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Information frictions and entrepreneurship

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Abstract

Research Summary: Why do individuals become entrepreneurs? Why do some succeed? We propose two theories in which information frictions play a central role in answering these questions. Empirical analysis of longitudinal samples from the United States and the United Kingdom reveals the following patterns: (a) entrepreneurs have higher cognitive ability than employees with comparable education, (b) employees have better education than equally able entrepreneurs, and (c) entrepreneurs' earnings are higher and exhibit greater variance than employees with similar education. These and other empirical tests support our asymmetric information theory of entrepreneurship that when information frictions cause firms to undervalue workers lacking traditional credentials, workers' quest to maximize their private returns drives the most able into successful entrepreneurship.

Managerial Summary: Steve Jobs, Bill Gates, Mark Zuckerberg, Rachael Ray, and Oprah Winfrey are all entrepreneurs whose educational qualifications belie their extraordinary success. Are they outliers or do their examples reveal a link between education and success in entrepreneurship? We argue that employers assess potential workers based on their educational qualifications, especially early in their careers when there is little direct information on work accomplishments and productivity. This leads those who correctly believe that they are better than their résumés show to become successful entrepreneurs. Evidence from two nationally representative samples of workers (from the

United States and the United Kingdom) supports our theory, which applies to equally to the immigrant food vendor lacking a high school diploma as well as the PhD founder of a science-based startup.

KEYWORDS

asymmetric information, education, entrepreneurship, job-matching, signaling

1 | INTRODUCTION

Hewlett-Packard apparently denied Steve Jobs' petition for employment in 1977, because he lacked a degree—Jobs had dropped out of Reed College in 1972. Twitter and Facebook rejected San Jose State dropout Jan Koum's job applications; a year later he founded WhatsApp!, a company he would sell in 5 years to Facebook for $19 billion. D. J. Patel's Indian geology degree was not recognized by U.S. employers when he arrived in 1997, so he worked in the fast food industry. Now he owns more than a dozen pizza franchises near Atlanta, GA. How general is the experience of Jobs, Koum, and Patel—all of whom became entrepreneurs after prospective employers overlooked their talents, evidently due to insufficient credentials?

In this paper, we formalize and test two theories of entrepreneurship that could explain these successful entrepreneurs' decisions to strike out on their own. Informational frictions about worker ability lie at the heart of both. The difference between the two lies in who faces the informational imperfection—potential employers or the worker himself.

The first explanation, driven by *asymmetric information*, argues that any individual has incentive to start his own venture if potential employers perceive his productive capacity as lower than he does. Building on the seminal contributions of Akerlof (1970) and Spence (1973) to asymmetric information and signaling, we develop a theory in which firms reward workers with wages based on observable signals of ability. Ability can be inferred from many traits and behaviors. For example, potential employers commonly accept educational attainment and work history as signals of unobservable ability. However, the signals are imperfect—if a worker believes his ability exceeds what potential employers can infer from his observable characteristics, then he chooses entrepreneurship and becomes residual claimant of his productivity, rather than join a firm in which he would be paid according to his observable signals. We show that these pressures exist whether signals arise exogenously or workers acquire them endogenously, like educational degrees, and whether they increase the holder's productivity or not.

Comparative advantage drives our second information-based theory of entrepreneurship. We draw from Roy's (1951) and Jovanovic's (1979) insights that occupational choice results from matching multidimensional human capital to job-dependent multifactor production functions. Others before us, most prominently Lazear (2004, 2005), have proposed that entrepreneurship arises from differentiated abilities but have not derived clear predictions about entrepreneurial entry and earnings when information about abilities is symmetrically imperfect (i.e., not known with certainty by either the worker or employer at the outset). We develop a model in which signals of ability are productive, like the specific skills one acquires through formal education. If these yield relatively more in existing firms, and innate cognitive ability produces relatively more in entrepreneurship, then workers will eventually sort into the respective occupation where their productivity is highest. The rate at which information imperfection resolves determines how fast individuals find their optimal mode of work.

Both models generate some similar propositions, particularly in static settings. Both predict that workers who choose entrepreneurship have higher ability and higher income than employees with the same signals, while entrepreneurs' signals are inferior to similarly able employees'. However, only asymmetric information indicates that entrepreneurs' incomes will exhibit higher variance among workers with the same signals. Dynamic analyses yield further telltale differences: With the reduction of informational asymmetries over worker careers, the hypothesized ability advantage of entrepreneurs relative to employees of the same signal *diminishes*. On the other hand, the resolution of symmetric informational imperfections predicts the opposite—as a worker and his (potential) employers simultaneously learn his relative strengths and weakness, the sorting of workers to matching occupations improves, which *increases* the ability gap between entrepreneurs and employees with the same educational credentials over time.

We test these theoretical predictions using data drawn from the nationally representative National Longitudinal Survey of Youth (NLSY), first administered to 12,686 individuals born between 1957 and 1964, and resident in the United States in 1979. The NLSY provides a detailed record of their education and work histories to the present. Analyzing this sample, we find that those who become self-employed (or entrepreneurs) scored higher on cognitive ability tests administered to them as adolescents than employees with similar educational credentials, our proxy for observable signals. Despite their higher ability scores, the self-employed have lower academic credentials. In fact, the larger the gap between an individual's own ability and the median ability of individuals with his same academic credentials, the more likely he is to choose entrepreneurship. A median self-employed worker earns 7.3% more than a comparably educated wage-employee, and entrepreneurial earnings have higher variance. These empirical differences between the self-employed and wage-employed prevail for both self-employed workers who incorporate their businesses as well as those who do not, with the results on income and wealth differences being particularly stark for incorporated entrepreneurs—those most likely to be residual claimants of high growth enterprises. We obtain these results after controlling for a variety of potential correlates of entrepreneurial choice, including worker wealth, noncognitive traits such as risk-taking and locus of control, and other demographic features. Analysis of a second nationally representative dataset constructed from the U.K. National Child Development Study (NCDS), which follows the lives of every U.K. resident born during one particular week in 1958 to the present yields qualitatively similar results.

However, further empirical analyses do not equally support both theories. We find no evidence that the returns to cognitive ability are higher in entrepreneurship or that the returns to education are higher in wage work—requisite conditions for comparative advantage. Further, although individuals with high ability relative to their educational pedigree tend to enter entrepreneurship, the effect attenuates over workers' careers—a pattern consistent with asymmetric information but contradictory to comparative advantage with imperfect information. Next, employees' returns to ability increase over time but show no significant evolution for entrepreneurs—suggesting that employers learn their employees' abilities but entrepreneurs get paid for their innate talents early on, again supportive of asymmetric information. Although the above evidence implies workers know themselves better than the labor market, workers' information about their own ability is also evidently imperfect, and occupational switching is not uncommon—those who give up entrepreneurship for wage work have higher credentials than ability, while employees transitioning to entrepreneurship have relatively higher ability, holding education and all else constant. Hence, while we cannot completely rule out comparative advantage, the case for asymmetric information appears more compelling.

Entrepreneurs are heroes of Schumpeterian creative destruction, but a large steam of the literature across the social sciences portrays the self-employed as overconfident and undereducated job-hoppers or social misfits. Our work contributes to resolving this paradox. By focusing on a single facet—information frictions about ability—as the driver of entrepreneurship, our models explain occupational choice and success across the spectrum of ability: from the corner food vendor lacking a high school diploma to the founder of a revolutionary, high-tech startup with a PhD from MIT—something existing theories, or empirical tests of entrepreneurship theories, cannot easily do. Our theories thus foreclose the bias inherent in studying entrepreneurial subclasses such as venture backed startups, or high-tech founders (Ruef 2010 describes the flawed generalizations that arise from such studies). We also delineate the subtle differences between two distinct classes of information frictions—asymmetric versus symmetric imperfect information—about worker ability as drivers of entrepreneurship.

Nevertheless, we emphasize that we neither explain the occupational choice of every entrepreneur nor rule out other explanations for entrepreneurship. Equally, we cannot resolve the debate on entrepreneurial earnings. However, by showing that entrepreneurs earn more conditional on their signals—as predicted by our theories of financially motivated workers—we identify those more likely to succeed as entrepreneurs, after controlling for known influences of entrepreneurial entry such as risk preferences, family wealth, and confidence. Our empirical findings imply that those who strike out on their own *because* their productive ability is undervalued by labor markets are successful. Still those who choose entrepreneurship for other reasons (e.g., due to overconfidence or lifestyle preferences) may not enjoy similar success. Thus, our findings suggest that the resolution of the entrepreneurial earnings puzzle hinges on *why* workers choose entrepreneurship in the first place.

The rest of this paper is organized as follows. The next section briefly, and thus partially, summarizes the related literature. Section 3 presents our two theories of entrepreneurial choice. Section 4 introduces our data and describes our empirical findings. Section 5 concludes. Formal proofs are relegated to Appendix A, while Appendices B and C, respectively, describe additional empirical robustness checks and analyses using the British NCDS sample.

2 | RELATED LITERATURE

Our study speaks to a vast literature across the social sciences that examines the determinants of entrepreneurship and conditions that affect entrepreneurial success. Since a study like ours cannot do justice to it, we refer readers to more comprehensive literature summaries in Parker (2009) and Hébert and Link (1988) and situate our study among its direct antecedents as follows.

2.1 | Dispositional versus contextual drivers

Sørensen (2007) divides the entrepreneurship literature into two camps: "dispositional" and "contextual." Dispositional study tradition argues that individuals' characteristics predispose them toward either entrepreneurship or traditional employment. For example, McClelland (1964) argues that individuals who believe their performance depends on their own actions—those with an internal locus of control—tend to become entrepreneurs. Camerer and Lovallo (1999) provide experimental evidence that overconfident, hubristic, individuals gravitate toward entrepreneurship. Kihlstrom and Laffont (1979) suggest that entrepreneurs are risk-loving. Lazear (2004, 2005) as well as Kacperczyk and Younkin (2017) theorize that they have less focused interests than employees. Levine and Rubinstein (2017) describe them as "smart and illicit." Nicolaou et al. (2008) uncover highly heritable entrepreneurial dispositions by comparing the activity of monozygotic and dizygotic twins. Summarizing the evidence from large sample studies, Evans and Leighton (1989, p. 521) conclude: "Poorer wage workers—that is, unemployed workers, lower-paid wage workers and men who have changed jobs a lot—are more likely to enter self-employment or to be self-employed at a point in time, all else equal. These results are consistent with the view of some sociologists that 'misfits' are pushed into entrepreneurship."

In contrast to the dispositional approaches, context-based explanations highlight environmental factors that goad workers into entrepreneurship. Studies in this camp highlight the roles of family origin (Halaby, 2003; Sørensen, 2007), professional and social networks (Stuart and Sorenson, 2005; Lerner and Malmendier, 2013), as well as the regional cultural and material environment (Saxenian, 1994; Sorenson and Audia, 2000; Schoonhoven and Romanelli, 2001). Our theories particularly relate to the "ability–job match" and "employee mobility" branches of the dispositional and contextual explanations, respectively.

2.2 | Ability–job match

Among dispositional explanations for entrepreneurship, a family of studies by Åstebro, Chen and Thompson (2011), Braguinsky, Klepper, and Ohyama (2012), and Ohyama (2015) casts the decision to found a firm as a matter of matching job to ability. These papers' formal models posit relationships between the distribution of worker ability and the production functions of employees vis-à-vis entrepreneurs to derive predictions about entrepreneurial choice as a function of ability. In Åstebro et al.(2011), when ability and job requirements are both uniformly distributed and production exhibits skill complementarity, labor market frictions disproportionately prevent high- and low-ability workers from matching to their optimal wage jobs, forcing them into entrepreneurship instead. Ohyama (2015) arrives at a similar conclusion by assuming entrepreneurial earnings are more convex in ability than wages, which allows entrepreneurial earnings to dominate wages at both tails of the ability distribution. Braguinsky et al. (2012) posit distinctive roles for innate ability and work-experience—the latter helps to identify good entrepreneurial ideas, while the former improves execution. From this setup, they predict late entrepreneurial entrants fail less (because they are less innately able but filter ideas better due to experience), but the highest earning entrepreneurs are those that survive early entry (because they are the most capable for executing anything that comes up and luckily had good ideas, despite poor filtering). Each of these papers finds empirical support for their predictions by treating *education as a proxy for ability* in large samples—effectively equating education and ability for empirical purposes.[1]

[1]In a related literature stream that does not treat education as a signal of ability per se, Stenard and Sauermann (2016) find that workers who end up in employment that does not utilize their education become dissatisfied inducing them to leave and start their own firms.

2.3 | Employee experience and mobility

Among contextual factors, work environments characterized by dissent drive some employees into entrepreneurship (e.g., Freeman, 1986; Carnahan et al., 2012).[2] Klepper and Thompson (2010) document "disagreements among leading decision makers concerning fundamental ideas about technology and management that prompt dissidents to leave and start their own firms." Shah, Agarwal and Echambadi (2019) find that interpersonal and ethical frictions within organizations push employees to spin out their own ventures. Similarly, Klepper (2007) shows that automobile manufacturers experiencing more disagreements between management and employees spun out more startups. Agarwal, Audretsch and Shakar (2007) point out that underutilized knowledge, embedded in employees, spurs many to strike out on their own.

2.4 | Entrepreneurial earnings

While the studies we discuss above have established that personality traits and environmental conditions goad individuals into entrepreneurship, excepting the ability–job match stream, they do not directly address when entrepreneurship can be more profitable than wage employment. In a pioneering study, Hamilton (2000) reports that entrepreneurs' earnings start lower and grow slower than paid employees', and suggests that entrepreneurs accept lower income to indulge their taste for "being their own boss." Moskowitz and Vissing-Jørgensen (2002) likewise find that entrepreneurial investments earn less, despite incurring greater risk. Levine and Rubinstein (2017) use NLSY data to report that self-employed workers who own incorporated businesses earn substantially more than employees (based on both medians and means), but not other self-employed workers. However, three other studies (Fairlie 2005, Hartog et al. 2010, and Van Praag et al. 2013) that also analyze the NLSY data report higher means and medians for self-employed earnings overall, relative to employee earnings.

To overcome the issues associated with earnings data, a recent stream of work examines expenditures. For example, Pissarides and Weber (1989) analyze data on household expenditures and find that the self-employed are likely to underreport their earnings in Britain. This suggests that traditional measures of entrepreneurs' incomes are downwardly biased. Hurst, Li, and Pugsley (2014) analyze data from the U.S. Consumer Expenditure Survey and Panel Study of Income Dynamics and establish that the self-employed underreport their income in household surveys by about 25%. Similarly, using 38-year longitudinal data, Sarada (2016) finds that while self-employed individuals (mis)report earning 26.2% less, their household expenditures are 4.5% higher than the traditionally employed's. This expenditure premium accrues with longer experience in self-employment and is not offset by lower savings or higher uncertainty, implying that entrepreneurs earn more than their salaried counterparts do.

2.5 | Connections to the present study

Our theories leverage the *interaction* of disposition and context as drivers of entrepreneurship. Although intrinsic ability (disposition) determines a worker's entrepreneurial potential,

[2]See Campbell, Kryscynski, and Olson (2017), and Agarwal, Gambardella, and Olson (2016) for comprehensive surveys of the literature connecting employee mobility to entrepreneurial entry.

stochastic signals and their workplace interpretation (context) generate the informational asymmetries, which spur the choice. Likewise, relative levels of innate ability and acquired skills (disposition) determine a worker's comparative advantage in wage work vis-à-vis entrepreneurship, but informational imperfections (context) determine whether he finds optimal occupation. Hence, we provide two nuanced bridges between dispositional and contextual approaches.[3]

Asymmetric information rationalizes observations from the employee mobility literature. The disagreements, frictions, and underutilized knowledge that push employees to leave suggest asymmetric information—employees who perceive opportunities or capabilities (perhaps their own) overlooked by their employers can exploit these outside the firm as entrepreneurs.

Although related to the ability–job matching models above, our asymmetric information theory casts entrepreneurial choice as neither a function of ability nor the imperfect signal of it (e.g., education) per se—but rather the wedge between them. Since our model is distinctly agnostic about the distribution of ability and only lightly restricts the functional form of productivity, we cannot generically relate ability or education to entrepreneurship, as others do.[4] Instead, whenever the *difference* between an individual's ability and signal is high, the resulting gap between productivity and wage drives him to choose residual claimancy as an entrepreneur. The empirical tests associated with other models in this class measure ability using educational pedigree—ours leverage the difference between that publicly observable ability proxy and a privately administered aptitude test, invisible to the labor market. Hence, both our asymmetric information theory and empirical tests complement rather than challenge extant studies connecting education/ability and entrepreneurship.[5]

While the economics literature has discussed asymmetric information (Akerlof, 1970; Spence 1973) and comparative advantage (Roy 1951; Jovanovic 1979) for decades, neither has been used to offer an integrated explanation for entrepreneurial choice and income. Exhibit 1 graphically depicts the relationship of our study to some of the distinct literature streams described here.

3 | THEORY

In this section, we present two distinct theories of entrepreneurial choice: the first, driven by asymmetric information about worker ability, and the second, by innate ability's comparative advantage relative to that of acquired skills in entrepreneurship vis-à-vis wage work. However, for parsimony, we do not present both theories in equal detail. Since our theory of asymmetric information is the most novel, we present it first and in the greatest generality

[3]See also Aldrich and Fiol (1994), Klepper (2007), Pontikes and Barnett (2017), for studies examining the interplay between dispositional and contextual factors in shaping occupational choice.

[4]The technical assumptions we impose to simply allow firms to survive even with adversely selected employees.

[5]Our comparative advantage theory more closely resembles extant ability–job matching models—as information imperfections resolve individuals sort into the occupation where their specific ability-education vector is most productive. That is, fit between workers' multidimensional skills and job requirements drive the match. However, like other ability–job matching models the functional form of production matters—our comparative advantage theory requires that innate ability be more productive than education in entrepreneurship vis-à-vis wage work—an assumption that we, ultimately, cannot empirically verify in our sample.

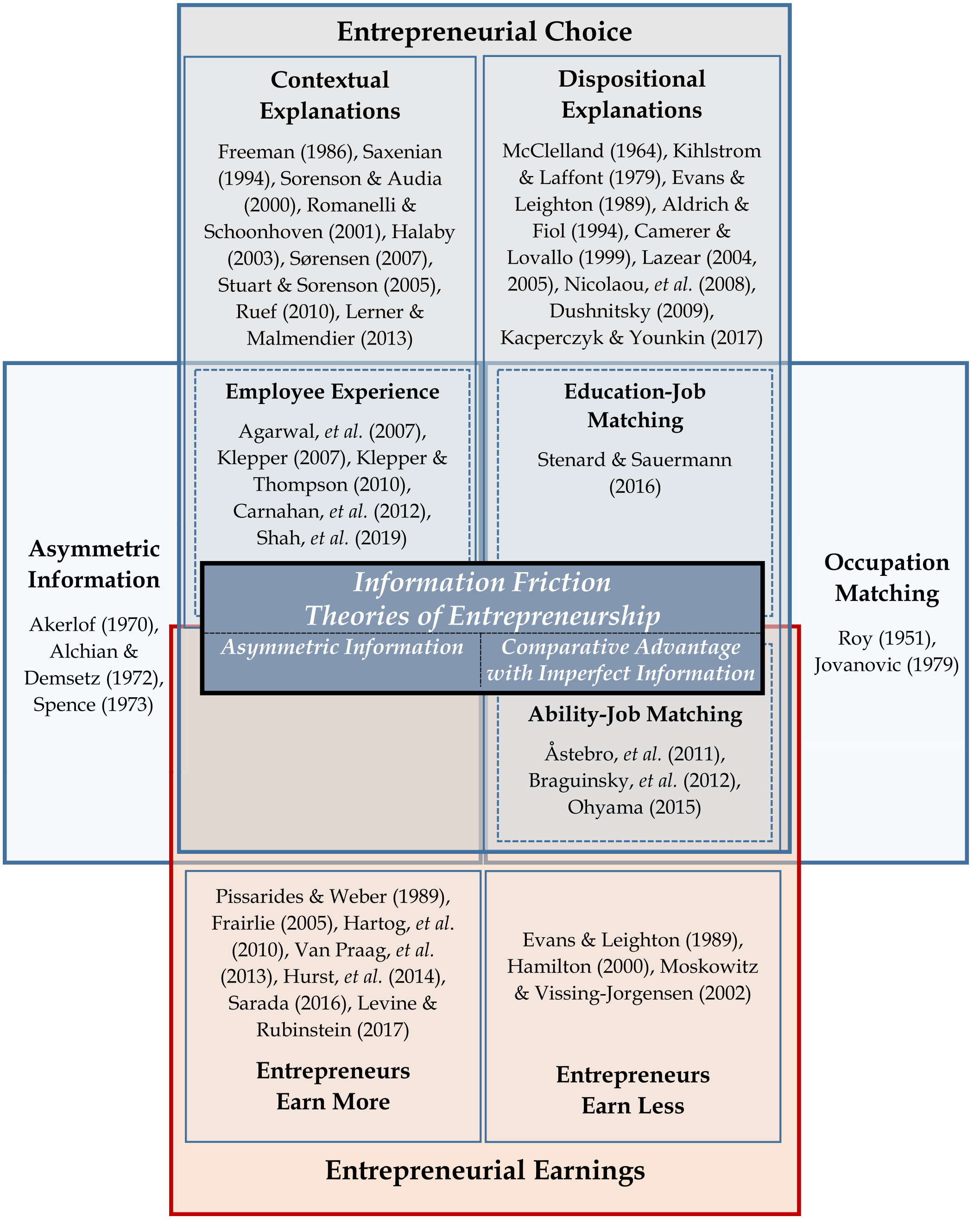

EXHIBIT 1 Literature map [Color figure can be viewed at wileyonlinelibrary.com]

and rigor. Because the concepts behind our theory of comparative advantage are more familiar, we only describe it verbally in the main text, reserving a stylized formalization to Appendix A. In their static forms, these theories generate similar empirical predictions. So, we extend both, again verbally in the main text and formally in Appendix A, to include the resolution of imperfect information about innate worker ability over time. Adding this dynamism produces opposing hypotheses in the two theories, and we use these to empirically adjudicate between them.

3.1 | Asymmetric information

Our asymmetric information theory of entrepreneurial choice applies Akerlof's (1970) "market for lemons" to labor. Workers are both the more informed sellers and the traded good, while employers are the less informed buyers. Employers offer wages based on observable signals, but to the extent that better-informed workers believe their ability exceeds the labor market's estimate of it, they prefer entrepreneurship, where they will be residual claimant of their talents. In the vernacular, *cherries* become entrepreneurs and employees are *lemons*.

3.1.1 | Intuition

A more detailed intuition is as follows. Suppose workers and firms are motivated solely by money. Workers' productivity depends on unobservable traits, collectively called ability. Although potential employers cannot observe workers' ability, they see a public, albeit noisy, signal of it. Employers base wage offers solely on this signal. Theoretically, this signal is a composite, comprised of a worker's educational pedigree, verifiable accomplishments and experience, the way he speaks, writes, looks, and carries himself, anything observable. Critically, the signal (a) does not perfectly reveal ability and (b) is the prevailing determinant of starting wages.[6]

When a worker accepts a wage offer, the hiring firm keeps his productivity minus his wage. The firm is the *residual claimant*, keeping what is left after all factors of production have been remunerated. However, the worker could reject all offers to become the residual claimant of his own productivity—an entrepreneur. The worker will do so whenever he believes that his productivity exceeds the prevailing wage for his signal, since this will yield higher income.

The central predictions of our theory arise from asymmetric information about worker ability. As an approximation, we assume workers perfectly know their own ability. Appendix A.1.4 contains an extension where the worker is also unsure about his ability. When workers know their own ability, then, among all workers with a given observable signal, those whose privately known ability is less than the wage associated with that signal will accept employment, and all whose ability exceeds the wage will become entrepreneurs.

The next section formalizes our theory of asymmetric information driven entrepreneurial choice, makes the assumptions behind the above verbal argument explicit, and derives our primary empirical hypotheses. We relegate all proofs to Appendix A.6 for clarity.

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[6]We implicitly assume that an employer will not (quickly) update the wage to reflect true ability after hiring the worker, perhaps because the random or complex nature of production obscures the ability of individual employees in a team, or because even if an employer learned exactly how able her employee was, she only needs to pay as much as other employers, who lack her private information, would offer to prevent him from changing employers (Alchian and Demsetz, 1972).

3.1.2 | Formal model

Individuals have privately known ability $\theta \in [\underline{\theta}, \bar{\theta}]$ and publicly observable signal of it $S \in [\underline{S}, \bar{S}]$ distributed such that the posterior density of ability $F^{'}(\theta|S)$ has full support over $[\underline{\theta}, \bar{\theta}]$ for all S. To guarantee that higher signals beget higher equilibrium wage offers, we assume that the monotone-likelihood-ratio property (MLRP) *strictly* holds: for all $\theta_h > \theta_l$ and $S_l < S_h$[7]

$$\frac{F'(\theta_h|S_h)}{F'(\theta_h|S_l)} > \frac{F'(\theta_l|S_h)}{F'(\theta_l|S_l)}$$

An individual chooses to work either as an entrepreneur, where he produces θ (i.e., normalized to his ability) and keeps all of his produce, or accepts wage work at a firm.[8] Individual productivity in a firm equals $\pi(\theta)$, finite and increasing in its argument. A (single) firm makes take-it-or-leave-it wage offers $w(S)$ to all individuals with signal S.

We make two regularity assumptions to guarantee optimal wages equalize marginal revenues and marginal costs: (a) $F(\theta|S)$ is log-concave for all S, and (b) $\pi(\theta)$ exhibits weakly decreasing differences with respect to θ (i.e., for all θ, $(\pi(\theta) - \theta)^{'} \leq 0$). Virtually all probability distributions commonly used in theoretical economics are log-concave.[9] The latter assumption means incrementally increasing an individual's innate ability will not *improve* his productivity as a wage worker more than his productivity as an entrepreneur. It could still be the case that all individuals are more productive as employees than as entrepreneurs. Although these assumptions guarantee that the firm's wage setting problem is well behaved (i.e., the second order condition is satisfied for all critical points), they are stronger than necessary and not used for any other purpose in the model.[10]

Two additional assumptions ensure that the equilibrium separates workers; that is, both entrepreneurship and traditional employment coexist. In order for traditional employment to exist, traditional employment must be more productive than entrepreneurship over at least some ability range.[11] So, to guarantee that the firm can profitably make at least one offer that will be accepted by some individual, we assume that the least able individuals are more productive in the firm (i.e., $\pi(\underline{\theta}) > \underline{\theta}$). To ensure that the firm cannot profitably entice everyone to join the firm, we assume that extremely high ability, regardless of signal, is vanishingly rare—in

[7]The MLRP means that observing any two individuals with signal S' and S'' such that $S' < S''$ and hypothesizing any two ability levels θ' and θ'' such that $\theta' < \theta''$, it is more likely that the higher ability θ'' belongs to the individual with the higher signal S''.

[8]For parsimony, we assume that entrepreneurs derive no benefit from signals. So long as the importance of signaling is less in entrepreneurship than in wage work, this simplication is unrestrictive.

[9]For example, Uniform, Normal, Exponential, Logistic, Extreme Value, Laplace, Power Function, Weibull, Gamma, Chi-Squared ($c \geq 2$), Chi ($c \geq 1$), Beta ($\nu \geq 1$, $\omega \geq 1$), Maxwell, Rayleigh, Pareto, and Lognormal distributions have log-concave cdfs (Bagnoli and Bergstrom 2005).

[10]For tight, but perhaps less intuitive, conditions for the second-order condition to hold, see equation (5) in the proof of lemma 4 in Appendix A.6.

[11]Without this assumption "lemons unraveling" in employment can occur. To see this, suppose employees were exactly as productive inside the firm as outside (i.e., $\pi(\theta) = \theta$). For any wage offer w, individuals accepting the offer will have ability in the range $[\underline{\theta}, w]$ and average productivity strictly less than w. Since the firm pays all the accepting workers w, such a high offer is clearly unprofitable. The firm may reduce the wage but then the most talented individuals who accepted before will now reject and the problem remains—no matter what the firm offers, the wage will always exceed the average productivity of those who accept.

particular, $\lim_{\theta \to \bar{\theta}} F'(\theta|S) = 0$, at least for some S. Again, as we explain in Appendix A.6, these conditions guarantee separation, but other reasonable alternative assumptions would suffice.

3.1.3 | Analysis

Individuals with signal S reject traditional employment if and only if their entrepreneurial outside option (ability) strictly exceeds the firm's offer of $w(S)$. Thus, for every signal S, the firm chooses a wage w to solve

$$\max_{w} \int_{\underline{\theta}}^{w} (\pi(\theta) - w) dF(\theta|S)$$

yielding a first-order condition for *every signal S*

$$(\pi(w) - w) F'(w|S) = F(w|S) \tag{1}$$

such that the marginal benefit of attracting employees with ability $\theta = w$ and signal S (LHS of Equation (1)) equals the cost of raising the wages of all less able employees with signal S (RHS of Equation (1)). The (continuous) set of these solutions over the domain of Ss constitute a wage function $w(S)$. Under our regularity assumptions, the firm's problem is well behaved:

Lemma 1 An interior, separating equilibrium exists, in which positive measures of individuals choose entrepreneurship and traditional employment.

Since all individuals with signal S and ability strictly greater than $w(S)$ choose entrepreneurship, and all with weakly lower ability choose employment, the following is immediate:

Proposition 1 Entrepreneurs are more able than employees of the same signal S.

Also observe that all employees with a given signal earn the same wage, despite the fact that they have a range of abilities, whereas, since entrepreneurs earn according to their ability, their incomes are not only higher but exhibit greater spread. That is,

Corollary 1 The incomes of entrepreneurs have higher median and variance than those of employees of the same signal.

Note that while we have no reason to reject the common notion that entrepreneurship is risky, the logic of Corollary 1 shows venture uncertainty is not required to create greater variance in entrepreneurial incomes than in wages.

Proposition 1's simplicity stems from the fact that for every signal level the unique minimum ability of entrepreneurs coincides with the unique maximum ability of employees. Before making the analogous argument for signals, we prove an intuitive property equilibrium wages:

Lemma 2 Wages strictly increase in signal (i.e., $w'(S) > 0$).

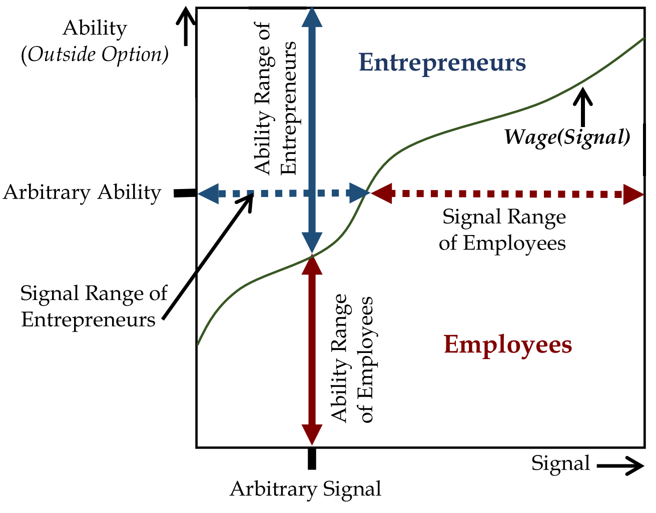

FIGURE 1 Ability, signal, and entrepreneurship. The figure depicts the signal-ability sample space. The horizontal axis denotes signal. The vertical axis denotes ability (equivalently entrepreneurial payoff). Wage, a function of signal, bisects the space, such that individuals with entrepreneurial productivity exceeding the wage commanded by their signal choose entrepreneurship. Thus, conditional on signal, entrepreneurs have higher ability than employees. The inverse wage function expresses the minimum signal an individual with a given ability would require to choose employment. Thus, conditional on ability, entrepreneurs have lower signal than employees [Color figure can be viewed at wileyonlinelibrary.com]

Since MLRP implies that (unconditional on occupational choice) a higher pedigree always *probabilistically* indicates higher ability, and productivity increases in ability, equilibrium wages intuitively increase in signal. Because wages increase in signal, someone who would accept the offer to individuals with signal S would accept all offers to individuals with higher signals. More formally, monotonicity implies $w(S)$ is invertible, and $w^{-1}(\theta)$ is the minimum signal, for which the firm makes an offer that a θ ability individual would accept. Of course, the firm might not make any offers that entice the most able workers. Similarly, there may be very low-ability individuals who would accept any offer the firms makes. Therefore, the following is immediate:

Proposition 2 Employees have better signals than entrepreneurs of the same ability θ (if there exist θ able individuals engaged in both occupations).

In developing the intuition for Proposition 1, we framed the question of occupational choice as, "Given my entrepreneurial productivity, what minimum *wage* would I need to keep me from entrepreneurship?" Since each signal induces a different wage, signals can be ordered according to their associated wages, and every worker could equivalently ask, "Given my entrepreneurial productivity, what minimum *signal* would I need to keep me from entrepreneurship?" Hence, at every ability level, there exists a threshold signal, such that those whose signal exceeds that threshold will receive an acceptable offer; those whose signal lies below the threshold will not—they open their own business. This is the essence of Proposition 2. Figure 1 depicts the joint sample space of ability and signal.[12] It graphically illustrates Propositions 1 and 2.

For several reasons, the conclusions of the model are sharper than should be expected empirically. First, *own true productive ability* is not really known to every worker, much less the empiricist. Neither does the empiricist have access to the *complete set of signals* observable to

[12]The figure shows the joint sample space of ability and signal but does not their depict joint density or require it. This is the key both to the theory's generality and why its predictions over ability or signal are only conditional on the other attribute—making unconditional predictions requires stronger distributional assumptions.

the labor market. The empiricist is limited to noisy proxies of these fundamental variables of the model. Furthermore, the model does not capture all of the many factors that determine occupational choice and earnings, just one—asymmetric information over ability. Hence, one should not expect the predictions of Propositions 1 and 2 and Corollary 1 to hold for every single individual in the real world. Nevertheless, taken as average effects, these results form our primary hypotheses that we empirically test.

Hypothesis (H1) *Entrepreneurs are more able than employees of the same signal, on average.*

Hypothesis (H2) *Employees have better signals than entrepreneurs of the same ability, on average.*

Hypothesis (H3) *The incomes of entrepreneurs have higher median (mean) and variance than those of employees of the same signal.*

3.1.4 | Robustness

In Appendix A.1, we extend the model in four ways: Particularly, relevant when formal education signals ability, we allow (a) workers to exert effort endogenously acquiring signals and (b) signals to be productive. The model is also robust to allowing (c) entrepreneurship itself to signal ability and (d) workers to be uncertain about their own ability. (e) We defer the model's further implications in a dynamic setting until Section 3.3.2.

In the next section, we present an alternative theory of entrepreneurial choice.

3.2 | Comparative advantage

Roy (1951) argued that when individuals have heterogeneous abilities across varying tasks, they sort into occupations where they have a comparative advantage. Could such a job-matching model over multidimensional skills deliver our previously outlined predictions as well, without the need for asymmetric information?

If innate ability is relatively more productive in entrepreneurship and formal education is relatively more productive in wage work, then, by and large, it can. Under this assumption and perfect information about ability, individuals sort into occupations where they are most productive: (1) Fix an innate ability level, and above the threshold education level where comparative advantage favors wage work, all individuals become employees, while the less educated become entrepreneurs. (2) Similarly, fix a level of education, and above some threshold, higher ability individuals follow their comparative advantage into entrepreneurship, while the less able accept wage offers. (3) Furthermore, assuming that higher levels of innate ability are productive in both occupations, then, given education, these smart entrepreneurs will earn more—that is, after all, why they chose the profession. Of course, if the direction of comparative advantage were reversed, then matching would deliver exactly the opposite predictions. Furthermore, we cannot generically say anything definitive about the relative variance of earnings in the two professions under comparative advantage-based job-matching, though, because if ability is observed, then rather than all employees with a common level of education earning the same wage (as in our model of asymmetric information), a wage contract can be written over both innate ability *and* education. Hence, income variance depends on the interplay of the two attributes' joint distribution and the production functions.

The difference, though, between the empirical implications of the two theories become much starker, when considered in a dynamic setting.

3.3 | Information frictions and dynamics

3.3.1 | Comparative advantage

If ability and education were perfectly observable, then, under the comparative advantage-based job-matching explanation above, their relative influence on income should not change in either occupation over time. However, plausibly, both workers and employers must learn workers' ability over time—imperfect information could be symmetric (see, e.g., Jovanovic 1979). Suppose that comparative advantage runs in the required direction, and that early in individuals' careers, education is the primary indicator of innate ability—if workers of a given education were more productive in entrepreneurship *on average*, then such educated individuals would gravitate toward entrepreneurship, and if not, those with these specific credentials would prefer wage offers. But, because information about ability is imperfect, many would be in the "wrong" occupation—entrepreneurs with particularly low innate ability (conditional on education) would produce more as employees, and conversely employees with relatively high ability (conditional on education) would be more productive running their own business. Thus, our basic empirical predictions would hold, but misplaced workers would weaken them. Over time though, both employers and workers receive more (symmetric) signals about workers' innate abilities, wages adjust to reflect not just education but the entire signal history, many discover they are (probably) in the wrong profession and switch. Individuals continue to choose the occupation where workers with signal sets just like their own are most productive *on average*, but as information about workers' innate ability improves, fewer are misplaced—the occupational match improves with the gradual revelation of information. Said differently, comparative advantage-driven job-matching implies that evidence for Hypothesis (H1) becomes stronger over time.

We formalize the static and dynamic comparative advantage-based job-matching model with symmetric, imperfect information over worker ability in Appendices A.2 and A.3, respectively.

3.3.2 | Asymmetric information

Notice that by amending the matching model above, such that the worker knows his ability from the outset but the manager continues to learn it over time, it become a *dynamic* asymmetric information model, albeit less general than the one presented in Section 3.1.2. This asymmetric information setup *reverses* the dynamic effect relative to the comparative advantage setup with imperfect information—the ability gap between entrepreneurs and employees of a given education, while remaining consistently positive, diminishes over time. We formalize this model and explain our numerical solutions to it in Appendix A.4.[13]

[13]Observe that the firm must compute a new wage for each education level and signal history in each period. Further, unlike in the symmetric comparative advantage model with imperfect information, the firm must also consider the strategic actions of better informed workers in making the offers. This complexity places a general analytical solution beyond the scope of this paper, and we rely instead, on numeric solutions under various ability distributions and specific signaling technologies. These yield qualitatively consistent results (see Appendix A.4).

The intuition is as follows. Asymmetric information about worker ability is highest at the beginning of a worker's career, when he has no documentable experience or output. This may force a worker, who knows he would be more productive in the right position inside a firm but has a relatively poor public signal, to adversely select into entrepreneurship, so that he can keep his productivity, instead of accepting an even less desirable wage. This is why, unlike in job-matching, asymmetric information's empirical predictions do not depend on the direction of comparative advantage (see the numerical example in Appendix A.5). Over time, though, employers get more information about a worker's ability than just education. Empirically this will manifest as wages becoming increasing driven by ability, conditional on education—the manager is still rewarding observable signals of ability, but this myriad is invisible to the empiricist. Furthermore, as ability is revealed to employers, adverse selection into entrepreneurship diminishes, causing the predictions of the asymmetric information model to soften over time. Those that chose entrepreneurship later in life are much more likely to do for other reasons than that the labor market cannot see their productive talents.

To summarize, we can use the following testable implications to adjudicate whether the patterns in our data are a consequence of comparative advantage or asymmetric information.

Hypothesis (H4) *Under matching (asymmetric information) and holding education constant, the positive difference between entrepreneurial and employee ability increases (decreases) as information imperfection resolves over time.*

Hypothesis (H5) *Matching requires that ability have a relatively stronger influence on entrepreneurial earnings and education is a relatively stronger driver of earnings for wage employees. (Asymmetric information does not depend on the direction of comparative advantage.)*

Hypothesis (H6) *Asymmetric information predicts that the positive correlation of wages to ability, conditional on education, will strengthen over time for wage employees. (Such a pattern may also hold under matching with imperfect information under some conditions.)*

We summarize the key assumptions, fundamental forces, and generated hypotheses from both our asymmetric and comparative advantage theories of entrepreneurial choice, in both their static and dynamic forms, in Exhibit 2.

[13]Observe that the firm must compute a new wage for each education level and signal history in each period. Further, unlike in the symmetric comparative advantage model with imperfect information, the firm must also consider the strategic actions of better informed workers in making the offers. This complexity places a general analytical solution beyond the scope of this paper, and we rely instead, on numeric solutions under various ability distributions and specific signaling technologies. These yield qualitatively consistent results (see Appendix A.4).

EXHIBIT 2 Theory Map.

<table>
<tr><th></th><th>Static asymmetric information Section 3.1</th><th>Static comparative advantage Section 3.2</th></tr>
<tr><td colspan="3">Key Assumptions:</td></tr>
<tr><td>Information</td><td>Signals correlate imperfectly to ability.
Workers know own ability better than the labor market (in equilibrium).[1, 2]</td><td>Perfect (symmetric) information: both worker and potential employers observe worker ability. [1]</td></tr>
<tr><td>Production</td><td>Productivity increases in ability (and potentially signals like education) in both occupations.[3]</td><td>Ability is relatively more productive in entrepreneurship. Signal is relatively more productive in employment.</td></tr>
<tr><td>Earnings</td><td>Employees get wages based on signal.</td><td>Employees are residual claimants.</td></tr>
<tr><td></td><td colspan="2">Entrepreneurs are residual claimants.</td></tr>
<tr><td>Incentive</td><td colspan="2">Workers choose entrepreneurship or wage work to maximize income.</td></tr>
<tr><td>Mechanism:</td><td>Workers whose ability exceeds the wage associated with their publicly observable signal choose entrepreneurship.</td><td>Workers self-select into the occupation where they have a productive comparative advantage.</td></tr>
<tr><td colspan="3">Hypotheses: (Empirically supported hypotheses in bold)</td></tr>
<tr><td>1.</td><td colspan="2">Entrepreneurs are more able than employees with same signals.</td></tr>
<tr><td>2.</td><td colspan="2">Entrepreneurs have signals weaker than employees of same ability.</td></tr>
<tr><td>3. a.</td><td colspan="2">Entrepreneurs earn more, conditional on signals.</td></tr>
<tr><td>3. b.</td><td>Entrepreneurs have greater earnings variance, conditional on signals.</td><td>(No prediction on earnings variance)</td></tr>
<tr><td></td><td>Dynamic Asymmetric Information
Section 3.3.2</td><td>Dynamic Comparative Advantage
Section 3.2.1</td></tr>
<tr><td colspan="3">Additional Key Assumptions:</td></tr>
<tr><td>Information</td><td>Workers know own ability.</td><td>Neither workers nor employers know.</td></tr>
<tr><td></td><td colspan="2">Signals of ability, revealed over time, are publicly observable.</td></tr>
<tr><td>Production</td><td colspan="2">One signal is productive (e.g. education); other signals are informational only.</td></tr>
<tr><td>Mechanism:</td><td>Undervalued workers are pressured to adversely select into entrepreneurship only until their ability is revealed.</td><td>Workers gradually sort into the occupation where they learn they have comparative productive advantage.</td></tr>
<tr><td colspan="3">Additional Hypotheses: (Empirically supported hypotheses in bold)</td></tr>
<tr><td>4.</td><td>Difference between entrepreneurial ability decreases over workers' careers.</td><td>Difference between entrepreneurial ability increases over workers' careers.</td></tr>
<tr><td>5</td><td>(No requirement on relative productivity of ability and education in either occupation.)</td><td>Ability is relatively stronger driver of entrepreneurial earnings. Education is relatively stronger driver of wages.</td></tr>
<tr><td>6.</td><td>Ability becomes a stronger driver of employee earnings over career.</td><td>No change in impact of ability on employee earnings over career.</td></tr>
</table>

[1]Both models can accommodate a "pre-stage" in which workers endogenously acquire their signals (e.g. education). An extension of the Spence (1973) signaling model, allowing workers to choose their education level but yielding (continuous) noisy ability signals, can be found in Appendix A.1.1. An extension where entrepreneurship itself signals ability is considered in Appendix A.1.3

[2]For clarity the base model assumes workers know their own ability. An extension where they have only a private signal of it is discussed in Appendix A.1.4.

[3]Since the model does not require multidimensional ability, the base model forecloses productive signals. However, the model is robust to their inclusion, and these are discussed in Appendix A.1.2.

4 | EMPIRICAL ANALYSIS

4.1 | NLSY sample and variables

We test our hypotheses using data from the U.S. National Longitudinal Survey of Youth 1979 (NLSY). The NLSY follows the lives of 12,686 men and women, who were 15–22 years old when first surveyed in 1979. These individuals were interviewed every year until 1994, and biennially thereafter, producing a 24-period panel until 2010, when respondents were 46–53 years old. The NLSY panel thus provides continuous employment and income history for each subject over a majority of his/her career, as well as detailed information on the subject's personality and socio-economic characteristics. The sample has been extensively used in labor economics to study educational attainment and earnings dynamics (see, e.g., Cameron and Heckman 2001, or Altonji, Bharadwaj and Lange 2012).

The NLSY was designed to represent the population of youth residing in the United States on January 1, 1979. Of the 12,686 original participants, 6,111 belonged to a sample representative of the civilian U.S. youth population in 1979. Another 5,295 individuals belonged to a supplemental sample of civilian Hispanic or Latino, black, and economically disadvantaged non-black/non-Hispanic respondents living in the United States in 1979. A further 1,280 respondents represented the U.S. military population as of September 30, 1978. Following 1984, 1,079 members of the military sample were no longer eligible for interview, leaving only 201 randomly selected military respondents. Following 1990, none of the 1,643 members of the economically disadvantaged, non-black/non-Hispanic sample were interviewed. Thus, by 1991, only 78.5% of the sample (9,964 individuals) remained.[14] Annual attrition, primarily due to death and emigration, left 7,757 survivors by 2010, the last year in our study.[15] We limit the sample to individuals who worked full-time (i.e., more than 35 hr/week on average), either as an employee or self-employed in at least one NLSY round between 1979 and 2010. Then, from each survey round, we collect information on the individuals' employment records, educational qualifications, family background, cognitive and noncognitive ability test scores, income, and wealth.

We measure workers' cognitive ability through their age-adjusted Armed Forces Qualification Test (AFQT) Score, a composite derived from the Armed Services Vocational Aptitude Battery, which includes tests on Arithmetic Reasoning, Math Knowledge, Word Knowledge, and Paragraph Comprehension. In this, we follow in a long tradition, both in the military and scholarly research, of using AFQT as a measure of cognitive ability or intelligence (e.g., Griliches and Mason 1972, Carneiro and Heckman 2002, Iyer et al. 2015, Levine and Rubinstein 2017). Workers' signals are measured by their educational qualifications, captured by their years of education or highest degree obtained, consistent with previous work at least since Spence (1973). Exhibit 3 describes these and other control variables used in our empirical analyses.

Several papers before ours have identified the existence of asymmetric information between employees and employers using the same NLSY data and AFQT measure for ability as our study (e.g., Kahn 2013, Schönberg 2007). Altonji and Pierret (2001) interpret increasing returns to

[14]The surveying agency dropped a segment of the military subsample due to interviewing difficulties and stopped interviewing a large subsample of the disadvantaged due to funding cutbacks.

[15]As of 2010, 573 main respondents (5.8% of the respondents eligible for interview) had been reported as deceased. See https: //www.nlsinfo.org/content/cohorts/nlsy79.

EXHIBIT 3 NLSY Variable Definitions.

Self-employed is equal to 1 if NLSY respondent indicated current job as “self-employed in his or her own business, professional practice, or farm;” NLSY defines an individual as self-employed if he or she owned at least 50 percent of the business, is principal managing partner, or files a form SE for Federal income taxes. Independent contractors, consultants, and freelancers are also classified as self-employed.

Self-employed Incorporated is equal to 1 if Self-employed individual reported his/her business as incorporated.

Armed Forces Qualification Test (AFQT) Score is indicated in percentiles and calculated from the Armed Services Vocational Aptitude Battery (ASVAB) which includes tests on Arithmetic Reasoning, Math Knowledge, Word Knowledge, and Paragraph Comprehension. NLSY respondents took the ASVAB in 1980, when they were 16-23 years of age. Scores are age-adjusted using the procedure described in Altonji, Bharadwaj, & Lange (2012).

Years of Education is measured on an ordinal scale such that 0 = No formal schooling, 1 = completion of 1st grade, 2 = completion of 2nd grade,..12 = completion of 12th grade (high school), 16 = completion of four-year college, and 20 = completion of eight years of college or higher.

Highest Degree Earned is measured on an ordinal scale which indicates 0 = No formal schooling, 1 = High School Diploma (or equivalent), 2 = Associate/Junior College, 3 = Bachelor of Arts, 4 = Bachelor of Science, 5 = Master’s, and 6 = PhD or other advanced professional degrees (MD, JD, LLD, DDS).

Annual Income is total net family income expressed in 2010$. Values are top-coded such that incomes of the top 2 percent of earners are coded as the average value of the top two percent.

Net-worth is created by summing all asset values and subtracting all debts of respondent’s family and expressed in 2010$. Net-worth of the top two percent are top-coded as the average of the top two percent.

Age is age of respondent in years

Risk-loving is from respondents’ answer to a question asking them how much they like taking risks on a scale between 0 indicating “unwilling to take any risks” and 10 indicating “fully prepared to take risks”

Sociability is derived from respondents’ answer to a question asking them how sociable they are on a scale between 1 indicating “Extremely shy” and 4 indicating “Extremely outgoing”

Self-esteem is based on respondent responses to the Rosenberg Self-Esteem Test designed to measure the self-evaluation that an individual maintains. 0 on the scale indicates the highest level, and 30 the lowest level of self-esteem.

Pearlin Mastery indicates a respondent’s score on The Pearlin Mastery Scale designed to measure the extent to which individuals perceive themselves to be in control of forces that significantly impact their lives. 0 indicates the highest level of mastery and 28 the lowest.

Industry dummies 13 dummy variables indicating industry of respondents’ primary job based on the 1970 census code such that 1 = Agriculture, Forestry, Fishing and Hunting; 2 = Mining; 3 = Construction; 4 = Manufacturing; 5 = Transportation, Communication, Utilities; 6 = Wholesale & Retail Trade; 7 = Finance, Insurance and Real Estate; 8 = Information, Business and Repair Services; 9 = Personal, Educational, and Health Services; 10 = Arts, Entertainment and Recreation; 11 = Professional, Accommodation and Other Services; 12 = Public Administration and 13 = Other.

Male, White, Born Abroad, Supplementary Sample and ***Military Sample dummies*** are binary variables set to 1 if respondent is male, non-black/non-hispanic, born outside of the U.S., is drawn from the NLSY supplementary sample and is drawn from the NLSY Military Sample respectively (the variables are set to 0 otherwise).

AFQT scores among the wage employed over time as evidence for the presence of asymmetric information and its resolution over time for wage workers. Hence, the existence of asymmetric information over worker ability is well established in the literature.

We derive a single measure of the *extent* of a worker's advantage in entrepreneurship relative to wage work, under either theory—we refer to it as *entrepreneurial advantage*. Consider first, the asymmetric information explanation. It is reasonable that an employer, observing a job candidate's level of education, attributes to him the median ability for all individuals with that particular qualification. Hence, we measure entrepreneurial advantage as difference between each individual's AFQT score and the median AFQT score for those sharing the individual's educational qualification. This measure can be positive, indicating that the employer will likely underestimate the worker's ability, or negative indicating a probable overestimate. Turning to the comparative advantage explanation, this measure captures the productivity difference a worker would have in entrepreneurship, relative to others with the same education.

4.1.1 | Summary statistics

Our final estimation sample is an unbalanced panel with 176,379 person-year observations on 11,476 unique individuals.[16] Of these, 7.1% of the observations are on self-employed individuals and the rest earn wages as employees. 1.2% of the sample's person-year observations are on self-employed individuals with incorporated businesses.

Table 1 presents summary statistics for the variables in this sample. Some variables (e.g., individuals' cognitive and noncognitive test scores, and parental education) have no within-individual variation across survey rounds, some variables have limited variation (e.g., individuals' educational qualifications increase during youth but stabilize after age 30), while employment related variables (e.g., annual income) vary over time. For the average person-year, self-employed individuals have higher ability scores than salaried workers (AFQT score of 45.4 vs. 43.4), comparable educational qualifications (12.9 years vs. 12.8 years of school), higher annual incomes ($90,985 versus $61,954) and higher net-worth ($237,090 vs. $83,704).[17] Self-employed workers also have larger gaps between their ability and signals, indicative of higher asymmetric information, relative to wage workers. On average, the self-employed are more likely to be male, white, born abroad, older, more risk-loving, and sociable; have higher self-esteem; and come from more wealthy families. As reported by Levine and Rubinstein (2017), self-employed individuals who own incorporated businesses appear to be a class of their own—they have higher ability scores, higher educational qualifications but also the largest gap between their ability and education (indicative of high asymmetric information about their cognitive ability) relative to other workers. Incorporated entrepreneurs also earn much more and have substantially larger wealth than salaried and other self-employed workers.

[16]Table B1 of Appendix B provides information on the number of unique individuals in full-time employment, and the fraction of individuals in self-employment, during each round of NLSY79 between 1979 and 2010.
[17]Table B2 of Appendix B shows that self-employed individuals scored higher, on average, than salaried individuals on several other tests of general intelligence, such as the PSAT, SAT, and ACT tests. We found this result quite striking, since these tests are used to secure entry into higher education, and, as we will show below, entrepreneurs systematically have lower educational qualifications.

TABLE 1 Summary statistics by occupational status, NLSY 1979-2010

	Salaried	Self-employed (All)	Self-employed (Uninc.)	Self-employed (Inc.)
Ability, Education, Earnings				
Mean AFQT Score	43.4	45.4	43.9	52.4
Median AFQT Score	40	44	41	54
Mean Years of Education	12.8	12.9	12.7	13.8
Median Years of Education	12	12	12	13
Mean Highest Degree	1.5	1.5	1.4	1.0
Median Highest Degree	1	1	2	1
Mean (AFQT-(Median AFQT | Years of Education))	0.56	3.83	1.61	3.32
Median (AFQT-(Median AFQT | Years of Education))	-1	3	0	4
Mean (AFQT-(Median AFQT| Highest Degree))	3.07	5.07	3.71	5.5
Median (AFQT-(Median AFQT| Highest Degree))	0	3	0	5
Mean Annual Income	61,954.1	90,985.2	62,206.8	148,264.6
Median Annual Income	48,094.5	56,220.5	47,176.9	88,993.0
Mean Net-Worth	83,704.6	237,090.9	92,405.6	525,635.6
Median Net-Worth	15,128.8	53,718.7	15,485.5	218,033.0
Control Variables				
Male	0.51	0.61	0.51	0.68
White	0.56	0.66	0.59	0.72
Born Abroad	0.07	0.08	0.07	0.09
Age	30.7	34.9	33.4	37.7
Risk-loving	2.38	2.94	1.27	3.56
Sociability	2.55	2.63	2.14	2.82
Self-esteem	21.48	21.56	19.71	22.76
Pearlin Mastery	18.55	19.08	15.64	20.21
Father Entrepreneur	0.09	0.12	0.09	0.20
Mother Entrepreneur	0.02	0.03	0.02	0.04
Father Years of Education	9.22	9.74	9.17	10.91
Mother Years of Education	10.15	10.48	10.10	11.22
Family Income in 1979	49,651.2	55,420.7	46,674.5	69,085.1
Family Net-worth in 1985	23,149.6	52,001.1	23,984.3	94,521.9
Supplementary Sample	0.40	0.32	0.42	0.24
Military Sample	0.03	0.02	0.07	0.01
Observations	171,204	13,035	10,797	2,238
	[92.9%]	[7.1%]	[5.9%]	[1.2%]

The table reports summary statistics for key variables from the NLSY sample. The NLSY tracks 12,686 individuals, drawn to represent the population of adolescents resident in the U.S. in 1979. The individuals are tracked through a series of surveys conducted annually between 1979 and 1993 and biennially since through 2010. The statistics above are calculated from 184,329 person-NLSY survey year observations although not all observations have non-missing values for each of the variables. See Exhibit 1 for variable definitions.

4.2 | Descriptive evidence

4.2.1 | Unconditional relationships

Our theory predicts that entrepreneurs' ability and income exceeds employees' *conditional* on observable signals, but their signals fall short *conditional* on ability. The summary statistics suggest that entrepreneurs have higher ability and lower educational qualifications, even *unconditionally*, which of course, our theory does not preclude.[18] In Appendix B, we examine the full distributions of ability scores, income, and net worth for salaried workers and entrepreneurs.[19] The figures confirm that outliers do not drive our findings regarding ability and wealth differences between wage workers and entrepreneurs. This provides evidence contrary to the popular notion that entrepreneurs' are outliers and that their ability and earnings concentrate at both tails of the corresponding population distributions.

Next, we turn to testing the conditional predictions of our theory.

4.2.2 | Conditional relationships

Figure 2 presents descriptive evidence for conditional Hypothesis (H1)—for *every level of formal education* other than master's degree, entrepreneurs have higher median AFQT scores than employees.

The second part of Hypothesis (H3) states that entrepreneurs' incomes exhibit higher variance than the incomes of their employed counterparts. Figure 3 presents the *distributions* of income and wealth as box plots for entrepreneurs and employees, conditional on the highest academic degree obtained. The boxes span the 25th to 75th percentiles, the horizontal bar in each denotes the median, while the whiskers extend from the 5th to 95th percentiles. Panel (a) shows that the median income and the income variance of entrepreneurs exceeds that of employees at all levels of education. Panel (b) shows that this pattern also holds in the wealth distributions.

The above evidence suggests that entrepreneurs generally have higher ability scores and higher earnings with greater variance at most education levels.

Could these findings be driven by biased sample attrition? In particular, might especially low ability, hence low-earning, self-employed workers fall into unemployment or part-time employment—and thus, out of our sample—more than low-ability wage workers? Table B3 in Appendix B shows that self-employed workers are slightly more likely than salaried workers to drop out of full-time work during a subsequent year in our panel (12.9 vs. 10.7%). However, the self-employed who drop out have, on average, higher AFQT scores, comparable years of education, and higher incomes, relative to the salaried workers who drop out. These relative patterns, preserved in the sample of survivors, compare to those from our full panel of worker-years reported in Table 1. Thus, we conclude that attrition bias does not drive our descriptive findings on the relative differences between salaried workers and self-employed.

[18]Although Hypotheses (H1) and (H3) hold at *every signal level* and Hypothesis (H2) holds at *every ability level*, guaranteeing that they hold unconditionally requires additional assumptions on the joint ability-signal distribution.

[19]Figure B1 of Appendix B plots the cumulative densities of AFQT scores for the self-employed and employees. Figure B2 plots the kernel density of log annual household income (Panel a) and household net-worth (Panel b) for the salaried employees versus the self-employed.

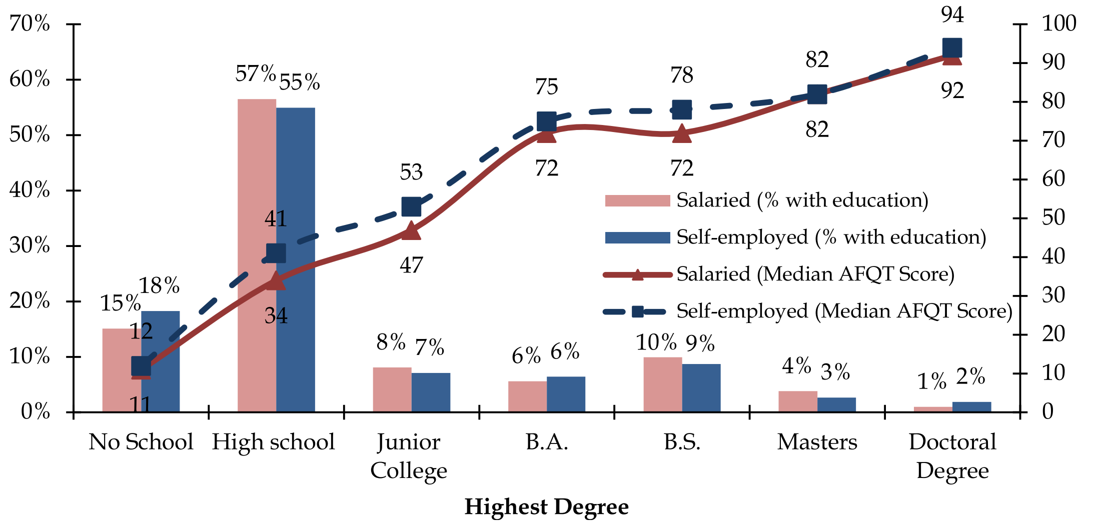

FIGURE 2 Ability scores and education, by occupational status. The figure compares median Armed Forces Qualification Test (AFQT) scores for self-employed and salaried individuals at various levels of individuals' educational qualifications. The vertical bars indicate the percentage of person-year observations during which the worker had attained the corresponding educational qualification by employment status. The figure is based on 9,922 person-year observations of self-employed individuals and 99,099 person-year observations of wage employees in the National Longitudinal Survey of Youth (NLSY) panel [Color figure can be viewed at wileyonlinelibrary.com]

Appendix C describes and analyzes a secondary dataset, the U.K. NCDS of 1958. The NCDS sample covers the population of U.K. residents born in a specific week in 1958. Since each subsequent survey round, conducted 4–8 years apart, focuses on different attributes, our analysis is primarily cross-sectional. Nevertheless, the descriptive findings from the NCDS sample qualitatively mirror those from the NLSY sample—entrepreneurs had scored higher on cognitive ability tests in primary school, both unconditionally and conditional on educational attainment, and median entrepreneurs' income exceeds that of wage earners', with higher variance, at most educational levels.

4.3 | Regression analysis

In this section, we test our hypotheses using multivariate regressions. Our first set of regressions estimate the probability that an individual is self-employed as a function of ability, educational qualifications, and our *entrepreneurial advantage* metric. The second set of regressions estimate annual income and net worth as a function of occupational choice (self-employed or salaried) and educational qualifications. Both sets control for demographic, attitudinal and background influences that may affect our outcomes of interest and the main explanatory variables.

[20]We report LPM estimates for all models with binary dependent variables due to the ease of interpreting the corresponding coefficients, but ensure the robustness of all our results with Probit estimations.

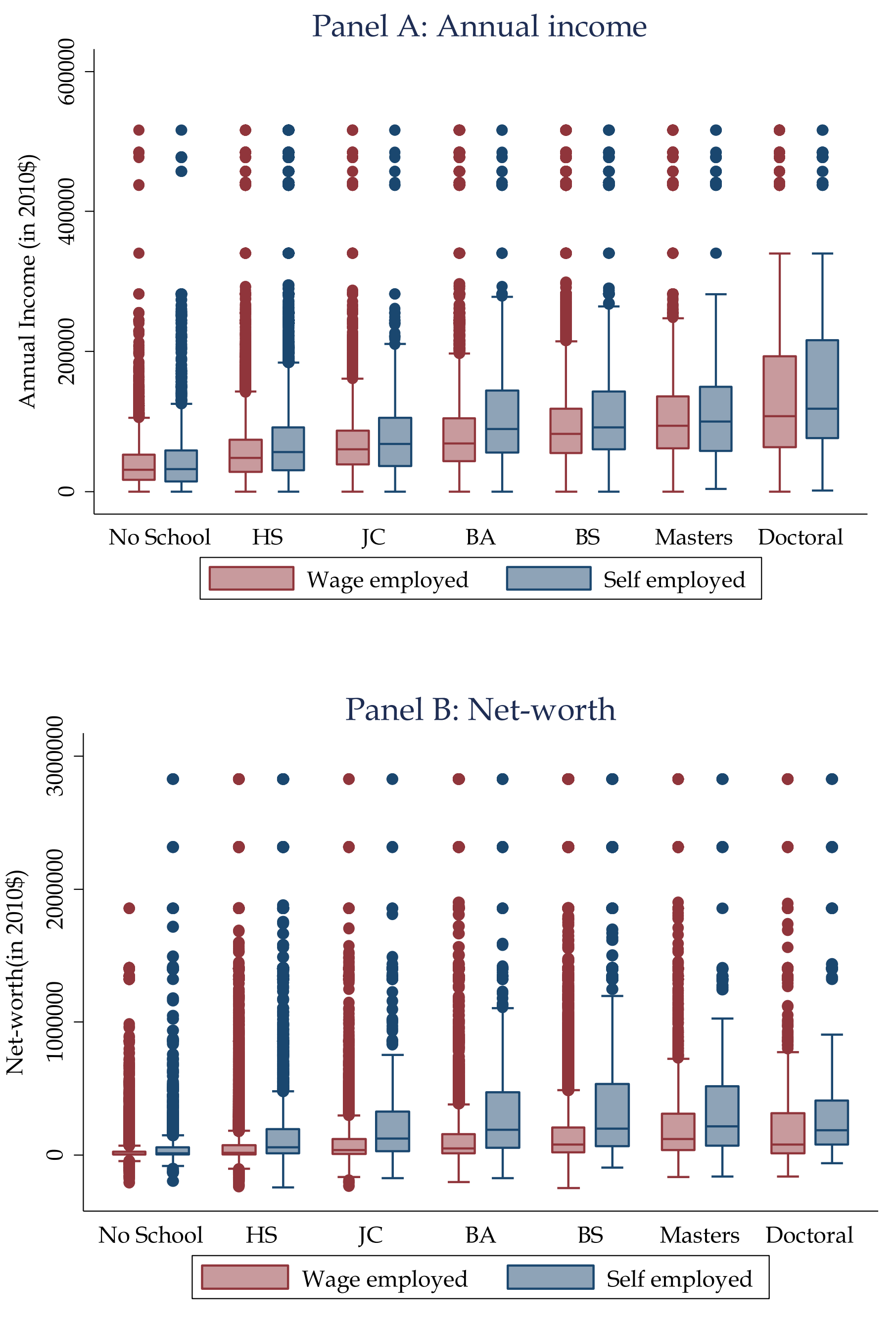

FIGURE 3 Distribution of income and wealth, by occupational status. The figure shows, on the x-axis, highest educational degree achieved by National Longitudinal Survey of Youth (NLSY) respondents, such that HS indicates High School Diploma (or equivalent), JC = Junior/Associate College, BA = Bachelor of Arts, BS = Bachelor of Science, MA/S = Master's, and MD/PhD includes doctoral and other advanced professional degrees (MD, LLD, DDS, and PhD). Panel (a) is based on 10,614 person-year observations of self-employed workers and 142,326 person-year observations of wage employees with nonmissing annual income data in the NLSY. Panel (b) is based on 8,184 person-year observations of self-employed workers and 99,386 person-year observations of wage employees with nonmissing annual household net-worth data in the NLSY [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 2 LPM estimates of the effect of ability and education on entrepreneurship

Dependent variable	(1) Self-employed	(2) Self-employed	(3) Self-employed	(4) Self-employed	(5) Self-employed
Log AFQT Score	0.0036	0.0062	0.0079		
	[0.0017]	[0.0023]	[0.0031]		
AFQT-Median AFQT |Years of Education				0.0002	
				[0.0001]	
Log Years of Education	-0.0054	-0.0522		-0.0295	-0.0976
	[0.0097]	[0.0130]		[0.0122]	[0.0191]
High school			-0.0184		
			[0.0072]		
Associate/Junior College			-0.0376		
			[0.0105]		
Bachelor of Arts			-0.0251		
			[0.0131]		
Bachelor of Science			-0.0443		
			[0.0110]		
Master's Degree			-0.0729		
			[0.0131]		
Doctoral Degree			-0.0045		
			[0.0319]		
Constant	0.0716	-0.3175	-0.4529	-0.3595	NA
Demographic variables	N	Y	Y	Y	Y
Non-cognitive traits	N	Y	Y	Y	Y
Family background & wealth	N	Y	Y	Y	Y
Year Dummies	N	Y	Y	Y	Y
Industry Dummies	N	Y	Y	Y	Y
Subsample Dummies	N	Y	Y	Y	Y
Person Fixed effects	N	N	N	N	Y
Observations	176,379	117,204	70,664	117,204	117,151
R-squared	0.0001	0.0735	0.0731	0.0736	0.3666

The table reports Linear Probability Model (LPM) estimates of the effects of ability, education and asymmetric information on the probability of being self-employed. The estimation sample consists of 176,379 person-NLSY survey year observations between 1979 and 2010. Columns [1] and [2] report estimates of the probability of being self-employed without and with control variables respectively. The reduction in sample size for models with control variables is because the estimations use only those observations with non-missing variables for each of the included explanatory variables. Column [3] measures educational signals by highest degree attained, with "No Schools" being the omitted category—again, the reduction in sample size is due to several observations with missing data on highest degree. Column [4] uses a measure of asymmetric information calculated as the workers' AFQT score minus the median AFQT score for the workers' educational qualification (signal). Column [5] adds worker fixed effects to the specification in Column [2]. All standard errors are clustered at the individual level. Exhibit 1 provides definitions of all variables.

4.3.1 | Ability and education

Table 2 presents linear probability model (LPM) regression estimates that test Hypotheses (H1) and (H2).[20] Column (1) shows our baseline regression model with no other controls and estimates that a 1% change in workers' ability score increases the probability of entrepreneurship by 0.4% ($p = .04$), relative to the 7.1% unconditional probability of being an entrepreneur. A 1% increase in the years of education appears to decrease the probability of entrepreneurship by 0.5% ($p = .57$). Column (2) shows that adding a battery of control variables specified in Table 1 to the model increases the estimated effect of a percent change in AFQT score on the probability of entrepreneurship to 0.6% ($p = .01$). Further, the estimated effect of a percentage increase in education falls to a 5.2% reduction in the probability of self-employment ($p = .01$).[21] Column (3) confirms that measuring signals by the worker's highest degree (by including a dummy variable for each of the possible educational degrees) rather than as the number of years of education yields qualitatively similar estimates.[22]

Column (4) reveals a statistically significant positive relationship between our entrepreneurial advantage measure and the probability of entrepreneurship. A unit increase in this gap, which can be interpreted as the individual having a 1 percentile higher AFQT score than the median score for the individual's educational qualification, increases the probability of entrepreneurship by 0.02% ($p = .01$). This estimated effect size translates into a 0.02 *SD* increase in the probability of self-employment for a 1 *SD* increase in the worker's ability-education gap. Column (5) incorporates person fixed effects and reveals that a 1% within-worker increase in education decreases the worker's probability of entrepreneurship by nearly 10% ($p = .01$). This model cannot identify the effect of ability scores on entrepreneurship since the scores remain fixed for each worker in our sample.

In all models, the estimated negative relationship between education and entrepreneurship includes both the effects of exogenously assigned credentials and of endogenously acquired education. In other words, the estimates do not rule out that individuals may decide to become entrepreneurs and thus choose to forgo higher educational qualifications. The objective of our study is to examine how ability and education influence selection into entrepreneurship. To the extent that high ability individuals forgo the next level of education because they correctly expect their future productivity will be higher than the market can infer from their educational signal, this endogenous mechanism is consistent with our explanation.[23]

Next, we examine how the gap between ability and education affects worker choice among (a) wage employment, (b) self-employment in an unincorporated business, and (c) self-employment in an incorporated business. We estimate worker choice as a function of explanatory and control variables using a multinomial logit model and report the corresponding results in Table 3. The reference, and thus omitted, class in these regressions is wage employment.

[21]Column (1) of Table B4 of Appendix B reports estimated effects of all controls—risk tolerant, more outgoing individuals, those with highly educated mothers, and greater wealth are more likely to become entrepreneurs.

[22]Table B5 of Appendix B shows that the results are also robust to controlling for the ranking of the college or university the worker obtained his highest degree from. The negative coefficient ($p = .02$) on College Tier indicates that controlling for all else, the self-employed graduate from lower tiered colleges, which is consistent with Proposition 2, because college rank imperfectly signals a graduate's ability.

[23]Table B6 of Appendix B suggests that the effect of asymmetric information on entrepreneurship is highest at lower educational levels (barring for the "no high-school" category). It is possible the endogenous acquisition of signals leads high ability individuals to forgo higher education, leading to a deepening of the ability–signal gap for entrepreneurs with low educational qualifications.

TABLE 3 MNLM estimates of the effect of ability and education on entrepreneurship

	(1)		(2)		(3)		(4)	
Dependent Variable	**Self-employed, UnInc.**	**Self-employed, Inc.**	**Self-employed, UnInc.**	**Self-employed, Inc.**	**Self-employed, UnInc.**	**Self-employed, Inc.**	**Self-employed, UnInc.**	**Self-employed, Inc.**
Log AFQT Score	0.0891	0.1021			0.0588	0.1836		
	[0.0195]	[0.0465]			[0.0272]	[0.0575]		
AFQT-Median AFQT | Years of Education			0.0052	0.0008			0.0044	0.0032
			[0.0007]	[0.0014]			[0.0009]	[0.0016]
Log Years of Education	-1.0797	1.1007	-0.7627	1.3285	-0.9810	0.7282	-0.7284	1.2124
	[0.0859]	[0.2172]	[0.0825]	[0.2073]	[0.1208]	[0.2588]	[0.1170]	[0.2506]
Constant	-9.7212	-18.046	-10.4596	-18.2671	-0.8893	-4.9091	-1.4938	-5.5726
Demographic variables	Y		Y		Y		Y	
Non-cognitive traits	Y		Y		Y		Y	
Family background & wealth	Y		Y		Y		Y	
Year Dummies	Y		Y		Y		Y	
Industry Dummies	Y		Y		Y		Y	
Subsample Dummies	Y		Y		Y		Y	
Observations	117,204		117,204		43,167		43,167	
Log-likelihood	-28046.62		-28028.606		-14726.058		-14720.822	

The table reports Multinomial logit models (MLNM) of the effect of explanatory variables on the choice among (a) wage employment, (b) self-employment, unincorporated, and (c) self-employment, incorporated. Reference category (omitted) is wage employment. Columns (1) and (2) present estimates for workers between 21 and 53 years of age, Columns (3) and (4) for workers between 32 and 53 years of age (since NLSY collected data only once every two years for rounds starting 1994, rather than every year, the number of observations for 32-53 year olds is smaller than for the sample of individuals between 21-53 years).

Column (1) of Table 3 shows unincorporated entrepreneurs have higher ability and lower education, as suggested by our theories, but that incorporated entrepreneurs have higher ability and higher education than the wage employed, holding other variables constant. Nevertheless, it is the gap between a worker's ability and his signal that best captures asymmetric information or comparative advantage, and Column (2) shows a positive relationship between our entrepreneurial advantage measure and unincorporated entrepreneurship ($p \approx .00$), and a null relationship between entrepreneurial advantage and incorporated entrepreneurship ($p = .56$). Most incorporated entrepreneurs start as unincorporated entrepreneurs or wage workers and the share of incorporated entrepreneurs in the sample increases with worker age. Hence, testing our hypotheses in a subsample of workers for whom the choice among the three occupational states is meaningful (i.e., workers above a certain threshold age, which we arbitrarily picked to be 32 years) as in Columns (3) and (4) confirms a positive and statistically significant effect of ability and entrepreneurial advantage on the choice of both incorporated and unincorporated entrepreneurship. This finding is consistent with the result in Levine and Rubinstein (2017) that incorporated entrepreneurs are "smart" (i.e., have scored higher than wage workers on ability tests) but have other negative signals (in their paper, a history of "illicit" activities) to counteract the positive signaling effect of their education.

4.3.2 | Earnings

Hypothesis (H3) predicts that entrepreneurs earn higher incomes than employees, conditional on signals. Table 4 reports quantile regression estimates of the effects of independent variables on annual income and net-worth.[24] Column (1) of Table 4 shows that, holding constant other variables that affect income, including education, self-employed individuals have an earnings advantage of 7.3% ($p \approx .00$).[25] Columns (2) and (3) show that unincorporated and incorporated business owners earn 2% ($p = .09$) and 30.7% ($p \approx .00$) more than employees, respectively.

Next, we examine whether the same person enjoys higher earnings as an entrepreneur than as a wage worker. That is, we estimate an individual fixed-effects model with log annual income as the dependent variable and self-employed as the independent variable of interest. In addition, to examine the effect of the gap between ability and education on entrepreneurial earnings, we interact the self-employed indicator with our entrepreneurial advantage measure (AFQT—median AFQT for the focal individual's educational level). This specification allows us to hold unobserved heterogeneity across individuals' constant and investigate how earnings of the same person respond to entrepreneurship driven by the gap between ability and education. Less than 3% of wage employees switch to entrepreneurship in any given year and there is no within-individual variation in the cognitive and noncognitive characteristics of individuals. This restricts identification of asymmetric information or comparative advantage to stem from

[24]We estimate quantile regressions since they are known to provide more robust estimates in the presence of outliers than OLS regressions, and both the annual income and net-worth variables in our sample can be expected to have outliers. Tables B7 and B8 show that the results are reasonably robust to OLS regressions, particularly in a subsample of younger workers, for who we expect asymmetric information to be highest.

[25]Columns (2) and (3) of Table B4 in Appendix B report estimated effects of all control variables on workers' income and net-worth—sociability, self-mastery, self-esteem, entrepreneurial and educated parents, and wealth endowments all have a positive effect on workers' income and wealth.

[26]It is possible this constraint placed by the fixed-effects model accounts for the somewhat large estimate of the effect of the main education variable seen in Columns (4) and (8).

TABLE 4 Quantile regression estimates of effects of entrepreneurship on income and wealth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Log Annual income				Net-worth			
Self-employed (all)	0.073			0.080	24,165.737			68,037.023
	[0.010]			[0.016]	[1,219.542]			[121,874.743]
Self-employed (unincorporated)		0.019				14,406.036		
		[0.011]				[1,276.531]		
Self-employed (incorporated)			0.307				180,884.901	
			[0.023]				[2,741.987]	
AFQT-Median AFQT |Years of Education				0.011				15,032.561
				[0.001]				[10,042.532]
Self-employed X (AFQT-Median AFQT |Years of Education)				0.001				387.488
				[0.001]				[5,200.318]
Log Years of Education	0.812	0.800	0.811	1.642	30,469.719	28,522.185	27,908.457	2,068,523.377
	[0.017]	[0.017]	[0.017]	[0.069]	[1,956.512]	[1,889.256]	[2,007.332]	[1318277.692]
Constant	6.765	6.796	6.666	-	-245,005.70	-235,389.07	-229,542.56	-
Demographic variables	Y	Y	Y	NA	Y	Y	Y	NA
Non-cognitive traits	Y	Y	Y	NA	Y	Y	Y	NA
Family background/wealth	Y	Y	Y	NA	Y	Y	Y	NA
Year Dummies	Y	Y	Y	NA	Y	Y	Y	NA
Industry Dummies	Y	Y	Y	NA	Y	Y	Y	NA
Subsample dummies	Y	Y	Y	NA	Y	Y	Y	NA
Person fixed effect	N	N	N	Y	N	N	N	Y
Pseudo-R2	0.136	0.135	0.138	NA	0.082	0.082	0.089	NA
Observations	103,212	101,923	98,191	146,807	72,815	71,880	68,667	103,155

The table reports quantile (median) regression estimates that examine whether entrepreneurs earn more than salaried individuals, conditional on educational qualifications. The reduction in sample size for models with control variables is because the estimations use only those observations with non-missing variables for the controls. The dependent variable is logged annual income in Columns 1-4, and net-worth in Columns 5-8 (net-worth is not logged since it has negative values). Data on net worth are not available for NLSY 1980-1984 resulting in a lower number of observations for the corresponding estimations. The estimates in Column [2] and Column [6] are obtained after excluding incorporated self-employed individuals and the estimates in Column [3] and Column [7] are obtained after excluding incorporated self-employed individuals from the estimation sample. The base class (Self-employed = 0) in all estimations is composed of full-time salaried individuals. Standard errors are shown in brackets.

within-person occupational switches and changes in education after the worker started her career.[26] Nevertheless, the corresponding estimates, reported in Column (4), reveal that the interaction term of self-employment and entrepreneurial advantage is positively related to annual income (p = .06). Although the effect sizes seem small at first glance, the estimates imply a one percentile point increase in the individual's AFQT score above the corresponding signal's median, is associated with a 0.1% increase in annual income providing further confirmatory evidence for Hypothesis (H3).

Several recent papers establish that entrepreneurs tend to underreport their incomes, and consumption data or household wealth data more accurately capture their financial status (e.g., Pissarides and Weber 1989, Hurst, Li and Pugsley 2014, and Sarada 2016). Hence, we repeat our analysis using households' net-worth as the outcome variable. Since net-worth can be negative for high-debt individuals, this analysis accounts for the possibility that entrepreneurs debt finance higher earnings. Column (5) shows that the median self-employed-year is associated with about $24,000 more net-worth, after holding other variables constant ($p \approx .00$). Columns (6) and (7) show that, respectively, unincorporated business owners and incorporated business owners have nearly $14,400 and $180,900 higher net-worth than employees (both estimates are statistically significant at $p \approx .00$). Column (8) shows the effects of entrepreneurial advantage driven self-employment on net-wealth, revealing a positive but noisily estimated effect ($p = .90$).

Our theories appear to explain success in entrepreneurship, the highest form of which is owning an incorporated business that employs and creates wealth for many others. In order to further test the economic relevance of our explanations, we examine support for our hypotheses in various industries after ranking them based on the median net worth (and income) of entrepreneurs in the industry. We find the strongest evidence for our hypotheses in the sectors where entrepreneurs' average earnings were the highest (i.e., in Manufacturing, Wholesale Trade and “Finance, Insurance and Real-estate”). Of the 13 industry classifications in our sample, “Manufacturing” and “Wholesale Trade” were also the two largest sectors by employment, together accounting for about 40% of the sample respondents (and presumably jobs since the survey represents the U.S. civilian working population).[27] Asymmetric information (or comparative advantage) appears to explain entrepreneurship in sectors that not only account for a high percentage of jobs, but also in industries that provide the greatest pecuniary incentives to become a residual claimant, as suggested by our asymmetric information theory.

Hence, we find robust support for our theories of entrepreneurial choice—asymmetric information and comparative advantage—in a representative U.S. data set. In Appendix C, we report qualitatively similar findings obtained from the U.K. NCDS sample. In the next section, we examine occupational dynamics with the goal of adjudicating whether asymmetric information or comparative advantage explains the empirical patterns we have documented thus far.

4.4 | Analysis of dynamics

We examine entrepreneurship dynamics in our NLSY sample, which tracks individuals from age 15 to 22 in 1979 until they turned 46–53 years old in 2010. Only about 18% of the panel

[26]It is possible this constraint placed by the fixed-effects model accounts for the somewhat large estimate of the effect of the main education variable seen in Columns (4) and (8).

[27]Tables B9 and B10 of Appendix B present corresponding results.

observations are for switchers—those who changed from entrepreneurship to wage work, or vice versa, after age 30.[28] Entrepreneurs comprise less than 3 % of the subsample of individuals who did not change occupations after turning 30. Thus, most entrepreneurs acquire some experience as wage workers prior to striking out on their own.

Workers can, and do, switch occupations multiple times during their careers, with only 2.9% of wage workers during a given year switching to entrepreneurship in the subsequent year. However, nearly a quarter of those who were self-employed during a given year switch to wage work in the subsequent year. Panel (a) of Table 5 shows how the frequency of switches in and out of self-employment varies by the highest educational qualification attained by the workers, without controls. Panel (b) of the same table shows mean AFQT scores of workers at different levels of education and switch status. The first two columns show that persistent entrepreneurs (i.e., those who did not switch out of entrepreneurship throughout their careers after turning 30) have higher AFQT scores than persistent wage workers for six out of the seven educational attainment levels; Columns (3) and (4) show that those who switch to entrepreneurship from wage employment have higher AFQT scores than those who stay as wage workers for three out of the seven educational levels; the last two columns show that those who switch out of entrepreneurship to take up salaried jobs have lower AFQT scores, on average, than those who remain entrepreneurs for six out of the seven education levels.

Next, Table 6 formally examines switching behavior as a function of ability and signals by means of controlled LPM regressions. Column (1) of Table 6 shows that among those who do not switch occupations after turning 30, entrepreneurs have higher AFQT scores than wage employees (this difference is not statistically significant at conventional levels, as can be expected given the small fraction—just 2.7%—of entrepreneurs among workers who did not change their occupation). A 1 % increase in education is associated with a 3% lower likelihood of entrepreneurship among workers who do not change occupations ($p \approx .00$). The estimates in Columns (3) and (4), respectively, suggest that workers with higher cognitive ability and lower educational qualifications are more likely to switch from wage employment to entrepreneurship, and workers with low ability but higher educational qualifications are more likely to switch out of entrepreneurship into wage employment (the latter estimate of the effect of education is not statistically significant at conventional levels). These findings suggest that although workers may know their ability better than the labor market, they too learn it over time and sort into entrepreneurship or wage employment in ways that are consistent with our theory. Finally, the estimates in Column (5) confirm a weakening of the positive difference between entrepreneurial and employee ability over the course of a worker's career, confirming Hypothesis (H4) in favor of asymmetric information rather than for comparative advantage based matching.

Table 7 investigates the returns to ability and education for entrepreneurs and wage workers. The first two columns show the average returns to ability over worker careers are virtually identical for entrepreneurs and wage workers (0.1182 vs. 0.1154; with closely overlapping confidence intervals) and, if anything, the returns to education are slightly higher for entrepreneurs (0.7062 vs. 0.8904; at $p = .04$). These patterns are difficult to reconcile with matching (see Hypothesis (H5)). As explained in Section 3.3.2, unlike matching, though, the asymmetric information explanation does not depend on the direction of comparative advantage—innate ability or education can be relatively more productive in either occupation.

TABLE 5 Summary statistics—ability, education and entrepreneurship dynamics

Panel (A) Highest degree	(1) Switched occupation? (%)	(2) Switched to self-employment (%)	(3) Switched to wage employment (%)
No School	12.1	3.8	27.8
High school diploma	20.2	2.8	24.2
Associate/Junior College	18.3	2.4	21.8
Bachelor of Arts	24.6	3.5	26.4
Bachelor of Science	19.3	2.6	21.8
Master's Degree	20.5	2.4	29.8
Doctoral Degree	33.2	5.5	18.6
Total (N= 148,029)	18.1	2.9	24.6

Panel (B) AFQT scores Highest degree	(1) Persistently wage employed	(2) Persistently self-employed	(3) Stayed in wage employment	(4) Switched to self-employment	(5) Stayed in self-employment	(6) Switched to wage employment
No School	16.3	16.2	16.8	16.3	17.5	16.7
High school diploma	37.0	41.3	37.7	39.5	43.6	39.6
Associate/Junior College	48.9	52.4	49.5	48.4	52.7	50.5
Bachelor of Arts	65.5	68.4	66.1	69.3	70.4	68.6
Bachelor of Science	66.6	70.7	67.3	70.6	74.3	70.9
Master's Degree	74.6	77.3	75.0	73.7	77.6	72.1
Doctoral Degree	85.1	88.8	85.7	84.9	88.0	88.8

Panel A shows the percentage and type of occupational switchers in the NLSY sample. Column 1 shows the fraction of full-time employees who switched from one occupation (i.e., wage employment or self-employment) during year t-1 to another during t. Column 2 shows the fraction of wage employees during t-1 who switched to self-employment in t and Column 3 shows the fraction of self-employed in t-1 who switched to wage employment in t. Unit of observation is worker-year. **Panel B** shows mean ability (AFQT) scores for workers by occupational status. Columns 1 and 2 compare the mean AFQT scores of the persistently wage employed v/s the persistently self-employed. Columns 3 and 4 compare the mean AFQT scores of those who stayed in wage employment (during year t-1 and t) v/s those who switched from wage employment (in year t-1) to self-employment (in year t). Columns 5 and 6 compare the mean AFQT scores of those who stayed in self-employment (during year t-1 and t) v/s those who switched from self-employment (in year t-1) to wage employment (in year t). The estimating sample in each case consists of person-year observations for those individuals most likely to have completed their educational attainment (that is, individuals aged 30 or over).

The regression models reported in Columns (3) and (4) of Table 7 investigate the returns to ability over time, holding education and other variables constant in subsamples of those who are persistently wage-employed and persistently self-employed during our study period. The estimates in Column (1) suggest that the returns to ability increase over time for salaried workers (significant at $p \approx .00$), while the payoffs for ability among the persistently self-employed do not appear to change significantly. This is consistent with the explanation that employers gradually learn about, and reward, the ability of employees—information about ability in wage employment is incomplete but resolves over time (thus providing evidence for Hypothesis (H6), consistent with the asymmetric information theory). No such pattern is

TABLE 6 LPM estimates of the effect of ability and education on entrepreneurship dynamics

Dependent variable	(1) Self-employed	(2) Persistently self-employed	(3) Switched into self-employment	(4) Switched out of self-employment	(5) Self-employed
Log AFQT Score	0.0062	0.0020	0.0016	-0.0327	0.0742
	[0.0023]	[0.002]	[0.001]	[0.010]	[0.040]
Log Years of Education	-0.0522	-0.0297	-0.0165	0.0424	-0.0579
	[0.0130]	[0.013]	[0.005]	[0.051]	[0.020]
Log AFQT X Log Age					-0.0185
					[0.011]
Log Age	0.1088	-0.0609	0.0205	-0.3497	0.0974
	[0.021]	[0.035]	[0.010]	[0.113]	[0.062]
Constant	-0.3175	0.2637	-0.0379	1.9998	-0.3029
Demographic variables	Y	Y	Y	Y	Y
Non-cognitive traits	Y	Y	Y	Y	Y
Family background/ wealth	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	Y	Y
Subsample dummies	Y	Y	Y	Y	Y
Observations	117,204	43,480	87,760	6,499	57,626
R-squared	0.0735	0.042	0.025	0.144	0.07

The table reports LPM estimates of the relationship between the probability of being self-employed and explanatory variables. Model [1] reproduces our baseline estimates of the relationship between ability scores, education and probability of self-employment in our full sample. Model [2] provides estimates of the effect of ability scores and education on the probability of being persistently self-employed relative to being persistently wage employed. The estimating sample consists of person-year observations for only those individuals who did not switch occupation after the age of 30. Model [3] estimates the probability of switching into self-employment from being salaried in the past year, relative to persisting with salaried employment in the current year, as a function of ability and education. Accordingly, the estimating sample consists of person-year observations for only those workers, above 21 years of age, who were wage employees in the past year. Model [4] estimates the probability of switching out of self-employment, relative to persisting with self-employment in the current year. Accordingly, the estimating sample consists of person-year observations for only those workers, above 21 years of age, who were self-employed in the past year. Model [5] reports estimates of the effect of the interaction of age and ability on the probability of self-employment in a sample of individuals who were most likely to have completed their educational attainment (that is, workers aged 30 or over). All standard errors are clustered at the individual level.

discernible in entrepreneurship, suggesting that incomplete information about ability is unlikely to drive entrepreneurial income.

Taken together, support for our theory is strongest early in individuals' careers, when asymmetric information about their ability is likely to be highest. At the early stage of their careers, individuals with ability much higher than their signals convey select into entrepreneurship

TABLE 7 Quantile regression estimates of returns to ability and education

Dependent variable	(1) Log annual income	(2)	(3)	(4)
Subsample	Wage employed	Self employed	Wage employed	Self employed
Log AFQT X Log Age			0.2102	0.2599
			[0.0253]	[0.2651]
Log AFQT Score	0.1182	0.1154	0.0915	0.0157
	[0.0042]	[0.0174]	[0.0081]	[0.0903]
Log Age	0.5081	0.0306	-0.3102	0.2173
	[0.0430]	[0.1800]	[0.1174]	[1.2537]
Log Years of Education	0.7062	0.8904	0.9470	1.9712
	[0.0207]	[0.0821]	[0.0281]	[0.3259]
Constant	4.7396	5.4765	6.1827	1.9482
Demographic variables	Y	Y	Y	Y
Non-cognitive traits	Y	Y	Y	Y
Family background & wealth	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	Y
Subsample Dummies	Y	Y	Y	Y
Observations	81,094	6,419	36,430	888

Table reports quantile (median) regression estimates of returns to ability for individuals in subsamples of the wage employed (Columns 1 & 3) and the self-employed (Column 2 & 4). Estimates in Columns 1 and 2 are derived from the sample of full-time workers aged over 21 years. Estimates in Columns 3 and 4 are derived from subsamples of workers who did not switch occupations (i.e., from wage employment to self-employment or vice versa) after turning 30. All regressions include the full set of controls for individuals' demographic variables, non-cognitive traits, family background & wealth, subsample dummies, year dummies and industry dummies.

even though they may be incorrectly placed in their first occupations. With the passage of time, two contrasting effects determine the average effect of ability on entrepreneurship—later entrants into entrepreneurship have lower ability than early entrants (presumably because later entrants switch into self-employment as a lifestyle choice or to maintain the work flexibility associated with self-employment) but some less able entrepreneurs—particularly those with superior educational qualifications—also switch into salaried work.

We emphasize these empirical tests provide evidence favoring asymmetric information but do not definitively rule out comparative advantage based matching, with switches in and out of entrepreneurship suggesting imperfect information about comparative advantage. Thus, workers may only be *better* rather than *perfectly* informed about their ability. Since we obtain these findings after examining the employment records of the same set of individuals over nearly their entire professional careers, we can also rule out that the findings are an artifact of sample selection or survival bias. Overall, we conclude from the weight of evidence that asymmetric information about worker ability is likely to be an important driver of entrepreneurship.

5 | CONCLUSION

5.1 | Summary

We proposed two theories of entrepreneurial choice driven by information frictions: (a) actuated by firms' reliance on imperfect credentials to assess workers' ability and (b) by matching multidimensional human capital to differing requirements in the entrepreneurial and wage sectors. Although the mechanisms—asymmetric information in the former theory and comparative advantage with symmetric imperfect information in the latter—differ starkly, the two theories hypothesize some similar relationships between innate ability and educational credentials on the one hand, and the decision to found a firm and its success on the other. As predicted by both formal models, our cross-sectional empirical analysis revealed that, holding other variables constant, entrepreneurs have higher cognitive ability scores, lower levels of educational attainment, and greater earnings. We confirmed these findings in two different data sets: (a) a longitudinal study following a representative sample of U.S. youth beginning in 1979, and (b) a dataset of U.K. residents born in one particular week in 1958.

Nevertheless, the data do not support the two theories equally. As asymmetric information predicts, entrepreneurial earnings exhibit higher variance, conditional on all else. Meanwhile comparative advantage requires higher returns to ability in entrepreneurship or to education in wage work, but our samples lack evidence of these preconditions. Furthermore, conditional on education, the dominance of entrepreneurs' ability weakened, while returns to cognitive ability in wage work strengthened over our subjects' careers—patterns predicted by asymmetric information but contradictory to comparative advantage. Hence, while we cannot definitively rule out that comparative advantage draws some to start their own business, we find clear and consistent evidence that asymmetric information pushes many to do so.

We thus offer, test, and provide evidence for a novel explanation for entrepreneurship: those who are undervalued by the traditional labor market, reject it and become entrepreneurs. Asymmetric information about ability leads incumbent firms to employ only "lemons," relatively unproductive workers. The relatively talented retain the benefits of their superior productivity by choosing entrepreneurship. This implication, that entrepreneurs are, in fact, "cherries" contrasts with a large literature in social science, which casts entrepreneurs as "lemons"—those who cannot find, cannot hold, or cannot stand real jobs.

5.2 | Limitations

While we have demonstrated our theories' robustness to several extensions, we cannot explore all possibilities here. First, entrepreneurial aspirations are beyond the model; in fact, we abstract from all motives except pecuniary ones. The interactions of the informational forces we introduce, with more traditional explanations of entrepreneurial choice may yield further insights. For example, we showed that our asymmetric information theory is robust to workers' educational choices in the pursuit of higher income, but we did not consider educational choices driven by nonpecuniary tastes. Since the average age of a U.S. founder is 42 (Azoulay et al., 2020), more than a decade after most individuals complete their formal education, educational choices in one's youth do not seem primarily driven by future entrepreneurial implications in middle-age. Nevertheless, entrepreneurial aspiration's potential impacts on educational attainment merit further investigation. Second, entrepreneurship is workers' response to asymmetric information about their ability, but how might firms respond? In industries where individual output, even if produced within a firm, is clearly measurable and verifiable, managers could offer output contingent wages, paying more for higher performance, thus making workers partial residual claimants of their ability. Hence, in sales or finance, where commissions and performance bonuses are commonplace, we would expect the best (relative to their signal) to choose contracts where the highest portion of their income is performance based. Similarly, Dushnitsky (2009) argues that inventors who require investor support signal their inventions' quality by electing payment schemes contingent on their success. Essentially, these contracts amount to *intra*preneurship, which our model does not comprehend.

5.3 | Broader implications

Although previous work has shown that individuals choose entrepreneurship for a variety of reasons—including desire to be ones' own boss, love of risk, overconfidence, flexible work hours—the one we introduce has peculiar implications for entrepreneurial outcomes, labor force productivity, education, and public policy. Many drivers of entrepreneurial entry do not predict extraordinary financial payoffs—in fact, those drawn to entrepreneurship by a taste for its nonpecuniary benefits should be expected to earn less than their employed counterparts. In contrast, asymmetric information about ability pushes the most productive workers into entrepreneurship in search of higher earnings. Thus, the puzzle of entrepreneurial earnings is intimately tied to why an individual sets up his own firm.

Our findings also suggest that the networks of families and friends that dominate financing for the earliest stage ventures have reasons beyond emotion to do so. These individuals know budding entrepreneurs best when asymmetric information about their quality is greatest (Stuart and Sorenson, 2005; Hegde and Tumlinson, 2014; Kerr et al. 2014). It is also possible tight-knit clusters of entrepreneurial activity offer some of the same advantages to the formation of entrepreneurial partnerships and investments (Gans, et al. 2002; Guzman and Stern 2015).

In light of our findings, the notion of "entrepreneurial success" becomes subtler, because although those driven into entrepreneurship by asymmetric information earn more than similarly credentialed employees, their selection into the occupation may still be adverse—they may be even more productive as employees, but the market failed to see it. Policies that stimulate entrepreneurship will only generate aggregate wealth if founders are truly more productive as entrepreneurs. For example, if educational institutions provide more precise signals of ability, information asymmetry, and with it adverse selection, could be reduced. Although this may imply less entrepreneurship, those who choose it will do so because of comparative advantage. Conversely, if educational institutions, which have traditionally served a credentialing purpose (e.g., business schools), muddle their signals through policies such as nondisclosure of student grades to employers, entrepreneurship may rise without stimulating growth.

Relatedly, asymmetric information may also explain why several groups, such as immigrants and the underprivileged, gravitate toward entrepreneurship. In a sense, entrepreneurship is undervalued workers' response to (statistical) discrimination (Tumlinson, 2012). Our empirical analysis exploits education as the attribute of (statistical) discrimination, but in principle, any observable attribute upon which employers base wage offers may elicit such a reaction from the more able, whether its use is fair or not. Understanding whether unrecognized academic credentials or other forms of discrimination drive these choices requires further research.

However, again, public policies reducing informational frictions with better credentialing for adults and accrediting foreign degrees may induce a societally productive drop in entrepreneurship.

Finally, we return to Steve Jobs, Jan Koum, and D. J. Patel, the entrepreneurs whose stories inspired our thinking about informational frictions and entrepreneurship. Few would doubt that their entrepreneurial productivity far exceeded whatever they might have accomplished if they had not started their own ventures. Yet, Koum went on to work for Facebook. Patel's franchisor enlisted him to expand the parent corporation into his native India with 400 stores over 10 years. Apple fired Jobs in 1985, only to hire him back (after he founded NeXT and funded Pixar) as CEO in 1997, a job he famously held until his untimely death. Each ultimately signaled their remarkable talents by means of their entrepreneurial success and leveraged it to become ... an employee. We save a deeper examination of entrepreneurial dynamics and transitions back to traditional employment for a future study.

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REFERENCES

Agarwal, R., Audretsch, D., & Sarkar, M. B. (2007). The process of creative construction: Knowledge spillovers, entrepreneurship, and economic growth. *Strategic Entrepreneurship Journal*, *1*(3–4), 263–286.

Agarwal, R., Gambardella, A., & Olson, D. M. (2016). Employee mobility and entrepreneurship a virtual special issue. *Strategic Management Journal*, *37*(13), E11–E21.

Akerlof, G. A. (1970). The market for 'lemons': Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500.

Alchian, A. A., & Demsetz, H. (1972). Production, information costs and economic organization. *American Economic Review*, *62*(5), 777–795.

Aldrich, H. E., & Fiol, C. M. (1994). Fools rush in? The institutional context of industry creation. *Academy of Management Review*, *19*(4), 645–670.

Altonji, J. G., Bharadwaj, P., & Lange, F. (2012). Changes in the characteristics of American youth: Implications for adult outcomes. *Journal of Labor Economics*, *30*(4), 783–828.

Altonji, J. G., & Pierret, C. R. (2001). Employer learning and statistical discrimination. *The Quarterly Journal of Economics*, *116*(1), 313–350.

Åstebro, T., Chen, J., & Thompson, P. (2011). Stars and misfits: Self-employment and labor market frictions. *Management Science*, *57*(11), 1999–2017.

Azoulay, P., Jones, B. F., Kim, J. D., & Miranda, J. (2020). Age and high-growth entrepreneurship. *American Economic Review: Insights*, *2*(1), 65–82.

Bagnoli, M., & Bergstrom, T. (2005). Log-concave probability and its applications. *Economic Theory*, *26*, 445–469.

Braguinsky, S., Klepper, S., & Ohyama, A. (2012). High-tech entrepreneurship. *The Journal of Law and Economics*, *55*(4), 869–900.

Camerer, C., & Lovallo, D. (1999). Overconfidence and excess entry: An experimental approach. *American Economic Review*, *89*(1), 306–318.

Cameron, S., & Heckman, J. (2001). The dynamics of educational attainment for black, Hispanic, and white males. *Journal of Political Economy*, *109*, 455–499.

Campbell, B. A., Kryscynski, D., & Olson, D. M. (2017). Bridging strategic human capital and employee entrepreneurship research: A labor market frictions approach. *Strategic Entrepreneurship Journal*, *11*(3), 344–356.

Carnahan, S., Agarwal, R., & Campbell, B. A. (2012). Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers. *Strategic Management. Journal*, *33*(12), 1411–1430.

Carneiro, P., & Heckman, J. J. (2002). The evidence on credit constraints in post-secondary schooling. *The Economic Journal*, *112*(482), 705–734.

Dushnitsky, G. (2009). Entrepreneurial optimism in the market for technological inventions. *Organization Science*, *21*(1), 150–167.

Evans, D. S., & Leighton, L. S. (1989). The determinants of changes in US self-employment, 1968–1987. *Small Business Economics*, *1*(2), 111–119.

Fairlie, R. W. (2005). Self-employment, entrepreneurship, and the NLSY79. *Monthly Labor Review*, *128*, 40.

Freeman, J. (1986). Entrepreneurs as organizational products: Semiconductor firms and venture capital firms. In G. Libecap (Ed.), *Advances in the study of entrepreneurship, innovation, and economic growth* (Vol. 1, pp. 33–58). Greenwich, CT: JAI Press.

Gans, J., Hsu, D., & Stern, S. (2002). When does start-up innovation spur the Gale of creative destruction? *The Rand Journal of Economics*, *33*(4), 571–586.

Griliches, Z. and Mason, W.M., 1972. "Education, income, and ability." *Journal of Political Economy*, *80*(3, Part 2), pp.S74-S103.

Guzman, J., & Stern, S. (2015). Where is silicon valley? *Science*, *347*(6222), 606–609.

Halaby, C. N. (2003). Where job values come from. *American Sociological Review*, *68*, 251–278.

Hamilton, B. (2000). Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, *108*(3), 604–631.

Hartog, J., Van Praag, M., & Van Der Sluis, J. (2010). If you are so smart, why aren't you an entrepreneur? Returns to cognitive and social ability: Entrepreneurs versus employees. *Journal of Economics & Management Strategy*, *19*(4), 947–989.

Hébert, R. F., & Link, A. N. (1988). *The entrepreneur: Mainstream views and radical critiques*. New York, NY: Praeger.

Hegde, D., & Tumlinson, J. (2014). Does social proximity enhance business partnerships? Theory and evidence from ethnicity's role in US venture capital. *Management Science*, *60*(9), 2355–2380.

Hurst, E., Li, G., & Pugsley, B. (2014). Are household surveys like tax forms: Evidence from income underreporting of the self employed. *Review of Economics and Statistics*, *96*(1), 19–33.

Iyer, R., Khwaja, A. I., Luttmer, E. F., & Shue, K. (2015). Screening peers softly: Inferring the quality of small borrowers. *Management Science*, *62*(6), 1554–1577.

Jovanovic, B. (1979). Job matching and the theory of turnover. *Journal of Political Economy*, *87*(5), 972–990.

Kacperczyk, A., & Younkin, P. (2017). The paradox of breadth: The tension between experience and legitimacy in the transition to entrepreneurship. *Administrative Science Quarterly*, *62*(4), 731–764.

Kahn, L. B. (2013). Asymmetric information between employers. *American Economic Journal: Applied Economics*, *5*(4), 165–205.

Kerr, W. R., Lerner, J., & Schoar, A. (2014). The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, *27*(1), 20–55.

Kihlstrom, R. E., & Laffont, J. J. (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of Political Economy*, *87*(4), 719–748.

Klepper, S. (2007). Disagreements, spinoffs, and the evolution of Detroit as the capital of the US automobile industry. *Management Science*, *53*(4), 616–631.

Klepper, S., & Thompson, P. (2010). Disagreements and intra-industry spinoffs. *International Journal of Industrial Organization*, *28*(5), 526–538.

Lazear, E. P. (2004). Balanced skills and entrepreneurship. *American Economic Review*, *94*(2), 208–211.

Lazear, E. P. (2005). Entrepreneurship. *Journal of Labor Economics*, *23*(4), 649–680.

Lerner, J., & Malmendier, U. (2013). With a little help from my (random) friends: Success and failure in post-business school entrepreneurship. *Review of Financial Studies*, *26*(10), 2411–2452.

Levine, R., & Rubinstein, Y. (2017). Smart and illicit: Who becomes an entrepreneur and do they earn more? *The Quarterly Journal of Economics*, *132*(2), 963–1018.

McClelland, D. C. (1964). *The achieving society*. Princeton, NJ: D. Van Norstrand.

Moskowitz, T. J., & Vissing-Jørgensen, A. (2002). The returns to entrepreneurial investment: A private equity premium puzzle? *The American Economic Review*, *92*(4), 745–778.

Nicolaou, N., Shane, S., Cherkas, L., Hunkin, J., & Spector, T. D. (2008). Is the tendency to engage in entrepreneurship genetic? *Management Science*, *54*(1), 167–179.

Ohyama, A. (2015). Entrepreneurship and job-relatedness of human capital. *Economica*, *82*(328), 740–768.

Parker, S. C. (2009). *The economics of entrepreneurship*. Cambridge: Cambridge University Press.

Pissarides, C., & Weber, G. (1989). An expenditure based estimate of Britain's black economy. *Journal of Public Economics*, *39*(1), 17–32.

Pontikes, E. G., & Barnett, W. P. (2017). The non-consensus entrepreneur: Organizational responses to vital events. *Administrative Science Quarterly*, *62*(1), 140–178.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford Economic Papers*, *3*(2), 135–146.

Ruef, M. (2010). *The entrepreneurial group: Social identities, relations, and collective action*, Princeton, New Jersey: Princeton University Press.

Sarada, S. (2016). "The unobserved returns to entrepreneurship." Working paper. Department of Economics, UCSD.

Saxenian, A. (1994). "*Regional networks: Industrial adaptation in Silicon Valley and route 128*, Cambridge, MA:" Harvard University Press.

Schoonhoven, C. B., & Romanelli, E. (2001). *The entrepreneurship dynamic: Origins of entrepreneurship and the evolution of industries*, Redwood City, California: Stanford University Press.

Schönberg, U. (2007). Testing for asymmetric employer learning. *Journal of Labor Economics*, *25*(4), 651–691.

Shah, S. K., Agarwal, R., & Echambadi, R. (2019). Jewels in the crown: Exploring the motivations and team building processes of employee entrepreneurs. *Strategic Management Journal*, *40*(9), 1417–1452.

Sørensen, J. B. (2007). Bureaucracy and entrepreneurship: Workplace effects on entrepreneurial entry. *Administrative Science Quarterly*, *52*(3), 387–412.

Sorenson, O., & Audia, P. G. (2000). The social structure of entrepreneurial activity: Geographic concentration of footwear production in the United States, 1940–1989. *American Journal of Sociology*, *106*(2), 424–462.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, *87*(3), 355–374.

Stenard, B. S., & Sauermann, H. (2016). Educational mismatch, work outcomes, and entry into entrepreneurship. *Organization Science*, *27*(4), 801–824.

Stuart, T. E., & Sorenson, O. (2005). Social networks and entrepreneurship. In *Handbook of entrepreneurship research* (pp. 233–252). Boston, MA: Springer.

Tumlinson, J. (2012). *Adverse selection in team formation under discrimination*. (Working Paper No. SSRN 2101064).

van Praag, M., van Witteloostuijn, A., & van der Sluis, J. (2013). The higher returns to formal education for entrepreneurs versus employees. *Small Business Economics*, *40*(2), 375–396.

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