Occupational Specialization, Job Mobility, and Transition to Self-Employment[*]

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Abstract

Some occupations are prevalent across a wider range of industries than others. This paper compares how occupational specialization by industry affects the mobility of workers within and across industries. The empirical results show that occupational specialization increases the probability of finding a job in the same industry while hurting chances of changing industries after involuntary termination. However, it increases the probability of voluntarily transitioning to self-employment in another industry. These findings suggest self-employment as a mechanism for overcoming structural barriers to inter-industry mobility.

Keywords: self-employment, entrepreneurial entry, inter-industry job mobility, occupational specialization, employment concentration, skill specificity

1 Introduction

Since the classical works of Knight (1921) and Schumpeter (1934), researchers have been interested in the determinants of entrepreneurial entry (Lucas, 1978; Kihlstrom and Laffont, 1979; Jovanovic, 1982). Although large businesses have attracted the most attention from economists (Brock and Evans, 1989), self-employment have been receiving growing interest in recent decades from researchers who have come to realize that it is more persistent than once thought (Bechhofer and Elliott, 1985). After years of monotonic decline during capitalist development, self-employment and small establishments grew considerably to form a significant section of labor markets in western economies (Blau, 1987; Brock and Evans, 1989; Boissevain, 1981; Granovetter, 1984; Steinmetz and Wright, 1989).[1] Policy makers now consider self-employment as the engine for economic growth

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[1]Analyzing the annual time-series data for the U.S. in the post-WW2 period, Steinmetz and Wright (1989) explained the steady increase in the rate of self-employment since 1970 by self-employment becoming more prevalent not only in the expanding postindustrial "new economy"sectors but also in the traditional ones.

(Rees and Shah, 1986). One-person organizations constitute a significant portion of businesses in U.S. as the number of organizations per capita has increased drastically since the early 1980s (Gartner and Shane, 1995; Katz, 1984). In 2015, the self-employed encompassed a large population, roughly 15 million people or 10 percent of all U.S. workers, and hired twice as many people, amounting to 30 percent of all U.S work force.[2] Despite their size, young and small firms are seen as a key element of a free market and superior generators of new jobs (Birch, 1979, 1981). They are disproportionately responsible for the variation in founding and mortality rates as they are the most frequent and most volatile type of organization (Evans and Leighton, 1989; Katz, 1984), thereby contributing to the formation and transformation of organizational populations (Carroll and Mosakowski, 1987).

The growing importance of self-employment makes understanding the dynamics behind individuals' decision to become entrepreneurs vital. Entry into entrepreneurship has been studied from various angles. Individuals' characteristics such as demographics (Simoes et al., 2015), entrepreneurial ability (van Praag and Cramer, 2001), and wealth (Evans and Jovanovic, 1989) are found to be correlated with their inclination to become entrepreneurs. Others have viewed organizations as incubators of entrepreneurship (Audia and Rider, 2006; Brittain and Freeman, 1986; Freeman, 1986). They analyzed differences among opportunity structures within organizations (Sørensen and Sharkey, 2014) and organizational roles (Dobrev and Barnett, 2005) with respect to propensity to facilitate entrepreneurial activity. Finally, spatial studies have demonstrated the influence of economic concentration and geographical proximity to resources on the rate at which startups are born (Sorenson and Audia, 2000; Stuart and Sorenson, 2003).

In this paper, we focus on the labor market context within which the employment choices are made. Stratification researchers have long recognized that job opportunities are structured by industry and occupation (Hachen, 1990, 1992; Stolzenberg, 1975; Stinchcombe, 1979). They have documented differences between either industrial or occupational segments in attainment and mobility patterns. However, there has been only a few attempts to investigate the associations between these two work structures in worker mobility.

We propose that the nature of an individual's prior job either encourages or discourages the likelihood of entrepreneurship, depending on how industry specific the individual's occupation is. The higher the specificity, the less likely workers are to be able to locate and take advantage of job opportunities in other industries. The lack of transferability of skills across sectors (Elliott and Lindley, 2006; Neal, 1995, 1999) and availability of alternative career options (Kalleberg and Sørensen, 1979; Spilerman, 1977) may induce workers to instead choose self-employment.

Following the lead of scholars who have studied entrepreneurship as a part of career dynamics (Carroll and Mosakowski, 1987; Dobrev and Barnett, 2005; Hachen, 1990), we adopt a careers perspective on entrepreneurship (Burton et al., 2016). Individuals compare different employment-related choices throughout their careers (Douglas and Shepherd, 2002) as they make transitions from one position to another within the labor force (Kerckhoff, 1995). Entrepreneurship is therefore seen

[2] http://www.bls.gov/spotlight/2016/self-employment-in-the-united-states/home.htm

as a *potential* step along the trajectory of jobs and hence treated as a special case of job mobility.

We contribute to the literature by investigating the degree of structural overlap between industry and occupation as a determinant of job mobility. Industries disproportionately employ workers in certain occupations to meet their demands for specific skill sets. Once acquired, industry-specific occupational skills are difficulty to transfer from one industry to another. This can create an employment relation between the worker and industry that is costly to replace for both parties (Autio and Acs, 2010).

One implication of this argument is that there is a trade-off between division of labor and labor market flexibility. One the one hand, most industries rely on tasks performed by workers who must invest in specialized training. Job mobility for such workers might be restricted to their current industries as their skills are less valuable outside the industry. When faced with restricted access to outside labor markets, individuals might be—willingly or forcibly—inclined to become self-employed. On the other hand, workers in occupations that are more evenly distributed across industries may have less incentive to do so as they find it easier to switch industries while staying in wage work.

In this paper, we employ panel data from the National Longitudinal Survey of Youth (NLSY) matched with Occupation Employment Statistics (OES). We measure industry-specificity of an occupation by employment concentration. We divide job shifts by (i) whether they are within or across industries, and (ii) whether they are transitions to self-employment or not. Using binary outcome and event history models, we explore the relationship between employment concentration and the probabilities of different types of job shifts. The relationship is positive for intra-industry movements. This can be due to formation of occupational labor markets where worker mobility between firms is high. Employment concentration is negatively associated with inter-industry mobility, but positively associated with entry into self-employment. In order to understand the mechanism behind the difference between job mobility and entrepreneurial entry for inter-industry movements, we make a distinction between voluntary and involuntary job shifts. The likelihood of changing industries as a paid employee (as a self-employed) decreases (increases) in employment concentration only after involuntary (voluntary) exits. We provide evidence that occupational specialization can restrict inter-industry job mobility, and that self-employment can act as a mechanism for overcoming structural barriers to inter-industry mobility.

The remainder of the paper is structured as follows. The following section presents an overview of the theoretical basis for the predictions. The next section describes the data and methods used. The penultimate section reports the empirical results. The final section concludes with a summary and a discussion of implications.

2 Theory

Industries differ in their production processes and occupational composition (Spilerman, 1977). There is a large diversity of jobs within an industry (Delfgaauw, 2007). Some occupations are unique to certain industries whereas others can be found in a wide range of sectors. This interrelationship between industrial and occupational categories with respect to worker mobility is not well understood.

In this paper, we explore the relationship between industry-specificity of occupations and worker mobility. First, we argue that inter-industry worker mobility frictions are exacerbated by occupational specialization due to limited transferability of skills while the intra-industry frictions are reduced. We hypothesize a positive association between occupational specialization by industry and the degree to which worker mobility is restricted to the current industry. We then examine whether individuals who are in specialized occupations are more likely to become self-employed. We argue that the closer the structural match between an individual's industry and occupation, the more able s/he is to identify and take advantage of entrepreneurial opportunities. We provide evidence that self-employment may be chosen as an alternative to paid employment in other industries. The reason for such a pattern would be twofold. On the one hand, individuals who are unable to find an alternative employment after a job loss may be pushed into self-employment. On the other hand, they may be choosing self-employment voluntarily in order to make a more drastic career change. We explore these two mechanisms.

2.1 Labor market segmentation

The sources of variations in attainment and mobility is a central topic in labor studies. Neoclassical economic theory holds that labor markets are frictionless—labor is perfectly mobile across sectors and regions. High-earning segments attract workers from low-earning segments, thereby reestablishing the competitive wage (Sørensen, 1983). Socioeconomic inequalities are largely explained by differences in human capital and worker productivity (Becker, 1994).

This view is often criticized for being unrealistic, in that it extrapolates from a very special case such as competitive spot markets with open employment relations where the laws of demand and supply apply perfectly (Berg, 1981; Sørensen and Tuma, 1981). Structuralist researchers instead focus on the segmentation and lack of uniformity between labor markets (Tilly and Tilly, 1994; Fevre, 1992). Mobility and attainment patterns are affected by the occupational structure (Hauser et al., 1975; Stolzenberg, 1975; Osterman, 1975). Persistent divergence from the equilibrium shows the existence of barriers to job mobility between segments (Kalleberg and Sørensen, 1979).

A form of stratification research called "new structuralism" argues that attainment processes depend on the structure of positional inequality (Baron and Bielby, 1980). Individual socioeconomic achievement is mediated by one's position within the labor market (Kalleberg and Griffin, 1978). Early new structuralists used simple typologies to distinguish between industries with respect to their capital-labor relations (Beck et al., 1978). Dual economy researchers divided the labor market into high-paying primary sector and low-paying secondary sector (Doeringer and Piore, 1971; Gordon, 1972).[3] Other sociological studies of labor markets emphasize the fragmentation of labor

[3]They have also argued that the demographic characteristics of individuals, such as gender and race, are often correlated with this bifurcation as disadvantaged groups such as women and ethnic minorities are employed dispro-

markets along industrial and occupational lines (Stolzenberg, 1975; Spilerman, 1977; Stinchcombe, 1979; Althauser and Kalleberg, 1981; Kalleberg and Berg, 1987). There are systematic differences between segments in terms of skill and training involved, job security, opportunities for advancement, and compensation (Tilly and Tilly, 1994). These differences persist as worker mobility across segments is limited due to "balkanization" of labor markets (Kerr, 1954).[4]

New structuralists have also sought to incorporate industry and occupation into individual-level models of the determinants of attainment and mobility (Kalleberg and Berg, 1987). The empirical emphasis has shifted from cross-sectional to longitudinal designs as complete life-course surveys and event history analysis tools became available for researchers (Allison, 1984; Tuma et al., 1979; Tuma and Hannan, 1984). These studies use retrospective or prospective data to follow individuals' work histories to model the time-dependent rate of transition between discrete states (e.g., jobs or class-of-worker statuses) as a function of factors such as open vs. closed employment relationships (Sørensen and Tuma, 1981), organizational boundaries (Sandefur, 1981), social class and organizational size (Carroll and Mayer, 1986), religion, occupation of parents, and prior experience (Carroll and Mosakowski, 1987), industrial characteristics (Hachen, 1992), organizational roles (Dobrev and Barnett, 2005), and previous unemployment (Martínez-Granado, 2002; Glocker and Steiner, 2007).

The present paper differs from past work in two ways. First, prior studies have commonly used very broad categories of industries and occupations, which may not fully capture the variation in labor market conditions affecting worker mobility (Kalleberg and Sørensen, 1979).[5] There is an inherent trade-off between the number of industrial-occupational categories used and inter-category homogeneity. Aggregation increases the danger of masking the heterogeneity in worker mobility across categories. We therefore use disaggregated categories of industry and occupation. Second, the relationship between industrial and occupational structures independent of their separable contributions to variations in worker mobility has not been explicitly addressed.[6] We instead explicitly define the type of interdependence between these two work structures that could potentially have important consequences for worker mobility. We introduce specificity as the mechanism that establishes sectoral mobility boundaries. We argue that, for workers who are in occupations that are

portionately in the secondary labor market (Reich et al., 1973).

[4]There are various reasons why persistent barriers to mobility may arise such as discrimination based on sex and race, trade union restrictions on entry, financial risks involved in changing geographies, insufficient information on opportunities, and educational credentials (Wachtel and Betsey, 1972).

[5]In his attempt to explain socioeconomic attainments of individuals by occupational-industrial point of entry at the beginning of their careers, Spilerman (1977, p. 560) laid stress on "specifying the trajectories empirically rather than employing a priori notions as to which specific jobs should be linked together" and warned that not using "a high level of disaggregation in the definition of a job would entail gross simplifications in the descriptions of career structures."

[6]In a simple specification of $y = \beta_1 I + \beta_2 O + \beta_3 X + \varepsilon$, β_2 and β_3 represents the degree of separable contributions of industry I and occupation O respectively. A more explicit representation of the intersection of industry and occupation would assume the specification $y = \beta_1 f(I, O) + \beta_2 I + \beta_3 O + \beta_4 X + \varepsilon$ which takes both separable and interdependent effects into account. Gordon (1971) and Wachtel and Betsey (1972) are early examples of industry and occupation categories used simultaneously, albeit not in a dynamic fashion. Osterman (1975, p. 514) addressed "the need for occupation-industry cells rather than the simple occupational classification" but could not employ them in his study because "their use would have entailed substantial additional expense."

industry-specific, it is easier to transfer skills within industry than across.

2.2 Occupational specialization and job mobility

The occupations are shaped by the formation of labor markets (Tilly and Tilly, 1994). They are sets of activities that collectively fulfill certain roles and functions in the economy (Wright and Perrone, 1977). They are also categorical representations of labor technology differentiated by the tasks involved and the kind of education or training required to perform them (Moscarini and Thomsson, 2008). In this respect, they correspond to the technical aspects of work (Kalleberg and Sørensen, 1979), often—but not necessarily always—crossing industry boundaries (Kalleberg, 1989).

Some occupations have applications across a wider range of industries than others. An occupation whose purpose is to meet the skill demands of a small number of industries represents a narrower labor force than an occupation with presence in a large number of industries. Symmetrically, the rate at which an industry employs an occupation compared to other industries indicates its relative requirement for that type of productive labor. The polarization of supply of and demand for occupational skills among industries may lead to a segmented labor market. Such a division of labor may limit worker mobility between industries (Stolzenberg, 1975).

Let an individual in any given employment situation has the skill set $S = \{p, f, i, o\}$ where elements represent person-, firm-, industry-, and occupation-specific components of work, respectively. We define specificity as a work component being inseparable from its structural dimension. Thus, specificity of a certain kind would entail an inability to transfer skills across its categories—at least not without considerable cost to job reallocation or loss in value (Gathmann and Schonberg, 2010). The first two types of specificities, p–person and f–firm, are widely discussed in human capital (Becker, 1994) and labor economics (Jovanovic, 1979) research. Other researchers have debated whether skills are tied to industries (Kletzer, 1996; Neal, 1995) or to occupations (Gathmann and Schonberg, 2010; Neal, 1999) rather than firms. Firms in the same industry are likely to have comparable organizational forms and rely on similar technologies and resources (Brittain and Freeman, 1980). Much of the variation between firms is therefore likely to derive from industry differences (Spilerman, 1977). For example, Neal (1995, p. 669) provided evidence for wage loss associated with switching industries due to "skills that are neither completely general nor firm-specific but rather specific to a set of firms that produce similar products and services". Complementary to previous empirical studies, we argue that industry- and occupation-specific skills, i-industry and o-occupation, are not mutually exclusive but rather connected and correlated, and that the degree of occupational specialization manifests the significance of their interdependence.

Skill specificity can lead to a tighter match between the worker and the industry.[7] Firms

[7]Our use of the term "skill specificity" may require some further clarification. Almost every job requires skills that are specific in one way or another (Doeringer and Piore, 1971). In the human capital tradition, it refers to firm differentials in marginal productivity gained by training (Becker, 1994). Whereas in internal market tradition, it refers to a vector of skills some of which can be utilized in all firms while others only in a single firm (Doeringer and Piore, 1971). In the present paper, however, it refers to the degree to which the set of skills associated with an occupation can be utilized in, or is transferable to, another industry. As will be argued later, disproportionately high employment in an occupation-industry group reflects specialization. This definition may but does not necessarily

depend on workers who are not easily replaceable while workers are sheltered from external competition to some degree (Althauser, 1989). *Occupational labor markets* are formed with the following characteristics (Althauser and Kalleberg, 1981).[8] First, workers acquire specialized skills through investment in human capital (Wildasin, 2000). Second, there is ample movement between jobs in the market. Worker mobility within a segment is easier than mobility across segments (Tilly and Tilly, 1994). Individuals who invest in education and training to obtain industry-specific occupational skills may thus find it difficult to relocate to another industry (Sorenson and Stuart, 2001). Displaced individuals who also switch industries face wage penalization as they forfeit the return to tenure in their previous industry (Neal, 1995). Occupational specialization can also make labor reallocation more costly (Elliott and Lindley, 2006) because the opportunity cost of leaving the current industry increases, while the outside value of the skill set decreases, in skill specificity. Therefore, occupational specialization leads to employment concentration through greater worker retention due to the lack the transferability of skills (Spilerman, 1977).

On the other hand, bargaining power derived from monopoly positions within the labor submarket can give insiders the ability to defend themselves against potential entrants (Kalleberg and Sørensen, 1979; Stinchcombe, 1979). Firms with similar production technologies and labor requirements may find it costly to replace occupations they rely on. Protection from outside competition by high barriers to entry and industry's reliance on particular skill set can provide incumbent workers greater flexibility to transfer skills to another organization conditional on staying within the same industry. New vacancies generate lateral and upward mobility opportunities through employer change and promotion (Sørensen, 1983). Industries may rely more extensively on preexisting labor pools for occupations with greater industry-specific knowledge. Upward progress within the same occupation through acquisition and further specialization of skills does not necessitate staying with the same employer. The abundance of job opportunities where acquired skills are valuable can also make lateral moves more likely, facilitating the transfer of knowledge between firms (Kalleberg, 1989).

We categorize job mobility into intra- and inter-industry to explore the forces driving the acquisition of industry-specific occupational skills (Carroll et al., 1992). We hypothesize intra-industry mobility to increase, and inter-industry mobility to decrease, in occupational specialization by industry:

Hypothesis 1a *Intra-industry job mobility increases in occupational specialization by industry.*

Hypothesis 1b *Inter-industry job mobility decreases in occupational specialization by industry.*

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imply the kind of complexity or difficulty that some jobs are believed to have (Kalleberg, 1989).

[8] An *occupational labor market* lacks the formality associated with *occupational internal labor market*, which has formal rules that govern entry, job ladders etc., often achieved through collective bargaining (Williamson et al., 1975). Professional and union organization may use such employment contracts to "restrict the supply of potential job applicants relative to the demand for their work" (Althauser and Kalleberg, 1981, p. 131). An occupational labor market, on the other hand, indicates a certain demand and supply distribution that emerges naturally through technical division of labor.

2.3 Occupational specialization and transition to self-employment

The study of entrepreneurial dynamics has evolved dramatically over the past decades. Early studies employed cross-sectional designs to explore the effects of economic opportunity structure as well as socio-psychological values of societies from a historical and comparative perspective (Alexander, 1967; Glade, 1967). Others have formulated entrepreneurial entry as a decision problem based on relative expected earnings from wage and self-employment (Rees and Shah, 1986). Fuchs (1982) was among the first to examine the transition of individuals from wage to self-employment, albeit in a static fashion, showing that the transition probability increases with previous experience in self-employment or in a managerial or professional job. Others have used longitudinal data within a cross-sectional framework. Based on a static model of entrepreneurship, Evans and Jovanovic (1989) provided evidence from National Longitudinal Survey of Young Men (NLS) that liquidity constraints prevent some from becoming entrepreneurs. Katz (1990) used the Panel Study of Income Dynamics (PSID) descriptively to show that a significant portion of individuals who become business owners do not report any intention to do so, and thus the entire workforce needs to be included in the analysis of entry into self-employment. However, although able to show which group of individuals are more likely to be self-employed at a point in time, cross-sectional studies obscure the temporal cause-effect relationship (Georgellis et al., 2005) as it assumes by design that "the process under investigation is in temporal equilibrium" (Carroll and Mayer, 1986, p. 325).

Availability of longitudinal panel data has spawned a growing body of research adopting a dynamic perspective on the effects of socio-structural variables such as career stages (Carroll and Mosakowski, 1987), prior unemployment experiences (Caliendo and Uhlendorff, 2008), intergenerational social capital (Blumberg and Pfann, 2016), and self-selection into bureaucratic organizations (Özcan and Reichstein, 2009). Others have argued that nascent entrepreneurs are "products" of existing organizations (Audia and Rider, 2006; Freeman, 1986). The exposure to entrepreneurial opportunities can vary on organizational dimensions such as age, size, and wage structure (Dobrev and Barnett, 2005; Sørensen and Sharkey, 2014). However, the influence of organizational characteristics may not be the same across all jobs. For example, Dobrev and Barnett (2005) show that the likelihood of leaving an organization to build a new one changes in an individual's role in the organization.

We propose that the labor market context of an individual can encourage or discourage entrepreneurial behavior, depending on the individual's position within the industry-occupation structure. An occupation's specificity to a given industry reflects its centrality to the industry's prevailing production processes (Jacobs, 1983). A key aspect of entrepreneurship is the access to information about opportunities (Burt, 2004; Kirzner, 1997; Shane and Venkataraman, 2000; Stinchcombe, 1965; Venkataraman, 1997). People vary substantially along industrial and occupational dimensions in their exposure to entrepreneurial opportunities. For example, a programmer who works in software publishing industry may be better positioned to discover and exploit such opportunities than a budget analyst working in the same industry. Similarly, the said programmer may also have an advantage compared to another programmer who works in a relatively less well-matched industry such as employment placement agencies. Individuals who hold central positions within their industries can gain technical and managerial skills that can facilitate generation of new ideas and increase the expected rewards from entrepreneurship (Campbell, 2012). They are also more likely to have better connections to resource holders, lower search costs, and access to a larger pool of potential employees (Stuart and Sorenson, 2005). Another reason to expect higher rate of movement into self-employment for specialized occupations pertains to the blocked mobility argument (Brittain and Freeman, 1986; Stinchcombe, 1965). Advancement in the organizational hierarchy, which tends to correlate with occupational specialization, reduces the likelihood of further advancement as the number of promotion opportunities goes down. Rather than switching employers, it may be more rewarding to establish a businesses to attain further advancement. Therefore, we expect the rate of transition into self-employment to be higher for individuals who are in more closely matched industry-occupation groups. We thereby challenge the assumption that socio-structural factors would operate similarly for both job mobility and movement into self-employment (Carroll and Mosakowski, 1987).

Hypothesis 2 *Entry into self-employment increases in occupational specialization by industry.*

We finally take a closer look at inter-industry movements into self-employment. Hypothesis 1b suggests a decrease in inter-industry mobility whereas Hypothesis 2 suggests an increase in entry into self-employment in occupational specialization by industry. The likelihood of a switch into self-employment from paid employment while moving across industries may be negatively affected for the same reasons that make job shifts across industries less likely. In particular, industry-specificity of occupational skills may also make the pursuit of self-employment in a different industry more difficult and less rewarding. However, self-employment can also act as a port of entry for the workers who are barred from paid employment in other industries. Individuals may be choosing to be self-employed when they are unable to find—or anticipate the difficulty in finding—an appropriate paid employment under current labor market conditions (Carroll et al., 1992; Dawson and Henley, 2009). When mobility across industries is restricted, self-employment might be preferred. If individuals who are in well-matched industry-occupation groups do leave their current industries, they may be more likely to do so through self-employment. One reason is that by being one's own boss, an individual can minimize the negative effect of the loss in value of skills associated with industry change on the likelihood of mobility as the need to prove one's value to an employer is no longer a constraining factor. Moreover, the opportunity cost of choosing self-employment over paid employment in a different industry is lower when the occupational skills are specific to the current industry (Sørensen and Sharkey, 2014). Self-employment may then become the more attractive mobility option.

We would also expect the overall effect to be positive due to Schumpeterian (1934) view of the entrepreneur who carries out new combinations. Individuals who leave their existing employment to pursue their entrepreneurial ideas and ambitions do not have to stay within the boundaries of their current industry. They often respond to blocked opportunities within their organizations by creating new organizational forms (Hannan and Freeman, 1988). The newly-formed organization may thus be classified in a different industry than the previous employer. While skill specificity limits mobility between industries through job changes, it may also be indicative of significant knowledge flows between industries through spin-offs. Distinct occupational skills that involve greater technical capabilities may in fact be more valuable outside of the current industry within the entrepreneurial context. Therefore, we expect the rate of transition into self-employment in another industry to increase with occupational employment concentration by industry.

Hypothesis 3 *Inter-industry entry into self-employment increases in occupational employment concentration by industry.*

3 Data and Methodology

To test our propositions, we adopt an individual rather than firm level of analysis to sample the whole workforce as candidates for entrepreneurship instead of only successful entrants, and to control for information on the founder characteristics (Evans and Leighton, 1989). We employ life-course data from the National Longitudinal Survey of Youth 1979 panel (NLSY79) sponsored by the U.S. Bureau of Labor Statistics (BLS). NLSY79 follows a nationally representative sample of American youth who are of age 14 to 22 when first interviewed in 1979 until 2014. Out of three subsamples that comprise the NLSY79 cohort, we exclude the supplementary samples of economically disadvantaged minorities and population serving in U.S. military, and use only the representative cross-sectional sample of 6,111 respondents.

The data is composed of three parts. The first part is the work history data that provides a week-by-week longitudinal record of associated job(s), if employed, which we use to construct continuous spells of tenure for each job held.[9] The use of weeks to construct job tenure is important as state dependence in mobility can take effect in early stages of a job (Farber, 1994; Neal, 1999). The second part is the employer history roster: a collection of annual surveys on all employers ever reported by the respondents.[10] It includes information on the type of industry and occupation as well as class-of-worker status. Respondents are asked to report for every job they have ever had whether they were self-employed or employees in public or private sectors.[11] Finally, NLSY79

[9] If a respondent holds multiple jobs concurrently, NLSY79 designates the "CPS employer", defined as the respondent's current or most recent job, as the primary or main job held.

[10] In NLSY79, the term "job" refers to a given employer, regardless of whether the employer is the same person as the respondent or not.

[11] Self-employed are defined by the Bureau of Labor Statistics (for example, see Bregger, 1963) as persons who operate their own business and derive personal income as profit from the enterprise. Note, however, that incorporated business owners who report their earnings as wages are sometimes recorded as wage workers (Hamilton, 2000; Becker, 1984). NLSY79 classifies respondents as self-employed if they own at least 50 percent of a business, are the chief executive officer or principal managing partner of a business, must file Schedule SE (Form 1040) for Federal income taxes, or identify themselves as independent contractors, independent consultants, or freelancers. It is therefore a heterogeneous group ranging from high-income professionals operating their own practices to small businessmen and low-income marginal workers. It has been acknowledged in the literature that entrepreneurial earnings follow

collects a wide array of information on respondents' demographic and socioeconomic characteristics in each survey year. We merge all three parts using unique identifying numbers assigned to each respondent and each job.

We combine NLSY79 with data from the Occupational Employment Statistics (OES) program of the BLS. OES reports annual estimates of employment and wages in cross-section of occupation and industry groups at the national level.[12] There are two main advantages of OES. First, it is a comprehensive source of information encompassing a wide range of detailed industry-occupation categories. Second, it has been regularly produced for a long period. However, there are two types of unpublished estimates in OES. If either an employment or a wage estimate is unavailable, the occupation appears in the data but the estimates are not released. If both estimates are unavailable, or an occupation is not surveyed at all, the occupation does not appear in the data. For the latter cases, there is not much we can do. For the former cases, we use linear interpolation to fill in the missing estimates in between years with released estimates.

To match these two datasets on industry and occupation, we adopt the following procedure. NLSY79 and OES use different coding schemes to classify occupations and industries. The former uses 2000 Census codes whereas the latter uses SOC and NAICS codes.[13] We developed crosswalks that link Census to the SOC and NAICS codes for each of the major revisions that these classifications have gone through over time. In particular, 2000/2002 Census codes used in NLSY79 are converted to detailed-level 2000 and 2010 SOC codes, and to 3-digit 2002, 2007 and 2012 NAICS codes. The way NAICS codes are used in OES involves a trade-off between the level of detail and the availability of estimates. 2-digit sector codes are too crude to account for the diversity (Carroll et al., 1992). On the other hand, there are too many unreleased estimates in OES at four or more digit level industry codes. Therefore, we use 3-digit codes which provide adequate disaggregation without compromising the amount of data available.[14]

The resulting matched dataset contains respondent-job observations whose durations are split at the time of interview into job episodes. Information on the employers and respondents are updated at the end of each episode. Industrial and occupational classification of a job can thus change episodically. Industry, occupation, and class-of-worker codes that are missing due to item nonresponse are replaced with the mode of the nonmissing values for a given job. This prevents spurious code changes from affecting our results.[15] We also exclude (1) industries that are not surveyed in

a bimodal pattern where some self-employed individuals are 'stars' and others are 'misfits' (Åstebro et al., 2011; Braguinsky et al., 2012). Others have explicitly divided the entrepreneurial class into high and low stratum in their theorization (Perry-Rivers, 2016). Regardless, however, of the exact composition of the self-employed, it is a common enough phenomenon worthy of research in itself. Katz (1990) discusses why considering self-employed rather than entrepreneurs or small business owners can be purposeful.

[12]Cross-sectional estimates are not available at narrower geographic levels such as state, country, or zip code.

[13]Before 2002, NLSY79 uses 1970 Census codes whereas OES uses SIC codes and a proprietary occupational classification system. Because of the difficulty in obtaining a reliable crosswalks between these historical classifications, we limit the period of study to 2002 through 2014.

[14]The only exception to this is that Census 2000 industry codes in 2002 NLSY79 survey are converted to 4-digit NAICS codes, which is the only level at which OES estimates were produced in 2002.

[15]An alternative is to use the first code reported for a given employer (Neal, 1999). However, it is not appropriate for our purposes as the codes used affect the main independent variable rather than the incidence rate (except to

OES including active military duty, (2) public administration, construction, and management of companies and enterprises sectors, and (3) industries without specific definition.[16]

We measure industry-specificity of an occupation by its employment concentration using *industry quotient* (henceforth IQ) defined in Watson (2014). IQ is a variant of location quotient and refers to the ratio of an occupation's share of employment in a specific industry to its share of employment in all industries combined. Formally,

$$IQ_{ijt} = \frac{E_{ijt} / \sum_{i=1}^{J} E_{ijt}}{\sum_{j=1}^{I} E_{ijt} / \sum_{j=1}^{J} \sum_{i=1}^{I} E_{ijt}}$$

where E_{ijt} is the employment in industry i and occupation j in year t for $i = 1, \ldots, I$ and $j = 1, \ldots, J$. IQ represents an industry's relative reliance on an occupation. It is equal to one if the occupation is employed by the industry at the same rate that it is employed in the whole economy. If, on the other hand, the occupation, given its share in the whole economy, constitutes a larger (smaller) segment of the industry's labor, it takes a value greater (less) than one. The advantage of this measure is that it is not sensitive to the absolute number of employment but rather concentration of it. We then take the natural logarithm of IQ as logarithmic transformation effectively alleviates skewness of the measure (Tian, 2013). Table 1 illustrates the variation in IQ and log-transformed IQ among several occupations for the Oil and Gas Extraction industry, and among several industries for Accountants and Auditors. Figure 1 shows that ln(IQ) is normally distributed with mean -0.45. However, this is not the case for individual occupations. Figure 2 demonstrates the substantial difference in how employment concentrations are distributed among industries for two occupations.

[Table 1 about here.]

[Figure 1 about here.]

[Figure 2 about here.]

There is a possibility of partial match between a job and OES whenever the job's Census codes for industry and occupation are converted to multiple SOC and/or NAICS codes.[17] For these

determine whether movement after job exit is within or across industries). This requires us to allow for occupational codes to change within firm over time. Any such change would then not be incorrectly counted as a job switch and appropriately account for the change in IQ, which will be described in a moment. By extension, IQ also takes care of intra-firm transfers or promotions that may lead to occupational shifts. As it is a time-variant measure, its magnitude can change over time during a job spell without resulting in a spurious transition.

[16]Refer to `https://www.bls.gov/oes/oes_ques.htm` for industries that are not surveyed in OES. There is no one-to-one correspondence between NAICS and Census codes for the public administration sector. There are no 3-digit NAICS equivalent of Census codes for the construction and management of companies and enterprises sectors. Lastly, several Census codes refer to unspecific industry definitions (e.g., "Not specified utilities") which cannot be matched with 3-digit NAICS codes.

[17]Any of the two reasons we have mentioned above for unpublished estimates in OES can be responsible for partial matches. In addition to the cases where an industry-occupation combination is completely missing in OES, we cannot calculate IQ when there is a successful match but the total employment estimate is not released.

instances, we choose to be cautious and treat them as if they cannot be matched. There are also cases where a job's Census codes are converted to multiple SOC and/or NAICS codes, and they can all be matched with OES. Each SOC and NAICS code combination would then point at different values of employment and wage. Annual wage estimates are averaged over all matches. To calculate a single IQ value for each job episode, we extend the boundary of industry and/or occupation to encompass multiple SOC and/or NAICS codes. For example, if a Census industry code is converted to two NAICS codes, then IQ provides the measure of the relative reliance of those two industries on a given occupation.

In addition to IQ as the main covariate, we also add two moments of the wage distribution associated with prior employment as measures of the opportunity cost of entrepreneurship (i.e., forgone earnings in paid employment) (Berkhout et al., 2016). OES provides annual wage data for each industry-occupation combination. First, we control for mean annual wage. Occupational status is found to be positively correlated with educational attainment and the propensity to be self-employed (Georgellis et al., 2005). However, higher income categories are also associated with better working conditions and greater job security. The opportunity cost of leaving paid employment for self-employment is also higher for such categories. Therefore, we expect the likelihood of leaving the current employment to be lower for high income jobs. We also add standard deviation around the mean annual wage to control for the degree to which the wage structure is compressed (see Appendix for calculation procedure). Looking at how organizational opportunity structure affects entrepreneurial entry, Sørensen and Sharkey (2014) used maximum wage as a measure of wage ceiling and found that lower maximum wage pushes individuals towards entrepreneurship. Berkhout et al. (2016), on the contrary, showed evidence that the probability of choosing entrepreneurship decreases in mean but increases in variance of the wage distribution in one's (abandoned) labor market segment. These studies, however, do not make a distinction between movements within or across segments. We expect a narrower wage structure to restrict opportunities for career advancement within the current industry and thus push individuals towards other industries and/or self-employment.

We control for potential demographic and family background factors such as gender, age, race, marital and immigrant status, and education (see Simoes et al., 2015, for an extensive review of individual determinants of self-employment). We add two measures of financial status. Total net family income can affect transition rates by two distinct pathways. On the one hand, it indicates attainment and productivity in current employment. A steady family income can make individuals less willing to take risks by switching to self-employment or moving out of their current industry. On the other hand, higher family income can alleviate liquidity constraints on entrepreneurship (Hurst and Lusardi, 2004). The net effect is therefore ambiguous. The other measure of family financial status, whether a family is in poverty in past calendar year, can reduce the ambiguity by controlling for the lower tail of the bimodal earnings distribution of the self-employed (Åstebro et al., 2011). Controlling for acute liquidity problems, we expect the first pathway to takeover and tilt the net effect of family income towards the status quo.

It is also well established in the literature that a history of frequent job changes (i.e., job hopping) increases the odds of subsequent ones as well as of entry into self-employment (Åstebro et al., 2011; Evans and Leighton, 1989; Farber, 1994). Hence, we control for the number of different jobs ever reported prior to the start of a job. Respondents in NLSY79 may also report more than one job in a given week. One reason for dual job holding may be that individuals at the lower end of the earnings distribution work in multiple jobs to generate extra income. Having a secondary job may also be indicative of "testing the waters" for entrepreneurial opportunities. Multiple job holding may be enabling individuals to acquire new skills without actually taking the risk of quitting their primary job, thereby making the transition into self-employment easier (Panos et al., 2014). We therefore conjecture that the dual job holders have a lower likelihood of changing employers but greater likelihood of moving into self-employment. Job episodes are split at the start and stop times of secondary jobs. We construct a dummy variable that indicates whether the main job is accompanied by a secondary job or not.

Respondents also report whether they are in unionized employment. Unions provide job security by creating barriers to entry to internal markets (Sørensen, 1983). Union membership may therefore protect workers from competition and economic uncertainties, thereby reducing their incentive to terminate the employment contract.

There might be geographic differences in mobility patterns as well. We utilize data from NLSY79 on whether the respondents' current residence is in urban or rural areas. The former possess thicker labor markets with greater employment opportunities. The effect of being located in an urban area on job change should thus be positive. Whether this effects carries over to entrepreneurial mobility is ambiguous. We also add region fixed effects.[18]

Respondents are also asked in either 2010 or 2012 to rate their willingness to take risks on a scale from 1 to 10. Less risk averse individuals may be more inclined to seek opportunities outside of their immediate organizational and industrial foci.

Finally, we include two variables that can correlate with the propensity to become an entrepreneur in our self-employment regressions. First, prior self-employment experience can increase the likelihood of subsequent entrepreneurial entries. People gain confidence and managerial experience from their previous ventures even if they fail (Jovanovic, 1982; Evans and Leighton, 1989) They also form ties to resource holders that they can take advantage of later on. Second, entrepreneurial tendencies may be passed on intergenerationally by the association between parents' and their children's occupation (Hauser et al., 1975). Parental involvement in self-employment increases the propensity to become entrepreneurs (Dunn and Holtz-Eakin, 2000). We utilize the data from NLSY79 on whether the occupation of adult male (i.e., father or father figure) present in household when the respondent was 14 is "Managers, Officials and Proprietors".

[18] Geographic regions are defined as Northeastern, Northern Central, Southern, and Western U.S.

4 Results

Table 2 provides descriptive statistics at the respondent-episode level for the variables used in our analyses, some of which are discrete time-varying covariates and some are time-invariant. Pairwise correlations are shown in Table 3.

[Table 2 about here.]

[Table 3 about here.]

We start by defining the types of mobility. Job shifts are separated in two dimensions: (1) intra- or inter-industry (i.e., stayers vs leavers), and (2) transitions to a non-self-employed (non-SE) or a self-employed (SE) job. The mobility events are defined as follows. A job is terminated if its last episode is followed either by another job or a period of unemployment.[19] There are 8,093 such cases where IQ can be calculated. In our sample, 64.5 percent of all job terminations are followed by a spell of unemployment while the rest is followed by another job.[20] An episode is censored if there is no information for the following episode. The rest of the transition types are conditioned by the occurrence of a job termination. We treat a transition as an intra-industry (inter-industry) job shift if the last episode of a job is eventually followed by another job with the same (different) nonmissing Census industry code. We lose 221 and 1,261 transitions due to missing industry code for origin and destination jobs, respectively. Of the remaining 7,243 job shifts, 4,525 (62.5 percent) are inter-industry. Movement across sectors is very common as 3,657 (81 percent) of all inter-industry job shifts are also inter-sector.[21] Next, we determine whether or not a transition to self-employment occurred. Our risk set consists of non-self-employed individuals who either change their employers or become self-employed. There are 6,796 job shifts with identifiable origin and destination class-of-worker status, 705 of which are transitions to self-employment (10.4 percent). If whether a particular type of job shift occurred or not cannot be determined due to missing data, it is coded as censored. Table 4 summarizes the transition probabilities.

[Table 4 about here.]

To test our main hypotheses, we start by looking at the associations between ln(IQ) and the probabilities of different types of mobilities conditional on having made a job shift. The decisions to change industry and to enter into self-employment are specified as binary choice variables. Figure 3 summarizes the results from logistic regression of transition probabilities on ln(IQ) and the control variables (we only report the coefficient on ln(IQ) for corresponding regressions). The

[19] There are some cases where a job is paused rather than terminated. We only count its last active period as termination. We do not reset the clock until there is such occurrence. The results are even stronger if we choose otherwise.

[20] The frequency distribution of unemployment duration after a job termination is highly skewed towards shorter times, with a mean of 10 months for employer changes and 13 months for transitions to self-employment.

[21] Note that we use Census sectors rather than NAICS, although the two are highly similar. Refer to NLSY79 Codebook Supplement Attachment 3 that lists all the industry and sector codes used.

upper section shows that an increase in IQ is associated with an increase in intra-industry mobility and a decrease in inter-industry mobility as predicted by the Hypotheses 1a and 1b respectively. In the lower section, we condition these probabilities on whether they occur after transitions to non-SE or SE. In both cases, the relationships hold. We then turn to Hypothesis 2. The lower section instead assumes that the decision to become self-employed comes before than the decision to stay or leave the industry. Probability of entry into self-employment increases in IQ, providing support for Hypothesis 2. As can be seen in the upper section, this relationship does not change with respect to whether the movement is also intra- or inter-industry.

[Figure 3 about here.]

We next shift the focus from separable effects of IQ on industry and class-of-worker choice to its combined effects. In particular, we use event history analysis to look at the individual associations between ln(IQ) and four different mobility types: (1) intra-industry non-SE to non-SE, (2) inter-industry non-SE to non-SE, (3) intra-industry non-SE to SE, and (4) inter-industry non-SE to SE. To analyze the duration-based data, we use semiparametric Cox proportional hazards regression to run a series of continuous-time discrete-state time-to-event models (Cox, 1972). The advantage of this model when the magnitude and direction of the effects of covariates is of the main interest is that the shape of time-dependence does not have to be specified (Blossfeld et al., 2007).[22] In particular, we employ partial likelihood estimation to estimate the effects of time-dependent covariates with episodically changing values on the instantaneous rates of transition into multiple destination states. The transition rate at time t for the transition to state k is modeled as:

$$r_k(t) = h_k(t) \exp\left\{\beta_1^{(k)} IQ^{(k)} + X^{(k)}(t)\beta^{(k)}\right\}$$

where $X^{(k)}(t)$ and $\beta^{(k)}$ are event-specific vectors of control covariates and their associated coefficients, and $h_k(t)$ is the baseline hazard at time t. We are interested in the sign and the magnitude of $\beta_1^{(k)}$ for different k to test our proposed hypotheses.

The results of Cox regressions with repeatable event (i.e., multiple failure) data with the duration set to time since labor market entry are presented in Table 5.[23] In all models, we control for sectoral and regional fixed effects. Models 1–3 in Table 5 show the transition rates with no reference to class-of-workers status. Model 1 contains all job exits: an event is experienced when an individual quits his or her job. Models 2 and 3 shows intra- and inter-industry job shifts respectively.[24]

[22] Replicating the analysis using exponential and Weibull models yields similar results.

[23] To make sure that our results are robust to duration and failure specification, we first replicated the analysis by resetting the clock at each job exit or change to effectively restart the same hazard function at every job change. Furthermore, it is possible for the hazard of transition into self-employment from a non-self-employed job to be dependent upon the total time spent as a wage employee. We set the duration to time spent in class-of-worker status (i.e., non-self-employed or self-employed) and the failure event to transition from paid employment to self-employment. The results remain materially the same in both procedures.

[24] Note the distinction between job "exits" and job "changes". The number of failures in model 1 is not equal to sum of number of failures in models 2 and 3. This is because some job exits happen without being followed by another job.

[Table 5 about here.]

Females are more likely than males to quit their jobs according to model 1. However, the effect holds for inter-industry movements in model 3 but becomes opposite for intra-industry movements in model 2. Limited advancement opportunities within their current industry may be pushing females towards more dispersed employment patterns. Whites are less likely to quit or switch their jobs, although the effect is statistically insignificant. We add age at the time of interview and its squared term to account for nonlinearity in age dependence. The negative coefficient on age and positive coefficient on age square suggests a convex function where the job stability increases with age and experience at a decreasing rate. This is perhaps due to older respondents reaching the age of retirement. There is a significant positive effect of being married and a negative effect of the number of children in household in model 1 but not in models 2 and 3. Log of family income in past calendar year is a negative and significant factor. This confirms our previous conjecture that higher family income attenuates the incentive to quit or change current employment status. We control for the variation that might arise due to some individuals having histories of job instability. Log of number of different jobs held prior to the current job has the expected positive effect on subsequent job changes. The strong and consistent negative coefficient on dual job holding may be due to how the data is structured: individuals try new employment and/or entrepreneurial ventures without actually quitting their main job. This would result in an underestimation of the number of job changes. By including a dummy variable for dual job holding, we are effectively restricting our results to the main job held net of the effect of having a secondary job. The sign of coefficient on having a union contract is consistent with our prior expectations in all three models. Risk-taking score has positive and significant coefficient both in models 1 and 3 but not in 2, suggesting that risk-seeking behavior is more relevant when making the jump from one industry to another. The coefficients of the two ethnic background variables, being born in the U.S. and being a U.S. citizen in 1984, are not significant. Whether the current residence is in urban area or not, and poverty status are also not significant predictors. Highest grade completed and its squared term also do not provide any conclusive evidence for the effect of education on mobility in our sample.

Models 1–3 in Table 5 suggest that ln(IQ) has a positive and significant effect on job exits. This relationship is mainly a consequence of greater intra-industry mobility. The sign of coefficient is negative on model 3 but not significant. These results support Hypothesis 1a but not 1b. This is, however, not conclusive as we have not yet differentiated between class-of-worker statuses. We isolate the transitions across non-SE jobs in Models 4–6, which present a more direct test of Hypotheses 1a and 1b by restricting the risk set to non-SE. As in model 1, model 4 represents all employer changes (i.e., it excludes self-employment as a potential destination). Models 5 and 6 show that, consistent with our predictions, ln(IQ) has positive effect on intra-industry and negative effect on inter-industry shifts, both of which are statistically significant at 10 percent and 5 percent levels respectively. Not only high IQ encourages intra-industry job mobility but it also hurts the chances of switching to another job in a different industry than the current one, providing support for Hypotheses 1a and 1b. The coefficients on controls are very similar to the ones we observe in models 1–3. Familial variables cease to be significant predictors. There is also a negative and highly significant effect of being in poverty for inter-industry employer changes. In other words, being in poverty decreases the likelihood of finding a job in another industry. Lastly, the effect of multiple job holding is reversed for employer changes. It might be that these individuals work in multiple jobs to earn extra income without quitting their main jobs.

Models 7–9 in Table 5 present the results for entry into self-employment. The transition rate is positively affected by ln(IQ) not only for intra-industry but also inter-industry movements. Comparing the magnitudes of coefficients on ln(IQ) in models 7–9 and with those in models 4–6, it is evident that (1) the positive effect of ln(IQ) on entry into self-employment is less strong for inter-industry movements that it is for intra-industry movements, lending support to Hypothesis 1a and 1b, (2) the overall positive effect of ln(IQ) is greater for the transition from a non-self-employed to a self-employed job than it is for the transition from a non-self-employed to another, lending support to Hypothesis 2, and (3) the effect of ln(IQ) on inter-industry entry into self-employment stays positive, lending support to Hypothesis 3.

Females and whites are less likely to become self-employed, and even less so within their current industry (see model 8). The likelihood of inter-industry transition into self-employment increases in education in a concave fashion. The coefficients on highest grade completed and its square term are highly significant in model 7 and 9, which suggests that movement involving change in both class-of-worker status (i.e., non-self-employed to self-employed) and industry requires a higher level of educational attainment. An interesting pattern appears for current residence. In contrast to regressions for employer change in models 4–6, models 7–9 suggest that living in urban areas reduces the likelihood of becoming self-employed, especially so for entries that involve industry change. Compared to models 4–6, the effect of multiple job holding reverses in direction in models 7–9. Individuals who hold a secondary job are more likely to transition to self-employment regardless of whether they are stayers or leavers. This provides an evidence to our earlier conjecture that dual job holding may signal entrepreneurial intent. Individuals may also be holding onto their primary paid employment before making the switch until they feel confident that their business can sustain them. As expected, risk-seeking individuals are more likely to switch to self-employment. The effect is null for models 4-6, which means the positive effect of risk-taking score in models 1-3 derives from models 7-9. Lastly, we include two additional variables that are found to correlate with entrepreneurial entry. In all three models, prior self-employment experience is a significant and positive predictor of subsequent ventures. Whether the adult male (i.e., father or father figure) present in household when the respondent was 14 had managerial or proprietor experience does not follow any significant pattern.

We have so far deferred the discussion on the industry-occupation group wage structure. Models 1–3 and models 4–6 present very similar results, although the latter are more conclusive as they specify origin and destination jobs as non-self-employed. Model 4 shows that log mean annual wage of the industry-occupation group has a negative effect on the likelihood of employer change. This effect remains significant only for intra-industry movements, suggesting a lower incentive to move out of current industry as a wage worker when the wage structure is more favorable. Model 5 provides some evidence for higher inter-industry mobility for industry-occupation groups of higher status, although the effect is not significant. Variance in wage measures how compressed the distribution of wages. It is a significant factor only in model 6. Log standard deviation around the mean wage is associated with a greater tendency to leave the industry. This result contradicts the expectation that a narrow wage structure induces individuals to seek further attainment elsewhere. For example, (Sørensen and Sharkey, 2014) demonstrate that a higher wage ceiling in an organization reduces the rate of movement to other employers. We observe that wage inequality in an industry-occupation group is associated with increased outflow. This might be due to increased chances of downward mobility and employment instability. Bureaucratized jobs with little variation in wages tend to provide more employment security. We then turn our attention to models 7–9 where the destination job is classified as becoming self-employed. Consistent with previous reports (Berkhout et al., 2016), we find a negative (positive) relationship between income level (variation) in prior employment and the propensity for choosing entrepreneurship (see model 7). However, entrepreneurial entry is affected by wage structure only for inter-industry movements, which is the opposite of what we observe for employer changes. Individuals in wage employment in high-wage high-variation segments might be facing a dilemma of whether to seek employment in other industries or become self-employed.

Figure 4 presents Nelson-Aalen cumulative hazard functions by ln(IQ) below and above its mean. All graphs start at around week 1145 when we start observing failure events within the period of observation that start with 2002 survey. The first column illustrates the positive effect of ln(IQ) on job quits. This effect is, however, only an average: the second and third columns show that the difference between above- and below-mean ln(IQ) groups is even larger for intra-industry moves but either subdued or reversed in direction for inter-industry moves. In particular, for movements across industries, cumulative hazard function of above-mean ln(IQ) is first-order dominated by that of below-mean ln(IQ) for job shifts, but vice versa for entrepreneurial entry. The labor market positions restrict inter-industry mobility for wage employees while making individuals more likely to become entrepreneurs while changing industries. Although the difference between above- and below-mean ln(IQ) groups is not as large in the third column as it is in the first two columns, empirical results have shown that the differences are significant.

[Figure 4 about here.]

Push vs. pull factors

Models 6 and 9 in Table 5 indicate a contrast between switching employers and becoming self-employed. The likelihood of entry into self-employment conditional on leaving the industry is increasing in ln(IQ) not only relative to switching employers (Hypothesis 2), but also in absolute terms (Hypothesis 3). The question then becomes one of identifying the mechanisms by which such difference arises.

It has been debated in the literature whether "push" or "pull" factors are more dominant in job mobility and entry into self-employment (Caliendo and Uhlendorff, 2007; Hachen, 1990; Martínez-Granado, 2002; Rosenfeld, 1992). Some workers may be pushed into self-employment following a layoff in the absence of available paid-employment opportunities (Dawson and Henley, 2009). Alternatively, they can voluntarily quit their jobs to pursue other opportunities.

Hence, we separate between involuntary and voluntary exits in order to see which type of mobilities are most affected by push or pull factors. Respondents in NLSY79 are asked to report the reason to quit their jobs. There is a range of different ways to answer this question, which we use to construct a dummy variable. Consistent with the prior research on job displacement (for examples Neal, 1995; Hachen, 1990), we define involuntary exits as leaving a job due to layoff, closure of the workplace, termination of contract, being fired, and ending of a government program. All other financial, personal, and family reasons of exit are classified as voluntary. We treat voluntary exits censored when analyzing involuntary exits, and vice versa. Table 6 and 7 reproduce the results in models 4–6 and 7–9 in Table 5, respectively, for involuntary and voluntary exits.[25]

[Table 6 about here.]

[Table 7 about here.]

In Hypothesis 1b, we predicted that for occupations that are more industry-specific, there is a lower chance of employment in another industry. This limitation may be exacerbated under adverse conditions such as industrial downturn or technological change resulting in worker displacement. Workers who lose their jobs involuntarily and become unemployed following a displacement may lack inter-industry mobility. We therefore expect the negative association between the rate of inter-industry job-to-job mobility and ln(IQ) to be more prevalent for involuntary exits.

We test this prediction in Table 6. As before, models 1 and 2 do not distinguish between the direction of movement with respect to industry. The coefficient on ln(IQ) is positive and significant for voluntary exits. Models 3 and 4 shows the results for intra-industry movements only. The effect of ln(IQ) is highly strong and consistent: it is positive and significant in both models. However, model 5 shows that for inter-industry moves the effect of ln(IQ) is negative and significant only for involuntary exits. What this reveals is that the negative effect observed in model 6 in Table 5 is mainly due to the fact that individuals in industry-specific occupations are less likely to find paid employment in another industry following involuntary job loss. The sign of coefficient on sex is positive and significant in model 6. The positive and significant effect observed in model 6 in Table 5 is a result of voluntary exits, perhaps due to maternal leaves. Women who quit their jobs due to pregnancy or child rearing may find it difficult to get their jobs back when they return to employment postpartum. They may be forced to disperse in search of a new job. Years of education makes involuntary job loss less likely while enabling inter-industry shifts, albeit the effect is not

[25] The number of failures do not necessarily add up across the models. This is due to missing values of reason to quit variable due to item nonresponse in NLSY79.

significant. As before, family income takes away the incentive to make any kind of move. As households get poorer, employed members are more likely to seek a different job.

The distinction between push and pull factors is less unambiguous for entry into self-employment. On the one hand, self-employment may be largely opportunistic (Georgellis et al., 2005). Unemployment might push some individuals into self-employment. On the other hand, self-employment might be motivated by positive reasons such as entrepreneurial aspirations, potential earning differentials, and desire for autonomy.

In Hypothesis 3, we predicted the rate of inter-industry transition to self-employment to increase in ln(IQ). There are several reasons to expect this relationship to be dominant for voluntary exits. Industries create higher relative demand for occupations that are central to their production processes. Individuals who occupy these roles may be more likely to develop technical capabilities and build stronger personal networks. Greater potential gains from entrepreneurship will increase their incentive to make a voluntary switch into self-employment. Individuals in such positions may have an advantage in perceiving and utilizing entrepreneurial opportunities available in other industries.

They may also be reacting in anticipation of the inter-industry labor mobility restrictions predicted by Hypothesis 1b. The process of starting a business usually requires significant time and resources. If inter-industry mobility as a wage worker is more difficult for individuals in concentrated occupations, they may choose to plan their transition before they leave their primary wage job. The restriction to stay within the current industry may not be as strong for entrepreneurship as it is for paid employment as individuals can start businesses without having to rely on the discretion of employers in other industries. In these circumstances, we expect pull factors to dominate push factors. Therefore, we predict the opposite mechanism to be prevalent here. The positive association between the rate of inter-industry entry into self-employment and ln(IQ) should be more prevalent for voluntary exits.

We test whether this prediction holds in Table 7 where the destination state is self-employment. As in Table 6, models 3 and 4 show the results for intra-industry movements. We have already observed a strong positive effect of ln(IQ) on inter-industry transition into self-employment in model 8 in Table 5. Models 3 and 4 replicate this result for both involuntary and voluntary shifts. Although the effect is significant at only 10 percent level, it might be because of the fact that relatively fewer number of intra-industry transitions into self-employment occurs after involuntary job loss. Models 5 and 6 replicate for involuntary and voluntary shifts separately what we have already observed in model 9 in Table 5: a positive and significant effect of ln(IQ) on inter-industry transition into self-employment. This relationship is much more likely to be observed for voluntary exits. In other words, individuals in specialized occupations are more likely to become self-employed in another industry after voluntarily quiting their jobs.

Table 8 summarizes the association between an increase in ln(IQ) on various transition rates. Models 1 and 2 in both Table 6 and 7 indicate a similar pattern for involuntary and voluntary exits: the former is not significantly affected but the latter is positively affected by ln(IQ). There is, however, a clear asymmetry between the two destination states for inter-industry moves. Ln(IQ) decreases the probability of transitioning to a wage job in an alternative industry after job loss. But it increases the probability of voluntary entry into self-employment.

[Table 8 about here.]

5 Conclusion

Researchers have long been interested in understanding the relationship between labor market structure and mobility. Although acknowledging that opportunities are distributed unevenly across industries and occupations, the literature has been silent on potential interplays between these two work structures. In this paper, we propose that the degree to which occupations are industry specific plays a role in mobility outcomes. Treating employment concentration as a manifestation of this specificity, we argue that occupational specialization by industry creates closed labor markets with high intra-industry mobility but low inter-industry mobility for workers.

We adopt a careers perspective on entrepreneurship (Burton et al., 2016; Rider et al., 2016), which portrays it as a career choice that needs to be studied in a life-course framework. We explored whether and how the propensity to switch employers or to become self-employed varies by the degree of match between industry and occupation. Entrepreneurial opportunities may be more readily identified and utilized by incumbent employees in industry-occupation groups with high employment concentration.

We test our predictions using data from NLSY79 and OES matched on industry and occupation. We show evidence that with greater occupational specialization (1) worker mobility becomes more fluid conditional on staying within the same industry, (2) mobility towards an alternative industry gets restricted, (3) transition from wage to self-employment becomes more likely, and (4) inter-industry mobility barriers can be overcome through self-employment. It is also evident that there is a difference between switching employers and becoming self-employed for those who leave their industries. Finding employment in an alternative industry becomes harder for individuals in industry-specific occupations as their skills are less valued outside. However, the relationship between specificity and the rate of inter-industry entry into self-employment remains positive. For nascent entrepreneurs in such industry-occupation groups, inter-industry mobility is not affected negatively as it is for those who remain paid employees. If individuals in high concentration positions leave their industries, they are more likely to do so through self-employment.

In order to explore the mechanism for the discrepancy between job mobility and entrepreneurial entry with respect to how they are affected by labor market structure, we make the distinction between involuntary and voluntary exits. The negative effect of occupational specialization on inter-industry job mobility is mainly because job losses are unlikely to end up in employment in a different industry. The opposite is true for entrepreneurial entry: individuals who voluntarily decide to quit their jobs were the ones who became self-employed in another industry. This suggests a different interpretation of self-employment than is suggested by the studies that portray it as a "shelter" from unemployment for people who are unable to find a job in other industries as a wage worker. In fact, entry into self-employment mostly comes after voluntary exits, suggesting that it may be acting as a mechanism for overcoming structural barriers to inter-industry mobility.

In this paper, we contribute to the entrepreneurship literature by showing that, after controlling for individual factors, structural factors have discernible effect on entry. We also contribute to labor market segmentation and mobility literature by analyzing an interrelationship between two work structures, industry and occupation. Analyzing intra- and inter-industry moves separately and using disaggregated industrial and occupational categories allows us to show that the pattern of mobility is more complicated than usually assumed. The dynamics of individuals' career decisions are highly varied. It is also important to note that assuming homogeneity among workers in a given work organization may miss important variation with respect to how they are influenced by their positions with respect to other work structures. Structural features of labor markets can affect job and entrepreneurial mobility differently. It is therefore important to recognize that labor market mobility is not a monolithic but a multifaceted phenomenon.

Appendix: Wage variation calculation

The extent to which the wage structure of an industry-occupation category is compressed is measured by wage variation. OES provides mean and percentile (10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th}) annual wages. Parameters can be inferred for a given distribution that satisfies quantile conditions (Cook, 2010).

Let Q be the quantile function of a given probability distribution with parameter vector $\boldsymbol{\theta}$. We solve for $\boldsymbol{\theta}$ that satisfies the following nonlinear system of equations:

$$\boldsymbol{q}_p = Q(\boldsymbol{p}, \boldsymbol{\theta})$$

where $\boldsymbol{p}$ is the vector of specified quantiles and $\boldsymbol{q}$ is the vector of observed values of the random variable at those quantiles. Let X be a random variable from a two-parameter family. The system is overdetermined when the dimension of $\boldsymbol{p}$ (or $\boldsymbol{q}$) is higher than two. In other words, only two quantiles can be used at the same time to compute the parameters. In case where $\overline{x}$ is known and thus θ is a scalar, we get different solutions for the unknown parameter for each known quantile values. To obtain exact solutions while utilizing information available on all quantiles, we instead solve for $\boldsymbol{\theta}$ that minimizes the discrepancy:

$$\big(\boldsymbol{q}_p - Q(\boldsymbol{p}, \boldsymbol{\theta})\big)'\big(\boldsymbol{q}_{\boldsymbol{p}} - Q(\boldsymbol{p}, \boldsymbol{\theta})\big).$$

If X is normally distributed with mean μ and standard deviation σ, it has the same distribution as $\sigma Z + \mu$ where Z is standard normal random variable. Given the CDF is continuous and strictly monotonically increasing, the quantile function is the inverse of CDF. Thus

$$P(X < x_p) = P(\sigma Z + \mu < x_p) = P\left(Z < \frac{x_p - \mu}{\sigma}\right) = Q_Z^{-1}\left(\frac{x_p - \mu}{\sigma}\right) = p$$

which yields the discrepancy

$$x_p - \mu - Q_Z(p)\sigma$$

for a certain p. For a set of p-values, we solve for σ and μ that minimizes

$$\big(\boldsymbol{x}_p - \boldsymbol{\mu} - Q_Z(\boldsymbol{p})\boldsymbol{\sigma}\big)'\big(\boldsymbol{x}_p - \boldsymbol{\mu} - Q_Z(\boldsymbol{p})\boldsymbol{\sigma}\big)$$

or

$$\sum_p \big(x_p - \mu - Q_Z(p)\sigma\big)^2.$$

Replacing μ with already known $\overline{x}$ and finding a zero of the first derivative yields

$$\sigma^* = \frac{\sum_p x_p Q_Z(p) - \sum_p \overline{x} Q_Z(p)}{\sum_p Q_Z^2(p)}.$$

If $\overline{x}$ is not known, partial derivative of the objective function with respect to μ yields

$$\tilde{\mu} = \frac{1}{n}\left(\sum_p x_p - \sum_p Q_Z(p)\sigma\right)$$

where n is the dimension of $\boldsymbol{p}$—or the number of quantiles used in estimation. Substituting $\overline{x}$ in σ^* with $\tilde{\mu}$ yields

$$\tilde{\sigma} = \frac{n\sum_p Q_Z(p)x_p - \sum_p Q_Z(p)\sum_p x_p}{n\sum_p Q_Z^2(p) - \Big(\sum_p Q_Z(p)\Big)^2}.$$

$\tilde{\mu}$ is then calculated simply by substituting σ with $\tilde{\sigma}$.

The procedure can be easily extended to log-normal distribution for the cases where $\overline{x}$ is not known. Partial derivatives of the objective function with respect to μ and σ yield the same $\tilde{\mu}$ and $\tilde{\sigma}$ as location and scale parameters, albeit with $\log(x_p)$ replacing x_p. For the other cases where $\overline{x}$ is known, however, μ and x_p in the objective function need to be replaced with $\log(\overline{x}) - \sigma^2/2$ (instead of $\overline{x}$) and $\log(x_p)$, respectively, before derivation. Because the derivative in this case is unwieldy and difficult to be solved for σ, we resort to numerical optimization using Mata's `optimize` function:

```
mata
mata clear
void eval0(todo, sigma, real scalar i, y, g, H)
{
p = (0.1 \ 0.25 \ 0.5 \ 0.75 \ 0.9)
xbar = st_data(i, "a_mean")
```

```
mu = J(5, 1, log(xbar) - (sigma^2)/2)
xp = log(st_data(i, "a_pct10 a_pct25 a_pct50 a_pct75 a_pct90")')
y = sum(((invnormal(p) :* sigma) + mu - xp):^2)
}
for(i=1;i<=st_nobs();i++) {
S = optimize_init()
optimize_init_which(S, "min")
optimize_init_evaluator(S, &eval0())
optimize_init_evaluatortype(S, "d0")
optimize_init_params(S, 0)
optimize_init_argument(S, 1, i)
sigma = optimize(S)
mu = log(st_data(i, "a_mean")) - (sigma^2)/2
std = sqrt((exp(sigma^2) - 1) * (exp(2*mu + sigma^2)))
st_store(i, "a_std", std)
}
end
```

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Figure 1: Histogram of Ln(IQ).

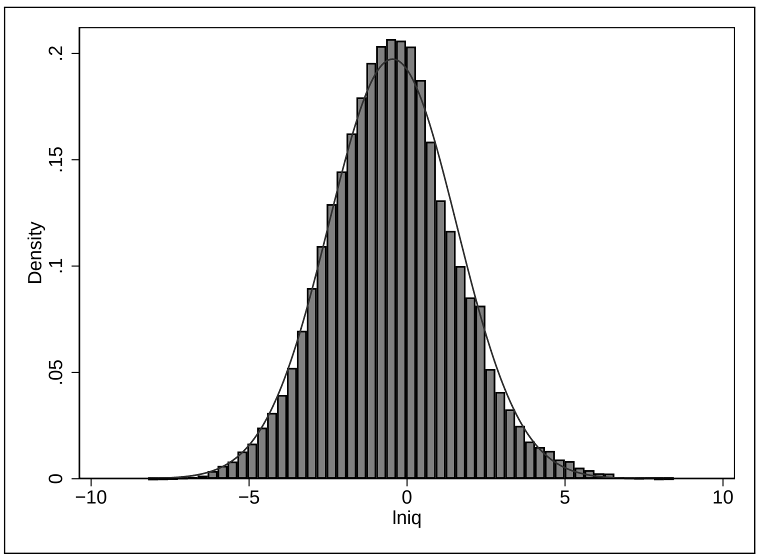
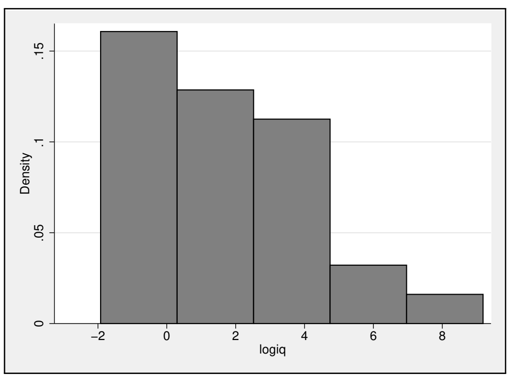


Figure 2: Histograms of Ln(IQ) for different occupations.

(a) Wind Turbine Service Technicians



(b) Accountants and Auditors

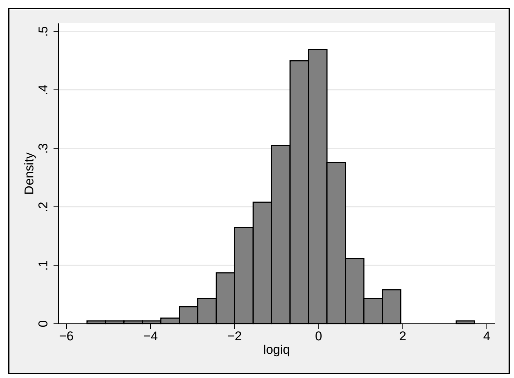
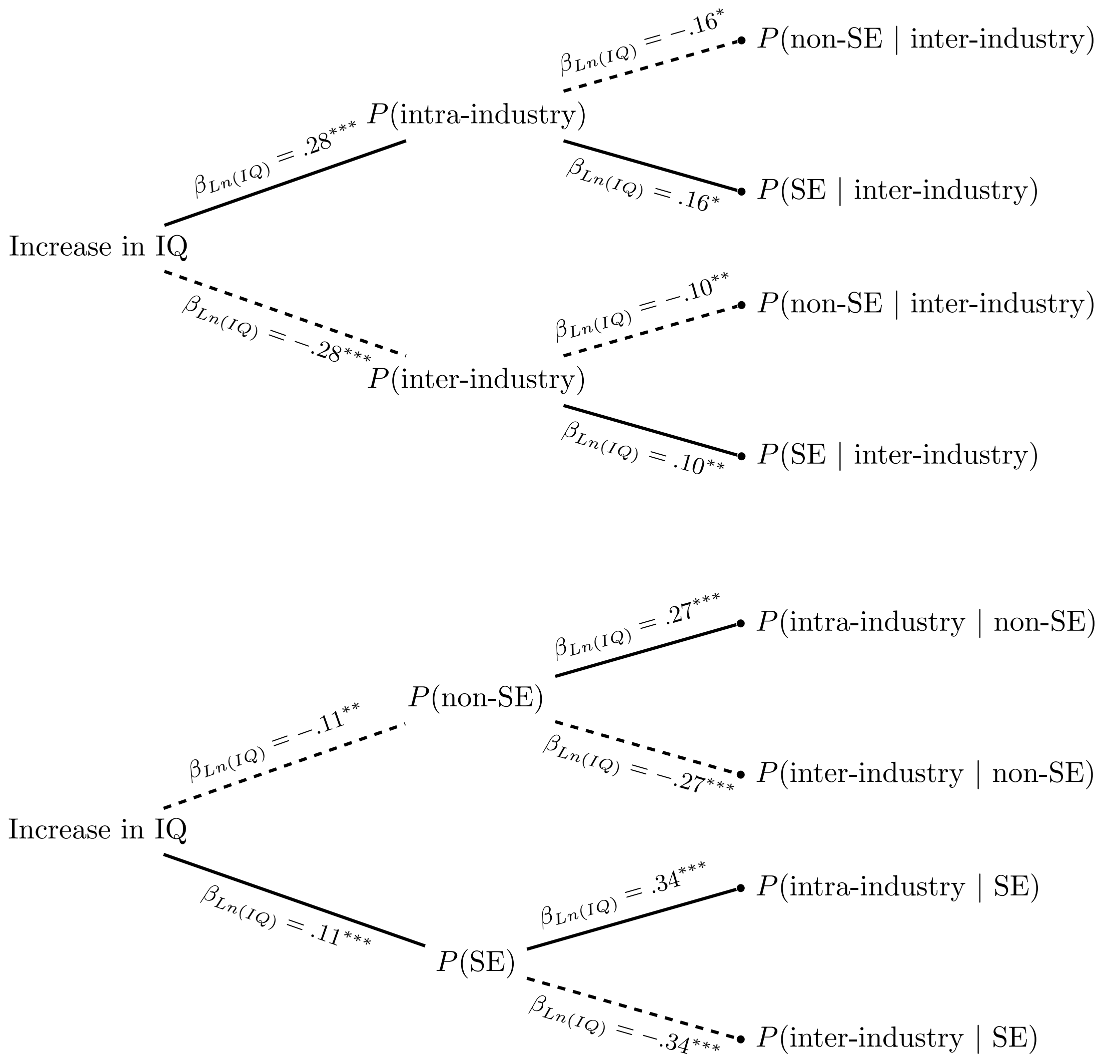


Figure 3: Effect of an increase in IQ on conditional probabilities



Note: Solid (dashed) lines denote positive (negative) effects. Results are derived from logistic regression of transitions on Ln(IQ) and the control variables with region and year fixed effects. Standard errors are clustered by individual. Sample is restricted to 6,298 job shifts with the following properties: (1) origin and destination industry codes are nonmissing, (2) origin job is non-self-employed, (3) class-or-worker status of destination job is reported (i.e., either non-self-employed or self-employed). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4: Nelson-Aalen cumulative hazard functions by Ln(IQ) group.

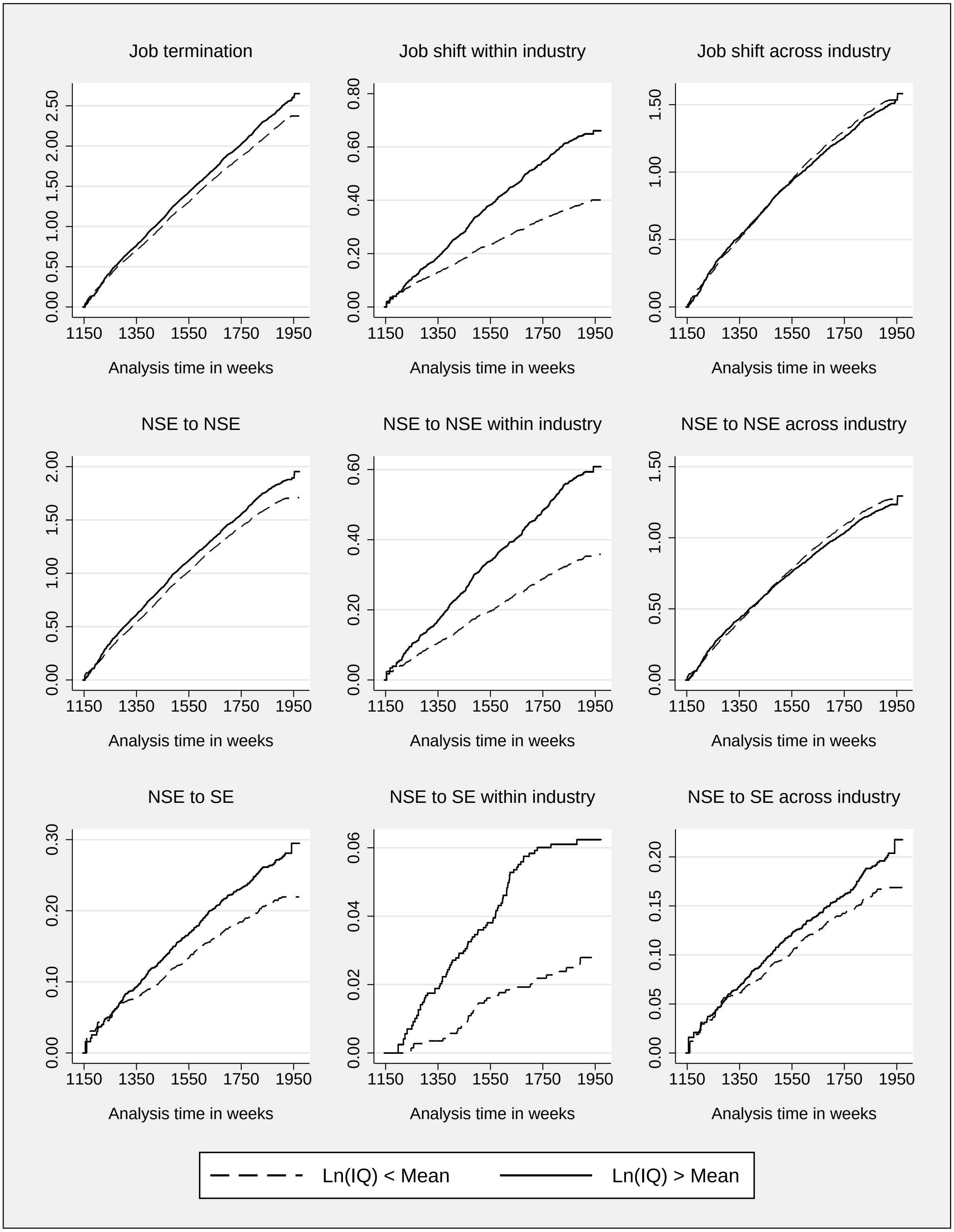


Table 1: Industry quotient for several industry-occupation combinations in 2015

NAICS	Industry	SOC	Occupation	IQ	Ln(IQ)
211	Oil & Gas Extraction	17-2171	Petroleum Engineers	279	5.63
		17-2112	Industrial Engineers	4.72	1.55
		13-2031	Budget Analysts	1.02	0.02
		41-2011	Cashiers	0.01	-5.09
551	Management of Companies	13-2011	Accountants & Auditors	4.69	1.55
333	Machinery Manufacturing			1.03	0.02
401	Air Transportation			0.26	-1.36
445	Food & Beverage Stores			0.06	-2.88

Table 2: Descriptive statistics

	N	Mean	SD	Min	Max
Main effect:					
Ln(industry quotient)	18,853	1.52	1.71	−5.89	7.62
Demographics:					
Female	18,853	0.58	0.49	0	1
White	18,853	0.84	0.37	0	1
Age	18,853	47.02	4.56	37	58
Born in the U.S.	18,853	0.96	0.19	0	1
U.S. citizen	18,853	0.97	0.17	0	1
Highest grade completed	18,853	13.98	2.56	0	20
Married	18,853	0.62	0.48	0	1
Number of children in household	18,853	1.07	1.13	0	8
Financial:					
Mean annual wage (in $1,000)	18,853	50.63	31.72	14.24	233.85
Std. dev. of annual wage (in $1,000)	18,853	18.63	14.31	1.42	98.62
Total net family income (in $1,000)	18,853	82.29	79.81	0	595.99
Family in poverty	18,853	0.06	0.24	0	1
Other controls:					
Current residence in urban	18,853	0.71	0.45	0	1
No. of jobs reported as of int. date	18,853	13.31	7.33	1	60
Secondary job held	18,853	0.17	0.38	0	1
Covered by union or employee contract	18,853	0.06	0.23	0	1
Risk-taking score	18,853	4.87	2.58	0	10
Entrepreneurial:					
Prior self-employment experience	18,853	0.35	0.48	0	1
Father had managerial experience	14,492	0.17	0.38	0	1

NOTE: Sample is restricted to individuals who experienced job termination. Descriptive statistics are at the respondent-episode level of analysis. Citizenship is recorded in 1984. Wealth is truncated if top-coded.

Table 3: Pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Ln(industry quotient)	1.00																		
(2) Female	−0.02	1.00																	
(3) White	−0.04	−0.01	1.00																
(4) Age	−0.04	0.01	0.03	1.00															
(5) Born in the U.S.	0.01	−0.00	0.14	0.01	1.00														
(6) Highest grade completed	−0.04	−0.02	0.14	0.05	0.05	1.00													
(7) Married	−0.02	−0.05	0.18	0.01	0.05	0.10	1.00												
(8) Number of children in household	−0.01	0.02	0.03	−0.20	0.01	0.13	0.33	1.00											
(9) Ln(mean annual wage)	−0.16	−0.20	0.16	0.17	0.03	0.45	0.14	0.07	1.00										
(10) Ln(std. dev. of annual wage)	−0.14	−0.22	0.17	0.14	0.03	0.44	0.14	0.08	0.96	1.00									
(11) Ln(total net family income)	−0.08	−0.11	0.22	0.10	0.04	0.40	0.50	0.21	0.49	0.47	1.00								
(12) Family in poverty	0.05	0.06	−0.17	−0.01	−0.04	−0.15	−0.21	0.00	−0.22	−0.22	−0.58	1.00							
(13) Current residence in urban	−0.04	−0.03	−0.15	0.03	−0.05	0.14	−0.12	0.01	0.08	0.08	0.03	0.03	1.00						
(14) Ln(no. of jobs reported as of int. date)	0.05	−0.00	−0.01	0.01	0.01	0.08	−0.15	−0.12	−0.07	−0.05	−0.16	0.06	0.08	1.00					
(15) Secondary job held	0.02	0.02	−0.01	0.01	−0.01	0.06	−0.01	0.01	−0.02	−0.02	0.02	−0.04	−0.02	0.12	1.00				
(16) Covered by union or employee contract	0.02	0.04	−0.00	0.02	0.00	0.13	0.04	0.04	0.03	0.03	0.05	−0.03	0.00	0.01	0.03	1.00			
(17) Risk-taking score	−0.02	−0.15	0.01	−0.02	−0.03	0.11	−0.01	0.02	0.13	0.14	0.10	−0.00	0.07	0.12	0.03	−0.03	1.00		
(18) Prior self-employment experience	0.03	−0.04	0.05	0.06	0.02	0.01	−0.00	−0.01	−0.01	0.02	−0.03	0.00	−0.01	0.26	0.11	0.01	0.11	1.00	
(19) Father had managerial experience	−0.00	−0.02	0.10	−0.01	0.02	0.18	0.05	0.07	0.11	0.13	0.12	−0.06	0.03	0.03	0.03	0.03	0.05	0.03	1.00

NOTE: Standard errors are in parentheses.

Table 4: Transition frequencies

	NSE to NSE		NSE to SE		Total	
	Involuntary	Voluntary	Involuntary	Voluntary	Involuntary	Voluntary
Intra-industry	.355		.029		.384	
	.111	.244	.010	.019	.121	.263
Inter-industry	.561		.055		.616	
	.190	.371	.020	.035	.210	.406
Total	.916		.084		1	
	.301	.615	.030	.054	.331	.669

NOTE: Sample is restricted to 5,913 job shifts with the following properties: (1) origin and destination industry codes are nonmissing, (2) origin job is non-self-employed, class-or-worker status of destination job is reported (i.e., either non-self-employed or self-employed), (4) whether the origin job is terminated voluntarily or involuntarily is reported.

Table 5: Cox regression of time to transition

Transition type:	Job termination/change			Non-self-employed to non-self-employed			Non-self-employed to self-employed		
Industry direction:	All	Intra	Inter	All	Intra	Inter	All	Intra	Inter
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Main effect:									
Ln(industry quotient)	0.024***	0.166***	−0.01	0.018*	0.157***	−0.023*	0.116***	0.221***	0.112***
	(0.009)	(0.000)	(0.361)	(0.077)	(0.000)	(0.064)	(0.001)	(0.003)	(0.007)
Demographics:									
Female	0.106***	−0.077	0.173***	0.123***	5.4e-03	0.184***	−0.04	−0.74***	0.238
	(0.002)	(0.277)	(0.000)	(0.001)	(0.943)	(0.000)	(0.745)	(0.005)	(0.109)
White	−0.044	−0.068	−0.033	−0.019	−0.033	−0.013	−0.434***	−0.727**	−0.396**
	(0.293)	(0.452)	(0.536)	(0.699)	(0.729)	(0.818)	(0.007)	(0.024)	(0.040)
Age	−0.16**	−0.137	−0.167	−0.158*	−0.166	−0.128	−0.146	0.138	−0.36
	(0.049)	(0.432)	(0.108)	(0.088)	(0.360)	(0.250)	(0.640)	(0.839)	(0.316)
Age squared / 100	0.115	0.113	0.113	0.096	0.128	0.054	−0.03	−0.373	0.211
	(0.181)	(0.541)	(0.308)	(0.332)	(0.504)	(0.649)	(0.927)	(0.610)	(0.580)
Born in the U.S.	0.181	−0.166	0.239	0.137	−0.242	0.204	0.035	−0.091	5.7e-04
	(0.238)	(0.623)	(0.217)	(0.435)	(0.479)	(0.323)	(0.961)	(0.955)	(0.999)
U.S. citizen	−0.179	0.347	−0.337*	−0.221	0.393	−0.349	0.548	0.051	0.7
	(0.270)	(0.354)	(0.097)	(0.234)	(0.305)	(0.107)	(0.479)	(0.975)	(0.426)
Highest grade completed	−9.8e-03	2.8e-04	0.04	−0.028	2.1e-03	−0.031	0.669***	−0.305	1.33***
	(0.845)	(0.998)	(0.545)	(0.622)	(0.985)	(0.639)	(0.008)	(0.345)	(0.000)
Highest grade completed squared / 100	0.095	0.077	−0.033	0.179	0.078	0.194	−2.15**	1.15	−4.26***
	(0.586)	(0.834)	(0.886)	(0.362)	(0.845)	(0.404)	(0.012)	(0.305)	(0.000)
Married	0.082**	0.029	0.039	0.025	−2.6e-03	0.04	0.134	0.694**	−0.056
	(0.031)	(0.721)	(0.411)	(0.571)	(0.976)	(0.435)	(0.347)	(0.028)	(0.742)
Number of children in household	−0.028*	0.027	−0.029	−0.014	0.022	−0.033	−0.022	−0.121	−0.036
	(0.066)	(0.389)	(0.130)	(0.413)	(0.514)	(0.111)	(0.674)	(0.268)	(0.582)
Financial:									
Ln(mean annual wage)	−0.598***	−0.087	−0.76***	−0.463***	0.217	−0.727***	−1.13***	−2.77***	−0.703
	(0.000)	(0.680)	(0.000)	(0.000)	(0.332)	(0.000)	(0.003)	(0.001)	(0.119)
Ln(std. dev. of annual wage)	0.225***	0.053	0.272***	0.126	−0.144	0.23**	0.787***	1.92***	0.488
	(0.005)	(0.741)	(0.008)	(0.167)	(0.392)	(0.038)	(0.006)	(0.002)	(0.149)
Ln(total net family income)	−0.204***	−0.1*	−0.21***	−0.21***	−0.118**	−0.239***	0.099	0.2	0.133
	(0.000)	(0.058)	(0.000)	(0.000)	(0.040)	(0.000)	(0.266)	(0.307)	(0.227)
Family in poverty	8.0e-03	−0.129	−0.132	−0.226***	−0.199	−0.221**	0.551**	0.738	0.619*
	(0.907)	(0.432)	(0.131)	(0.006)	(0.258)	(0.018)	(0.049)	(0.229)	(0.063)
Other controls:									
Current residence in urban	0.013	0.051	4.4e-03	0.061	0.091	0.056	−0.378***	−0.29	−0.367**
	(0.715)	(0.514)	(0.923)	(0.147)	(0.285)	(0.259)	(0.003)	(0.246)	(0.016)
Ln(no. of jobs reported as of int. date)	0.843***	0.904***	0.92***	0.863***	0.889***	0.86***	0.717***	0.382	0.767***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.107)	(0.000)
Secondary job held	0.202***	0.224**	0.326***	−0.216***	−0.2*	−0.207***	1.17***	1.12***	1.22***
	(0.000)	(0.025)	(0.000)	(0.000)	(0.084)	(0.004)	(0.000)	(0.000)	(0.000)
Covered by union or employee contract	−0.231***	−0.4**	−0.272***	−0.266***	−0.315*	−0.24**	−0.725**	−1.67*	−0.859**
	(0.004)	(0.020)	(0.007)	(0.004)	(0.077)	(0.027)	(0.025)	(0.099)	(0.040)
Risk-taking score	0.021***	0.014	0.023***	8.5e-03	−1.8e-04	0.01	0.082***	0.117**	0.067**
	(0.000)	(0.278)	(0.001)	(0.205)	(0.990)	(0.188)	(0.000)	(0.014)	(0.015)
Entrepreneurial:									
Prior self-employment experience							0.969***	1.08***	0.896***
							(0.000)	(0.000)	(0.000)
Father had managerial experience							0.068	−0.391	0.132
							(0.629)	(0.245)	(0.421)
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,853	18,853	18,853	18,458	18,458	18,458	14,197	14,197	14,197
Number of subjects	3,223	3,223	3,223	3,187	3,187	3,187	2,425	2,425	2,425
Number of failures	4,302	964	2,752	3,325	850	2,363	336	82	234
Log likelihood	−31147.08	−6,933.10	−19871.73	−24239.62	−6,148.52	−17164.54	−2,200.87	−501.61	−1,525.46
LR χ^2	1,745.62	511.25	1,317.83	1,328.21	422.73	1,087.09	465.51	188.57	334.71

NOTE: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Cox regression of transition across non-SE jobs by reason to quit

Industry direction:	All		Intra		Inter	
Reason to quit:	Involuntary	Voluntary	Involuntary	Voluntary	Involuntary	Voluntary
	(1)	(2)	(3)	(4)	(5)	(6)
Main effect:						
Ln(industry quotient)	-0.021	0.039^{***}	0.107^{**}	0.186^{***}	-0.059^{**}	$-6.6\text{e-}03$
	(0.301)	(0.006)	(0.014)	(0.000)	(0.011)	(0.688)
Demographics:						
Female	0.026	0.084^{*}	-0.063	-0.062	0.063	0.175^{***}
	(0.728)	(0.097)	(0.682)	(0.522)	(0.468)	(0.004)
White	-0.012	-0.033	0.201	-0.103	-0.086	$-1.3\text{e-}03$
	(0.902)	(0.605)	(0.320)	(0.397)	(0.440)	(0.987)
Age	-0.297^{*}	-0.032	-0.257	-0.04	-0.201	-0.016
	(0.092)	(0.797)	(0.489)	(0.864)	(0.336)	(0.915)
Age squared / 100	0.266	-0.025	0.229	0.023	0.156	-0.052
	(0.156)	(0.847)	(0.558)	(0.925)	(0.482)	(0.741)
Born in the U.S.	0.038	0.483^{**}	-1.23^{***}	0.658	0.561	0.435
	(0.911)	(0.043)	(0.006)	(0.208)	(0.224)	(0.113)
U.S. citizen	0.227	-0.532^{**}	1.51^{**}	-0.415	-0.211	-0.564^{**}
	(0.546)	(0.028)	(0.016)	(0.428)	(0.656)	(0.044)
Highest grade completed	-0.124	0.143^{*}	0.023	0.233	-0.178	0.121
	(0.208)	(0.084)	(0.921)	(0.158)	(0.107)	(0.217)
Highest grade completed squared / 100	0.329	-0.419	-0.434	-0.708	0.605	-0.348
	(0.350)	(0.144)	(0.605)	(0.208)	(0.125)	(0.307)
Married	0.013	1.3e-03	-0.209	0.067	0.099	-0.038
	(0.879)	(0.983)	(0.234)	(0.551)	(0.312)	(0.579)
Number of children in household	-0.011	-0.034	-0.053	0.02	-0.01	-0.056^{**}
	(0.750)	(0.141)	(0.481)	(0.654)	(0.794)	(0.044)
Financial:						
Ln(mean annual wage)	-0.418^{*}	-0.178	0.07	0.167	-0.662^{**}	-0.289
	(0.090)	(0.260)	(0.881)	(0.554)	(0.025)	(0.138)
Ln(std. dev. of annual wage)	0.316^{*}	-0.059	0.119	-0.078	0.418^{*}	-0.058
	(0.088)	(0.619)	(0.737)	(0.715)	(0.059)	(0.687)
Ln(total net family income)	-0.306^{***}	-0.124^{***}	-0.142	-0.092	-0.34^{***}	-0.13^{***}
	(0.000)	(0.001)	(0.244)	(0.223)	(0.000)	(0.003)
Family in poverty	-0.294^{*}	-0.042	-0.505	-0.073	-0.235	$-6.1\text{e-}03$
	(0.058)	(0.688)	(0.170)	(0.741)	(0.180)	(0.960)
Other controls:						
Current residence in urban	$-8.4\text{e-}03$	0.036	0.137	0.068	-0.032	0.026
	(0.918)	(0.509)	(0.434)	(0.528)	(0.736)	(0.692)
Ln(no. of jobs reported as of int. date)	0.821^{***}	0.976^{***}	0.809^{***}	0.928^{***}	0.828^{***}	1^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary job held	-2.24^{***}	-1.47^{***}	-1.85^{***}	-1.7^{***}	-2.37^{***}	-1.35^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covered by union or employee contract	-0.141	-0.475^{***}	-0.187	-0.417^{*}	-0.126	-0.484^{***}
	(0.439)	(0.000)	(0.631)	(0.086)	(0.549)	(0.003)
Risk-taking score	9.8e-03	0.011	0.014	1.4e-03	7.7e-03	0.012
	(0.450)	(0.203)	(0.604)	(0.934)	(0.610)	(0.235)
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,458	18,458	18,458	18,458	18,458	18,458
Number of subjects	3,187	3,187	3,187	3,187	3,187	3,187
Number of failures	865	1,929	206	525	630	1,342
Log likelihood	$-6{,}241.62$	-13946.19	$-1{,}468.90$	$-3{,}759.11$	$-4{,}519.56$	$-9{,}672.27$
LR χ^2	474.38	1,012.35	147.44	332.80	400.89	782.53

NOTE: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Cox regression of transition from non-SE job to SE job by reason to quit

Industry direction:	All		Intra		Inter	
Reason to quit:	Involuntary	Voluntary	Involuntary	Voluntary	Involuntary	Voluntary
	(1)	(2)	(3)	(4)	(5)	(6)
Main effect:						
Ln(industry quotient)	0.138^{*}	0.197^{***}	0.459^{*}	0.36^{***}	0.084	0.183^{**}
	(0.087)	(0.001)	(0.066)	(0.003)	(0.353)	(0.014)
Demographics:						
Female	−0.378	−0.111	−1.41	-1.05^{**}	−0.08	0.313
	(0.177)	(0.572)	(0.107)	(0.012)	(0.798)	(0.212)
White	-0.655^{*}	−0.393	−1.12	−0.42	−0.673	−0.41
	(0.068)	(0.132)	(0.156)	(0.393)	(0.101)	(0.205)
Age	0.266	−4.3e-03	1.34	0.15	0.085	−0.114
	(0.728)	(0.993)	(0.536)	(0.889)	(0.923)	(0.850)
Age squared / 100	−0.471	−0.119	−1.48	−0.359	−0.338	0.023
	(0.568)	(0.827)	(0.512)	(0.760)	(0.725)	(0.971)
Born in the U.S.	−1.58	0.696	0.022	0.067	-1.66^{*}	0.772
	(0.106)	(0.549)	(0.997)	(0.975)	(0.095)	(0.573)
U.S. citizen	1.11	0.066	−1.36	−0.152	1.13	0.402
	(0.331)	(0.955)	(0.789)	(0.943)	(0.346)	(0.769)
Highest grade completed	0.826	0.155	−0.159	-0.761^{**}	1.57^{**}	0.972^{*}
	(0.144)	(0.634)	(0.881)	(0.018)	(0.038)	(0.079)
Highest grade completed squared / 100	−2.63	−0.4	0.546	2.66^{**}	-5.04^{**}	−3.04
	(0.164)	(0.718)	(0.876)	(0.021)	(0.046)	(0.102)
Married	−0.309	−0.025	−0.099	1.04^{**}	−0.256	-0.547^{*}
	(0.356)	(0.911)	(0.899)	(0.048)	(0.499)	(0.051)
Number of children in household	−0.017	−0.084	0.311	−0.285	−0.161	−0.093
	(0.895)	(0.358)	(0.225)	(0.105)	(0.293)	(0.443)
Financial:						
Ln(mean annual wage)	-1.54^{*}	−0.75	−0.561	-3.73^{***}	-1.86^{*}	0.25
	(0.078)	(0.219)	(0.778)	(0.003)	(0.064)	(0.742)
Ln(std. dev. of annual wage)	1.39^{**}	0.939^{**}	1	2.98^{***}	1.55^{**}	0.272
	(0.040)	(0.040)	(0.510)	(0.002)	(0.046)	(0.632)
Ln(total net family income)	0.202	−0.12	0.056	0.489	0.346	−0.206
	(0.379)	(0.391)	(0.927)	(0.143)	(0.180)	(0.190)
Family in poverty	0.08	0.448	−44.4	1.39	0.79	0.356
	(0.912)	(0.271)	(.)	(0.141)	(0.300)	(0.458)
Other controls:						
Current residence in urban	−0.303	-0.574^{***}	−0.275	−0.034	−0.276	-0.786^{***}
	(0.336)	(0.004)	(0.736)	(0.929)	(0.440)	(0.002)
Ln(no. of jobs reported as of int. date)	1.07^{***}	1.04^{***}	1.91^{**}	0.893^{**}	0.804^{***}	0.999^{***}
	(0.000)	(0.000)	(0.020)	(0.013)	(0.009)	(0.000)
Secondary job held	-1.81^{**}	-1.42^{***}	−0.447	−1.03	-2.25^{**}	-1.46^{**}
	(0.013)	(0.002)	(0.688)	(0.168)	(0.027)	(0.014)
Covered by union or employee contract	0.092	−0.41	−43.8	−0.725	−0.083	−0.152
	(0.881)	(0.429)	(.)	(0.484)	(0.911)	(0.801)
Risk-taking score	0.19^{***}	0.123^{***}	0.34^{**}	0.091	0.166^{***}	0.127^{***}
	(0.001)	(0.001)	(0.041)	(0.209)	(0.009)	(0.006)
Entrepreneurial:						
Prior self-employment experience	0.845^{***}	0.61^{***}	0.984	0.469	0.793^{**}	0.668^{***}
	(0.003)	(0.002)	(0.222)	(0.202)	(0.011)	(0.007)
Father had managerial experience	0.079	0.118	−0.859	−0.708	0.304	0.178
	(0.811)	(0.615)	(0.445)	(0.208)	(0.385)	(0.539)
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,197	14,197	14,197	14,197	14,197	14,197
Number of subjects	2,425	2,425	2,425	2,425	2,425	2,425
Number of failures	63	125	11	36	49	78
Log likelihood	−398.52	−823.88	−51.22	−212.82	−310.55	−504.33
LR χ^2	116.48	165.99	56.35	98.67	89.79	121.67

NOTE: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of an increase in industry quotient on transition rates

	All		Intra-industry		Inter-industry	
	Involuntary	**Voluntary**	**Involuntary**	**Voluntary**	**Involuntary**	**Voluntary**
Job change	$+^{***}$		$+^{***}$		0	
	0	$+^{***}$	$+^{***}$	$+^{***}$	$-^{***}$	0
NSE to NSE	$+^{*}$		$+^{***}$		$-^{**}$	
	0	$+^{***}$	$+^{**}$	$+^{***}$	$-^{***}$	0
NSE to SE	$+^{***}$		$+^{***}$		$+^{***}$	
	$+$	$+^{***}$	$+^{*}$	$+^{***}$	$+$	$+^{**}$

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.