Information Frictions and Entrepreneurship

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Abstract

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 U.S. and the U.K. reveal the following patterns: (i) entrepreneurs have higher cognitive ability than employees with comparable education, (ii) employees have better education than equally able entrepreneurs, and (iii) 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.

Key words: Entrepreneurship; Asymmetric Information; Signaling; Education; Job-matching

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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 five 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, Georgia. 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 multi-dimensional human capital to job-dependent multi-factor 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 U.S. 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. The median self-employed worker earns 7.3 percent more than the 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, non-cognitive 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 neither evidence that the returns to cognitive ability are higher in entrepreneurship nor to education 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 literature across the social sciences portrays the self-employed as overconfident and under-educated 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 incompletely and 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, which 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 Hebert and Link (1998) and situate our study among its direct antecedents below.

Dispositional versus Contextual Drivers. Sørensen (2007) divides the entrepreneurship literature into two camps: "dispositional" and "contextual." Dispositional studies tradition argue that individuals' characteristics pre-dispose them towards 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.

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 to execute anything that comes up and luckily had good ideas, despite poor filtering). Each of these papers find 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]

Employee Experience and Mobility. Among contextual factors, work environments characterized by dissent drive some employees into entrepreneurship.[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 orga-

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

nizations 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.

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-Jorgensen (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. But three other studies (Fairlie 2005, Hartog *et al.* 2010, and Van Praag *et al.* 2013) which 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 under-report 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 under-report their income in household surveys by about 25 percent. Similarly, using 38 years of longitudinal data, Sarada (2016) finds that while self-employed individuals (mis)report earning 26.2% less, their household expenditures are 4.5 percent 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.

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, 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 which 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.

Exhibit 1 here

3 Theory

In this section we present two distinct theories of entrepreneurial choice: the first, driven by asymmetric information about worker ability, the second, by innate ability's comparative

[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.

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 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 (1) does not perfectly reveal ability and (2) 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

[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).

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.

3.1.2 Formal Model

Individuals have privately known ability $\theta \in \left[\underline{\theta}, \overline{\theta}\right]$ and publicly observable signal of it $S \in \left[\underline{S}, \overline{S}\right]$ distributed such that the posterior density of ability $F'\left(\theta | S\right)$ has full support over $\left[\underline{\theta}, \overline{\theta}\right]$ 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]

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

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 $\pi\left(\theta\right)$, finite and increasing in its argument. A (single) firm makes take-it-or-leave-it wage offers $w\left(S\right)$ to all individuals with signal S.

We make two regularity assumptions to guarantee optimal wages equalize marginal revenues and marginal costs: (1) $F\left(\theta | S\right)$ is log-concave for all S, and (2) $\pi\left(\theta\right)$ exhibits weakly decreasing differences with respect to θ (*i.e.* for all θ, $\left(\pi\left(\theta\right) - \theta\right)' \leq 0$). Virtually all probability distributions commonly used in theoretical economics are log-concave.[9] The latter assumption

[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).

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; *i.e.,* 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 particular, $\lim_{\theta \to \overline{\theta}} F'(\theta | S) = 0$, 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 (FOC) 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 (1)) equals the cost of raising the wages of all less able employees with signal S (RHS of

[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 unravelling" 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.

(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., $w'(S) > 0$).*

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 which 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.

Figure 1 here

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 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, 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.

H1: Entrepreneurs are more able than employees of the same signal, on average.

H2: Employees have better signals than entrepreneurs of the same ability, on average.

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 (1) workers to exert effort endogenously acquiring signals and (2) signals to be productive. The model is also robust to allowing (3) entrepreneurship itself to signal ability and (4) workers to be uncertain about their own ability. (5) We defer the model's further implications in a dynamic setting until Section 3.3.2.

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

[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.

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. But 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 towards 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 *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]

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

[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).

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.

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.

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.)

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.

Exhibit 2 here

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 till 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 socioeconomic 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 U.S. 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 U.S. 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 percent 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 hours/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 non-cognitive 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.

Exhibit 3 here

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

[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 percent of the respondents eligible for interview) had been reported as deceased. See https://www.nlsinfo.org/content/cohorts/nlsy79

(*e.g.*, Kahn 2013, Schönberg 2007). Altonji and Pierret (2001) interpret increasing returns to 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 percent of the observations are on self-employed individuals and the rest earn wages as employees. 1.2 percent of the sample's person-year observations are on self-employed individuals with incorporated businesses.

Table 1 here

Table 1 presents summary statistics for the variables in this sample. Some variables (*e.g.*, individuals' cognitive and non-cognitive 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 versus 43.4), comparable educational qualifications (12.9 years versus 12.8 years of school), higher annual incomes ($90,985 versus $61,954) and higher net-worth ($237,090 versus $83,704).[17] Self-employed workers also have larger gaps between their ability and signals,

[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

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, 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.

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 here

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

Figure 3 here

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.

[18] Although *H1 and H3* hold at *every signal level* and *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.

The second part of *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 25^{th} to 75^{th} percentiles, the horizontal bar in each denotes the median, while the whiskers extend from the 5^{th} to 95^{th} 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 percent versus 10.7 percent). 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.

Appendix C describes and analyzes a secondary dataset, the U.K. National Childhood Development Study (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 four-to-eight 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.

4.3.1 Ability and Education

Table 2 here

Table 2 presents Linear Probability Model (LPM) regression estimates that test *H1* and *H2*.[20] Column 1 shows our baseline regression model with no other controls and estimates that a one percent change in workers' ability score increases the probability of entrepreneurship by 0.4 percent ($p = 0.04$), relative to the 7.1 percent unconditional probability of being an entrepreneur. A one percent increase in the years of education appears to decrease the probability of entrepreneurship by 0.5 percent ($p = 0.57$). 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 percent ($p = 0.01$). Further, the estimated effect of a percentage increase in education falls to a 5.2 percent reduction in the probability of self-employment ($p = 0.01$).[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 one percentile higher AFQT score than the median score for the individual's educational qualification, increases the probability of entrepreneurship by 0.02 percent ($p = 0.01$). This estimated effect size translates to a 0.02 standard deviation increase in the probability of self-employment for a one standard deviation increase in the worker's ability-education gap. Column 5 incorporates person fixed effects and reveals that a one percent within-worker increase in education decreases the worker's probability of entrepreneurship by nearly 10 percent ($p = 0.01$). This model cannot identify the effect of ability scores on entrepreneurship since the scores remain fixed for each worker in our sample.

[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.

[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 ($p = 0.02$) 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.

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 (i) wage employment, (ii) self-employment in an unincorporated business, and (iii) 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.

Table 3 here

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 ($p \approx 0.00$), 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 (that is, 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" (that is, have scored higher than wage workers on

[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.

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

Table 4 here

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 percent ($p \approx 0.00$).[25] Columns 2 and 3 show that unincorporated and incorporated business owners earn 2 percent ($p = 0.09$) and 30.7 percent ($p \approx 0.00$) 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 responds to entrepreneurship driven by the gap between ability and education. Less than 3 percent of wage employees switch to entrepreneurship in any given year and there is no within-individual variation in the cognitive and non-cognitive characteristics of individuals. This restricts identification of asymmetric information or comparative advantage to stem from 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 ($p = 0.06$). 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

[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.

signal's median, is associated with a 0.1 percent increase in annual income providing further confirmatory evidence for *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 ($p \approx 0.00$). 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 $p \approx 0.00$). Column 8 shows the effects of entrepreneurial advantage driven self-employment on net-wealth, revealing a positive but noisily estimated effect ($p = 0.90$).

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 (that is, 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 percent 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.

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

4.4 Analysis of Dynamics

We examine entrepreneurship dynamics in our NLSY sample, which tracks individuals from age 15-22 in 1979 till they turned 46-53 years old in 2010. Only about 18 percent of the panel observations are for switchers—those who changed from entrepreneurship to wage-work, or vice versa, after age 30.[28] Entrepreneurs comprise less than three percent 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.

Table 5 here

Workers can, and do, switch occupations multiple times during their careers, with only 2.9 percent of wage workers during a given year switching to entrepreneurship in the subsequent year. But 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 (that is, 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.

Table 6 here

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 percent–of entrepreneurs among workers who did not change their

[28]We pick the age 30 since most individuals stop acquiring educational signals after this age: choosing an earlier age threshold increases the per-worker frequency of switches, since workers move back and forth among self employment, wage employment and part time employment before completing their educational attainment. Changing the age thresold wihthin a five year window does not qualitatively alter our findings.

occupation). A one percent increase in education is associated with a 3 percent lower likelihood of entrepreneurship among workers who do not change occupations ($p \approx 0.00$). 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 *H4* in favor of asymmetric information rather than for comparative advantage based matching.

Table 7 here

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 $p = 0.04$). These patterns are difficult to reconcile with matching (see *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.

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 $p \approx 0.00$), 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 *H6,* consistent with the asymmetric information theory). No such pattern is 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 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

Summary. We proposed two theories of entrepreneurial choice driven by information frictions: the first, actuated by firms' reliance on imperfect credentials to assess workers' ability, the second, 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 datasets: (1) a longitudinal study following a representative sample of U.S. youth beginning in 1979, and (2) a dataset of U.K. residents born in one particular week in 1958.

Nevertheless, the data does 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 pre-conditions. 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 either cannot find, cannot hold, or cannot stand real jobs.

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 non-pecuniary tastes. Since the average age of a US 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.

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 non-pecuniary 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 non-disclosure 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. But again, public policies reducing informational frictions with better credentialling 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 till 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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Exhibit 1. Literature Map.

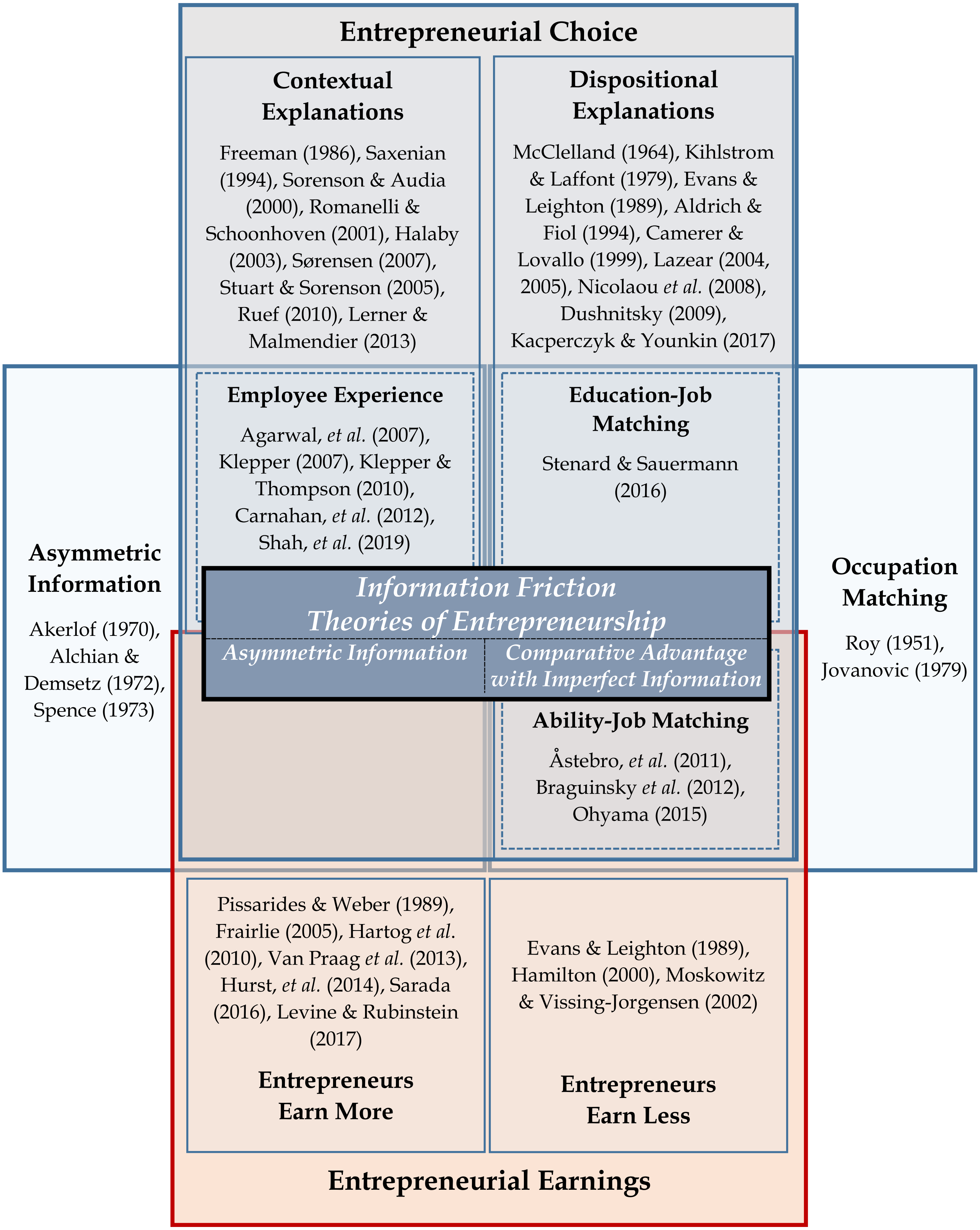


Exhibit 2. Theory Map.

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

[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.

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).

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.

Table 2: LPM estimates of the effect of ability and education on entrepreneurship

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Self-employed	Self-employed	Self-employed	Self-employed	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.

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).

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.

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).

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

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Self employed	Persistently self employed	Switched into self employment	Switched out of self employment	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

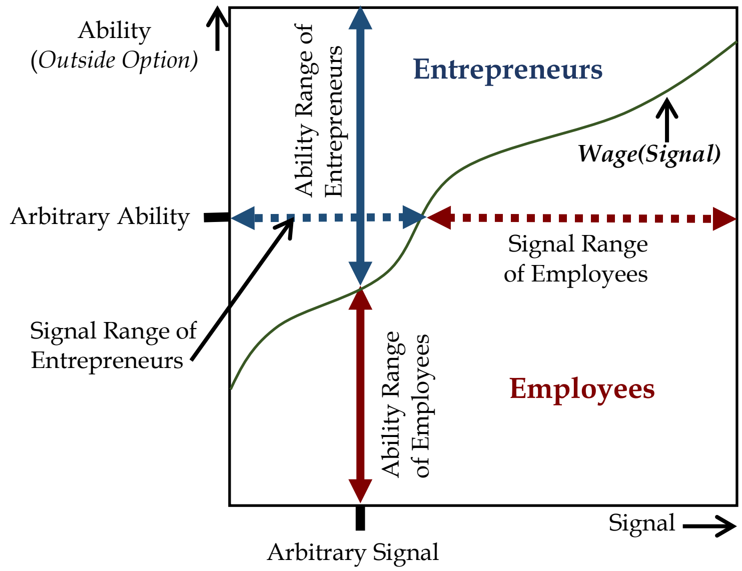
The table reports LPM estimates of the relationship between the probability of being self-employed and explanatory variables. Model [1] reproduces our baseline estimates of the relationship between ability scores, education and probability of self-employment in our full sample. Model [2] provides estimates 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.

Table 7: Quantile regression estimates of returns to ability and education

	(1)	(2)	(3)	(4)
Dependent Variable		Log Annual income		
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

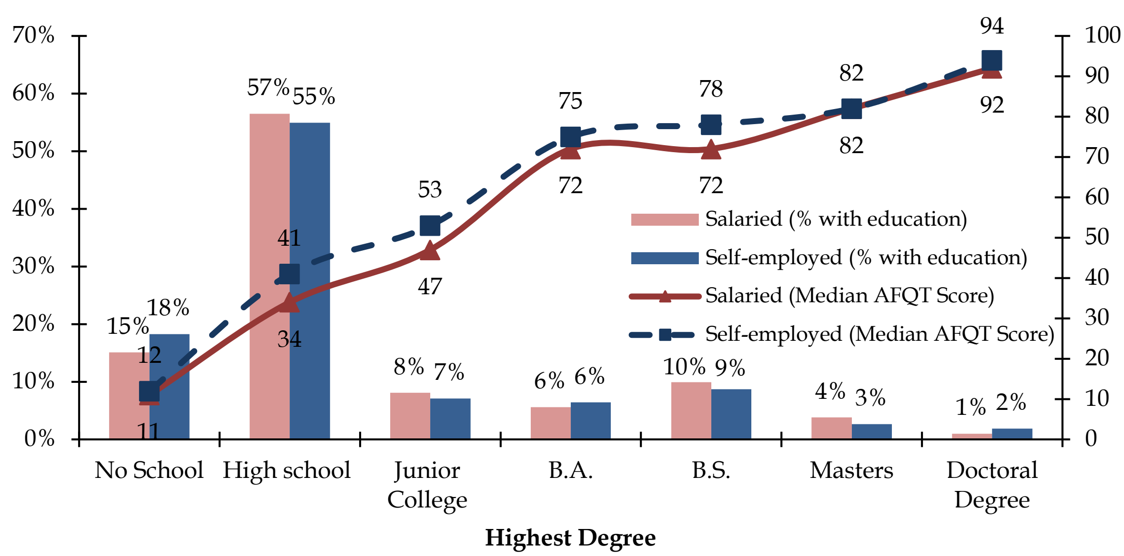
Table reports quantile (median) regression estimates of returns to ability for individuals in subsamples of the wage employed (Columns 1 & 3) and the self-employed (Column 2 & 4). Estimates in Columns 1 and 2 are derived from the sample of full-time workers aged over 21 years. Estimates in Columns 3 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.

Figure 1: Ability, Signal, and Entrepreneurship



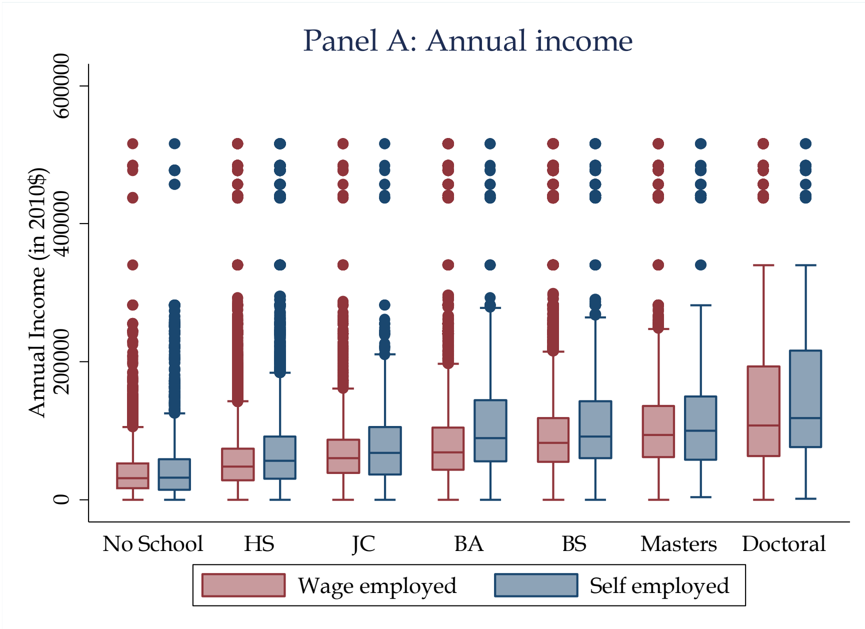
The figure depicts the signal-ability sample space. The horizontal axis denotes signal. The vertical axis denotes ability (equivalently entrepreneurial payoff). Wage, a function of signal, bisects the space, such that individuals with entrepreneurial productivity exceeding the wage commanded by their 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.

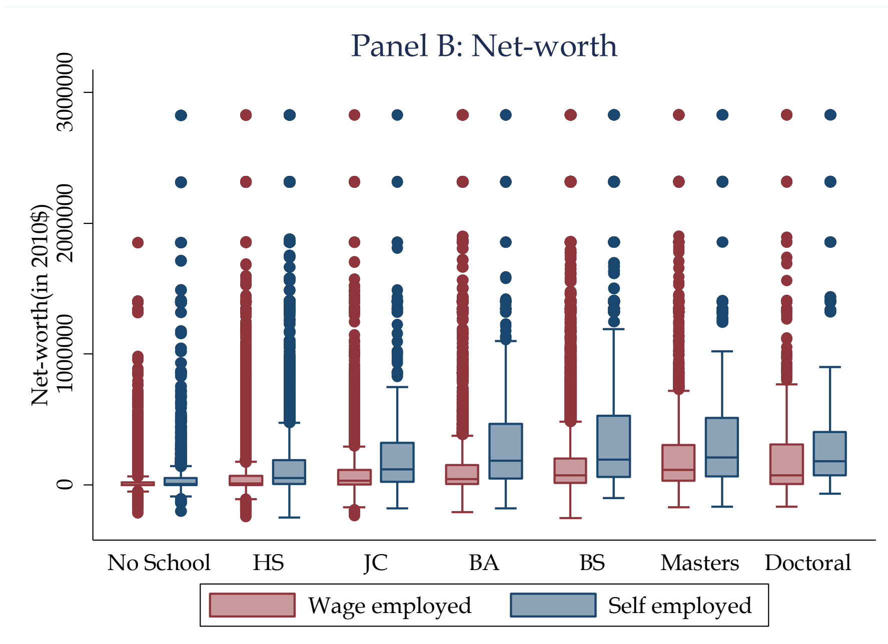
Figure 2: Ability scores and education, by occupational status



The figure compares median 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 NLSY panel.

Figure 3: Distribution of income and wealth, by occupational status





The figure shows, on the x-axis, highest educational degree achieved by 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 non-missing 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 non-missing annual household net worth data in the NLSY.

A Theoretical Appendix

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A.1 Extensions to Static Asymmetric Information

A.1.1 Endogenous Signal Acquisition

In certain situations, an exogenous signal of ability is not just a simplification but the only reasonable model; *e.g.* observable but hard to cultivate physical traits like height and chiselled cheekbones (noisily) signal fitness for certain occupations like basketball or fashion modelling. But in other settings workers make decisions which influence the signals of their ability that employers see. Our leading empirical example, formal educational attainment, is clearly a case where the individual *endogenously* influences the signal. Does this difference play a meaningful role in the theory?

To answer this, consider an additional stage, expanding on Spence's (1973) canonical job-market signaling model, that occurs *before* the occupational choice decision—one where each individual chooses how much effort to exert in the acquisition of an educational signal. Individuals have privately known ability θ distributed according to log-concave density F', such that $\lim_{\theta \to \overline{\theta}} F'(\theta) = 0$. In childhood (Stage 1) individuals invest effort in an observable educational signal. The signal is the sum of chosen effort e and noise ε distributed according to log-concave density G' (*i.e.,* $S(e) = e + \varepsilon$). Effort in education costs $C(e, \theta)$. Higher effort levels cost more ($C_e > 0$, where the subscript denotes the partial derivative with respect to e), but any level of effort is less costly for more able individuals ($C_\theta < 0$). We also assume that C is *sufficiently* convex in effort for individuals' second-order-condition (SOC) to hold (see proof of Lemma 7 in the Theoretical Appendix A.6) and the standard Spence-Mirrlees (or single crossing) property $C_{e\theta} < 0$ holds. In adulthood (Stage 2) individuals choose either to enter entrepreneurship, where they earn their ability θ, or accept a wage $w(S)$ as described in the main model.

In order for the results of our main model to hold for *endogenously* determined signals, the resulting posterior distribution of ability given a signal must be log-concave and satisfy the MLRP in equilibrium. In Appendix A.7 we show that it does:

Lemma 3 *Equilibrium effort exerted in pursuit of signal (and average signal) increases in ability, such that (i) the posterior distribution of ability $F(\theta|S)$ is log-concave and (ii) the posterior density of ability $F'(\theta|S)$ satisfies the MLRP.*

Therefore,

Proposition 3 *When workers endogenously acquire signal before making an occupational choice, all results of Section 3 continue to hold.*

In summary, the employer does not care whether signals are exogenously endowed or endogenously acquired *per se*. She only cares about their statistical relationship to unobservable productivity. This is why the addition of a pre-stage where workers endogenously cultivate signals does not change results from the base model, where signals are acquired exogenously.

It may seem counterintuitive that entrepreneurs would invest in a signal at all, because in our base model, a strong signal does not help them. Indeed, if the signal were a deterministic function of ability and effort, then individuals of some ability levels would all become education eschewing entrepreneurs, and individuals of other ability levels would engage in just enough education to signal their ability (and fitness for wage work). But the assignment of a signal is stochastic. So, all individuals of a given ability in the pre-stage have the same motivation and the same *ex ante* chance of becoming an entrepreneur. They invest optimally based on the prior odds. Effort exerted pursuing a signal depends only on ability in equilibrium—all individuals of a given ability try just as hard to earn a degree. *Ex post,* though, those with good random signal draws will accept wage offers, while those with poor draws will become entrepreneurs.

Note that this extension, like Spence's original model, is one of pure signalling—that is, effort exerted in acquiring education does not alter ability. But it could be that education fundamentally improves productivity (as in Becker 1962 and Mincer 1970). Does this parsimony motivated omission matter? In our model, the amount of effort exerted is, in equilibrium, an increasing function of ability. Thus, if the human capital added by education increases in effort and innate ability, then in equilibrium, final human capital becomes a transform of ability itself. So, although education changes human capital, and individuals seek more of it for its productive value, the signal will still have the required statistical properties with respect to total human capital, and our model's propositions hold.[29]

We now show that our asymmetric explanation of entrepreneurial choice extends to this setting, where productivity depends on both privately and publicly observable human capital.

A.1.2 Productive Signals

Treating ability as unidimensional and signal as unproductive distills the model to its simplest essence, but a signal is often productive in its own right. For example, although innate ability

[29]Formally, so long as the human capital enhanced by education is modelled as a noisy function of effort and ability, such that the posterior distribution of ability given pedigree remained log-concave and satisfied the MLRP, our results will continue to hold.

positively correlates to educational attainment, it is generally accepted that skills acquired through formal education are productive, increasing human capital itself. Similarly, documented job experience signals productivity but it often makes one more productive too. Here we show that allowing productivity to depend both on hidden innate ability and observable signal does not alter our predictions. For simplicity, we revert to our base model of exogenously determined signals but allow them to be productive.

Suppose that productivity in entrepreneurship and wage work are respectively given by $\pi_T(\theta, S)$ and $\pi_W(\theta, S)$, increasing in both parameters, where θ, S and F are defined as in Section 3.1. Again the worker chooses entrepreneurship if and only if her payoff from doing so exceeds the wage she is offered by the firm, which is a function of S: $\pi_T(\theta, S) > w(S)$. Although slightly more complex than simply the wage, as it is when human capital is unidimensional, there is still a cutoff level of innate ability above which the worker chooses entrepreneurship $\theta > \bar{\theta}_S = \pi_T^{-1}(w(S), S)$, where $\pi_T^{-1}(\bullet, S)$ denotes the inverse function of entrepreneurial productivity, which yields innate ability, given signal S. Thus, when $\bar{\theta}_S$ lies within the support of innate ability, the logic of Proposition 1 and Corollary 1 remain unchanged. Analogous to the one-dimensional ability case, for every S, the firm chooses w to solve

$$\max_w \int_{\underline{\theta}}^{\bar{\theta}_S} (\pi_W(\theta, S) - w)\, dF(\theta | S)$$

With assumptions analogous to those in the one dimensional ability model, this problem is also well-behaved, and the equilibrium wage increases in signal.[30] Thus, Proposition 2 continues to hold. A numerical example is included in Appendix A.5.

A.1.3 Entrepreneurship as a Signal

Another potential form of endogenous signalling stems directly from our theory itself. Since workers who reject their offers are more able than those who accept, might not rejecting an offer (and becoming an entrepreneur) signal higher ability and trigger a higher wage offer from an employer? It depends on the information credibly contained in a wage offer rejection. The key learning from Spence's (1973) model is that a separating equilibrium can only exist if higher signals are relatively more costly for low ability workers to obtain, so that in equilibrium, high signals are more likely to indicate high ability (*i.e.* the MLRP is satisfied). If rejecting a wage offer and setting up a firm costs workers of all abilities approximately the same amount, then

[30] Since the fact that wages increase in the quality of pedigree, especially education, is generally uncontroversial, and the proofs are no more enlighting than those for the one dimensional case, we omit them.

this key requirement fails.[31] In the short term, saying 'no' to an offer, adding a brief period of self-employment on one's CV and even filing incorporation paperwork, is unlikely to separate high ability individuals from low—if firms offered wage premia that exceeded these costs, every employee, regardless of ability, would incur them. So, firms have no incentive to pay for the simple signal of wage offer rejection or even brief entrepreneurial stints. Hence, the model does not unravel due to workers "playing hard to get."

On the other hand, a key implication of our theory is that conditional on signal, entrepreneurs are higher ability—so occupational choice must eventually be a signal of ability. In the long term, the signal of entrepreneurship is more costly for low ability workers than for high ability workers, because entrepreneurs are residual claimants of their respective abilities. This differential, if large enough, can satisfy the requirements for a separating signalling equilibrium. Assuming time invariant production functions in entrepreneurship and wage employment, and without knowing anything about the performance of the venture, the longer the entrepreneurial stint the greater the ability signal, and the better the ultimate wage offer. Having a history of long term entrepreneurship then simply becomes part of one's signal, just like education or any other observable characteristic. Thereafter, to attract an entrepreneur the firm would have to offer a wage that exceeds the individuals' *future* entrepreneurial payoffs. Again, our static model is agnostic about how signal is obtained and simply requires that the signal composed of all observables be related to underlying ability by the MLRP at the time a wage offer is made.

Of course, over a worker's career the labor market gets other signals of her ability beyond entrepreneurial history, many of which the empiricist does not observe. When the labor market gets more signals of an employee's type over time, asymmetric information, and with it adverse selection into entrepreneurship, diminishes. We discuss this further in Section 3.3.2 and Appendix A.4.

A.1.4 Imperfect Worker Information

Any worker knows his strengths and weakness better with experience than when his career started. Thus, a more realistic model would reveal to each worker, in addition to his public signal

[31] To understand why, suppose that a firm offered $w(S)$ to all workers with signal S and that starting a new venture costs $c \geq 0$, regardless of ability. Then all workers with ability $\theta > w(S) + c$ choose entrepreneurship. What if the firm offered $w_E(S) > w(S)$ to those who rejected $w(S)$ (i.e. entrepreneurs)? First, the highest ability workers (i.e. $\theta > w_E(S) + c$) still reject the new offer and continue with their ventures. Second, if $w_E(S) - c > w(S)$, then *all* workers with ability $\theta \leq w_E(S) + c$ will reject $w(S)$, start firms and accept offer $w_E(S)$; it is more profitable for even the least able workers. If $w_E(S) - c \leq w(S)$, then *all* workers with ability $\theta \leq w_E(S) + c$ will forego setting up a venture and simply accept $w(S)$. There is no information in the signal of rejecting an offer and setting up a firm by itself; paying for it makes no sense.

S, a private signal y_t of ability, rather than ability θ itself. Here we mean y_t to be an aggregate of accumulated private signals over time, such that the precision of y_t exceeds the precision of y_{t-1}. Then the worker, rather than knowing his actual ability θ,could compute its distribution conditional on his private and public signals: $H(\theta| y_t, S)$. Were he risk neutral, then the worker would become an entrepreneur in period t if and only if his expected ability (equivalently entrepreneurial payoff) exceeded the market wage for his public signal type: $E[\theta| y_t, S] > w(S)$. Subject to H satisfying the MLRP in θ with respect to y_t for all S, the LHS will increase in y_t such that all S pedigreed workers whose private signal exceeds some cutoff $\bar{y}_t$ will choose entrepreneurship, all whose signal falls below will accept wage work, and all of the original intuitions of our base model hold.

The one significant difference yielded by adding imperfection to the worker's information about his ability is that some individuals who should have chosen wage work become entrepreneurs—since their private signals are noisy, although they *expect* their entrepreneurial productivity to exceed the wage offer, their *actual* entrepreneurial productivity is lower. As the precision of workers' private signals improves over time, these choices will be corrected—those that *switch from entrepreneurship into employment* will tend to have higher public signals relative to their ability compared to those who remain entrepreneurs. Indeed, we will show exactly this pattern in the data in Section 4.4.

Lastly, not only might workers' observe private signals of their own ability, but employers may also observe private signals of job applicants' ability. Furthermore, while it is intuitive that workers' information about their ability is more precise than the labor market's, the worker can have an asymmetric informational advantage in equilibrium, even when *ex ante* less informed of his own ability than his potential employers. To see this, suppose a worker has unobservable ability, but in addition to a public signal, both worker and employer get private signals of the worker's ability, such that conditional on that ability, they are independent. The employer makes the worker a wage offer based on her public and private signals of the worker's ability, knowing that any worker who believes his ability higher will reject, and that since the worker does not know his own ability with certainty, the wage offer itself may covey information to the employee, and alter his beliefs about his own ability, in equilibrium. In particular, if the employer offers all workers the same wage, then there is no information in the wage offer, but if the employer offers a wage (strictly) increasing in her private signal, then the worker can (perfectly) back out the employer's private signal of his ability from her wage offer. Thus in this setting, due to the fact that offers are made by employers, regardless of whose raw signal is noisier *ex ante*, the worker is always better informed of his ability in equilibrium than the employer, and our model's predictions hold.

A.2 Static Comparative Advantage

In Section 3.2 of the main text, we verbally argue that a matching model can deliver Propositions 1 and 2 together with the first part of Corollary 1, if and only if innate ability has a relative comparative advantage in entrepreneurship, while educations' relative advantage is in wage work. To see this more formally, consider a simple matching model of entrepreneurial choice with perfectly observable two dimensional ability $\langle \theta, S \rangle$ and linear production function

$$\pi_Y(\theta, S) = X_Y \theta + (1 - X_Y) S \tag{2}$$

where $X_Y \in [0,1]$ captures the productivity of innate ability θ relative to education S in either entrepreneurship or wage work ($Y \in \{T, W\}$). In a competitive market, each worker earns his productivity. Hence, a worker, chooses entrepreneurship if and only if he earns more by doing so (*i.e.,* $\pi_T(\theta, S) > \pi_W(\theta, S)$), which reduces simply to (i) $\theta > S$ if innate ability has a comparative advantage in entrepreneurship (*i.e.,* $X_T > X_W$) or (ii) $\theta < S$ if innate ability has a comparative advantage in wage work (*i.e.,* $X_T < X_W$). In the former case, this simple matching model yields the predictions of the asymmetric information model, except on income variance.[32] In the latter case it predicts precisely the opposite.

A.3 Dynamic Comparative Advantage

This simple matching model is easily extended to multiple periods with incomplete information about worker ability by allowing the worker to accumulate a pedigree—a series of publicly observable signals, each positively correlated to his unobservable, innate ability. To be precise, let hidden innate ability θ be distributed with full support over the reals. In each period t, each worker is assigned an additional publicly observable signal $\hat{\theta}_t \in \{H, L\}$ of his innate ability, such that smarter individuals are more likely to receive H signals (formally, let $p(\theta) \equiv \Pr\left\{ \hat{\theta}_t = H \middle| \theta \right\}$, for all t, and for all $\theta' > \theta''$, $p(\theta') > p(\theta'')$). We denote the number of H signals by time t as K_t. Assume that the first signal of ability is the worker's education (*i.e.,* $S \in \{S_L, S_H\}$ where $S = S_{\hat{\theta}_1}$). Unlike all subsequent signals, education also increases worker productivity directly, as specified in eqn. (2).

[32] To obtain the "variance" result from matching would require which would additionally require that the joint distribution of ability and education satisfy: $X_T^2 Var[\theta | \theta > S, S] > X_W^2 Var[\theta | \theta \leq S, S]$.

Since there is no information asymmetry, worker and employer always agree on the worker's expected innate ability. Hence, they also agree on his expected productivity in each occupation. A worker will choose entrepreneurship in period t if and only if he expects to earn more as an entrepreneur: $E\left[\pi_T(\theta, S)\middle| S, K_t\right] > E\left[\pi_W(\theta, S)\middle| S, K_t\right]$, or equivalently. Similar to the perfect information case above, this implies that if innate ability has a comparative advantage in entrepreneurship (*i.e.,* $X_T > X_W$), an individual will choose entrepreneurship if and only if his expected innate ability conditional on his signal exceeds his education: $E\left[\theta\middle| S, K_t\right] > S$. Observe that, since all individuals with the same education and signal set $\{S, K_t\}$ have the same expected ability, they will enter the same occupation.

Suppose that in the first period, all individuals with education S choose entrepreneurship (because $E\left[\theta\middle| S\right] > S$). Then in the first period, all entrepreneurs with education S have average ability $E\left[\theta\middle| S\right]$. In the second period, the first period entrepreneurs with education S either (1) all stay in entrepreneurship, because regardless of what the new signal is, their expected productivity is higher in entrepreneurship (*i.e.,* $E\left[\theta\middle| S, H\right] > E\left[\theta\middle| S, L\right] > S$), or (2) only those with high signals ($\hat{\theta}_2 = H$) stay in entrepreneurship, while those with low signals ($\hat{\theta}_2 = L$) become employees (because $E\left[\theta\middle| S, H\right] > S \geq E\left[\theta\middle| S, L\right]$). In case (1) the average ability of entrepreneurs in the second period is $E\left[\theta\middle| S\right]$, exactly as in the first period, while in case (2) the average ability of entrepreneurs is $E\left[\theta\middle| S, H\right]$ in the second period, which is strictly greater than $E\left[\theta\middle| S\right]$.

Suppose, instead, that in the first period, all individuals with education S choose wage employment (because $S \geq E\left[\theta\middle| S\right]$). Then in the first period, all employees with education S have average ability $E\left[\theta\middle| S\right]$. In the second period, the first period employees with education S either (1) all stay in wage employment (because $S \geq E\left[\theta\middle| S, H\right] > E\left[\theta\middle| S, L\right]$), or (2) only those with $\hat{\theta}_2 = L$ signals stay in employment, while those with $\hat{\theta}_2 = H$ signals become entrepreneurs (because $E\left[\theta\middle| S, H\right] > S \geq E\left[\theta\middle| S, L\right]$). In case (1) the average ability of employees in the second period is $E\left[\theta\middle| S\right]$, exactly as in the first period, while in case (2) the average ability of employees is $E\left[\theta\middle| S, L\right]$ in the second period, which is strictly less than $E\left[\theta\middle| S\right]$.

This pattern continues period after period—for every level of education S, entrepreneurs will have weakly higher innate ability, and employees will have weakly lower innate ability from period t to period $t+1$, and for some t large enough the inequalities will be strict.[33] Intuitively, the matching improves over time—eventually, every individual sorts into the occupation where he has a comparative advantage (e.g. all with $\theta > S$ eventually become entrepreneurs and stay

[33] This follows because θ has full support over $\mathbb{R}$ and $X_T > X_W$, which implies that for every finite S, there exists a threshold ability above which a positive measure of workers are more productive as entrepreneurs and below which a positive measure are more productive as workers.

there). Thus, if matching under symmetric, incomplete information were true, we would expect to see our empirical predictions strengthen over time. As explained in the main text though, this is not empirically the case.

A.4 Dynamic Asymmetric Information

The dynamic comparative advantage model with symmetric imperfect information above can be readily be recast as an asymmetric information model by allowing the worker to know his ability from the outset. As before, employers, in the competitive labor market, offer the expected productivity of the worker given the observables, but they cannot observe either ability or the worker's previous work history.[34] Employers also condition on the fact that workers who can make more as entrepreneurs will reject the offer.[35] Formally, the firm offers

$$w_t\left(S, K_t\right) = E\left[\pi_W\left(\theta, S\right) \middle| S, K_t, \pi_T\left(\theta, S\right) \leq w_t\left(S, K_t\right)\right]$$

knowing workers will accept the offer if and only if $\pi_T\left(\theta, S\right) \leq w_t\left(S, k\right)$. The wage acceptance condition is easily rewritten in terms of private ability:

$$\theta \leq \bar{\theta}_t\left(S, K_t\right) \equiv \frac{w_t\left(S, k\right) - \left(1 - X_T\right) S}{X_T}$$

This yields a fixed point problem in the wage

$$w_t\left(S, K_t\right) = X_W \frac{\int_{-\infty}^{\bar{\theta}_t\left(S, K_t\right)} \theta p\left(\theta\right)^{K_t} \left(1 - p\left(\theta\right)\right)^{t-K_t} dF\left(\theta\right)}{\int_{-\infty}^{\bar{\theta}_t\left(S, K_t\right)} p\left(\theta\right)^{K_t} \left(1 - p\left(\theta\right)\right)^{t-K_t} dF\left(\theta\right)} + \left(1 - X_W\right) S$$

that can, in principle, be solved for every signal and education level over time.

The difference between the expected abilities of entrepreneurs and employees with signal S in period t is given by

$$\begin{aligned} \Delta_t\left(S\right) &= E\left[\theta \middle| S, Entrepreneur, t\right] - E\left[\theta \middle| S, Employee, t\right] \\ &= \sum_{k=0+I\{S=S_H\}}^{t-1+I\{S=S_H\}} \begin{pmatrix} E\left[\theta \middle| S, K_t = k, \theta > \bar{\theta}_t\left(S, k\right)\right] \\ -E\left[\theta \middle| S, K_t = k, \theta \leq \bar{\theta}_t\left(S, k\right)\right] \end{pmatrix} \Pr\left\{K_t = k \middle| S\right\} \end{aligned}$$

[34] The assumption that workers' career histories are invisible to employers is a non-innocuous simplification. It eliminates strategic considerations—workers choosing entrepreneurship now to signal quality later and employers' response to this behavior.

[35] Note that firm of the asymmetric infomation model presented in Section 3.1 had market power in setting wages, and here workers get paid their expected productivity (conditional on signal). This illustrates that market structure is not fundamental to the theory.

where $I\{S = S_H\}$ is an indicator denoting that individual received an H education (and first signal).

Although generically computing the change in $\Delta_t(S)$ with respect to time is beyond the scope of this paper, we have numerically computed Δ_1 and Δ_2 for ability $F(\theta)$ distributed according $Uniform\,[0,1]$, a variety of $Triangular\,[0,1]$ and $Beta$ distributions with signaling technology $p(\theta) = \theta$ and many parameterizations of $0 < X_W < X_T < 1$ and $0 < S_L < S_H < 1$.[36] In each case, we find that $\Delta_1(S_H) > \Delta_2(S_H)$ and $\Delta_1(S_L) > \Delta_2(S_L)$. As explained in the main text, this is consistent with our empirical findings, namely that support for our hypotheses are strongest earlier in individuals' careers. Hence, we conclude that asymmetric information is a significant driver of entrepreneurial choice, especially when asymmetric information is strongest, early on.

A.5 Numerical Example

Here we present a numerical example of the asymmetric information model of Section A.1.2. It is also constructed so that innate ability is more productive in wage work and signal is more productive in entrepreneurship to illustrate that the asymmetric information explanation is not subject to any comparative advantage restrictions.

Example 1 *Let the distribution F of private innate ability θ be $Beta(\alpha,\beta)$, and signal $S \in \{H, L\}$, where $S = H$ with probability θ . Thus, by Bayes' Rule, the conditional distributions of ability are given by $F'(\theta|H) = \theta F'(\theta)/E[\theta]$ and $F'(\theta|L) = (1-\theta)F'(\theta)/(1-E[\theta])$ where $E[\theta] = \alpha/(\alpha+\beta)$ and*

$$F'(\theta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{\int_0^1 x^{\alpha-1}(1-x)^{\beta-1}\,dx}$$

Let productivity in entrepreneurship and wage work be given by Cobb-Douglas productivities $\pi_T(\theta,S) = k_T\theta^T S^{1-T}$ and $\pi_W(\theta,S) = k_W\theta^W S^{1-W}$ respectively. Thus, a worker with signal S chooses entrepreneurship if and only if

$$\theta > \bar{\theta}_S = \pi_T^{-1}(w_S, S) = \left(\frac{w_S}{k_T S^{1-T}}\right)^{\frac{1}{T}}$$

where w_S solves

$$\max_{w_S} \int_0^{\bar{\theta}_S} \left(k_W\theta^W S^{1-W} - w_S\right)\left(\theta^{\alpha}(1-\theta)^{\beta-1}\right)d\theta$$

[36] The Mathematica code is available upon request.

Assume the following parameter set: $\alpha = \beta = 10$*,* $H = \frac{5}{4} > L = 1$*,* $k_T = 1$*,* $k_W = 2$*, and* $T = \frac{1}{2} < W = \frac{2}{3}$*. The firm optimally offers* $w_H^* \approx 0.944$ *to workers with signal* H*, and all with innate ability below* $\bar{\theta}_H \approx 0.713$ *accept; all more able workers with signal* H *become entrepreneurs. The firm optimally offer* $w_L^* \approx 0.816$ *to workers with signal* L*, and all with innate ability below* $\bar{\theta}_L \approx 0.665$ *accept; all more able workers with signal* L *become entrepreneurs. Figure A1 illustrates the solution.*

Figure A1 here

A.6 Proofs for Base Model

Lemma 4 *Any interior solution to the FOC is the unique global optimum.*

Proof. Taking the derivative of (1) with respect to w yields the following Second Order Condition (SOC):

$$(\pi(w) - w)' F'(w|S) + (\pi(w) - w) F''(w|S) - F'(w|S) < 0 \tag{3}$$

We can write the FOC from (1) as

$$(\pi(w) - w) \frac{F'(w|S)}{F(w|S)} = 1 \tag{4}$$

Thus, dividing (3) by $F(w|S)$ and multiplying the final term by the LHS of (4), we see that the SOC holds at a critical point if and only if

$$(\pi(w) - w)' \frac{F'(w|S)}{F(w|S)} + (\pi(w) - w) \left[\frac{F''(w|S)}{F(w|S)} - \left(\frac{F'(w|S)}{F(w|s)} \right)^2 \right] < 0$$

which is equivalent to

$$(\pi(w) - w)' \frac{F'(w|S)}{F(w|S)} + (\pi(w) - w) [\ln F(w|S)]'' < 0 \tag{5}$$

The first term is negative due to decreasing differences in the production technologies (*i.e.,* for all θ, $(\pi(\theta) - \theta)' \leq 0$), and the second term is also negative because (a) any w satisfying (4) is less than $\pi(w)$ and (b) $F(w|S)$ is log-concave. Thus, the SOC holds at all critical points. ■

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

Proof. The employer can profitably offer $w(S)$ that some individuals will accept if and only if the marginal benefit of hiring individuals of some ability level (LHS of (1)) exceeds the marginal cost of hiring all less able workers (RHS). Formally, traditional employment exists if and only if there exists $\hat{\theta} \in [\underline{\theta}, \overline{\theta}]$ and $\hat{S} \in [\underline{S}, \overline{S}]$ such that

$$\pi\left(\hat{\theta}\right) - \hat{\theta} \geq F\left(\hat{\theta}\middle|\hat{S}\right) / F'\left(\hat{\theta}\middle|\hat{S}\right) \tag{6}$$

Since $\pi(\underline{\theta}) > \underline{\theta}$ and $F'(\theta | S)$ has full support over $\theta \in [\underline{\theta}, \overline{\theta}]$, for all S, this condition is always satisfied for $\hat{\theta} = \underline{\theta}$; the LHS is positive and the RHS equals zero. To see why this condition suffices, notice that the firm generically faces adverse selection in hiring. If it offers a wage of $w(S)$ to a set of individuals bearing imperfect signals, the average ability of individuals who accept the offer (if any) is generally less than $w(S)$, because all more able individuals reject the offer in favor of entrepreneurship. If though, traditional employment is, over at least some ability range, more productive than entrepreneurship, a lemons unraveling problem can be averted. The assumption $\pi(\underline{\theta}) > \underline{\theta}$ suffices, because it is always profitable for the firm to hire the least able. Of course, while $\pi(\underline{\theta}) > \underline{\theta}$ is sufficient, it is not necessary. The advantage of traditional employment over entrepreneurship might instead exist only at higher ability levels, but if this is the case then the advantage must be large enough that it can overcome losses from hiring those at the bottom of the ability distribution (with the same signal) for the same price.

Considering the opposite end of the ability spectrum, the employer cannot profitably attract all individuals with signal S if and only if the marginal benefit of hiring individuals of some ability level (LHS of (1)) is less than the marginal cost of hiring all less able workers (RHS). Formally, entrepreneurship exists if and only if there exists $\hat{\theta} \in [\underline{\theta}, \overline{\theta}]$ and $\hat{S} \in [\underline{S}, \overline{S}]$ such that

$$\pi\left(\hat{\theta}\right) - \hat{\theta} < F\left(\hat{\theta}\middle|\hat{S}\right) / F'\left(\hat{\theta}\middle|\hat{S}\right) \tag{7}$$

Since $\pi(\overline{\theta}) - \overline{\theta}$ is finite, $\lim_{\theta \to \overline{\theta}} F\left(\hat{\theta}\middle| S\right) = 1$ for all S, and we have assumed that $\lim_{\theta \to \overline{\theta}} F'(\theta | S) = 0$, for some S, say S', this condition is always satisfied for a neighborhood around $\hat{\theta} = \overline{\theta}$ and S'. ■

Note that our standard distributional assumptions imply that entrepreneurship will coexist with traditional employment even when traditional employment is much more productive than entrepreneurship over the *entire ability range.* Alternatively we might have assumed that at high ability levels the productive advantage of traditional employment is sufficiently small. For example, rather than assuming that extremely high talent is vanishingly rare (***i.e.*** $\lim_{\theta\to\overline{\theta}} F'(\theta|S) = 0$), we could have assumed that at the highest ability individuals are no more productive as employees: $\pi\left(\overline{\theta}\right) \leq \overline{\theta}$. Since the LHS of (7) is weakly negative, and the RHS is strictly positive for all S condition 7 holds for all S.

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

Proof. Rewrite the FOC (eqn. (1))

$$\left((\pi(w) - w) - \int_{\underline{\theta}}^{w} \frac{F'(\theta|S)}{F'(w|S)} d\theta\right) F'(w|S) = 0$$

Since we have shown in Lemma 4 that the SOC holds at all critical points, from the Implicit Function Theorem (IFT), it suffices to show that for all S,

$$\frac{\partial}{\partial S}\left(\left[(\pi(w) - w) - \int_{\underline{\theta}}^{w} \frac{F'(\theta|S)}{F'(w|S)} d\theta\right] F'(w|S)\right) > 0$$

or equivalently

$$\begin{aligned} &\left(-\int_{-\infty}^{w} \frac{\partial}{\partial S}\frac{F'(\theta|S)}{F'(w|S)} d\theta\right) F'(w|S) \\ &+ \left((\pi(w) - w) - \int_{\underline{\theta}}^{w} \frac{F'(\theta|S)}{F'(w|S)} d\theta\right) \frac{\partial}{\partial S} F'(w|S) > 0 \end{aligned}$$

The first factor of the second term is zero wherever the FOC is satisfied, yielding the condition

$$\int_{\underline{\theta}}^{w} \frac{\partial}{\partial S}\frac{F'(\theta|S)}{F'(w|S)} d\theta < 0$$

where MLRP implies that the integrand is negative for all θ, since $w > \theta$. ■

A.7 Proofs for Endogenous Pedigree Extension

In this subsection we show that under the assumptions of the endogenous pedigree first stage, the resulting posterior distribution of ability conditional on pedigree $F'(\theta|S)$ is log-concave and satisfies the MLRP.

Lemma 5 *The posterior density of ability $F'(\theta|S)$ is log-concave.*

Proof. By Bayes' Rule

$$F'(\theta|S) = \frac{\Pr\{S|\theta\} F'(\theta)}{\Pr\{S\}} = \frac{G'(S - e(\theta)) F'(\theta)}{\int_{\underline{\theta}}^{\overline{\theta}} G'(S - e(t)) \, dF(t)} \tag{8}$$

Thus, $F'(\theta|S)$ is log-concave, because multiplication preserves log-concavity (the denominator is a constant, given S). ■

Lemma 6 *If equilibrium effort increases in ability, then the posterior density of ability $F'(\theta|S)$ satisfies the MLRP.*

Proof. Differentiating the likelihood ratio yields (using equation (8))

$$\begin{aligned}\frac{\partial}{\partial S}\frac{F'(\theta|S)}{F'(w|S)} &= \frac{F'(\theta)}{F'(w)}\frac{\partial}{\partial S}\frac{\Pr\{S|\theta\}}{\Pr\{S|w\}} = \frac{F'(\theta)}{F'(w)}\frac{\partial}{\partial S}\frac{G'(S-e(\theta))}{G'(S-e(w))} \\ &= \frac{F'(\theta)}{F'(w)}\frac{G''(S-e(\theta))G'(S-e(w)) - G'(S-e(\theta))G''(S-e(w))}{G'(S-e(w))^2}\end{aligned}$$

Thus, $\frac{\partial}{\partial S}\frac{F'(\theta|S)}{F'(w|S)} < 0$ for all $\theta < w$ if

$$\frac{G''(S-e(\theta))}{G'(S-e(\theta))} < \frac{G''(S-e(w))}{G'(S-e(w))}$$

which holds, because the log-concavity of G' implies $(\log(G'))'' = (G''/G')' < 0$, and $e(\theta) < e(w)$ implies $S - e(\theta) > S - e(w)$. ■

Since average pedigree moves with ability exactly as effort does, because $E[S(e(\theta))|\theta] = e(\theta) + E[\varepsilon]$ and the expected noise term is independent of ability, Lemma 6 can be equivalently written

Corollary 2 *If in equilibrium, average pedigree increases in ability, then the posterior density of ability $F'(\theta|S)$ satisfies the MLRP.*

In other words, so long as a separating equilibrium exists in the first stage signalling game, such that higher ability individuals receive higher pedigrees on average, all of the results of the baseline model also hold when pedigree is endogenously determined. As previously stated, that pedigrees increase in ability can readily be observed in the data, but for completeness we establish that this is true under our assumed conditions, which are standard to signaling models:

Lemma 7 *Equilibrium effort exerted in pursuit of signal increases in ability.*

Proof. In Stage 1 , individuals maximize payoff considering both Stage 2 occupational choices,

$$\max_e \theta \Pr\{\theta > w(S)\} + E[w(S)|\theta \le w(S)]\Pr\{\theta \le w(S)\} - C(e,\theta)$$

or in integral form

$$\max_{e} \theta G\left(w^{-1}(\theta)-e\right)+\int_{w^{-1}(\theta)-e}^{+\infty} w(e+\varepsilon)\, dG(\varepsilon)-C(e, \theta)$$

Differentiating with respect to e yields the following FOC

$$-\theta G'\left(w^{-1}(\theta)-e\right)+w\left(e+w^{-1}(\theta)-e\right) G'\left(w^{-1}(\theta)-e\right)$$

$$+\int_{w^{-1}(\theta)-e}^{+\infty} w'(e+\varepsilon)\, dG(\varepsilon)-C_1(e, \theta)=0$$

which readily simplifies to the marginal benefit of all possible 'good' pedigree realizations resulting from an increase in effort must equal the marginal cost of that effort increase:

$$\int_{w^{-1}(\theta)-e}^{+\infty} w'(e+\varepsilon)\, dG(\varepsilon)=C_1(e, \theta)$$

Thus, a (continuously) separating equilibrium exists if the solution to this implicit equation for e strictly increases in θ . We have assumed that cost is sufficiently convex for the SOC to be satisfied. Thus, from the IFT, $\frac{de}{d\theta}$ has the same sign as

$$\begin{aligned}
&\frac{\partial}{\partial \theta}\left(\int_{w^{-1}(\theta)-e}^{+\infty} w'(e+\varepsilon)\, dG(\varepsilon)-C_1(e, \theta)\right) \\
&=-w'\left(w^{-1}(\theta)\right) G'\left(w^{-1}(\theta)-e\right) \frac{\partial}{\partial \theta}\left(w^{-1}(\theta)\right)-C_{12}(e, \theta) \\
&=G'\left(w^{-1}(\theta)-e\right)-C_{12}(e, \theta)>0
\end{aligned}$$

which is positive, because G' is a probability density and $C_{12}<0$ by assumption (*i.e.,* the Spence-Mirrlees condition). ■

Lemma 3*Equilibrium effort exerted in pursuit of signal (and average signal) increases in ability, such that (i) the posterior distribution of ability $F(\theta|\, S)$ is log-concave and (ii) the posterior density of ability $F'(\theta|\, S)$ satisfies the MLRP.*

Proof. Part (i): Since log-concave density implies log-concave distribution (See Bagnoli and Bergstrom 2005, Theorem 1) the result follows from 5.

Part (ii): Follows immediately from Lemmas 7 and 6, together with the fact that average signal moves with ability exactly as effort does, because $E[S(e(\theta))|\,\theta]=e(\theta)+E[\varepsilon]$ and the expected noise term is independent of ability. ■

B Supplementary Empirical Appendix

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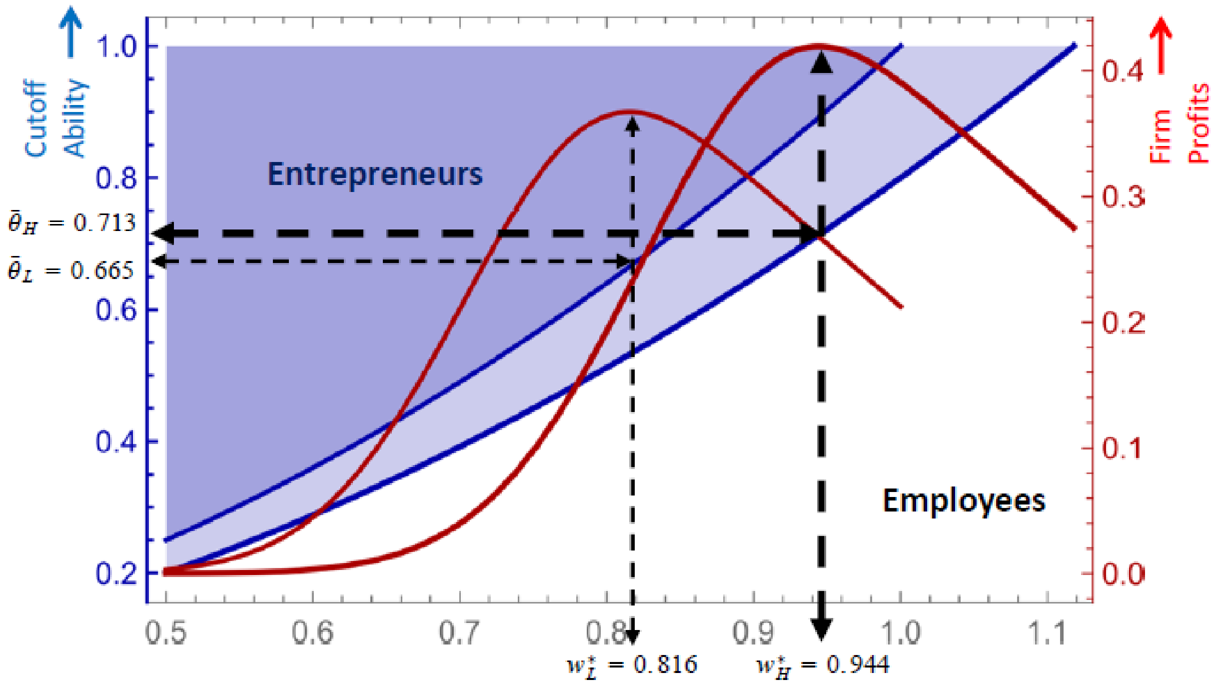
Figure A1: Graphical Solution to Numerical Example 1



The figure plots the cutoff abilities (blue curves) and firm profits (red curves) for both signal types as a function of wage (horizontal axis). Curves for H signals are thick, while those for L signals are thin. The firm chooses wages for each signal yielding the highest profits. These wages imply a cutoff ability level for each signal above which all individuals choose entrepreneurship. Parameters are as described in the example. In particular, although innate ability is here assumed to have a comparative advantage in wage work and acquired skills a comparative advantage in entrepreneurship, the most able of each signal group choose entrepreneurship. Matching with this parameterization would yield the opposite result.

Appendix B—Supplementary Descriptives and Findings

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Table B1: NLSY79 Survey years and occupational status, 1979-2010

NLSY Survey Round	Salaried	Self-employed	Total full-time employed individuals
1979	96.5%	3.5%	5,108
1980	97.4%	2.6%	5,704
1981	97.5%	2.6%	6,305
1982	97.2%	2.8%	9,241
1983	96.8%	3.2%	9,387
1984	96.1%	3.9%	9,507
1985	95.6%	4.5%	9,009
1986	95.0%	5.0%	8,977
1987	94.1%	5.9%	8,895
1988	93.5%	6.5%	8,987
1989	93.0%	7.0%	9,035
1990	92.9%	7.1%	8,951
1991	92.2%	7.8%	7,627
1992	91.9%	8.1%	7,644
1993	91.6%	8.4%	7,534
1994	91.5%	8.5%	7,238
1996	91.0%	9.0%	7,518
1998	90.9%	9.1%	7,467
2000	90.8%	9.2%	7,191
2002	89.8%	10.3%	6,867
2004	88.3%	11.7%	6,604
2006	87.5%	12.6%	6,572
2008	87.3%	12.7%	6,619
2010	87.4%	12.6%	6,252
Total Observations	92.9%	7.1%	184,239

The table reports the years during which the 24 rounds of NLSY79 surveys conducted, the percentage of individuals during each round that reported being full-time employed in a salaried job (Column 2), the percentage of individuals during each round that reported being self-employed (Column 3), and the total number of individuals in full-time employment (worked for more than 35 hours per week on average during the year) during the survey round.

Table B2: Cognitive ability test scores by occupational status

Cognitive Ability Tests	Mean Scores		Median Scores	
	Salaried	Self-employed	Salaried	Self-employed
PSAT MATH	44.3	46	43	44
PSAT VERBAL	40.2	40.9	40	40
SAT MATH	444.6	453.1	430	440
SAT VERBAL	407.2	410.7	400	390
ACT MATH	17.2	18.8	17	19
ACT VERBAL	17.4	17.7	18	18

The table reports mean and median scores for salaried versus self-employed person-year observations from the 1979-2010 rounds of the NLSY79 surveys. The Preliminary Scholastic Aptitude Test (PSAT) is a test that is intended to provide firsthand practice for the Scholastic Aptitude Test (PSAT). The Scholastic Aptitude Test (SAT) is intended to assess a student's readiness for college in the United States. The American College Testing scores (ACT) is based on a standardized test for high school achievement and college admissions in the United States produced by ACT, Inc.

Table B3: Survival as full-time employed in year t, by full-time occupation in t-1

PANEL A Drop-out rates by education level Past year full-time employment status	Drop-out rate, full sample	Drop-out rate, high school & lower	Drop-out rate, junior college & above
Salaried	10.7%	10.5%	6.9%
Self-employed	12.9%	13.4%	9.7%
Sample drop-out rate	10.9%	10.7%	7.1%

PANEL B: Drop-outs of current-year full-time employment sample Past year full-time employment status	Mean AFQT Score	Mean Years of Education	Mean Annual Income
Salaried	37.4	12.2	52,042.0
Self-employed	39.8	12.3	75,254.8

PANEL C: Survivors in current-year full-time employment sample Past year full-time employment status	Mean AFQT Score	Mean Years of Education	Mean Annual Income
Salaried	44.1	12.9	48,754.1
Self-employed	46.3	12.9	57,737.5

Panel A of the Table reports drop-out rates in the overall sample by employment status, as well as drop-out rates for those with low education and drop out rates for those with higher education (junior college or above) and those with lower educational qualifications (high school or lower). Panel B of the Table reports mean ability (AFQT) scores, mean years of education, mean annual income, and survival statistics, for individuals who were full-time employed in t-1, but dropped out of full time employment in t, by full-time occupation status in year t-1. Panel C of the Table reports mean ability (AFQT) scores, mean years of education, mean annual income, and survival statistics, for individuals who were full-time employed in t-1, but survived in full time employment in t, by full-time occupation status in year t-1.

Table B4 Full table for main results

Dependent Variables	(1) Self-employed	(2) Log Annual Income	(3) Net-worth
Self employed		0.0733	24,165.7369
		[0.0104]	[1,219.5416]
Log AFQT Score	0.0062		
	[0.0023]		
Log Years of Education	-0.0522	0.8121	30,469.7186
	[0.0130]	[0.0165]	[1,956.5121]
Male	0.0144	0.0229	136.5559
	[0.0034]	[0.0055]	[666.0226]
White	0.0185	0.1154	12,886.8866
	[0.0049]	[0.0080]	[950.4226]
Born Abroad	0.0086	0.1787	8,737.0993
	[0.0074]	[0.0106]	[1,265.1048]
Log Age	0.1088	-0.1718	53,910.7025
	[0.0205]	[0.0339]	[4,377.5221]
Risk Loving	0.0014	-0.0015	-20.6263
	[0.0004]	[0.0006]	[70.9041]
Sociability	0.0073	0.0082	501.4675
	[0.0022]	[0.0035]	[423.0597]
Self-Esteem	-0.0002	0.0045	229.9281
	[0.0003]	[0.0004]	[46.7658]
Self-Mastery	-0.0003	0.0054	178.1737
	[0.0002]	[0.0004]	[44.5706]
Father Self-employed	0.0108	0.0315	6,903.1715
	[0.0076]	[0.0091]	[1,128.2433]
Mother Self-employed	0.0179	0.0405	754.6339
	[0.0143]	[0.0183]	[2,224.0801]
Mother's education	0.0012	0.0033	66.9056
	[0.0005]	[0.0007]	[86.1458]
Father's education	0.0002	0.0042	142.4355
	[0.0003]	[0.0005]	[65.5062]
Family income in 1979	-0.0008	0.1881	2,703.7465
	[0.0024]	[0.0033]	[397.0483]
Family worth in 1985	0.0047	0.0599	2,761.7053
	[0.0005]	[0.0009]	[99.4778]
Supplementary Sample	0.0030	0.0375	310.6185
	[0.0043]	[0.0080]	[940.2204]
Military Sample	-0.0258	0.1733	-4,864.6574
	[0.0130]	[0.0197]	[2,323.0807]
Constant	-0.3175	6.7652	-245005.7006
Industry effects	Y	Y	Y
Year effects	Y	Y	Y
Observations	117,204	103,212	72,815
R-squared	0.0735	NA	NA

Column 1 reports LPM estimates of the effect of explanatory variables on probability of self-employment and corresponds to the specification in Column 2 of Main Table 2. Column 2 and 3 are estimated using quantile regressions and correspond to the specifications in Columns 2 and 6 of Main Table 4 respectively. Column 1 standard errors are clustered at individual level.

Table B5: LPM estimates of the effect of ability and education on entrepreneurship

Dependent Variable	(1) Self-employed	(2) Self-employed
Log AFQT Score	0.0079	0.0040
	[0.0031]	[0.0021]
High school diploma	-0.0184	-0.0488
	[0.0072]	[0.0103]
Associate/Junior College	-0.0376	-0.0543
	[0.0105]	[0.0106]
Bachelor of Arts	-0.0251	-0.0392
	[0.0131]	[0.0109]
Bachelor of Science	-0.0443	-0.0625
	[0.0110]	[0.0106]
Master's Degree	-0.0729	-0.0844
	[0.0131]	[0.0113]
Doctoral Degree	-0.0045	0.0107
	[0.0319]	[0.0132]
College Tier		-0.0062
		[0.0026]
Log Age	0.0996	0.1731
	[0.0364]	[0.0178]
Constant	-0.4529	-0.6193
Demographic variables	Y	Y
Non-cognitive traits	Y	Y
Family background & wealth	Y	Y
Year Dummies	Y	Y
Industry Dummies	Y	Y
Subsample Dummies	Y	Y
Observations	70,664	56,657
R-squared	0.0731	0.0690

Table reports effect of ability (AFQT score) and education on the probability of self-employment. Column 1 measures education by the highest degree of individuals during a given year. Column 2 additionally uses the college tier (ranked 1-4 such that 4 represents the most selective schools) of the institution that the individual obtained her highest degree from as a measure of educational qualification. Information on this variable is available only for those individuals who received their degree from a four-year degree granting institution or higher. 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. We restrict estimation samples to those who are at least 28 years old to ensure sufficient time for individuals to acquire Masters and Doctoral degrees prior to their employment decisions. Regression standard errors are clustered at individual level.

Table B6: LPM estimates of the effect of asymmetric information on entrepreneurship at low and high levels of education

	(1)	(2)
Subsample	Low education	High education
Dependent Variable	Self-employed	Self-employed
AFQT-Median AFQT | Years of Education	0.0004	-0.0001
	[0.0001]	[0.0003]
Constant	-0.2576	0.1627
Demographic variables	Y	Y
Non-cognitive traits	Y	Y
Family background & wealth	Y	Y
Year Dummies	Y	Y
Industry Dummies	Y	Y
Subsample Dummies	Y	Y
Observations	57,430	5,728
R-squared	0.0758	0.0932

Table reports effect of the asymmetric information variable, calculated as Individual's AFQT – the median AFQT for those with the same years of education, on the probability of self-employment. Column 1 reports effect on the subsample of individuals with a four-year year bachelor's degree or below of education. Column 2 reports effect on the subsample of individuals with at least a Master's degree (i.e., > 16 years of schooling). We restrict the sample to those who are at least 28 years old to ensure sufficient time for individuals to acquire Masters and Doctoral degrees prior to their employment decisions. 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. All standard errors are clustered at individual level.

Table B7 OLS 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)	0.093	0.038			153,386.303	125,707.723		
	[0.025]	[0.026]			[10,110.877]	[11,696.175]		
Self-employed (unincorporated)			-0.043				70,688.976	
			[0.029]				[10,033.379]	
Self-employed (incorporated)				0.418				384,134.937
				[0.049]				[38,335.885]
Log Years of Education		0.949	0.934	0.944		163,101.230	151,858.872	153,574.449
		[0.069]	[0.069]	[0.071]		[16,027.105]	[15,036.927]	[15,372.366]
Constant	10.601	5.442	5.48	5.328	83,704.59	-1052788.359	-1047000.486	-1088590.213
Demographic variables	N	Y	Y	Y	N	Y	Y	Y
Non-cognitive traits	N	Y	Y	Y	N	Y	Y	Y
Family background/wealth	N	Y	Y	Y	N	Y	Y	Y
Year Dummies	N	Y	Y	Y	N	Y	Y	Y
Industry Dummies	N	Y	Y	Y	N	Y	Y	Y
Subsample dummies	N	Y	Y	Y	N	Y	Y	Y
Observations	152,940	103,212	101,923	98,191	107,570	72,815	71,880	68,667
R-squared	0.000	0.144	0.142	0.147	0.021	0.156	0.144	0.172

The table reports OLS regression estimates that examine whether entrepreneurs earn more than salaried individuals, conditional on educational qualifications. 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 years 1980-1984 resulting in a lower number of observations for the corresponding estimation samples. The estimates in Column [3] and Column [7] are obtained after excluding incorporated self-employed individuals and the estimates in Column [4] and Column [8] 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 clustered at individual level are shown in brackets.

Table B8 OLS regression estimates of effects of entrepreneurship on income and wealth (worker age 40 years or below)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Log Annual income				Net-worth			
Self-employed (all)	0.142	0.142			128,602.614	118,314.052	71,484.278	
	[0.025]	[0.026]			[8,712.320]	[10,439.443]	[9,098.330]	
Self-employed (unincorporated)			0.084					
			[0.028]					
Self-employed (incorporated)				0.761				369,037.594
				[0.065]				[36,838.011]
Log Years of Education		0.769	0.761	0.449		108,938.357	99,546.857	101,741.332
		[0.064]	[0.064]	[0.054]		[12,040.202]	[11,270.407]	[11,506.094]
Constant	10.562	5.65	5.542	5.461	62,019.17	-844,627.68	-807,415.01	-795,596.67
Demographic variables	N	Y	Y	Y	N	Y	Y	Y
Non-cognitive traits	N	Y	Y	Y	N	Y	Y	Y
Family background/wealth	N	Y	Y	Y	N	Y	Y	Y
Year Dummies	N	Y	Y	Y	N	Y	Y	Y
Industry Dummies	N	Y	Y	Y	N	Y	Y	Y
Subsample dummies	N	Y	Y	Y	N	Y	Y	Y
Observations	124,514	84,108	83,344	80,187	92,446	62,762	62,115	59,374
R-squared	0.001	0.145	0.142	0.147	0.024	0.129	0.114	0.146

The table reports OLS regression estimates that examine whether entrepreneurs earn more than salaried individuals, conditional on educational qualifications, limiting sample observations to workers 40 years or younger. 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 years 1980-1984 resulting in a lower number of observations for the corresponding estimation samples. The estimates in Column [3] and Column [7] are obtained after excluding incorporated self-employed individuals and the estimates in Column [4] and Column [8] 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 clustered at individual level are shown in brackets.

Table B9 Workers' income by industry and occupation

Industry	(1) Wage employed	(2) Self employed	(3) Difference
Mining	$66,539	$283,447	$216,909
Manufacturing	$71,669	$136,403	$64,733
Wholesale & Retail Trade	$59,187	$110,460	$51,273
Arts, Entertainment, Recreation	$69,218	$118,347	$49,129
Agriculture, Forestry, Fishing, Hunti	$43,195	$89,806	$46,611
Finance, Insurance, Real Estate	$95,151	$141,086	$45,934
Professional, Accommodation, Other Svcs	$69,492	$109,619	$40,127
Construction	$58,742	$89,804	$31,062
Information, Business, Repair Scvs	$85,913	$114,397	$28,483
Public Administration	$77,348	$102,924	$25,576
Transportation, Communication, Utilities	$76,244	$98,699	$22,455
Other, Uncodeable	$86,574	$91,570	$4,996
Personal, Educational, Health Svcs	$68,608	$73,113	$4,505

Table shows mean annual incomes for wage-employees and the self-employed across the thirteen industries in our sample.

Table B10 LPM estimates of the effect of ability and education on entrepreneurship by industry

	(1)	(2)	(3)	(4)	(5)	(6)
Industry Sample	Agriculture, Forestry & Fishing	Mining	Construction	Manufacturing	Transportation, Communication, Utilities	Wholesale & Retail Trade
Dependent Variable	Self-employed	Self-employed	Self-employed	Self-employed	Self-employed	Self-employed
Log AFQT Score	0.0224	-0.0151	0.0105	0.0041	0.0043	0.0072
	0.0175	0.0149	0.0116	0.0024	0.0092	0.0031
Log Years of Education	-0.0700	0.0942	0.0468	-0.0072	-0.1034	0.0276
	0.0544	0.1039	0.0667	0.0141	0.0478	0.0223
Constant	-1.1846	-0.2077	-0.7933	-0.2009	0.2879	-0.3969
Demographic variables	Y	Y	Y	Y	Y	Y
Non-cognitive traits	Y	Y	Y	Y	Y	Y
Family background & wealth	Y	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	Y	Y	Y
Subsample Dummies	Y	Y	Y	Y	Y	Y
Observations	2,931	765	7,986	20,434	6,828	23,753
R-squared	0.1676	0.1550	0.0693	0.0196	0.0515	0.0411

Continued…

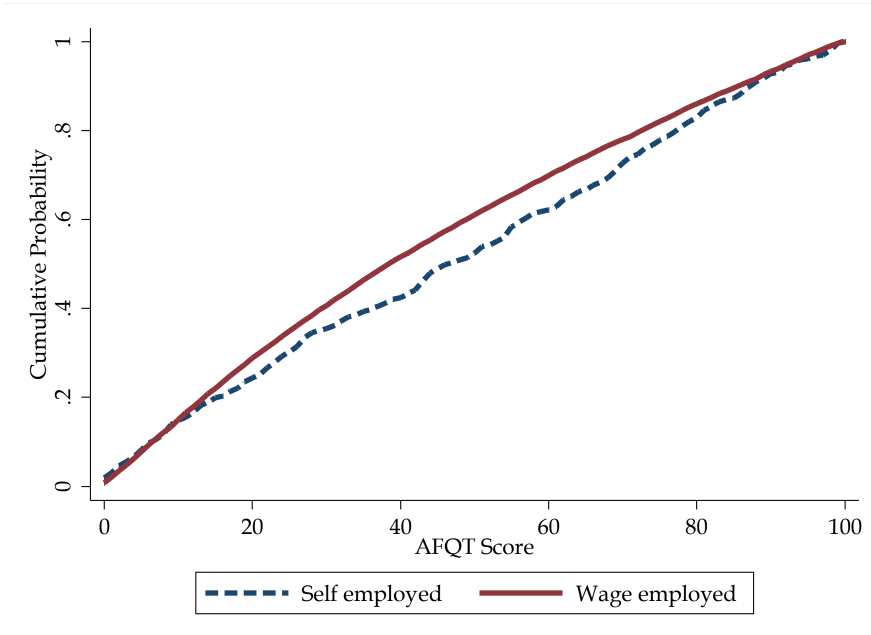
Table B10, Continued

	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Industry Sample	Finance, Insurance, Real Estate	Information, Business, Repair Scvs	Personal, Educational, Health Svcs	Arts, Entertainment, Recreation	Professional, Accomodation, Other Svcs	Public Administration	Other
Dependent Variable	Self-employed	Self-employed	Self-employed	Self-employed	Self-employed	Self-employed	Self-employed
Log AFQT Score	0.0128	0.0105	0.0034	0.0125	0.0045	0.0009	0.0036
	0.0067	0.0080	0.0089	0.0178	0.0038	0.0007	0.0097
Log Years of Education	0.0060	-0.1326	-0.1492	0.1213	-0.0009	-0.0179	-0.1201
	0.0457	0.0556	0.0450	0.1051	0.0211	0.0121	0.0493
Constant	-0.2314	-0.6501	-0.4971	-1.6966	-0.0361	0.1084	1.6937
Demographic variables	Y	Y	Y	Y	Y	Y	Y
Non-cognitive traits	Y	Y	Y	Y	Y	Y	Y
Family background & wealth	Y	Y	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	Y	Y	Y	Y
Subsample Dummies	Y	Y	Y	Y	Y	Y	Y
Observations	6,704	8,483	10,454	1,885	19,615	6,472	894
R-squared	0.0936	0.0407	0.0979	0.1122	0.0876	0.0142	0.0632

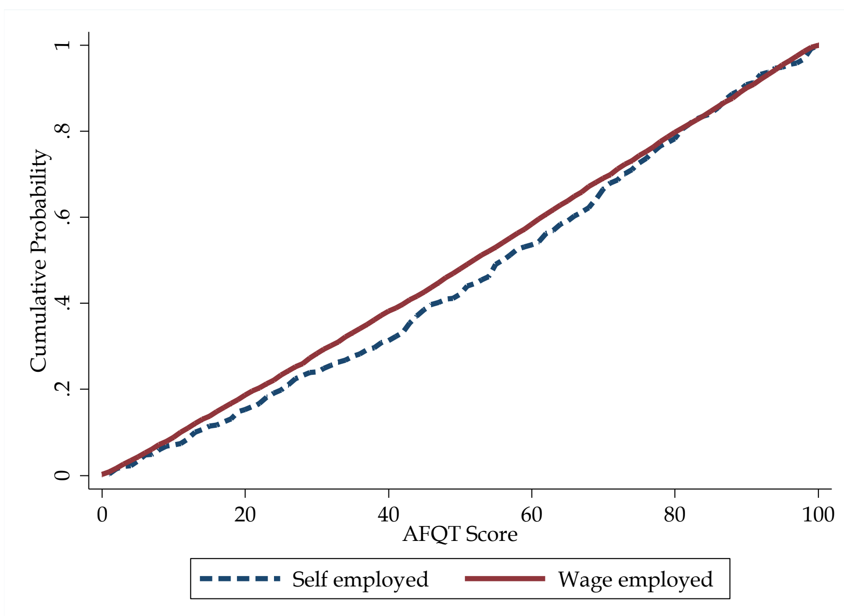
Table reports LPM estimates of the relationship between the probability of self-employment and explanatory variables (ability scores and education and controls). All standard errors are clustered at individual level.

Figure B1: Cumulative density function of AFQT scores by occupational status

Panel A: Full Sample

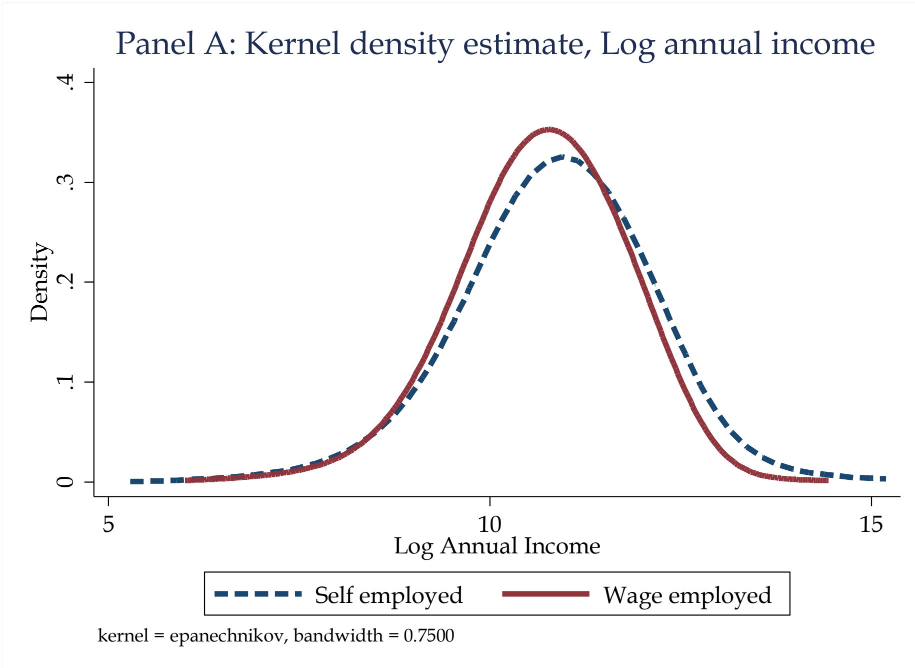


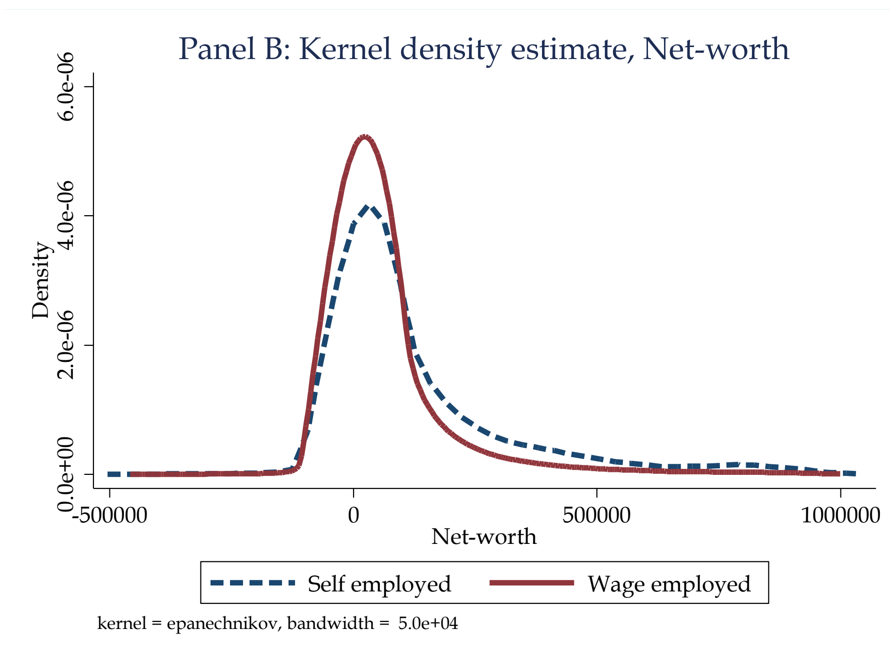
Panel B: After removing supplementary and military subsamples



The figure shows the cumulative probability distributions of AFQT scores, expressed in percentiles for self employed and wage employed individuals. R3.1 is plotted from the NLSY94 subsample of all full-time employed workers. PANEL B is plotted from the NLSY94 subsample of all full-time employed workers after leaving out the subsamples of economically disadvantaged and workers who had been enlisted in the military. In both figures, Self employed have higher AFQT scores than the wage employed for any cumulative probability value.

Figure B2: Distribution of income and wealth by occupational status





The figures show the kernel density distribution of logged annual income in 2010$ (Panel A), and logged net worth in 2010$ (Panel B) for self-employed and wage employed workers. Panel A is based on 10,614 person-year observations of self-employed workers and 142,326 person-year observations of wage employees with non-missing 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 non-missing annual household net worth data in the NLSY.

Appendix C—Description and Analysis of UK NCDS

For Online Publication Only

NCDS Variable Definitions.

All variables and data are from the U.K.s 1958 National Child Development Survey (NCDS). The NCDS follows the lives of all 18,558 individuals born in England, Scotland and Wales in one particular week of March 1958. The NCDS tracks the same respondents in eight 'sweeps' of surveys carried out in years 1965, 1969, 1974, 1981, 1991, 1999-2000, 2004, 2008 and 2013. Complete data dictionaries are currently available only through Sweep 8 conducted in 2008.

Self-employed is equal to 1 if NCDS—Sweep7 respondent indicated current job as "Full-time self-employed;" Self-employed is set to 0 if NCDS—Sweep 7 respondent indicated current job as "Full-time paid employee (30 or more hours per week)". Respondents were aged 46 during Sweep 7.

Outstanding Ability is set to 1 if the respondent was identified as having "Any Outstanding Ability" by the respondent's teacher in school at age 11 (information collected in NCDS—Sweep 2).

Copying Design Test (CDT) Score is the score the respondent achieved, ranging from 0-12, on a test that required them to copy and reproduce designs. The scores were collected in NCDS—Sweep 1 when the respondents were aged 7.

Draw-a-man Test (DMT) Score is the score the respondent achieved, ranging from 0-53, on a test that required them to draw a man. The scores were collected in NCDS—Sweep 1 when the respondents were aged 7.

Educational Attainment is measured by National Vocation Qualification (NVQ) equivalents for the highest academic qualification attained by the respondent as reported in NCDS—Sweep 8 when respondents were aged 50. The NVQ equivalents range from 0 for no formal schooling, to 5 for Master's Degree or Higher.

Annual Income is total family income from all sources before tax deductions. All values are expressed in 2007 GBP and collected during NCDS—Sweep 7.

Social functioning score is derived from respondents' answers to a questionnaire designed to evaluate their level of social adjustment and ranges from 0-100. Scores were collected during NCDS—Sweep 8 when respondents were aged 50.

Extraversion score is based on respondent responses to the "IPIP Personality Inventory-Extraversion" Test and ranges between 10-50. Scores were collected during NCDS—Sweep 8 when respondents were aged 50.

Male and Born Abroad are binary variables set to 1 if respondent is male, and born outside of the UK respectively (the variables are set to 0 otherwise).

Marital Status is indicated by a vector of five dummies, indicating Single, Legally Married, Separated, Divorced and Widowed during NCDS—Sweep 4.

Family Background is indicated by a vector of 18 dummies indicating socio-economic group of the head of the respondent's household during NCDS—Sweep 2 when the respondent was aged 11.

Table C1: Summary statistics by employment type, NCDS 1965-2008

	Salaried	Self-employed
Ability, Education, Earnings		
Mean Outstanding Ability	0.23	0.30
Median Outstanding Ability	0.00	0.00
Mean Copying Design Test Score	7.21	7.34
Median Copying Design Test Score	7.00	8.00
Mean Draw-a-man Test Score	24.31	25.10
Median Draw-a-man Test Score	24.00	25.00
Mean Educational Attainment	2.26	2.13
Median Educational Attainment	12.00	12.00
Mean Annual Income	47,503.8	52,146.8
Median Annual Income	38,000.0	40,000.0
Control Variables		
Male	0.60	0.79
Born Abroad	0.04	0.04
Social functioning score	50.01	47.94
Extraversion Score	26.19	26.05
Observations	6,562	1,039
	[84.2%]	[15.8%]

The table reports summary statistics for the key variables in our analysis. The statistics are calculated from the cross-section of 6,562 individuals who reported being employed (salaried or self-employed) full-time during NCDS—Sweep 7. See Appendix A for variable definitions. Marital Status (indicated by five dummy variables) and Family Background (indicated by 18 dummy variables) are used as controls in regressions, but summary statistics for the variables are not reported here due to space constraints.

Table C2: Ability and educational attainment by employment type

	Outstanding Ability		Copying Design Score		Draw-a-man Score	
	Salaried	Self-employed	Salaried	Self-employed	Salaried	Self-employed
Educational Attainment						
No formal Schooling	0.13	0.25	6.47	6.65	21.78	22.39
NVQ-Level 1	0.16	0.26	6.69	6.93	22.14	22.6
NVQ-Level 2	0.22	0.25	7.34	7.48	24.5	26.33
NVQ-Level 3	0.3	0.37	7.71	7.61	26.36	25.6
NVQ-Level 4	0.32	0.43	7.61	7.83	26.01	27.46
NVQ-Level 5	0.35	0.43	7.74	7.9	26.38	26.55

The table reports sample means of test scores for different levels of educational attainment by employment status.

Table C3: Who becomes an entrepreneur?

Dependent Variable	Self-employed?				
	[1]	[2]	[3]	[4]	[5]
Outstanding Ability	0.043	0.054	0.051		
	[0.012]	[0.013]	[0.014]		
Copying Design Score				0.004	
				[0.003]	
Draw-a-man Score					0.003
					[0.001]
Educational Attainment		-0.011	-0.011	-0.012	-0.010
		[0.004]	[0.004]	[0.004]	[0.004]
Demographic variables	N	N	Y	Y	Y
Non-cognitive traits	N	N	Y	Y	Y
Family background	N	N	Y	Y	Y
Log-likelihood	-2406.78	-2124.78	-1604.14	-1652.68	-1615.94
Observations	5,602	4,978	3,916	3,999	3,929

The table reports marginal effects estimates from Probit regressions of the effects of ability and education on the probability of being self-employed. The baseline estimation sample consists of 5,602 full-time employed individuals with information on Outstanding Ability Score. Columns [1] and [2] report estimates of the probability of being self-employed without and with educational attainment respectively. The difference in the number of observations is due to observations that are left out of the estimations due to missing values of control variables. All standard errors are heteroscedasticity-consistent.

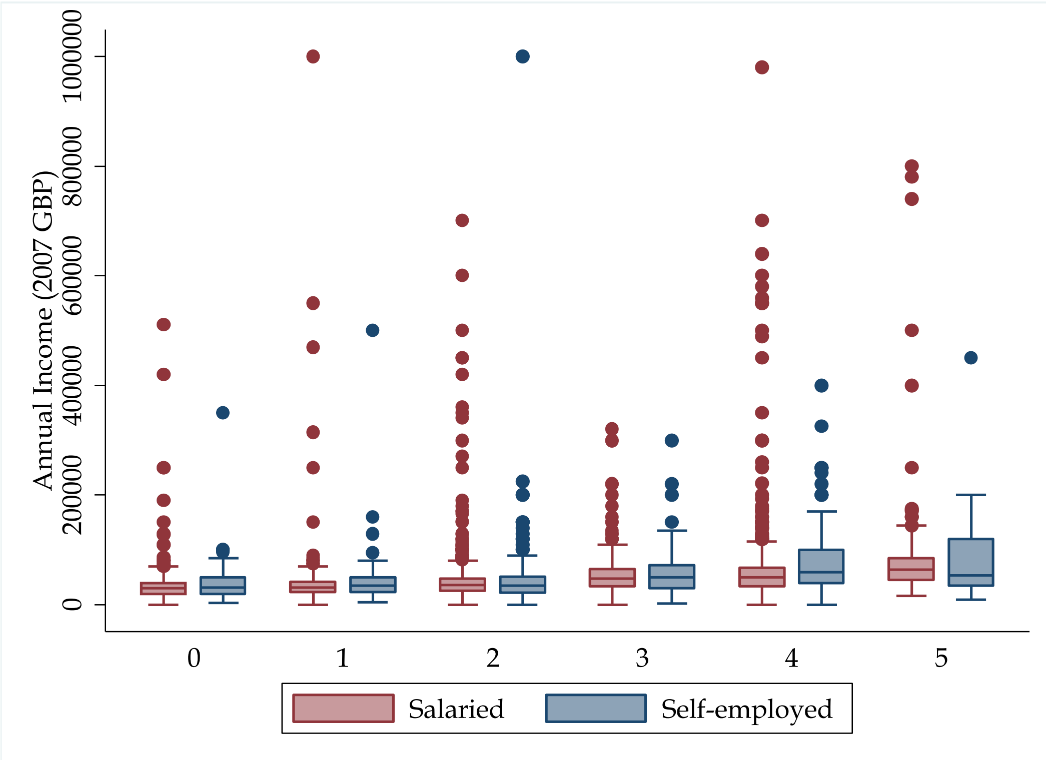
Table C4: Do entrepreneurs earn more, conditional on education?

Dependent Variable	Log Annual Income		
	[1]	[2]	[3]
Self-employed (all)	0.051	0.058	0.057
	[0.023]	[0.026]	[0.029]
Educational Attainment		0.145	0.148
		[0.006]	[0.007]
Demographic variables	N	N	Y
Non-cognitive traits	N	N	Y
Family background	N	N	Y
Constant	10.54	10.24	10.08
Pseudo-R2	0.002	0.069	0.094
Observations	5,502	4,891	3,766

The table reports quantile (median) regression estimates that examine whether entrepreneurs (self-employed individuals) earn more than salaried individuals. The dependent variable is logged annual income in Columns 1-3. Data on educational attainment and control variables are not available for some individuals resulting in a lower number of observations for the estimation samples in Columns [2] and [3]. The base class (Self-employed = 0) in all estimations is composed of full-time salaried individuals. Standard errors are shown in brackets.

NCDS Figures

Figure C1: Distribution of income, Salaried v/s Self-employed



The figure shows, on the x-axis, highest educational attainment achieved by NCDS respondents, such that 0 indicates No formal schooling, and 5 represents NVQ Level that corresponds to a Master's degree or higher. The figure is based on the responses of 1,039 self-employed individuals and 5,523 salaried individuals as reported in Sweep #7 of the NCDS.