Self-Employment Dynamics and the Returns to Entrepreneurship*

Eleanor W. Dillon
Arizona State University

Christopher T. Stanton
Harvard Business School,
NBER, and CEPR

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Abstract

Small business owners and others in self-employment have the option to transition to paid work. If there is initial uncertainty about earnings in entrepreneurship, this option increases the lifetime expected value of entering self-employment relative to the expected pay in a single year. This paper first documents that moves between paid work and self-employment are common and consistent with experimentation to learn about entrepreneurial earnings. This motivates estimating the expected returns to entering self-employment within a dynamic lifecycle model that allows for non-random selection in and out of self-employment and gradual learning about the entrepreneurial earnings process. The option value of returning to paid work is found to be large enough to reverse the result from cross-sectional studies that the median male worker should expect to earn less from self-employment than what he could earn from paid work.

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1 Introduction

The median self-employed worker earns less in a given year than the median paid worker.[1] Proposed explanations for this gap include non-pecuniary benefits from being one's own boss, mis-reported self-employment earnings, and improper accounting for nonrandom selection. Given that many spells in self-employment last only a few years, dynamic selection is likely of particular importance. Nonetheless, most existing analyses of the self-employment decision calculate static (cross sectional) returns: individuals are either self-employed or paid workers. With the exception of Vereshchagina and Hopenhayn (2009) and Manso (2016), there has been little work that studies entrepreneurial earnings in a dynamic model.

In the model considered here, workers cycle in and out of self-employment in part because they are initially uncertain about their potential earnings in entrepreneurship. Workers enter self-employment to learn about their earnings potential by observing their outcomes.[2] In time, unsuccessful entrepreneurs shift back to paid work. We document that movements between paid work and self-employment in the Panel Study of Income Dynamics (PSID) are consistent with resolving uncertainty about entrepreneurial earnings.[3] We then build and estimate a semi-structural model of lifecycle choices that incorporates features of the Bayesian learning model presented in seminal papers by Jovanovic (1979) and Miller (1984). We find that the option to return to paid work significantly increases lifetime expected earnings from entrepreneurship relative to estimates from static comparisons. In fact, the median male worker in the PSID can expect to earn more over his life if he enters self-employment than if he spends all his working years in paid jobs.[4] Experience in entrepreneurship does not appear to increase paid earnings after returning to paid work, suggesting this increase in expected earnings comes from the option value itself.

The first contribution of the paper is to present empirical support for the theory that workers

[1] This gap is documented here and in a number of earlier studies discussed in Section 2.

[2] In this paper we define entrepreneurs as anyone who reports working for themselves in their main job and therefore use entrepreneurship and self-employment as synonyms. We discuss this choice in the data section.

[3] This may be due to uncertainty about sector-specific ability or uncertainty about the value of an idea. For exposition purposes we focus on uncertainty about sector-specific ability, but both are consistent with the empirical exercises documented later. Kerr et al. (2014) discuss the role of venture capital in experimenting with different businesses or products, suggesting there is some uncertainty that must be resolved about the idea itself.

[4] This comparison does not include costs to enter self-employment, in keeping with prior studies that compare self-employment and paid earnings. In the data, average monetary investments at entry are small.

are initially uncertain about their entrepreneurial earnings, but can learn about them by working in self-employment. First, we show that many workers in the PSID have spells of self-employment, but few stick it out. Nearly a quarter of the individuals in the PSID enter entrepreneurship at some point in their careers, but almost half of those who do so return to the paid sector within five years. Workers also seem unable to forecast whether they will be good entrepreneurs: the mean person who moves into entrepreneurship experiences a drop in earnings relative to his last paid job. Third, the least successful entrepreneurs are more likely to return to paid work, while those with higher earnings are more likely to persist in entrepreneurship.

If workers view self-employment as an experimental trial that can be reversed, then simple comparisons of earnings across sectors do not provide unbiased estimates of the lifetime expected earnings from entering entrepreneurship. Suppose that one calculates the expected value of entering entrepreneurship by comparing earnings for current entrepreneurs and current paid workers, controlling for observed worker characteristics. This cross-sectional estimate may overstate or understate the expected value of entering entrepreneurship because of two competing forces. On the one hand, a cross-section of self-employed workers includes some new entrepreneurs with low earnings who will eventually return to paid work. For these workers, their current low earnings understate their expected remaining lifetime earnings. On the other hand, successful entrepreneurs are more likely to remain in self-employment and will be over-represented among all entrepreneurs. Survivorship bias will inflate cross-sectional estimates relative to what an average person can expect to gain from entering entrepreneurship.

We assess the relative importance of these two concerns and quantify the option value of experimenting in entrepreneurship. To do so, we compare the model-simulated expected discounted lifetime earnings from working in self-employment in all future years to the simulated expected discounted lifetime earnings from entering self-employment with the option to return to paid work. The primary purpose of the model here is to predict moves in and out of self-employment over the lifecycle, not to recover structural primitives or evaluate counter-factual policies. We therefore specify a reasonably flexible semi-structural model that encompasses the key monetary and non-monetary determinants of labor sector choice. We use data from the PSID to estimate the model parameters. Using each individual's sequence of predicted choices, we then project expected lifetime earnings conditional on sector choice next year while allowing workers to move between sectors in future years to maximize utility. The average difference between the expected discounted lifetime earnings conditional on choosing entrepreneurship next year and on choosing paid work is an unbiased estimate of the monetary returns to entering entrepreneurship. We also calculate these projections under the counterfactual assumption that workers must remain in one sector in all future periods. The difference between the estimated value of entrepreneurship with and without the opportunity for later sector changes defines the value of the option to return to paid employment.

In the model, individuals make choices to work in paid work or self-employment in each period, taking into account the expected flow earnings from each choice plus the discounted continuation value of future choices. This continuation value encompasses the option value. To compute flow earnings, we allow workers to have heterogeneous, sector-specific abilities. Workers do not know their entrepreneurial ability with certainty and must learn about it by working in self-employment. Doing so requires paying a utility entry cost to move into self-employment that varies with paid earnings ability and past entrepreneurial experience. We also allow for non-monetary heterogeneous preferences over being self-employed.

Individuals are risk-neutral except for a possible loading of risk preferences onto tastes for entrepreneurship. We choose to work with risk neutrality because it allows us to abstract from intertemporal consumption and savings decisions, which are not well recorded in the PSID. As a result, the model is semi-structural, and the non-monetary preference parameters are best interpreted as capturing a mix of heterogeneous tastes for risk and self-management and differences in opportunities and ex-ante perceived entry costs. Data on moves between paid work and self-employment, along with data on earnings, identify the distribution of preferences, entry costs, and the scaling of flow earnings relative to an unobserved Type-1 extreme value shock to each sector. In this framework, we cannot distinguish among the underlying sources of these preferences. However, the labor sector choices generated by these preferences, and their associated earnings streams, are directly comparable to observed patterns and to past studies. The model is able to match dynamic movements between paid work and self-employment over the lifecycle quite accurately despite its relative sparsity, even along dimensions that are not explicitly targeted in estimation.

In addition to documenting several new stylized facts about transitions in and out of self-employment over the lifecycle, we reach four key conclusions about the returns to entrepreneurship. First, selection bias in cross-sectional comparisons of earnings is substantial, particularly at the mean. In the PSID, the mean earnings for a 32 year old who is observed in entrepreneurship is $63,712 per year, a 12% more than the mean earnings for workers observed in paid jobs.[5] In contrast, we estimate that if all 32 year old workers chose to work as entrepreneurs for a year, their mean earnings would be $58,010, much closer to the mean earnings of $57,233 that we project these workers would earn in a year of paid work. Second, while median earnings remain lower in self-employment after controlling for selection, entering self-employment becomes more attractive when we consider earnings in all future years. Discounted lifetime earnings from working in self-employment at age 32 are 7.5% higher at the mean and 1.6% higher at the median than expected returns to working in a paid job that year. Third, these differences between the static and dynamic returns are largely driven by the opportunity for future sector changes, not by differences in the returns to experience across sectors. When shutting down the option to return to paid work, median expected lifetime earnings in entrepreneurship are lower than median lifetime earnings in paid work. Finally, tastes for self-employment vary considerably across workers. We estimate that 15% of men experience a positive non-pecuniary benefit in self-employment, while the majority of the sample would require substantial compensation to overcome their dis-utility from working for themselves. Modeling this heterogeneity helps to match observed patterns of entrepreneurial choice.

The next section discusses the literature and provides an illustrative example of the potential value of switching sectors. Section 3 describes the data and presents stylized facts to motivate considering returns to entrepreneurship in a dynamic context. Section 4 presents the full model while section 5 describes the estimation algorithm. Section 6 presents our estimates and discusses fit, section 7 evaluates the value of entering entrepreneurship, and section 8 concludes.

[5] The median entrepreneur enters self-employment in his early 30s, making this a particularly relevant comparison age; the model allows discussion of these statistics at other ages as well.

2 Literature and Motivation

A long literature examines the selection and earnings of entrepreneurs. Evans and Leighton (1989) and Hamilton (2000) use survey data to document that the median self-employed worker earns less than the median paid worker after controlling for observed worker characteristics.[6] While we replicate these findings in our static comparison, we show that the dynamic returns to entering entrepreneurship are positive, resolving this previously puzzling finding of low returns to entrepreneurship.

This finding complements the work of Manso (2016), who articulates that cross-sectional estimates of entrepreneurial earnings are biased because of dynamic concerns. He uses a matching on observables approach to show that realized lifetime earnings in the NLSY79 are higher for workers who spend at least some time as entrepreneurs than for those who never work for themselves. Manso's findings on the realized lifetime earnings of one cohort of workers reinforces our estimates that rely on projecting lifetime earnings from an unbalanced panel. Relative to Manso's work, our more structural approach has the advantage of identifying the option value of experimenting in entrepreneurship separately from bias due to selection. Both papers build on the theoretical contribution of Vereshchagina and Hopenhayn (2009), who derive the potential value of learning about entrepreneurial ability in a dynamic model.

This paper also fits into the literatures on selection in and out of entrepreneurship and on the experience of former entrepreneurs. Caliendo and Uhlendorff (2008), Caliendo et al. (2010), Levine and Rubinstein (2013), and Hurst and Pugsley (2011) discuss the heterogeneity of self-employed workers and the reasons they select into self-employment. We find that selection into self-employment in the PSID is consistent with these papers, in particular the pattern of slight adverse selection into entrepreneurship, but the process of learning about entrepreneurial ability appears relevant for all entrants. Sarada (2015) shows that those who persist in self-employment have increasing consumption and savings, consistent with selection of the best entrepreneurs. Hamilton (2000), Evans and Leighton (1989), and Bruce and Schuetze (2004) provide some evidence on the

[6] A related literature (Moskowitz and Vissing-Jorgensen (2002) and Hall and Woodward (2010)) finds even larger gaps between the returns to private businesses and investments in publicly traded equities, despite the higher risk of these largely undiversified business holdings.

return to self-employment experience in paid work, while Gottlieb et al. (2016) exploit a Canadian reform guaranteeing extended job protection to show that switching costs, both into and out of self-employment, may deter some potential entrepreneurs.

Finally, our theoretical framework builds on a long line of papers that characterize the process by which workers learn about their relative skills across jobs and occupations, beginning with Jovanovic (1979) and Miller (1984). Moscarini (2005) integrates search costs into these models of experimentation and Papageorgiou (2014) finds, as we do, that skills are correlated across sectors. We adapt this experimental framework to the unique context of experimentation with self-employment, including modeling more general entry costs.

To illustrate how the learning model with the option to change back to paid work affects inference about earnings in self-employment, consider a simple problem of choosing entrepreneurship for a risk neutral individual. His earnings in entrepreneurship equal his entrepreneurial ability, η_i, which has an ex-ante normal distribution with mean μ_i and standard deviation σ^2. If he works in the paid sector, he earns \$1,200 with certainty. Without non-measured benefits from entrepreneurship, in a single period model, the worker chooses entrepreneurship if and only if μ_i, his expected earnings, exceeds \$1,200.

Now consider a two period model with the option to move between sectors. Suppose entrepreneurial ability is unknown before entering entrepreneurship, but learned with certainty after one period. In this case, the threshold mean required to choose entrepreneurship is weakly less than \$1,200. Expected lifetime earnings from choosing entrepreneurship in the first period equal

$$\eta_i + E\left\{\max\left(\eta_i, \$1,200\right)\right\}.$$

The second term captures the option to switch from entrepreneurship back into the paid sector if earnings in entrepreneurship do not justify continuation. For any possible value of of σ^2, it is possible to solve for the critical value μ_i^* such that $\mu_i^* + E\left\{\max\left(\eta_i, \$1,200\right)\right\} \geq \$2,400$.[7] When $\sigma = 0$, the critical value $\mu_i^* = 1,200$, the certain earnings in the paid sector. As σ increases,

[7]Using the moments of the truncated normal distribution, this is $\mu_i^* + \left\{\mu_i^* + \sigma\frac{\phi(c)}{1-\Phi(c)}\right\}(1-\Phi(c)) + 1200\Phi(c) =$ \$2400 where $c = (1200 - \mu_i)/\sigma$.

the mean of the distribution required to experiment in entrepreneurship declines monotonically, reflecting the increased option value associated with variability.

This exercise also illustrates career dynamics across paid and self-employment. Individuals who are revealed to have $\eta_i \leq \$1200$ return to the paid sector while those who have $\eta_i > \$1200$ remain entrepreneurs. The full model makes this structure more realistic, allowing for non-pecuniary benefits (or costs) from self-employment, costs of entering entrepreneurship, sector-specific returns to experience, and unobserved heterogeneity. Before getting there, the next section shows that career dynamics observed in the data are consistent with this declining hazard of leaving entrepreneurship over time.

3 Data, Summary Statistics, and Evidence of Learning

3.1 The Sample

The data are from the 1976-2011 waves of the Panel Study of Income Dynamics (PSID). The PSID interviewed respondents annually until 1997 and bi-annually from 1999 onward. The long panel structure of the PSID allows us to observe workers before, during, and sometimes after spells of entrepreneurship. The original PSID sample includes a representative group of American households in 1968 and an oversample of low-income households. The PSID has continued to interview members of these households, their offspring, and individuals who marry into these families. Over time, some original families have been dropped and the sample has been augmented with several samples of recent immigrants to better reflect the current mix of US households. The baseline sample includes all households interviewed in each year; PSID-constructed weights are used to adjust for probability of inclusion in the survey. These changes in the sample, along with workers aging into and out of the workforce and occasional non-response, create an unbalanced panel.

From this baseline sample, the estimation sample is constrained by the need to keep track of accumulated work experience in each sector. We include individuals in the sample only when we can follow their work experience starting at age 25 or earlier. We also restrict the sample to men. Women in the PSID are far more likely to persist in self-employment despite low relative earnings, suggesting a larger role for non-pecuniary considerations or a fuzzy divide between self- and non-employment. It seems clear that men and women should not be pooled to estimate a single model. Women's entrepreneurial decisions are explored in Lim (2015) and remain a fruitful area for future research. We discuss sample construction and variable definitions in more detail in the Data Appendix. After restrictions, the sample includes just under 7,000 men. On average, we observe 10 years of earnings for each individual in the sample, with a maximum of 29 observations spanning 36 years.

3.2 Identifying Entrepreneurs

We define an entrepreneur as someone who is self-employed in their main job. We choose this definition, rather than one based primarily on business ownership, because entrepreneurship here is modeled as a labor supply choice that may also represent a financial investment, rather than primarily as an investment choice. Light and Munk (2015) investigate the difference between self-employment and business ownership in more detail.

Table 1 describes workers who ever spend time in entrepreneurship and those who only ever work in the paid sector. Of the set of individuals with experience in entrepreneurship, 82% own a business at some point during the sample. Workers who report being self-employed without owning a business are generally contractors or work in low-physical capital occupations like consulting and may not consider themselves business owners.[8] Entrepreneurs are more likely to be white and slightly better educated on average than the paid-only group, but generally look similar to other workers.

Moves in and out of entrepreneurship are quite common. The average member of the sometime entrepreneur sample is observed for 12 years in paid work and only 9 years in entrepreneurial work. The median entrepreneur is 32 when he first enters entrepreneurship. Figure 1 plots the cumulative transitions back to the paid sector and changes in business ownership by years since workers first enter entrepreneurship. Overall 40% of workers who experiment with entrepreneurship return to

[8] 22% of workers who always work in the paid sector also own businesses in at least one year, but these businesses are run on the side while working for someone else on the main job.

the paid sector within 5 years. Experienced entrepreneurs are substantially more likely to own a business and that business is more likely to be incorporated, which Levine and Rubinstein (2013) find is a good proxy for business sophistication and profits.

However, using business ownership to define entrepreneurship likely understates experimentation in self employment. As shown in Table 2, there is a composition change of business ownership that occurs with experience in self employment both because workers who enter entrepreneurship as business owners are more likely to persist and because some workers who begin without a business establish one several years into self-employment. This ability to "upgrade" into business ownership is a likely consequence of experimenting in self employment without first paying the costs of incorporation.

3.3 Earnings in Paid Work and Entrepreneurship

In the PSID, paid workers are asked about their total labor earnings from wages, salaries, bonuses, commissions, and tips. Most owners of incorporated businesses are also asked about total labor earnings, but owners of unincorporated businesses are instead asked about their net profit from that business. Our first choice for both paid and self-employed workers is to use reported annual labor earnings. For entrepreneurs who do not report labor income but do report profit from a business, reported net profit is used as their labor earnings.

Earnings in entrepreneurship are more variable than earnings in the paid sector. Figure 2 plots the distribution of real weekly earnings in each sector. The distribution of earnings for workers currently in entrepreneurship is flatter than for paid workers, with more weight on the lowest values and a thicker long right tail. Using the Survey of Income and Program Participation, Hamilton (2000) finds that the mean of earnings in entrepreneurship is somewhat higher than the mean in paid work, but the median is lower. We replicate his finding using our PSID sample in Appendix Table A1. Past literature uses estimates at the median to ask why some individuals stay in self-employment even though they appear to earn less than they would earn in paid work. The benchmark non-pecuniary benefit at the median in the static model necessary to rationalize this decision is thus about 3.5% of paid earnings. As will be seen later, the average non-pecuniary benefit estimated from the dynamic model deviates significantly from this figure.

3.4 Learning and Selection In and Out of Entrepreneurship

Figure 1 shows that moves from entrepreneurship back to the paid sector are quite common. Figure 3 illustrates that these transitions back to the paid sector are not random. The top line of this figure plots the experience profile of earnings in entrepreneurship for workers who remain in entrepreneurship for 6 or more years. This profile is strictly above the experience profile of workers who leave within 5 years, which is in turn higher than the earnings in entrepreneurship for workers who leave after one year. Workers who persist longer in entrepreneurship earn more in that sector from their first year. The same pattern holds when we consider entrepreneurial earnings relative to expected earnings in the paid sector. Figure A1 plots the same series of observed earnings in entrepreneurship, now relative to projected counterfactual earnings had these individuals instead worked in the paid sector. The estimates we use to construct these counterfactual earnings are described in Section 6.1.[9] All entrepreneurs earn less in their first year of entrepreneurship than we would expect them to earn had they remained in paid work. Those who remain in entrepreneurship for at least 6 years begin earning more than their counterfactual paid earnings by their second year of entrepreneurship, while individuals who return to the paid sector within 5 years continue to earn less than their projected paid earnings.

This negative correlation between entrepreneurial earnings and the probability of leaving entrepreneurship could be consistent with a learning model or, at the extreme, with a model in which workers know their abilities with certainty but experience large sector-specific taste shocks. A more subtle form of this concern is that workers have better information about their likely entrepreneurial earnings than the econometrician. However, a number of additional stylized facts suggest learning is important. First, the majority of workers in their first year of entrepreneurship earn less than they did in their last year of paid work, suggesting the willingness to take on possible low earnings

[9] These counterfactual earnings are constructed using only parameters from the first stage of estimation, described below. While these estimates are designed to be robust to the kinds of selection we hypothesize, their identification is more general and does not depend on these model assumptions. The figure is also similar when using residual earnings.

for the potential to learn about future opportunities.[10] New entrepreneurs earn $660 less per year at the mean and $5,600 less at the median than their most recent year of paid earnings. The median new entrepreneur earns 15% less than he did in his last year of paid work.

Second, if workers have some understanding of their entrepreneurial abilities even before entering entrepreneurship, then we would also expect workers with high entrepreneurial abilities to be willing to invest more when starting their businesses. The last three columns of Table 3 look at how initial investments in business covary with individual average paid earnings and entrepreneurial earnings. These averages for each sector are essentially individual fixed effects estimated from realized earnings in each sector with an adjustment for sampling variation. Paid and entrepreneurial earnings sare positively correlated, so initial investments should be rising in paid earnings whether or not individuals also have advanced knowledge of their entrepreneurial ability. The ratio of entrepreneurial earnings to paid earnings is thus a better measure of outcomes in entrepreneurship. The third column of Table 3 shows that the ratio of mean entrepreneurial earnings fixed effects to mean paid earnings fixed effects rises slightly with investment amounts given that investment is positive. Individuals who invest between $1 and $5,000 in their business have entrepreneurial fixed effects that are 2% lower than their paid fixed effects, on average, while those investing more than $65,000 have entrepreneurial fixed effects that are 5% higher than their paid ability, on average. However, as shown in the last column, these differences in averages are dwarfed by the standard deviation of this ratio.[11] In addition, if larger initial investments increase the probability of entrepreneurial success or if there is a return to capital investment that is being omitted, then initial investments will be positively correlated with the entrepreneurial earnings fixed effect even if workers do not know this ability in advance. Finally, individuals who make no investment have earnings in entrepreneurship that are about 5% higher than paid earnings, which is about the same ratio as individuals who invest more than $65,000.

Third, the most likely source of unobserved shocks to push individuals back to paid work is

[10] These estimates are based on a restricted sample of 208 individuals because it is necessary to observe earnings in the first year of entrepreneurship and paid earnings within the previous two years without having to drop transition years. These estimates are consistent with the differences between observed entrepreneurial earnings and projected paid earnings, which we can calculate for all new entrepreneurs, plotted in Figure A1.

[11] There are no statistically significant differences found using regression.

shocks to capital availability. These and other time-varying shocks cannot be measured easily, so we may risk attributing exit behavior to learning rather than to unobserved factors. To test for whether entrepreneurial exits hit some constraint on their ability to finance operations or consumption, we look at differences in patterns of exits to paid work by average industry capital intensity. If exits are driven by financing constraints, we would expect to see a higher exit hazard in capital intensive businesses for a fixed level of entrepreneurial earnings. The learning model has a null of no-differences by capital intensity; behavior due to unobserved shocks to capital availability would reject equality of effects by industry. Results from Cox proportional hazards models are presented that begin to assess this conclusion in Table 4. In no model is the high capital intensity dummy found to be statistically different from zero, indicating a common baseline hazard across industries. High capital intensity is also interacted with earnings quartiles and projected earnings differences between entrepreneurial and paid work. In no case are these interactions jointly statistically different from zero, so the null from the learning model cannot be rejected.[12]

Once workers have entered entrepreneurship and observed their earnings in that sector, those with low relative entrepreneurial earnings are far more likely to return to the paid sector. We see much weaker evidence that workers who have not yet worked as entrepreneurs have any advance knowledge of their potential earnings in that sector.

With these stylized facts about the decision to become an entrepreneur, we turn now to a model of behavior that allows us to measure preferences for money and entrepreneurship. The model will be used to measure returns and the option value of experimentation.

4 Model

In each period $t = 0, 1, ..., T_i$, starting after the last year of schooling and continuing to retirement, risk-neutral individual i chooses between supplying labor in the paid sector ($d_{it} = 0$) or the

[12] In addition, unobserved capital constraints do not appear to be the primary cause of exits from entrepreneurship as reported in surveys of business owners. Data from the 2007 Survey of Business Owners (SBO) Public Use Microdata sample suggests that the minority of exits from entrepreneurship are due to capital constraints. Of those who report that their past business no longer operates, 7.9% cite lack of business credit and 4% cite lack of personal credit as the cause of lack of operations. In contrast, 29% of these respondents cite insufficient sales or cash flow, suggesting the business failed to materialize.

entrepreneurial sector ($d_{it} = 1$). Once the sector is chosen, earnings shocks are realized and flow payoffs are received. This assumption means that the individual makes sectoral choices without knowing earnings in advance, and adverse shocks cannot be escaped before their realization. This is consistent with a world in which there is some earnings risk over the course of a period, perhaps from job loss, or where earnings, even in the paid sector, depend partially on bonuses or profit sharing.

Our assumption of risk neutrality is reasonable if workers have some ability to smooth consumption. The option to return to paid work limits individual downside risk from entering entrepreneurship to a few periods. With smoothing, low earnings in entrepreneurship today affect total consumption only through the lifetime budget constraint. As a result, and consistent with the data presented in Hurst et al. (2014), flow consumption changes are likely to be much smaller than the change in flow earnings for those who have low earnings in entrepreneurship. Model complexity and data issues make adding risk aversion difficult for this paper. Adding endogenous savings and consumption decisions greatly complicates the model solution. The PSID includes very limited data on assets, which limits our ability to discipline these choices in the model. The approach taken here does could capture some aspects of risk aversion, among other factors, through heterogeneous non-pecuniary benefits from entrepreneurship and from the utility costs of entering self-employment.[13] Modeling risk aversion directly awaits future work.

The expected flow utility from choosing the paid sector, $d_{it} = 0$, is

$$u\left(d_{it} = 0, S_{it}, \varepsilon_{it}^{0}\right) = \beta_1 E\left[W_{it} | S_{it}\right] + \varepsilon_{it}^{0}, \tag{1}$$

where S_{it} summarizes the individual's employment history, sectoral experience, age, and beliefs about entrepreneurial ability at time t, W_{it} is wage earnings in the paid sector and ε_{it}^{0} is a transitory taste shock for choosing paid work that is unobserved to the econometrician. The parameter β_1 translates earnings into units of utility, scaled relative to the variance of the taste shock. As a normalization, the expected utility of working in the paid sector for a wage of zero is set to $E\left(\varepsilon_{it}^{0}\right)$.

[13] Setting a relatively high real interest rate also means that there is an adjustment for the risk of future earnings

To keep the model simple, we abstract from savings, eliminating intertemporal reasons that wage earnings do not equal consumption.[14] Abstracting from savings is innocuous under risk neutrality.

The expected flow utility from choosing entrepreneurship, $d_{it} = 1$, is

$$u\left(d_{it} = 1, S_{it}, \beta_{0i}, \varepsilon_{it}^{1}\right) = \beta_{0i} + \beta_1 E\left[R_{it}|S_{it}\right] + \beta_2\left(d_{it-1} = 0\right)\tilde{W}_i + \beta_3\left(x_{Rit} = 0\right)\tilde{W}_i + \varepsilon_{it}^{1}. \qquad (2)$$

The components of utility in entrepreneurship include an unobserved taste or opportunity shock, ε_{it}^{1}, utility from expected entrepreneurial earnings, R_{it}, flow utility from working in entrepreneurship, β_{0i}, and costs to entering entrepreneurship that are proportional to baseline wages in paid work, $\tilde{W}_i$. β_{0i} is a random parameter that varies across individuals, but is fixed for each individual over time. Individuals with $\beta_{0i} > 0$ are, all else equal, willing to give up some earnings to remain in self-employment; individuals with $\beta_{0i} < 0$ would need to earn more in self-employment than their projected paid earnings to remain self-employed.

The parameter β_2 captures the utility cost of entering entrepreneurship. Similar to Evans and Jovanovich (1989), who model constraints on borrowing as a function of wealth, we assume that entry costs are proportional to baseline paid earnings ability, $\tilde{W}_i$, which is a proxy for expected lifetime wealth. These reduced-form entry costs may capture many constraints to entering entrepreneurship, including capital investments, effort costs of creating a new venture, the lost earnings associated with changing jobs, or the ex-ante psychological costs of uncertainty about a new enterprise. Some of these costs may be greater for workers entering self-employment for the first time. β_3 captures any additional costs for entrants with no prior entrepreneurial experience, $x_{Rit} = 0$.

We specify a flexible parametric model for earnings in each sector. If the agent is employed in the paid sector, his earnings depend on his accumulated work experience in the paid sector, x_{Wit}, and in entrepreneurship, x_{Rit}, along with fixed individual earnings ability in the paid sector, α_i, a

[14]We also abstract from taxes. Measuring effective taxes for business owners is difficult in the PSID; however, this issue is unlikely to have a major effect on the estimates. The parameter β_1 is identified based on within-individual differences in expected earnings across sectors, up to scale. To the extent that differences in earnings across sectors do not cause drastic changes in the tax rate, interpreting the scale of β_1 becomes difficult but there are no spillover effects for the other parameters. Finally, note that the effective tax rate for most small business owners is very similar to individual income taxes; many small business are taxed as pass-through entities, equalizing tax schedules across paid work and self-employment. Businesses set up as C corporations will face a different tax schedule on any earnings that are not distributed as salary; these earnings are subject to the corporate tax rate, and distributions are subject to sharehold taxes.

transitory shock M_t, and a log AR(1) persistent shock, $P_t = P_{t-1}^{\phi}\zeta_t$. Paid earnings are given by

$$W_{it} = \exp\left(\alpha_i + G_W\left(x_{Wit}, x_{Rit}\right)\right) P_{it} M_{it}. \tag{3}$$

The shocks ζ_{it} and M_{it} are distributed log-normally, with $\ln \zeta_{it} \sim N\left(0, \sigma_\zeta^2\right)$ and $\ln M_{it} \sim N\left(0, \sigma_M^2\right)$. Individual log earnings ability is also drawn from a normal distribution, $\alpha_i \sim N\left(\mu_\alpha, \sigma_\alpha^2\right)$, and we assume that individuals know this ability with certainty at the time they enter the model. While this assumption implies an asymmetry in information between sectors, it can be reframed as an assumption that workers have had sufficient informal work experience prior to entering the paid sector to deduce their ability with very little uncertainty.[15]

Expected earnings in the paid sector in period t are therefore

$$E\left[W_{it}|S_{it}\right] = \exp\left[\alpha_i + G_W\left(x_{Wit}, x_{Rit}\right) + \phi \log\left(P_{it-1}\right) + \frac{\sigma_\zeta^2 + \sigma_M^2}{2}\right] \tag{4}$$

where $\frac{\sigma_\zeta^2+\sigma_M^2}{2}$ is the convexity adjustment from the first moment of the log normal distribution. The state variables necessary to calculate this expectation are lagged years of experience in the paid sector and entrepreneurship, α_i, and the lagged value of the persistent shock.

We assume that P_{it} continues to depreciate during periods when agents work in self-employment, but does not experience any new innovations. The persistent shock in the paid sector therefore influences moves in and out of entrepreneurship as agents with low P_{it} will find self-employment temporarily more attractive.

Earnings for entrepreneurs are described by

$$R_{it} = \exp\left[\eta_i + G_R\left(x_{Wit}, x_{Rit}\right)\right]\xi_{it}, \tag{5}$$

where ξ_{it} is a log-normally distributed transitory shock, $\ln\left(\xi_{it}\right) \sim N\left(0, \sigma_\xi^2\right)$ and $\eta_i \sim N\left(\mu_\eta, \sigma_\eta^2\right)$ is log entrepreneurial ability. Expected earnings in self-employment differ from earnings in paid work in several respects. Most importantly, while agents are assumed to know α_i with certainty,

[15] Workers may also estimate paid earnings ability quite accurately upon receiving job offers.

they know only the distribution of η_i given their paid ability but not their own endowment of entrepreneurial ability. Initial belief about η_i are based on α_i, but entrepreneurial experience is necessary to refine beliefs about η_i. Those who enter entrepreneurship then update this belief based on their observed earnings in that sector. In addition, earnings in entrepreneurship depend on only a transitory shock, with no persistent stochastic element. This assumption is partially practical; a persistent shock would substantially complicate the process by which agents update their beliefs about η_i. We also interpret the persistent shock in the paid sector as capturing employment shocks, which are less relevant in self-employment. Finally, accumulated experience affects earnings in each sector differently, through the function $G_R(\cdot)$ rather than $G_W(\cdot)$.

To reiterate, expected earnings in entrepreneurship depend on the beliefs about entrepreneurial ability. For individuals with no entrepreneurial experience, their prior belief is based on α_i. To pin down this relationship, α_i and η_i are assumed to have a bivariate normal distribution with correlation ρ; this form fits the data well and provides a tractable way to calculate the conditional distribution of η_i given α_i. This conditional prior is thus normally distributed with mean

$$\hat{\eta}_{i0} = \mu_\eta + \frac{\sigma_\eta}{\sigma_\alpha}\rho\left(\alpha_i - \mu_\alpha\right) \tag{6}$$

and variance $\sigma^2_{\eta 0} = \sigma^2_\eta\left(1-\rho^2\right)$. For individuals with x_{Rit} years of entrepreneurial experience, the mean belief is denoted $\hat{\eta}_{ix}$ and is updated according to Bayes' rule. This yields

$$\hat{\eta}_{ix} = \frac{\sigma^2_\xi \hat{\eta}_{i0} + x_{Rit}\sigma^2_{\eta 0}\overline{\log\left(\tilde{R}_{it-1}\right)}}{x_{Rit}\sigma^2_{\eta 0} + \sigma^2_\xi} \tag{7}$$

where $\overline{\log\left(\tilde{R}_{it-1}\right)}$ is the mean of the residual log earnings history in entrepreneurship from experience levels 0 through x_{Rit-1}, net of the experience profile in entrepreneurship, $G_R(\cdot)$. The variance of the prior distribution is updated in a deterministic fashion in each period. For $x_{Rit} > 0$, the variance of the prior is $\sigma^2_{\hat{\eta}_{ix}} = \frac{\sigma^2_{\eta 0}\times\sigma^2_\xi}{x_{Rit}\sigma^2_{\eta 0}+\sigma^2_\xi}$, which declines with experience in entrepreneurship.

The risk-neutral agents in this problem care about the level of earnings. Expected earnings in entrepreneurship are given by

$$E\left(R_{it}\right)=\exp\left[\hat{\eta}_{ix}+G_R\left(x_{Wit},x_{Rit}\right)+\frac{\sigma^2_{\hat{\eta}_{ix}}+\sigma^2_{\xi}}{2}\right]. \tag{8}$$

As is clear from Equation 8, the expected flow value of entrepreneurial earnings is increasing in $\sigma^2_{\hat{\eta}_{ix}}$. Holding fixed $\hat{\eta}$, expected entrepreneurial earnings change in two ways as workers accumulate entrepreneurial experience. Experienced entrepreneurs are more certain about their skills, which lowers $\sigma^2_{\hat{\eta}_{ix}}$ and therefore expected earnings. However, more experience raises expected earnings through $G_R\left(x_{Wit},x_{Rit}\right)$. Person i chooses to work in the sector that maximizes the present value of expected utility,

$$V_{it}\left(S_{it},\beta_{0i},\varepsilon_{it}\right)=\max_{d_i}E\left[\sum_{\tau=t}^{T_i}\delta^{\tau-t}u\left(d_{i\tau},S_{i\tau},\beta_{0i},\varepsilon_{i\tau}\right)|S_{it}\right], \tag{9}$$

where δ is the discount rate and d_i is the state-contingent sequence of choices made by the individual.

5 Model Solution and Estimation

The previous section describes a dynamic discrete choice model with unobserved heterogeneity in the taste parameter β_{0i}. Non-parametric point identification of β_{0i} (up to the other parametric assumptions imposed on the model) is not possible for the majority of workers who never take up entrepreneurship. We can bound the preferences of these workers from above by identifying the largest β_{0i} consistent with choosing the paid sector in all observed periods, but any preference below this threshold is equally consistent with the data. Because of that, we impose the distributional assumption that $\beta_{0i}\sim N\left(\mu_{\beta_0},\sigma^2_{\beta_0}\right)$. This added discipline rules out thick tails in the preference distribution but allows flexibility through $\sigma^2_{\beta_0}$.

To estimate the model we must first define the expected value to workers of choosing to work in each sector. Because choices today affect future payoffs, the alternative-specific, or conditional, value functions include a flow-utility term and a continuation value. These conditional value functions describe the present value of the agents' problem at time t conditional on choosing sector d_t

and then following an optimal strategy in the future. Omitting i subscripts to conserve notation except to make clear heterogeneity in parameters, the lifetime maximization problem in equation (9) can be rewritten as a sequence of single-period decisions using the Bellman equation,

$$V(S_t, \beta_{0i}, \varepsilon_t) = \max_{d_t \in \{0,1\}} \{u(d_t, S_t, \beta_{0i}, \varepsilon_t) + \delta E[V(S_{t+1}, \beta_{0i}, \varepsilon_{t+1}) \mid d_t, S_t, \beta_{0i}]\}. \tag{10}$$

The value of arriving at time t with state variables S_t, preferences β_{0i}, and shocks ε_t is the maximum of the conditional value functions. Recall that ε_t is a vector of sector-specific taste shocks that are iid across sectors and over time from distribution $g(\varepsilon_t)$. Define $f(S_{t+1}|S_t, d_t; \theta)$ as the transition density function describing the evolution of the observed state variables, parameterized by θ. If β_{0i} is known, the conditional value function is therefore

$$\begin{aligned} v(d_t, S_t, \beta_{0i}, \varepsilon_t; \beta) &= u(d_t, S_t, \beta_{0i}, \varepsilon_t; \beta) + \delta E[V(S_{t+1}, \beta_{0i}, \varepsilon_{t+1}) | d_t, S_t, \beta_{0i}] \qquad (11) \\ &= u(d_t, S_t, \beta_{0i}, \varepsilon_t; \beta) + \delta \iint V(S_{t+1}, \beta_{0i}, \varepsilon_{t+1})\, dg(\varepsilon_{t+1})\, df(S_{t+1}|S_t, d_t; \theta). \end{aligned}$$

The flow utilities from choosing each sector, described in equations (1) and (2), depend on the common parameters β and the heterogeneously distributed parameter β_{0i}.

The probability of observing $d_t = j$, where $j \in \{0, 1\}$ indexes labor sector choice, is given by integrating over the unobserved taste shocks ε_t

$$p_t(d_t = j \mid S_t, \beta_{0i}; \beta) = \int I\left\{\arg\max_{d_t \in \{0,1\}} v(d_t, S_t, \beta_{0i}, \varepsilon_t; \beta) = d_j\right\} dg(\varepsilon_t). \tag{12}$$

The individual's likelihood contribution at time t is therefore

$$\mathcal{L}_t(d_t, S_{t+1}|S_t, \beta_{0i}; \theta, \beta) = p_t(d_t|S_t, \beta_{0i}; \beta)\, f(S_{t+1}|d_t, S_t; \theta). \tag{13}$$

However, since the individual's fixed preferences are also unobserved we instead use the marginal likelihood of workers' choices by integrating over the distribution of β_{0i}. Using this approach to recover parameters, we solve

$$\left(\hat{\theta}, \hat{\beta}, \hat{\mu}_{\beta_0}, \hat{\sigma}^2_{\beta_0}\right) = \underset{\theta,\beta,\mu_{\beta_0},\sigma^2_{\beta_0}}{\arg\max} \sum_{i=1}^{N} \log \left[\int \prod_{t=1}^{T_i} \mathcal{L}_t \left(d_{it}, S_{it+1} \mid S_{it}, \beta_{i0}; \beta, \theta\right) d\phi \left(\frac{\beta_{0i} - \mu_{\beta_0}}{\sigma_{\beta_0}}\right)\right]. \quad (14)$$

The parameters to be estimated are $\hat{\theta}$, which describe the determinants of earnings and the transitions of the observed state variables, $\hat{\beta}$, the parameters of the flow utility functions, and $\mu_{\beta_0}, \sigma^2_{\beta_0}$, the parameters of the distribution of non-pecuniary benefits in entrepreneurship. From equation (11), the likelihood for individual i at time t depends on the continuation value of each choice, so each calculation of the likelihood involves solving the full lifecycle model. Estimating some parameters in a first step eases the computational burden by minimizing the number of parameters that must be estimated within the full solution.

Further detail about the first and second stage of estimation is contained in B.

6 Estimates

6.1 Determinants of Earnings

The estimates from the first stage are presented in Table 5. Earnings in the paid sector rise by 5% on average with the first year of paid experience and 42% with ten years of experience. Accumulated paid experience is also associated with higher earnings in self-employment. A worker who accumulated ten years of paid experience before entering self-employment earns 20% more on average in self-employment than a worker who entered with no paid experience. Entrepreneurial earnings also rise with entrepreneurial experience, but not as rapidly as paid earnings rise with paid experience. Entrepreneurs with ten years of self-employment experience earn 23% more than new entrepreneurs on average.

The next panel of Table 5 describes the distributions of individual fixed effects for log earnings in each sector. The mean earnings in entrepreneurship is slightly lower than mean paid earnings. The average worker with no experience would earn 1.8% less in entrepreneurship than in paid work, a loss of about $600 if he worked all year. Workers who have worked in the paid sector will face larger average drops in earnings upon entering entrepreneurship because of the smaller returns to paid experience.

Ability in entrepreneurship has more than twice the variance of ability in the paid sector, 0.63 compared to 0.19. Abilities in the two sectors are strongly correlated, with $\rho = 0.7$, so the variance of a worker's belief about his own entrepreneurial ability is smaller than the population variance. With no experience in entrepreneurship, the variance of an individual's belief of his entrepreneurial ability is $\sigma_\eta^2 \left(1 - \rho^2\right) = 0.32$. This means that taking the standard-deviation around the mean forecast of entrepreneurial ability changes earnings by about 56%.

The relative variance of entrepreneurial ability and the transitory shock to entrepreneurial earnings, the last panel of Table 5, imply that this uncertainty dissipates quickly as workers gain entrepreneurial experience. The variance of a worker's belief about his ability falls to 0.07 after observing one year of entrepreneurial earnings and 0.02 after five years. This correlation and the remaining variation indicate that workers may predict their average entrepreneurial earnings based on paid earnings, but there is significant variation around that prediction, creating the basis for learning about entrepreneurial earnings.

The bottom two panels of Table 5 present the stochastic parameter estimates from the first stage. We estimate that 83% of the persistent shock in the paid sector remains after a year. The transitory shock to earnings in entrepreneurship is larger than the combined shocks in the paid sector, but the main reason workers face more uncertainty about entrepreneurial earnings is the variance of permanent ability, η.

6.2 Determinants of Utility

This section discusses the flow payoff parameters estimated in the second stage, which makes use of the parameters described in 6.1. Recall that these parameter estimates come from maximizing the probability of choices that individuals make. Table 2 presents some data on these choices and the transitions between sectors that identify parameters. Notice in particular that entering entrepreneurship from paid work is somewhat rare, yet the average difference in flow pay is only $600 between sectors. If earnings from entrepreneurship with the option value make it look like an attractive choice, then the model will fit the low observed entry rate into entrepreneurship through the startup/entry costs into entrepreneurship, the distribution of non-pecuniary benefits, or the scaling of money relative to the taste shock.

Table 6 presents the flow payoff parameters estimated in the second stage of estimation. The first column presents estimates from our baseline model with heterogeneous tastes for entrepreneurship, while the second presents the estimates that result from shutting down any preference heterogeneity. The scale of utility is normalized by the Type-1 extreme value taste shocks, which have a standard deviation of $\frac{\pi}{\sqrt{6}}$. The parameter estimates in the top panel are therefore not easily interpretable. The second panel provides transformations of these parameters into 2010 dollars equivalents, using the coefficient on earnings in the flow utility function, β_1.

The model allows the cost of entering entrepreneurship to differ for repeat entrepreneurs and workers entering entrepreneurship for the first time. In our baseline model, returning entrepreneurs face a utility cost of entering self-employment equivalent to a one-time payment of about \$455,000. First-time entrepreneurs pay an additional \$56,000, for a total entry cost of just over \$500,000. These entry costs appear large in monetary terms, which is underscored by comparing these estimates to the figures in Table 3. This comparison makes clear that the estimated utility entry costs must capture far more than the direct financial investments in new businesses. While entering entrepreneurship will involve additional financial costs in terms of foregone earnings during the transition, these utility costs are likely to capture the stress and pressure of developing a new business, a low arrival rate of business ideas, and, since we do not explicitly model risk-aversion, a distaste for the large initial uncertainty about entrepreneurial earnings ability. Because we do not model any costs of returning to paid work, these estimated entry costs will also capture the risk of incurring a second set of transition costs if self-employment proves unfruitful.[16]

We estimate wide variation in tastes for entrepreneurship. The mean worker would accept \$94,400 less in annual paid earnings to avoid working as an entrepreneur, more than average annual earnings in either sector. This estimate, along with high entry costs, is driven by the large share

[16]We rely on exits from entrepreneurship to identify the distribution of tastes for entrepreneurship. We cannot identify these tastes and a separate exit cost. A potential modeling alternative is to enforce equal transition costs for entering and exiting entrepreneurship, which does a poor job of fitting the data, or to omit exit costs altogether.

of workers who never enter self-employment despite substantial potential gains to experimentation. However, the standard deviation of preferences is equally large; many workers have a far smaller distaste for entrepreneurship and 15% of workers derive a positive flow utility from working for themselves. The transitory taste shocks are also fairly large, with a standard deviation of $125,000. These shocks perturb the expected lifetime value of choosing to work in each sector, including the discounted lifetime earnings stream. This standard deviation represents 9% of the average expected value of choosing paid work.

When we shut down this preference heterogeneity, the most conspicuous change is a far smaller distaste for entrepreneurship, $1,600 per year rather than $94,400. Most individuals who persist in self-employment earn only modestly more as entrepreneurs than they would in paid work. When all workers are constrained to have the same preferences, this pattern pushes the disutility from working in entrepreneurship towards zero. The other changes in the second column stem from this key difference. When all workers are roughly indifferent between paid work and self-employment, smaller taste shocks are sufficient to prompt a return to paid work, so the estimated standard deviation of the taste shock falls. In turn, the smaller taste shocks reduce the entry barrier necessary to prevent most workers from ever entering self-employment, so the estimated entry costs also fall slightly. As shown in section 6.3, this simpler model cannot predict movements between sectors as well as the full model with heterogeneity.

The last panel of Table 6 presents the average means and standard deviations of the posterior preference distributions, in dollar equivalents, separately for workers who we ever observe in entrepreneurship and those workers who we only observe choosing paid work. These posterior distributions have the interpretation of being the Bayesian posterior distribution of β_{0i} for each person in the sample given their likelihood of choices. The appendix provides details about this calculation.

There is a sharp divide between the posterior distributions for those who enter entrepreneurship and those who do not. For workers who enter entrepreneurship, the average mean of the posterior distributions is positive: $950 per year. Our estimates are consistent with earlier studies, surveyed in Åstebro et al. (2014), that estimate positive tastes for entrepreneurship among workers who choose to work in that sector. In contrast, much of the rest of the population appears to have a strong distaste for entrepreneurship. Those who never enter entrepreneurship have posterior preference distributions centered around a mean of -$117,000.

The posterior preference distributions for all workers have smaller standard deviations than the population distribution, reflecting the added information from observed choices. This contraction is far more pronounced for workers observed in entrepreneurship, who have an average posterior standard deviation of $41,000, than for the never entrepreneurs, with an avererage of $78,000. Entrepreneurs' tastes for entrepreneurship are identified off both their initial decision to enter self-employment and their annual decisions to persist in self-employment or return to paid work, allowing for narrow posterior distributions. In contrast, preferences for never entrepreneurs can only be bounded above: they must dislike entrepreneurship at least enough to have never entered.

6.3 Model Fit

Unobserved heterogeneity and taste shocks play important roles in determining sector choices at the individual level, particularly moves into entrepreneurship. We now assess the ability of the full model to predict which workers will select into each sector and compare that performance with two simpler models. Table 7 presents the average model-predicted probability of choosing entrepreneurship, separately for workers who worked in each sector last year and who we observe choosing each sector this year.

Within each cell, the first row shows the prediction of a dynamic model where workers are forward-looking income maximizers who have no preferences for either sector and face no entry costs. Expected lifetime earnings are projected imposing sector choice this year and then assuming workers make the lifetime income-maximizing choice in all future periods.[17] Income maximization predicts some of the observed variation in sector choice; among workers who were in the paid sector last year, 51% of workers who choose entrepreneurship this year have higher projected lifetime earnings from that choice, compared to only 37% of workers who remain in paid work. For workers who were entrepreneurs last year, 74% of workers who continue in entrepreneurship have higher

[17]With no entry costs, workers have an incentive to enter self-employment to "wait out" any negative persistent shocks to paid earnings. To prevent frequent moves between sectors, in this exercise we impose that workers who leave self-employment for paid work cannot return for a second entrepreneurial spell.

projected earnings from that choice, compared to 51% of workers who return to the paid sector. While income maximization correctly predicts that those workers who choose entrepreneurship are more likely to do so, it predicts far too much entrepreneurship overall. Overall, the income-maximizing model predicts that 35% of paid workers will choose to become entrepreneurs next year when only 2% do.

The next row in each cell presents the choice probabilities predicted by our utility-maximizing model with no heterogeneity in preferences. We construct these predictions using the parameters reported in the second column of Table 6. Under this model, high entry costs push down the share of paid workers who are predicted to move into entrepreneurship, but they do so for everyone. Workers who choose to move from the paid sector to entrepreneurship this period have only a 3.7% predicted probability of doing so, not much higher than the 2.4% average predicted probability for those workers who remain in the paid sector.

The final row of each cell presents the predicted likelihood of selecting entrepreneurship using the estimates of the full model and the individual posterior preference distributions described in the previous section. These estimates incorporate differences in observed characteristics across workers and also differences in unobserved tastes, as revealed by workers' history of choices. We use each individual's full sequence of sector choices to estimate their posterior preference distributions, so the predicted likelihood of choosing entrepreneurship in year t is partially determined by the observed future choices of each worker. This row should therefore not be interpreted as a test of ex ante predictive power, but rather as a measure of how well the key features of our fairly simple model, time-invariant individual tastes for entrepreneurship and time-varying earnings shocks and beliefs about entrepreneurial ability, can match observed choices. Incorporating these predicted individual tastes improves the model's predictive power considerably. We estimate that workers who move into entrepreneurship are more than five times more likely to make that choice than workers who remain in paid jobs. Workers who exit back into paid work are also substantially more likely to make that choice than workers who remain in entrepreneurship.

Overall, these comparisons yield four key insights. First, entry costs are essential to quantitatively match the flow of workers into entrepreneurship. Second, preference heterogeneity is essential to understand who enters entrepreneurship. The first two rows, which use only observable worker characteristics, do a relatively poor of separating those who select entrepreneurship from those who do not compared to the model with heterogeneity. This finding is consistent with Levine and Rubinstein (2013), who find that entrepreneurs look similar to paid workers in terms of education, aptitude, and family background.[18] Third, these utility components are far less important for understanding who leaves self-employment. The income-maximizing model does nearly as good a job as our full model in predicting which entrepreneurs will return to paid work each year. Finally, even our best model does a poor job predicting the exact timing of individual transitions. We predict that workers who move from paid work to entrepreneurship had a 12% chance of doing so that year, far higher than the 2% chance assigned to workers who remain, but well below 100%. Workers who return to paid work had a 33% predicted probability of doing so. These remaining prediction errors suggest an important residual role for time-varying shocks. We characterize these iid shocks as taste shocks in our model, but they may also capture other time-varying unobserved states. For example, they may represent the arrival of an innovative idea or access to capital on the entry margin, or bankruptcy or other business destruction on the exit margin.

The model does a particularly good job of matching the aggregate rate of transitions in and out of entrepreneurship over the lifecycle. Figure 4 plots the probability of moving from the paid sector into entrepreneurship by age. The data series plots the share of paid workers with no entrepreneurial experience who choose to enter self-employment at each age, while the model series plots the average predicted likelihood of selecting entrepreneurship for these workers using the posterior taste distributions. The predicted likelihoods match the broad pattern of the data: entry rates are higher for younger workers, averaging over 2% for workers in their 20s, and fall as workers age, to an average of close to 1% for workers over 45. The fall in entry rates later in life reflects two factors. First, paid experience increases earnings in the paid sector more than it increases earnings in entrepreneurship, so more experienced workers are less likely to improve their earnings by entering entrepreneurship. Second, the option value of learning one's entrepreneurial ability is highest for younger workers, who have more remaining working years to make use of that information. In the

[18] They find that non-cognitive measures have some additional predictive power to identify future entrepreneurs. Those traits will be part of what we capture in our individual tastes for entrepreneurship.

data, the probability of becoming self-employed rises through the early 20s, peaking at 2.6% at age 27, while the median age of those observed in entrepreneurship is 32. The model predicts that the youngest workers are most likely to move to entrepreneurship.

Figure 5 plots the probability of returning to the paid sector by years in self-employment, again comparing predicted probabilities using posterior preference distributions to observed patterns. In our model, as in the data, the hazard rate of leaving entrepreneurship falls sharply with entrepreneurial experience. This decline reflects the sharp fall in uncertainty about entrepreneurial ability. 23% of workers leave entrepreneurship after 1 year, while only 14% of workers who remain after five years exit the following year. The exit rates predicted by our model closely follow the empirical hazard rates.

7 Decomposing the Value of Entering Entrepreneurship

7.1 Selection into Entrepreneurship

Cross-sectional differences in earnings across sectors, that is comparisons of average earnings for workers observed in each sector, are a poor predictor of individual expected gains to entering entrepreneurship for two reasons. First, these cross-sectional differences are biased estimates of expected static earnings because of selection. Second, because of the option value of experimentation, even unbiased estimates of the single-period earnings in each sector will misstate the expected lifetime value of entering entrepreneurship.

The first two panels of Table 8 quantifies the selection bias. The set of workers currently in entrepreneurship overweights workers with high relative entrepreneurial earnings because those workers are most likely to persist in entrepreneurship. The first panel of this table displays observed earnings for 32 year olds who worked in each sector. We focus on this one age group to eliminate the effect of different average ages across sectors and to simplify the interpretation when we move to forward-looking projections. 32 is the median age for workers entering self-employment for the first time. Consistent with Table 1, and earlier research, workers in entrepreneurship earn more at the mean and less at the median.

The next panel of this table summarizes projected current-year earnings in each sector for all 32 year olds in the sample, based on the parameter estimates in Table 5. In the first panel, workers contribute to only one column each: entrepreneurs are included in the entrepreneurial average and paid workers in the paid average. In this second panel, all 32 year olds contribute to both averages. The difference between these first two panels quantifies the selection bias in cross-sectional earnings. The mean annual entrepreneurial earnings for current entrepreneurs is $63,700, $5,700 higher than the mean expected earnings in entrepreneurship across all workers. This gap indicates considerable positive selection in the entrepreneur sample. 32 year old entrepreneurs earn 12% more than 32 year old paid workers at the mean, but the average 32 year old would expect to earn only $777 more in entrepreneurship, 1.4% of average paid earnings. The selection bias is smaller and of the opposite sign at the median. The small but important oversample of super-star entrepreneurs distorts the mean upwards in the first panel, but initial entry into self-employment is slightly negatively selected, bringing down the median.[19] The median entrepreneur earns $4,900 less than the median paid worker, but if all 32 year olds were self-employed median earnings would be only $2,200 lower than if all 32 year olds worked for others.

7.2 The Option Value of Experimentation

Both of these first two panels describe a single year of earnings. We now consider the importance of incorporating projected earnings in future years. The last two panels of Table 8 describe expected discounted lifetime earnings, conditional on choosing each sector today. To make these numbers comparable to one-year earnings we convert the discounted sum of lifetime earnings to annual equivalents: the constant annual earnings that would generate the same discounted lifetime earnings as our estimates.

The third panel describes expected lifetime earnings in a static model where workers must remain in one sector for all future periods. Because earnings in both sectors rise with experience, these annualized projected lifetime earnings are all higher than the single-year projections in the second

[19] Initial entry into self-employment is U-shaped in paid earnings ability; very low earners are the most likely to enter, followed by very high earners, with middling earners entering at the lowest rate.

panel. The increase between the second and third panels is larger for entrepreneurial earnings than for paid because of the patterns of accumulated sector experience among 32 year olds and the concavity of returns to experience. Most of these workers have accumulated close to a decade of paid experience, so their current earnings in the paid sector reflect that experience and their projected future earnings incorporate only modest gains to additional experience. Few workers have any entrepreneurial experience, so the one-year projected earnings in entrepreneurship are lower, but the lifetime projections anticipate sharp earnings growth over the first several years in that sector.

The last panel of Table 8 describes projected lifetime earnings imposing sector choice today and then assuming workers choose the sector that maximizes expected utility in all future years as described by our full model and using the posterior estimates of individual tastes. The difference between this panel and the one above it measures the option value of entering entrepreneurship. At both the mean and the median, 32 year olds expect to earn $2,500 more per year by entering entrepreneurship with the option to return to the paid sector than by working as an entrepreneur in all future years. This option value makes mean lifetime earnings from choosing entrepreneurship next year 7.5% higher than mean lifetime earnings from choosing paid work, rather than 4.1% in the static model. The option value also makes entrepreneurship more attractive at the median rather than less.

Comparing the top panel of Table 8 to the bottom panel, we see that simple cross-sectional comparisons of average earnings across sectors do a reasonably good job of characterizing the expected returns to entering entrepreneurship at the mean, but a poor job of characterizing returns at the median. Selection bias overwhelms the omission of the option value at the mean; the simple cross-sectional comparison suggests that workers can expect to earn 12% more at the mean while the full model implies a gain of only 7.5% at the mean. The reverse is true for the median worker. According to the cross-sectional estimates, the median worker should expect to lose 9.4% of his earnings if he enters entrepreneurship, while the full model predicts a 1.6% gain.

7.3 Heterogeneity in the Option Value

The averages presented in Table 8 mask considerable heterogeneity in expected earnings in each sector, expected gains from entering entrepreneurship, and the expected value of the option to return to paid work. The largest determinant of individual expected gains is past entrepreneurial experience. Workers who have never been entrepreneurs have considerable uncertainty about their entrepreneurial ability. Their expected gains from entering entrepreneurship are positive and narrowly distributed. The main expected benefit from entering entrepreneurship is experimentation to learn whether they can earn even more working for themselves. Once workers have entered entrepreneurship, that uncertainty resolves and the anticipated gains from entrepreneurship become more dispersed. Workers now know with confidence whether they can earn substantially more in entrepreneurship, substantially less, or about the same.

Figure 6 illustrates these patterns by plotting the difference between the static and dynamic expected lifetime returns to entering entrepreneurship, separately for 32 year old workers with and without entrepreneurial experience. For workers without entrepreneurial experience, this difference captures the expected value of experimentation. Under the joint distribution of worker fixed effects estimated in Section 6.1, these workers' expected earnings in entrepreneurship are centered close to their current earnings in paid work. The option value captures the benefit of being able to bound potential losses from entering self-employment, by exiting, while retaining the potential gains. On average, this option to return to paid work increases the annualized value of lifetime earnings from entering entrepreneurship by $2,300 per year for 32 year olds without entrepreneurial experience, which translates into about 4.2% of their expected lifetime earnings if they remain in the paid sector.

Experienced entrepreneurs have already discovered whether they earn more or less in self-employment relative to paid work. Workers with high realized entrepreneurial earnings know they will benefit by remaining in self-employment. The option to return to paid work is not valuable for them because they have no intention of exercising it. In fact, their expected earnings in the full dynamic model may be lower than the static model, because in the dynamic model taste shocks may push them back to paid work despite higher earnings in self-employment. These workers fill in the left tail of the distribution of the option value for experienced entrepreneurs. In contrast, workers who have discovered that they earn less in self-employment have much higher expected lifetime earnings in the dynamic model relative to the static model. The option to return to paid work is no longer just a potentially valuable contingency plan; it is the clear income-maximizing path. These workers are in the right tail of those with experience in entrepreneurship.

So far we have focused entirely on the value of entrepreneurship for 32 year olds. The qualitative patterns we find at this one age hold for all other ages, but there are some subtle differences over the lifecycle. The earlier workers learn about their entrepreneurial ability, the longer they will be able to spend in their identified higher-earning sector. Therefore, experimentation is most valuable, in terms of total lifetime earnings, for the youngest workers. Balancing this option value is the expected loss in earnings from foregoing some of the returns to one's accumulated paid experience. Once workers enter self-employment they will begin climbing the experience profile in that sector, but older workers will have to work for many years before they can confidently expect to earn as much in self-employment as they did as experienced paid workers. Both of these patterns cause the expected earnings gains from entering entrepreneurship to fall with age. This decline explains why, in both the data and our simulations, entrances into self-employment are more common for younger workers.

8 Conclusion

Observed earnings for entrepreneurs are higher than earnings for paid workers at the mean, but lower at the median. In our Panel Study of Income Dynamics sample, the median 32 year old entrepreneur earns 9% less than the median 32 year old paid worker. Self-employment requires ingenuity, self-discipline, and a wide range of skills. It also involves more income volatility than paid work. For all these reasons, we would expect earnings to be higher in entrepreneurship at both the mean and the median in order to rationalize selection in. These puzzlingly low median earnings have inspired a large literature that seeks to explain why workers would enter self-employment when so many entrepreneurs earn so little. We find that uncertainty about entrepreneurial earnings ability can reconcile entry rates with observed earnings distributions.

We lay out a model where workers have heterogeneous earnings abilities in self-employment. Workers are initially uncertain about their potential earnings, but can learn about them by entering self-employment and observing how well they fare. If they discover that they cannot earn as much as an entrepreneur as they could working for someone else, they have the option to return to paid work. We document that the patterns of movements in and out of self-employment in the PSID are consistent with this kind of initial uncertainty, experimentation, and strategic returns to paid work. We then estimate a lifecycle model of labor sector choice that incorporates learning about earnings abilities and dynamic re-optimization.

We estimate that workers face substantial ex ante uncertainty about the potential earnings in self employment. Workers who have never worked as an entrepreneur have a standard deviation of expected entrepreneurial earnings of 56%, or $33,000 per year on average. This uncertainty makes experimenting with entrepreneurship attractive; workers may find they earn much more working for themselves, but are cushioned from the symmetric downside risk by the option to return to paid work. In fact, we estimate that, for young workers, the expected lifetime earnings from entering self-employment are 7.5% at the mean and 1.6% higher at the median than the expected lifetime earnings from remaining in paid work. The option to return to paid work drives these returns. If workers were forced to remain in self-employment for all future years, they would expect to earn 2% less at the median than what they would earn in paid work.

Earlier studies, see Åstebro and Thompson (2011) for a review, have hypothesized that workers experience non-pecuniary benefits from working for themselves, which is one way to explain low median entrepreneurial earnings. We identify a more nuanced role for tastes for entrepreneurship. We allow for heterogeneous tastes for entrepreneurship and estimate wide dispersion. Because dynamic experimentation makes entering entrepreneurship more attractive than remaining in paid work, we estimate that the average worker must dislike working for himself in order to rationalize low entry rates to self-employment. However, the variance around this mean is large enough to span positive and negative values. In particular, the average worker who we observe entering self-employment has an ex post positive estimated taste for entrepreneurship. These heterogeneous preferences play an important role in matching the behavior of both those who enter entrepreneurship and those who do not.

If workers are initially uncertain about their entrepreneurial earnings ability, than programs that facilitate resolving this uncertainty should improve the allocation of workers across sectors. Lerner and Malmendier (2011) find that Harvard Business School graduates who interacted with more former entrepreneurs during school were less likely to become entrepreneurs themselves, but more likely to succeed if they did so. Gottlieb et al. (2016) find that a Canadian reform that lowered the cost of returning to paid work after a temporary absence encouraged more workers to enter self-employment. Both of these findings suggest that helping people learn about their potential earnings in entrepreneurship, either by learning from other's experiences in self-employment or by experimenting themselves, can improve the efficiency of sorting workers across sectors. However, our estimates suggest that preferences may dillute this sorting by ability. Many workers have strong tastes for either paid work or self employment. These non-pecuniary considerations may dominate any modest differences in potential earnings.

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Table 1: Summary Statistics for Men in the PSID

	Never Entrepreneurs	Sometime Entrepreneurs
Number of individuals	5,287	1,550
Years spent in paid work	17.3	11.0
Years spent in entrepreneurship	0.0	8.8
Ever own a business	0.21	0.82
White	0.79	0.88
Black	0.12	0.05
Hispanic	0.07	0.05
Other race	0.02	0.01
Less than HS diploma	0.08	0.08
High school diploma	0.33	0.28
Some college	0.31	0.32
College graduate	0.19	0.20
Graduate degree	0.08	0.11

Source: PSID 1976-2011. Averages use sampling weights. Years spent in each sector is as of last/most recent survey wave.

Table 2: Transitions between Sectors and Incorporation Status

	Paid	Entrepreneurs		
		No Business	Unincorporated	Incorporated
Paid sector	97.7	1.2	0.8	0.3
Entrepreneurs, no business	17.8	39.0	29.5	13.7
Entrepreneurs, unincorporated	10.0	9.5	71.3	9.2
Entrepreneurs, incorporated	4.9	5.6	9.8	79.7

Source: PSID 1976-2011. Annual transition probabilities in an out of entrepreneurship and across business ownership and incorporation status, estimated with sampling weights.

Table 3: Initial Capital Investments for New Businesses

Distribution of investments	Share of observations	Mean Paid Fixed Effect, α	Mean Entrep. Fixed Effect $/\alpha$	Std. dev. of Ent. Effect $/\alpha$
No investment	32%	6.60	1.04	0.10
\$1-5,500	18%	6.35	0.98	0.07
\$5,501-25,000	25%	6.59	1.01	0.09
\$25,001-65,000	16%	6.65	1.02	0.09
More than \$65,000	9%	6.61	1.09	0.13

Source: PSID 1984-2011. This table describes the behavior of the 267 PSID respondents who are asked about assets and investments in their business within 5 years of entering entrepreneurship and covers total investments over the first 2-5 years. We include investments of \$0 when individuals are asked about investing in their business and report no investment. The median reported starting investment, including zeros, is \$5,400 while the mean is \$27,000. This measure likely overstates the direct financial cost of entering self-employment because it excludes individuals who become self-employed without starting a business. Statistics are separated roughly by quartiles of initial investment, with the top few investors separated out. The last three columns describe the relationship between initial investments, individual fixed earnings effects in the paid sector, which we later assume are known by workers at the time the enter entrepreneurship, and individual fixed (subsequent) earnings effects in entrepreneurship, which we later assume are unknown at the time workers enter entrepreneurship. A regression of initial investments on these two fixed effects indicate no statistically significant role for either in predicting initial investments.

Table 4: Exit Rates from Entrepreneurship

Measure of high cap.	% Startup < \$25k				% Startup=\$0
	(1)	(2)	(3)	(4)	(5)
In high-capital ind.	1.24	1.10	1.00	1.14	0.79
	(0.10)	(0.52)	(0.98)	(0.50)	(0.26)
Ent. earn quartile 2	0.75	0.80			
	(0.08)	(0.24)			
Ent. earn quartile 3	0.61	0.58			
	(0.01)	(0.02)			
Ent. earn quartile 4	0.36	0.27			
	(0.00)	(0.00)			
High cap.* Ent. earn q2	0.91	0.75			
	(0.68)	(0.24)			
High cap.* Ent. earn q3	0.94	0.79			
	(0.80)	(0.40)			
High cap.* Ent. earn q4	0.95	0.91			
	(0.87)	(0.78)			
Paid earn quartile 2		0.70	0.61	0.60	0.63
		(0.11)	(0.01)	(0.01)	(0.02)
Paid earn quartile 3		1.00	0.82	0.82	0.84
		(0.98)	(0.33)	(0.33)	(0.39)
Paid earn quartile 4		1.57	1.04	1.04	1.06
		(0.04)	(0.85)	(0.84)	(0.75)
High cap.* Paid earn q2		1.71	1.57	1.54	1.73
		(0.05)	(0.08)	(0.10)	(0.03)
High cap.* Paid earn q3		1.40	1.44	1.46	1.59
		(0.22)	(0.15)	(0.14)	(0.07)
High cap.* Paid earn q4		1.10	1.04	1.09	1.15
		(0.73)	(0.87)	(0.73)	(0.54)
Ent - Paid earn q2			0.87	0.87	0.83
			(0.39)	(0.40)	(0.24)
Ent - Paid earn q3			0.70	0.69	0.61
			(0.07)	(0.06)	(0.01)
Ent - Paid earn q4			0.27	0.27	0.20
			(0.00)	(0.00)	(0.00)
High cap.* Ent - Paid q2			1.11	0.97	1.19
			(0.64)	(0.87)	(0.38)
High cap.* Ent - Paid q3			0.89	0.82	1.10
			(0.66)	(0.43)	(0.69)
High cap.* Ent - Paid q4			0.90	0.76	1.53
			(0.77)	(0.47)	(0.23)
Observations	5,929	5,929	5,929	5,288	5,929
Log likelihood	-3,652	-3,640	-3,638	-3,273	-3,637

Table reports hazard ratios with **p-values from z-tests in parentheses.** In each specification, high-capital industries are those with an above-median share of workers who invest at least \$25,000 when entering entrepreneurship (for the first four columns) or invest any money in the last column. This measure is taken from the 2007 Survey of Business Owners (SBO) Public Use Microdata. Column (4) omits workers in "Other Service" industries (NAICS=81). This industry group is characterized by 50% lower than average exit rates coupled with lower than average starting capital requirements.

Table 5: Determinants of Log Earnings

Experience profiles in paid sector		
1 year paid experience		0.051
		(0.005)
10 years paid experience		0.421
		(0.385)
Experience profiles in entrepreneurship		
1 year paid experience		0.028
		(0.036)
10 years paid experience		0.202
		(0.440)
1 year entrepreneurial experience		0.031
		(0.012)
10 years entrepreneurial experience		0.229
		(0.147)
Distribution of abilities		
Mean log ability in paid sector	μ_α	6.450
		(0.017)
Variance of log ability in paid sector	σ^2_α	0.193
		(0.020)
Mean log ability in entrepreneurship	μ_η	6.432
		(0.089)
Variance of log ability in entrepreneurship	σ^2_η	0.631
		(0.055)
Correlation of abilities across sectors	ρ	0.702
		(0.063)
Paid sector earnings shocks		
Variance of AR(1) innovation	σ^2_ζ	0.024
		(0.009)
Annual persistence of AR(1)	ϕ	0.831
		0.079)
Variance of transitory shock	σ^2_m	0.022
		(0.009)
Entrepreneurship earnings shock		
Variance of transitory shock	σ^2_e	0.096
		(0.008)

PSID 1976-2011. Estimated on weekly earnings as described in the text. Bootstrapped standard errors from 200 draws in parentheses. Paid earnings depend on a cubic in paid experience. Entrepreneurial earnings depend on a quadratic in paid experience and a cubic in entrepreneurial experience. The order of these polynomials were determined by a series of specification F-tests. We discuss omitting entrepreneurial experience from the paid earnings equation in the text. In the simulations annual earnings are projected from these estimates assuming 50 weeks of work per year.

Table 6: Utility Parameters

	Full model	No heterogeneous tastes
Parameter estimates		
β_1: Utils per \$10,000	0.103	0.145
	(0.018)	(0.009)
β_3: Startup cost, as share of paid fixed effect	-1.441	-1.702
	(0.049)	(0.053)
β_2: Additional cost of first entry	-0.177	-0.465
	(0.137)	(0.071)
μ_{β_0}: Mean non-pecuniary benefit	-0.969	-0.023
	(0.225)	(0.013)
σ_{β_0}: Std. dev. of non-pecuniary benefit	0.945	
	(0.146)	
Dollar equivalent interpretations		
Mean cost to enter self-emp.	-455,053	-380,351
Mean add'l cost of first entry	-55,733	-103,975
Std. dev. of transitory preference shock	125,029	88,494
Mean non-pecuniary benefit	-94,445	-1,588
Std. dev. of non-pecuniary benefit	92,101	0
% of workers with $\beta_{0i} > 0$	15	0
Posterior distributions of non-pecuniary benefit		
Mean $\mu_{\beta_0 i}$, never entrepreneurs	-117,067	
Mean $\sigma_{\beta_0 i}$, never entrepreneurs	77,896	
Mean $\mu_{\beta_0 i}$, sometime entrepreneurs	947	
Mean $\sigma_{\beta_0 i}$, sometime entrepreneurs	41,370	

The utility parameter per \$10,000 has no independent interpretation except to scale the variance of the extreme-value taste shock. Dollar equivalents are in 2010 USD. Entry costs are scaled to individual fixed earnings ability in paid work, $50 * exp(\alpha_i)$, so the table reports mean entry costs across individuals. See text for details of estimation.

Table 7: Estimated Probability of Choosing Entrepreneurship

	Observed Choice this Year	
Sector Last Year:	Paid Sector	Entrepreneurship
Paid sector		
Income maximizing	37.3%	50.7%
Full model, homogeneous tastes	2.4%	3.7%
Full model, posterior	2.1%	11.8%
Workers in cell	58,713	1,024
Share of total workers	88.2%	1.5%
Entrepreneurship		
Income maximizing	50.9%	73.9%
Full model, homogeneous tastes	76.1%	83.8%
Full model, posterior	66.8%	88.9%
Workers in cell	568	6,292
Share of total workers	0.9%	9.4%

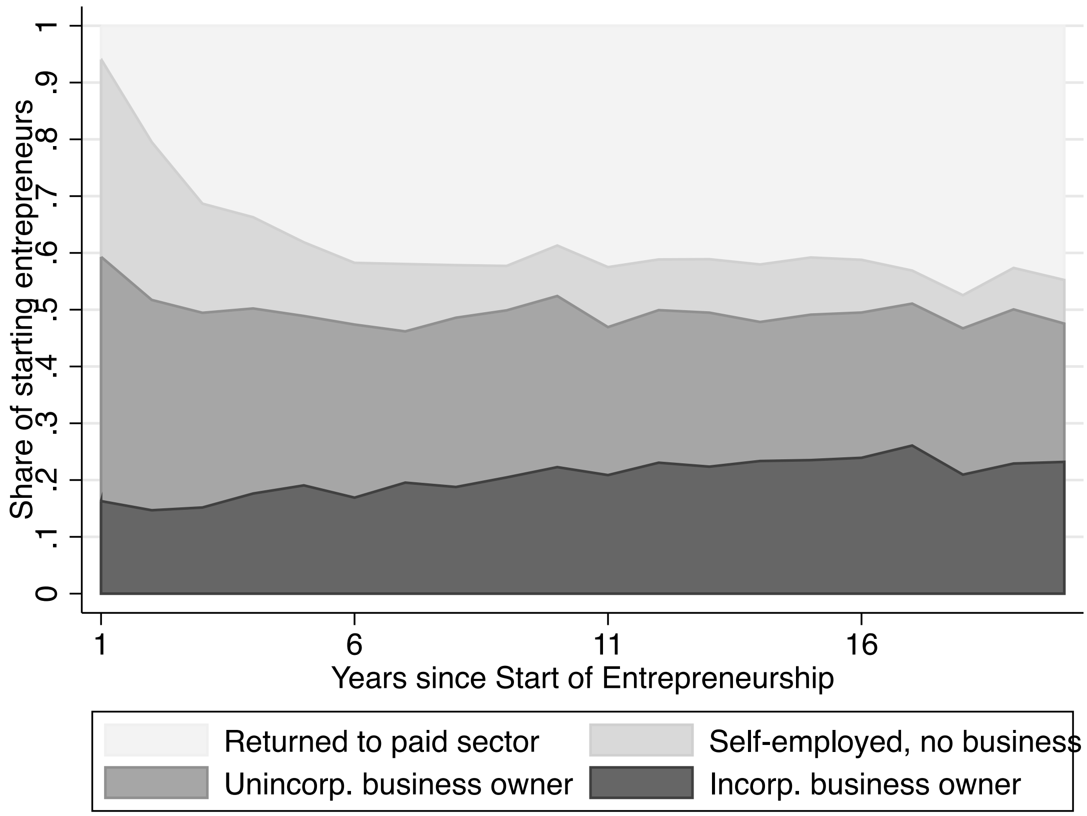
Each column presents the model-predicted probability of choosing entrepreneurship, separately for workers who were in each sector last year and are observed to choose each sector this year. If the model predicted choices perfectly, we would assign workers observed choosing paid work this year (the first column) a 0% chance of choosing entrepreneurship and workers observed choosing entrepreneurship (the second column) a 100% chance of doing so. The first row in each cell gives the prediction of a model where workers are income maximizers with no entry costs or non-pecuniary benefits of entrepreneurship. The next row presents predictions from a model where agents are utility maximizers with our full preference specification, but without any heterogeneity of preferences. The final row presents predictions of the full model, using individual posterior distributions of preferences.

Table 8: The Value of Entering Entrepreneurship at age 32

	Value of Paid	Value of Entrep.	Difference	Pct. Difference
Annual observed earnings in chosen sector				
Mean	57,009	63,712	6,703	11.8%
Median	52,294	47,365	-4,929	-9.4%
N	2,594	255		
Projected annual earnings for all workers				
Mean	57,233	58,010	777	1.4%
Median	52,611	50,374	-2,237	-4.3%
N	2,849	2,849		
Projected lifetime earnings, static model				
Mean	65,544	68,247	2,703	4.1%
Median	60,482	59,264	-1,218	-2.0%
N	2,849	2,849		
Projected lifetime earnings, dynamic model				
Mean	65,785	70,711	4,925	7.5%
Median	60,162	61,136	973	1.6%
N	2,849	2,849		

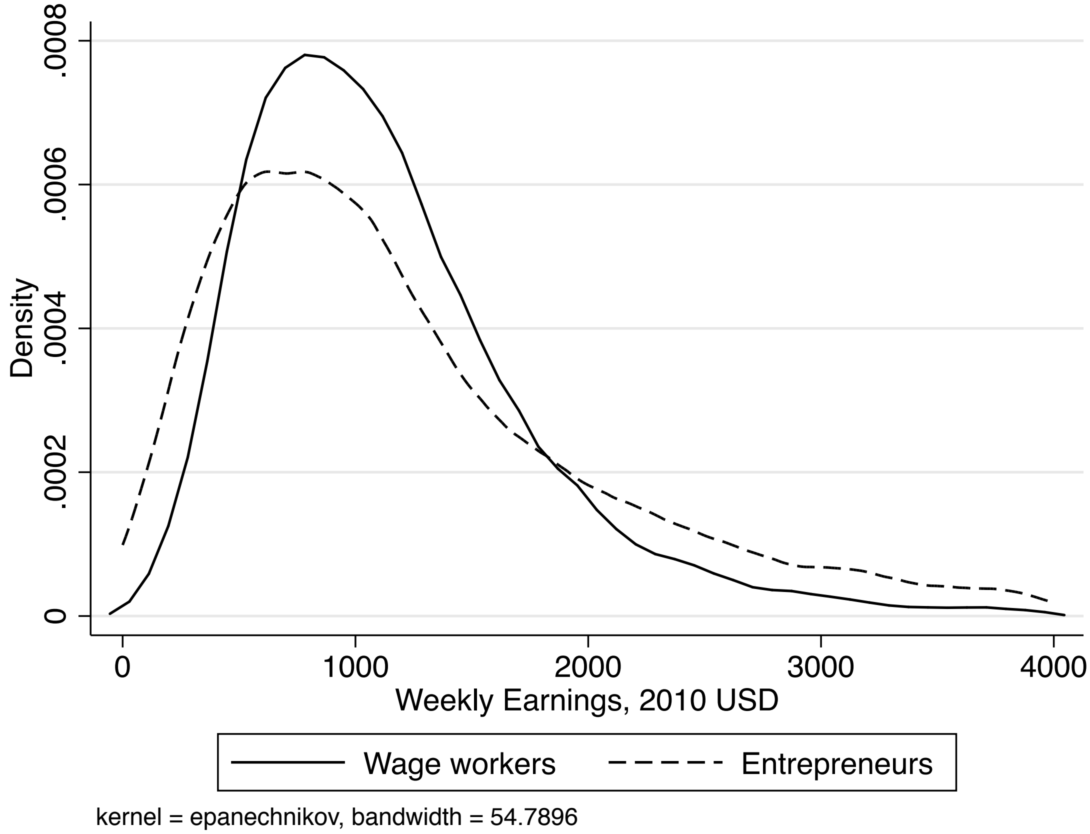
The first panel of this table summarizes observed annual earnings for 32 year old paid workers and entrepreneurs. In this panel the workers contributing to the paid averages are different from the workers contributing to the entrepreneurial average. In the remaining panels, earnings are projected for all 32 year old workers conditional on choosing each sector, so the same sample of workers contributes to the averages for each sector. For easier comparison, the projected lifetime earnings are converted to constant-annual-income equivalents, $\bar{C}$ such that $\sum_{s=t}^{T}\left(\frac{1}{1+r}\right)^{s} Y_s = \bar{C}\sum_{s=t}^{T}\left(\frac{1}{1+r}\right)^{s}$. The third panel projects discounted lifetime earnings assuming that workers choose each sector this year and remain there for all future years. The last panel projects discounted lifetime earnings assuming workers choose each sector this year and then behave optimally according to the full model in each subsequent year.

Figure 1: Composition of Entrepreneurs Over Time



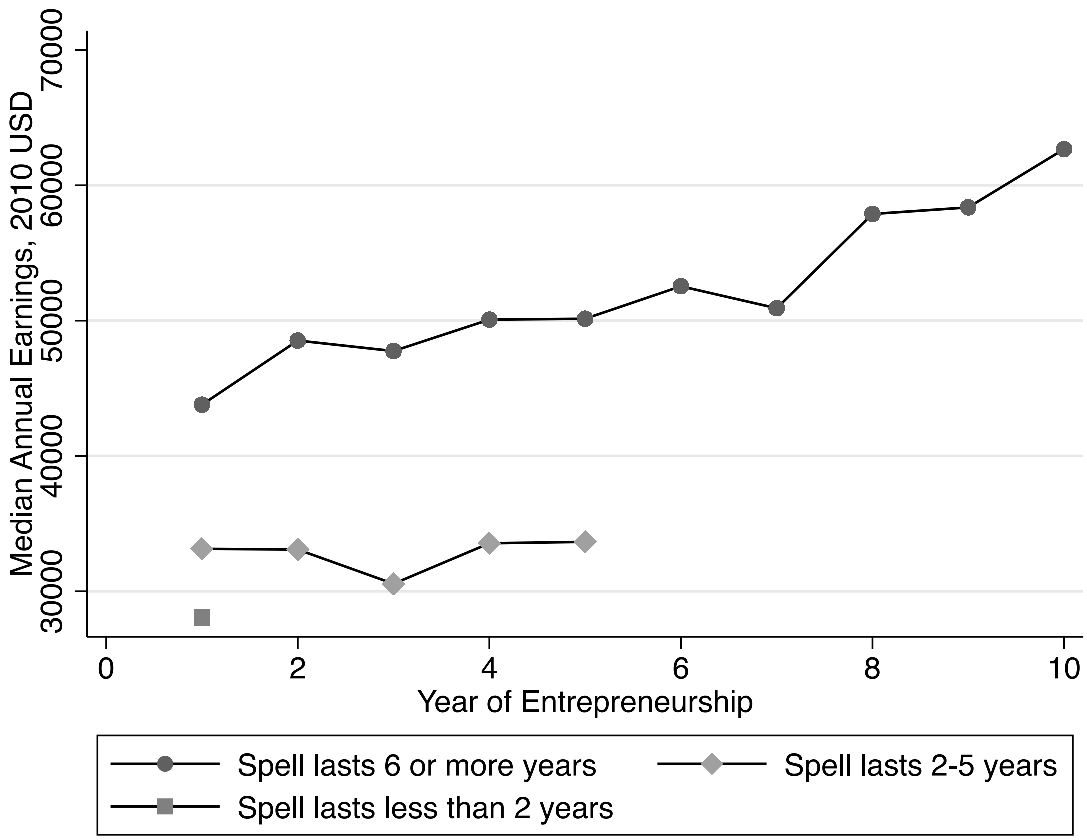
Source: PSID 1976-2011. Note: Because of bi-annual interviews after 1997 the sample is not consistent over years since entering entrepreneurship. For example, we may see some workers 2 and 4 years post-entry and others 3 and 5 years post-entry.

Figure 2: Distribution of Earnings in Wage Work and Entrepreneurship



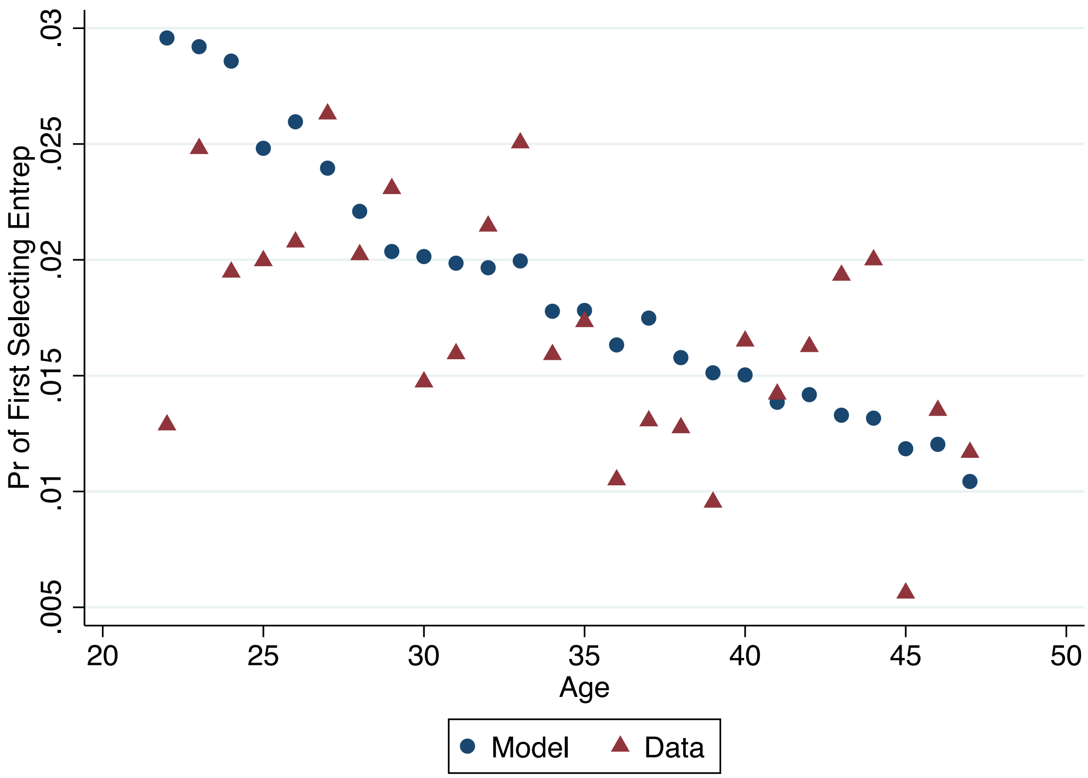
Source: PSID 1976-2011. Distribution of real weekly earnings in 2010 dollars. Truncated at $4,000 per week, which excludes the top 2% of earnings. Weighted as described in the text.

Figure 3: Earning Profiles by Persistence in Entrepreneurship



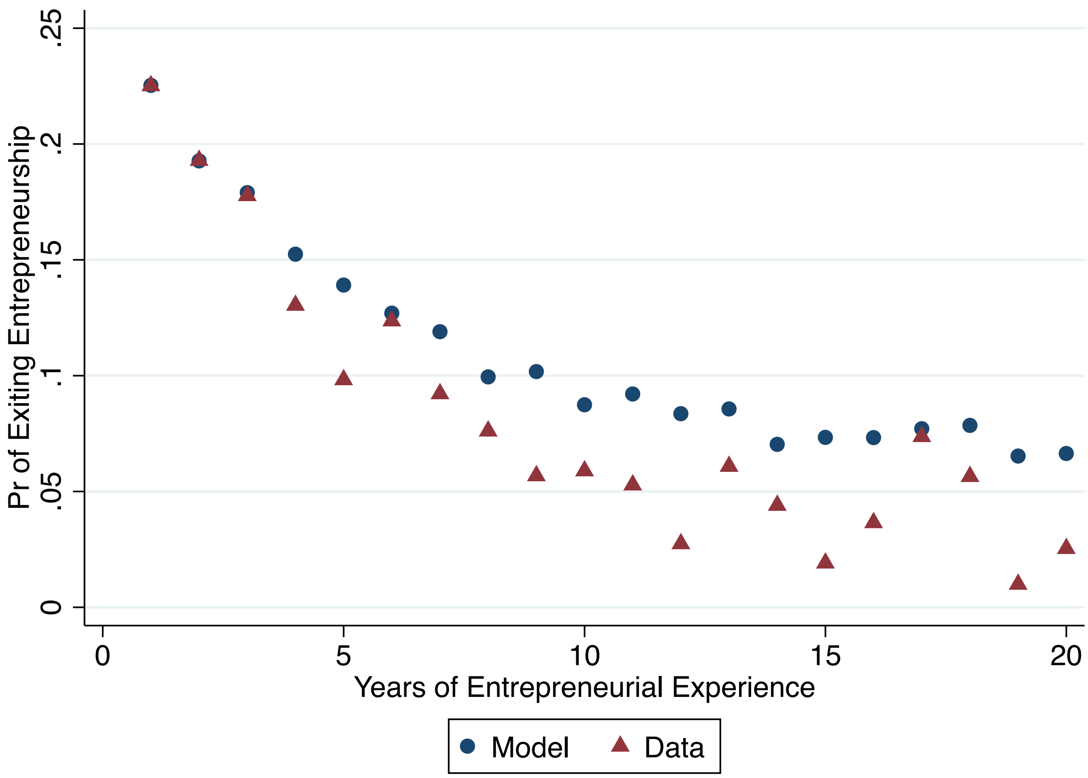
Source: PSID 1976-2011. Profiles are average real annual earnings for entrepreneurs in 2010 dollars. Weighted as described in the text. The gap between each of the two lower profiles and the top profile are statistically significant with 99% confidence.

Figure 4: First Entry into Entrepreneurship by Age



Source: PSID 1976-2011 and predicted likelihood of choosing entrepreneurship from the model. Both series describe the average probability of choosing to work in entrepreneurship for individuals who worked in the past sector in the previous year and have no past entrepreneurial experience. Data are weighted as described in the text.

Figure 5: Returns to Paid Sector by Time in Entrepreneurship



Source: PSID 1976-2011 and predicted likelihood of choosing paid work from the model. Both series describe the probability of selecting paid work for individuals who worked as entrepreneurs in the previous year. Data are weighted as described in the text.

Figure 6: Distribution of the Annualized Option Value for 32 Year Olds

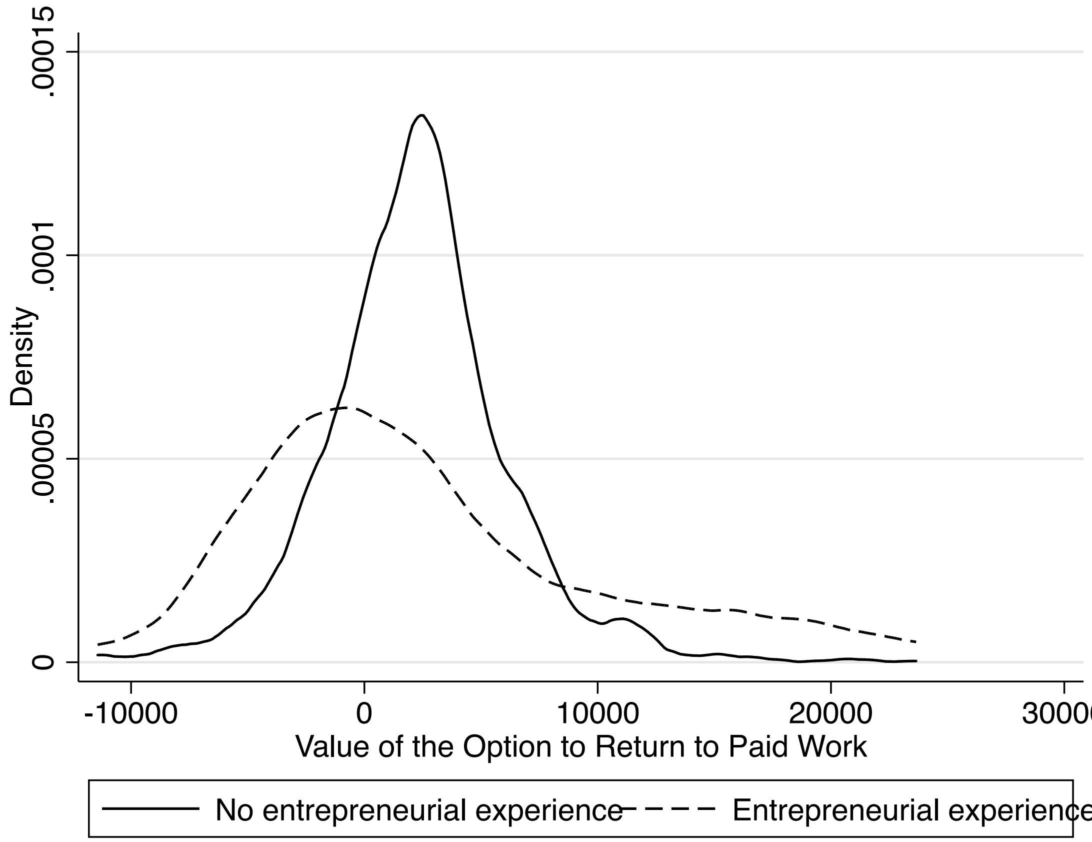


Figure plots the annualized expected lifetime earnings conditional on choosing entrepreneurship this year and behaving optimally in future years less the annualized expected lifetime earnings conditional on choosing entrepreneurship in all future years for 32 year olds. The average values of these projections are presented in the 4th and 3rd panels of Table 8, respectively. The solid line plots the option value for workers who have no entrepreneurial experience by age 32. The dashed line plots the option value for workers with some entrepreneurial experience, both current and former entrepreneurs.

A Data Appendix

Our PSID estimation sample is constrained by the need to keep track of accumulated work experience in each sector. Individuals are included in the sample only when we can follow their work experience starting at age 25 or earlier. Both survey responses and the panel dimension of the data are used to construct measures of accumulated experience in each sector. In other words, we keep all workers who enter the sample by age 25, plus any worker who enters the sample at an older age but reports being in their current job since before they were 25. We follow respondents starting with the 1976 survey, the year the PSID began asking about job tenure, but, where possible, we use reported paid or self-employed work from the 1968-1975 waves to help construct experience measures. In the first year a worker is observed, we initialize their sector experience using their report of how long they have been at their current job. For example, if a worker enters the sample working in the paid sector and has been working at that job for 8 years, we say he has 8 years of paid experience and no entrepreneurial experience. Experience in each sector is then updated with observed work going forward.

Because we estimate individual-specific earnings effects, we must also restrict the sample to workers who we observe over multiple years. We estimate experience profiles and the other determinants of earnings on all workers. To estimate the relationship between paid and entrepreneurial ability, and in second stage estimation which depends on individually-estimated fixed effects, we restrict the sample to individuals with at least 5 years of earnings. Finally, to abstract from early retirement behavior and schooling decisions, we include only men between the ages of 22 and 55.

We define an entrepreneur as someone who is self-employed in their main job. In most cases, this simply means the worker is self-employed. The PSID asks workers who hold more than one job simultaneously to identify their main job, which tends to be the job that accounts for the majority of hours worked and earnings. We classify individuals who work for someone else on their main job and for themselves in a side job as paid workers, and vice versa. In the later part of the PSID sample, business owners are asked if they work in their business.

In these later years we observe that some business owners who report working in their business and having only one job nonetheless report working for someone else. This combination of responses is somewhat puzzling, but on the whole we would like to classify these workers as entrepreneurs throughout the sample. To do so consistently, we also identify workers as entrepreneurs when their first report of owning a business coincides with a job change. This rule captures most of the respondents who report working in their businesses in the later half of the sample.

Most workers in the PSID sample report total labor earnings, but unincorporated business owners are instead only asked about total net profits from their business. For these workers, we use net profits as our measure of labor income. One potential drawback is that using net profits will overstate labor earnings in cases where workers have also invested substantial financial capital in their businesses. Information about business assets are too incomplete in the PSID to allow us to adjust net profits for a reasonable return to capital. However, the data that are available suggest that these adjustments would be small. As shown in Table 3, the median worker who opens a business upon entering entrepreneurship invests \$5,000 over the first 1-5 years. This number likely overstates the median entry investments for all self-employed workers, since workers who become self-employed without reporting ownership of a business are not asked about capital investments. Even at the 90^{th} percentile, unincorporated business owners invest only \$59,000. At a 5% rate of return, that suggests self-employment earnings may be overstated by only about \$2,900 per year.

Because work hours are difficult to define for self-employed workers, earnings are measured at the weekly level using annual earnings divided by reported weeks worked. Both labor income and business profits are reported over the past calendar year, while job tenure is reported as of the survey date. Earnings for years when individuals spent part of their time in the paid sector and part in entrepreneurship are excluded from earnings regressions. To estimate the effect of sector experience on earnings we construct experience as of the beginning of the last calendar year, using reports from both the current and previous waves of the survey.

B Estimation Appendix

B.1 Determinants of Earnings and State Variable Transitions

The set of state variables, S_{it}, includes age, accumulated experience in each sector, x_{itR} and x_{itW}, paid sector ability, α_i, expected entrepreneurial skill, $\hat{\eta}_{ix}$, the lag of the persistent shock in the paid sector, P_{it}, and the lagged sector choice, d_{it-1}. Within the model, age and experience evolve deterministically based on sectoral choices, α_i is fixed, and $\hat{\eta}_{ix}$ and P_{it}, depend only on sector choice and exogenous shocks. Because none of these processes depend on β_{0i}, when we substitute equation (13) into (14), $f(S_{t+1}|d_t, S_t; \theta)$ moves outside of the integral over β_i and is additively separable in the log likelihood. We can therefore estimate $\hat{\theta}$ separately in a first stage, with appropriate controls for non-random selection into each sector.[20]

To estimate the effects of sector experience on earnings we must account for workers' strategic transitions between sectors. Depending on the joint distribution of abilities in each sector, transitions from paid work to self-employment may be positively or negatively correlated with paid ability, α. We estimate a version of Equation 3, describing paid earnings, that includes individual fixed effects to purge permanent components from the estimates.

While this strategy yields reasonable estimates for the effect of paid experience on paid sector earnings, individual fixed effects are unlikely to remove entirely selection bias from the estimated effects of entrepreneurial experience on paid sector earnings. For example, if workers sometimes know the realization of shocks before choosing their sector, say because they are offered a particularly attractive new job, then workers who return to the paid sector will have disproportionately high paid earnings. Evans and Jovanovic (1989) and Hamilton (2000) both find positive effects of entrepreneurial experience on earnings, but neither study controls for selection. Like Bruce and Schuetze (2004), we find small and imprecise returns to entrepreneurial experience after various attempts to control for non-random selection between sectors. Because of the difficulty of fully accounting for this selection, in the current specification we impose that entrepreneurial experience

[20] This approach rules out some potentially interesting extensions. For example, if x_{itR} and x_{itW} represent accumulated skills rather than years of experience, individuals could have heterogeneous learning abilities. However, with the relatively small sample in the PSID, it would be difficult to allow additional flexibility.

has no effect on paid sector earnings. This zero relationship suggests that experimenting with entrepreneurship involves an opportunity cost of lost paid sector experience, but no additional costs or benefits. Even without separate indicators for entrepreneurial experience, our specification of the paid sector earnings process does a good job of fitting earnings for workers who are newly returned to the paid sector from spells of entrepreneurship.

After netting out the experience profile, residual paid earnings, w_t, consist of fixed paid ability, the persistent wage shock $log(P_t) = \phi log(P_{t-1}) + \zeta_t$, and the transitory shock $\log(M_t)$. Following Carroll and Samwick (1997), we distinguish the persistent and transitory shocks by comparing the variance and covariance of residuals over long and short intervals. We use two-, four-, and six-year intervals, which we can construct both before and after the PSID's move to bi-annual interviews in 1997. The variance-covariance moments are

$$\begin{aligned} \text{var}(w_t) &= \sigma_\alpha^2 + \frac{\sigma_\zeta^2}{(1-\phi^2)} + \sigma_m^2 \\ \text{cov}(w_t, w_{t-2}) &= \sigma_\alpha^2 + \frac{\phi^2\sigma_\zeta^2}{(1-\phi^2)} \\ &\vdots \\ \text{cov}(w_t, w_{t-6}) &= \sigma_\alpha^2 + \frac{\phi^6\sigma_\zeta^2}{(1-\phi^2)}. \end{aligned} \tag{15}$$

These moments provide a consistent estimate of the population variance of paid ability, σ_α^2. In the second stage, the conditional value functions depend on each individual's paid ability, α_i. Average residual earnings in the paid sector are an unbiased estimator of individual paid ability, but they are inconsistent in short panels, assuming fixed-T asymptotics. With only a few years of paid earnings, we cannot distinguish an individual with low paid ability from an individual with a low persistent shock. We employ a correction to deal with these difficulties. To do so, we first adjust for time-series dependence by re-weighting residuals within individuals to place more weight on years that are less correlated with other observations. We then follow Lazear et al. (2015) and shrink individual predictions towards the consistently estimated cell-specific means using an empirical Bayes approach. The resulting estimator is

$$\widehat{\alpha}_i = \overline{w}_z + \sigma_\alpha^2 \left(\Sigma + \sigma_\alpha^2\right)^{-1} \left(w_{it} - \overline{w}_z\right), \tag{16}$$

where Σ is the variance-covariance matrix of the residuals using the consistent estimates of σ_α^2 and σ_ζ^2 and $\overline{w}_z$ is the within-cell average residual from the paid wage equation.[21] Finally, we use the average $\widehat{\alpha}_i$ as the measure of mean paid sector ability, μ_α. This estimate of μ_α is unbiased if there is no selection into being observed at least once in the paid sector and is consistent with large N asymptotics.

Experience-earnings profiles in entrepreneurship are subject to the same selection concerns as profiles in the paid sector. In entrepreneurship, the bias is a direct consequence of the learning model: workers refine their beliefs about entrepreneurial ability through observing earnings in entrepreneurship. As beliefs become more precise, workers who are now confident they could earn more in the paid sector are more likely to return to that sector. This selection out of entrepreneurship will overstate the effect of entrepreneurial experience on entrepreneurial earnings. Instead, we account for selection out of entrepreneurship by instrumenting entrepreneurial experience with individually de-meaned experience, as in Altonji and Williams (2005).

A second source of potential bias involves selection into entrepreneurship. Workers who wait to enter entrepreneurship, and therefore enter with more paid experience, are more likely to have been pushed into self-employment by negative shocks in the paid sector. If this negative selection is correlated with entrepreneurial performance, then estimates of the effect of paid experience on entrepreneurial earnings will also be biased (probably downwards). Because most workers have only one spell in entrepreneurship, during which paid experience remains constant, we cannot estimate the effect of paid experience on entrepreneurial earnings within a fixed effect model. To control for this selection, we include the worker's persistent paid-sector earnings shock in the last period before entering entrepreneurship in the entrepreneurial earnings equation.[22] We also include a set

[21] We take means within bins by race/ethnicity and years of completed schooling.

[22] This shock is estimated in the paid earnings equation and does not depend on the experience-earnings profile in entrepreneurship. Omitting this control variable leads us to estimate negative effects of paid experience on entrepreneurial earnings.

of indicator variables for race and completed schooling. These covariates improve the precision of our experience profile estimates, but they all capture elements of the entrepreneurial fixed effect, η_i. To estimate the stochastic components of entrepreneurial earnings we construct residual earnings, r_t by netting out only the effects of the experience profile, leaving any heterogeneity captured by these other covariates as part of the residual. The stochastic components governing entrepreneurial earnings are identified by

$$\begin{aligned} \operatorname{cov}(r_{t+1}, r_t) &= \sigma_\eta^2 \\ \operatorname{cov}(r_{t+1} - r_t, r_t - r_{t-1}) &= -\sigma_\xi^2. \end{aligned} \tag{17}$$

In the final step of this stage, we estimate mean entrepreneurial ability, μ_η, and the correlation between abilities in each sector, ρ. These estimates describe the transferability of skills across sectors and allow us to recover $\hat{\eta}_{i0}$ and $\sigma^2_{\hat{\eta}_{ix}}$. For workers who we observed in entrepreneurship, we construct $\hat{\eta}_i$ in the same way as $\widehat{\alpha}_i$. The set of entrepreneurs may not reflect the full distribution of entrepreneurial abilities. To account for this selection, we estimate $\widehat{\mu_\eta}$ as $\widehat{\mu_\alpha}$ plus the average difference between $\widehat{\alpha}_i$ and $\widehat{\eta}_i$ for individuals who we observe in both sectors. We use this same sample of workers who appear in both sectors to estimate ρ, the correlation between α and η. We construct $\hat{\eta}_{ix}$, the worker's belief about his η with x years of entrepreneurial experience, using equations (6) and (7). Finally, we construct $\hat{\alpha}_i$ for workers observed only in the entrepreneurial sector from $\hat{\eta}_i$ by inverting equation (6).

B.2 Estimates of Flow Payoff Parameters

In the second stage, we take $\hat{\theta}$ as given and maximize the likelihood function to estimate $\hat{\beta}, \hat{\mu}_{\beta_0}$, and $\hat{\sigma}^2_{\beta_0}$. In each interview, the PSID asks about about employment and earnings in the last calendar year and about employment at the time of the interview, generally in late spring. This second stage maximizes the likelihood of being self-employed at the time of the interview, conditional on the state variables at the end of the past calendar year.[23]

[23]This approach does not require linking interviews in two subsequent years and is therefore not affected by the PSID's transition to bi-annual interviews after 1997. We adjust sector choice if later interviews indicate that a worker

We follow Rust (1987) and assume that the shocks ε_{it}^0 and ε_{it}^1 are serially independent with Type-1 extreme value distributions. This gives a conditional logit form for the conditional value function

$$\begin{aligned} v\left(d_t, S_t, \beta_{0i}, \varepsilon_t; \beta\right) &= u\left(d_t, S_t, \beta_{0i}, \varepsilon_t\right) + \delta E_t\left[\max\left\{v\left(0, S_{t+1}, \beta_{0i}, \varepsilon_{t+1}; \beta\right), v\left(1, S_{t+1}, \beta_{0i}, \varepsilon_{t+1}; \beta\right)\right\}\right] \qquad (18) \\ &= u\left(d_t, S_t, \beta_{0i}, \varepsilon_t\right) + \delta \int \log\left(\sum_j \exp\left[v\left(d_{t+1}, S_{t+1}, \beta_{0i}, \varepsilon_{t+1}; \beta\right)\right]\right) df\left(S_{t+1} | S_t, d_t; \theta\right) + \delta\gamma, \end{aligned}$$

where γ is Euler's constant. We use these conditional value functions, Equation (12), and estimates of $\hat{\theta}$ to maximize the likelihood in Equation (14) for $\hat{\beta}$, $\hat{\mu}_{\beta_0}$, and $\hat{\sigma}^2_{\beta_0}$. We set the discount rate at $\delta = \frac{1}{1.10}$. The integral is over next year's stochastic state variables: the persistent shock in the paid sector and the belief of entrepreneurial ability. We approximate both distributions using 5-point Gaussian quadrature.

The likelihood of the choices is then given by the conditional logit formula, $p_t\left(d_t = 1 \mid S_t, \beta_{0i}; \beta\right) = \frac{\exp(v(1,S_t,\beta_{0i};\beta))}{\exp(v(1,S_t,\beta_{0i};\beta))+\exp((v(0,S_t,\beta_{0i};\beta)))}$. To get the marginal likelihood for sequences of choices, we integrate over the distribution of β_{0i},

$$\mathcal{L}\left(d_i | \beta, \theta, \mu_{\beta_0}, \sigma^2_{\beta_0}\right) = \int \prod_{t=1}^{T} p_t\left(d_t = 1 \mid S_t, \beta_{0i}; \beta\right)^{d_t=1} p_t\left(d_t = 0 \mid S_t, \beta_{0i}; \beta\right)^{d_t=0} d\phi\left(\frac{\beta_{0i} - \mu_{\beta_0}}{\sigma_{\beta_0}}\right).$$

Again, we approximate the integral over β_{0i} using 5-point Gauss-Hermite quadrature. We then maximize $\sum_{i=1}^{N} \log\left(\mathcal{L}\left(d_i | \beta, \theta\right)\right)$, the log likelihood, with respect to β, μ_{β_0}, and $\sigma^2_{\beta_0}$.

B.3 Posterior Preference Distributions

The parameters governing the distribution of β_{0i} describe the population distribution of preferences for entrepreneurship. It is also possible to estimate where in this distribution each individual in the PSID sample is likely to fall based on their estimated earnings potential and their observed sequence of sector choices. Define $h\left(\beta_{0i} | d_i, S_i; \mu_{\beta_0}, \sigma^2_{\beta_0}\right)$ as the posterior probability density of preferences for individual i, given their history of choices, d_i, and sequence of state variables, S_i. As derived in

spent most of the year in one sector but reported the other at the time of the interview.

Train (2009) using Bayes' rule, this posterior distribution is determined by

$$h\left(\beta_{0i}|d_i, S_i; \mu_{\beta_0}, \sigma^2_{\beta_0}\right) = \frac{\mathcal{L}\left(d_i|\beta, \theta, \beta_{0i}\right)\phi\left(\frac{\beta_{0i}-\mu_{\beta_0}}{\sigma_{\beta_0}}\right)}{\mathcal{L}\left(d_i|\beta, \theta, \mu_{\beta_0}, \sigma^2_{\beta_0}\right)}, \tag{19}$$

where $\mathcal{L}\left(d_i|\beta, \theta, \beta_{0i}\right) = \prod_{t=1}^{T} \mathcal{L}_t\left(d_{it} \mid S_{it}, \beta_{i0}; \beta, \theta\right)$ is the probability of a sequence of choices conditional on having preference β_{0i}, $\phi\left(\frac{\beta_{0i}-\mu_{\beta_0}}{\sigma_{\beta_0}}\right)$ is the population probability distribution of that preference, and $\mathcal{L}\left(d_i|\beta, \theta, \mu_{\beta_0}, \sigma^2_{\beta_0}\right)$ is the unconditional probability of those choices as defined in Equation (19).

The mean and variance of the individual posterior distributions are given by

$$\mu_{\beta_0 i} = \int \beta_{0i} h\left(\beta_{0i}|d_i, S_i; \mu_{\beta_0}, \sigma^2_{\beta_0}\right) d\beta_{0i} = \frac{\int \beta_{0i}\mathcal{L}\left(d_i|\beta, \theta, \beta_{0i}\right)\phi\left(\frac{\beta_{0i}-\mu_{\beta_0}}{\sigma_{\beta_0}}\right) d\beta_{0i}}{\mathcal{L}\left(d_i|\beta, \theta, \mu_{\beta_0}, \sigma^2_{\beta_0}\right)} \tag{20}$$

and

$$\sigma^2_{\beta_0 i} = \frac{\int \left(\beta_{0i} - \mu_{\beta_{0i}}\right)^2 \mathcal{L}\left(d_i|\beta, \theta, \beta_{0i}\right)\phi\left(\frac{\beta_{0i}-\mu_{\beta_0}}{\sigma_{\beta_0}}\right) d\beta_{0i}}{\mathcal{L}\left(d_i|\beta, \theta, \mu_{\beta_0}, \sigma^2_{\beta_0}\right)}. \tag{21}$$

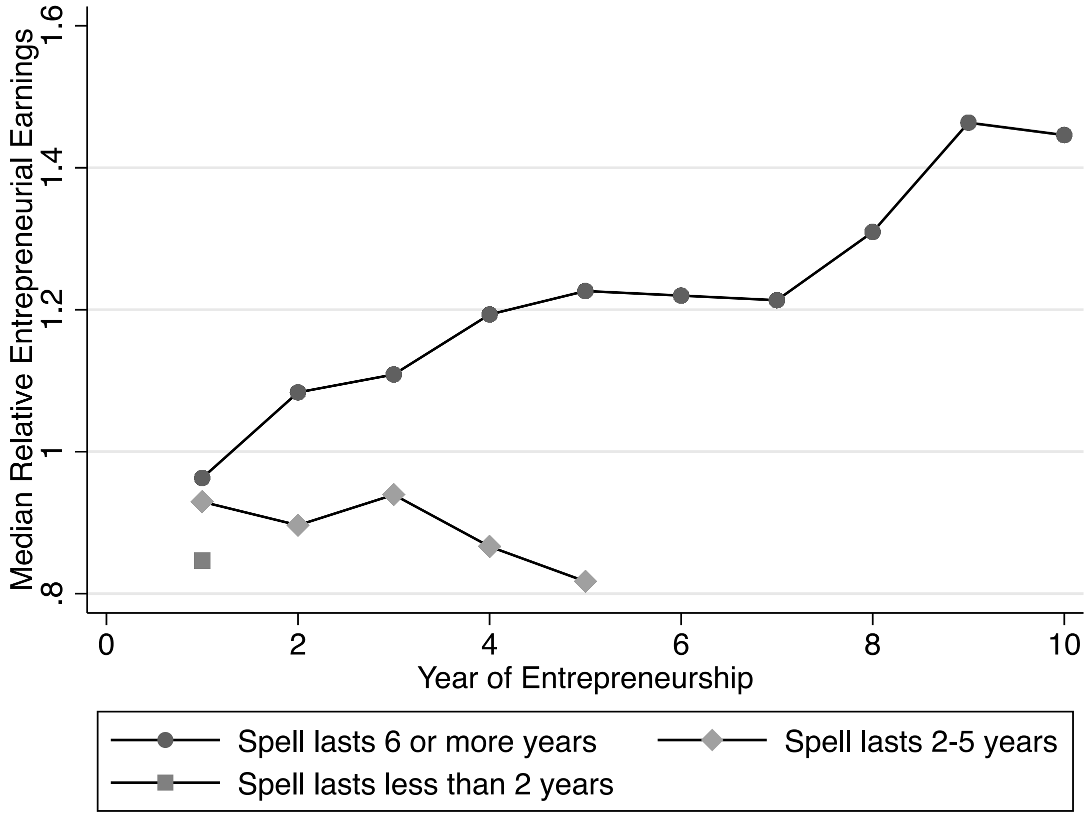
We can then calculate the individual posterior likelihoods using Equation (19) and substituting these individual posterior distributions in for the population distribution of preferences.

Table A1: Determinants of Weekly Earnings

	OLS	25th pctile	50th pctile	75th pctile
Entrepreneur	415.3*	-175.4*	-39.4*	272.0*
	(42.7)	(10.8)	(14.9)	(26.0)
Age	71.7*	56.9*	71.5*	70.7*
	(7.8)	(2.7)	(3.0)	(4.6)
Age-squared	-0.5*	-0.6*	-0.7*	-0.5*
	(0.1)	(0.0)	(0.0)	(0.1)
Black	-241.7*	-190.5*	-215.6*	-252.1*
	(9.8)	(6.7)	(8.9)	(11.0)
Hispanic	30.4	-57.3*	-66.3*	-88.5*
	(28.5)	(14.4)	(11.1)	(18.0)
Other race	159.2*	85.6*	44.9	123.7*
	(72.6)	(29.2)	(47.2)	(50.9)
Less than HS	-223.5*	-188.7*	-204.8*	-224.6*
	(10.6)	(7.3)	(8.7)	(14.2)
Some college	87.8*	59.7*	80.2*	92.0*
	(8.0)	(5.8)	(6.4)	(8.7)
College Grad	575.9*	247.9*	383.0*	523.9*
	(23.2)	(8.7)	(9.4)	(14.3)
Grad Degree	896.3*	440.1*	582.6*	775.0*
	(31.1)	(12.8)	(14.4)	(21.7)
Mean fitted value for paid	1,198	787	1,088	1,454
Observations	66,597	66,597	66,597	66,597

PSID 1976-2011. Columns present OLS and quantile regressions where the dependent variable is real weekly earnings in 2010 dollars. Standard errors in parentheses. Estimates use sampling weights from the PSID as described in the text.

Figure A1: Relative Earning Profiles by Persistence in Entrepreneurship



Source: PSID 1976-2011. Profiles are the ratio of average observed annual earnings for entrepreneurs to their projected earnings had they worked in the paid sector that year, constructed using the estimates in Table 5 . Weighted as described in the text.