The startup employee earnings gap: The long-term income consequences of joining small and young firms

Olav Sorenson  
Yale University  
olav.sorenson@yale.edu

Michael S. Dahl  
Aarhus University  
Department of Management  
msd@mgmt.au.dk

Rodrigo Canales  
Yale University  
rodrigo.canales@yale.edu

M. Diane Burton  
Cornell University  
burton@cornell.edu

Abstract

Startups and other small firms have been found to pay less. But how do these differences influence long-term earnings as firms age and grow and as individuals move across employers? We explore how joining a startup as an employee affects the long-term earnings of an individual. Analyzing Danish registry data, we find that individuals who join startups earn roughly 25% less than the employees of large, established firms over the subsequent ten years. Although about half of this gap stems from sorting ? from the fact that individuals who can command higher wages disproportionately work in large, established firms ? a large share of who ends up employed at small and young firms appears to depend on chance and, even after accounting for the observed and unobserved characteristics of individuals, those employed at startups still earn less than their peers at large, established firms. If anything, moreover, these earnings disparities grow over time. These differences in earnings trajectories appear to stem from two factors: Young and small firms fail at higher rates, creating costly spells of unemployment for their employees. Job mobility patterns also diverge: Once employees join small firms they tend to stay in them, rarely returning to the larger, established employers that pay more.
The startup employee earnings gap: The long-term income consequences of joining small and young firms

Olav Sorenson† Michael S. Dahl‡ Rodrigo Canales§ M. Diane Burton¶

April 7, 2018

Abstract: Startups and other small firms have been found to pay less. But how do these differences influence long-term earnings as firms age and grow and as individuals move across employers? We explore how joining a startup as an employee affects the long-term earnings of an individual. Analyzing Danish registry data, we find that individuals who join startups earn roughly 25% less than the employees of large, established firms over the subsequent ten years. Although about half of this gap stems from sorting – from the fact that individuals who can command higher wages disproportionately work in large, established firms – a large share of who ends up employed at small and young firms appears to depend on chance and, even after accounting for the observed and unobserved characteristics of individuals, those employed at startups still earn less than their peers at large, established firms. If anything, moreover, these earnings disparities grow over time. These differences in earnings trajectories appear to stem from two factors: Young and small firms fail at higher rates, creating costly spells of unemployment for their employees. Job mobility patterns also diverge: Once employees join small firms they tend to stay in them, rarely returning to the larger, established employers that pay more.

*All authors contributed substantially to the paper. Authorship order simply represents a reverse alphabetical assignment. We thank Yale University for generous financial support and Jesper Sørensen, Kim Weeden, and the participants of seminars at INSEAD, Johns Hopkins, Stanford, and Yale for their comments on earlier versions of this paper. The usual disclaimer applies.

†Yale University
‡Aarhus University
§Yale University
¶Cornell University
INTRODUCTION

For most of the twentieth century, industrial policy meant finding ways to attract and foster the growth of large firms, titans of the global economy, with the notion that these juggernauts would provide good jobs and promote economic expansion (e.g., Johnson 1982; Dertouzos et al. 1989). But beliefs about the best means of stimulating the economy have changed dramatically over the past three decades. Policymakers increasingly see entrepreneurs, not large enterprises, as the engines of economic growth. Many recent changes in regulation, such as the JOBS Act of 2012, have therefore sought to ease the process of starting a firm (e.g., Bush 2004; Stemler 2013). Subsidies and government programs oriented at supporting startups – from grants for the commercialization of technology to accelerators and makerspaces that provide shared resources for entrepreneurs – have similarly been expanding (Lerner 1999; Cohen and Hochberg 2014; Browder et al. 2017). Recent academic research, moreover, provides empirical support for this shift in policy, arguing that most net job creation comes from startups (Haltiwanger et al. 2013; Ayyagari et al. 2014; Glaeser et al. forthcoming).

Largely absent from this shift in orientation, however, has been a consideration of how these changes might affect employees. An industrial policy that favors entrepreneurial firms, by design, influences the rate of firm founding, the success and survival prospects of startups and incumbents, the characteristics of firms in the economy, and the composition of the organizational landscape. Because this organizational landscape – the ecology of employers – determines the opportunity structure for employees, changes in the landscape will in turn translate into changes in the jobs and career paths available to individuals (Carroll et al. 1992; DiPrete 1993; Haveman and Cohen 1994; Sørensen 1996; Sørensen and Sorenson 2007).

Given the substantial literature on the firm size wage effect, one might expect that startups – typically being both young and small – would provide less attractive jobs and
careers, particularly in terms of pay and rewards. Although the magnitude of the gap varies across countries and, even within countries, has fluctuated somewhat over time, small firms pay less than large firms, even within the same regions and industries (Baron 1984; Villemez and Bridges 1988; Kalleberg and Van Buren 1996; Hollister 2004; Burton et al. 2018). They also offer fewer fringe benefits, such as health care and retirement plans (Kalleberg and Van Buren 1996; Litwin and Phan 2013).

But the literature on the firm size wage effect has been focused entirely on the short term, on what employees earn in a given year. Startups grow and mature. As they do, one might expect that they would converge in their pay practices and benefits to those of larger, more established firms. Employees who entered these organizations early might even benefit from getting in on the ground floor. To the extent that hiring occurs at levels below them in the hierarchy, they might rise in the ranks faster than they would have in a larger organization (Rosenbaum 1979; Stewman and Konda 1983). If they move to another employer, employment in a startup may also provide these individuals with a richer range of experiences, allowing them to move to other firms at higher levels of pay and responsibility (Baron et al. 1986; Sørensen and Phillips 2011; Campbell 2013; Luzzi and Sasson 2016). Any penalty associated with joining a startup may therefore end up being short lived or even being outweighed in the long run by these benefits.

We examined this question using registry data from Denmark, from 1992-2012. Employees who joined startups – defined as being one of the first 50 employees in a firm that had been operating for no more than four years – earned, on average, 25% less over the subsequent ten years than those at established, large firms – organizations that had been operating for more than four years and that had more than 50 employees. About half of this difference stems from sorting. Startups tend to employ younger and less qualified indi-
viduals who would earn less at any employer (Ouimet and Zarutzkie 2014). They may also hire people who have a preference for working in a startup and who may therefore accept lower wages in exchange for the experience (Roach and Sauermann 2015; Sauermann forthcoming). But even accounting for this sorting of employees to employers, individuals who joined small, young firms earned about 10% to 15% less over the subsequent decade than comparable individuals employed by larger, more established firms. The trajectory of their earnings relative to that of employees at large, established firms, moreover, did not improve over time. If anything, those who joined startups appeared to fall further and further behind.

We also explored what might account for this earnings penalty. Two factors, in particular, appeared important. First, the employees of small firms, and particularly of small, young firms, had less stable jobs and therefore more frequent cross-firm mobility and spells of unemployment. Consistent with past research on the effects of unemployment, these spells appeared to result both in a short-term loss of income and in a shallower trajectory for future earnings growth (Brand 2004; Gangl 2006; Cha and Morgan 2010; Brand 2015). Second, entry into small firm employment seemed to become a near-absorbing state. Most startups remained small. They never became large employers and therefore they never converged with larger firms in their pay practices. And even when those who joined startups moved to other firms, they tended to join other small firms. This path dependency essentially created a bifurcated structure, with one set of individuals progressing steadily through careers in large, stable employers and a second set holding far less secure positions at a series of startups and small firms (Doeringer and Piore 1971).

Our results have implications not only for the ways in which the changing ecology of employers influences the career opportunities available to individuals but also for the changing structure of income inequality at a societal level. Most people rely on employment as
their main source of income and wealth, so the wage-setting practices of employers largely
determine the distribution of rewards in society (Baron 1984). Large organizations, indeed,
have been seen as important to the reduction of inequality (Sørensen and Sorenson 2007;
Davis and Cobb 2010; Cobb and Stevens 2017). But our results point to variation in the
size categories of firms and to the porousness of the boundaries to movement across these
categories as another important dimension in this equation. To the degree that small and
large employers diverge in the rewards that they offer – and particularly to the extent that
they also represent segregated labor pools – access to job opportunities in large, established
firms becomes an important agent of stratification. In our setting, even among those who
appear to have become employees of small firms due purely to chance, the lifetime income
consequence of that event appears roughly equivalent to that of completing a college degree.
The fact that startups disproportionately hire the disadvantaged, moreover, interacts with
this pay penalty, exacerbating the income and wealth disparities between these individuals
and those advantaged in the system.

STARTUP EMPLOYMENT

Despite the growing prominence of entrepreneurship in public policy and in the public sphere,
and in contrast to the large literature on entrepreneurs, relatively little research has examined
the employees of startups. What processes sort individuals into startups? How does startup
employment influence career progression and earnings? What other effects does being part
of a startup have on professional and personal lives?

Prior research nevertheless provides some insight into the probable answers to these
questions, at least with respect to earnings. Social scientists have long been aware that
small firms pay less than large firms (Baron 1984; Villemez and Bridges 1988; Kalleberg and
Van Buren 1996; Oi and Idson 1999; Hollister 2004). Since the average startup begins both young and small, one would expect startups to pay less than older (and likely larger) firms. Indeed, they do (Davis and Haltiwanger 1991; Brown and Medoff 2003; Burton et al. 2018). But recent research that has tried to separate the effects of age and size also points to an interesting nuance. Conditional on size, young firms actually appear to pay a premium over older employers (Brown and Medoff 2003; Schmieder 2013; Burton et al. 2018).

The sources of these pay differences, however, have been less clear. In part, the lower pay among the employees of startups and other small firms seems to stem from sorting. Small firms, whether young or old, tend to hire younger individuals with less education and less experience (Nystrom and Elvung 2014; Ouimet and Zarutzkie 2014). Such individuals would earn less in any job. But even after accounting for these differences, small firms still pay substantially less than large firms for employees with equivalent characteristics (Abowd et al. 1999; Troske 1999; Brown and Medoff 2003; Burton et al. 2018).

Although sociologists may simply see these residual differentials as reflecting the rewards attached to the jobs (Doeringer and Piore 1971; Baron 1984; Kalleberg and Van Buren 1996), these differentials pose more of a puzzle to economists. In a world with a surplus of employees and with modest search costs — in terms of employers finding able employees — pay premiums should reflect the productivity of the individuals hired relative to the next best alternative employee (Becker 1964). Since such marginal differences in ability would usually seem slight, one would expect no more than small differences in the amount that employers would pay similar individuals.

One possible resolution is that these residual differences reflect variation in bargaining power — either due to the scarcity of able employees or due to collective bargaining. But this explanation has fallen short in empirical analyses (e.g., Hollister 2004; Schmieder 2013).
Another possible resolution is that it reflects sorting on another dimension. Much has been written about the non-pecuniary benefits of starting a business. Entrepreneurs become their own bosses. They can set their own hours. Not surprisingly given this autonomy, they regularly report higher levels of job satisfaction (Blanchflower and Oswald 1998; Benz and Frey 2008; Binder and Coad 2013). The employees of startups might similarly gain satisfaction from the social cohesion of a small firm or from having more flexible or more meaningful jobs. Indeed, like founders, the employees of startups appear to expect and to experience higher levels of job satisfaction (Idson 1990; Roach and Sauermann 2015).

But note that all of the research to date has examined only the short-term earnings effects of startup employment.\(^1\) Employee decisions about whether to join startups, however, will depend not only on the initial attributes of and rewards associated with those jobs but also on how much they can expect jobs in these firms to influence their earnings trajectories and their career progression (Bidwell and Briscoe 2010). Similarly, any stratifying effects of firm age and size depend not just on the contemporaneous relationship between these firm characteristics and income but also on the path dependencies associated with these jobs. We have ample reason to believe, moreover, that these earnings effects might evolve over time. A complete understanding of the career consequences of joining a startup and of the choices potentially available to individuals therefore requires information on both the short-term and the long-term effects associated with these jobs.

---

\(^1\)Campbell (2013) provides a notable exception, though his study only considers the employees of startups in the semiconductor industry in California during the period of the dotcom boom and it only follows them if they remain employed in the industry.
Long-term advantages

We see at least two potential long-term advantages to joining a startup in terms of career – and earnings – progression. The first stems from the greater growth prospects of these firms (Barron et al. 1994; Haltiwanger et al. 2013). One of the attractive features of startup employment is the opportunity to get in on the ground floor. Because these firms operate at smaller scale and have fewer resources available, individuals can often enter them at higher levels than they would a larger organization. Someone coming out of business school might become the Chief Marketing Officer of a startup as opposed to a regional brand manager at a large, established firm. If the startup grows and hires below these individuals, early employees could attain a senior position in a large company at a much earlier point in their career than they ever could have hoped to achieve through climbing the internal ladder of a large firm (Rosenbaum 1979; Stewman and Konda 1983).

The second advantage stems from the lesser degree of role differentiation in these firms (Blau 1970; Blau and Schoenherr 1971). The employees of startups and of small firms must often wear multiple hats. Small employers do not have sufficiently extensive needs in most areas to keep a full-time employee busy with one set of activities. They also do not have adequate resources to allow employees to have much spare capacity. Employees of startups, and of other small firms, therefore regularly help out where needed. When a crisis strikes, even a mini one, it’s all hands on deck. As a result, the average employee of a startup or small firm engages in a much wider variety of activities and assumes more responsibilities (Sørensen 2007; Campbell 2013).

This greater variation in activities and expanded responsibility may in turn influence the future job opportunities available to these individuals. Much of the acquisition of human capital comes through learning-by-doing on the job rather than through formal education.
Senior levels in the hierarchies of large, established firms require a broader range of expertise than more junior levels (Blau 1970). But individuals attempting to climb the internal ladders of these organizations often have few opportunities to acquire the abilities necessary to succeed at the next level. To the extent that it helps to provide this broader expertise, having experience in a startup or small firm prior to joining a larger one may accelerate career progression and earnings growth. Although research has not explicitly looked at whether startup employment produces such a benefit, entrepreneurs themselves do appear to rise more rapidly through the ranks if they return to being employees (Campbell 2013; Luzzi and Sasson 2016), presumably because the expertise and experiences that they acquired as entrepreneurs help them to outshine their peers.

Experience in a startup could also help employees become entrepreneurs themselves. Entrepreneurs, because they must manage and engage in nearly all of the activities of their firms, benefit from being jacks-of-all-trades (Lazear 2005; Sørensen 2007). The employees of small firms also more commonly have connections with the external environment, with suppliers and customers (Blau 1977). These connections put them in a better position to spot opportunities (Sorenson and Audia 2000; Sørensen 2007). Consistent with this expectation, studies have found that those employed by small firms become entrepreneurs at higher rates than their peers at larger ones (Dobrev and Barnett 2005; Gompers et al. 2005; Sørensen 2007). Although that entry into entrepreneurship may stem simply from a preference for being in a startup rather than from greater acumen as an entrepreneur, prior experience as the employee of a small-firm has also been positively associated with success as an entrepreneur (Sørensen and Phillips 2011; Dahl and Sorenson 2014)
Long-term disadvantages

But joining a startup also has at least two potential long-term disadvantages. The first concerns the fragility of these firms and the consequent instability of employment with them. Startups fail at much higher rates than larger and older firms (Freeman et al. 1983; Carroll and Hannan 2000). When they do, employees find themselves involuntarily out of jobs (Carroll et al. 1992; Haveman and Cohen 1994). Not only do these spells of unemployment imply an immediate loss of income but also they affect the ability of the individual to secure another attractive job. Unemployment, even when due to firm failure, may come with a stigma, a sense that the job loss must reflect something about the individual. The former employees of failed firms may therefore find themselves disadvantaged when competing for jobs. When unemployed individuals do receive job offers, moreover, they have little bargaining power with which to negotiate better salaries and terms. Consistent with these issues, spells of unemployment have been found to have negative effects on both short-term and long-term income (Brand 2004; Gangl 2006; Cha and Morgan 2010; Brand 2015).

Job loss due to the failure of a startup, moreover, may prove even more problematic than job loss due to a plant closing or a mass layoff. Since startups seem particularly vulnerable to economic downturns, the (former) employees of startups may find themselves searching for a job at precisely the times when those jobs are most scarce, potentially leading to more prolonged spells of unemployment. These individuals may also suffer an additional stigma associated with the failure of their former employers. In firms with a small number of employees, outsiders may perceive each individual as being more responsible for the fate of the firm.

The second disadvantage stems from the downside of lesser role differentiation. Engaging in a large number of activities means less time spent learning to do any one of these activities.
The employees of startups and other small firms therefore sacrifice depth for breadth in the development of human capital (Rosen 1983). The inherent instability of startup jobs compounds this issue. Because the needs of the firm shift over time, the scope of jobs within the company fluctuate. As a result, the employees of startups may end up disadvantaged in the development of the specialized skills valued by large firms (Rosen 1983). These broad experience sets might appeal primarily to other small firms.

Precisely because startups have less role differentiation, the employees of startups and other small firms also often find themselves performing atypical jobs with unusual aggregations of responsibilities (Beckman and Burton 2008). These employees therefore acquire highly idiosyncratic sets of skills and may have unusual progressions of jobs in their careers. Employers can find these employment histories difficult to understand and therefore may discount them (Leung 2014). Unless these individuals can find other employers in need of the same unusual configurations of responsibilities, their idiosyncratic experience will also likely have less value in the external labor market (Barnett and Miner 1992; Beckman and Burton 2008).

**LONG-TERM EARNINGS**

We examined these issues using Danish registry data, specifically the Integrated Database for Labor Market Research (commonly referred to by its Danish acronym, IDA). This matched employer-employee database, which includes all individuals legally residing in the country each year, contains details on the characteristics of individuals and of their employers and comprehensive information on their annual earnings.

Although the IDA database begins in 1980, we only analyzed data from 1991 onwards. In the late-1970’s and 1980’s, Denmark underwent a series of regulatory reforms dismantling
much of the centralized system for setting wages (Madsen et al. 2001). Denmark now has one of the most liberal labor markets in Europe, similar in its dynamics to larger economies such as Canada, the United Kingdom, and the United States (Bingley and Westergård-Nielsen 2003; Sørensen and Sorenson 2007).

Startup employees enter our analyses the first time that they join a startup after 1991. If they have multiple spells of startup employment, they only appear in our data as joining a startup for the first one (after 1991). We considered employees to have joined a startup if they joined a firm that had been operating for no more than four years and that had fewer than 50 employees at the time of their hiring. We chose four years as the age threshold because that represents the half-life of a firm in Denmark (Dahl and Sorenson 2012); failure rates of firms begin to decline when they survive longer than that. The choice of the first 50 employees as the dividing line between small and large, however, has been more arbitrary. But analyses using both lower and higher thresholds for both age and size found similar patterns of results (see also, Burton et al. 2018).

We measured income as the total amount of wages and bonuses received by an individual in a year. One might worry that this measure fails to capture certain forms of compensation, such as fringe benefits or stock options. But the Danish state provides most benefits, so they vary little from firm to firm. Few companies in Denmark, moreover, reward employees with equity or stock options (Eriksson 2001). Because Denmark taxes equity awards as income rather than as capital gains and has historically taxed them in the year awarded (rather than in the year exercised), such awards end up being unattractive to employees.2 Most companies in Denmark therefore use bonuses as a means of paying for performance.

2By contrast, the United States both taxes most equity awards at a lower rate than other types of income and usually does not impose those taxes until the equity has been sold (in other words, until it has been converted into income).
To assess long-term income effects, our analyses followed individuals for ten years after they joined a startup.\textsuperscript{3} We treat joining a startup as an event rather than as a state variable. In other words, even if an individual leaves their original employer and even if they move to an employer of older age or of larger size, our indicator variable for having joined a startup continues to have a value of one. Doing so means that our estimates capture the total long-term earnings effects associated with joining a startup from a multitude of channels—disparities in initial earnings, differing slopes of earnings trajectories, spells of unemployment, and path dependence in the sequences of employers. To ensure that we could observe most individuals for at least ten years following their initial entry into a startup, we restricted our analyses to individuals who first joined a startup between the ages of 18 and 50. That effectively restricts the age range for analysis to individuals from 18 to 60, largely removing retirement from the equation.

We began by examining the average long-term differentials in accumulated earnings for startup employees relative to the employees of large, established firms (employers that had been operating for more than four years and that had more than 50 employees). We took a simple random sample, equal in size to the number of startup employees, of individuals employed by large, established firms to estimate the earnings distribution for the comparison set. Figure 1 depicts the probability density distributions of ten-year aggregate earnings for these two groups (in Danish kroner).\textsuperscript{4} The solid line displays the distribution for those who joined small, young firms while the dashed line displays it for the employees of large, established firms. This figure reveals two facts: First, although the distributions have similar

\textsuperscript{3}Models exploring even longer windows, up to 25 years, suggest that the earnings disparities reported here persist far past this first decade.

\textsuperscript{4}Over the period being analyzed, the DKK exchange rate to the USD averaged about 6.5:1. Note that the graph truncates the top 1% of the distributions so that the scaling of the horizontal axis can better depict the majority of the mass.
shapes, startup employees earned, on average, 17% less in the ten years after joining the startup than those employed in large, established firms. Second, in contrast to startup founders (Hamilton 2000), the distribution of earnings for their employees do not exhibit a long, fat right-hand tail. In other words, employees do not appear to experience a trade-off where they accept lower average earnings in exchange for the possibility of becoming rich.5

Employee sorting

The accumulated earnings depicted in Figure 1, however, do not account for any differences in the characteristics of the employees of startups versus those of larger, more established firms. Recent research has nevertheless found that startups do not hire at random from the population. On average, their employees are younger, less educated, and less experienced than the average person in the labor force (Nystrom and Elvung 2014; Ouimet and Zarutzkie 2014; Burton et al. 2018). Since these individual-level characteristics would influence the amount that an employee could expect to earn at any job, one would want to adjust for this sorting to separate the effects of the job from those of the characteristics of the individual (Burton et al. 2018). In studies of short-term earnings, these compositional differences in the characteristics of the employees of startups relative to large, established employers usually account for one-third to two-thirds of the pay differentials associated with firm age and firm size (Burton et al. 2018). To assess the extent to which sorting occurs in the Danish context, we began by estimating a set of logistic regressions. The results of these models appear in Table 1. The sample comprises four subsets: (i) individuals entering their first spell of employment in a small, young firm after 1991; individuals entering their first post-1991 spell of employment in a

5Related literatures in economics and finance often label this trade-off as a “preference for skewness” (e.g., Moskowitz and Vissing-Jørgensen 2002).
(ii) small, old firm (i.e. firms that had been operating for more than four years but with fewer than 50 employees) or a (iii) large, young firm (i.e. firms with more than 50 employees but that had been operating for four or fewer years) after 1991; and, as a baseline, two randomly-selected individuals employed by large, established firms for each of the individuals in groups (i)-(iii). The first column compares those who joined a startup to the other groups of individuals. The dependent variable has a value of one if the individual belonged to the group that joined a startup and a value of zero if he or she represents a member of the comparison set. The coefficients therefore characterize the extent to which each individual-level characteristic appears associated with joining a startup. To determine whether sorting seems to reflect more of an age effect or a size effect, the next two columns report parallel regressions for those who joined small, old firms and large, young firms.

Comparing across the columns, one can see that small firms, whether young or old, hire younger employees, more men, fewer white collar workers, and individuals with substantially lower prior wages than do large, established firms.\(^6\) Small, old firms also hire somewhat less educated individuals. Even once they reach 50 employees, young firms continue to hire more men and fewer white collar workers than older large firms. Given this sorting, it seems likely that at least some of the disparity in income between employees in startups and those in large, established firms stems from the composition of their workforces.

**Case-Control Triplets**

**Random baseline.** We account for this sorting by using the method introduced by Burton et al. (2018). We pair each focal individual joining a startup with two (control) individuals employed at large, established firms. In the random sample that provides a baseline, these

\(^6\)Note that most of those in the undefined occupation category come from small firms, where perhaps the firm does not have sufficient role differentiation to classify employees into even broad occupational categories.
controls have been chosen at random from the set of all individuals employed by firms that
had been operating for more than four years and that had more than 50 employees in the
year that the focal individual joined the startup.

To disentangle whether any long-term effects associated with joining a startup stem from
firm age versus from firm size, we used the same procedure to create two additional subsets.
The first captures those who joined a young firm (a firm operating for no more than four
years) but who joined after the firm had already reached a size of at least 50 employees.
The second includes those who joined a small firm (one with fewer than 50 employees) that
had been operating for more than four years. Note that a person can only appear as a focal
individual in one of the three subsets and can only appear in that subset once. If a person
has multiple events of joining small and/or young firms, only the first one would enter our
analyses. For each of these subsets, we followed the same procedure for creating case-control
triplets. We then pooled the subsets to estimate the effects.

Matched sample. To account for sorting and to adjust for the effects of individual-level
characteristics, we next created a sample of matched case-control triplets. In the matched
sample, each of the control individuals has exactly the same characteristics as the focal
individual in terms of gender, year of birth, years of education, and prior occupation.\textsuperscript{7}
Although this matching accounts for differences across individuals in observed characteristics,
individuals also differ on a host of unobserved dimensions that may also affect productivity

\textsuperscript{7}We used a one-digit version of occupation codes. These codes distinguish between skilled and unskilled
jobs and between white collar and blue collar occupations but they do not introduce a fine-grained clas-
sification that would distinguish between industries. They therefore represent something closer to the big
classes used in the classic research on stratification than the micro-classes that have received much attention
more recently (Weeden and Grusky 2005). Note also that many of the individuals who do not have a prior
occupation end up dropping out of the matched samples because they have no exact matches in the large,
established firms. Analyses of samples that do not match on occupation – and therefore that do not drop
these individuals – nevertheless produce nearly equivalent results.
and pay. To account for those differences, from the set of available individuals who matched exactly on gender, age, education, and prior occupation, we selected as control individuals the two nearest neighbors on the prior year’s wage distribution—the closest observation above and the closest below what the focal employee earned in that year. In essence, our approach combines coarsened-exact matching with nearest-neighbor matching on income.\footnote{Many approaches to matching have been developed. Coarsened-exact matching has the advantage of guaranteeing balance between the cases and the controls on all dimensions used for matching. For extended discussions of the advantages of coarsened-exact matching relative to propensity score matching, see Iacus et al. (2012); King and Nielsen (2015).}

**Matched movers.** We also have a second sample of matched case-control triplets. This second matched sample follows exactly the same procedure as the first matched sample, with one exception: It only includes as eligible control individuals those who moved to a new job at a large, established employer in the same year that the focal individual first joined a small and/or young firm.

Across all of our samples, the control individuals have been selected with replacement, so they may appear in more than one case-control triplet. Matching with replacement introduces some correlation across triplets into the error structure, but it has the advantage of ensuring the retention of more treated cases and therefore of generating estimates that are more representative of the population average effect. In total, we have three sets of matched samples. We match more than 90% of the focal individuals in each of them.

**Average differences**

We regress annual logged income on a set of indicator variables for joining a small and/or young firm. For estimation, our models on the matched samples always include triplet-level fixed effects to adjust for all of the common observed and unobserved characteristics.
of these triplets. Note that this approach has a number of advantages relative to including the individual-level characteristics as regressors. Most notably, because the fixed effect for each triplet adjusts for a particular combination of attributes, it effectively allows those attributes, such as education, prior earnings, and experience, to have flexible independent and joint effects in the determination of wages (Burton et al. 2018). In other words, it does not assume any functional forms in the relationships between these factors and income. The models also include indicator variables for the year, to adjust for factors such as inflation and changes in average wages over time.

The primary coefficients of interest then become the indicator variables that identify the individuals who joined small and/or young firms. We have one indicator variable for each of our three firm age-size subsets (small young, small old, large young). Table 2 reports our regression estimates of the average ten-year differences in earnings for these groups relative to the employees of large, old firms. The first column, the random baseline, corresponds closely to the comparison depicted in Figure 1, except that our regression estimates adjust for year-to-year differences in average wages and for the year in which “treatment” occurred (the year in which each focal individual first joined a small and/or young firm).\(^9\)

On average, those joining startups as one of the first 50 employees, earned about 25% less over the subsequent ten years than those employed at large, established firms.\(^10\) This effect appears to be more of a size effect than an age effect. Those joining small firms that have nonetheless been operating for more than four years experienced a similar earnings shortfall, with average incomes of roughly 27% less than those employed at large, established firms. In

\(^9\)It also includes individuals who joined small or young firms near the end of our observation window and who therefore have been observed for fewer than ten years. Restricting the analyses to being a balanced panel, where every individual has ten years of observations, produced statistically equivalent results.

\(^10\)The coefficient \(-.287\) estimates the difference in logged earnings. One can approximate this difference in percentage terms using the antilogarithm (i.e. \(e^{-0.287}\)).
contrast, those joining young firms that had already reached a size of at least 50 employees, only experienced about 6% lower income over the subsequent decade.

The second column reveals that a large portion of these long-term earnings differentials stem from the characteristics of the employees themselves. Yet, even after adjusting for this sorting of employees to employers, those who joined small, young firms still earned about 11% less than their observationally-equivalent peers at large, established firms. This difference again appears more a function of firm size than of firm age. Those who joined small, older firms suffered an almost equal-sized penalty. Meanwhile, the employees hired by young firms after they had already become large had nearly identical long-term incomes to those employed by large, established firms.

The third column further matches the cases and the controls in each group on one additional dimension, having just moved to a job. It therefore controls more tightly for any relationship between tenure in a firm and income, as well as for potential differences between movers and stayers (Burton et al. 2018). The fact that income for the focal cases becomes more positive relative to the controls suggests that, on average, moving involves some adverse selection. But those joining small firms, whether young or old, still earn about 10% less over the following ten years of their careers.\textsuperscript{11}

These effects do not appear limited to any particular sort of firm. In unreported models, they hold even within broad sectors of the economy – manufacturing, services, and high technology – and even when adjusting for fine-grained industry differences in income. They also do not appear to vary much over time. In unreported models splitting the sample into subperiods, the pay penalties associated with joining small firms appear roughly as

\textsuperscript{11}In unreported quantile regression, we found some evidence that those at the bottom of the income distribution suffered larger penalties from joining small firms. But, overall, the effects appeared quite stable across the distribution.
pronounced in the early 1990’s as they do after the financial crisis of 2008.

**Earnings trajectories.** The estimates in Table 2 report average differences over a ten-year period. Figure 2 examines how these earnings differences unfold over time for the matched movers (the sample used in the third column of Table 2). We created the figure by estimating a separate coefficient for each age-size category for each year post-treatment—ten coefficients for each age-size category (e.g., one year after joining a small, young firm; two years after joining a small, young firm; etc.).

Overall, the penalties associated with becoming the employee of a small firm appear relatively stable—if anything, they increase with time. That suggests that those joining small firms never recover. These differentials end up being near-lifetime effects.

In contrast, joining a startup after it has already become large – after it had hired at least 50 employees – appears associated with a small pay premium. But that premium only lasts a few years. Over time, the employees joining large, young firms converged in their average earnings to those of large, established firms.

**Instrumental variables**

Although the matching of individuals to similar others removes many factors as possible explanations for the observed earnings differentials, matching may not account for certain sorts of unobserved individual-level differences. Some people, for example, may decide to join startups because they prefer to work in smaller, more dynamic environments (e.g., Roach and Sauermann 2015; Sauermann forthcoming). If so, those individuals may accept less income in exchange for being a part of a startup, what an economist might call a compensating differential. To determine whether there is indeed a “startup penalty” associated with joining
small, young firms, we would want to distinguish any effects due to individuals who prefer to work for these firms and who are therefore happy to accept lower pay from the effects for those who had little choice, those who may have had a lower income imposed on them.

To address these potential issues of sorting on unobserved dimensions, we estimated the effects of joining a firm of younger age and/or smaller size using instrumental variables (IV). An instrument uses variation unrelated to the outcome to estimate the causal effect of a treatment (Morgan and Winship 2007). We used the proportion of jobs available in a particular age and size quadrant in an industry and region at the time when the focal individual changed jobs as an instrument for the age and size of the firm that they joined. To eliminate any possible reverse causality, in calculating these proportions, we did not include the job entered by the focal individual. Our instrument builds on the idea that most individuals search for jobs in their industry and in their region. In essence, the instrument identifies the effects of joining a small and/or young firm based simply of the job opportunities available in an industry at a given time and place. Note that we actually need three instruments, one for each of our age-size category variables (small young, small old, large young). We therefore calculated three instruments based on the proportions of jobs available in each age-size category in a particular region, industry, and year.

Table 3 reports the results of these IV estimates. The first three columns present the first stages for these models. As one would want, in each case, the prediction of the endogenous variable loads primarily on the associated age-size instrument. The proportion of jobs in small, young firms, for example, has more than triple the effect of the other two instruments in predicting the probability that an individual joins a small, young firm. All of the instruments have t-statistics in excess of 100 for the variables that they instrument and, overall, the demography of jobs available in a particular industry and region at a particular point in
time explains roughly 20% of the variance in the ages and sizes of the firms joined. We therefore need not worry about the instrument not being strong enough to eliminate any bias in the fixed effects estimates.\textsuperscript{12}

The second-stage coefficients interestingly suggest that the estimates in Table 2 may actually underestimate the penalties associated with joining a small firm. Becoming an employee of a small firm – young or old – reduces income over the subsequent decade by roughly 14%. Joining a large, young firm, by contrast, boosts earnings by a small amount, about 4%. These larger effect sizes may stem from the fact that fixed effects both absorb any stable differences across case-control triplets but also exacerbate attenuation bias due to measurement error in the variables. Note, however, that the 95% confidence intervals around these point estimates overlap with the confidence intervals for the coefficients reported in Table 2. One therefore cannot reject the null hypothesis that the instrumental variables produce equivalent estimates of the causal effect.

**MECHANISMS**

Although these results strongly suggest a causal effect – that is, that joining a startup or an older, small firm reduces long-term earnings – it provides little insight into why individuals who join startups and other small firms suffer from these earnings shortfalls.

Expanding on the long-term disadvantages discussed above, we see three potential sources of this effect: job instability, a stigma of failure, and path dependency in employment. To explore which of these factors might account for the effects, we introduced covariates

\textsuperscript{12}The Angrist-Pischke $F$-statistic has values ranging from 6,113 to 8,888. Although no critical values are available for this test, it has the same distribution as the $F$ statistic for which Stock and Yogo (2005) calculated critical values. To ensure that the instrument has sufficient strength to have no more than 5% of the endogeneity bias in the OLS estimates, they calculated critical values in the range of 10-20. Our first stages exceed these minimal recommended values by orders of magnitude.
that should capture each of these mechanisms. To the extent that their inclusion reduces the residual earnings effects associated with joining small and/or young firms, it would suggest that these mechanisms may well mediate the causal effect. The hierarchical models introducing these variables appear in Table 4 (for ease of comparison, the first column of estimates in that table repeats those in the third column of Table 2—the baseline model).

**Job instability.** One of the most obvious ways in which both young and small firms differ from larger, older firms is in their odds of failing. Although many have called attention to the idea that all jobs have become more unstable over the last decades, in any given year small firms almost certainly offer less stable employment than large ones. Small firms do not necessarily have a greater proclivity to shed people. Higher levels of social integration in these firms probably mean that they do everything possible to protect their employees. But small firms – and particularly small, young firms – simply fail at much higher rates (Freeman et al. 1983; Carroll and Hannan 2000), leaving all of their former employees in search of jobs.

To assess the importance of job instability to the income gap, we included a variable that measures, for each individual, the proportion of each year spent in the labor force. *Time in labor force* divides the number of days worked (across all employers) by the total number of possible workdays for the year. Column 2 reveals that the inclusion of this variable accounts for a large share of the negative earnings effects associated with joining small firms: 80% of the effect for small, young firms and 66% for small, old firms. It also appears to enhance the positive effects associated with joining a young firm that has already grown to be large.

Note also that the coefficient for time in labor force substantially exceeds one. The negative earnings effects of unemployment therefore do not stem solely from lost wages—in which case the coefficient would have a value of roughly one (because it has been scaled to the proportion of the year in employment). Unemployment due to job loss also imposes
a penalty on employees even after they secure another job, just as has been found in past research on the scarring effects of unemployment (Brand 2004; Gangl 2006; Cha and Morgan 2010; Brand 2015).

A number of factors might account for this unemployment penalty. Career advancement and pay increases often depend on tenure within a given firm (Bidwell and Briscoe 2010; Bidwell and Mollick 2015). Every time an employee of a small or young firm changes jobs they start anew, their tenure clock resets to zero. They must start over. In addition, the former employees of failed firms have no backup option and have much less bargaining power when they search for jobs. They therefore probably end up settling for positions that pay less, perhaps even less than their previous job. Each of these setbacks, however small, builds on each other, creating increasingly divergent paths.

**Stigma of failure.** Beyond losing a job, leaving a firm that failed, particularly a small one, may have a stigma associated with it. Potential future employers may see the individual as somehow partially responsible for that failure and therefore consider the firm failure a negative signal of their abilities. Numerous studies, moreover, have found that merely being associated with undesirable actors can lead to stigmatization (Goffman 1963; Neuberg et al. 1994; Pontikes et al. 2010)

To capture the potential stigma associated with being employed at a failing firm, we included two additional variables. One, *left firm*, captures the general effects of leaving an employer. It turns on when individuals leave their original employers and remains turned on in all subsequent years. The second, *stigma*, captures the effects of leaving a firm close to its time of failure. It has a value of one – and remains one for all subsequent years – when an individual departs a firm in the same year that the firm ceases to exist.

The third column reports a model that includes these variables. In general, moving across
employers has a negative, though very small (less than 1%), effect on income. The effects of leaving a firm just before or when it fails, moreover, appears slightly positive. Individuals who remained on board until the very end earn just over 1% more in subsequent years. Notice, however, that the inclusion of left firm and stigma has a negligible influence on the point estimates for the long-term effects of joining small and/or young firms.

**Path dependency in employment.** The final model accounts for the ages and sizes of employers in the current year. These could matter for at least two reasons. First, even if individuals do not change employers, their firms may grow and mature. One might then expect the income differentials for the employees of these firms to narrow over time. (The growing penalties in Figure 2 may stem entirely from those experiencing spells of unemployment.) Second, if some of the individuals who joined small, young firms later returned to large, established ones or if some of those in the control group left their employers for smaller and/or younger ones, then our estimates might actually understate the penalties associated with joining a startup.

We therefore included indicator variables to capture the age-size category of each individual’s employer in each year. Interestingly, the effects for the age and size of the current employer appear far more negative for small, young firms than for small, old ones. Once one includes these measures, however, the residual long-term effect associated with joining small, old firms declines almost to zero. The effect associated with joining small, young firms, in fact shifts to being positive, though small (about 2%). That suggests that the early employees of startups that do not fail and that grow large enjoy a small premium in their long-term earnings. Overall, the negative long-run effects of joining small firms appears to come entirely through two channels: job instability and path dependency in employer size.
**Firm-to-firm mobility**

Although the estimates in Table 4 suggest that the age and size of current employers accounts for an important piece of the penalty associated with joining a startup, it does not give us a sense of just how strong this path dependency might be. We therefore estimated log-linear models, using maximum likelihood Poisson regression, to assess the strength of the age and size inertia in mobility across employers, controlling for the distributions of origin and destination states.

We estimated our log-linear models on two three-dimensional tables. In the first, the age and size quadrant for each individual’s employer in the current year represents one marginal distribution and the age and size quadrant of the employer in the subsequent year represents a second marginal distribution. The third dimension is time as we cross-tabulate these origin and destination states for every year in our data. In the second three-dimensional table, only individuals who changed employers contribute to the numbers in each cell. One marginal distribution then represents the age and size quadrant for the origin firm of a job changer while the other marginal distribution captures the age and size quadrant of the destination firm for the individual. Again, the third dimension is time.

Table 5 summarizes the results of these log-linear models. Because our models include such large counts in each cell, the traditional measures of model fit for log-linear analyses – the chi-squared tests – would almost never suggest that one should prefer a more parsimonious model. We therefore report and focus on the amount of variance explained by each model.

We begin by estimating the independence model, which essentially tells us the degree to which the observed patterns in the relationships between the origin and destination states stem simply from the distributions of employment opportunities available from year to year—in other words, the extent to which individuals sort more-or-less randomly into employers
of varying age or size according to the availability of jobs. The independence model alone can account for roughly 58% of the variance in employer age-size transitions and 76% of the age-size mobility across firms. A very large share of the movement of individuals across employers of varying ages and sizes therefore appears to stem from the opportunity structure rather than from sorting.

To assess the extent to which sorting occurs on firm age and firm size, the second and third models include terms for age and size inheritance, respectively—the odds that an individual remains with an employer of small size or young in age. The inclusion of these two terms at the same time explains almost all of the remaining variance (model four). Looking at the odds ratios for these terms, sorting occurs more strongly on size than on age. When moving across firms, an individual has about a 2.4 times greater odds of joining a firm in the same size category. The overall odds of being in the same size category from one year to the next are 9.2 times greater than one would expect by chance. Most small firms stay small and most large firms stay large. By contrast, the models reveal less age inheritance. Some of that stems from the fact that all firms get older even if they do not all grow. But even when moving across firms, employees appear more likely to join another firm in the same age category (an odds ratio of 1.8).

More complicated specifications only add marginally to the fit of the model. Model five, for example, adds an age-size interaction term, to capture the extent to which transitions occur primarily within an age-size quadrant. Although this term does improve the model, it only captures another 1% of the variance. More generally, model four already explains more than 92% of the variance using only 29 degrees of freedom, 26 of which simply capture the marginal distributions. Because a fully saturated model would involve interactions between the inheritance terms and each year, it would require more than 300 additional terms to
explain the remaining 3% to 8% of the variance.

A number of factors may contribute to this constrained mobility. The fact that the employees of small and young firms end up with broad and idiosyncratic sets of responsibilities may mean that they find it hard to fit into the highly structured and specialized roles available in large, established firms (Beckman and Burton 2008). It may also relate to the structure of social relationships. These relationships often prove pivotal to recruiting (Fernandez et al. 2000). But due to homophily, the employees of young and small firms may well have social relationships that primarily connect them to other small and young employers, restricting their mobility options. Or, even if individuals do not choose startup firm employment, they may nonetheless enjoy the experience and develop a taste for working in small and/or young firms.

**DISCUSSION**

Entrepreneurship and startups have increasingly been seen as a solution to a wide variety of economic problems, from high levels of unemployment to the dislocation of employees due to technological change (see, for example, recent statements from President Bush or from Romano Prodi, the President of the European Commission: Thurik 2003; Bush 2004). Public policy therefore has increasingly been directed in ways that favor these fledgling firms. Yet, relatively little research has considered how these shifts in the landscape of employers might affect the careers and earnings of employees.

Using Danish registry data, we examined the long-term earnings trajectories associated with joining startups. Individuals who joined firms in their first four year of operations and as one of the first 50 employees earned, on average, 25% less over the subsequent ten years than who employed at firms with more than 50 employees and with more than four years
of operating experience. These differences appear to reflect more of a firm size effect than a firm age effect. Startups with more than 50 employees pay roughly the same, on average, as other large firms.

But a large share of this difference stems from the sorting of individuals into organizations. Similar to what one sees in other parts of Europe and in the United States (Nystrom and Elvung 2014; Ouimet and Zarutzkie 2014), small and young firms in Denmark hire younger and less skilled individuals and ones who had been earning less in their previous jobs. In other words, these firms disproportionately hire disadvantaged individuals who would probably receive less in pay from any employer.

We account for the sorting of individuals into organizations in two ways. First, the large number of cases available allow us to match individuals who joined small and/or young employers tightly to peers with nearly-identical characteristics who joined large, established firms. Second, we used the opportunity structure of jobs available in a particular industry and region at a particular time to instrument for the probability that an individual would end up employed by a small and/or young firm. The first method adjusts for sorting on observable characteristics while the second also accounts for potential sorting on factors not observed by the researcher.

Both methods yield similar size estimates of the causal effects: Joining a startup reduces long-term earnings by 10% to 15%. These effects appear almost entirely related to employer size. Becoming an employee of a small firm that has been operating for more than four years results in a similar penalty to long-term earnings. By contrast, joining a young firm that has already grown to have more than 50 employees has little effect on long-term earnings. These penalties, moreover, appear across industries, operate independent of occupation effects, and remain relatively stable over time.
Two mechanisms, job instability and path dependence in employment, appear to account for these effects. First, those in small and young firms have less stable jobs. They more frequently experience spells of unemployment. Even when they find work again, they fall behind in income relative to those continuously employed. Second, those who join small firms appear to find themselves segregated into employment in small firms. The second mechanism helps to explain both a portion of the lost earnings and why those caught in lower-paying jobs do not leave them.

These mechanisms interact to produce a variety of career trajectories for those joining startups. The most probable sequence—and the one that produces the largest long-term earnings penalties—involves becoming unemployed when the startup fails and then rejoining the labor force in another small firm, which in turn raises the risk of experiencing additional cycles of firm failure, job loss, and reemployment in a small firm. The next most probable path, which also leads to a large long-term earnings penalty—has the startup surviving but failing to grow, leaving these individuals employed in mature but still small firms.

Only two paths yield positive outcomes for those joining startups. In the first, the employees leave the startup voluntarily, before it fails, and enter positions at larger firms. That scenario, however, ends up being unlikely because of the path dependency in these inter-firm moves. Those coming from small firms tend to go to other small firms. In the second path, the startup survives and becomes a large firm. Though also unlikely, this second scenario often seems salient to those considering startup employment (Neff 2012). But note that even in this best of scenarios, employees only experience a small boost in their long-term earnings, of roughly 2%. In contrast to the founders of the firms (Hamilton 2000), we found no evidence that individuals who joined startups as employees could expect to get rich.

Although our research has focused on Denmark, to take advantage of the high quality
of the country’s registry data, one might reasonably question whether other countries would exhibit similar dynamics. We suspect that they would. Research on the short-term earnings effects of joining small and/or young firms has revealed surprisingly consistent effects, and even effect sizes, across Denmark, Germany, Sweden, and the United States (Schmieder 2013; Nystrom and Elvung 2014; Burton et al. 2018; Babina et al. 2018). Babina et al. (2018), for example, confirm that the United States has almost the same gross earnings differential between startups and more established firms and that the sorting of employees to employers accounts for almost exactly the same proportion of this differential as Burton et al. (2018) found in Denmark.

If anything, the penalties associated with joining a startup might prove larger in the United States. Whereas employers in Denmark offer relatively consistent protections, benefits such as health care insurance and retirement plans in the United States vary with firm age and size, with older and larger firms offering better fringe benefits (Kalleberg and Van Buren 1996; Litwin and Phan 2013).

Although one might counter that the employees in startups in the United States also receive equity and options, these awards probably do little to change the picture. Across the economy as a whole, very few employees receive equity compensation—their use has been concentrated in high tech. Even at those startups that do provide equity awards, the odds of them paying out end up being very low and, even when they do, they typically have little value. The janitor or receptionist who became rich from being employed at a high tech startup makes a great public interest story, but is as likely and as representative of the common experience of startup employees as is the multi-million-dollar lottery winner among those buying tickets.

The earnings penalties associated with being employed in small firms also has impli-
cations for inequality and the overall patterns of stratification in society. These are large differences in long-term earnings. They are of roughly the same magnitude as the returns to an additional two to three years of schooling in Denmark or to the earnings effects associated with completing a college degree (e.g., Harmon et al. 2001; Sorenson and Dahl 2016). In the case of education, an effect of that size has been sufficient to motivate a literature of hundreds if not thousands of papers.

The fact that the mere distribution of jobs available accounts for much of the sorting of individuals to firm of particular ages and sizes, as evidenced by both the log-linear analysis and the first-stages of the instrumental variables models, also means that a large number of people find themselves in their situations by accidents of circumstance rather than choice. Put differently, a large proportion of individuals may end up employed in startups and other small firms because they had no other options at the time. Yet this random event has lasting and large consequences for their lifetime earnings. That fact should concern scholars of stratification as much as any factor that substantially influences the odds of an individual obtaining a college degree.

The fact that sorting also plays an important role in determining who works for startups offers little solace on this dimension. Recall that small and young firms primarily hire those who would earn less at any firm—the young, the less skilled, and those with inconsistent employment histories. The fact that they disproportionately end up employed in small and young firms means that the small firm penalty saddles these individuals with a double disadvantage, further distancing their earnings from those considered more desirable as employees.
References


Cobb, J. Adam and Flannery G. Stevens. 2017. “These unequal states: Corporate organiza-


Figure 1: Ten-year accumulated earnings for the employees of startups versus those of large, old firms
Table 1: Logistic regression estimates of sorting by age-size categories

<table>
<thead>
<tr>
<th></th>
<th>Small young</th>
<th>Small old</th>
<th>Large young</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td>-0.041**</td>
<td>-0.041**</td>
<td>-0.024**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td>0.088**</td>
<td>0.107**</td>
<td>0.136**</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>Years of education</strong></td>
<td>-0.004</td>
<td>-0.025**</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.005)</td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top management</td>
<td>-0.087*</td>
<td>-0.185**</td>
<td>-0.341**</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.031)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Upper white collar</td>
<td>-0.219**</td>
<td>-0.336**</td>
<td>-0.184**</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.017)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Lower white collar</td>
<td>-0.425**</td>
<td>-0.405**</td>
<td>-0.288**</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.015)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Unskilled blue collar</td>
<td>-0.028</td>
<td>0.046**</td>
<td>0.089*</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.016)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Undefined or missing</td>
<td>0.465**</td>
<td>0.338**</td>
<td>0.354**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.012)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Prior wage</td>
<td>-0.273**</td>
<td>-0.281**</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Treatment year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>322,617</td>
<td>339,341</td>
<td>280,505</td>
</tr>
</tbody>
</table>

* p <0.05, ** p <0.01. Robust standard errors in parentheses.
Figure 2: Earnings trajectories for the matched employees of small and/or young firms relative to those of large, old firms

Table 2: Fixed effects estimates of long-term differences in logged income

<table>
<thead>
<tr>
<th></th>
<th>Random</th>
<th>Matched</th>
<th>Matched movers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small young</td>
<td>-0.287**</td>
<td>-0.123**</td>
<td>-0.105**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Small old</td>
<td>-0.317**</td>
<td>-0.115**</td>
<td>-0.093**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Large young</td>
<td>-0.066**</td>
<td>-0.013*</td>
<td>0.022**</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Triplet FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Treatment year FE</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>2,017,476</td>
<td>1,664,268</td>
<td>1,440,984</td>
</tr>
</tbody>
</table>

* p < 0.05; ** p < 0.01. Clustered standard errors in parentheses.
Table 3: Instrumental variables regression estimates of the long-term effects on logged income

<table>
<thead>
<tr>
<th></th>
<th>First stages</th>
<th>Second stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Small young</td>
<td>Small old</td>
</tr>
<tr>
<td>Small young instrument</td>
<td>0.837**</td>
<td>0.338**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Small old instrument</td>
<td>0.246**</td>
<td>0.874**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Large young instrument</td>
<td>0.106**</td>
<td>0.103**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Small young</td>
<td>-0.152**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>Small old</td>
<td>-0.159**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>Large young</td>
<td>0.041**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$F$ statistic</td>
<td>6,853</td>
<td>8,888</td>
</tr>
</tbody>
</table>

Based on 106,741 triplets over 1,367,962 person-years. * $p < 0.05$, ** $p < 0.01$. Clustered standard errors in parentheses.
Table 4: Exploring the mechanisms underlying the long-term differences in logged income

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small young ((t = 0))</td>
<td>-0.105**</td>
<td>-0.022**</td>
<td>-0.021**</td>
<td>0.020**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Small old ((t = 0))</td>
<td>-0.093**</td>
<td>-0.032**</td>
<td>-0.031**</td>
<td>-0.006*</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Large young ((t = 0))</td>
<td>0.022**</td>
<td>0.041**</td>
<td>0.041**</td>
<td>0.044**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Time in labor market</td>
<td>1.852**</td>
<td>1.851**</td>
<td>1.801**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Left firm</td>
<td>-0.007**</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stigma</td>
<td>0.013**</td>
<td>0.011**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small young ((t))</td>
<td>-0.130**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small old ((t))</td>
<td>-0.035**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large young ((t))</td>
<td>0.004*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Triplet FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,440,984</td>
<td>1,393,525</td>
<td>1,393,525</td>
<td>1,317,322</td>
</tr>
</tbody>
</table>

* \(p < 0.05\), ** \(p < 0.01\). Clustered standard errors in parentheses.

Table 5: Log-linear analysis of employer age-size mobility

<table>
<thead>
<tr>
<th>Label</th>
<th>Specification</th>
<th>d.f.</th>
<th>Year-to-year Pseudo (R^2)</th>
<th>Job changes Pseudo (R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Conditional independence</td>
<td>(A_o \times S_o + A_d \times S_d)</td>
<td>26</td>
<td>.576</td>
<td>.760</td>
</tr>
<tr>
<td>2 Age inheritance</td>
<td>[1] (+A_o \times A_d)</td>
<td>27</td>
<td>.708</td>
<td>.780</td>
</tr>
<tr>
<td>3 Size inheritance</td>
<td>[1] (+S_o \times S_d)</td>
<td>27</td>
<td>.833</td>
<td>.880</td>
</tr>
<tr>
<td>4 Additive inheritance</td>
<td>[1] (+A_o \times A_d + S_o \times S_d)</td>
<td>28</td>
<td>.961</td>
<td>.914</td>
</tr>
<tr>
<td>5 Joint inheritance</td>
<td>[4] (+A_o \times A_d \times S_o \times S_d)</td>
<td>29</td>
<td>.971</td>
<td>.920</td>
</tr>
</tbody>
</table>