# DO START-UPS PAY LESS?

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The authors analyze Danish registry data from 1991 to 2006 to determine how firm age and firm size influence wages. Unadjusted statistics suggest that smaller firms paid less than larger firms paid, and that firm age had little or no bearing on wages. After adjusting for differences in the characteristics of employees hired by these firms, however, they observe both firm age and firm size effects. Larger firms paid more than did smaller firms for observationally equivalent individuals but, contrary to conventional wisdom, younger firms paid *more* than older firms. The size effect, however, dominates the age effect. Thus, although the typical start-up—being both young and small—paid less than a more established employer, the largest start-ups paid a wage premium.

Policymakers around the globe have become interested in promoting entrepreneurship as a means of creating jobs and stimulating economic growth. But there has been relatively little discussion about the quality of the jobs start-ups create, particularly in terms of the salaries they pay and the benefits they offer. If the process of creative destruction involves replacing higher-paying jobs at incumbent firms with lower-paying ones at start-ups, then a simple examination of the number of jobs created, even net of jobs lost, may overstate the value of entrepreneurial activity to the economy and society.

Although some research has examined the wages of start-ups, the findings have been mixed and we cannot yet say with certainty whether start-ups pay more or less than what established firms pay. Some of the inconsistencies across studies arise from varying methodological choices. But some of the uncertainty arises from flawed assumptions about the ways that firm age and firm size relate to wages and from a failure to account for employee

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characteristics that influence both pay and the probability of joining a start-up.

We study the extent to which pay varies as a function of firm age and firm size using comprehensive registry data on the population of Danish workers, from 1991 to 2006. We expand on the existing literature in four important ways:

1) by estimating the age and size effects as categories, we allow firm age and firm size to have flexible relationships with pay;
2) by focusing on new hires to the firm, we eliminate the extent to which variation in average job tenure might account for firm age and size effects;
3) by matching employees of smaller and younger firms with observationally equivalent counterparts at large, established firms, we account for human capital differences that might explain earnings differentials; and
4) by including fixed effects for fine-grained industry categories, we adjust for the fact that firm age and size might vary with industry competitiveness and employment growth.

Across our analyses, younger firms paid *more* than older ones, and smaller firms paid less than larger ones. We document how methodological choices have substantial implications for the estimated magnitudes of annual earnings differentials across firms. First, our approach to treating firm age and size as categories (bins) yields relationships as much as twice those found by the standard approach that uses logged firm age and size as covariates. Second, although focusing on new hires had little influence on the relationship between firm size and pay, the differences in pay with respect to firm age more than doubled once the confounding effects of employee tenure had been eliminated. Third, factoring in differences in the human capital characteristics of employees accounts for roughly one-third of the firm size wage effect and almost two-thirds of the firm age wage effect. Industry adjustments and other methodological choices, by contrast, make little difference to our wage estimates.

Through a variety of methodological adjustments, and consistent with prior research, we find a firm size wage penalty. The smallest firms paid less than the largest ones paid, by a factor of 10 to 15%. Somewhat unexpectedly, however, younger firms paid more than older firms (though by less than 5%). In fact, large young firms appeared to pay a wage premium over established employers. In most cases though, the size effect dominates the age effect, meaning that the typical start-up—being both small and young—pays less than the average incumbent employer.

## Firm Age, Firm Size, and Wages

Young firms account for an outsized share of all net job creation in the United States (Haltiwanger, Jarmin, and Miranda 2013), in Denmark (Ibsen and Westergård-Nielsen 2011; Malchow-Moller, Schjerning, and Sorensen

2011), and in most other countries (Ayyagari, Demirguc-Kunt, and Maksimovic 2014; de Wit and de Kok 2014; Lawless 2014; Anyadike-Danes et al. 2015). Yet, despite enthusiasm for entrepreneurship on the part of policymakers and the evidence that start-ups account for the majority of net job creation, there are reasons to be pessimistic about entrepreneurship as an engine for creating good jobs and generating broad-based economic benefits. For starters, firms typically begin small. But large firms enjoy economies of scale and scope and can therefore increase employee productivity. Indeed, an extensive empirical literature has examined the relationship between firm size and average compensation, finding that larger firms pay more and offer better benefits than do smaller firms (for a review, see Oi and Idson 1999).

Start-ups may pay less than older firms even independent of these size effects. Fledgling firms have not had the opportunity to improve their operations through learning-by-doing (Arrow 1962) or by investing in equipment (Thompson 2001). Nor have they had time to build social capital (Sorenson and Rogan 2014). To the extent that these factors complement production (Griliches 1969), start-ups should operate at lower levels of productivity than more established firms and consequently pay their employees less. Only a handful of studies to date, however, have examined the relationship between firm age and wages, net of firm size effects. Troske (1998), for example, reported that the youngest manufacturing plants in the United States paid nearly 20% less than the oldest ones in the late 1980s, even after adjusting for differences due to firm size. Similarly, Brixy, Kohaut, and Schnabel (2007), examining evidence from Germany, found that newly founded firms paid roughly 8% lower wages on average than did their older counterparts in the late 1990s.

Although studies typically found that older firms pay more, on average, than younger ones (Audretsch, van Leeuwen, Menkveld, and Thurik 2001; Brixy et al. 2007), most of the studies informing our understanding of firm age and wages have had information on only the average wages paid by firms and therefore have been unable to adjust for differences in the characteristics of the employees of start-ups relative to other firms. Start-ups may prove less appealing to employees, however, because of their lower levels of capital investment and uncertain prospects. Indeed, recent research has documented that smaller and younger firms hire younger, less-educated, and less-experienced individuals (Nystrom and Elvung 2014; Ouimet and Zarutskie 2014). These employees have less human capital and would earn less at any employer, young or old, large or small. The observed firm age effects may therefore reflect differences in who firms hire rather than in how much they pay.

Another complication to understanding firm age effects on wages stems from the fact that employees gain firm-specific experience over time, thereby increasing their value to their employers. Older firms have employees with longer tenure. The typical approach to this problem has been to

assume that wages adjust linearly with firm tenure (e.g., Brown and Medoff 2003; Heyman 2007). But, given that younger firms and older firms do not even overlap over most of the range of the tenure variable, that assumption is often problematic. A two-year-old firm, for example, cannot have any employees with more than two years of experience at the firm, but an established firm might have few employees with less than two years of tenure at the firm. Comparing average pay across firms of different ages conflates the effects of firm age with those of employee tenure.

These methodological challenges imply that the apparent effects of firm age and size on wages could stem more from employee selection and retention than from differences across firms in their productivity or ability to pay (e.g., Abowd, Kramarz, and Margolis 1999). At least four studies have addressed these issues. The studies have found conflicting results, particularly with respect to the effects of firm age, which may reflect their differing methodological choices. Brown and Medoff (2003), in the first study of this type, included the characteristics of employees, firm age, and logged firm size in estimates of the wages of 1,410 US workers. In initial specifications that included only firm characteristics, they found average pay rising with firm age. But this relationship flipped after they accounted for employee characteristics.

Heyman (2007) and Nystrom and Elvung (2014), however, using registry data from Sweden, both found that older firms paid somewhat higher wages. Heyman (2007) took an approach similar to Brown and Medoff (2003), including a variety of individual-level characteristics in a wage equation for roughly 500,000 employee-years observed in three cross sections (1987, 1991, and 1995). Although he could adjust for firm-specific experience in only the latter two cross sections (by including a linear term for tenure), in models adjusting for tenure, he found non-negative relationships between firm age and pay. In the 1995 cross section, moreover, older firms consistently paid more than the younger firms paid.

Nystrom and Elvung (2014), by comparison, adopted a propensity score matching approach to adjust for an even larger set of employee characteristics among a sample of more than 150,000 entrants to the labor market. By definition, these individuals had no experience at the firm; the research design, therefore, eliminated firm tenure as a potential confound. In contrast to other studies that have accounted for employee characteristics, however, their adjustments for employee sorting had little effect on the estimated wage penalty of joining a young firm, perhaps because the models they used to create propensity scores explained less than 2% of the variation in who joined a start-up.

Schmieder (2013), meanwhile, found the opposite relationship between firm age and wages using registry data from Germany, with young firms offering as much as a 6% *premium* over older employers. To address the tenure problem, Schmieder focused only on job changers (movers). To adjust for heterogeneity in employees and employers, he used individual-

level and firm-level fixed effects. His estimates therefore focused on the changes in pay associated with moving across firms as those firms mature and grow in size. Although his empirical approach addressed both the tenure issue and the sorting of employees into firms, the German data that he used primarily captured older and larger employers. To the extent that firm age and size effects have decreasing marginal returns, his results may have underestimated the overall importance of these firm characteristics. He also did not allow firm age and size to interact in their determination of wages.

As this brief review reveals, although scholars have begun to address how wages vary with firm age and size, many questions remain. For example: Do firm age and size effects follow the functional forms typically used? Do they interact in their determination of wages? To what extent do the apparent age effects confound firm age with employee tenure? To what extent might unobserved heterogeneity either on the side of the employee or on the side of the firm account for differences after adjusting for the observed characteristics of employees and employers? Many studies, moreover, have treated firms and establishments interchangeably without careful attention to distinguishing newly created firms from either foreign subsidiaries or expansions of an existing enterprise. We tackle these questions below.

## Empirical Strategy

To advance our understanding of the relationships between firm age, firm size, and wages, and to explore whether start-ups pay more or less than established firms, we examine Danish registry data, the Integrated Database for Labor Market Research, commonly referred to by its Danish acronym, IDA (for a useful English-language overview of the data, see Timmermans' 2010 paper). These data cover every employee in the country; we begin by restricting the sample to full-time employees between the ages of 18 and 60 to focus on adults and on those who had not yet begun to shift their employment choices in anticipation of retirement.

Although the IDA database begins in 1980, we consider only the post-1991 period. In the late 1970s and 1980s, a series of regulatory reforms dismantled most of the centralized wage-setting system, allowing firms much more flexibility in their compensation practices (Madsen, Andersen, and Due 2001). Denmark now has some of the least restrictive labor market policies in Europe (Bingley and Westergård-Nielsen 2003; Sørensen and Sorenson 2007), usefully allowing comparison to larger economies such as Canada, the United Kingdom, and the United States. Although Denmark has made it easy to hire and fire employees, and has a flexible wage-setting regime, the country nevertheless retains a strong social support net, a combination sometimes referred to as *flexicurity* (Madsen 2004).

Unlike the setting in the United States, for example, in Denmark benefits, such as health insurance and retirement plans, come from the central

state rather than from employers. For our purposes, this model has the advantage of ensuring that most of the differences between employers in the quality of jobs stems from how much they pay, rather than from a combination of wages and benefits.

Two additional features of the Danish context help to simplify our analysis. First, the Danish tax system does not encourage the use of equity as a form of compensation. Denmark taxes equity awards as income rather than as capital gains. As a consequence, most companies use bonuses rather than stock or stock options as a means of paying for performance (Eriksson 2001). Eriksson (2001), moreover, found that small firms in Denmark use equity compensation—as well as all other forms of variable compensation—less than large firms do. Because bonuses appear as income, our analyses should include all forms of compensation for the vast majority of employees.

Second, Denmark has strong norms against long work hours. In 2015, for instance, only 2% of Danish full-time workers reported working more than 50 hours per week compared to an Organisation for Economic Co-operation and Development (OECD) average of 13% (OECD 2015). Any observed annual pay differences therefore are not likely to reflect differences in the number of hours worked.

## Average Wages by Firm Age and Size

We first classify each employer into one of four full-time employee categories: 1 to 10, 11 to 49, 50 to 249, and more than 250 full-time employees. We also classify each employer into one of four age categories: 1 to 2 years, 3 to 4 years, 5 to 8 years, and 9 or more years.[1] Although we chose these categories for their consistency with and comparability to the categories routinely applied to employers in the United States, we note that our age and size characteristics refer to the firm (organization), not to the establishment or plant (sub-unit).

We exclude foreign subsidiaries and other cases of incumbent firms creating new establishments. To err on the conservative side, we also remove from the analysis start-ups in which a large proportion of the employees had worked together in the prior year for an employer in the same industry and region, but with a different firm identification code. Although this procedure likely eliminates some start-ups that had been founded by groups of individuals from the same employer, treating some well-established entities as start-ups seems more problematic than does the exclusion of a few employee spin-offs.

[1]Occasionally, a firm had no employees associated with it for one or more years. For cases in which a firm had no employees for a single year, we treat it as though it had been operating continuously. In cases in which a firm had no employees for multiple consecutive years, we reset its age to 1 upon reentry.

*Table 1.* Mean and Median Annual Earnings for All Employees by Firm Size and Firm Age

| *Firm size bin* | *1–2 years* | *3–4 years* | *5–8 years* | *9+ years* | *Total* |
|---|---|---|---|---|---|
| **1–10 employees** | | | | | |
| Mean | 239,938 | 239,224 | 235,315 | 225,448 | 231,334 |
| Median | 216,996 | 216,217 | 214,478 | 210,107 | 212,791 |
| Standard deviation | 160,620 | 325,958 | 153,750 | 133,422 | 217,292 |
| Observations | 414,349 | 325,888 | 474,790 | 1,363,716 | 2,578,743 |
| Number of firms | 110,634 | 77,100 | 66,470 | 72,007 | 326,211 |
| **11–49 employees** | | | | | |
| Mean | 278,311 | 282,161 | 281,200 | 265,256 | 270,050 |
| Median | 246,560 | 249,440 | 249,078 | 239,992 | 242,641 |
| Standard deviation | 185,361 | 188,510 | 184,084 | 160,083 | 179,867 |
| Observations | 208,350 | 221,110 | 405,741 | 1,861,437 | 2,696,638 |
| Number of firms | 8,720 | 8,445 | 9,930 | 16,293 | 43,388 |
| **50–249 employees** | | | | | |
| Mean | 291,341 | 292,146 | 297,941 | 284,591 | 286,493 |
| Median | 253,899 | 252,599 | 257,594 | 251,433 | 252,176 |
| Standard deviation | 191,051 | 194,368 | 196,895 | 182,429 | 191,264 |
| Observations | 122,053 | 127,559 | 261,668 | 2,265,351 | 2,776,631 |
| Number of firms | 1,255 | 1,268 | 1,658 | 4,061 | 8,242 |
| **250+ employees** | | | | | |
| Mean | 311,357 | 309,104 | 305,273 | 289,589 | 292,215 |
| Median | 283,171 | 279,605 | 270,175 | 255,302 | 258,268 |
| Standard deviation | 167,542 | 172,877 | 191,917 | 174,679 | 176,990 |
| Observations | 167,406 | 167,064 | 326,370 | 3,917,366 | 4,578,206 |
| Number of firms | 302 | 289 | 307 | 940 | 1,838 |
| **Total** | | | | | |
| Mean | 268,688 | 272,397 | 274,698 | 274,273 | 273,794 |
| Median | 240,832 | 243,042 | 244,098 | 244,790 | 244,307 |
| Standard deviation | 176,584 | 228,829 | 182,432 | 163,723 | 189,494 |
| Observations | 912,158 | 841,621 | 1,468,569 | 9,407,870 | 12,630,218 |
| Number of firms | 120,911 | 87,102 | 78,365 | 93,301 | 379,679 |

Table 1 reports the median, mean, and standard deviation of the annual earnings for all full-time employees, between the ages of 18 and 60, in each of these size and age categories across the entire period, 1991 to 2006, for our population of more than 12 million employee-years. We also report the number of employee observations and the number of firms for each category of firm age and size. Looking down the columns, one can see a clear size gradient. Within each age range, larger firms paid more than smaller ones. The smallest employers—those with 1 to 10 employees—paid their employees 18 to 23% less than those with 250 or more employees. Looking across the rows, patterns become more difficult to detect.

## Movers

One of the most consistent complications noted in the prior literature on the relationship between firm age and wages has been that older firms also tend to employ individuals who have longer tenure with the firm (Brown

and Medoff 2003; Heyman 2007; Ouimet and Zarutskie 2014). Prior research has typically dealt with this issue by including firm tenure as a covariate. But if the returns to firm tenure decline over time or vary across individuals, any linear adjustment for firm tenure may underestimate the "true" firm tenure effect and would then probably attribute a portion of these tenure differences to firm age.

We adopt a quite conservative approach to addressing this issue by examining only new hires and the wages they earned. By definition, these individuals have no prior experience in the firm; therefore, our estimates compare similar individuals—at least in terms of firm tenure—across both young and old firms. In particular, we restrict the sample to those who had worked for a firm for at least 30 days but no more than one year. We exclude all individuals listed as founders, employers, or entrepreneurs, as their compensation may involve equity as well as wages. These restrictions reduce our sample size, but still leave us with more than 3.1 million observations across more than 260,000 firms.

Table 2 reports the median, mean, and standard deviations of the wages for these recent hires as well as the number of observations and firms for each age and size category. Note that Table 2 reports consistently lower wages than Table 1, reflecting the fact that pay rises with firm tenure. Reading down the columns, one continues to see the strong relationship between firm size and wages, with the largest firms paying new hires 18 to 21% more than the smallest firms. But the pattern for firm age changes noticeably. Looking across the rows, one now notices a *negative* relationship between firm age and the average wages paid to recent hires. Within each of the size categories, the oldest firms paid the lowest wages. The youngest firms paid 9 to 13% more to new hires than did the oldest firms, and both mean and median wages at firms in the youngest two age categories (4 or fewer years old) consistently exceeded the overall mean and median for each size category.

## Adjusted Wages by Age and Size

### Employee Sorting

Although restricting the sample to recent hires accounts for differences on the most obvious dimension on which young and old firms differ—firm tenure—employees might nonetheless sort into firms on a host of other characteristics related to productivity and, therefore, also to expected wages. We first explore the extent to which young and small firms differed from the overall population of firms in terms of the individuals they hired. Although past studies have reported differences between younger and older firms in the characteristics of their employees (Nystrom and Elvung 2014; Ouimet and Zarutskie 2014), the cross-sectional information on which those studies have relied depends on the joint combination of differential hiring,

*Table 2.* Mean and Median Annual Earnings for New Hires by Firm Size and Firm Age

| *Firm size bin* | *1–2 years* | *3–4 years* | *5–8 years* | *9+ years* | *Total* |
|---|---|---|---|---|---|
| **1–10 employees** | | | | | |
| Mean | 221,932 | 212,674 | 207,906 | 199,925 | 209,133 |
| Median | 209,496 | 202,911 | 199,888 | 193,638 | 200,382 |
| Standard deviation | 140,783 | 128,440 | 123,108 | 112,021 | 126,512 |
| Observations | 142,098 | 84,950 | 105,506 | 216,144 | 548,698 |
| Number of firms | 63,030 | 40,195 | 38,360 | 46,720 | 188,305 |
| **11–49 employees** | | | | | |
| Mean | 259,284 | 252,437 | 249,179 | 235,099 | 242,785 |
| Median | 237,420 | 232,509 | 230,577 | 220,225 | 225,746 |
| Standard deviation | 161,576 | 147,481 | 140,816 | 136,324 | 146,859 |
| Observations | 70,738 | 59,604 | 95,501 | 306,166 | 532,009 |
| Number of firms | 7,785 | 7,480 | 8,876 | 14,556 | 38,697 |
| **50–249 employees** | | | | | |
| Mean | 274,507 | 264,220 | 266,412 | 253,423 | 257,130 |
| Median | 242,250 | 234,108 | 238,448 | 230,167 | 232,253 |
| Standard deviation | 190,235 | 172,847 | 155,758 | 146,250 | 167,119 |
| Observations | 33,856 | 30,255 | 58,874 | 363,947 | 486,032 |
| Number of firms | 1,118 | 1,155 | 1,530 | 3,818 | 7,621 |
| **250+ employees** | | | | | |
| Mean | 298,975 | 276,950 | 267,888 | 258,301 | 262,858 |
| Median | 263,854 | 250,740 | 243,772 | 232,402 | 236,495 |
| Standard deviation | 187,801 | 141,998 | 148,116 | 152,463 | 158,600 |
| Observations | 42,794 | 28,501 | 62,318 | 496,044 | 629,657 |
| Number of firms | 275 | 269 | 298 | 889 | 1,731 |
| **Total** | | | | | |
| Mean | 248,597 | 241,012 | 242,431 | 242,750 | 243,313 |
| Median | 228,186 | 222,936 | 224,518 | 223,062 | 223,939 |
| Standard deviation | 171,308 | 148,566 | 142,464 | 137,629 | 150,545 |
| Observations | 289,486 | 203,310 | 322,199 | 1,382,301 | 2,197,296 |
| Number of firms | 72,208 | 49,099 | 49,064 | 65,983 | 236,354 |

maturation, and differential retention. Whether young firms, in fact, hire different kinds of individuals therefore remains an open question.

Table 3 reports the demographic characteristics for the full population of new hires and for two relevant subsets. The first column presents averages across all firms for any new hire. The second column, meanwhile, restricts this set to those hires coming from a business establishment that closed. We include this group because one might worry that movers self-select into moving and therefore differ in important ways from non-movers. Focusing on those who had to find a new job because their prior establishment closed should eliminate most—if not all—self-selection (Gibbons and Katz 1991; Gruetter and Lalive 2009). Although our sample includes the service sector, we refer to this subsample as the "plant closings" group. Note that our sample size falls dramatically from more than two million observations to fewer than 215,000. Within this restricted set of involuntary movers, the means and medians rise for all age and size bins, suggesting adverse selection on

*Table 3.* Sample Demographics by Move Type and Destination

| | *All* | | *Young (<5 years)* | | *Small (<50 employees)* | |
|---|---|---|---|---|---|---|
| *Firm size bin* | *All hires* | *Plant closing* | *All hires* | *Plant closing* | *All hires* | *Plant closing* |
| Age | 34.02 | 37.15 | 34.42 | 37.09 | 33.88 | 36.15 |
| | (10.17) | (10.68) | (10.12) | (10.61) | (10.31) | (10.86) |
| Female | 0.34 | 0.33 | 0.34 | 0.34 | 0.33 | 0.34 |
| | (0.47) | (0.47) | (0.48) | (0.47) | (0.47) | (0.47) |
| Months of education | 148.31 | 147.79 | 148.51 | 147.65 | 146.71 | 144.98 |
| | (28.28) | (29.24) | (28.25) | (28.97) | (27.46) | (28.06) |
| Type of education | | | | | | |
| Primary school | 0.27 | 0.28 | 0.27 | 0.27 | 0.29 | 0.31 |
| | (0.44) | (0.45) | (0.44) | (0.45) | (0.45) | (0.46) |
| High school/gymnasium | 0.10 | 0.08 | 0.09 | 0.08 | 0.09 | 0.08 |
| | (0.30) | (0.28) | (0.29) | (0.28) | (0.28) | (0.28) |
| Vocational training | 0.44 | 0.45 | 0.45 | 0.46 | 0.47 | 0.46 |
| | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) |
| College | 0.13 | 0.13 | 0.12 | 0.12 | 0.11 | 0.10 |
| | (0.33) | (0.34) | (0.33) | (0.32) | (0.31) | (0.30) |
| University | 0.06 | 0.06 | 0.07 | 0.06 | 0.05 | 0.04 |
| | (0.25) | (0.25) | (0.25) | (0.24) | (0.22) | (0.20) |
| Labor market experience | 13.80 | 16.04 | 13.65 | 15.55 | 13.53 | 14.62 |
| | (8.88) | (9.26) | (8.83) | (9.19) | (8.73) | (9.09) |
| Unemployment history | 1.27 | 1.13 | 1.34 | 1.18 | 1.37 | 1.42 |
| | (1.93) | (1.84) | (1.99) | (1.89) | (2.01) | (2.06) |
| Ln(Prior wage) | 9.22 | 10.10 | 9.11 | 9.99 | 9.00 | 9.17 |
| | (5.20) | (4.67) | (5.28) | (4.74) | (5.28) | (5.19) |
| Observations | 2,197,296 | 213,692 | 492,796 | 57,306 | 1,080,707 | 84,011 |

*Note:* Standard deviation in parentheses.

average among movers. Adverse selection can also be observed by comparing the average prior wages across the first and second columns in Table 3.

The next two columns report means for the subsets of all hires and of plant closing movers shifting to young firms. The final two columns do the same for those moving to small firms. Across all employee characteristics, few differences exist between the populations of new hires in the first and second columns and those going to young firms in the third and fourth columns. Somewhat larger differences appear between smaller and larger firms, comparing the first and second columns to the fifth and sixth columns. Smaller employers, particularly in the plant closing group, hired less-educated individuals, who had less labor market experience and longer spells of unemployment. The compositional differences in who start-ups hire, therefore, appears to be more of a size effect than an age effect.

## Employee Matching

Although few prior studies have adjusted for these differences, those that have done so have generally relied on adjustments through linear

regression. In other words, researchers estimated a wage equation, effectively assuming each of the relevant human capital dimensions had additive effects on the expected wage, or its logged value (e.g., Brown and Medoff 2003). Having data on the entire population allows us to adopt a more flexible and non-parametric approach to adjusting for individual differences. Rather than estimating a wage equation with linear adjustments for the effects of age, gender, education, and other factors, we instead match on these characteristics and include a fixed effect for each matched group. Because the fixed effect adjusts for a specific combination of attributes, it effectively allows these attributes, such as education and experience, to have completely flexible relationships to earnings and to interact in their determination of wages (i.e., allowing the returns to one dimension of human capital to depend on the others).

To minimize the possibility that a confounding factor accounts for the results, one would ideally match cases and controls *exactly* on all relevant observed dimensions. Of course, with continuous variables, this approach proves impractical if not impossible as no two individuals have been born at precisely the same instant, for example, nor do they earn exactly the same amount. We therefore adopt a modified version of this approach, combining coarsened exact matching (CEM) on several dimensions with nearest-neighbor matching on income in the previous year. Extended discussions of the advantages of this approach are offered in Iacus, King, and Porro (2012) and in King and Nielsen (2015).

Our matching procedure operates as follows. We treat each cell in the firm age-size matrix as a subsample. For each employee within a subsample, such as those beginning jobs at companies with 1 to 10 employees that have been operating for 1 to 2 years, we find all observationally equivalent individuals in our baseline category of large, established firms (those beginning jobs at employers with at least 250 employees and that have been operating for at least nine years). We consider two individuals to be observationally equivalent if they have the same gender (male/female), the same age (coarsened to the year of birth), the same level of education (coarsened to the highest degree: primary school only, high school or gymnasium, a vocational training certification, undergraduate college, or graduate level), and the same prior occupation (using the one-digit version of the occupational codes for Denmark, which delineates 10 major occupational categories to distinguish between skilled and unskilled jobs and between white- and blue-collar occupations).[2]

Although this matching accounts for differences across employees on some of the most important factors influencing wages, workers differ on a host of difficult-to-observe dimensions that also affect productivity and pay.

[2]The number of available matches limited our ability to employ more fine-grained occupational categories at this stage. Including more-detailed two-digit occupational categories as fixed effects, however, did not absorb much additional variance. This outcome is consistent with the results reported by Schmieder (2013).

Most of these factors should, however, remain relatively stable for a given individual over relatively short intervals of time. We therefore use information on the prior wages of individuals to account for these differences. From the set of available individuals who matched exactly on gender, age, education, and occupation, we include only the two nearest neighbors on the prior year wage distribution—the closest observation above and the closest below what an employee earned in that previous year—in the comparison set. To achieve high-quality matches and ensure that the matching estimator replicates the population average treatment effect (Abadie and Imbens 2006), we match with replacement, meaning a control could serve as a match for multiple focal individuals. This procedure yielded statistically identical average wages across all sets of cases and controls.

Consider first, for example, the individuals who joined small (1–10 employees), young (1–2 years) firms (the top left cell in our tables). For the 142,098 "focal" individuals who joined these firms (see Table 2), we find control individuals who joined large (250+ employees), established (9+ years) firms (the baseline category) in the same year, who matched the focal individuals on age, gender, education, and prior occupation. For each focal individual, we select the exact match closest but just above the person in earnings ($t+1$) and the exact match closest but just below in earnings ($t-1$) to form an observation triad. We successfully identify matches for 135,530 (98%) of the focal individuals.[3]

## Adjusting for Human Capital

For each of our 15 matched samples, we estimate the effect of being in the treated group (that is, not being employed by a firm in the oldest and largest category). Specifically, we estimate the following equation:

$$Ln(W_i) = \beta_{as} AS_i + \gamma_j + E_i, \quad (1)$$

where $W_i$ represents the starting wage for individual $i$, $AS_i$ denotes a dummy variable that takes the value 1 when the individual in question works for a firm in the younger age and/or smaller size category, $\gamma$ represents a vector of fixed effects specific to each triad $j$ (i.e., a focal individual plus two matched controls), and $E_i$ denotes an individual-specific error term. By adjusting for individual characteristics through a series of fixed effects, this model controls flexibly for any shape the relationship between each of these factors and wages might take, as well as for any interactions between these characteristics in the determination of wages. Because both the cases and the controls in each set changed jobs in the same year, these fixed effects

[3]In total, we have 15 sets of matched samples (one for each cell in the age-size matrix, except for the baseline category), and we obtain a match rate of 97% or better across 11 of them. Our lowest match rate, 78%, occurs in the smallest (1–10 employees) and oldest (9+ years) category.

*Table 4.* Regression Matrix: New Hires Matched on Age, Gender, Education, Prior Job, and Prior Earnings

| *Firm size bin* | *1–2 years* | *3–4 years* | *5–8 years* | *9+ years* |
|---|---|---|---|---|
| 1–10 employees | –0.179* | –0.204* | –0.206* | –0.192* |
| | (0.003) | (0.003) | (0.003) | (0.002) |
| Triads | 135,520 | 81,548 | 101,582 | 208,930 |
| 11–49 employees | –0.046* | –0.061* | –0.062* | –0.071* |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| Triads | 68,300 | 57,598 | 92,550 | 297,818 |
| 50–249 employees | –0.006 | –0.013* | –0.014* | –0.019* |
| | (0.004) | (0.004) | (0.003) | (0.001) |
| Triads | 32,744 | 29,322 | 57,147 | 354,571 |
| 250+ employees | 0.094* | 0.041* | 0.021* | |
| | (0.003) | (0.004) | (0.003) | |
| Triads | 41,319 | 27,603 | 60,507 | |

*Notes:* Robust standard errors in parentheses. All regressions include fixed effects for each matched triad of one individual from the treatment cell and two matched individuals from the baseline cell of firms with 250 or more employees that are more than 9 years old.
*$p < 0.01$.

also absorb any period effects, such as the business cycle. We repeat this procedure for each of the 15 matched samples.

Table 4 reports the $\beta_{as}$ values from these 15 regressions. In the interest of saving space, each cell in the table simply reports the $\beta_{as}$ coefficient and standard errors for the regression using the relevant matched sample. We also report the number of case-control triads used in each regression.

The value in each cell is the estimated pay for observationally equivalent new hires in a firm in that particular age and size bin relative to the pay offered in an established (9+ years), large (250+ employees) firm. Thus, for example, the top left cell indicates that an individual hired by a firm in the smallest, youngest group would receive an annual wage only 84% ($\exp(-0.179) = 0.836$) as large as a similar individual hired by a large, established firm. Given that the average new hire in a large, established firm earned about 258,300 Danish kroner (DKK), the comparable person hired by the small start-up would earn about DKK 216,000, an annual difference of approximately US$6,500.

Reading across the first row, all four firm age categories have negative wage coefficients, revealing a sizable wage penalty for employees hired by the smallest firms. The steepest gradient, moreover, appears as one moves across the first two age groups. Reading these coefficient values down the columns to compare wages in similarly aged firms of different sizes reveals a strong positive size effect. Wage penalties decrease as firm size increases. The size effects nevertheless appear larger for younger firms than for older ones, suggesting that firm age and size interact to some extent in determining wages.

*Table 5.* Firm Age and Firm Size Effects for Different Samples and Modeling Choices

| *Sample and model* | *Firm age 1–10 (%)* | *Firm size 5–250 (%)* |
|---|---|---|
| (1) Population (Brown and Medoff; Heyman) | –2.52 | 12.69 |
| (2) Movers (Brown and Medoff; Heyman) | –3.68 | 16.98 |
| (3) Population (bins) | –3.96 | 33.14 |
| (4) Movers (bins) | –9.31 | 35.84 |
| (5) + matched individuals (Table 4) | –3.99 | 23.70 |
| (6) + industry FEs | –5.25 | 20.30 |
| (7) Plant closings (bins, matched, industry FE) | –4.79 | 23.78 |
| (8) Movers (bins, matched, industry FE, future growth) | –3.87 | 18.68 |
| (9) Entrants (bins, matched, industry FE) | –3.21 | 14.95 |

*Note:* FE, fixed effects.

Notably, some start-ups paid wages equivalent to or higher than the largest, most established firms. And, all three columns of the largest size category (250+ employees) have positive wage coefficients. Start-ups, particularly those that begin large or become large rapidly, would appear to create the highest-paying jobs. But how common are such firms and how prevalent are these jobs? In terms of firms, recall that nearly 90% of firms in the youngest column occupy the top-left cell, being both young and very small. Low-paying start-ups therefore dominate the mix. But in terms of the typical job offering, because the larger firms account for more jobs, the numbers are more encouraging. Roughly one-quarter of jobs in start-ups pay a premium over those of large, established firms.

## Methodological Choices and Their Implications

Although our approach accounts for a variety of issues not addressed in previous studies, to what extent do the differences in our estimates (compared to earlier ones) stem from our modeling choices rather than from our setting? On the one hand, better accounting for firm tenure and employee characteristics may address issues in the estimates found in prior studies. On the other hand, Denmark may simply exhibit a distinct pattern of pay with respect to firm age and size. Even the prior inconsistencies in the estimates may stem not from the approaches used but from the fact that the results have variously been from samples in the United States, Sweden, and Germany.

To address these issues, we estimate the magnitudes of the firm age and the firm size effects using a variety of methods to mimic prior research. We summarize these results in Table 5. In the first column, we report the estimated wage differential associated with moving from a start-up to a firm that has been operating for 10 years. The second column shows the estimated

wage differential associated with moving from a firm with five employees to one with 250. Each row corresponds to a set of estimation choices.

We first replicate the approach employed by both Brown and Medoff (2003) and Heyman (2007). This model uses the full population as a sample, adjusting for a variety of employee and firm characteristics as covariates. We estimate the effects of firm age and of firm size as log functions. As noted above, accounting for employee tenure may represent one of the most important adjustments, particularly when trying to understand the effects of firm age. In the second row, therefore, we show results from the same method but use the sample of job changers instead of including firm tenure as a covariate. (Full results and a more detailed explanation of these analyses are available in the online Appendix.)

Beginning with the third row, the table presents the various elements of our modeling approach. It reports the results of the estimated effect sizes using our approach to binning age and size. Although the splining used by Heyman (2007), in his supplementary analysis, and by Schmieder (2013) also allows for nonlinearity, the binning further allows for firm age and firm size to interact in their determination of wages. Note that when calculating the average effects of firm age and firm size in our binned models, the reported values weight the effect in each row (column) according to the number of jobs represented by that row (column). The third row reports these estimates for the full population, the fourth row for only job changers (movers). The fifth row reports estimates for the models that we report in Table 4, on the sets of matched observationally equivalent individuals.

Comparing across these five rows, we see three effects. First, the binned approach, with its flexible functional form, generally produces much larger firm age and firm size effects. Two factors combine to produce this result: 1) the interactive effects of firm age and firm size, and 2) the rate of change in the firm size–wage relationship. As shown in Table 4, the youngest firms differ more in their wages as a function of size than do the oldest firms. The largest firms also differ most in their wages as a function of age. Those effects remain consistent across all variations of the models discussed below, suggesting a strong interaction between firm age and firm size. In addition, the effects of firm size reach an asymptote faster than a linear or log function would predict.

Second, focusing on job changers yields much larger effects, particularly for firm age. The larger age effect likely stems from the linear effect for tenure under-correcting for the relationship between firm tenure and pay. Such an under-correction can lead to a positive bias in the estimates of the relationship between firm age and wages. Note that, if the positive bias is large enough, failure to account adequately for tenure effects could even flip the sign of the firm age effect positive, such that older firms would appear to pay more. In other words, using a linear adjustment for tenure may account for Heyman (2007) finding a positive relationship between firm age and wages.

Third, adjusting for compositional differences in the characteristics of the employees of firms of different ages and sizes accounts for a large share of the average observed differences at the firm level—roughly one-third of the size effect and more than one-half of the age effect. These results are similar in magnitude to those reported by Brown and Medoff (2003) and Heyman (2007). Failure to account for these differences, therefore, generally leads to an overestimation of the firm age and size effects.

### Adjusting for Industry

Although the adjustments made up until this point address most of the factors that might confound the relationship between firm age and wages, they do not account for the fact that the firm age and size distributions might vary systematically across industries. New, rapidly growing industries, for example, might have an unusual number of small, young firms. They may also face a thin labor market in which talent commands a wage premium. What appears to be a firm age or a firm size effect might then actually reflect an industry effect on wages.

To account for the differences across industries, we re-estimate the models including fixed effects for four-digit industries. We find that the firm age penalty increases slightly and the firm size premium declines somewhat. But the addition of more than 500 industry intercepts notably has relatively little effect on either the magnitudes or the patterns of the wage differentials.

### Accounting for Selection into Mobility

Although our approach—considering only the wages of recent hires—has the advantage of holding constant firm tenure, one might worry that these job changers differed systematically on other factors from those who remained with their employers. But the direction of this bias remains uncertain. Whereas the least productive employees might be fired and need to find new jobs, the most productive ones might move in search of more attractive job opportunities.

To prevent such selection from influencing our estimates, we further restrict the sample to include only those individuals who had left their prior employers because the plant or business location at which they had been working closed (‘‘plant closings’’). Although this restriction reduces our sample size dramatically, it allows us to examine the subset of individuals who plausibly sought employment for reasons exogenous to their individual ability or productivity (Gibbons and Katz 1991; Gruetter and Lalive 2009). Again, the general patterns of wage penalties and premia with respect to firm age and size appear largely the same for these involuntary movers.

## Exploring Alternative Explanations

Although our results suggest that the firm age and firm size effects remain robust to a variety of modeling choices, unobserved heterogeneity is a potential concern. For example, if firms can accurately assess the quality of potential employees not captured in their prior wages, and if individuals accurately evaluate the prospects of their potential employers, then assortative matching might be occurring—that is, the most productive employees join the start-ups with the greatest potential. Perhaps the "sure bets" can pay higher wages and therefore attract the best employees? Dahl and Klepper (2015), for example, found that those firms with the best survival prospects, based on the attributes of the founders and of the firm at the time of its founding, paid somewhat higher wages than did firms with worse survival prospects. Note that differences in the future prospects of firms stem from a variety of possible factors. They might result from quality differences in the founders or their ideas. They could stem from externalities, such as being located in an industrial cluster. Or they might reflect the underlying ambitions of the founders of the firm. Although the industry intercepts likely capture some of these differences, substantial variation probably exists even within industries.

### Unobserved Firm Characteristics

To address this possibility, we take advantage of the longitudinal nature of our data. For each year of the sample and for each firm in the sample, we consider its *future* growth for the next five years (defined in terms of the number of employees in year $t + 5$ divided by the number in year $t$). Schmieder (2013) also argued that growth rates should account for the wage differential between young and old firms to the extent that those differences emerge from older firms effectively having more bargaining power vis-à-vis employees. Although distinguishing monopsony from assortative matching would prove difficult, for our purposes, we care simply whether accounting for differential growth rates attenuates the observed negative relationship between firm age and wages. Note that we do not have five-year forward projections for all firms, because many firms fail. We exclude any firms without $t + 5$ data from this analysis. To allow for a flexible relationship between firm growth and wages, we use future growth to assign each firm to a growth decile (across all firms in the sample for that year) and include a vector of indicator variables to capture any wage differentials associated with firm growth rates.

Although the general patterns with respect to firm age and firm size remain the same, they do contract somewhat in magnitude—on the order of 25% for firm age and 8% for firm size (see row (8) in Table 5). We note that these results seem quite consistent with those of Gibson and Stillman (2009). Using rich and detailed measures of worker skills, they found little evidence that the sorting of better employees into larger firms could

account for the firm-size wage effect. Our results also suggest that sorting is unlikely to account for the firm-age wage effect.

### Unobserved Employee Characteristics

Because the analyses above match individuals according to their wages in their prior jobs, they effectively restrict the sample to those already in the labor market. Although this approach has some advantages, in terms of more tightly accounting for difficult-to-observe differences in human capital and productivity, it potentially also raises some issues. Movers within this sample, for example, may sort into larger or smaller firms and into younger or older firms based on their prior labor market experience. Focusing on involuntary movers—those employed at plants that closed—partially accounts for these differences, but prior experience may still allow workers to signal their quality.

We therefore estimate the wage premia and penalties again using only new entrants to the labor market, following Nystrom and Elvung (2014). Firms hiring labor market entrants necessarily have much weaker signals of worker quality. This subpopulation should therefore have much less potential for sorting employees to employers on the basis of quality or productivity. Although these estimates parallel those for Table 4, plus industry fixed effects, because these individuals have not had jobs, we could not include nearest-neighbor matching on prior wages. Though somewhat smaller in magnitude, the same pattern of results appears in this subpopulation (see the last row of Table 5). Some form of assortative matching therefore seems unlikely to account fully for either the firm age or the firm size effect.

## Discussion

Do start-ups pay well? Our answer seems mixed: most do not, but a few do. We explore the relationship between the amount that firms paid and firm age and size among the population of Danish employers and employees and find both a firm size effect and a firm age effect on the wages of new hires. Larger firms paid recent hires more than smaller firms did, even for observationally equivalent individuals who had earned roughly the same amount in their previous jobs. In firms of similar size, however, young firms actually paid recent hires *more* than older firms paid. But firm size had larger effects than firm age. Hence, to the extent that start-ups begin both young and small—nearly 90% of firms in our population do—they do tend to pay less than large, established firms.

But those rare start-ups that begin large, or become large very quickly, actually pay a premium relative to more established employers. Firms four years of age or less with at least 250 employees paid substantial premia over more established firms. Although these firms amounted to a small minority of employers, because each of them hired hundreds of individuals, they

accounted for roughly one-fifth of the jobs created by firms in their first four years.

Our most novel finding, however, is that young firms paid more than older ones did. Why might they have done so? One possibility is that start-ups need to compensate for the greater instability of the jobs they offer. Because the average start-up has a half-life of only four years, employees face a substantial risk of losing their jobs as a consequence of the firm failing. Higher wages, therefore, may provide a compensating differential for this instability. If they do, one might reasonably ask whether start-ups should pay even larger premia. Not only do these firms fail at high rates, meaning that employees may find themselves involuntarily unemployed or looking for a job, but also the probability of failure likely rises during periods of economic contraction, precisely the times during which laid-off employees would find it most difficult to secure another job.

A second possibility is that start-ups, particularly those that start at a larger scale or that grow rapidly, face labor market challenges that differ from those facing established firms. In particular, start-ups may want to hire numerous employees in a short period of time. They may therefore need to offer something akin to signing bonuses to entice would-be employees (Schmieder 2013). Although this explanation might account for a portion of the differential, the fact that controlling for future growth had only a modest effect on the relationship between firm age and wages suggests that it cannot be the full story.

In addition to establishing a set of empirical facts about wages for the jobs created by start-ups, we believe that our research offers multiple methodological contributions. First, we disentangle the effects of firm age and firm tenure on wages by comparing new hires to all employees. In eliminating the effects of firm-specific human capital accumulation, we reveal that prior research that fails to account for employee tenure likely biases the estimates toward finding a more positive relationship between firm age and wages. Although this bias simply attenuates the negative relationship in our sample, this bias might account for Heyman's (2007) conclusion that older firms pay more.

Second, we demonstrate that firm age and size are neither linearly (nor log linearly) related to wages nor are they independent in their effects. Instead, firm age and firm size jointly affect wages. Failure to accommodate these interactions appears to lead to underestimation of the effects of firm age and firm size. Although our strategy of binning firms into age and size categories challenges common empirical practice, it accords well with the idea that firms fall into conceptual categories (e.g., micro-enterprises, mittlestand or SMEs, high-growth firms or gazelles). Though not a concern in the Danish context, this approach can also account for the fact that laws and regulations often come into play only above specific size thresholds (for a thorough discussion of these thresholds in the United States, see Eyal-Cohen 2013).

Third, we provide additional evidence that human capital characteristics can confound the effects of firm characteristics given that firms of different ages and sizes draw from somewhat different labor pools. One of the difficulties in assessing job quality is that one cannot determine whether one job is better than another without understanding the characteristics of the would-be occupants of those jobs. Being a truck driver, for example, might pay well relative to the alternatives for someone lacking a high school degree. Although the extant research has addressed this issue, the typical approach to adjusting for jobholder characteristics has been to include the observed characteristics of jobholders as covariates in a wage equation (or in regressions on some other measure of job quality). That approach, however, has the limitation of essentially requiring one to assume that these characteristics have additive (and usually linear or log-linear) relationships to productivity and wages.

The increasing availability of longitudinal registry data, however, opens the door for alternative approaches. The Danish data, for example, include more than 20 million person-years of information. Instead of adjusting for observed characteristics through regression, in the current study we use matching to create sets of cases and controls nearly identical on the observed dimensions and allow each group—with its potentially unique combination of characteristics—to have its own intercept. Doing so allows us to adjust for the characteristics of the employees without requiring any assumptions about the functional forms of the relationships between these characteristics and wages, or about the ways in which these attributes may interact in determining wages.

Overall, these methodological issues appear sufficient to account for apparent inconsistencies in the prior literature. But without estimating similar sets of models on data from each of the countries, one cannot say for certain whether they do. Notably, Heyman (2007) found somewhat inconsistent results even using the same method on different cross sections from the same country. The relationships between firm age, firm size, and wages likely also depend to some extent on the context.

Although our results provide some initial insight into the question of whether start-ups create good jobs, they represent more of a first step in a research agenda than a definitive answer. Consider some of the closely related questions that remain open: Although young firms pay their employees a premium in the first year, how do these effects evolve? Do the employees of younger and older firms experience similar wage trajectories or do their wages change at different rates? It would seem that these effects might go either way. On the one hand, rapidly growing firms might promote employees faster and give them larger raises. On the other hand, the managers of young firms with higher probabilities of failure may invest less in firm-specific human capital that would enhance their productivity over time.

Entrepreneurship has been and will continue to be an important driver of economic vitality. As such, understanding better how the jobs created by entrepreneurs affect the earnings and lives of the people who occupy them will inform both policy and practice.

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