Early Employees of Venture-Backed Startups: Selection and Wage Differentials

by

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ABSTRACT

While much attention has been paid to company founders, very little is known regarding the first set of non-founder employees who join high-growth startups ("early employees"). This paper explores the wage differential between venture capital-backed startups and established firms given that the two firm types compete for talent. Using data on graduating college students from MIT, I find that VC-backed startups on average pay 8%-13% higher wages than their more established counterparts. I explore two channels for the cross-sectionally observed startup wage premium: compensating differentials and selection. The startup wage premium is robust after identifying and controlling for worker preferences for the three firm attributes (firm reputation, impactful work, and job security) that most strongly predict MIT graduates' entry into startups vs. established firms. To account for unobserved heterogeneity across workers, I exploit the fact that many MIT graduates receive multiple job offers and find that wage differentials are statistically insignificant from zero when individual fixed effects are employed. This implies that much of the startup wage premium can be attributed to selection rather than between-firm compensating differentials, and that VC-backed startups pay competitive wages for talent.

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1 Introduction

Broadly, there are three key inputs behind the birth and growth of innovation-driven enterprises: technological opportunities, financing, and human capital (Stuart and Sorenson, 2005). Technological innovation is an important component of economic growth, which has motivated scholars to explore the processes by which entrepreneurs encounter and commercialize technological opportunities (Schumpeter, 1934; Romer, 1990; Kirzner, 1997; Shane, 2000). In addition, external financing – whose common sources include venture capital and government funding – plays a salient role in aiding the commercialization process (Evans and Jovanovic, 1989; Samila and Sorenson, 2011; Howell, 2014). Furthermore, the entrepreneurship literature unpacks the role of human capital in high-growth entrepreneurship by focusing on the founder's individual traits and skills as well as the composition of the founding team (Lazear, 2005; Ruef et al., 2003).

However, the prevailing theoretical and empirical focus on the founders leaves the human capital piece of entrepreneurship under-explored. Largely due to data constraints, very little is known regarding the first set of non-founder employees that join startup companies ("early employees") (Stuart and Sorenson, 2005; Roach and Sauermann, 2015). Although founders are undoubtedly important, highly skilled employees play a critical role in the growth and success of nascent firms. Attracting and retaining high quality workers is a challenge for early-stage companies because they compete against established firms for talent. In fact, initial career data from the Massachusetts Institute of Technology (MIT) show that many graduates receive job offers from both venture capital-backed startup companies and mature firms.

This paper explores the wage differential between venture capital-financed startups and large established firms, and the channel through which those differences persist. Using data on graduating college students from MIT, I find that VC-backed startups on average pay 8%-13% higher wages than their more established counterparts holding all observable individual-level covariates constant. Given that VC-backed firms are – by construction – young and small, this finding stands in contrast to the literature's well-documented wage premium associated with large and old firms. Nonetheless, relatively high wages associated with VC-backed startups are robust across several regression specifications. Given that venture capital investors typically concentrate their deals in a few select industries, I condition the sample to the high-tech sector and find that the startup wage premium remains statistically significant albeit slightly attenuated in magnitude. Furthermore, the results are consistent for a subset that excludes firms in the financial sector which generally offers a distinctly lucrative early career path for top school graduates.

Next, I assess the two main channels for the cross-sectionally observed startup wage premium: compensating differentials and selection. First, in a compensating differentials framework, equilibrium wages in a competitive market for high talent reflect both the pecuniary and non-pecuniary features of employment. I identify the firm attributes that most strongly predict MIT graduates' entry into startups vs. established firms – namely, firm reputation, opportunity for impactful work, and job security. After controlling for worker preferences for the three determinant non-pecuniary features of startup employment, differences in earnings remain robust. This suggests that the compensating differentials are not the primary driver behind the two firm types' disparate wage structures.

Second, I test for selection as the source of cross-sectional wage differentials between startups and established firms. To account for unobserved heterogeneity across workers (i.e. ability), I exploit the fact that many MIT graduates receive multiple job offers. Originally employed by Stern (2004), this identification strategy allows for multiple price points to be observed for the same labor service.[1] As a result, the demand curve for startup employment can be traced out while holding the supply curve fixed. Based on empirical specifications in which individual fixed effects are employed, I find that the effect of startup employment on wages reverses its sign to negative although the coefficients are statistically insignificant from zero. At minimum, these results reject the large, positive wage premium associated

[1]This methodology is also used by Hsu (2004)

with entrepreneurial employment in the cross-section. More broadly, these findings suggest a positive selection of high-ability workers into startups; counterfactually, they would also command relatively high wages at established firms. Overall, much of the startup wage premium can be attributed to selection rather than between-firm compensating differentials. Furthermore, albeit faced with liquidity constraints relative to large firms, VC-backed startups appear to pay competitive wages for talent.

Empirical exploration of high-growth startups vis-à-vis established firms is an important exercise for several reasons. In terms of startup entry, the allocation of productive workers provides significant implications for economic growth (Baumol, 1990; Murphy et al., 1991; Philippon, 2010). Given the recent surge in venture capital activity (See Figure 1), hiring at venture capital-backed firms has risen.[2] As a result, talented young workers have increasingly joined early-stage companies financed by venture capital. For instance, the share of MIT graduates joining VC-backed startups rapidly grew from less than 2% to 14% between 2006 and 2014 (See Figure 1). There appears to be a direct trade-off of high-quality workers between entrepreneurial ventures and other sectors that attract talent such as financial services (See Figure 2). If workers' career paths are endogenous to the set of skills and social capital developed during initial employment, then this phenomenon has larger implications for the future supply of innovators and entrepreneurs.

[INSERT FIGURE 1]

[INSERT FIGURE 2]

In terms of wages, a comparison of wages between VC-backed companies and established corporations is insightful because early labor market outcomes are often persistent with long-run earnings implications (Jacobson et al., 1993). Although this study explores only the first year salaries, small differences in starting wage levels are likely to generate considerable long-run differences over time. This is especially important for young workers given that

[2]Venture Capital Activity at 13-Year High" Ernst & Young Global Limited. 5 February 2015 <http://www.ey.com/GL/en/Newsroom/News-releases/News-EY-venture-capital-activity-at-13-yearhigh>

a disproportionately high share of young workers is employed by young firms (Ouimet and Zarutskie, 2014). In addition, a career start in an entrepreneurial firm may change not only the level of wages, but also the slope of the worker's earnings growth; it is not clear whether the labor market penalizes or rewards the young workers for their early startup experience. Using a sample of graduating students from MIT between 2006 and 2014, this study offers one of the first set of empirical evidence of wage differentials between established firms and high-growth startups among a highly selected group of talented workers.

MIT is a well-suited empirical setting to study the allocation of top technical talent in the labor market because it produces a large number of workers directly engaged in innovative work in both large R&D laboratories as well as in entrepreneurial settings. A significant portion of MIT graduates are productive inventors responsible for nearly 25,000 patents and over 300,000 patent citations (Shu, 2012). In terms of entrepreneurship, MIT alumni account for tens of thousands of companies that were estimated to generate global revenues of $2 trillion and employ more than 3 million people as of 2009 (Roberts and Eesley, 2009). Therefore, it is unsurprising that many graduating college seniors at MIT possess skills valued by both high-growth startups and established corporations. The preponderance of individuals with several job offers is an important feature because in the compensating differentials framework, the estimated wage differentials are identified from the preferences of the marginal worker, who has a choice between the two jobs and yet remains indifferent.

My study contributes to the entrepreneurship literature by adding to the limited understanding of the workers who join nascent companies as non-founder employees. The rising phenomenon of young, talented workers joining startup companies is an important trend especially in the context of today's rapidly evolving knowledge economy. Although many assume that founders and early employees are similar in their day-to-day functional roles, the two groups should be treated as distinct sets of entrepreneurial actors. Founders and early employees operate on different margins for entry because the former bears a much greater risk in terms of capital and career reputation. Furthermore, the two groups experience different wage dynamics not only in the level and growth of earnings, but also in the form of compensation (e.g. equity position, bonus).

This paper also contributes to the rich literature on wage differentials by documenting a startup wage premium. Although prior studies have shown wage differentials along many firm characteristics such as firm size (Brown and Medoff, 1989; Oi and Idson, 1999) and firm age (Davis and Haltiwanger, 1991; Brown and Medoff, 2003; Haltiwanger et al., 2012), none have explored earnings differences between early-stage VC-backed companies and established firms. Startup employment is a policy-relevant area because young firms create a disproportionately high number of jobs (Haltiwanger et al., 2013). Given that young firms account for 70% of gross job creation in the US (Haltiwanger et al., 2012), the questions remains as to what kind of jobs they create.[3]

The remainder of this paper is structured as follows: Section II reviews the relevant prior literature and forms a hypothesis on the relationship between firm maturity and wages. Section III discusses the theoretical channels behind wage differentials between startups and established firms. Section IV explains the identification strategy exploiting multiple job offers and the empirical setting. Section V describes the results on the startup wage differential as well as on the mechanism. Finally, Section VI concludes with this study's main insights, limitations, and implications for future research.

2 Existing Literature

In theory, should startup salaries be meaningfully different from those at large established companies? If so, what is the equilibrium wage that a startup must pay in order to induce a worker into the young company who would otherwise sort into an established firm? As a useful starting point, the literature on the returns to entrepreneurship may offer relevant insights because in a sense, early employees are an extension of the founding team. Unfortunately, the financial returns to entrepreneurship appear to be puzzle. While many studies show that

[3]Haltiwanger et al. (2012)define young firms as those younger than two years old.

entrepreneurs earn less than their salaried counterparts (Borjas and Bronars, 1989; Evans and Leighton, 1989; Hamilton, 2000; Hall and Woodward, 2010), more recent studies argue that the pecuniary returns to entrepreneurship are relatively high (Levine and Rubinstein, 2013; Kartashova, 2014; Sarada, 2014; Manso, 2014).

Another relevant set of insights comes from the rich literature in labor economics around wage differentials across firms. In particular, employer size and age appear to be salient drivers of persistent gap in earnings. Extensive evidence documents that large firms tend to pay higher wages than their smaller counterparts (Brown and Medoff, 1989; Oi and Idson, 1999). Similarly, old firms generally pay higher wages relative to young firms (Davis and Haltiwanger, 1991; Brown and Medoff, 2003; Haltiwanger et al., 2012) although the strength of this relationship is questionable after accounting for worker characteristics (Brown and Medoff, 2003). Nonetheless, the well-documented employer-age wage premium informs the relationship between VC-financed startups and wages which can be organized into a simple econometric framework with worker i, firm j, and a vector of individual-level traits $\mathbf{X_i}$:

$$\log(WAGES_{i,j}) = \beta_0 + \beta_1 STARTUP_j + \mathbf{X}_i'\Theta + \varepsilon_{i,j} \tag{1}$$

Equation (1) is a cross-sectional relationship between startup employment and wages in which the unit of observation is the individual. Only the accepted job offer is observed for each individual. Previous literature provides a prior on the magnitude and direction of β_1. In particular, Haltiwanger et al. (2012) compute the real monthly earnings of US workers at both young and established firms.[4] The authors show that, in 2011, workers at young firms earned roughly 70% as much as their counterparts at mature firms. Therefore, prior evidence from the literature estimates β_1 at roughly -0.30. Since VC-backed startups are – by construction – young, the existing prior on the negative relationship between firm age and wages leads to the first hypothesis:

[4]Young firms are defined to be 0-1 years old while established 11+ years old.

H1: VC-backed startups on average pay lower wages than do established companies.

Next, I assess the following primary theoretical channels through which startups pay meaningfully different wages than do established firms: (1) compensating differentials for idiosyncratic firm attributes and (2) selection based on unobservable margins related to wages.

3 Conceptual Framework

Compensating Differentials

Compensating differentials for particular firm attributes (e.g. flexible work hours) may be the reason for the discrepancy in wages between startups and mature firms. In equilibrium, observed wages reflect not only the price that the employer pays for the worker's labor services, but also the job attributes that the employer provides (Rosen, 1987). In the compensating differentials framework, the worker pays a positive price for preferred job attributes and receives compensation for disamenities. While firms are heterogeneous in the numerous (dis)amenities associated with them, I identify and focus on the three job attributes that most strongly predict MIT graduates' entry into established firms vs. VC-backed startups: job security, employer reputation, and opportunity for impactful work.

The wage-relationship of each of the three job attributes is relatively easy to sign based on whether the attribute positively or negatively enters the worker's utility function. However, it is unclear how these job attributes in aggregate shape the direction of the startup wage differential. On the one hand, entrepreneurial firms may pay a wage premium to compensate for the inherently risky nature of the company. In early-stage companies, there exists a formidable probability that the company will be out of business in the near future, suppressing the worker's expected future income toward zero. Andersson et al. (2009) similarly suggest that innovative firms operating in riskier spaces – in which growth-oriented startups most often find themselves – tend to pay more. In other words, workers are compensated for low job security. Kihlstrom and Laffont (1979) formally show the risk-wage trade-off in a related model in which more risk averse individuals become company employees rather than entrepreneurs and subsequently earn less.

In addition, given that workers generally value employer reputation, startups may compensate for their lacking reputation with higher wages. For instance, potential job switchers derive signaling value from affiliating with a high status organization, leading them to accept a lower wage at an established company in order to leverage its status during their next job search (Bidwell et al., 2014; Phillips, 2001). Furthermore, entrepreneurs effectively pay for affiliation with a high status financier by assuming a discount in their company valuation (Hsu, 2004). Therefore, employee quality being equal, startup workers may receive higher salaries relative to those in established firms who pay for firm reputation.

On the other hand, the opportunity for impactful work may lower the relative wages at startups. If entrepreneurial workers derive utility from autonomy and being able to make major contributions in a less bureaucratic environment, they are expected to take a wage penalty in exchange for employment at a startup. For example, scientists are inclined to forego a higher salary to work for a science-oriented firm that allows them to autonomously conduct their own research and publish their findings (Stern, 2004). Early employees may exhibit similar economic behavior since they typically make significant investments in the development of their technical expertise and thus prefer environments in which they can freely put their own ideas into practice.

The three job attributes can be added to Equation (1) in a hedonic wage regression in order to assess the impact of equalizing differences on the relationship between startups and wages:

$$\log(WAGES_{i,j}) = \beta_0 + \beta_1 STARTUP_j + \gamma_1 REP_j + \gamma_2 SEC_j + \gamma_3 IMP_j + \mathbf{X}_i'\Theta + \varepsilon_{i,j} \quad (2)$$

If compensating differentials form the main channel through startups and established firms pay meaningfully different wages, then $STARTUP_j$ should bear little to no explanatory power in predicting wages after controlling for the aforementioned job attributes. This leads to the following hypothesis regarding the mechanism behind startup wage differentials:

H2: After controlling for worker preferences for job security, employer reputation, and opportunity for impactful work, VC-backed startups and established firms pay statistically equal salaries.

Selection

An alternative explanation for the startup wage differential is selection. In other words, workers may sort into startups or established firms based on unobservable worker characteristics that are also related to wages. In early empirical examination of compensating differentials, Brown (1980) contends that cross-sectional evidence of wage differentials does not necessarily lend support to the theory because several key variables are omitted – namely, worker ability.

Omission of worker ability is problematic because ability is typically positively correlated with the individual's earnings capacity. In addition, ability may be related to the worker's entry into startups. For instance, Dahl and Klepper (2015) theorize that high quality workers are matched to large – presumably more productive – firms, leaving low quality workers to be matched to new firms. Given that worker ability is systematically related to both wages and entry into startups, the estimated β_1 in Equations (1) and (2) is likely biased. The true link between wages and startups conditional on worker ability is the following:

$$\log(WAGES_{i,j}) = \pi_1 STARTUP_j + \pi_2 ABILITY_i + \eta_{i,j} \tag{3}$$

The model in Dahl and Klepper (2015) predicts that startups are matched to lower quality workers, who generally command lower wages. In this case, β_1 in Equations (1) and (2) would be downward biased because ability is negatively correlated with startups while positively linked to wages. Sorting of low quality workers into new firms would then be the mechanism through which startups appear to pay lower wages than established firms. In such scenario, entrepreneurial employment is expected to be unrelated to wages after accounting for individual ability. This leads to the following hypothesis:

H3: After controlling for worker ability, VC-backed startups and established firms pay statistically equal wages.

4 Methodology and Data

Identification Strategy

The true startup-wage relationship in (3) cannot be directly tested because $ABILITY_i$ is unobserved. In order to estimate the startup-wage relationship while accounting for selection, I exploit bundles of job offers – both accepted and rejected – that MIT graduates receive before entering the labor market. This framework allows the econometrician to compare wage offers across firms while holding the individual constant. Since multiple price points are observed for the same labor service, the demand curve for startup employment can be traced out while holding the supply curve fixed. As a result, the effect of startup employment on wages can be cleanly identified. Econometrically, individual fixed effects are employed to essentially difference out the unobservable individual-level factors that may be systematically correlated with wages:

$$\log(WAGES_{i.j}) = \beta_0 + \beta_1 STARTUP_j + \delta_i + \mathbf{X}_i'\Theta + \varepsilon_{i,j} \tag{4}$$

Contrary to the previous empirical relationship, the unit of observation in Equation (4) is the job offer such that the individual is separately observed for each of his job offer. As a result, individual fixed effects δ_i account for the effects of unobserved factors that are individual-specific but fixed over time – most notably, worker ability or attractiveness to employers. The β_1 in Equation (4) is the estimated effect of idiosyncratic firm attributes on wages. If hypothesis 3 is true, meaning that wages are uncorrelated with entrepreneurial employment conditional on worker ability, then β_1 will be statistically insignificant from zero. In contrast, if hypothesis 3 is false, β_1 will be statistically significant and lend empirical support to the story of compensating differentials separating the wage structures between mature firms and startups.

A key identification assumption behind the multiple job offers methodology is that those who receive one job offer are not fundamentally different from workers with multiple offers. This methodology requires narrowing the sample to only the individuals with multiple offers in order to employ individual fixed effects. Selection issues may weaken the internal validity of the following analysis if, for instance, multiple offers are systematically drawn from a different part of the worker ability distribution. It is possible that workers with higher ability attain more job offers because they are presumably more attractive to employers. However, many top MIT graduates have a single job offer because they receive and accept a full-time job offer from their summer internship prior to their senior year and thus do not participate in the ensuing full-time job recruiting. I revisit this assumption in Section V by testing for differences in observable individual traits between the two groups.

Empirical Setting

Massachusetts Institute of Technology (MIT) serves as the empirical setting in which I study wage differentials between VC-backed startups and established firms. Although MIT is a highly selected sample of talented workers and therefore may not be representative of the broader labor market, it serves as a favorable setting for three reasons.

First, given both its highly selective admissions process and rigorous technical training, MIT serves as a hotbed of top talent that is sought by both young and mature companies. This is an important feature because the underlying assumption in the compensating differentials framework is that the marginal worker – before trading off a portion of his wages for a particular (dis)amenity – is given a choice between multiple employment conditions. This assumption does not hold in a broader setting in which certain individuals sort into startups simply because they do not have any outside options. For instance, if the Dahl and Klepper (2015) model discussed earlier represents the true matching process between workers and firms, compensating differentials is not an appropriate framework since earnings differences are determined not by worker preferences, but instead by sorting based on worker ability.

Second, while job offers from startup are relatively rare and often difficult to observe, many MIT graduates join early-stage firms whose salary offers are observable. In fact, the portion of MIT graduates joining startups as non-founder employees has substantially increased especially since the 2008 financial crisis. In 2014, roughly 14% of the graduating class chose employment at VC-backed startups compared to less than 2% in 2006 (see Figure 1). Thus, MIT provides a lab to study and compare offers from entrepreneurial companies and established firms distributed among a pool of highly talented labor market entrants.

Third, there is rich heterogeneity in the job offers that graduating MIT students receive and in the ultimate decisions that they make. While only 400 of the 1,100 graduating class seek full-time employment in a typical year, roughly 350 companies actively recruit at MIT. As a result, the average student on the job market receives two competing job offers. Resulting data on bundles of job offers, which include both accepted and declined offers, allow for offer-level estimation of the wage differential between startups and established companies. This allows for the multiple offers methodology as discussed above.

Data

The data come from the two following surveys on full-time recruiting outcomes for graduating college students at MIT: (1) Graduating Student Survey and (2) MIT Early Careers

Survey. The Graduating Student Survey, which is annually administered by MIT Career Services, collects information regarding each student's post-graduation plans, job offers that the individual received, and motivations for accepting a particular offer. The survey data coverage extends from 2006 to 2014 with response rates consistently around 80% and includes 18,789 total respondents from undergraduate, and master's, and doctoral programs. The sample is reduced to undergraduate seniors who indicate plans to be employed full-time during the year following graduation; immediately following graduation, approximately half of MIT college graduates enter graduate school. Furthermore, those entering into non-private sector employment are removed from the sample. The final sample includes 2,281 individuals. Table 1 shows the summary statistics.

[INSERT TABLE 1]

In addition, MIT Early Careers Survey, launched in 2014, is an online survey of recent MIT alumni and the set of offers they received upon graduation. Respondents were asked to provide information on various job characteristics (e.g. salary, title, industry) and motives for choosing the accepted offer. Respondents with job offers from startups were additionally asked about stock options (e.g. number and percentage of shares, then-current company valuation, vesting schedule). Since the survey was motivated by the initial results from the Graduating Student Survey, it was designed to cover the exact same time frame and population (i.e. college graduates who select into full-time employment). The final sample contains 1,014 private sector job offers among 626 individuals.

Wages are measured as the annual salary offered to the job candidate. Signing bonus and other forms of extra compensation made at the time of the job offer are also measured.[5] Ex-post measures of non-salary compensation (e.g. performance bonus) are not observed because individuals are surveyed before they begin their jobs.

Moreover, equity compensation is not included in this study. Although MIT Early Careers

[5]Analysis below uses only the salary component as wages. Nonetheless, main findings are robust after using total compensation which also non-salary compensation.

Survey collects some information regarding stock options, the data are difficult to interpret. Especially for an early-stage company, the real value of the shares are almost impossible to assess ex-ante given the uncertainty around the company's underlying idea or business model (Kerr et al., 2014); even with information on the most recent company valuation, the actual value of the employee's shares is not realized until the company eventually exits via an acquisition or initial public offering. Therefore, it is not clear how the job candidates perceive and value the proposed stock options at young private firms during the time of the job offer. Due to issues around both measurement and interpretation, equity compensation is not captured in this study.[6]

A potential concern for the MIT Early Careers Survey is the non-response bias. Given that online surveys typically yield low response rates, the MIT Early Careers Survey has a response rate of 25%. The low response rate is problematic if the 25% who responded to the survey are fundamentally different from those who did not. In this case, the multiple offers analysis based on this survey data may not be generalizable to the full labor market of MIT graduates. For instance, MIT alumni with "less successful" early careers may be less likely to participate in the survey which would upward bias the observed earnings distribution.

Fortunately, non-response bias can be rigorously assessed since MIT contains administrative data on both the survey respondents and non-respondents. Table A1 in the Appendix shows difference in means tests of observable individual characteristics between respondents and non-respondents. Overall, the two groups appear to be similar in their individual traits (e.g. gender, number of offers received) as well as in the characteristics of their accepted job offer (e.g. VC-backed startup, offered salary). One exception worth highlighting is US citizenship. Respondents are significantly more likely to US citizens compared to non-respondents. However, this is not a major concern because US citizenship does not appear to

[6]Typically, college graduates entering into entry-level positions are not offered significant stock options at large established companies. In contrast, VC-backed startups generally offer considerable equity to their early employees. Given the assumption that VC-backed startups tend to pay equity more frequently than large established companies, it is likely that the startup wages estimated in this study are downward biased since equity compensation is omitted in the analysis.

be a plausible source of variation in wage differences between startups and established firms; the correlation coefficient of US citizenship and employment in a venture-backed startup is –0.0008. Therefore, the interpretation of the results from the MIT Early Careers Survey does not seem to be threatened by non-response bias.

It is important to discuss why venture capital financing is salient in the definition of a startup in this sample. While many studies in the entrepreneurship literature generalize all small or young firms as startups, many small businesses are not viable employment alternatives to large established corporations. Most small businesses never intend to grow large or innovate in a meaningful way (Hurst and Pugsley, 2011), implying that they do not typically recruit for the type of human capital that large corporations seek. Since a small firm's intentions are unobservable, VC financing is used to distinguish lifestyle businesses from young high-growth firms, which presumably compete against established firms for talent.[7] In addition, VC financing is relevant because early-stage companies tend to actively hire new workers immediately after receiving investor capital; venture-capital backed companies typically spend a majority of their cash on paying employee salaries. Consequently, I define a startup as any for-profit company that receives early-stage institutional capital – either venture capital or angel financing – within five years of the employee's join date. All results are robust to narrowing the venture capital financing window to three years.

5 Empirical Results

Wage Differentials

This section examines the cross-sectional relationship between offered salaries and startup employment for MIT graduates from 2006 to 2014. The analysis is at the individual-level

[7] Aulet and Murray (2013)similarly categorize young firms into two distinct types: small and medium-sized enterprises (SMEs) and innovation-driven enterprises. They contend that firms in the latter category are typically supported by external financing because they require investment capital in order to develop novel products and scale their businesses.

and wages are those of the accepted job offer. The following regression specifications in Table 2 closely follow Equation (1). All specifications include graduation year fixed effects to account for idiosyncratic time trends in the labor market.

[INSERT TABLE 2]

In the simple bivariate case shown in Specification (2-1), the association between startup employment and log wages is positive and statistically significant at the 1% level. The economic significance is also large; relative to established firms, VC-backed startups on average pay 13% higher salaries. This is a surprising finding because while VC-backed startups are typically young and small, the labor economics literature widely supports firm size- and age-wage premium as an empirical regularity. This suggests that, contrary to the general population, workers selected from the right tail of the human capital distribution experience a fundamentally different dynamic between firm age and wages.

Specifications (2-2), (2-3), and (2-4) control for individual characteristics that are potentially linked to the worker's earnings capacity. These characteristics include gender, US citizenship, number of offers received, and the MIT school in which the graduate was academically trained. The estimated effect of startup employment on wages is attenuated after accounting for individual traits related to earnings. This is consistent with Brown and Medoff (2003) who find that the empirical relationship between firm age and wage is highly sensitive to controlling for worker characteristics. Even after attenuation in the main effect, specification (2-4) shows that at a lower bound, startup wage premium effect is robust. Therefore, I reject Hypothesis 1 at the 1% statistical significance level and find support for the following claim: VC-backed startups on average pay 8-13% higher wages than their mature counterparts.

As a robustness check, I limit the tests to particular subsamples to assess whether the effect is being driven by a peculiar sector or industry. One potential concern is that since venture capital investments tend to be concentrated in a few select industries such as computer software, the estimated wage effect may be driven by wage differences in industry composition rather than those between startups and established firms. Specification (2-5) subsets on the high-tech sector which represents 73% of the VC-backed startups in the labor market for MIT graduates. The effect of startup employment is attenuated to a wage increase of roughly 6% which is statistically significant at the 10% level. This is not surprising given that inter-industry wage differentials tend to be large and persistent (Katz and Summers, 1989). Nonetheless, even after conditioning on only the high-sector in which VC-backed startups are heavily concentrated, the startup wage premium is positive and significant.

In addition, specification (2-6) explores the startup-wage relationship across only non-finance jobs. Although VC investments are relatively rare in the financial sector, finance jobs are an important aspect of the labor market outcomes for MIT graduates because it is a lucrative early career track that draws a large share of talent each year. Although Shu (2013) claims that MIT graduates who become financiers versus those enter into the innovation sector are not substitutable in their skill sets, Figure 2 suggests that the allocation of talent has qualitatively shifted from the financial sector to entrepreneurial firms in the recent decade. Therefore, a comparison of the magnitude and sign of the startup wage premium from the full sample against those drawn from only the non-finance jobs is insightful. Specification (2-6) shows that the estimated startup wage premium, which remains statistically significant at the 1% level, is larger than in (2-4). This is expected because finance jobs are generally the most lucrative early career tracks. Overall, these tests on subsamples show that the startup wage premium is not primarily driven by sectoral differences.

[INSERT TABLE 3 AND FIGURE 3]

Moreover, I explore the startup-wage relationship at other points in the distribution in order to check that the mean effect is not predominantly driven by outliers. Table 3 presents the quantile regression points estimates at each decile of the conditional wage distribution. All specifications use the same controls as in Specification (2-4). Figure 3 maps the resulting coefficients along with the 90% confidence interval. I find that the startup wage premium is highest for workers at middle to high range of the conditional earnings distributions while much lower for those at either tail of the distribution. Overall, the effect of entrepreneurial employment on wages is qualitatively homogenous given the positive, albeit not always statistically significant, startup-wage relationship at every point in the conditional earnings distribution.

Mechanisms

I assess the two main channels that may explain the startup wage premium: (1) compensating differentials and (2) selection. First, I identify the firm attributes that separate salaries between startups and established firms for MIT graduates. Survey respondents asked to rate – on a 4-point Likert scale – the importance of eight non-pecuniary job attributes in their decision to accept their chosen job offer.

[INSERT TABLE 4]

Table 4 shows the logit estimates of individual preference for each job attribute in predicting the worker's entry into startup employment. The dependent variable is an indicator equal to 1 if the respondent considers the particular job attribute "essential" or "very important". Preferences for three job attributes are strongly related to workers' entry decision between startups and established firms – namely, those for firm reputation, job security, and opportunity for impactful work. All specifications control for main demographic variables as well as year and MIT school effects. Specification (4-1) shows that relative to graduates accepting job offers at large established firms, would-be startup employees are roughly 60% less likely to strongly prefer job security. In other words, early employees are less risk-averse. Similarly, specification (4-2) shows that early employees are 64% less likely to prioritize employer reputation. Lastly, specification (4-3) reveals that early employees are 72% more likely to prioritize opportunities for impactful work. These results parallel Sauermann (2014), who finds that academic scientists who join small firms place a lower value on job security but prioritize independence and challenging work.

Overall, Table 4 illustrates that the two types of workers are fundamentally different in the job attributes they prioritize when selecting their future employer. This suggests that the three non-pecuniary employment traits play a major role in driving wage differentials between startups and established firms. In theory, workers trade off a portion of their wages for preferred firm attributes – namely firm reputation, job security, and opportunity for impactful work.

[INSERT TABLE 5]

In Table 5, I directly test the impact of preferences for firm attributes on the observed wages. If compensating differentials explain the disparate wages between entrepreneurial and established firms, then controlling for preferences for job attributes – particularly the three that strongly predict entry into VC-backed startups – is expected to attenuate the explanatory power of entrepreneurial employment on wages. Specification (5-1) is the main effect documented in Table (2-4). Specifications (5-2) through (5-4) examine each non-pecuniary firm attribute's wage relationship holding all else equal. A preference for impactful work is negatively related to wages, implying that workers pay a positive price for this amenity. However, the coefficients on firm reputation and job security are puzzling because they are positive and statistically significant.

Nonetheless, Specifications (5-5), (5-6), and (5-7) show how the estimated startup wage premium changes after including preferences for firm attributes. The startup wage premium is robust at the 1% significance level for both the full sample and two subsamples. Moreover, the magnitude is higher than estimated in Specification (5-1). Overall, firm attributes do not seem to explain why early employees earn higher salaries than those in established firms. Therefore, I reject Hypothesis 2.

Finally, I test whether selection serves as the mechanism behind the startup wage premium. As explained in the Theory section, the primary concern for selection is found in

Dahl and Klepper (2015). The model shows that high quality workers are matched to large productive firms, leaving low quality workers to be allocated to startups. Although Equation (3) cannot be directly tested because worker ability is unobservable, I use bundles of offers for each individual to account for both observed and unobserved individual characteristics. Before the analysis of wages at the offer-level rather than at the individual level, I revisit the key identification assumption that individuals who receive a single job offer are not systematically different from those who receive multiple. Table 6 presents a series of t-tests of equality of means for both individual and employer characteristics associated with the job offer.[8]

[INSERT TABLE 6]

Administratively observable individual traits such as gender, citizenship, graduation year, MIT school of affiliation are statically the same between the two groups. Moreover, individuals with a single offer relative to those with multiple offers express similar preferences for the three job attributes (firm reputation, job security, and impactful work) that are related to startup entry. Overall, single and multiple offers appear to be drawn from two demographically similar groups of workers.

For employer characteristics, the share of offers from VC-backed startups is statistically equivalent although the percentage is slightly higher for multiple offers (8% vs. 13%)[9]. However, offered salary and firm age appear to be statistically different for the two groups. It may simply be the case that individuals who are more attractive to employers receiver higher salaries and more job offers. While it is possible that the individuals with multiple offers are drawn from higher points in the ability distribution compared to single-offer individuals, offer salaries are likely inflated due to ex-post bargaining process between the workers and firms. Furthermore, many top MIT graduates have a single job offer because they receive

[8]Formula for normalized differences is adopted from Imbens and Wooldridge (2009)

[9]It is empirically advantageous to have VC-backed startups to account for a significant share of the pool of multiple offers; the identification strategy in Table 7 pins down the true wage effect from the individuals with job offers from *both* VC-backed startups and established firms.

and accept a full-time job offer from their summer internship prior to their senior year and thus do not participate in the ensuing full-time job recruiting. Nonetheless, while selection is a potential issue, the balanced individual-level covariates as well as the subsequent results consistent with the startup wage premium documented in Table 2 are reassuring.

[INSERT TABLE 7]

Table 7 presents the offer-level relationship between entrepreneurial employment and wages. Consistent with the findings in Table 2, specification (7-1) shows that job offers from VC-backed startups are roughly 10% higher in compensation than those from established firms. This effect is positive and statistically significant at the 1% level. Results are consistent for job offers from both high-tech (7-3) and non-finance sectors (7-5).

Finally, I introduce individual fixed effects to account for both observed and unobserved individual traits including ability. All controls are omitted because they are time-invariant individual-level covariates whos effects are absorbed by the individual fixed effects. Specification (7-2) shows that the effect of startup employment on wages is statistically insignificant from zero. The sign flips to negative to roughly -6% although the point estimate is not statistically significant. Nonetheless, it is clear that accounting for heterogeneity across workers erases the relatively high wages associated with startup employment. The results are consistent for both high-tech (7-4) and non-finance (7-6) job offers. This indicates that the cross-sectionally observed startup wage premium is primarily driven by selection. In other words, conditional on worker quality, startups and established employers pay similar wages. Therefore, I accept Hypothesis 3.

It is worth highlighting that many high ability workers appear to select into entrepreneurial firms, which then pay high wages for superior talent. In a counterfactual world in which these workers are assigned to large corporations, these workers would also earn similarly high salaries. This implies that VC-backed startups pay competitive wages for talent. While not much is known regarding the personnel economics inside early-stage VC-financed companies, it is surprising that VC-backed startups tend to competitive salaries in spite of liquidity constraints.

6 Conclusion

Human capital is undoubtedly a central component of entrepreneurship. In addition to the company founders, early employees are an indispensable force behind the growth and success of nascent companies. However, little is known regarding the type of workers who self-select into startups as well as the wages early employees earn relative to employees at large established firms. This study offers an empirical treatment of wage differentials between VC-backed startups and established firms – two firm types that compete for high talent.

Using data from graduating college students from MIT, I show that early employees earn roughly 10% higher salaries than their counterparts at established firms. Although compensating differentials for risk, firm reputation, and entrepreneurial work environment form a plausible mechanism, it appears that selection is the primary channel through which startups appear to pay a wage premium in the cross-section. Holding worker ability constant in a framework of multiple job offers, I show that early employees earn statistically equal wages as employees at large established firms. Together, these findings suggest that high-ability workers, who command high wages in both employment settings, tend to select into VC-backed startups, thereby creating an illusion of a cross-sectional wage premium associated with startups. In addition, VC-backed startups appear to pay competitive wages for high talent.

A limitation of this study is that its findings may not be generalizable to the broader labor market since MIT represents a highly selected sample of workers at the right-tail of the ability distribution. However, the narrow nature of the sample is advantageous in many ways. For instance, unlike many other labor markets, MIT students typically receive numerous job offers – some of which are from established firms and others from VC-backed startups. This is an important feature because the interpretation of wage differentials in the lens of compensating differentials is based on the marginal worker who is indifferent between the two employment choices. Similarly, the multiple offers methodology turns on the fact that a sufficient number of workers receive offers from both established firms and VC-backed startups. In addition, while many studies on the financial returns to entrepreneurship include both lifestyle businesses and high-growth startups in their comparison to large employers, the former are not appropriate in this setting because they often employ low-skilled workers who are not fit for high-productivity roles at large established firms. In constrast, MIT graduates generally possess the type of human capital that is sought after by both high-growth startups and mature firms. Nevertheless, the insights drawn from MIT graduates and their labor market outcomes are generally limited to high-skilled young workers.

This study motivates numerous questions for future research. First year salaries for college graduates provide a setting for meaningful comparisons because these individuals possess almost identical pre-entry levels of education, social capital, and work experience. However, there are several open empirical questions regarding the real effects of entrepreneurial employment in the long-run. Do early employees develop a different set of skills as well as social ties that directly shape their follow-on productivity and earnings? If entrepreneurship is a skill that can be learned, does experience as an early employee directly affect the individual's future entry into business ownership and conditional on entry, the individual's performance (changes at the extensive and intensive margin, respectively)? Given that entrepreneurial success is extremely difficult to predict ex-ante (Kerr et al., 2014) and that most startups fail, how much of the real effects of entrepreneurial employment vary around the performance of the startup employer? It is vital that scholars at the intersection of labor economics and entrepreneurship examine more deeply the role and impact of early employees.

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Figure 1: Allocation of MIT Graduates into VC-Backed Startups Relative to Total VC Investments

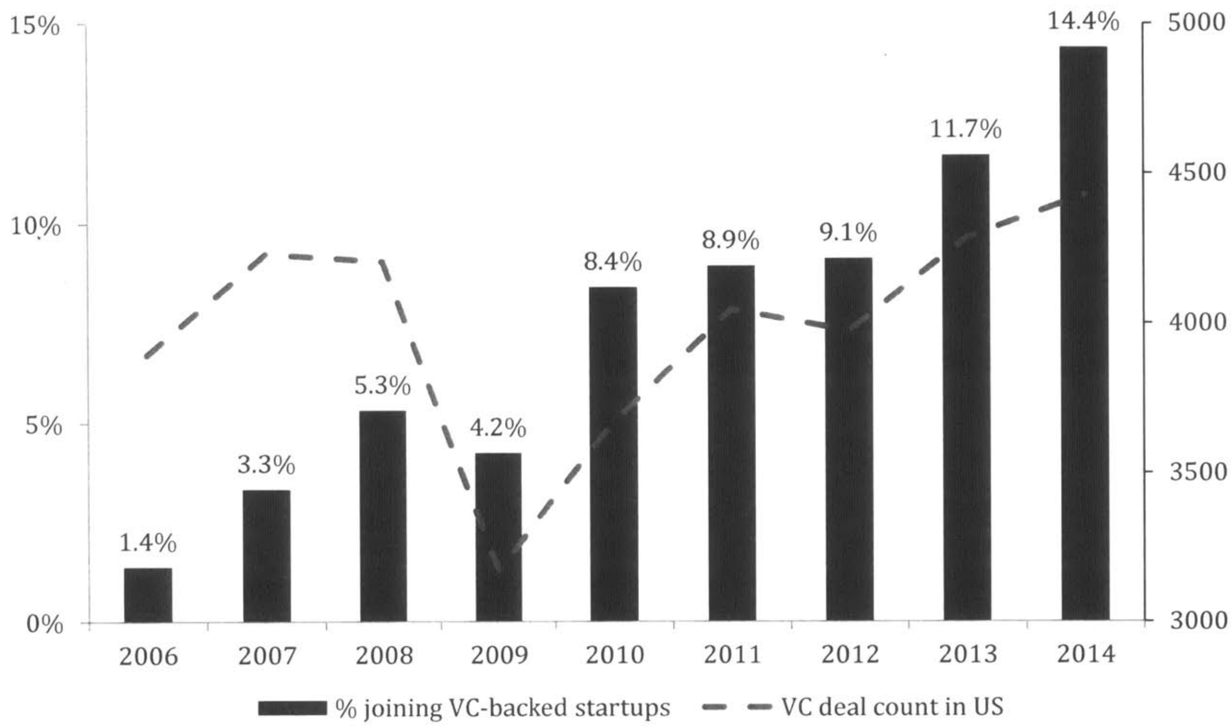


Figure 2: Allocation of MIT Graduates into VC-Backed Startups vs. Finance, 2006-2014

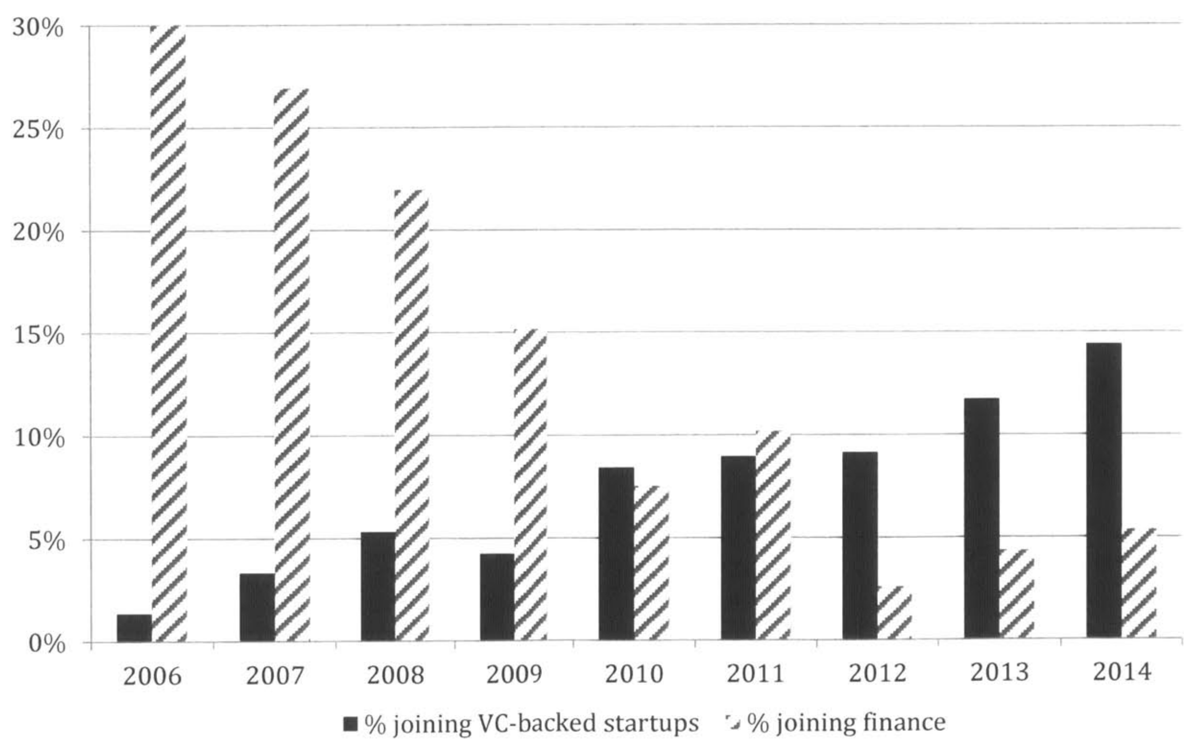


Table 1: Summary Statistics (N=2064 workers)

Individual Characteristics	**Mean**	**Median**	**SD**	**Min**	**Max**
Male	0.43	0	0.49	0	1
US Citizen	0.87	1	0.33	0	1
Graduation year	2010.27	2011.00	2.63	2006	2014
Number of offers received	1.94	1	1.34	1	12
MIT School					
Architecture and Planning	0.01	0	0.08	0	1
Engineering	0.63	1	0.48	0	1
Humanities, Arts, & Social Sciences	0.06	0	0.25	0	1
Management	0.10	0	0.30	0	1
Science	0.20	0	0.40	0	1

Employer Characteristics (Accepted Offer)	**Mean**	**Median**	**SD**	**Min**	**Max**
Salary ($2006)	61,614	60,094	19,033	10,537	187,271
Firm age (at graduation year)	54.06	34	52.94	1	348
VC-Backed	0.08	0	0.27	0	1
Industry					
Aerospace and Defense	0.07	0.00	0.25	0	1
Automotive and Transportation	0.01	0.00	0.12	0	1
Business Services (Advertising, Real Estate, Retail)	0.02	0.00	0.15	0	1
Chemicals and Materials	0.02	0.00	0.14	0	1
Computer Hardware/ Electrical Engineering	0.03	0.00	0.18	0	1
Computer Software	0.17	0.00	0.37	0	1
Consulting	0.15	0.00	0.36	0	1
Education	0.02	0.00	0.16	0	1
Energy and Utilities	0.04	0.00	0.19	0	1
Engineering	0.09	0.00	0.28	0	1
Financial Services	0.06	0.00	0.23	0	1
Health/Medicine	0.04	0.00	0.19	0	1
Industrial and Consumer Manufacturing	0.02	0.00	0.13	0	1
Money Management	0.13	0.00	0.34	0	1
Pharmaceutics (Biotech, Medical Device)	0.03	0.00	0.17	0	1
Other	0.06	0.00	0.23	0	1

Table 2: OLS Cross-Sectional Wage Regression

	Dependent Variable: Log Salary of Accepted Offer					
	All	All	All	All	High-Tech only	Non-Finance
	(1)	(2)	(3)	(4)	(5)	(6)
VC-Backed Startup	0.129***	0.110***	0.0955***	0.0800***	0.0591*	0.108***
	(0.0257)	(0.0255)	(0.0262)	(0.0253)	(0.0310)	(0.0267)
Male		0.121***	0.111***	0.113***	0.0609**	0.0857***
		(0.0170)	(0.0167)	(0.0163)	(0.0240)	(0.0177)
US Citizen		-0.0698***	-0.0626***	-0.0589***	-0.0616	-0.0506*
		(0.0227)	(0.0230)	(0.0222)	(0.0398)	(0.0262)
Number of offers received				0.0554***	0.0376***	0.0469***
				(0.00602)	(0.00796)	(0.00622)
Constant	10.96***	11.02***	10.79***	10.75***	10.94***	10.71***
	(0.0209)	(0.0290)	(0.108)	(0.104)	(0.0805)	(0.107)
MIT School Fixed Effects	No	No	Yes	Yes	Yes	Yes
Observations	2064	2064	2052	2052	718	1667

All specifications include graduation year fixed effects

Robust standard errors in parentheses

* p < 0.10; ** p < 0.05; *** p < .01

Table 3: Quantile Wage Regression

	Dependent Variable: Log Salary of Accepted Offer								
Percentiles	10	20	30	40	50	60	70	80	90
VC-Backed Startup	0.0769	0.0247	0.0295	0.0933***	0.108***	0.115***	0.0926***	0.0754**	0.0559
	(0.0787)	(0.0304)	(0.0382)	(0.0294)	(0.0207)	(0.0223)	(0.0263)	(0.0309)	(0.0394)
Constant	10.41***	10.48***	10.54***	10.64***	10.64***	10.82***	10.92***	11.06***	11.22***
	(0.276)	(0.107)	(0.134)	(0.103)	(0.0727)	(0.0782)	(0.0921)	(0.108)	(0.138)
Observations	2052	2052	2052	2052	2052	2052	2052	2052	2052

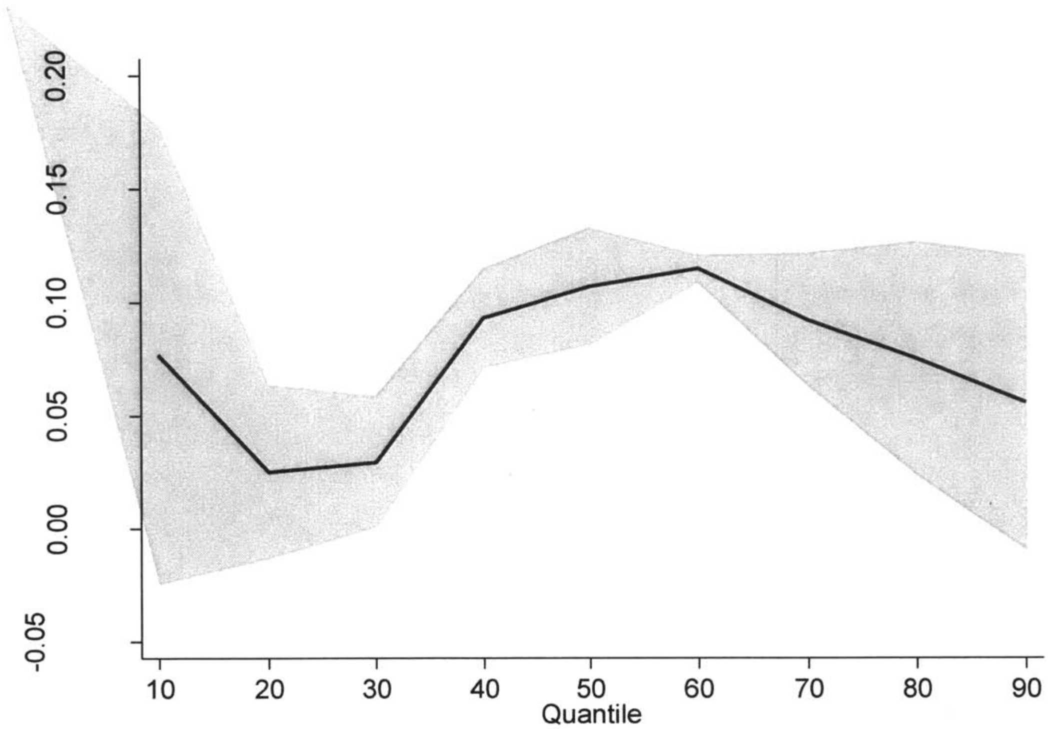
All specifications include graduation year and MIT school fixed effects

All specifications include controls used in Table (2-4)

Robust standard errors in parentheses

* p < 0.10; ** p < 0.05; *** p < .01

Figure 3: Quantile Regression Estimates



Note: This figure plots the quantile regression coefficients (and 90% confidence intervals in gray) of *VC-Backed Startup* from Table 3.

Table 4: Logit Regressions of Individual Preferences for Job Characteristics: Early Employees vs. Workers in Traditional Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Job security	Reputation of Employer	Impactful work	Location	Fit with skills and experience	Benefits	Student loans / debt payments	Job flexibility
VC-Backed Startup	0.391	0.369	1.718	1.229	1.022	0.801	0.772	1.074
	[-0.940]***	[-0.998]***	[0.541]***	[0.206]	[0.0214]	[-0.222]	[-0.259]	[0.0714]
	(0.188)	(0.172)	(0.206)	(0.185)	(0.188)	(0.171)	(0.228)	(0.174)
Male	0.697	0.909	0.982	0.814	0.989.	1.132	0.938	0.964
	[-0.361]***	[-0.0957]	[-0.0185]	[-0.206]*	[-0.0110]	[0.124]	[-0.0636]	[-0.0364]
	(0.103)	(0.111)	(0.116)	(0.110)	(0.117)	(0.102)	(0.127)	(0.105)
US Citizen	0.724	0.592	0.721	0.941	1.024	0.938	0.759	1.199
	[-0.323]**	[-0.525]***	[-0.327]**	[-0.0605]	[0.0236]	[-0.0637]	[-0.276]	[0.181]
	(0.135)	(0.157)	(0.155)	(0.147)	(0.147)	(0.136)	(0.168)	(0.134)
Constant	-0.625	-0.104	2.117*	1.240*	0.553	-0.194	-0.525	-0.633
	(0.679)	(0.591)	(1.158)	(0.687)	(0.682)	(0.583)	(0.663)	(0.616)
Observations	2052	2052	2052	2052	2052	2052	2052	2052

... = odds ratio
[...] = coefficient on logit
(...) = standard error on logit

All specifications include graduation year and MIT school fixed effects
* p < 0.10; ** p < 0.05; *** p < .01

Table 5: OLS Cross-Sectional Hedonic Wage Regression

	Dependent Variable: Log Salary of Accepted Offer						
	All	All	All	All	All	High-Tech only	Non-Finance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VC-Backed Startup	0.0800***	0.0888***	0.0889***	0.0850***	0.105***	0.0712**	0.129***
	(0.0253)	(0.0252)	(0.0257)	(0.0252)	(0.0255)	(0.0309)	(0.0269)
Male	0.113***	0.113***	0.116***	0.113***	0.117***	0.0635***	0.0904***
	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0162)	(0.0241)	(0.0176)
US Citizen	-0.0589***	-0.0552**	-0.0557**	-0.0623***	-0.0557**	-0.0600	-0.0490*
	(0.0222)	(0.0223)	(0.0223)	(0.0222)	(0.0224)	(0.0398)	(0.0261)
Number of offers received	0.0554***	0.0546***	0.0550***	0.0567***	0.0557***	0.0381***	0.0484***
	(0.00602)	(0.00603)	(0.00607)	(0.00598)	(0.00603)	(0.00819)	(0.00633)
Individual Preferences for Job							
Reputation		0.0367**			0.0415***	0.0138	0.0232
		(0.0158)			(0.0160)	(0.0225)	(0.0173)
Job Security			0.0426***		0.0435***	0.0255	0.0552***
			(0.0142)		(0.0143)	(0.0226)	(0.0159)
Impactful Work				-0.0574***	-0.0705***	-0.0427*	-0.0725***
				(0.0155)	(0.0158)	(0.0254)	(0.0180)
Constant	10.75***	10.74***	10.74***	10.80***	10.77***	10.93***	10.74***
	(0.104)	(0.104)	(0.103)	(0.104)	(0.103)	(0.0831)	(0.106)
Observations	2052	2052	2052	2052	2052	718	1667

All specifications include graduation year and MIT school fixed effects
Robust standard errors in parentheses
* p < 0.10; ** p < 0.05; *** p < .01

Table 6: Univariate Difference in Means Test: Single vs. Multiple Job Offers

	Single offers (n=328)	Multiple offers (n=658)	*t*-Stat: Equal Means	Norm. Diff.
Individual Characteristics				
Male	0.42	0.42	0.11	0.01
US Citizen	0.89	0.86	1.06	0.05
Graduation Year	2011.41	2011.59	0.88	0.04
MIT School				
Architecture and Planning	0.01	0.00	1.29	0.06
Engineering	0.66	0.72	1.97	0.10
Humanities, Arts, & Social Sciences	0.06	0.05	0.82	0.04
Management	0.07	0.06	0.74	0.04
Science	0.20	0.17	1.16	0.06
Job Preferences				
Firm Reputation	0.65	0.64	0.24	0.01
Job Security	0.40	0.38	0.32	0.02
Opportunity for Impactful Work	0.70	0.72	0.61	0.03
Employer Characteristics				
Offer Salary ($2006)	58,752	67,482	6.70	0.35
VC-Backed Startup	0.08	0.13	1.90	0.10
Firm Age	56.79	47.56	2.67	0.13
Industry				
Aerospace and Defense	0.09	0.08	0.85	0.04
Automotive and Transportation	0.03	0.02	1.64	0.08
Business Services (Advertising, Real Estate, Retail)	0.01	0.01	0.24	0.01
Chemicals and Materials	0.01	0.02	0.17	0.01
Computer Hardware/ Electrical Engineering	0.02	0.03	0.12	0.01
Computer Software	0.15	0.23	2.80	0.15
Consulting	0.16	0.18	0.79	0.04
Education	0.03	0.01	2.25	0.10
Energy and Utilities	0.06	0.10	1.95	0.10
Engineering	0.06	0.05	0.59	0.03
Financial Services	0.07	0.09	0.72	0.04
Health/Medicine	0.06	0.02	3.00	0.14
Industrial and Consumer Manufacturing	0.04	0.02	1.45	0.07
Money Management	0.07	0.08	0.40	0.02
Pharmaceutical (Biotech, Medical Device)	0.05	0.03	1.86	0.09

Table 7: OLS Offer-Level Wage Regression with Individual Fixed Effects

	Dependent Variable: Log Offer Salary					
	All		High-Tech only		Non-Finance	
	(1)	(2)	(3)	(4)	(5)	(6)
VC-Backed Startup	0.101***	-0.0643	0.125***	-0.0693	0.107***	-0.0598
	(0.0332)	(0.0731)	(0.0418)	(0.115)	(0.0375)	(0.0669)
Male	0.0731***		0.0265		0.0609**	
	(0.0278)		(0.0406)		(0.0295)	
US Citizen	-0.144***		-0.117*		-0.133***	
	(0.0328)		(0.0597)		(0.0332)	
Constant	11.33***	11.26***	11.12***	11.29***	11.32***	11.26***
	(0.0736)	(1.62e-13)	(0.101)	(4.01e-13)	(0.0797)	(2.16e-13)
Individual fixed Effects	No	Yes	No	Yes	No	Yes
Observations (offers)	658	658	320	320	556	556

All specifications include graduation year and MIT School fixed effects

Standard errors clustered at the individual level

* $p < 0.10$; ** $p < 0.05$; *** $p < .01$

Appendix

Table A1: Assessment of Survey Response Bias through Difference in Means Test

	Non-Response (n=1,554)	Response (n=510)	t-Stat: Equal Means	Norm. Diff.
Individual Characteristics				
Male	0.44	0.40	1.48	0.05
US Citizen	0.86	0.91	2.98	0.11
Graduation Year	2010.30	2010.23	0.59	0.02
Offer Count	1.94	1.95	0.07	0
MIT School				
Architecture and Planning	0.01	0.01	0.14	0.01
Engineering	0.63	0.64	0.46	0.02
Humanities, Arts, & Social Sciences	0.06	0.08	1.52	0.05
Management	0.10	0.08	1.30	0.05
Science	0.20	0.19	0.49	0.02
Employer Characteristics (Accepted Offer)				
VC-Backed Startup	0.08	0.08	0.54	0.02
Salary ($2006)	61698.81	61289.86	0.42	0.02
Industry				
Aerospace and Defense	0.07	0.07	0.19	0.01
Automotive and Transportation	0.01	0.02	1.65	0.06
Business Services (Advertising, Real Estate, Retail)	0.02	0.04	2.17	0.07
Chemicals and Materials	0.02	0.02	0.62	0.02
Computer Hardware/ Electrical Engineering	0.03	0.03	0.75	0.03
Computer Software	0.17	0.15	1.44	0.05
Consulting	0.14	0.18	1.88	0.07
Education	0.02	0.04	2.09	0.07
Energy and Utilities	0.04	0.04	0.79	0.03
Engineering	0.08	0.10	0.94	0.03
Financial Services	0.06	0.05	0.93	0.03
Health/Medicine	0.04	0.03	1.33	0.05
Industrial and Consumer Manufacturing	0.02	0.02	0.60	0.02
Money Management	0.14	0.10	2.61	0.10
Pharmaceutical (Biotech, Medical Device)	0.03	0.03	0.73	0.03
Other	0.06	0.06	0.33	0.01

Table A2: OLS Cross-Sectional Wage Regression, US Citizens Only

	Dependent Variable: Log Salary of Accepted Offer					
	All	All	All	All	High-Tech only	Non-Finance
	(1)	(2)	(3)	(4)	(5)	(6)
VC-Backed Startup	0.137***	0.119***	0.107***	0.0923***	0.0688**	0.121***
	(0.0276)	(0.0272)	(0.0280)	(0.0272)	(0.0330)	(0.0286)
Male		0.129***	0.114***	0.113***	0.0686***	0.0863***
		(0.0182)	(0.0178)	(0.0174)	(0.0253)	(0.0189)
Number of offers received				0.0531***	0.0365***	0.0459***
				(0.00639)	(0.00828)	(0.00660)
Constant	10.95***	10.95***	10.79***	10.75***	10.88***	10.73***
	(0.0221)	(0.0221)	(0.0902)	(0.0866)	(0.0635)	(0.0873)
MIT School Fixed Effects	No	No	Yes	Yes	Yes	Yes
Observations	1800	1800	1796	1796	632	1480

All specifications include graduation year fixed effects

Robust standard errors in parentheses

* $p < 0.10$; ** $p < 0.05$; *** $p < .01$