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Conference Paper

Job Mobility and Sorting: Theory and Evidence

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2015: Ökonomische Entwicklung - Theorie und Politik - Session: Labor - Search, No. E18-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Stijepic, Damir (2015) : Job Mobility and Sorting: Theory and Evidence, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2015: Ökonomische Entwicklung - Theorie und Politik - Session: Labor - Search, No. E18-V3, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft

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Job Mobility and Sorting: Theory and Evidence[☆]

May 2015

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Abstract

I derive a measure of job mobility that reflects the individual's ability to sort into the preferred jobs. In particular, the measure accounts for the negative effect of separations into unemployment on sorting. Relying on the *Survey of Income and Program Participation*, I find that educational attainment tends to have a strong positive effect on internal (i.e., within firms) and external (i.e., between firms) job mobility. General experience and occupation-specific human capital have only a limited effect on both internal and external mobility. The impact of being versatile on an individual's external job mobility is substantial and similar in magnitude as the effect of a college degree on a high school dropout's external mobility.

Keywords: gross worker flows, job mobility, employer–employer transitions, occupational mobility, sorting, Survey of Income and Program Participation

JEL: J62, J24, I24, I26

[☆]I thank Guido Friebe, Nicoal Fuchs-Schündeln, Peter Funk, Andrey Launov, Sigrid Röhrs, Thorsten Schank and Klaus Wälde for helpful comments. The paper was previously circulated under the title “Determinants of Job Mobility: Evidence from the Survey of Income and Program Participation.” The usual disclaimer applies.

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1. Introduction

Job-to-job flows are large in the U.S. labor market. 3.2 percent of employed male workers change employers each month and 3.5 percent change occupations at the three-digit level (Moscarini and Thomsson, 2007). In this paper I derive a measure of job mobility that reflects the individual's ability to sort into the preferred jobs. In particular, the measure accounts for the negative effect of separations into unemployment on sorting. I then rely on the *Survey of Income and Program Participation* to identify the determinants of job mobility—with a particular emphasis on educational attainment, versatility, and human capital.

Economists are interested in job mobility for at least two reasons. First, the allocation of resources across economic activities is an important determinant of aggregate productivity. Hsieh and Klenow (2009) analyze the resource allocation across firms in a cross country study. They argue that aggregate productivity could rise by as much as 50 percent in China and 60 percent in India if resources were as efficiently allocated in those countries as in the United States. Lentz and Mortensen (2008) estimate a Schumpeterian growth model using Danish data. They find that more than half of the aggregate growth is accounted for by resource reallocation from less to more productive firms. Second, the literature stresses the importance of job mobility and sorting for understanding wage patterns. Card et al. (2013) fit linear models à la Abowd et al. (1999) with additive person and establishment fixed effects for Western Germany for 1985–2009. They find that two-thirds of the increase in the wage gap between higher- and lower-educated workers are attributable to a widening in the average establishment wage premia received by different education groups. Increasing workplace heterogeneity and rising assortativeness between high-wage workers and high-wage establishments likewise explain over 60 percent of the growth in inequality across occupations and industries. Stijepic (2015b) develops a model of technology diffusion with limited worker mobility across firms. Calibrated to match differences in inter-firm mobility between skill groups and rising productivity dispersion across firms, the model ascribes one-third of the sharp increase in the skill premium in U.S. manufacturing from 1977 to 1997 to skill-neutral technical progress and the technology diffusion process itself.¹ Ransom and Oaxaca (2010) estimate labor supply

¹Stijepic (2015a) integrates frictional labor markets with on-the-job search into an otherwise standard heterogeneous firm model of intra-industry trade. He shows that the returns to workers inter-firm mobility are higher in a trade equilibrium than in autarky. Intuitively, by favoring large and productive firms, international trade amplifies the disparities in profitability between small and

elasticities *at the firm level* in the U.S. retail grocery industry. They find that differences in supply elasticities between women and men explain well the lower relative pay of women.²

In general, the sorting of workers into jobs depends on three factors in the canonical on-the-job search model: (i) the worker's ranking of jobs, (ii) the degree of job mobility, i.e., the worker's ability to reallocate across jobs, and (iii) the directedness of job mobility, i.e., the degree to which the mobility is directed towards the preferred jobs. In an initial methodological contribution I show that an increase in the employed worker's degree of job mobility as measured by the risk ratio of a job-to-job transition to a separations into unemployment induces *ceteris paribus* first order stochastic dominance in the distribution of workers over jobs. In other words, the higher this risk ratio the larger the share of workers employed in the preferred jobs. Intuitively, separations into unemployment represent negative mobility shocks. The more pronounced the shocks, the less likely are individuals to sort into a specific job. Therefore, job-to-job transitions are to be scaled by separations into unemployment in order to obtain an adequate measure of a worker's ability to reallocate across jobs. This risk ratio is the principle measure of job mobility in the subsequent analysis. However, I also report results for employer–employer transitions, occupational changes within firms and separations into unemployment separately.

In a further methodological contribution I show that the risk ratio of a job-to-job transition to a separation into unemployment is independent of workers' ranking of jobs and the directedness of their job mobility. This has two main implications. First, analyzing sorting through mere mobility does not require an explicit specification of the ranking of jobs. This is an appealing property since it is methodologically difficult to recover the ranking of jobs from the data (Eeckhout and Kircher, 2011). Second, the analysis of sorting through the intensity of job mobility is separable from the directedness of the mobility. Motivated by the latter implication, I focus on sorting through mere job mobility in this paper and leave the exploration of the potential importance of the directedness of mobility to further research.

In the empirical analysis I study both external and internal job mobility. The

large firms. Hence, the returns to labor reallocation across firms rise.

²Kambourov and Manovskii (2009a) develop a general equilibrium model with occupation-specific human capital and heterogeneous experience levels within occupations. The model, calibrated to match the rise in occupational mobility, explains over 90 percent of the increase in wage inequality in the United States between the 1970s and the 1990s.

employed worker's risk ratio of an employer–employer transition to a separation into unemployment is referred to as external job mobility. Internal job mobility is measured by the employed worker's risk ratio of an occupational change within the firm to a separation into unemployment. While I account for standard characteristics, that are supposed to affect the individual's job mobility, I also introduce a proxy for versatility in the sense of being able to perform various tasks or activities eventually even across occupations. Specifically, I rely on the number of different courses attended in high school while controlling for course choices. The idea is that, in an environment where jobs differ in task requirements, versatility increases an individual's external job mobility since less transitions are prevented by unmet job requirements. Similarly, if the job requirements change, versatile workers are likely to adapt, whereas less versatile workers are likely to separate into unemployment as a consequence of a mismatch between the tasks required for the job and the tasks the workers are able to perform. See Stijepic (2015b,c) for an explicit microfoundation.

I find that differences in external job mobility across intermediate education categories are reasonably well accounted for by an extensive set of controls. However, the strong negative effect of not graduating from high school and the strong positive effect of an education exceeding a bachelor's degree remain mostly unexplained. The positive relationship between education and internal mobility persists even after controlling for an extensive set of covariates. General experience and occupation-specific human capital have only a limited impact on both internal and external job mobility. The relationship between versatility and internal job mobility is positive, however, not statistically significant. The impact of being versatile on a individual's external job mobility is substantial and similar in magnitude as the effect of a college degree on a high school dropout's external job mobility. Specifically, above-median versatile individuals are 1.52 times likelier to switch employers than to separate into unemployment relative to individuals with below-median versatility.

This paper contributes to the literature on job mobility and sorting. Bagger and Lentz (2014) stress the role of the intensity of the search for better jobs in explaining the sorting of workers into firms. They emphasize, in particular, differences in search intensities between skill groups. I complement the study by additionally highlighting differences in the separation rates into unemployment between skill groups and the impact of those differences on sorting patterns. My finding that versatility is an important determinant of job mobility supports theoretical models that feature multidimensional skills (Charlot et al., 2005; Lise and Postel-Vinay, 2014). Furthermore, my empirical study is in line with theoretical models that

stress the impact of versatility on both the job-finding rate and the separation rate into unemployment (Stijepic, 2015b,c).

The paper is structured as follows. Section 2 provides the theoretical background for the empirical analysis. I describe the data set and the variables in Section 3. Empirical statistics on labor market transitions are in Section 4. Section 5 presents the paper's main empirical findings on job mobility. Section 6 draws some conclusions.

2. Measuring Job Mobility

To motivate the subsequent empirical analysis theoretically, I rely on an on-the-job search framework à la Burdett and Mortensen (1998).

2.1. Assumptions

Let the mass of workers be normalized to unity. Both unemployed *and* employed workers find jobs according to a Poisson process at rate λ . There is a continuum of jobs in the economy. Furthermore, there exists a ranking of jobs that reflects workers' preferences over these jobs.³ Specifically, let $p \in [0, 1]$ denote workers' rank of a given job. Workers' ranking of jobs may be based on differences in pay across jobs, but may also account for other job characteristics, e.g., working conditions. I also assume that jobs are sufficiently heterogeneous so that jobs between which workers are indifferent may not have a non-zero mass.

Job offers are randomly drawn from a sampling distribution denoted by $F(\cdot)$, i.e., $F(p)$ is the share of offers associated with jobs ranked p or lower. The sampling distribution $F(\cdot)$ reflects the directedness of workers' search and need not to coincide with the actual distribution of jobs. In particular, workers may find it optimal to oversample the most preferred jobs. For instance, consider two sampling distributions $F(\cdot)$ and $\tilde{F}(\cdot)$. Let $F(\cdot)$ first order stochastically dominate $\tilde{F}(\cdot)$, i.e., $F(p) \leq \tilde{F}(p)$ for all admissible job ranks and with strict inequality for some job ranks. Hence, offers are associated with higher job ranks under the sampling distribution $F(\cdot)$ than under the sampling distribution $\tilde{F}(\cdot)$ in expectations. In other words, workers' search is more directed towards the most preferred jobs under the sampling distribution $F(\cdot)$ than under the sampling distribution $\tilde{F}(\cdot)$.

I assume the sampling distribution $F(\cdot)$ to be continuously differentiable. This assumption excludes, in particular, cases in which workers dedicate a non-zero

³Strictly speaking, I assume that there exists a preference relation over jobs that is complete and satisfies transitivity.

mass of sample draws to jobs of a specific rank. In other words, workers' search for jobs is sufficiently diversified. Finally, once a worker accepts a job, the match is at risk of being dissolved at rate δ .

2.2. Sorting

The workers' optimal behavior is as follows. When information about a new job opportunity arises, workers quit their current job and move to the new job provided that the new job's rank exceeds that of the current job. Without loss of generality, I assume that unemployed workers are at least indifferent between unemployment and the least preferred job in the economy. Therefore, unemployed workers accept all job offers.

Let u denote the steady state unemployment rate, and $G(p)$ the steady state proportion of workers employed in jobs of rank p or lower. I refer to $G(\cdot)$ as the workers' cross sectional job distribution. Finally, let $\kappa \equiv \lambda/\delta$ denote the ratio of the job finding rate to the separation rate into unemployment. Proposition 1 establishes a link between the cross sectional job distribution, $G(\cdot)$, and the ratio of the job finding rate to the separation rate into unemployment, κ .

Proposition 1 (Sorting). *For $\kappa > \tilde{\kappa} > 0$, let $G(\cdot)$ and $\tilde{G}(\cdot)$ denote the corresponding cross sectional job distributions, respectively. For a given sampling distribution, $F(\cdot)$, it follows that $G(\cdot)$ first order stochastically dominates $\tilde{G}(\cdot)$. That is:*

- i) $G(p) \leq \tilde{G}(p)$ for all $p \in [0, 1]$
- ii) $G(p) < \tilde{G}(p)$ for some $p \in [0, 1]$

PROOF. In a steady state equilibrium, the flow of workers into employment, λu , equals the flow into unemployment, $\delta(1-u)$. Therefore, the steady state unemployment rate is given by $u = \delta/(\delta + \lambda)$. Furthermore, the flow of unemployed workers into jobs with a rank no greater than p , $\lambda F(p)u$, equals the flow into unemployment, $\delta G(p)(1-u)$, and into higher ranked jobs, $\lambda(1-F(p))G(p)(1-u)$. Therefore, the steady state cross sectional job distribution is $G(p) = F(p)/(1 + \kappa(1 - F(p)))$. It follows immediately that a higher κ induces first order stochastic dominance. \square

Workers sort into the most preferred jobs by moving from lower ranked to higher ranked jobs. Job separation shocks prevent workers from staying employed in the preferred jobs. For a given sampling distribution, $F(\cdot)$, it is the ratio of the job finding rate to the separation rate into unemployment, κ , that reflects how effectively workers sort into the preferred jobs.

2.3. Worker Flows

Workers employed in jobs ranked p quit their current job in the event of a separation shock, δ , or if they find higher ranked jobs, $\lambda(1 - F(p))$. Therefore, the separation rate conditional on the job rank p is given by $\delta + \lambda(1 - F(p))$. Proposition 2 provides the analytical expression for the unconditional steady state risk ratio of separating to another job to separating into unemployment, denoted by $\bar{\kappa}$. Note that this risk ratio coincides with the ratio of the unconditional steady state separation rate to another job, denoted by $\bar{\lambda}$, to the separation rate into unemployment, δ .⁴

Proposition 2 (Job Mobility). *The unconditional steady state risk ratio of separating to another job to separating into unemployment, $\bar{\kappa}$, is*

$$\bar{\kappa} = \bar{\lambda}/\delta = \frac{1 + \kappa}{\kappa} \ln(1 + \kappa) - 1. \quad (1)$$

PROOF. Integrating the conditional separation rate, $\delta + \lambda(1 - F(p))$, over the cross sectional job distribution, $G(\cdot)$, yields following expression for the unconditional separation rate

$$\delta + \bar{\lambda} \equiv \int_0^1 [\delta + \lambda \bar{F}(p)] dG(p) = \frac{\delta(\delta + \lambda)}{\lambda} \ln\left(\frac{\delta + \lambda}{\delta}\right). \quad (2)$$

Equation (1) follows immediately from Equation (2). \square

Note that the unconditional steady state separation rate to another job, $\bar{\lambda}$, does not depend on the sampling distribution, $F(\cdot)$; nor does the unconditional steady state risk ratio of separating to another job to separating into unemployment, $\bar{\kappa}$. Intuitively, workers who direct their search towards top-ranked jobs are more likely to obtain better offers at a given job. Therefore, they are more likely to separate from that job. However, workers who direct their search towards top-ranked jobs are more likely to be in top-ranked jobs, so that there are only few jobs that are preferred. Therefore, they are less likely to separate from a job. The positive and negative effect of the directedness of a worker's search on the unconditional separation rate exactly cancel.

⁴Proposition 2 is reminiscent of Ridder's and van den Berg's unconditional inference method (Ridder and van den Berg, 2003).

The unconditional steady state risk ratio of separating to another job to separating into unemployment, $\bar{\kappa}$, is the principal measure of job mobility in the subsequent empirical analysis.⁵ This risk ratio is an appealing measure of job mobility for at least three reasons. First, $\bar{\kappa}$ is solely a function of the model’s primitive mobility parameters, i.e., κ . Furthermore, $\bar{\kappa}$ is increasing in κ for $\kappa > 0$. Hence, ordinality is preserved. Therefore, realized mobility patterns, $\bar{\kappa}$, allow direct inference about the underlying mobility characteristics, κ .

Second, $\bar{\kappa}$ reflects a worker’s ability to sort into the preferred jobs. Since $\bar{\kappa}$ is an ordinal transformation of κ , Proposition 1 applies to $\bar{\kappa}$ as well. Therefore, the higher $\bar{\kappa}$, the likelier are workers to be employed in top-ranked jobs. In an environment where more productive firms offer *ceteris paribus* higher wages—which is both an equilibrium outcome in this framework and in line with empirical evidence— $\bar{\kappa}$ also reflects the ability to allocate to the most productive jobs or firms in the economy.⁶ As stressed in the introduction, the resource allocation across firms is a potentially important determinant of aggregate productivity (see, e.g., Hsieh and Klenow, 2009; Lentz and Mortensen, 2008).

Third, $\bar{\kappa}$ reflects the fierceness of competition between firms for workers. κ , of which $\bar{\kappa}$ is an ordinal transformation, is the average number of outside contracts per employment spell. The more firms are expected to interact during an employment spell, the lower is the employers’ monopsonistic power. Hence, the higher is the rent share the workers are able to appropriate. Differences in employers’ monopsonistic power across worker groups play potentially an important role in explaining relative wages (see, e.g., Ransom and Oaxaca, 2010; Hirsch et al., 2010).

3. Data and Variables

The subsequent analysis is based on a subsample of the 1996 Panel of the *Survey of Income and Program Participation*. A description of the data set and

⁵Strictly speaking, I consider the employed worker’s unconditional risk ratio of *being* employed at another job to *being* unemployed after a given time period in the empirical analysis of Section 5. It is only for infinitesimal changes in time that this ratio exactly corresponds to the employed worker’s unconditional risk ratio of *separating* to another job to *separating* into unemployment, $\bar{\kappa}$.

⁶Bontemps et al. (2000) analyze the on-the-job search equilibrium with continuous firm productivity dispersion. They find, indeed, that more productive—and hence larger—firms pay higher wages. This is well in line with empirical evidence. See, e.g., Oi and Idson (1999).

the sample selection is in Section 3.1. I introduce the relevant variables in Section 3.2. Summary statistics are in Section 3.3. See Appendix A for further details.

3.1. Survey of Income and Program Participation

The *Survey of Income and Program Participation* was designed to be a nationally representative sample of households in the civilian non-institutionalized U.S. population, for which interviews were conducted every four months for four years. For each interview, information about the worker's current employer, occupation and wage, as well as a complete weekly employment history for the past four months was recorded. In line with the paper's focus on the steady state equilibrium, the U.S. economy was approximately in the same phase of the business cycle during the covered period, i.e., 1996 to 2000.

In principle, the *Survey of Income and Program Participation* allows for a weekly account of gross worker flows (see Nekarda, 2008). However, to avoid the particularities arising from the retrospective nature of the weekly records and since time aggregation is not a major concern for the key results of this study, I limit the analysis to the four months intervals of the interviews.

The sample selection is as follows. First, I restrict the analysis to private for profit employees, since wage setting and mobility patterns in the government sector or in non-profit activities may be partially affected by non-market considerations. Second, only full-time employed individuals aged 25 to 55 may enter the final sample. Therefore, I abstract from particularities of the early and late stages of the working life and of part time work. Third, I exclude individuals with potentially work preventing or limiting conditions, who may also exhibit different mobility patterns. Fourth, the sample encompasses only white males since non-white individuals' and women's opportunities and decisions may also be influenced by non-market considerations. For instance, firms' discrimination against specific worker groups due to distaste à la Becker (1971), i.e., a concept of discrimination that is not dictated by profit maximization, is a potential source for differences in labor market outcomes across the respective worker groups. Finally, I exclude respondents from Hawaii, since individuals on islands may exhibit different mobility patterns as well. The final sample encompasses 10,316 individuals and a total of 68,058 observations.

3.2. Variables

In this section I introduce the variables used in the subsequent analysis. While the majority of the variables are standard, the measures of versatility, occupation-

specific human capital and match quality are mostly specific to this paper. I discuss these variables in detail.

3.2.1. Transitions

I classify currently employed respondents into five categories according to their employment status four months later: *(i)* stay with the same employer and do not switch occupations, *(ii)* stay with the same employer and switch their occupation, *(iii)* separate into unemployment, *(iv)* separate to another employer, or *(v)* leave the labor force. Additionally, there is a small share of individuals who become self-employed. I do not account for such changes in the employment status and discard the respective observations. Occupational changes are identified on the basis of the 1990 Census Occupational Classification system. The final sample encompasses 413 distinct occupations.

On average, 7.7 percent of employed individuals experience a change in their employment status every four months: 0.9 percent separate into unemployment, 2.1 percent change their occupations within the firm, 3.8 percent switch employers, and 0.9 percent leave the labor force. Therefore, 92.32 percent of employed individuals do not experience any of the changes in the employment status that are accounted for in this study.

3.2.2. Wages and Standard Controls

The hourly wage is defined as the monthly earnings from the main job divided by the product of usual hours worked per week at the main job and the number of weeks with a job in the respective month. I discard all observations below the 1st percentile and above the 99th percentile. The average hourly wage in the sample amounts to 10.36 in 1982–84 US-Dollars.

In all regressions I include a second order polynomial in age. Furthermore, I control for the individual's marital status and the number of children in the household. Specifically, I form four categories for marital status: *(i)* married and spouse present, *(ii)* married but spouse absent, *(iii)* widowed, divorced or separated, and *(iv)* never married. The five categories for the number of children in the household are none, one, two, three, and at least four children, respectively. I also include year, month, and state fixed effects. Furthermore, I control for differences across worker groups in the distribution over occupations and industries. However, given the limited number of observations, I form broader categories encompassing several of the original 1990 Census occupations and industries. All in all, the subsequent regressions include 69 occupation and 16 industry indicator variables. See Appendix A for further details.

3.2.3. Education and Versatility

Respondents are grouped into five education groups according to their educational attainment: individuals who have completed at most the 12th grade and have no high school diploma (*no high school*), high school graduates (*high school*), individuals with some college but no degree or an associate degree (*some college*), individuals with a bachelor's degree (*college*), and individuals with a master's, professional school or doctorate degree (*advanced*).

Beyond the standard questions on educational attainment, there is additionally a topical module with detailed information on respondents' educational background in the *Survey on Income and Program Participation*. In particular, I exploit information on courses attended in high school to construct a proxy for an individual's versatility. Specifically, all survey participants who have at least completed the 9th grade are asked whether they took at least two or more years of (i) advanced math, (ii) advanced science, (iii) English composition or literature, (iv) foreign language, (v) industrial art, shop or home economics, (vi) business courses, or (vii) fine arts.

Figure 1 depicts on the left-hand side the percentage share of individuals who took the respective course in high school. English composition or literature is the most frequent course with an attendance rate of 74.4 percent. Business is the least frequent course with a share of 27.3 percent. All in all, none of the courses is attended by a vast majority of the survey respondents nor is a course only attended by a small minority. There is always at least a quarter of respondents who do not attend and always at least a quarter of respondents who do attend a given course. Figure 1 depicts on the right-hand side the distribution of the number of courses that survey participants took. Most frequently, the survey participants indicate to have attended four of the seven courses (24.6 percent). The average number of courses is 3.4 in the sample. Only 4 individuals indicate to have not taken any of the courses.

I identify all respondents who have attended at least four courses in high school as versatile. Therefore, 48.2 percent of individuals are versatile and 51.8 percent are not versatile. To control for differences beyond the mere number of courses in the course portfolios between the two groups, I also include indicator variables for each of the seven courses in all subsequent regressions. Therefore, the versatility proxy captures predominately the diversity within each course portfolio and not its composition.

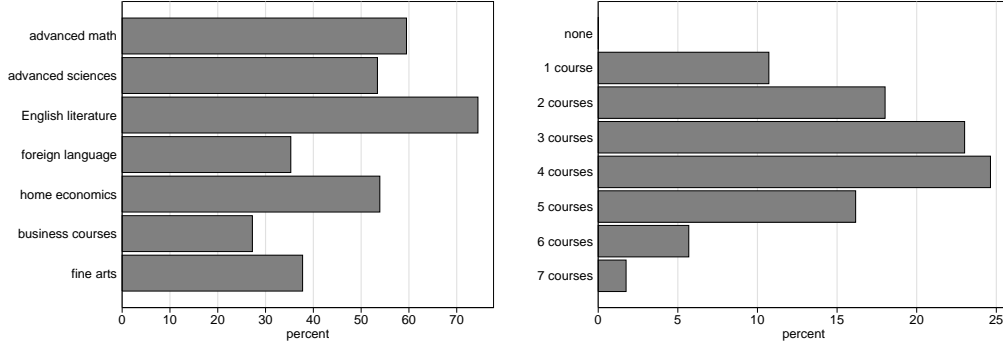


Figure 1: Courses and number of courses that respondents attended in high school. Sample restricted to full-time employed white males aged 25 to 55. Author's calculations based on the *Survey of Income and Program Participation* data as provided by the National Bureau of Economic Research (<http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html>).

3.2.4. General Experience and Human Capital

It has recently been argued that the returns to occupational tenure and labor market experience are both substantial and of similar magnitude, whereas the returns to firm or industry tenure are much smaller (Kambourov and Manovskii, 2009b). Therefore, I focus on two measures of human capital: general experience and occupation-specific human capital.

General experience is defined as the difference between the survey year and the respondent's highest degree graduation year. On average, survey participants have a 17.6 years' general experience. I compute an individual's occupation-specific human capital as follows. For each the 69 broader occupation categories, I estimate a standard reduced form wage regression:

$$\ln(w_{ij}) = \mathbf{x}_{ij}\boldsymbol{\beta}_j + \epsilon_{ij}, \quad (3)$$

where w_{ij} is the hourly wage of an individual i working in occupation j , \mathbf{x}_{ij} is a vector of worker characteristics, $\boldsymbol{\beta}_j$ is the accompanying coefficient vector, and ϵ_{ij} is the unexplained residual. The explanatory variables in \mathbf{x} include a second degree polynomial in general experience and occupational tenure, and the educational attainment indicators.⁷ An individual's occupation-specific human capital is then defined as the predicted wage premium due to occupational tenure. I truncate the

⁷Survey participants are asked to indicate their occupational tenure only in the the first interview. For all subsequent periods I impute occupational tenure. Specifically, I proceed as follows:

distribution for occupation-specific human capital from below at the 1st percentile and from above at 99th percentile. Furthermore, I replace all negative estimates with zero.

Figure 2 juxtaposes the distribution of occupational tenure and the distribution of occupation-specific human capital. 11.1 percent of individuals in the sample have occupational tenure of less than one year. The share of individuals with occupation-specific human capital corresponding to a wage premium of less than one log-point is 17.0 percent in the sample. On average, survey respondents have 10.9 years of occupational tenure and occupation-specific human capital corresponding to a wage premium of 10.4 log-points.

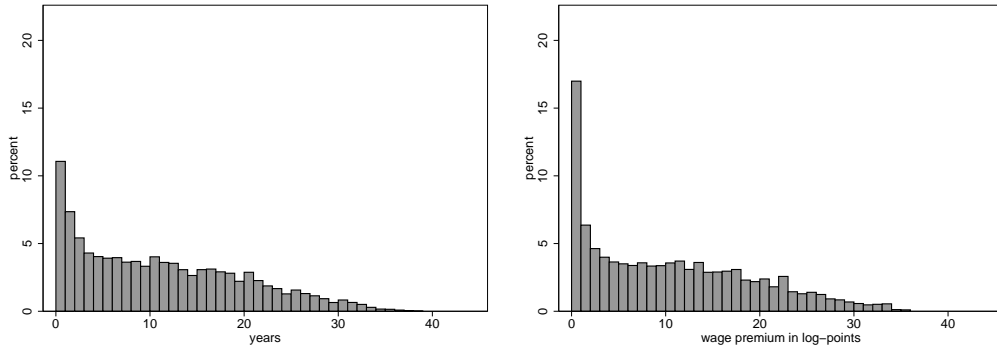


Figure 2: Distribution of occupational tenure on the left-hand side and occupation-specific human capital in terms of log-points wage premia on the right-hand side. Sample restricted to full-time employed white males aged 25 to 55. Author's calculations based on the *Survey of Income and Program Participation* data as provided by the National Bureau of Economic Research (<http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html>).

(i) If the respondents are still employed in the same occupation as in the preceding interview, I set occupational tenure to the preceding interview's value plus four months. (ii) If the respondents start working in an occupation they have already been employed in during the period covered by the survey, I set occupational tenure to the previously reported level for that occupation plus two months. (iii) If the respondents leave the occupation reported in the previous interview and start working in a new occupation they have not already been employed in during the period covered by the survey, I set occupational tenure to two months. (iv) For all remaining cases, I use estimates from a least squares regression including all other controls.

3.2.5. Match Quality

I use two measures for the quality of a worker–job match.⁸ First, I consider establishment size in terms of the number of employees. I use this proxy to assess the quality of the worker–establishment match. Specifically, I consider three establishment size classes: (i) less than 25 employees, (ii) 25 to 99 employees, and (iii) at least 100 employees. It is a well-known stylized fact that larger establishments tend to be more productive and that employees at larger establishments are less likely to separate (see, e.g., Oi and Idson, 1999).

Second, I use the workers’ position in the distribution of residual wages in their occupation as a proxy for the quality of the worker–occupation match. Specifically, I rely on the workers’ position in the distribution of the residual ϵ_{ij} in their occupation obtained from Equation (3). Kircher et al. (2009) document that for most occupations mobility is U-shaped and directional. It is both the low-wage and the high-wage workers within an occupation who have a particularly large probability of leaving that occupation, while the lowest probability of leaving is associated with the medium wage workers within the occupation. Furthermore, while those earning low wages relative to other workers in the same occupation tend to leave for new occupations that on average pay less to their workforce than the old occupation, those with high relative wages in their occupation tend to leave for occupations that on average pay more to their workforce.⁹

3.3. Summary Statistics

Table 1 presents summary statistic for the overall sample and for the five education groups separately. The statistics reveal some well-known regularities across education groups. On average, more educated workers are older, have less general experience, receive higher hourly wages, and are more likely to work at large establishments.

The average number of courses that respondents took in high school is increasing in education. Respondents without high school attend on average 3.0 courses

⁸The paper’s main results are not sensitive to the additional two controls presented in this section. See Appendix A for further details.

⁹Kircher et al. (2009) argue that these patterns are consistent with vertical sorting of workers under absolute advantage. High ability workers within an occupation tend to earn high wages and may find it optimal to move to a more skill-intensive occupation. Medium ability workers within an occupation tend to earn wages close to the middle of the occupational wage distribution. They are less likely to leave the occupation since it reflects well their skill level. Low ability workers within an occupation tend to earn lower wages and may find it optimal to move to an occupation with lower skill requirements.

	<i>Overall</i>	<i>Education</i>				
		No high school	High school	Some college	College	Ad- vanced
<i>Share (in %)</i>	—	7.05 (0.10)	33.72 (0.19)	32.20 (0.19)	20.42 (0.16)	6.61 (0.10)
<i>Age</i>	38.68 (0.03)	37.77 (0.12)	38.57 (0.06)	38.76 (0.06)	38.33 (0.07)	40.85 (0.12)
<i>High school courses</i>	3.42 (0.01)	3.02 (0.02)	2.92 (0.01)	3.44 (0.01)	4.07 (0.01)	4.24 (0.02)
<i>Versatile (in %)</i>	48.24 (0.20)	33.78 (0.72)	32.98 (0.34)	47.90 (0.35)	69.84 (0.40)	76.43 (0.65)
<i>General experience</i>	17.57 (0.04)	21.07 (0.14)	20.68 (0.06)	15.51 (0.06)	15.56 (0.07)	14.15 (0.12)
<i>Occupational tenure</i>	10.87 (0.04)	10.79 (0.13)	11.22 (0.07)	10.88 (0.06)	10.21 (0.07)	11.23 (0.12)
<i>Occupation-specific human capital (in %)</i>	10.38 (0.03)	11.46 (0.14)	11.47 (0.06)	10.57 (0.06)	8.25 (0.07)	9.31 (0.12)
<i>Residual occupation-wage percentile</i>						
100th–75th	25.70 (0.17)	28.01 (0.68)	25.44 (0.30)	25.13 (0.31)	25.79 (0.38)	27.09 (0.67)
75th–25th	49.83 (0.20)	50.42 (0.75)	49.74 (0.35)	50.25 (0.35)	49.28 (0.44)	49.35 (0.76)
25th–1st	24.46 (0.17)	21.57 (0.62)	24.81 (0.31)	24.62 (0.30)	24.92 (0.38)	23.56 (0.66)
<i>Hourly wage (in 1982–84 Dollars)</i>	10.36 (0.02)	7.11 (0.06)	8.61 (0.03)	9.96 (0.03)	13.11 (0.06)	16.26 (0.12)
<i>Establishment size</i>						
1–24 employees	31.43 (0.19)	42.78 (0.75)	33.81 (0.33)	30.83 (0.33)	27.80 (0.39)	21.30 (0.63)
25–99 employees	25.40 (0.17)	26.43 (0.66)	26.22 (0.31)	26.03 (0.31)	24.34 (0.38)	20.26 (0.62)
100+ employees	43.18 (0.20)	30.79 (0.69)	39.97 (0.35)	43.14 (0.35)	47.87 (0.44)	58.43 (0.75)

Table 1: Various summary statistics for full-time employed white males aged 25 to 55. Standard errors in parentheses. Author’s calculations based on the *Survey of Income and Program Participation* data as provided by the National Bureau of Economic Research (<http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html>).

whereas the respective number is 4.2 among respondents with advanced education. This is also reflected in the share of versatile individuals by education. On the one hand, only one-third of high school dropouts are classified as versatile. On the other hand, more than three-fourths of individuals with advanced education are versatile.

Some statistics do not reveal a clear pattern by education. Average occupational tenure is the highest among individuals with advanced education and

high school graduates amounting to 11.2 years. Occupational tenure among college graduates is 10.2 years and, therefore, the overall lowest. With respect to occupation-specific human capital, it is the high school graduates and dropouts who accumulate the highest levels. The average wage premium due to occupational tenure among these two worker groups is estimated to be 11.5 log-points. College graduates have the lowest levels of occupation-specific human capital corresponding to an average wage premium of 8.3 log-points. In conclusion, while respondents with advanced education have the highest levels of occupational tenure, other worker groups enjoy larger returns to occupational tenure. Hence, it is not individuals with advanced education who accumulate the highest levels of occupation-specific human capital but high school graduates and dropouts.

Table 2 summarizes transition probabilities and risk ratios for the overall sample and separately by education. EU, OO, EE and EN denote separations into unemployment, occupational changes within the firm, employer–employer transitions, and separations into inactivity, respectively. OO/EU and EE/EU denote the risk ratio of occupational changes within the firm to separations into unemployment, and the risk ratio of employer–employer transitions to separations into unemployment, respectively.

More educated individuals tend to have more stable employment relations. While 91.9 percent of high school dropouts stay with the same employer every four months, the respective share among individuals with advanced education is 95.8 percent. More educated individuals are both less likely to separate into unemployment and less likely to separate to another employer. For high school dropouts (individuals with advanced education) the shares amount to 2.1 (0.3) and 4.36 (3.17) percent, respectively. However, more educated individuals are disproportionately less likely to separate into unemployment than to switch employers relative to less educated individuals. Therefore, external job mobility as measured by the risk ratio of employer–employer transitions to separations into unemployment, EE/EU, is increasing in education. The risk ratio is 2.1 among high school dropouts and 9.3 among individuals with advanced education. In other words, high school dropouts are 2.1 times likelier to move to another employer than to separate into unemployment. Respondents with advanced education are 9.3 times likelier to move to another employer than to separate into unemployment.

The probability to switch occupations while staying with the same employer is increasing in education up to the level of a bachelor’s degree. For instance, 1.5 (2.8) percent of high school dropouts (college graduates) change occupations within the firm every four months. However, only 1.9 percent of individuals with advanced education change occupations and are, therefore, less likely to expe-

	<i>No transition</i>	<i>Transitions</i>				<i>Risk ratios</i>	
		EU	OO	EE	EN	OO/EU	EE/EU
<i>Overall</i>	92.32 (0.11)	0.90 (0.04)	2.11 (0.06)	3.75 (0.08)	0.93 (0.04)	2.35 (1.05)	4.19 (1.05)
<i>Education</i>							
No high school	90.35 (0.45)	2.12 (0.22)	1.53 (0.19)	4.36 (0.31)	1.64 (0.19)	0.72 (1.17)	2.05 (1.14)
High school	92.45 (0.18)	1.03 (0.07)	1.80 (0.09)	3.85 (0.13)	0.87 (0.06)	1.75 (1.09)	3.74 (1.08)
Some College	92.29 (0.19)	0.79 (0.06)	2.17 (0.10)	3.78 (0.14)	0.97 (0.07)	2.74 (1.10)	4.77 (1.09)
College	92.29 (0.24)	0.59 (0.07)	2.77 (0.14)	3.55 (0.17)	0.80 (0.08)	4.68 (1.13)	5.99 (1.13)
Advanced	93.93 (0.36)	0.34 (0.09)	1.91 (0.21)	3.17 (0.27)	0.65 (0.12)	5.60 (1.31)	9.27 (1.30)
<i>Versatility</i>							
Non-versatile	92.20 (0.15)	1.06 (0.06)	2.09 (0.08)	3.71 (0.11)	0.94 (0.05)	1.96 (1.07)	3.49 (1.06)
Versatile	92.44 (0.15)	0.71 (0.05)	2.13 (0.08)	3.80 (0.11)	0.91 (0.06)	2.98 (1.08)	5.32 (1.08)

Table 2: Transitions in percent of employment in columns 1 to 4 and risk ratios to unemployment in columns 4 to 5. EN, EU, OO, and EE denote separations into inactivity, separations into unemployment, occupational changes within the same firm, and employer–employer transitions, respectively. Sample restricted to full-time employed white males aged 25 to 55. Standard errors in parentheses. Author’s calculations based on the *Survey of Income and Program Participation* data as provided by the National Bureau of Economic Research (<http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html>).

rience an occupational change than individuals with some college, of whom on average 2.2 percent switch occupations every four months. Nevertheless, internal job mobility as measured by the risk ratio of occupational changes within the firm to separations into unemployment, OO/EU, is increasing in education throughout all categories. For instance, the ratio is 0.7 among high school dropouts and 5.6 among respondents with advanced education.

Versatile individuals are only slightly more likely to switch occupations within the firms and to separate to another employer. However, versatile individuals are substantially less likely to separate into unemployment. While 1.1 percent of non-versatile individuals separate into unemployment every four months, the respective share is only 0.7 percent among versatile individuals. Therefore, both the risk ratio of occupational changes within the firm to separations into unemployment, OO/EU, and the risk ratio of employer–employer transitions to separations into unemployment, EE/EU, are increasing in versatility.

4. Determinants of Labor Market Transitions

In this section I present estimates from multinomial logit regressions. Throughout this section, risk ratios relative to the base group are displayed, i.e., relative risk ratios. Individuals with the following characteristics serve as the base group: (i) no high school diploma, (ii) non-versatile, (iii) employed at an establishment with at most 24 employees, and (iv) a position in the 75th to 90th percentile of the residual wage distribution of the respective occupation.

Let E denote the probability of staying with the same employer without an occupational change. Table 3 displays (relative) risk ratios of separating into unemployment (EU/E), of switching occupations within the firm (OO/E), and of separating to another employer (EE/E) to staying with the same employer without an occupational change.¹⁰ In the first three columns only education dummies enter the regression. The estimates mirror Table 2's results. The risk ratio of separating into unemployment to staying with the same employer without an occupational change, EU/E , is decreasing in education. For instance, high school dropouts are 6.5 ($= 1/0.155$) times likelier to separate into unemployment than to stay with the same employer without an occupational change relative to individuals with advanced education. The risk ratio of separating to another employer to staying with the same employer without an occupational change, EE/E , is decreasing in education as well. For instance, high school dropouts are 1.5 ($= 1/0.669$) times likelier to separate to another employer than to stay with the same employer without an occupational change relative to individuals with advanced education. The risk ratio of switching occupations within the firm to staying with the same employer without an occupational change, OO/E , is not decreasing in education throughout all categories. High school dropouts have the lowest risk ratio and college graduates the highest risk ratio. College graduates are 1.8 times likelier to switch occupations within the firm than to stay with the same employer without an occupational change relative to high school dropouts.

Controlling for the full set of covariates, that are described in Section 3, substantially decreases the disparities in risk ratios across education categories (see columns four to six in Table 3). For instance, high school dropouts are now only 2.1 ($= 1/0.475$) times likelier to separate into unemployment than to stay with the same employer without an occupational change relative to individuals with advanced education. The risk ratios of separating to another employer to staying

¹⁰Estimation results for the risk ratio of leaving the labor force to staying with the same employer without an occupational change (EN/E) are not displayed, but available upon request.

	<i>Relative risk ratios</i>					
	EU/E	OO/E	EE/E	EU/E	OO/E	EE/E
<i>Education</i>						
High school	0.474*** (0.000)	1.151 (0.309)	0.863 (0.124)	0.649*** (0.005)	1.160 (0.287)	1.006 (0.950)
Some college	0.365*** (0.000)	1.385** (0.017)	0.849* (0.090)	0.610*** (0.008)	1.311* (0.080)	0.940 (0.597)
College	0.273*** (0.000)	1.771*** (0.000)	0.797** (0.026)	0.669* (0.091)	1.710*** (0.003)	0.947 (0.700)
Advanced	0.155*** (0.000)	1.202 (0.302)	0.699*** (0.007)	0.475** (0.034)	1.382 (0.165)	0.933 (0.710)
<i>General experience</i>	—	—	—	0.982** (0.049)	0.996 (0.543)	0.983*** (0.001)
<i>Occupation-specific human capital (in %)</i>	—	—	—	0.133*** (0.004)	0.029*** (0.000)	0.145*** (0.000)
<i>Versatility</i>	—	—	—	0.689** (0.042)	0.838 (0.123)	1.046 (0.622)
<i>Log-wage</i>	—	—	—	0.412*** (0.000)	0.838 (0.352)	0.785* (0.077)
<i>Residual occupation-wage percentile</i>						
100th–90th	—	—	—	1.196 (0.431)	1.338** (0.022)	1.428*** (0.000)
75th–50th	—	—	—	0.934 (0.709)	1.074 (0.494)	1.062 (0.490)
50th–25th	—	—	—	1.102 (0.627)	0.918 (0.536)	1.166 (0.149)
25th–10th	—	—	—	0.848 (0.512)	1.059 (0.761)	1.350** (0.031)
10th–1th	—	—	—	0.854 (0.640)	0.859 (0.575)	1.733*** (0.005)
<i>Establishment size</i>						
29–99 employees	—	—	—	0.817* (0.075)	1.245** (0.012)	0.847*** (0.003)
100+ employees	—	—	—	0.672*** (0.002)	1.627*** (0.000)	0.744*** (0.000)
<i>High school courses, year, month, children, marital status, age, age², state, occupation, industry</i>	—	—	—	X	X	X

Table 3: Multinomial logit regressions. Relative risk ratios displayed. EU, OO, EE and E denote separations into unemployment, occupational changes with the same employer, employer-employer transitions and no changes in employment status, respectively. Sample restricted to full-time employed white males aged 25 to 55. *p*-values in parentheses. Standard errors clustered at the individual level. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Log-pseudolikelihood: -86284103 (columns 1 to 3) and -81802406 (columns 4 to 6). Author's calculations based on the Survey of Income and Program Participation data as provided by the National Bureau of Economic Research (<http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html>).

with the same employer without an occupational change, EE/E, are not substantially different across education groups nor statistically significant after controlling for the additional variables. The inverted-U relationship between the risk ratio of switching occupations within the firm to staying with the same employer without an occupational change, OO/E, and education is preserved, however, less pronounced.

General experience has a negative effect on all risk ratios displayed in Table 3. For instance, 24 years' general experience and a high school diploma have the same impact on the risk ratio of separating into unemployment to staying with the same employer without an occupational change, EU/E.¹¹ Occupation-specific human capital reduces the displayed risk ratios as well. For instance, an individual experience the same increase in the risk ratio of an occupational change within the firm to no occupational change within the firm, OO/E, either by graduating from college or by losing occupation-specific human capital corresponding to a wage premium of 15 log-points. Both events raise the risk ratio by a factor of 1.7.

Versatility has only a limited—and statistically not significant—impact on occupational changes within the firm and employer–employer transitions. However, versatility substantially reduces the risk ratio of separating into unemployment to staying with the same employer without an occupational change, EU/E. The effect is of the same magnitude as graduating from high school or college. An individual experiences the same reduction in the risk ratio by either gathering 21 years of general experience or accumulating occupation-specific human capital corresponding to a wage premium of 18 percentage points.

Higher wages lead to lower risk ratios as displayed in Table 3. For instance, the risk ratio of separating into unemployment to staying with the same employer without an occupational change, EU/E, falls by the same factor if either the wage rises by ten log-points, the individual's general experience increases by five years, or the individual accumulates occupation-specific human capital corresponding to a wage premium of four log-points. The effect of employees' position in the residual wage distribution of their occupation on employer–employer transitions is

¹¹By solving for *years* in Equation (4), one obtains the number of years of general experience necessary to increase the relative risk ratio by the same amount as a high school diploma. Equation (4) is

$$rrr(high\ school) = rrr(general\ experience)^{years}, \quad (4)$$

where *rrr* denotes relative risk ratios as displayed in Table 3. In this example the required number of years of general experience is equal to $\log(0.649)/\log(0.982) \approx 24$.

U-shaped. This is in line with the findings of Kircher et al. (2009). I do not obtain a clear and statistically significant pattern for separations into unemployment and occupational changes within the firm.

In line with well-known stylized facts, workers employed at larger establishments are estimated to be less likely to separate into unemployment or to another employer relative to staying with the same employer without an occupational change. However, workers employed at larger establishments are likelier to switch occupations within the firm than to stay with the same employer without an occupational change, OO/E, relative to workers in smaller establishments. The estimated effect of establishment size on occupational changes within firms is well in line with the literature. Idson (1989), using direct information on job changes from the 1973 Quality of Employment Survey, finds that nonunion workers in larger establishments enjoy more job changes than workers in small establishments. He stresses, in particular, the employers' incentive to stimulate and to protect the higher levels of training investments in workers at larger establishments by providing superior internal labor markets. Papageorgiou (2010) argues that larger firms offer superior internal labor markets, such that workers in large firms replace external mobility for internal mobility. In equilibrium, workers in large firms are employed in better matches and earn higher wages. This gives rise to a employer-size wage premium. Furthermore, a calibrated model indicates that superior internal labor markets account for up to one-third of the employer-size wage premium.

5. Determinants of Job Mobility

In this section I present the paper's main findings on job mobility. Table 4 displays, on the one hand, estimates of internal job mobility as measured by the (relative) risk ratio of occupational changes within the firm to separations into unemployment, OO/EU. On the other hand, Table 4 also displays estimates of external job mobility as measured by the (relative) risk ratio of separating to another employer to separating into unemployment, EE/EU. As discussed in Section 2, the ratio of job-to-job transitions to separations into unemployment is an appealing measure of an individual's job mobility. Most importantly, it accounts for the negative effect of unemployment on the worker's ability to sort into the preferred jobs.

In Table 4's first two columns only education dummies enter the regression. The estimates mirror Table 2's findings. Internal job mobility, OO/EU, is increasing in education. For instance, respondents with advanced education are 7.8 times

	<i>Relative risk ratios</i>			
	OO/EU	EE/EU	OO/EU	EE/EU
<i>Education</i>				
High school	2.427*** (0.000)	1.819*** (0.000)	1.787*** (0.004)	1.550** (0.011)
Some college	3.791*** (0.000)	2.324*** (0.000)	2.148*** (0.001)	1.540** (0.035)
College	6.481*** (0.000)	2.917*** (0.000)	2.557*** (0.002)	1.417 (0.184)
Advanced	7.758*** (0.000)	4.513*** (0.000)	2.912** (0.012)	1.967* (0.082)
<i>General experience</i>	—	—	1.015 (0.201)	1.002 (0.869)
<i>Human capital</i>	—	—	0.215* (0.079)	1.089 (0.913)
<i>Versatility</i>	—	—	1.217 (0.356)	1.519** (0.034)
<i>Residual occupation- wage percentile, log- wage, establishment size</i>	—	—	x	x
<i>High school courses, year, month, children, marital status, age, age², state, occupation, industry</i>	—	—	x	x

Table 4: Multinomial logit regressions. Relative risk ratios displayed. EU, OO, and EE denote separations into unemployment, occupational changes with the same employer, and employer–employer transitions, respectively. Sample restricted to full-time employed white males aged 25 to 55. *p*-values in parentheses. Standard errors clustered at the individual level. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Log-pseudolikelihood: -86284103 (columns 1 to 2) and -81802406 (columns 3 to 4). Author’s calculations based on the Survey of Income and Program Participation data as provided by the National Bureau of Economic Research (<http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html>).

likelier to switch their occupation within the firm than to separate into unemployment relative to high school dropouts. External job mobility, EE/EU, is also increasing in education. For instance, respondents with advanced education are 4.5 times likelier to separate to another employer than to separate into unemployment relative to high school dropouts.

Controlling for the full set of covariates, that are described in Section 3, decreases disparities in both internal and external job mobility across education groups. For instance, individuals with advanced education are now only 2.9 times likelier to switch occupations within the firm than to separate into unemployment relative to high school dropouts. Also, individuals with advanced education are

only 2.0 times likelier to separate to another employer than to separate into unemployment relative to high school dropouts after controlling for the additional variables. Internal job mobility remains positively related to education. Differences in external job mobility across intermediate education categories are well accounted for by the extensive set of controls. However, the strong negative effect of not graduating from high school and the strong positive effect of an education exceeding a bachelor's degree persist.

General experience tends to have a positive effect on job mobility. However, the effect is relatively small and not statistically significant. An individual needs to gain 39 years of general experience in order to obtain the same increase in the risk ratio of switching occupations within the firm to separating into unemployment, OO/EU, that results from graduating from high school. Graduating from high school increases the the risk ratio of employer–employer transition to separations into unemployment, EE/EU, by the same factor as 219 years of general experience.

Occupation-specific human capital negligibly increases external mobility and the effect is not statistically significant. Specifically, an individual needs to accumulate occupation-specific human capital corresponding to a wage premium of 514 log-points in order to obtain the same increase in external job mobility, EE/EU, that results from graduating from high school. The effect of occupation-specific human capital on internal job mobility is negative, but not substantial. Not graduating from high school decreases internal mobility, OO/EU, by the same factor as human capital corresponding to a wage premium of 38 log-points.

Versatility increases both internal and external job mobility, however, only the latter effect is statistically significant. The impact of versatility on external job mobility is similar in magnitude as the effect of a college or high school degree on a high school dropout's external job mobility. Specifically, above-median versatile workers' risk ratio of employer–employer transitions to separations into unemployment, EE/EU, exceeds that of below-median versatile workers by a factor of 1.52.

All in all, the results suggest the importance of versatility besides educational attainment for understanding workers' external job mobility and, hence, workers' sorting into firms. This is well in line with Stijepic's (2015b) microfoundation for differences in external mobility across worker groups. Jobs posted by firms differ in requirements. Being able to perform various tasks and activities eventually even across occupations allows workers' to sort more efficiently into the preferred firms. First, efficient reallocations across firms are less likely to be hindered by unmet job requirements. Second, if job requirements change, versatile workers—

being able to perform a wider range of tasks or activities—are likely to adapt, whereas non-versatile workers are forced to separate from the preferred firm into unemployment. Therefore, versatile workers have a higher risk ratio of employer–employer transitions to separations into unemployment and are more likely to be employed at the preferred firms relative to non-versatile workers.

6. Conclusion

In this paper I analyze the determinants of job mobility. Specifically, I study two dimension of job mobility: *(i)* internal job mobility measured by the risk ratio of switching occupations within the firm to separating into unemployment, and *(ii)* external job mobility measured by the risk ratio of separating to another employer to separating into unemployment. Both measures account for the negative impact of unemployment on workers’ ability to sort into the preferred jobs. Furthermore, the measures of job mobility do not require an explicit specification of workers’ ranking of jobs, which is methodologically difficult to recover from the data.

The positive relationship between education and internal job mobility prevails even after controlling for an extensive set of covariates, however, it becomes less pronounced. Differences in external job mobility across intermediate education categories are reasonably well accounted for by the extensive set of controls. However, the strong negative effect of not graduating from high school and the strong positive effect of an education exceeding a bachelor’s degree remain mostly unexplained. General experience and occupation-specific human capital have only a limited impact on both internal and external job mobility. While general experience and occupation-specific human capital decrease the probability of occupational changes within firms and employer–employer transitions, they also reduce the risk of separating into unemployment. The risk ratio of occupational changes within the firm or employer–employer transitions relative to separations into unemployment remains mostly unaffected.

Versatility and internal mobility are positively related, however, the estimate is not statistically significant. The impact of being versatile on a individual’s external job mobility is substantial and similar in magnitude as the effect of a college degree on a high school dropout’s external job mobility. Specifically, individuals with above-median versatility are 1.52 times likelier to switch employers than to separate into unemployment relative to individuals with below-median versatility.

This suggests a potentially prominent role for versatility in understanding recent increases in the skill premium. First, versatility is highly correlated with educational attainment (see Table 2). Second, recent empirical evidence suggests

that rising workplace heterogeneity and differences in sorting patterns between education groups have substantially contributed to the increase in the skill premium (see, e.g., Card et al., 2013).¹² Therefore, differences in versatility between education groups and, consequently, differences in external job mobility and the ability to sort into the most preferred or productive firms are likely to have contributed to the observed rise in the skill premium as well.

All in all, the findings suggest that it is potentially not the specialization into particularly productive specific tasks or activities that allowed high-skill workers to obtain relative wage raises, but rather the ability to perform various tasks and activities eventually even across occupations. This versatility enhance workers' mobility across firms and, consequently, allows them to sort into the most productive firms. This is of particular importance in times of rising heterogeneity across firms.¹³ In that vein, Stijepic (2015c) studies the link between the returns to versatility—relying on the same proxy as in this paper—and log-sales per worker dispersion across firms in the United States in the late 1990s. He finds a significantly higher versatility wage premium in industries with higher log-sales per worker dispersion across firms. Specifically, an increase in the standard deviation of sales by 50 log-points is estimated to raise above-median versatile workers relative wage by 14 log-points.

¹²See Andersson et al. (2012) for a study of the U.S. labor market.

¹³Productivity dispersion among firms and the between-firm components of wage inequality have surged in many countries over the last decades (see, e.g., Dunne et al., 2004; Faggio et al., 2010). Dunne et al. (2004) find that the between-plant wage and productivity dispersion increased substantially in U.S. manufacturing from 1975 to 1992 and that “virtually the entire increase in overall dispersion in hourly wages for U.S. manufacturing workers from 1975 to 1992 is accounted for by the between-plant components” (Dunne et al., 2004, pg. 399).

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Appendix A. Data Appendix – For Online Publication

In this section I provide a detailed description of the industry and occupation classifications employed in the main text (Appendix A.1). Furthermore, I also investigate the robustness of the paper’s main finding on the effect of versatility on employed workers’ external job mobility (Appendix A.2).

Appendix A.1. Industry and Occupation Classifications

I form sixteen broad industry categories that are based on the 1990 Census Industry Classification System. I exclude public administration (codes: 900–932) and active duty military (codes: 940–960) from the final sample. Table A.5 displays the industry categories and the corresponding three-digit 1990 Census Industry Codes.

<i>Label</i>	<i>1990 Census Industry Code</i>
<i>Agriculture, forestry, and fisheries</i>	010–032
<i>Mining</i>	040–050
<i>Construction</i>	060
<i>Manufacturing – nondurable goods</i>	100–222
<i>Manufacturing – durable goods</i>	230–392
<i>Transportation</i>	400–432
<i>Communications</i>	440–442
<i>Utilities and sanitary services</i>	450–472
<i>Wholesale trade – durable goods</i>	500–532
<i>Wholesale trade – nondurable goods</i>	540–571
<i>Retail trade</i>	580–691
<i>Finance, insurance, real estate</i>	700–712
<i>Business and repair services</i>	721–760
<i>Personal services</i>	761–791
<i>Entertainment and recreation services</i>	800–810
<i>Professional and related services</i>	812–893

Table A.5: Industry categories based on the 1990 Census Industry Classification System. Public administration (codes: 900–932) and active duty military (codes: 940–960) excluded.

Similarly, I also form broader occupation categories. Table A.6 displays the occupation categories and the corresponding three-digit 1990 Census Occupation Codes. I exclude infrequent occupations that do not allow a meaningful grouping with adjacent occupations. Only 64 observations are affected. Finally, respondents in military occupations (codes: 903–905) also do not enter the final sample.

<i>Label</i>	<i>1990 Census Occupation Code</i>
<i>Executive, administrative, and managerial occupations</i>	003–021
<i>Managers and administrators, n.e.c.</i>	022
<i>Management related occupations</i>	023–037
<i>Architects</i>	043
<i>Engineers</i>	044–063
<i>Mathematical and computer scientists</i>	064–068
<i>Natural scientists</i>	069–083
<i>Health diagnosing occupations</i>	084–089
<i>Health assessment and treating occupations</i>	095–097
<i>Therapists</i>	098–106
<i>Teachers, postsecondary</i>	113–154
<i>Teachers, except postsecondary</i>	155–163
<i>Librarians, archivists, and curators</i>	164–165
<i>Social scientists and urban planners</i>	166–173
<i>Social, recreation, and religious workers</i>	174–177
<i>Lawyers and judges</i>	178–179
<i>Writers, artists, entertainers, and athletes</i>	183–199
<i>Health technologists and technicians</i>	203–208
<i>Engineering and related technologists and technicians</i>	213–218
<i>Science technicians</i>	223–225
<i>Technicians, except health, engineering, and science</i>	226–235
<i>Supervisors and proprietors, sales occupations</i>	243
<i>Sales representatives</i>	253–259
<i>Sales workers</i>	263–274
<i>Sales counter clerks, cashiers, streets sales workers, news vendors</i>	275–278
<i>Sales related occupations</i>	283–290
<i>Supervisors, administrative support occupations</i>	303–307
<i>Computer equipment operators</i>	308–309
<i>Secretaries, stenographers, and typists</i>	313–315
<i>Information clerks</i>	316–323
<i>Records processing occupations, except financial</i>	325–336
<i>Financial records processing occupations</i>	337–344
<i>Duplication, mail, communication and other office machine operators</i>	345–353
<i>Mail and message distributing occupations</i>	354–357
<i>Material recording, scheduling, and distribution clerks</i>	359–374
<i>Adjusters and investigators</i>	375–378
<i>Miscellaneous administrative support occupations</i>	379–391

Table A.6: Occupation categories based on the 1990 Census Occupation Classification System. Respondents in military occupations (codes: 903–905) are excluded from the final sample.

<i>Label</i>	<i>1990 Census Occupation Code</i>
<i>Private household occupations</i>	403–408
<i>Protective service occupations</i>	413–427
<i>Food preparation and service occupations</i>	433–444
<i>Health service occupations</i>	445–447
<i>Cleaning and building service occupations, except household</i>	448–455
<i>Personal service occupations</i>	456–469
<i>Farm operators and managers</i>	473–476
<i>Farm occupations, except managerial</i>	477–484
<i>Related agricultural occupations</i>	485–489
<i>Fishers, hunters, trappers, forestry and logging occupations</i>	494–499
<i>Supervisors, mechanics and repairers</i>	503
<i>Vehicle and mobile equipment mechanics and repairers</i>	505–519
<i>Electric and electronic equipment repairers</i>	523–534
<i>Miscellaneous mechanics and repairs</i>	535–549
<i>Supervisors, construction occupations</i>	553–558
<i>Construction trades, except supervisors</i>	563–599
<i>Extractive occupations</i>	613–617
<i>Supervisors, production occupations</i>	628
<i>Precision metal working occupations</i>	634–655
<i>Precision woodworking occupations</i>	656–659
<i>Precision textile, apparel, and furnishing machine workers</i>	666–674
<i>Precision workers, assorted materials</i>	675–684
<i>Precision food production occupations</i>	686–688
<i>Precision inspectors, testers, and related workers</i>	689–693
<i>Plant and system operators</i>	694–699
<i>Metalworking and plastic working machine operators</i>	703–717
<i>Metal and plastic processing machine operators</i>	719–725
<i>Woodworking machine operators</i>	726–733
<i>Printing machine operators</i>	734–737
<i>Textile, apparel, and furnishings machine operators</i>	738–749
<i>Machine operators, assorted materials</i>	753–779
<i>Fabricators, assemblers, and hand working occupations</i>	783–795
<i>Production inspectors, testers, samplers, and weighers</i>	796–799
<i>Motor vehicle operators</i>	803–815
<i>Rail transportation occupations</i>	823–826
<i>Water transportation occupations</i>	828–834

Table A.6 (continued): Occupation categories based on the 1990 Census Occupation Classification System. Respondents in military occupations (codes: 903–905) are excluded from the final sample.

<i>Label</i>	<i>1990 Census Occupation Code</i>
<i>Material moving equipment operators</i>	843–865
<i>Helpers, construction and extractive occupations</i>	866–874
<i>Freight, stock and material handlers</i>	875–890

Table A.6 (continued): Occupation categories based on the 1990 Census Occupation Classification System. Respondents in military occupations (codes: 903–905) are excluded from the final sample.

Occupations are eventually miscoded for multiple job holders in the 1996 Panel of the Survey of Income and Program Participation. For further details see the “1996 Panel Waves 1 – 12 Labor Force User Note” from May 12, 2006.¹⁴ All in all, I obtain similar occupational transition rates as in other studies, e.g., Moscarini and Thomsson (2007), with the exception of the first rotation group in the second wave. For this group, I identify occupational changes with the same employer as spurious if either

- (i) the occupation is imputed in the subsequent interview,
- (ii) the start date of the job changes,
- (iii) the industry code changes,
- (iv) neither the union membership, the union contract coverage, nor the payment modalities (paid by the hour, frequency of payments, e.g., weekly, monthly, etc.) change, or
- (v) the wage and hours worked change by less than five percent.

Appendix A.2. Auxiliary Results

In this section I investigate whether controlling for match quality affects the paper’s main finding on the effect of versatility on employed workers’ external job mobility. Table A.7 displays the coefficient estimates under three different specifications: (i) not controlling for establishment size, (ii) not controlling for residual occupation-wage percentile, and (iii) not controlling for establishment size and residual occupation-wage percentile. The estimates of the effect of versatility on job mobility are virtually insensitive to controlling for match quality. Versatility increases internal job mobility by a factor of 1.21 and external job mobility by a

¹⁴<http://www.census.gov/programs-surveys/sipp/tech-documentation/user-notes/1996-Cross-Section.html>

factor of 1.52 in all three specification. This is in line with the estimates presented in the main text.

	<i>Relative risk ratios</i>					
	OO/EU	EE/EU	OO/EU	EE/EU	OO/EU	EE/EU
<i>Education</i>						
High school	1.868*** (0.002)	1.557** (0.011)	1.775*** (0.004)	1.675*** (0.002)	1.846*** (0.002)	1.682*** (0.002)
Some college	2.263*** (0.001)	1.548** (0.034)	2.136*** (0.001)	1.764*** (0.003)	2.231*** (0.000)	1.770*** (0.003)
College	2.757*** (0.001)	1.421 (0.183)	2.531*** (0.001)	1.727** (0.021)	2.697*** (0.000)	1.729** (0.021)
Advanced	3.272*** (0.006)	1.973* (0.082)	2.827*** (0.010)	2.518** (0.012)	3.133*** (0.004)	2.526** (0.012)
<i>General experience</i>	1.013 (0.268)	1.001 (0.891)	1.014 (0.203)	1.005 (0.581)	1.012 (0.285)	1.005 (0.602)
<i>Human capital</i>	0.215* (0.079)	1.069 (0.932)	0.204* (0.054)	1.561 (0.547)	0.200* (0.051)	1.522 (0.571)
<i>Versatility</i>	1.213 (0.367)	1.518** (0.035)	1.212 (0.366)	1.520** (0.034)	1.208 (0.378)	1.520** (0.034)
<i>Residual occupation-wage percentile</i>	x	x	—	—	—	—
<i>Establishment size</i>	—	—	x	x	—	—
<i>Log-wage</i>	x	x	x	x	x	x
<i>High school courses, year, month, children, marital status, age, age², state, occupation, industry</i>	x	x	x	x	x	x

Table A.7: Multinomial logit regressions. Relative risk ratios displayed. EU, OO, and EE denote separations into unemployment, occupational changes with the same employer, and employer–employer transitions, respectively. Sample restricted to full-time employed white males aged 25 to 55. *p*-values in parentheses. Standard errors clustered at the individual level. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Log-pseudolikelihood: -81960653 (columns 1 to 2), -81927248 (columns 3 to 4), and -82088473 (columns 5 to 6). Author’s calculations based on the Survey of Income and Program Participation data as provided by the National Bureau of Economic Research (<http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html>).