rate from non-employment. The job-to-job transition rate declined by over 20% between 1996 and 2016 for workers of all education levels. The decline in the switching rate between jobs has been remarkably common between workers of different education levels, which points towards broad based changes in the labor market. The job finding rate out of unemployment has declined somewhat. Again, the behavior over time is remarkably common for workers of different education levels. The trend decline in job finding rates can be driven by many factors related to the value of employment, costs of creating worker-employer relationships and frictions in the labor market. In this paper, I focus on how changes in technology affect labor demand and in turn the distribution of potential jobs a worker can obtain.

Table 1: Occupation Groups by Tasks

Tasks	Census Occupations
Non-routine Cognitive	Management
	Business and financial operations
	Computer, Engineering and Science
	Education, Legal, Community Service, Arts and Media Occupations
	Healthcare Practitioners and Technical Occupations
Routine Cognitive	Sales and Related
	Office and Administrative Support
Routine Manual	Construction and Extraction
	Installation, Maintenance and Repair
	Production
	Transportation and Material Moving
Non-routine Manual	Service Occupations

See Cortes, Jaimovich, Nekarda, and Siu (2014) for details on classification and mapping to Census Occupation codes.

Figure 1: Job Finding Rates



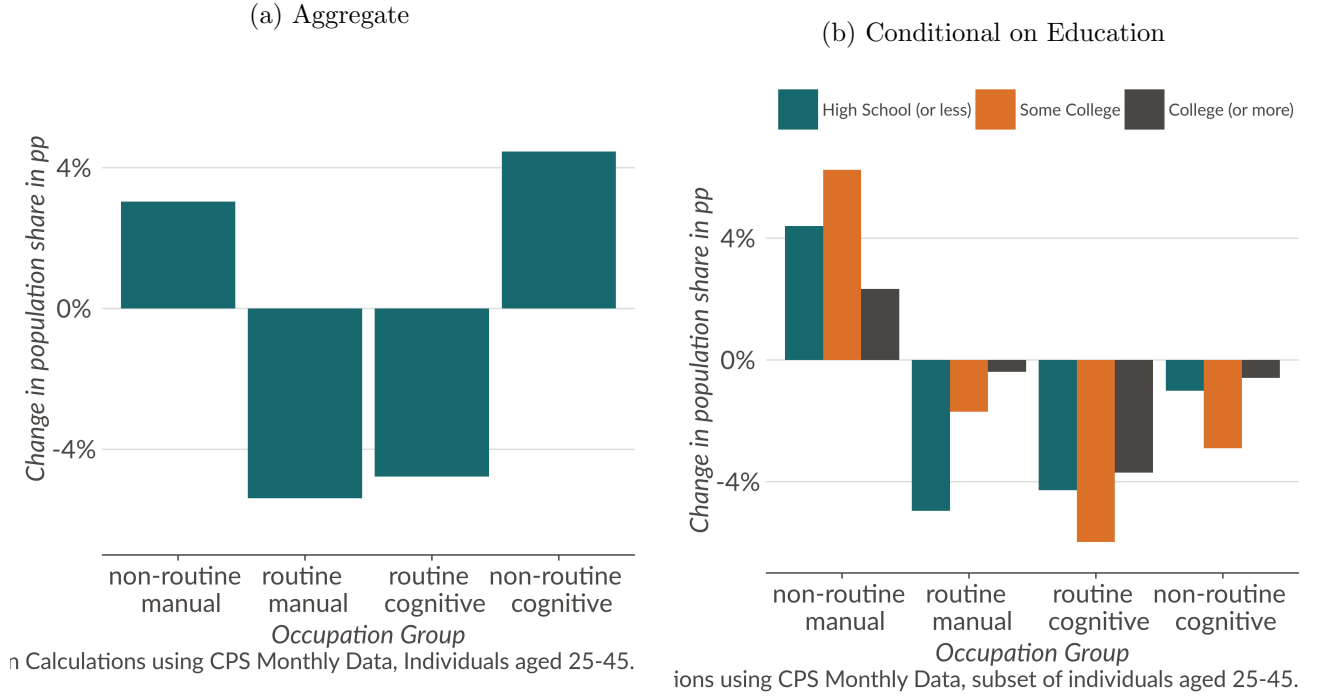
(a) Job-to-Job Transition Rate. Own Calculations using CPS Basic Monthly Files. Trend calculated from monthly transition rates using HP Filter with smoothing parameter 129600.

(b) Unemployment-Employment Transition Rate. Own Calculations using CPS Basic Monthly Files. Trend calculated from monthly transition rates using HP Filter with smoothing parameter 129600.

Particularly, I document that employment shifted away from mid skill (routine) employment towards low and high skill (non-routine) jobs. This trend has been called job polarization and a large literature following the contributions of Autor et al. (2003) and Goos and Manning (2003) has argued that routine biased technological change is behind such changes, but also that trade and off-shoring are other potential causes (Autor, Dorn, and Hanson, 2016, Blinder and Krueger, 2013). Here I do not focus on the specific causes for changes in the composition of labor demand across jobs, but on its

impacts on workers mobility and will henceforth combine those different mechanisms under the term “technology”.

Figure 2: Change in Employment per Capita by Job Type: 1996-2016



In Figure 2a I show the change in employment per capita between 1996 and 2016 for each occupation group, as defined in table 1. Employment rose in non-routine jobs, while employment in routine jobs declined. The rise in non-routine employment took place both at the bottom and top of the wage distribution, while the decline in routine employment is situated in the middle of the wage distribution². This trend has been termed “Job Polarization” by Goos and Manning (2003). This shift in composition of employment is closely connected to worker mobility. The different types of jobs form a job ladder that workers try to climb. However, the part of the ladder which is relevant for a worker depends upon her education level. For instance, for workers with at most a high school degree employment is concentrated in non-routine manual and routine jobs. For college educated workers instead employment is concentrated in routine and non-routine cognitive jobs³. Thus, as employment shifts away from mid skill jobs it becomes harder for workers with low education levels to move to better jobs, as they have low job finding rates at high skill jobs⁴. They can not easily move to high skill jobs, because they have to compete with college educated workers whose skills are likely more suited for such jobs. Thus, I argue that the opportunity to move up out of low skill employment have diminished for workers

²The relative pay of these occupation groups has been widely documented. See appendix D for the weekly earnings of those occupation groups, calculated using the CPS outgoing rotation group.

³See appendix D for the distribution of employment by job type and education level of workers

⁴The differences in job-finding rates from non-employment to jobs by education and occupation are shown in section 4.

with low education levels. For workers with a college degree the decline in demand for mid-skill jobs, instead means that they have fewer opportunities to take a stepping stone job. Therefore, once they find employment they are on average more likely to be employed further up the job ladder, and thus they are less likely to move up. However, as workers compete with each other for jobs it is not only the demand for jobs, but also the supply of educated workers that is linked to mobility and employment. In Figure 2b the change in employment by occupation group is shown again, but conditional on a workers education level. There is a clearly distinct pattern in the cross-section compared to the aggregate. First, there does not seem to be an increase in employment in non-routine cognitive jobs. This is driven by the increase in supply of college graduates by over 10pp over the same time period, as shown in appendix D. Therefore, conditional on a workers education level employment shifts towards low skill jobs. This suggests that the supply of college graduates outpaced demand for high-skill jobs which in turn puts pressure on labor markets from top to bottom. This interpretation is further corroborated by the evidence in Beaudry et al. (2016) and Aum (2017). For the main analysis in the paper I will therefore not only take into account potential changes in the demand for skills, but also in the supply of skills.

3 Framework

In this section I develop an equilibrium framework of the labor market incorporating skill heterogeneity across workers and technology differences across jobs. The framework allows for sorting and endogenous mobility of workers. Output from different occupations is aggregated into a final good with a finite elasticity of substitution. As I focus on stationary equilibria I drop time as a subscript.

Agents and Technology. Time t is continuous. There is a measure one of risk-neutral workers in the economy. Workers differ in their level of skill $x = 1, \dots, X$ which has an exogenous distribution $G(x)$. A worker is either unemployed and searching for a job or employed and searching for another job. The worker chooses search effort s at cost $c(s)$, which is increasing and convex. The search effort cost on the job is multiplied by a constant ϕ_1 , capturing potential differences in the level of search costs on and off the job. Each unit of search effort translates into a proportional increase in the job finding rate. Workers also direct their job search, that is they observe the distribution of vacant jobs and choose to which vacancy to apply for. Among vacancies between they are indifferent workers potentially randomize. Furthermore, I assume that workers can not coordinate their applications, that is application strategies treat two vacancies with the same characteristics in the same way⁵. This assumption gives rise to matching frictions, as identical vacancies receive zero, one or many applications. This leaves some vacancies unfilled, while other vacancies have to turn away applicants.

There is a large measure of potential jobs. Each job chooses its occupation y before entry. There are

⁵See Shimer (2005a) for a discussion of this assumption and how it gives rise to matching frictions.

$y = 1, \dots, Y$ occupations, which are ordered by their skill intensity y . The productivity of labor $f(x, y)$ in a job of type y depends both upon the workers skill x and the jobs occupation y . Furthermore, flow output depends upon match-specific productivity ϵ , which is redrawn at rate θ_y from the distribution $F_y(\epsilon)$. The flow revenue of a job of type y employing a worker of type x is flow output times price $p_y \epsilon f(x, y)$. The price of output p_y of an occupation is determined in equilibrium. The allocation of workers to jobs in equilibrium will then strongly depend upon the properties of $f(x, y)$. The differences in productivity across jobs driven by y and ϵ form a job ladder for workers, which will also depend upon the workers human capital level x through its impact on labor productivity $f(x, y)$. A new job opens by posting a vacancy at flow cost $k(y)$. The amount of entry of vacant jobs into the different occupations will be determined in equilibrium and the price of occupation output will adjust accordingly. The output of individual jobs within an occupation are perfect substitutes. Thus, occupation output follows $Q_y = \sum_x \int \epsilon f(x, y) e(x, y, \epsilon) d\epsilon$. The output of each occupation is turned into a single final good Q_F by a CES aggregator with elasticity of substitution σ , that is $y_F = \left[\sum_y \omega_y Q_y^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$, where $\sum \omega_y = 1$. The production shares ω_y would allow for a situation where more productive jobs do not represent a larger share of employment, which occurs when their output represents only a small share of inputs in final goods production. The market for occupation output Q_y is competitive. Therefore, the input costs of final goods producers will exhaust revenue. The final good is the numeraire $p_F = 1$.

Labor Market Frictions and Search. Meetings between workers and jobs are stochastic and are modeled by an urnball matching function, most closely related to the static setup in Shimer (2005a)⁶. A model with similar features as Shimer (2005a) and the current setup was studied in Shi (2002). A worker applies for jobs sequentially, but many applications potentially arrive simultaneously at a job. Jobs hire their preferred candidate, as they can only hire one worker. In comparison to the standard setup job finding rates of workers do not simply depend upon the overall tightness of the labor market, but also on the ranking among the set of applicants. In order to incorporate on-the-job search, which alters the outside option of a worker at time of hiring, I extend the type space. A worker is now described by a tuple x, S_o where S_o denotes the value of his outside option over unemployment. If there is no match-specific heterogeneity $B_y(x, S_o)$ denotes the set of workers ranked above worker x, S_o . However, the match-specific productivity ϵ is drawn in the moment when workers and jobs meet, therefore the set of better ranked workers will also depend upon ϵ , that is $B_y(x, S_o, \epsilon)$. Now, I define job finding rate for a worker of type x, S_o who sends an application to a job of type y . For that define a queue of workers $\lambda_y(x, S_o)$ as the effective number of searchers of type (x, S_o) applying for type y vacancies over

⁶See Peters (1991) and Burdett, Shi, and Wright (2001) for microfoundations of the urnball matching function. Shimer (2005a) extends this to a setting with two-sided heterogeneity where jobs rank workers.

the number of vacancies v_y . Then, we can also define the total queue of better ranked workers

$$\Lambda_y(x, S_o, \epsilon) = \sum_{(h', S'_o, \epsilon') \in B_y(x, S_o, \epsilon)} \lambda_y(x', S'_o) f_y(\epsilon').$$

The flow job finding rate at jobs of type y for worker of type (x, S_o) is then

$$\nu_y(x, S_o) = \int e^{-\Lambda_y(x, S_o, \epsilon)} \frac{1 - e^{-\lambda_y(x, S_o) f(\epsilon)}}{\lambda_y(x, S_o)} \{S(x, \epsilon, y) > S_o\} d\epsilon.$$

The filling rate for a job of type y by a worker of type (x, S_o) is then $\nu_y(x, S_o) \lambda_y(x, S_o)$, as the urnball matching function exhibits aggregate returns to scale. The actual job finding rate for a worker not only depends upon the choice where to apply, potentially following a mixed strategy, but also her total search effort $s(x, S_o)$. Search effort translates one-to-one into job finding rates, that is the flow job finding rate conditional on applying for job y is $s(x, S_o)$. Job separations happen at an exogenous rate δ and when a draw of match-specific productivity below the reservation threshold $\underline{\epsilon}_y(x)$ arrives, so the effective separation rate is $\delta + \lambda_y F_y(\underline{\epsilon}_y(x))$.

Individual Decision Problems and Bellman Equations. I denote the value of unemployment by $U(x)$, the value of a vacant job of type y by $V(y)$, the value of a filled job by $J(x, S_o, \epsilon, y)$ and the value of employment for a worker in job y by $E(x, S_o, \epsilon, y)$. Furthermore, I will denote deviations of values relative to outside options by hats, that is $\hat{E}(x, S_o, \epsilon, y) = E(x, S_o, \epsilon, y) - S_o$. The surplus value of a match is defined as $S(x, S_o, \epsilon, y) = E(x, S_o, \epsilon, y) + J(x, S_o, \epsilon, y) - U(x) - V(y)$. The surplus value relative to the outside option is then $\hat{S}(x, S_o, \epsilon, y) = S(x, S_o, \epsilon, y) - S_o$.

Workers choose how much to search and at which type of job. Vacant jobs choose which types of contracts to post. Contracts are complete and enforceable, that is jobs and workers commit to fulfilling the conditions of the contract. To describe a workers search decisions define the value of one unit of search effort spend on applications at job type y

$$W_y(x, S_o) = \int \nu_y(x, S_o, \epsilon) \hat{E}(x, S_o, \epsilon, y) d\epsilon. \quad (1)$$

As workers freely choose to which type of job to apply to, they will only apply to a job of type y if the application has at least as much value as their second best option.

$$W_y(x, S_o) \geq \max_{y'} W_{y'}(x, S_o) \perp \lambda_y(x, S_o) \geq 0, \quad (2)$$

where the two conditions hold with complementary slackness.

The workers search effort solves

$$\max_s sW(x, S_o) - c(s),$$

which has an interior solution $s \geq 0$ as $c(s)$ is increasing, monotone and convex.

The vacant jobs contract posting decision maximizes expected discounted profits. The expected discounted revenue of filling the job is the flow rate at which the job is filled times the total surplus value left after compensating the worker for his outside option. However, a job does not enjoy the remaining value \widehat{S} by itself, but posts contract values \widehat{E} under commitment that promise the worker a specific amount of the remaining value conditional on his characteristics. Following Shimer (2005a) I will formulate the decision problem of the vacant job as one of attracting queues of workers, instead of maximizing over contract values directly. The contract values will be defined implicitly. Using the workers indifference condition (2) we can write the vacant jobs problem as

$$\max_{\{\lambda_y(x, S_o)\}} \sum_{x, o} \int \mu_y(x, S_o) \widehat{S}(x, S_o, \epsilon, y) d\epsilon - \sum_{x, o} \lambda_y(x, S_o) W(x, S_o), \quad (3)$$

where $\lambda_y(x, S_o) \geq 0$. The corresponding set of first order conditions is

$$W(x, S_o) \geq \int f_y(\epsilon) e^{-\lambda_y(x, S_o) f_y(\epsilon)} e^{-\Lambda_y(x, S_o, \epsilon)} \widehat{S}(x, S_o, \epsilon, y) d\epsilon \dots \quad (4)$$

$$- \sum_{x', o'} \iint \mathbf{1}\{\widehat{S}' < \widehat{S}\} f_y(\epsilon) e^{-\Lambda_y(x', S_{o'}, \epsilon')} (1 - e^{-\lambda_y(x', S_{o'}) f_y(\epsilon')}) \widehat{S}(x', S_{o'}, \epsilon', y) d\epsilon d\epsilon'$$

$$\lambda_y(x, S_o) \geq 0, \quad (5)$$

where the two conditions hold with complementary slackness. If no application is attracted $\lambda_y(x, S_o) = 0$ any contract value below what equation 4 specifies could be offered, but this indeterminacy is without any consequence as no one applies. Replacing $W(x, S_o)$ with its definition in (2) one obtains a definition of expected contract values as a function of queue lengths. I assume that contracts are complete and enforceable, such that they can not only specify the value promised to the worker, but also on-the-job search and continuation decisions in case of match specific productivity shocks. Therefore, contracts will be specified to maximize the total value of the match. See Garibaldi, Moen, and Sommervoll (2016) for a setup with a similar assumption. Contracts will maximize surplus, so we do not need to specify the value of the match separately for the worker and firm. It is sufficient to describe the joint surplus to describe allocations, as the surplus value does not depend on its split between worker and firm. The

Bellman equations defining the values thus follow

$$rU(x) = \max_s b(x) + sW(s, 0) - c(s) \quad (6)$$

$$rV(y) = -k(y) + \sum_{x,o} \int \mu_y(x, S_o, \epsilon) \hat{S}(x, S_o, \epsilon, y) d\epsilon - \sum_{x, S_o} \lambda_y(x, S_o, \epsilon) W(x, S_o) \quad (7)$$

$$(r + \delta)S(x, \epsilon, y) = \max\{0, \max_s p_y \epsilon f(x, y) + sW(x, S) - c(s) - b(x) - s(x, 0)W(x, 0) - c(s(x, 0))\} \quad (8)$$

$$+ \theta_y \int \max\{S(x, \epsilon', y) - S(x, \epsilon, y), 0\} dF_y(\epsilon')). \quad (9)$$

Here I already set the derivative of the values with respect to time to zero, as I focus solely on stationary equilibria. See appendix A.1 for omitted derivations.

Distribution of Workers and Jobs. Denote the unemployment rate of workers with skill x by $u(x)$ and employment in job of type y and match-specific productivity ϵ by $e(x, y, \epsilon)$. The hiring rate of a worker of type (x, S_o) at a job of type y , while drawing ϵ , is $s_y(x, S_o)\nu_y(x, S_o, \epsilon)$ and the rate of separation to unemployment of type x workers at type y jobs is denoted as $\delta_y(x) = \delta + \lambda_y F_y(\underline{\epsilon}(x, y))$. Then the distribution of workers across unemployment $u(x)$ and jobs $e(x, y, \epsilon)$ evolves according to

$$\dot{u}(x) = -u(x) \sum_y \int s_y(x, 0)\nu_y(x, 0, \epsilon) d\epsilon + \sum_y \int \delta_y(x)e(x, \epsilon, y) d\epsilon \quad (10)$$

$$\dot{e}(x, \epsilon, y) = -e(x, \epsilon, y) \sum_{y'} \int s_{y'}(x, S')\nu_y(x, S', \epsilon) d\epsilon' - e(x, \epsilon, y)\delta_y(x) \quad (11)$$

$$\begin{aligned} & + \lambda_y f_y(\epsilon) \{S(x, \epsilon, y) > 0\} \int e(x, \epsilon', y) d\epsilon' \\ & + \int s_y(x, S')\nu_y(x, S', \epsilon) dH(x, S') \\ G(x) & = u(x) + \sum_y \int e(x, \epsilon, y) d\epsilon \end{aligned} \quad (12)$$

where $H(x, S')$ is the distribution of individuals by skill x and current surplus value S' , $h(x, 0) = u(x)$ and $H(x, S') = u(x) + \sum_y \int e(x, \epsilon, y) \{S(x, \epsilon, y) \leq S'\} d\epsilon$ for $S' > 0$.

A stationary distribution satisfies the above law of motion with $\dot{u}(x) = 0$ and $\dot{e}(x, \epsilon, y) = 0$.

Goods Market The final good is a CES aggregate of the occupation output $y_F = \left[\sum_y \omega_y Q_y^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$. The intermediate inputs Q_y , the occupation level output, is bought at price p_y , which is taken as given by competitive final goods producers. Intermediate input demand follows

$$Q_y = \omega_y \left(\frac{p_y}{p_F} \right)^{-\sigma} Q_F. \quad (13)$$

The price index of the final good is

$$p_F = \left[\sum \omega_y p_y^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \quad (14)$$

Costinot and Vogel (2010) provide a model with a similar production structure, but analyze solely assignment between workers and jobs without frictions.

Stationary Equilibrium

Definition 1. A pair $\{U(y), V(y), S(x, \epsilon, y), u(x), e(x, \epsilon, y), \widehat{W}(x, S_o), \lambda_y(x, S_o)\} \forall x, o, \epsilon$ is a stationary equilibrium, if:

1. the workers indifference condition (2) holds;
2. the Bellman equations (17), (7) and (9) hold;
3. there is free entry of jobs, that is $V(y) = 0 \forall y = 1, \dots, Y$;
4. the distribution of workers and jobs is constant over time, that is (10) holds with $\dot{e} = 0$ and $\dot{u} = 0$;
5. p_y , the price of occupation output, is such that (13) and $Q_y = \sum_x \int \epsilon f(x, y) e(x, \epsilon, y) d\epsilon$ hold;
6. the market for applications clears, that is $s(x, S_o) h(x, S_o) = \sum_y \lambda_y(x, S_o) v_y \forall x, o$;
7. (4) and $\lambda_y(x, S_o) \geq 0$ hold with complementary slackness.

Computation of equilibria is implemented using the solver for mixed complementarity problems by Ferris and Munson (1999), see appendix C for details.

3.1 Examples: Sorting

In the model are several forces that drive sorting and in this section I give examples to clarify those mechanisms. First, I focus on the role of job output $f(x, y)$. Second, I will discuss the role of entry costs. Here sorting is defined as first order stochastic dominance.

Definition 2. An allocation exhibits positive assortative matching (PAM), if the distribution over jobs y for workers of type x_2 first order stochastically dominates that of workers with type x_1 when $x_1 < x_2$.

1. The conditional distribution of employment across jobs for a worker of type x is $\pi(y|x) = \frac{\sum_{j=1}^Y \int e(x, \epsilon, j) d\epsilon}{\sum_{j=1}^Y \int e(x, \epsilon, j) d\epsilon}$
2. An allocation exhibits PAM, if $\pi(y|x_i) \leq \pi(y|x_{i'}) \forall i, i' > i \in 1, \dots, X$ with the inequality strict for at least one $y \in \{1, \dots, Y\}$ and $x_i < x_{i'}$.

Negative assortative matching (NAM) is defined analogously. Note that I define sorting globally across all pairs of workers. To clarify under which conditions sorting occurs it is useful to consider when no sorting occurs.

Proposition 1. *Assume match productivity $f(x, y)$ is log-modular, entry costs are independent of job type $k(y) = k_0$ and the distribution of ϵ is independent of job type. Then no sorting according to definition 2 occurs in a stationary equilibrium. Proof see appendix.*

The no sorting condition is the same as in the frictionless case when $k_0 \rightarrow 0$. In the frictionless limit there are no wage differences across jobs, but even in the case with frictions a similar condition holds in terms of surplus. Thus, the model presented in Shimer (2005a) by itself does not directly generalize to explain evidence from matched employer employee datasets highlighting differences in wages across jobs for similar workers. To explain such evidence, one needs to assume that firms have different entry costs in order to sustain surplus differences across jobs in equilibrium.

For the following examples, consider a simplified version of the model above where the only form of heterogeneity is in worker skill x and job type y . There are two types of workers $x_L < x_H$ and two types of jobs $y_L < y_H$, and there is no match specific productivity variation. The home production value is $b(x) = \bar{b}$. In that case, surplus follows

$$(r + \delta)S(x, y) = p_y f(x, y) - b - s(x, 0)W(x, 0) + c(s(x, 0)) - s(x, S)W(x, S).$$

The production technology is

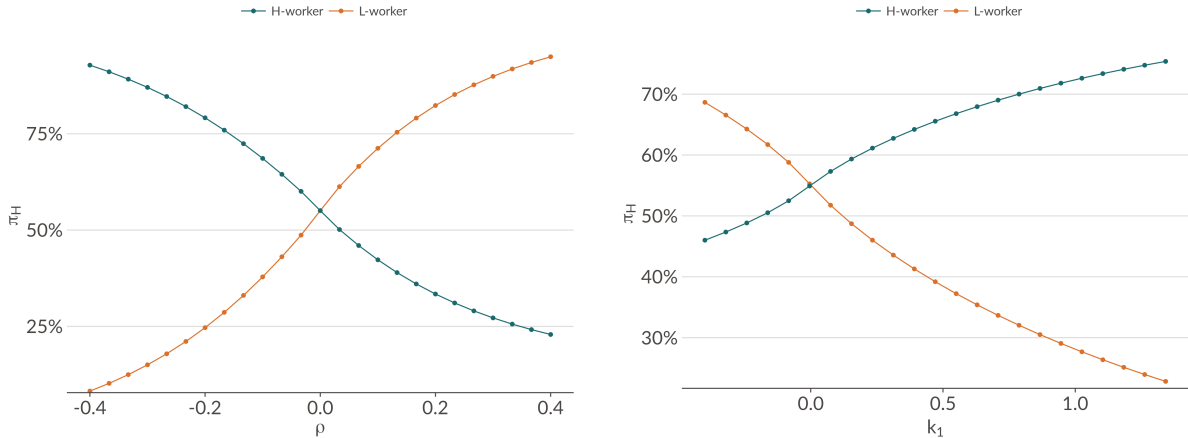
$$f(x, y) = [x^\rho + y^\rho]^\frac{1}{\rho},$$

where ρ governs whether skill x and job type y are complementary. In general, the properties of surplus $S(x, y)$ determine sorting. Shimer (2005a) discusses some examples under which sorting arises. However, in this paper there is free entry and therefore higher surplus in some types of job are only sustainable to the extent that they reflect lower filling rates μ_y or higher posting cost k . In equilibrium additional entry will lead to a decrease in p_y up until the free entry condition is satisfied. In the following I give examples in which sorting occurs.

Comparative Advantage in Production. Assume $k(y) = k_0 \forall y$. Then, the conditions for sorting are the same, as in the frictionless limit $k_0 \rightarrow 0$. Costinot and Vogel (2010) show that in the frictionless assignment model sorting arises when $f(x, y)$ is log-supermodular, that is high skill workers have a comparative advantage in high skill intensive occupations. In the current example, the production function is log-supermodular if $\rho < 0$. In the two-type example we can summarize the distribution of workers across jobs, as the share of workers in high skill intensive jobs $\pi_H(x) = \frac{e(x, y_H)}{e(x, y_L) + e(x, y_H)}$. Figure 3a plots $\pi_H(x)$ for low and high skilled workers for various values of ρ in a numerical example. The condition for PAM is satisfied if $\pi_H(x_H) > \pi_H(x_L)$. PAM occurs in equilibrium when $f(x, y)$ is log-

supermodular. In this example with a CES production function, log-supermodularity holds when $\rho < 0$. When $\rho = 0$, there is no sorting and when $\rho > 0$ ($f(x, y)$ is log-submodular) the allocation exhibits NAM.

Figure 3: Sorting with comparative advantage and heterogenous entry costs.



(a) Employment Share in y_H Jobs and ρ . Log-supermodular (-submodular) production function $\rho < 0$ ($\rho > 0$) implies PAM (NAM). Entry Cost $k(y) = k_0$.

(b) Employment share in y_H jobs with heterogeneous entry cost $k(y) = k_0 y^{k_1}$. Increasing entry cost in job type $k_1 > 0$ implies PAM in absence of comparative advantage $\rho = 0$.

The reason that the condition for sorting is not stronger with frictions in the labor market relative to the frictionless case is that jobs select workers at the hiring stage. When they receive multiple applications, they hire the worker delivering the highest value to the firm, which coincides with the worker who provides the highest surplus. Therefore, when deciding which worker to hire the firm ranks according to the same criterion as in the frictionless case and sorting arises under the same conditions. However, there is mismatch. Some firms receive only applications by L type workers, while others only receive applications by H type workers. Therefore, sorting is not perfect as it would be in the frictionless case. Mismatch is sustained in equilibrium despite directed search, because firms post contracts conditional on worker heterogeneity rendering workers indifferent between applying at different jobs.

Heterogeneous Entry Cost. Differences in entry costs across occupations y induce sorting, even when the production function is log-modular. The reason is that differences in entry costs are reflected in surplus values due to free entry. However, those differences are larger for more skilled workers even in absence of comparative advantage ($\rho = 0$). Consider the same setup, as in the previous example, but with $k(y) = k_0 y^{k_1}$. Figure 3b plots the share of employment in high skill jobs π_H for low and skill workers. When high skill jobs are more costly to create, $k_1 > 0$, the equilibrium exhibits PAM even with a log-modular production function. When entry cost are increasing in y the productivity advantage of

y_H jobs is not fully competed away due to entry. When $k_1 > 0$, the relative price of output of y_H jobs is larger compared to an equilibrium with $k_1 = 0$. As the price of output for high type jobs does not fall as much, surplus can be supermodular without $f(x, y)$ being log-supermodular.

3.2 Examples: Allocation

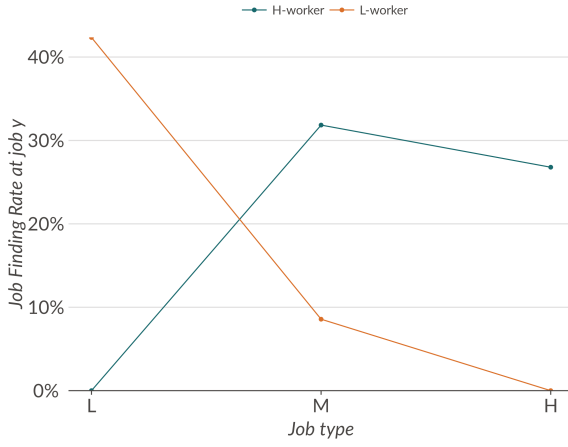
In this section I first show an example allocation to illustrate how job finding rates are affected by competition between workers, not just surplus value of jobs. Then I show how job-to-job mobility reacts to a displacement of mid-skill jobs. In this example I keep with the previous setup, but allow for heterogenous match-specific productivity. The production function is chosen to be log-supermodular and $\omega_L < \omega_M < \omega_H$ and the posting cost is $k(y) = k_0 \omega_y$.⁷ The allocation features positive assortative matching, as defined above.

Panel 4a shows the flow job finding rate of L,H type workers at L,M,H type jobs. Low type workers only find jobs at L,M type jobs, while high type workers find jobs only at M,H type jobs. Workers segregate to the tails of the skill distribution, but mix in the middle. However, surplus is increasing in job type for both low and high skilled workers, as shown in Panel 4b. In equilibrium, low skilled workers do not apply at high type jobs, because the contract offered to them does not compensate them enough for the increased competition by high skilled worker, which lowers their job-finding rate. At mid-skill jobs the productivity advantage of high skill workers is not as large, thus the posted contracts optimally offer sufficient value to also attract low type workers. On the other hand, high type workers require too much compensation in order to be attracted for low type jobs, as their option value of searching is larger. Panel 4c shows the rate at which a workers application meets a job and is among the best applicants. High type workers are more likely to be among the best applicants at all jobs. However, the probability to be among the best applicants decreases in job type, as the share of high type applicants increases. The increased competition lowers job finding rates relatively more for low-skilled workers, as they are more frequently sent to the back of the queue. Finally, in equilibrium workers apply to different jobs at different rates. Panel 5 shows the flow rate of applications for each type of job. Low skill workers apply predominantly for low skill jobs and high skill workers mix relatively evenly between mid and high skill jobs. Here I focused on workers who are looking for jobs from unemployment, but the exact same mechanism applies for all searchers independent of employment status. Once employed workers continue searching for jobs and move up the job ladder, that is low skill workers stochastically move to mid skill jobs and high skill workers move to high skill jobs.

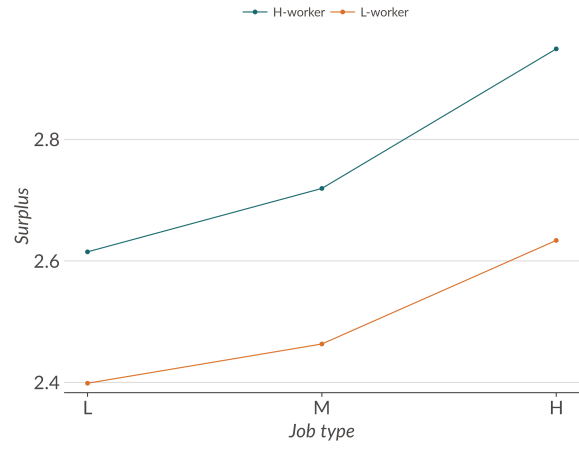
Consider the displacement of mid-skill jobs driven by a decline in ω_M . Job-to-job hires into mid-skill jobs decline as expected because the share of mid skill vacancies decreases. Overall job-to-job hires decline. Workers as a response decrease their search intensity as it became harder to find a job and redirect their search, which is the reason for a subdued response in job-to-job hires at low and high skill

⁷See appendix B for the full list of parameters

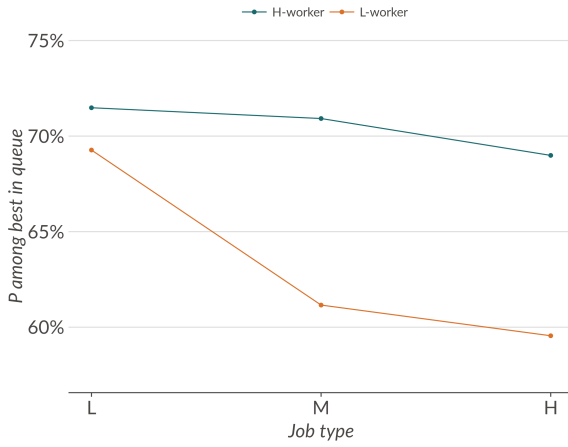
Figure 4: Job Finding Rates, Competition and Directed Search



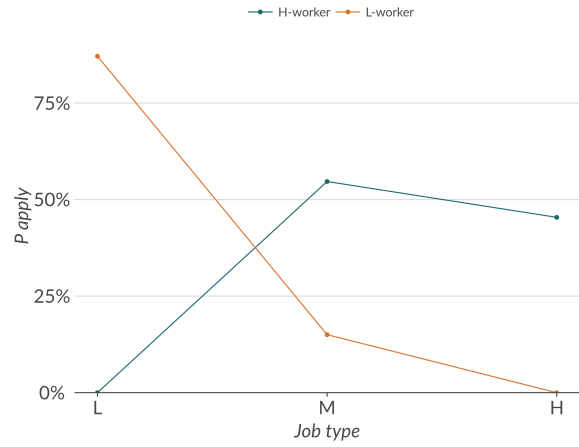
(a) Flow job finding rate of L,H type workers at L,M,H type jobs: $s_y(x, 0)\nu_y(x, 0)$



(b) Surplus: $S(x, \epsilon = 1, y)$



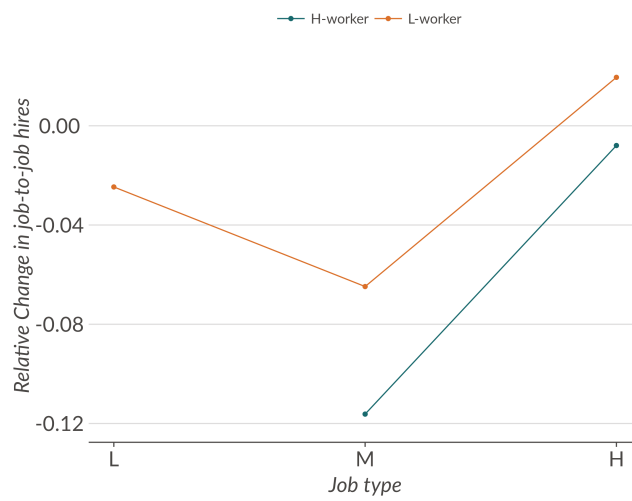
(c) Flow rate of applications at which the worker is the best applicant: $E_\epsilon e^{-\Lambda_y(x, 0)}$



(d) Flow rate at which worker applies for job: $s_y(x, 0)$

jobs. In appendix D I show evidence of similar changes in job-to-job hires in the data. This indicates, that the displacement of mid-skill jobs is a potential driver of the decline in job-to-job mobility.

Figure 5: Change in job-to-job hires in response to 7% decline in ω_M .



4 Estimation

4.1 Setup

The goal of the estimation is to identify the structural parameters governing production and matching in the economy. The model parameters are estimated by Indirect Inference following Gourieroux, Monfort, and Renault (1993). I pick a set of moments m to identify the model parameters θ . The estimation procedure minimizes the weighted square distance between model $m(\theta)$ and data moments \bar{m} by choosing parameters⁸.

$$\min_{\theta} (\bar{m} - m(\theta))' \Omega (\bar{m} - m(\theta)) \quad (15)$$

where Ω is a weighting matrix. The estimation is done separately for the period 1995-1997 and 2015-2017, while treating each allocation as stationary. Discounting is large and the half-life of distributions is short, because labor market flow rates are large. Thus, treating allocations as approximately stationary does not result in large errors. In practice the model parameters are estimated following the approach in Chernozhukov and Hong (2003). The simulation of model parameters by a Markov Chain Monte Carlo (MCMC) method is done using the Differential Evolution Markov Chain (DEMC) approached developed in ter Braak and Vrugt (2008). The DEMC allows to efficiently simulate from highly correlated parameter distributions and achieve fast convergence.

Moments and Identification To estimate the model parameters I mainly use moments on labor market flows. The reason for not using wage moments is that the theory does not specify a unique wage contract. As wage contracts are not unique the model is consistent with a wide range of observed wage moments and therefore additional assumptions would be needed to use information from wages.

To be estimated are the production function $f(x, y)$, the entry cost $k(y)$, the distribution of match-specific productivity shocks $F(\epsilon)$, the arrival rate of productivity shocks θ and the search cost parameters η and ϕ_1 . The production function is parameterized as

$$\log(f(x, y)) = \alpha_y + \beta_x + \gamma xy \quad (16)$$

The worker type x and job type y are specified as uniform spaced points in $(1, 2)$. The parameters α_y , β_x and γ are to be estimated. The comparative advantage of workers in different types of jobs is governed by γ , which can be identified from flows of workers by type x to jobs y . I use the flow rate of unemployed workers by education level to jobs by occupation group to identify γ . The parameter β_x governs the relative productivity of workers x and thus can be identified by their relative job finding rates. The occupation level productivity shifter α_y affects the level of employment by job type and can

⁸The model equilibrium is solved for by using the “PATH” solver (Ferris and Munson, 1999). Furthermore, the model implied stationary distribution is used for calculating model moments

be identified by the job finding rate by job type y . The entry cost $k(y)$ affects the surplus value of jobs. Thus, as the surplus value of jobs implies a ranking of jobs in terms of continuation value, the observed job-to-job mobility between job types y identifies $k(y)$. I use the job-to-job hires at a particular job type to identify the entry cost parameters. A similar strategy to rank jobs has been implemented by Bagger and Lentz (2014), who uses the share of hires from other employers out of all hires. The match specific productivity distribution is parameterized as a two point distribution with equal weight on both points. To be estimated is the distance between the two points $\Delta\epsilon$. We identify the match-specific productivity dispersion by matching the share of job-to-job moves that result in a move down the job ladder in terms of y . The arrival rate of shocks to match-specific productivity θ is identified from job-to-job mobility at high tenures. The search cost parameters η and ϕ_1 are disciplined by job-to-job mobility relative to job finding rates out of unemployment.

Table 2: Targeted Moments

(a) Unemployment-Employment Transition Rate

Education	Occupation	Model 96	Data 96	Model 16	Data 16	Δ Model	Δ Data
High School	non-routine manual	6.5	6.7	8.1	7.9	1.6	1.2
	routine	21.6	20.8	17.3	16.5	-4.3	-4.3
	non-routine cognitive	0.0	1.5	0.0	1.7	0.0	0.1
Some College	non-routine manual	4.4	5.5	7.6	7.3	3.2	1.9
	routine	23.1	21.7	18.7	17.2	-4.4	-4.5
	non-routine cognitive	6.0	7.3	4.6	6.1	-1.4	-1.3
College	non-routine manual	0.0	2.9	1.6	3.7	1.6	0.8
	routine	14.5	14.5	10.6	10.0	-3.9	-4.6
	non-routine cognitive	21.4	19.4	21.7	20.6	0.3	1.2

(b) Job-to-Job Hires by Occupation

	Model 96	Data 96	Model 16	Data 16	Δ Model	Δ Data
non-routine manual	0.13	0.32	0.15	0.38	0.02	0.06
routine	1.11	1.36	0.53	0.84	-0.57	-0.52
non-routine cognitive	1.07	0.78	1.17	0.82	0.1	0.04

(c) Job-to-Job Moves down Ladder and Decline by Tenure

	Model 96	Data 96	Model 16	Data 16	Δ Model	Δ Data
$\frac{j^2 j_{n' < n}}{j^2 j}$	13.47	12.23	9.64	12.19	-3.84	-0.04
$\frac{j^2 j_{t \in (2,4)}}{j^2 j_{t \in (0,2)}}$	15.35	17.55	16.23	18.65	0.88	1.09

Notes: Own Calculations using CPS Basic Monthly Files and Tenure Supplements.

The home production value $b(x)$ is set following Hall and Milgrom (2008) and Shimer (2005b) who set the home production value proportional to the average wage. I set $b(x) = 0.7E_y f(x, y)$, where $E_y p_y f(x, y)$ is the average revenue productivity of employed workers of type x . A similar strategy for setting the value of home production was used in Lise and Robin (2017). The elasticity of substitution σ of occupation level output is set to 3, a value within the range of empirical studies. Table 3 summarizes the parameters that are set based on external targets.

Table 3: External Targets

	Parameter	Value	Source
Home Production	b	70% avg productivity	Shimer (2005b) Hall and Milgrom (2008)
Posting Cost	k	see Table 4 b)	Vacancy Index by Barnichon (2010)
EOS Occupations	σ	3	$\sigma \in [0.3, 10]$ Eden and Gaggl (2018)

Parameter Estimates

The estimated parameters are summarized in table 4a, 4b and 4c. The production function estimates are summarized in 4a for both 1996 and 2016. The productivity shifter α_y across occupations shows the expected ordering, increasing from non-routine manual up to non-routine cognitive occupations. The change over time of the productivity shifter α_y is also in line with expectations, it decreases for routine occupations, while productivity in non-routine occupations increases, but to a much lesser extent. Furthermore, I estimate a (small) positive γ , which means that the output is weakly log-supermodular in workers skill x and job type y . The estimated value of γ hardly changes between the periods. The productivity advantage of college education β_{SC} and β_C stays roughly constant over time, that is the productivity advantage of higher education that is independent of job type.

Table 4b shows the estimated posting cost parameter k_y and the search cost parameters of workers ϕ_1 and η . The posting cost parameters decrease somewhat and most for routine occupations. For both periods the entry cost parameters are increasing in job type, lowest for non-routine manual jobs and highest for non-routine cognitive jobs. This is consistent with a common job ladder for all worker types and highlights the importance of entry costs for sorting alongside productivity differences across workers. The search cost parameters ϕ_1 is estimated to be slightly negative, meaning on-the-job search is more efficient than unemployed search. However the difference is small and not statistically significant in both periods. The curvature η rises from 4.8 to 5, but is estimated with substantial noise and therefore the difference is not statistically significant.

Table 4c shows the estimated productivity dispersion $\Delta\epsilon$ of the match specific productivity shocks and their arrival rate θ . The estimated productivity dispersion between good and bad matches is es-

Table 4: Parameter Estimates

(a) Production Function

	α_{NRM}	α_R	α_{NRC}	β_{SC}	β_C	γ
1996	-1.8 (0.033)	0.44 (0.048)	0.36 (0.058)	0.17 (0.0077)	0.29 (0.011)	0.014 (0.0011)
2016	-1.6 (0.017)	-0.34 (0.014)	0.39 (0.015)	0.15 (0.0072)	0.33 (0.0057)	0.016 (0.00052)

(b) Posting and Search Cost

$c^e(s) = \phi_1 \frac{s^\eta}{\eta}$

	$\log(k_{NRM})$	$\log(k_R)$	$\log(k_{NRC})$	$\log(\phi_1)$	η
1996	-0.13 (0.039)	0.046 (0.04)	0.34 (0.042)	-0.023 (0.085)	4.8 (0.23)
2016	-0.22 (0.014)	-0.18 (0.014)	0.27 (0.019)	-0.11 (0.041)	5.0 (0.16)

(c) Productivity Dispersion $\Delta\epsilon$ and arrival rate of shocks λ

	$\log(\Delta\epsilon)$	$\log(\theta)$
1996	-1.1 (0.034)	-2.3 (0.042)
2016	-1.3 (0.0047)	-2.8 (0.02)

estimated to be approximately 33% for 1996 and 27% for 2016, indicating a decline in match specific productivity dispersion. The arrival rate of shocks declines from 0.1, on average match specific productivity is redrawn every 10 months, down to 0.06. Those results indicate that match productivity, unrelated to the worker and job characteristics, is becoming less dispersed over time and more persistent.

5 Results

Mobility Decomposition

To evaluate the importance of technological change, particularly routine-biased technological change, for the decline in labor market mobility I use the estimated model to perform a decomposition of the decline in job-to-job mobility. The model based decomposition allows me to take into account the rich equilibrium interactions between workers and jobs.

While the main focus is the relative decline in productivity in routine occupations, it is important to also take into account the changes in the supply of college educated labor as the demand for and supply of skills jointly determine mobility rates. The supply of skills has an important effect on mobility, because the rising share of college graduates rises implies that lower skilled workers are more likely to

compete with higher skilled workers for jobs and thus their opportunities to move up to better jobs are potentially diminished.

Table 5: Decomposition: Job-to-Job Transition Rates

	Δ Data in %	Δ Model in %	$\Delta \alpha$	$\Delta \alpha \& k$	$\Delta \alpha \& k \& G(x)$
j2j	-18.9	-19.6	-7.8	-6.0	-4.7

Table 5 summarizes the results regarding the average job-to-job transition rate in the economy. The first two column show the change in the job-to-job transition rate in the data and model. The model can capture the decline in mobility well. The third column $\Delta \alpha$ shows the change in the job-to-job transition rate when only the productivity level across occupations would change. By itself, the change in productivity can account for roughly 40% of the decline in job-to-job transitions. Taking together the change in productivity and the relative change in entry costs, in column $\Delta \alpha \& k$, we can account for 30% of the overall decline in job-to-job transitions. The decline in entry costs for all job types leads to less transitions between employers, as differences in value across jobs decline moves are less frequent. The increasing share of college graduates actually mitigates the decline in aggregate job-to-job transitions. While these results are indicative that both technology and shifts in skill supply are important for determining worker mobility, it is illustrative to perform the same decomposition conditional on the education level of workers.

Table 6: Decomposition: Job-to-Job Transition Rates by Education Level

	Δ Data in %	Δ Model in %	$\Delta \alpha$	$\Delta \alpha \& k$	$\Delta \alpha \& k \& G(x)$
High School	-22.0	-14.0	4.6	2.7	1.9
Some College	-17.3	-17.8	-13.8	-11.1	-2.7
College	-17.4	-25.4	-11.8	-10.7	-9.5

In table 6 I show the results of the decomposition in the decline in job-to-job mobility conditional on the education level of workers. The results show that changes in technology and skill supply have heterogeneous effects across the skill distribution. First, the shift in productivity lowers job-to-job transition rates particularly for mid and high skill workers. However, lower skill workers are actually moving more frequently between jobs. As competition for routine jobs intensifies due to technological change, they are more likely to start employment in non-routine manual jobs right out of unemployment. Therefore, they are more frequently trying to move to better paying jobs, albeit higher competition. Second, the shift in entry costs mitigates the decline in mobility for mid and high skill workers. For lower skill workers it actually leads to less mobility. An increase in the supply of college graduates increases the mobility of workers, particularly for those with some college education. When the share of college graduates rises, they diminish the opportunities for lower skilled workers they compete with. Thus, the competition between workers trickles down from top to bottom. However, there are countervailing forces on job-to-job mobility. Workers sort down right out of unemployment, thus starting out further

down the ladder and therefore switch jobs more often once employed. However, the competition by higher skilled workers also makes it harder to move to a different job. In this instance, for workers with some college education the net effect on job-to-job mobility is positive, that is the impact of sorting down out of unemployment leads to more job-to-job transitions despite more competition. There is an additional effect of the rising college share, it leads actually to more entry, as the average worker is becoming more skilled the return to posting a vacancy rises and therefore more jobs are posted. With more vacancies posted it becomes easier for all workers to find a job.

Overall, the demand shifts captured by α can account for over half the decline in job-to-job mobility by workers with some college education and almost half of the decline for college educated workers. However, it can not account for the decline in mobility by workers with at most a High School degree.

6 Conclusion

A growing literature documents job polarization and declining worker mobility. My analysis suggests that these two phenomena are linked. To study the phenomena, I propose a theoretical framework of the labor market with two sided heterogeneity, search frictions and on-the-job search where the demand for occupations is endogenous. I apply this framework to study the recent decline in job-to-job mobility and find that routine-biased technological change not only gives rise to job polarization, but also shortens the job ladders of workers. With shorter job ladders, workers move less often between jobs and therefore mobility declines. The shifts in demand for labor across jobs can account for 40% of the total decline in job-to-job mobility, where workers without a college degree are affected the most. The results indicate, that to understand recent trends in the labor market it is important to consider underlying changes in demand for and supply of skills. Those shifts matter above and beyond composition, it is their equilibrium interactions that are important to understand the observed trends.

The framework presented in the paper has many possible applications as it provides an appealing way to take into account the role of two-sided heterogeneity and sorting for labor market outcomes. For example, studying sorting based on unobserved heterogeneity using matched employer-employee datasets is a fruitful application of the framework. Card, Heining, and Kline (2013) indicated that sorting based on unobserved heterogeneity may have contributed to rising wage inequality in Germany. However, interpretations of the common two-way fixed effects approach pioneered by Abowd, Kramarz, and Margolis (1999) in terms of sorting are difficult. The model presented here is a useful tool to interpret the findings from reduced form wage regressions. A first step in that direction was taken by Abowd, Kramarz, Pérez-Duarte, and Schmutte (2014) who apply the static assignment model of Shimer (2005a) directly to US administrative data. However, it is important to take into account entry of jobs and individual labor market dynamics to account for sorting.

Another line of future research would extend the framework to study business cycle dynamics in sorting, employment and wages. This would enrich our understanding of how different types of workers

are affected by aggregate transitory fluctuations and what mechanisms they use to insure against income risk.

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A Derivations

A.1 Value Functions

Surplus. Define the value of unemployment and a vacant job

$$rU(x) = \max_s b(x) + sW(s, 0) - c(s) \quad (17)$$

$$rV(y) = -k(y) + \sum_{x,o} \int \mu_y(x, S_o, \epsilon) J(x, S_o, \epsilon, y) d\epsilon \quad (18)$$

A contract specifies a sequence of payments w depending on the worker type x , job type y , match specific productivity ϵ and the outside option of the worker S_o when the worker was hired. Additionally the contract specifies a transfer $P(x, S_o, \epsilon, y)$ between worker and job in case the worker makes a job-to-job move.

$$\begin{aligned} rE(x, S_o, \epsilon, y) &= \max_s w(x, S_o, \epsilon, y) + \lambda_y \int \Delta E(x, S_o, \epsilon', y) dF_y(\epsilon') - \delta(E - U) \dots \\ &\quad + sW(x, E + P - U) - c(s) \\ W_{y'}(x, S_o) &= \int \nu_y(x, S_o, \epsilon) [E(x, S_o, \epsilon', y') - S_o - U] d\epsilon' \\ W(x, S_o) &= \max_{y'} W_{y'}(x, S_o) \\ s &= \sum_{y'} s_{y'} \\ rJ(x, S_o, \epsilon, y) &= p_y \epsilon f(x, y) - w(x, S_o, \epsilon, y) + \lambda_y \int \Delta E(x, S_o, \epsilon', y) dF_y(\epsilon') - \delta(J - V) \dots \\ &\quad - \sum_y^I s_{y'} \nu_{y'}(x, E - P - U, \epsilon) [\min\{E' - E, J\} + P(x, S_o, \epsilon', y)]. \end{aligned}$$

I assume that contracts are complete and can be enforced. Therefore, the contract will maximize the total value of the match, as any contract that does not is Pareto dominated.

Now, I specify which penalty schedule $P(x, S_o, \epsilon, y)$ maximizes total match value. To that end separate the set of alternative jobs $\{y', \epsilon'\}$ into two non-overlapping sets: (1) jobs whose total value is lower than that of the current match, (2) jobs whose total value is at least as large as that of the current match. For jobs in the first set, any application presents a net loss in terms of total private value, because the maximum possible amount of contract value offered to the worker can not compensate for the loss of value for the job owner. For jobs in the second set, applications are valuable because the worker will be able to compensate the job owner for his losses. Specify the penalty for a job-to-job move as $P(x, S_o, \epsilon, y) = [\min\{E(x, S_o, \epsilon', y') - E(x, S_o, \epsilon, y), J(x, S_o, \epsilon, y)\}]$. It follows that applications to jobs which offer $E' \leq E + J$ offer no value to the worker. Therefore, she will only apply to jobs

which offer $E' > E + J$. Note that in equilibrium the value of a vacancy is $V(y) = 0$. It follows, that

$$\begin{aligned}
rJ(x, S_o, \epsilon, y) &= p_y \epsilon f(x, y) - w(x, S_o, \epsilon, y) + \lambda_y \int \Delta E(x, S_o, \epsilon', y) dF_y(\epsilon') - \delta(J - V) \\
r[E(x, S_o, \epsilon, y) + J(x, S_o, \epsilon, y)] &= p_y \epsilon f(x, y) + \lambda_y \int \Delta[E(x, S_o, \epsilon', y) + J(x, S_o, \epsilon', y)] dF_y(\epsilon') - \delta(E + J - U - V) \dots \\
&\quad - c(s^*) + s^* W(x, J + E - U) \\
S(x, \epsilon, y) &= E(x, S_o, \epsilon, y) + J(x, S_o, \epsilon, y) - U(x) \\
rS(x, \epsilon, y) &= p_y \epsilon f(x, y) + \lambda_y \int \Delta S(x, \epsilon', y) dF_y(\epsilon') \dots \\
&\quad + \max_s s W(x, S) - c(s) \dots \\
&\quad - \delta S(x, \epsilon, y) \dots \\
&\quad - b(x) - s^U W(x, 0) + c(s^U)
\end{aligned}$$

Surplus is independent of the current surplus split, because the gain from on-the-job search to the worker is only whatever the new job offers above and beyond the total match value of the current match. This is achieved by setting the penalty for a job-to-job move equal to the loss for the job owner. This contract maximizes surplus value, because the worker already maximizes his private value and the jobs valuation of the match is independent of on-the-job search as the job is compensated for any loss.

Contract Posting. Each vacant job posts contract values $E(x, S_o, \epsilon, y)$. The flow value of a vacancy follows

$$rV(y) = -k(y) + \sum_{x,o} \int \mu_y(x, S_o, \epsilon) J(x, S_o, \epsilon, y) d\epsilon$$

Replacing $J = S - (E - U)$ and using the workers indifference condition

$$W(x, S_o) = \max_{y'} \nu_y(x, S_o, \epsilon') [E(x, S_o, \epsilon', y') - S_o - U] d\epsilon',$$

we can replace also $E - U$ and write the value of a vacancy as

$$rV(y) = -k(y) + \sum_{x,o} \int \mu_y(x, S_o, \epsilon) S(x, \epsilon, y) d\epsilon - \sum_{x,o} \lambda_y(x, S_o) W(x, S_o).$$

I used $\mu_y = \lambda_y \nu_y$ to simplify the equation.

A.2 Proposition 1

Proof. To proof proposition 1, one needs to verify no sorting occurs if $f(x, y)$ is log-modular and entry costs are independent of job type $k(y) = k \geq 0$. For simplicity we also assume θ and match-specific productivity distribution $F(\epsilon)$ are independent of job type.

Guess that surplus is independent of job-type, that is $S(x, \epsilon, y) = S(x, \epsilon, y') \forall y, y' = 1, \dots, Y$. Optimal contract posting (4) and worker indifference (2) then imply that the same contract values are posted for all jobs y and that all jobs have the same job finding rate per unit of search effort.

The free entry condition is

$$k = \sum_{x, S_o} \int \mu_y(x, S_o, \epsilon) \hat{S}(x, S_o, \epsilon, y) - \lambda_y(x, S_o) W(x, S_o)$$

As surplus is the same across jobs, it follows that also the job filling rate (and queue length λ) are independent of job type.

As $f(x, y)$ is log-modular we can write it as $f(x, y) = f_1(x)f_2(y)$.

We need to show that $e(x, y, \epsilon) = e_1(x)e_2(y, \epsilon)$. Denote the number of matches created of a type $m(x, S_o, y)$ and following the definition of μ it holds that

$$m(x, S_o, y) = \mu_y(x, S_o)v_y.$$

Thus the ratio of matches created across jobs

$$\frac{m(x, S_o, y)}{m(x, S_o, y')} = \frac{v_y}{v_{y'}},$$

is the same as the ratio of vacancies, because job filling rates are the same. Thus the distribution of inflow into employment is independent of worker type. There is no sorting in hiring. Then sorting could still occur if for example low skill workers are more likely to separate from high skill jobs than high skill jobs or vice versa. However, as $S(x, y, \epsilon) = S(x, y', \epsilon)$ it directly follows that separation rates are independent of job type. That is workers of different types might separate at different rates from jobs, but they do so independent of a jobs type. Thus, employment rates differ across jobs and workers, but they are independent of each other in the sense that $e(x, y) = e_1(x)e_2(y)$. Output in each occupation follows

$$Q_y = e_2(y)f_2(y) \sum_x \int e_1(x, \epsilon)f_1(x) d\epsilon.$$

Thus, the relative price of output across job types follows

$$\frac{p_y}{p_{y'}} = \left(\frac{e_2(y)f_2(y)\omega_{y'}}{e_2(y')f_2(y')\omega_y} \right)^{-\frac{1}{\sigma}}, \quad (19)$$

which holds because v_y adjusts. Search effort satisfies the definition of λ_y and market clearing $\sum_y \lambda_y(x, S_o)v_y = s(x, S_o)h(x, S_o)$. Thus all equilibrium conditions are satisfied and no sorting occurs. \square

B Examples: Parameters

C Computation

In order to solve the system of equations that defines a stationary equilibrium I use the PATH Solver (Ferris and Munson, 1999). The distribution is solved for at any given guess of parameters. The stationary distribution is a solution (a zero) to the linear system (10) with the constraint that the supply of workers is exhausted.

C.1 Standard Errors

$$\hat{\theta} = \arg \min_{\theta} \sum_i \omega_i \left(\frac{\bar{m}_i - m_i(\theta)}{\bar{m}_i} \right)^2 \quad (20)$$

then variance covariance matrix of the estimates \hat{V} is

$$\hat{V} = (\hat{M}'\Omega\hat{M})^{-1}\hat{M}'\Omega\hat{\Sigma}\Omega\hat{M}(\hat{M}'\Omega\hat{M})^{-1} \quad (21)$$

where $\hat{\Sigma}$ is the variance covariance matrix of the moments m_i . \hat{M} is the jacobian of the moments with respect to the parameters. And Ω is the weight matrix, here $\Omega = \text{diag}(\frac{\omega_i}{\bar{m}_i})$

D Additional Descriptive Statistics

In this section I provide some additional labor market statistics related to the main evidence in the paper.

Occupation and Education Composition and Job-to-Job Transitions. I perform a shift-share analysis to show that the decline in job-to-job mobility is not simply driven by a reallocation of employment to jobs with lower mobility rates. Consider the following decomposition of the job-to-job transition rate

$$j2j_t = \sum_{x,y} j2j_{t,x,y} \pi_{t,x,y},$$

where $\pi_{t,x,y}$ denotes the share of type x workers in jobs y in period t . I perform a simple descriptive decomposition, that is I hold the conditional job-to-job mobility rates constant and only let the employment shares vary over time. The share of variation that is explained solely by the shift in employment shares I will attribute to a pure composition shift.

Table 7 shows the aggregate job-to-job mobility in the CPS sample, as described in section 2, for 1996 and 2016. Then the second row of the table compares this, with the job-to-job mobility rate that would have been observed if job-to-job mobility conditional on education and occupation would have

Table 7: Job-to-job Mobility actual vs only composition shift in education and occupations

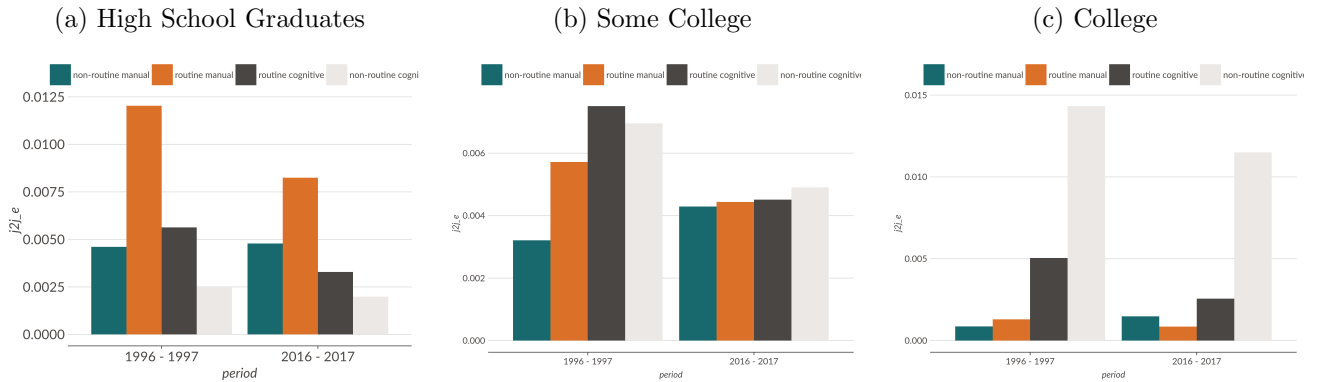
j2j	1996	2016	rel. change
Actual	2.46	2.01	-18.3
Education and Occupation Share	2.46	2.42	-1.6

remained constant. The changes in composition can hardly explain any part of the decline, the actual decline is -18.3% while pure composition explains only -1.3% .

Job Ladders. Here I want to illustrate that (1) workers of different education levels move to the different types of jobs at different rates and (2) that job ladders hollowed out in the middle.

In Panel 6a the job-to-job transition rate of High School Graduates split up by the occupation group of the destination occupation is shown. The most likely destination occupation for high-school graduates are routine manual jobs, followed by routine cognitive jobs. From 1996-2016 there has been a substantial drop in such moves to routine jobs. This is consistent with the main hypothesis of the paper. Panel 6b shows a similar picture for workers with Some College education. Routine Jobs are still frequently the destination, but moves to non-routine cognitive jobs are also frequent in contrast to lower educated workers. The decline in job-to-job moves for workers with some college education was concentrated in routine jobs, but also there are fewer moves to high-skill non-routine cognitive jobs. At the same time moves to lower skill jobs actually increased. This is consistent with (a) the decline in routine employment and (b) more competition by college graduates. Finally, for College graduates job-to-job moves are mostly to non-routine cognitive jobs. While job-to-job moves to routine jobs also decline, these make up only a small share. The decline in job-to-job moves to high skill jobs are potentially driven by changes in sorting directly out of unemployment and changes in competition. Both mechanisms are captured in the theoretic framework.

Figure 6: Job-to-Job Moves by destination Occupation



In table 8 the change in job-to-job moves originating in the row occupation group and moving to the column occupation group are shown. Note that job-to-job transitions to routine jobs have declined

substantially from all occupations. The decline in job-to-job hires to routine jobs make up 67% of the decline in job-to-job moves originating from non-routine manual jobs. Indicating a strong decline in moves up the job ladder. For job-to-job transitions originating in routine jobs, basically the whole decline in job-to-job moves is concentrated in moves to routine jobs. For job-to-job transitions from non-routine cognitive jobs there is a decline in the moves towards routine jobs, indicating that workers in high skill jobs might take those routine jobs as insurance to not be unemployed and over time this option is diminished. Overall the evidence points towards that the declining demand for routine jobs is closely related to the decline in job-to-job mobility.

Table 8: Change in Monthly Job-to-Job Transition Rate from row to column occupation group. Data Source: CPS Basic Monthly Files. Own Calculations.

(a) Change 1996-2016

	NRM	RM	RC	NRC	total
NRM	-0.15	-0.18	-0.07	0.03	-0.37
RM	0.02	-0.47	-0.01	-0.04	-0.49
RC	0.06	-0.0	-0.49	-0.05	-0.48
NRC	0.0	-0.07	-0.16	-0.05	-0.27

Table 9 shows the job-to-job transition rate between and within occupation groups, from row to column.

Table 9: Monthly Job-to-Job Transition Rate from row to column occupation group. Data Source: CPS Basic Monthly Files. Own Calculations.

(a) 1995-1997

	NRM	RM	RC	NRC	total
NRM	1.7	0.47	0.38	0.31	2.86
RM	0.2	2.09	0.21	0.21	2.72
RC	0.16	0.25	1.53	0.5	2.45
NRC	0.09	0.15	0.32	1.39	1.95

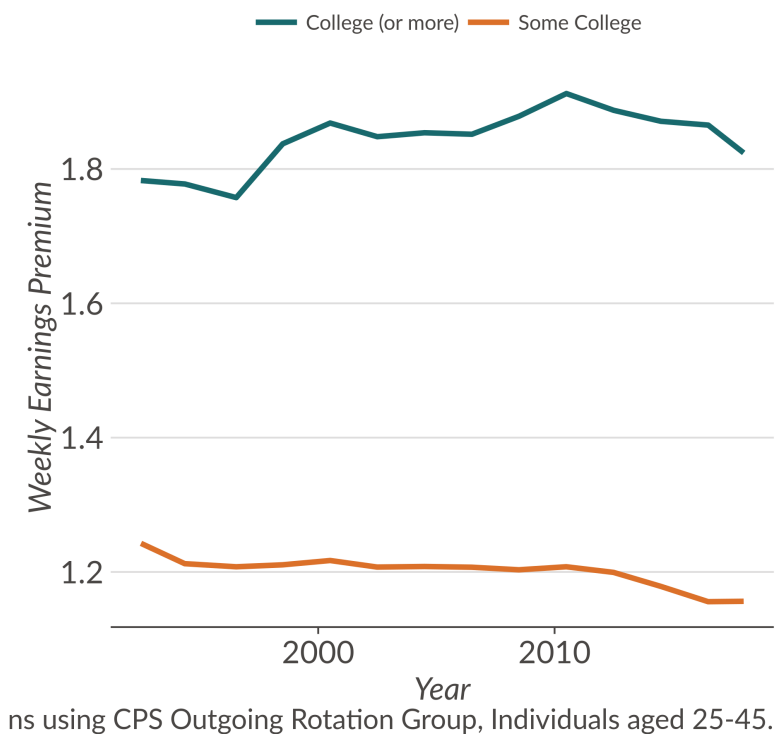
(b) 2015-2017

	NRM	RM	RC	NRC	total
NRM	1.55	0.29	0.31	0.34	2.48
RM	0.22	1.63	0.21	0.17	2.23
RC	0.23	0.25	1.04	0.45	1.97
NRC	0.09	0.08	0.16	1.35	1.68

Wage Premia The average wage premium relative to “High School Graduates”, where wages are measured as weekly earnings, in the Outgoing Rotation Group of the CPS, is shown in figure 8. The “College” Premium is relatively stable over the last 20 years, while it increases slightly for workers with a full year degree or more education, it decreases somewhat for workers who went to college but did not finish a 4 year degree. Figure 7 shows the wage premium of the occupation groups defined in

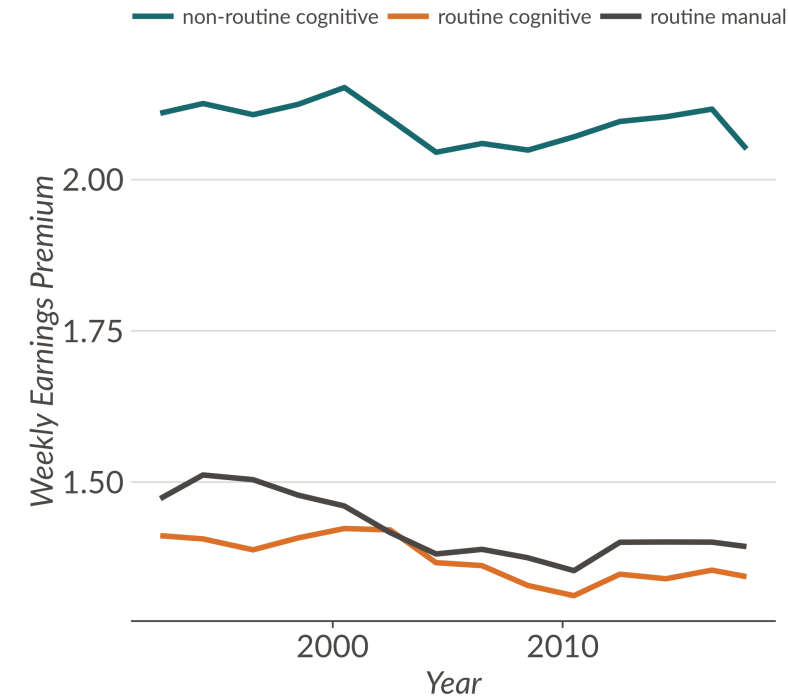
section 2 relative to the average pay in “non-routine manual” occupations. The pay premium of routine occupations decreased from roughly 50% to 40%, while that of non-routine cognitive occupations stayed roughly constant at about 110%.

Figure 7: Wage Premium of Education



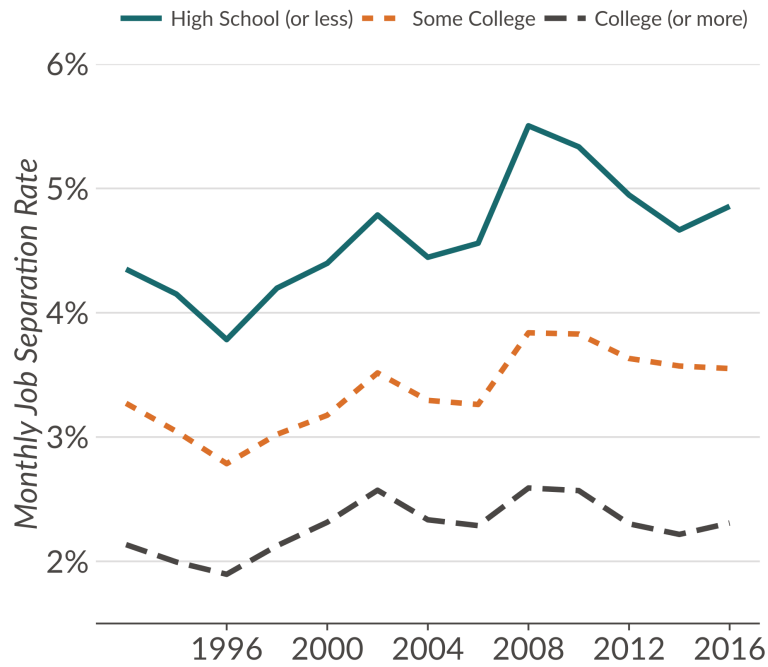
Employment outflows. Figure 9 shows the separation rates out of employment to non-employment conditional on the education level of workers. The separation rates increased somewhat, particularly for lower skilled workers. This is in contrast with findings in Fujita (2015) and Cairo (2013), however their analysis focuses on a different time period and different definitions of separation rates, job destruction and separations to unemployment respectively, while also focusing on average rates in the economy.

Figure 8: Wage Premium - Occupation Groups



ns using CPS Outgoing Rotation Group, Individuals aged 25-45.

Figure 9: Job Separation Rates



n Calculations using CPS Monthly Data, Individuals aged 25-45.