Prior Work Experience and Entrepreneurship: The Careers of Young Entrepreneurs

Nicolas Gendron-Carrier *†

McGill University

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Abstract: Using Canadian administrative data, I study the careers of young entrepreneurs and the heterogeneity among them. I investigate both the mechanisms that drive entry into entrepreneurship and the determinants of entrepreneurial success. Empirically, entrepreneurs who have previously worked in high-wage firms tend to do better. I explain this finding using a dynamic model of career choice that features heterogeneous employers, human capital accumulation, and unobserved heterogeneity across individuals. Among other things, I find that prior work experience is particularly valuable for relatively low ability individuals. I use the estimated model to evaluate policies designed to promote entrepreneurship.

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†Department of Economics, McGill University, 855 Sherbrooke St. West, Montreal, QC, Canada, H3A2T7. e-mail: nicolas.gendron-carrier@mcgill.ca. website: https://www.nicolasgendroncarrier.com.

Understanding the effectiveness of policies designed to promote successful entrepreneurship is challenging because there is tremendous heterogeneity across entrepreneurs (Schoar, 2010). Although start-ups are known to contribute substantially to both job creation and productivity growth, these results are driven by a small number of exceptional entrepreneurs (Haltiwanger et al., 2013; Decker et al., 2014; Haltiwanger et al., 2016). The vast majority of entrepreneurs start small businesses, earn less than the average worker, and have no desire to grow over time (Hamilton, 2000; Hurst and Pugsley, 2011).[1] Policies may therefore increase the supply of entrepreneurs in the economy without necessarily attracting individuals with high-growth potential in entrepreneurship.

In this paper, I study the careers of young entrepreneurs and the heterogeneity among them. I investigate both the mechanisms that drive entry into entrepreneurship and the determinants of entrepreneurial success. I pay particular attention to the value of prior work experience in entrepreneurship and how the decision to become an entrepreneur fits into the broader career decisions of individuals.

I use administrative Canadian matched owner-employer-employee data to conduct my investigation. This dataset allows me to precisely characterize the career histories of individuals before they become entrepreneurs, and then track their business income. I have access to 12 years of data, 2001-2012, and I follow individuals' careers from age 25 onwards during this period.

I begin by documenting some stylized facts. There are two distinct types of entrepreneurs. Incorporated entrepreneurs, who are often considered a proxy for successful entrepreneurship (Levine and Rubinstein, 2016), earn more than workers on average and are likely to stay in entrepreneurship from one year to the next. By contrast, unincorporated entrepreneurs tend to earn less than workers and exit entrepreneurship at higher rates. Based on observed career transitions, unincorporated entrepreneurship appears to be a closer substitute to non-employment and employment in low-wage firms. I show that individuals who become unincorporated entrepreneurs are fundamentally different from those that become incorporated entrepreneurs. Among incorporated entrepreneurs there is substantial heterogeneity as well, both in earnings levels and growth rates. Empirically, the earnings distribution of incorporated entrepreneurs is more dispersed than the earnings distribution of workers. Allowing for heterogeneity in the population is essential to explain this variation.

At first glance, the type of work experience individuals acquire before starting a business appears to be important. Entrepreneurs who have previously worked in high-wage firms tend to do better: their business income starts at a higher level and grows faster. This could

[1] Non-pecuniary benefits are thought to play an important role in the decision to become an entrepreneur (Hurst and Pugsley, 2011, 2015).

be explained by (1) human capital accumulation or (2) a non-random sorting of individuals across firms and dynamic selection. On the one hand, individuals may acquire skills in the labour market that also happen to be valuable in entrepreneurship. Moreover, skills acquired in high-wage firms could be particularly valuable. Human capital accumulation could also account for earnings growth in entrepreneurship through learning-by-doing. On the other hand, perhaps individuals with high innate ability or high learning abilities are more likely to be employed at high-wage firms and do better in entrepreneurship if they eventually decide to start a business. Distinguishing between these competing explanations requires a model that accounts for heterogeneity across firms and individuals, human capital accumulation, and endogenous career choices over time.

To improve our understanding of the careers of young entrepreneurs, I use information on the career choices and earnings of individuals to estimate a dynamic Roy model of career choice. I recover parameters governing: (a) the returns to various types of experience in the labour market and in entrepreneurship, (b) the non-pecuniary benefits associated with being a worker and an entrepreneur, and (c) career-specific entry costs. As in Keane and Wolpin (1997), I specify a finite mixture model to capture unobserved heterogeneity across individuals. This means that I separate individuals into a finite number of unobservable types, and that I allow key parameters of the model to vary by type. My use of a finite mixture model allows for the career choices and earnings of individuals to be correlated with each other and over time. As such, it allows the model to handle sorting on unobservables at labour force entry and across careers over the life cycle. I use a computationally light two-stage procedure developed by Arcidiacono and Miller (2011) to estimate the parameters of the model.

My model uniquely captures four key determinants of entrepreneurial success which could explain the empirical patterns described above. First, the model allows for differences in innate entrepreneurial ability across individuals. Specifically, to capture unobserved absolute and comparative advantages between individuals, I allow the earnings process in each career to flexibly depend on an individual's unobservable type. Second, individuals can acquire skills that are valuable in entrepreneurship by accumulating prior work experience. In the labour market, individuals can sort into heterogeneous firms that offer different pay schedules and different learning opportunities. By working in high-quality firms, future entrepreneurs have the potential to acquire skills that are necessary to run a successful business. Third, the model allows for learning-by-doing in entrepreneurship. Finally, to capture heterogeneous learning abilities, I allow for the returns to various types of experience to depend on an individual's unobservable type. As such, different people may face different incentives and choose career paths accordingly.

My results indicate that only a small fraction of the population has a comparative advantage in entrepreneurship at age 25. This subpopulation can be divided into two types: (1) individuals who can earn more as entrepreneurs because they have low earnings potential in the labour market at age 25 and (2) individuals who have high earnings potential in all careers at age 25, but can earn more as entrepreneurs than as workers in lower-quality firms. They represent roughly 9% and 10% of the population, respectively. Interestingly, these two types, which have emerged from the data, fit the profiles of subsistence and transformational entrepreneurs, as described by Schoar (2010).[2] For simplicity, I use the labels *subsistence* and *transformational* to refer to them from here on in.

Allowing for heterogeneous returns to experience reveals important insights into the determinants of entrepreneurial success. I confirm recent empirical evidence that experience in entrepreneurship is an important channel through which individuals acquire skills that are valuable in entrepreneurship (e.g., Gompers et al., 2010; Lafontaine and Shaw, 2016). I find, however, that this channel is mostly relevant for the two types mentioned above, who have a comparative advantage in entrepreneurship at labour force entry. For the vast majority of the population, the estimated returns to experience in entrepreneurship are small.

I find that prior work experience is of limited value in entrepreneurship, unless it has been accumulated in high-quality firms. Experience in high-quality firms is particularly valuable for the subsistence type. For these individuals, five years of work experience in high-quality firms more than doubles their baseline earnings in entrepreneurship. Prior work experience is of limited value in entrepreneurship for the transformational type, however. Broadly, these results are consistent with Lazear (2005)'s theory that individuals must have a balanced set of skills to be successful in entrepreneurship. The subsistence type, who lack innate entrepreneurial skills compared to the transformational type, can acquire those skills by working in high-quality firms.

The parameter estimates suggest that there are various reasons why few individuals choose a career in entrepreneurship. For most people, entrepreneurship is not an attractive career because (1) they have the potential to earn more as workers than as entrepreneurs and (2) they dislike the amenities associated with entrepreneurship. For the subsistence type, the main deterrents are large entry costs into entrepreneurship. For the transformational type, two kinds of opportunity costs deter them from pursuing a career in entrepreneurship. First, transformational individuals have the potential to earn more in high-quality firms than in entrepreneurship. Second, they have low returns to entrepreneurship experience in the labour market, so any time spent in entrepreneurship is a forgone opportunity to accumulate skills that are valuable in the labour market.

[2]See also Poschke (2013) on necessity and opportunity entrepreneurs.

Understanding the heterogeneous profiles of entrepreneurs is essential to guide policy-makers tasked with fostering entrepreneurship. To give a simple example, a commonly held belief is that there is no better way to acquire the skills necessary to run a successful business than to be an entrepreneur and learn from experience. If this is true, promoting entrepreneurial success means helping individuals become entrepreneurs early on in their careers. At the same time, many academics and practitioners have emphasized the importance of prior work experience for entrepreneurial success (e.g. Lazear, 2005; Liang et al., 2018; Azoulay et al., 2020). If prior work experience is an important channel through which individuals acquire entrepreneurial skills, then policies that incentivize early career individuals to become entrepreneurs may be misguided. Perhaps it would be more effective to help young people acquire skills in the labour market and target older workers instead. My results paint a more nuanced picture of the interaction between career decisions and entrepreneurship.

I use my estimated model to evaluate the effectiveness of various subsidies designed to promote entrepreneurship. I highlight selection and the heterogeneous effects of the subsidies across individual types. By and large, I find that the effects of subsidies tend to be short-lived. Moreover, if the goal of the policy is to attract individuals with high-growth potential to entrepreneurship, then untargeted subsidies seem costly to implement. This is because they induce a large fraction of individuals with relatively low entrepreneurial skills to become entrepreneurs.

This paper contributes to our understanding of the relative importance of factors affecting the decision to become an entrepreneur, as well as the determinants of entrepreneurial success. A recent set of papers has documented substantial heterogeneity in the ambition, ability, and preferences of entrepreneurs (e.g., Schoar, 2010; Hurst and Pugsley, 2011, 2015; Levine and Rubinstein, 2016). My paper is part of a small literature in economics that takes into account such heterogeneity in modelling the dynamic career decisions of individuals (Dillon and Stanton, 2017; Hincapié, 2020; Humphries, 2021; Catherine, 2022). Closest to my paper is Humphries (2021), who uses rich administrative data from Sweden and a dynamic Roy model to understand how entrepreneurship fits into the broader career decisions of individuals. Among other things, he finds that cognitive and non-cognitive skills, education, and past experience are important determinants of entrepreneurial success.

I add to the existing literature by considering heterogeneity in the returns to experience across types.[3] I provide the first evidence that the returns to various types of experience in entrepreneurship are heterogeneous and correlated with unobserved ability. Another distinguishing feature of my model is that it accounts for the presence of heterogeneous employers

[3] Belzil and Hansen (2007) and Baum-Snow and Pavan (2012) similarly allow for the returns to schooling and returns to experience in large cities to be indexed by an individual's unobservable type in their dynamic structural models.

in the labour market. Firm heterogeneity is a pervasive feature of the labour market and the firm a worker chooses matters for earnings outcomes (e.g., Abowd et al., 1999; Oreopoulos et al., 2012; Card et al., 2018; Bonhomme et al., 2019). As in Bonhomme et al. (2019), I group firms into different classes ex-ante and account for the endogenous sorting of individuals across firm classes. I provide the first evidence that the returns to prior work experience in entrepreneurship depend on the quality of the firm in which it has been acquired.[4] Considering heterogeneity across firms and individuals provides new insights relevant to policymakers. One key challenge in policy design is identifying which types of entrepreneurs are most likely to respond to a given policy. I demonstrate that career histories contain valuable information about individual types that can be leveraged to more effectively target high-growth entrepreneurs. Specifically, I find that a subsidy for entrepreneurship, available only to individuals who have worked at high-wage firms, narrows in on individuals with higher entrepreneurial skills.

2 Data

My investigation uses Canadian matched owner-employer-employee data. The dataset contains information on the universe of workers, firms, and business owners in the country between 2001 and 2012. It is created by merging various administrative tax files. Information on workers comes from individual tax returns (Form T1). These individual tax returns are merged to firm records of employment remuneration (Form T4). Additional information on firms comes from corporate income tax returns (Form T2) and firm book values. Information on business owners comes from unincorporated business declaration files and shareholder information for private corporations (Form T2 - Schedule 50). The business owner files, which are linked to both the worker file and the firm file, allow me to identify entrepreneurs in the data and to follow them over time.

2.1 Identifying Start-up Firms

The primary definition of entrepreneurship used in this paper requires information on start-ups. I rely on the longitudinal nature of the firm-level data to identify start-up firms, following Azoulay et al. (2020). Specifically, I define start-up firms as firms that appear in the data with non-missing employment, revenue, or payroll for the first time after 2001 and have an incorporation year within two years of their panel entry year.

[4] A number of recent empirical papers similarly emphasize the dynamic effects of employment at heterogeneous firms. For example, Nix (2020), Gregory (2021), Arellano-Bover and Saltiel (2022), and Arellano-Bover (2022) show that the value of work experience in the labour market is positively correlated with the average education of co-workers, firm-specific components of earnings growth, and firm size.

2.2 Information on Career Choices and Earnings

Individuals derive earnings from three main sources: employment income, unincorporated business income, and incorporated business income. I define incorporated business income as the sum of all employment income received from incorporated businesses owned by the individual.[5] All dollar amounts are converted into constant 2012 dollars using Bank of Canada's core CPI index.

I now describe the procedure used to construct a panel dataset with information on the career choices and earnings of individuals each year. Because individuals may derive earnings from multiple sources in a year, any rules used to create annual data on career choices will be somewhat arbitrary. I assign individuals to mutually exclusive career alternatives in a hierarchical fashion, as follows.

1. Incorporated Entrepreneurship. I assign individuals to incorporated entrepreneurship if the incorporated business income they draw from their own start-up firms is above \$10,400, regardless of the earnings they derive from other sources.[6]

2. Unincorporated Entrepreneurship. I assign individuals to unincorporated entrepreneurship if (1) they are not incorporated entrepreneurs and (2) they have a net unincorporated business income above \$10,400.

3. Work. I consider individuals to be workers if (1) they are not entrepreneurs and (2) they have employment income above \$10,400. To characterize work experience, I assign workers who hold multiple jobs in a given year to the employer from which they derive most employment income during the year.

4. Non-Employment. I assign unemployed individuals and individuals that are out of the labour force to non-employment.[7] I also assign individuals who make less than \$10,400 from any single income source to non-employment.

5. Annual Earnings. I give individuals the annual earnings associated with their assigned career, ignoring other sources of income if they have any. That is, the annual earnings of workers is their total employment income, the annual earnings of incorporated entrepreneurs is their incorporated business income, and the annual earnings of unincorporated entrepreneurs

[5] This incorporated business income measure corresponds to the "draw" in Hamilton (2000). I exclude retained earnings from my definition of incorporated business income because I am interested in entrepreneurs who actively work at the firm, not passive investors who hold equity in the firm but do not work there.

[6] I use a minimum income threshold to minimize the effect of part time work and, more generally, to make sure that individuals have a non-negligible attachment to the labour force and their career. \$10,400 is roughly equal to 26 weeks of work full-time at the prevailing minimum wage during the sample period. In the main sample, about 8% of individual-year observations categorized under incorporated entrepreneurship exhibit employment income that exceeds incorporated business income. See Online Appendix D for a discussion of robustness to alternative definitions of incorporated entrepreneurship.

[7] I observe most individuals who are unemployed or out of the labour force because individuals need to file a T1 to claim benefits in Canada.

is their unincorporated business income.

Figure 1 shows the distribution of annual earnings for workers, unincorporated entrepreneurs, and incorporated entrepreneurs in 2012. The sample used to create this figure includes all non-immigrant men age 25-55. Among other things, this figure illustrates why it is important to make a distinction between the two types of entrepreneurs in the data. Unincorporated entrepreneurs earn significantly less, on average, than workers.[8] In contrast, incorporated entrepreneurs tend to earn more than workers. As Levine and Rubinstein (2016) argue, entrepreneurs with high-growth potential tend to start incorporated businesses.[9] Figure 1 also reveals substantial heterogeneity among incorporated entrepreneurs. Empirically, the earnings distribution of incorporated entrepreneurs is more dispersed than the earnings distribution of workers.

2.3 Definition of the Firm Quality Ladder

I assign firms to one of three classes: high-, medium-, or low-quality. These classes are defined using quartiles of the average firm wage distribution, as in Oreopoulos et al. (2012) and Haltiwanger et al. (2018). Specifically, I calculate average log payroll per employee at the firm level, taking out industry-year fixed effects.[10] I then calculate quartiles, weighting firms by their average employment over the entire firm panel. I classify firms as high-quality if they are in the top quartile, medium-quality if they are in the next quartile, and low-quality if they are below the median. Firm classes refer to permanent firm attributes so they remain unchanged over the entire panel. The only way a worker can change firm classes is by moving to a different firm.

In principle, I could have used alternative measures of firm quality to classify firms. As I show in Online Appendix Table A.1, higher quality firms have higher revenue per employee, higher payroll per employee, and higher firm-specific components of pay. Empirically, the firm quality ladder is similar when using Abowd et al. (1999) (AKM) style firm fixed effects or average revenue per worker to classify firms instead of average firm wage. However, these alternative measures of firm quality yield a less complete classification of firms because of missing data.[11] As documented elsewhere (e.g., Haltiwanger et al., 2018; Bilal et al., 2022),

[8]This is a robust finding in the empirical literature on entrepreneurship (e.g., Evans and Leighton, 1989; Hamilton, 2000; Hurst and Pugsley, 2011).

[9]Two key features of incorporation underlie this fact: (1) incorporation encourages risk-taking because of limited liability and (2) it facilitates financing through the issuance of bonds to investors.

[10]Industries are defined using two-digit NAICS codes.

[11]In a previous version of the paper, I used the two-way fixed effects model developed by Abowd et al. (1999) to identify the quality of firms in the data (see Gendron-Carrier, 2018). One issue with the AKM firm fixed effects is that they are often not identified for small firms and start-ups (e.g., about 40% of firms in the 2012 cross-section have missing firm fixed effects). Because prior work experience in start-up firms could be particularly valuable for entrepreneurship, having a firm quality ladder that includes such firms is important.

I find that firm size is only weakly correlated with firm wage and labour productivity.

2.4 Sample Restrictions

I now describe the main sample restrictions. I provide complete details about the estimation sample in Online Appendix A.1. My analysis hinges on the ability to observe the career histories of entrepreneurs before they start their businesses. Because I only observe career histories between 2001 and 2012, I restrict my attention to individuals who start their careers during this sample period. Specifically, I estimate the model using individuals aged 25 or older that are born between 1976 and 1985. These are cohorts of individuals for which I observe right-truncated career histories starting at age 25.[12] I further restrict my attention to men only. Few women are entrepreneurs in the data and their career decisions early in the life cycle would require a different model that takes into account fertility decisions. I exclude immigrants because their background prior to arrival is unobserved and it is likely to be different than that of natives. Finally, to form a homogeneous sample, I keep only individuals who are employed at age 25.[13] This leaves me with a sample of 721,730 individuals and 4,906,785 individual-year observations. I exclude observations from 2012 to estimate the model and use these observations only to evaluate out-of-sample fit. The model is therefore estimated using 4,283,785 individual-year observations.

3 Some Stylized Facts about Entrepreneurship

Figure 2 shows the fraction of individuals that are incorporated entrepreneurs at each point in time between 2001 and 2012, cohort by cohort. The black lines indicate the cohorts that I consider in the main estimation sample. The grey lines indicate other cohorts of individuals born 1946-1975 and 1986-1987. The horizontal lines indicate the fraction of incorporated entrepreneurs at different point in the life cycle. This figure highlights that (1) few individuals become incorporated entrepreneurs over the course of their career, (2) the fraction of incorporated entrepreneurs increases steadily over the life cycle, reaching about 7.5% at age 55, and (3) the patterns are remarkably stable across cohorts.[14]

[12] I follow individuals starting at age 25 to abstract from schooling decisions. A limitation of the Canadian matched owner-employer-employee data is that it does not include information on education. In unreported results, I have found that the results are similar if I follow individuals starting at age 24 or 26. I explain how I account for ex-ante heterogeneity in Section 4.

[13] Individuals who are non-employed at age 25 have a very weak attachment to the labour force (about 80% of all individual-year observations for this group are in non-employment). My estimation sample is therefore not a random sample, and over-samples from the more educated population.

[14] Online Appendix Table A.2 reports the fraction of individuals in various careers between age 26 and 35 for the main estimation sample. I summarize the statistics from this table in Online Appendix A.2.

Table 1 describes the types of career transitions observed in the main sample. For each origin-destination pair, it reports (1) the percentage of transitions from career of origin to destination career (row %) and (2) the percentage of observations in a destination career that comes from each career of origin (column %). I report career transitions at age 30 because they are representative of the sample average. Focusing on career transitions in- and out- of entrepreneurship, the results show that individuals are more likely to become unincorporated entrepreneurs than incorporated entrepreneurs, regardless of their origin. With this said, we can see that individuals are relatively more likely to become unincorporated entrepreneurs if they come from low-quality firms. Coming from non-employment, the majority of individuals that transition into entrepreneurship choose to be unincorporated entrepreneurs (19% become incorporated entrepreneurs). Looking at transitions out of entrepreneurship, we can also see important differences between incorporated and unincorporated entrepreneurs in terms of destination career. Incorporated entrepreneurs are relatively more likely to transition into high-quality firms than unincorporated entrepreneurs. They are also less likely to transition into non-employment.

Table 1 reveals that career choices are highly persistent from one year to the next. It also reveals systematic differences in the degree of persistence across careers. Perhaps surprisingly, I find that incorporated entrepreneurs are likely to remain in their career from one year to the next. This finding challenges the idea that most entrepreneurship spells are short-lived. I find that 86.5% of all incorporated entrepreneurs at age 30 remain in that career from one year to the next. This degree of persistence is roughly comparable to the one observed among workers in high- and medium-quality firms (89.6% and 84.8% remain in their firm class from one year to the next, respectively). In contrast, about 66% of all unincorporated entrepreneurs remain in that career from one year to the next, a degree of persistence only slightly larger than the one observed in non-employment. In all, there seems to be a hierarchy of careers in terms of persistence. The most absorbing careers are (in decreasing order): (1) employment in high-quality firms, (2) incorporated entrepreneurship, (3) employment in medium-quality firms, (4) employment in low-quality firms, (5) unincorporated entrepreneurship, and (6) non-employment. This hierarchy is also reflected in the average logarithm of annual earnings across careers, as reported in Table 2.

Table 2 provides more information about the estimation sample. The average log earnings in the sample is 10.67. In the labour market, average log earnings increase monotonically with firm quality. In entrepreneurship, we can see that incorporated entrepreneurs earn about the same on average as workers in medium-quality firms and that unincorporated entrepreneurs earn less than workers in low-quality firms. Incorporated entrepreneurs tend to be older than unincorporated entrepreneurs and they tend to accumulate work experience in better firms than unincorporated entrepreneurs.

Using information on residential postal codes, I construct a few variables which help me paint a richer picture about the type of individuals who become entrepreneurs. I focus on three baseline characteristics: (1) living in a high income area at age 25, which I take as a proxy for initial wealth, (2) living in an entrepreneurial area at age 25, which I take as a measure of initial learning opportunities about entrepreneurship (Guiso et al., 2021), and (3) living in a large city at age 25, which tends to be associated with higher levels of educational attainment (Glaeser and Maré, 2001; Baum-Snow and Pavan, 2012; De la Roca and Puga, 2016).[15] Table 2 reveals that incorporated entrepreneurs are more likely to come from high income areas and entrepreneurial areas at age 25. About 31% of observations in incorporated entrepreneurship come from high income areas at age 25, a larger percentage than for workers in any firm class. Even more striking is the fact that 38% of observations in incorporated entrepreneurship come from entrepreneurial areas at age 25. In terms of initial city size, I find that incorporated entrepreneurs are less likely to be in a large city at age 25 than the average.

Table 3 documents first spells in incorporated entrepreneurship. I observe 14,465 first spells in total and report survival rates and average log earnings in each year of the spell until Year 6. Pooling all spells together, I find that more than 55% of individuals survive until Year 6. This suggests that the fraction of individuals who transition out of incorporated entrepreneurship declines with time spent in this career.[16] I also find that earnings profiles in incorporated entrepreneurship are steep: on average, earnings increase by 126% between Year 1 and Year 6 among those that survive. This average masks substantial heterogeneity in earnings growth, however.

In the other columns of Table 3, I break down these statistics by the type of prior work experience acquired by individuals before the start of their first spell, focusing on the interaction of career of origin and potential work experience (age). The patterns are complex but quite informative. First, looking at survival rates, it looks like individuals with better outside options (i.e., individuals with more prior work experience and those coming from high-quality firms) have lower survival rates in incorporated entrepreneurship, although the patterns are not clear cut. Turning our attention to earnings, we can see that baseline earnings in entrepreneurship increase with potential work experience. Older individuals tend to start more

[15] I consider individuals to be living in a high income area at age 25 if the average annual earnings among all residents in their postal code at age 25 is in the top quartile of the distribution in the estimation sample. I consider individuals to be living in an entrepreneurial area at age 25 if the density of business owners in their postal code at age 25 is in the top quartile of the distribution in the estimation sample. Large cities include Toronto, Montreal, and Vancouver.

[16] 84% of individuals survive the first year. If the year-to-year survival rate remained constant, we would expect about 42% of individuals to survive until Year 6 ($0.84^5 = 0.42$).

profitable businesses.[17] We can also see that the type of prior work experience matters. Individuals who come from better firms earn more in Year 1 and have steeper earnings profiles.[18] Online Appendix Table A.3 summarizes these earnings results in a regression form. Column 1 shows that, on average, an additional year of prior work experience is associated with a 2.3% increase in baseline earnings in incorporated entrepreneurship. Column 2 reveals that this is mostly driven by prior work experience in high-quality firms. Online Appendix Table A.4 reproduces the statistics reported in Table 3 on a balanced sample of individuals that survive until Year 6. Similar patterns of earnings growth can be observed within-person.

4 The Model

In this section, I develop a dynamic Roy model of career choice that flexibly incorporates various mechanisms driving entry into entrepreneurship and entrepreneurial success. I specify a finite mixture model, which means that there is a finite number of unobservable individual types in the population and that key parameters of the model are allowed to vary by type.[19] I index types by $z \in Z$ and I allow the probability that an individual belongs to each type to depend on his first observed career choice at age 25. I also allow unobservable types to depend on three baseline characteristics which are intended to capture a combination of initial wealth, initial ability, and initial learning opportunities about entrepreneurship: (1) an indicator for living in a high income area at age 25, (2) an indicator for living in an entrepreneurial area at age 25, and (3) four indicator variables capturing initial city size.[20] As such, an individual's unobservable type can be interpreted as unobserved heterogeneity that is either innate or acquired before age 25. Because finite mixture models are demanding in terms of identification and estimation, I limit the number of unobservable types in the population to five.[21]

In the model, individuals decide each year whether they want to pursue a career in the

[17] Comparing individuals who enter incorporated entrepreneurship for the first time from high-quality firms at age 30+ (with at least 5 years of potential work experience) to individuals who enter from the same career of origin at age 26-27, we see that older individuals earn 17% more in Year 1.

[18] Consider individuals who enter incorporated entrepreneurship for the first time at age 30+ (with at least 5 years of potential work experience). Those who come from high-quality firms earn about 33% more in Year 1 than those who come from low-quality firms. The earnings gap between these two groups of entrepreneurs widens over time spent in incorporated entrepreneurship.

[19] This way of accounting for unobserved heterogeneity is based on the influential work of Heckman and Singer (1984) and Keane and Wolpin (1997).

[20] I use four initial city size categories: large cities (Toronto, Montreal, Vancouver), medium-sized cities (e.g., Ottawa, Calgary, Halifax), small cities (with a population smaller than 350K in the 2006 Census), and rural areas.

[21] In Online Appendix D.1, I report parameter estimates and model fit for a model with three unobservable types instead of five.

labour market or in entrepreneurship. They derive flow utility from the sum of their expected log earnings, career-specific amenities (net of mobility costs if they change career), and an idiosyncratic preference shock. Individuals are assumed to be forward-looking and they make their career decisions to maximize the expected discounted value of lifetime utility.[22]

There are six career options in the model, indexed by $j \in J$. In the labour market, individuals can choose to work in low-quality firms ($j = 1$), in medium-quality firms ($j = 2$), or in high-quality firms ($j = 3$). In entrepreneurship, individuals can choose to be unincorporated entrepreneurs ($j = 4$) or incorporated entrepreneurs ($j = 5$). Individuals can also choose to be non-employed ($j = 0$). Let $a_{i,j,t} \in a_{i,t}$ denote an action variable that is equal to 1 if individual i chooses career j at time t and is equal to 0 otherwise.

4.1 Timing and Flow Utility

The timing of the model is as follows. Individuals enter each period with their time-invariant unobservable type, z_i, and a vector of observable individual characteristics, $x_{i,t}$, which includes the number of years of experience they have in each career and a set of indicator variables that identify their previous career choice. Individuals are perfectly informed about their skills.[23] Upon entering the period, they receive a vector of career-specific idiosyncratic preference shocks, $\epsilon_{i,t}$. Given z_i, $x_{i,t}$, and $\epsilon_{i,t}$, they optimally choose a career $j \in J$. After making their decisions, individuals receive an ex-post productivity shock, $\mu_{i,j,t}$, which affects realized earnings during the period. I assume the career decisions of individuals are not affected by the uncertainty associated with the ex-post productivity shock. As I explain below, I allow each career to offer different amenities. This allows the model to capture the disutility associated with choosing a career that is inherently more risky, such as entrepreneurship.

Individual i derives the following flow utility from choosing career j at time t:

$$u_j(z_i, x_{i,t}, \epsilon_{i,j,t}) = \alpha \mathbb{E}[\ln(y_j(z_i, x_{i,t}, \mu_{i,j,t}))] + \phi_j(z_i) - \psi_j(z_i, x_{i,t}) + \epsilon_{i,j,t} \tag{1}$$

where $\mathbb{E}[\ln(y_j(z_i, x_{i,t}, \mu_{i,j,t}))]$ denotes the expected log earnings of individual i in career j at time t, $\phi_j(z_i)$ are the amenities associated with career j, and $\psi_j(z_i, x_{i,t})$ are the mobility costs incurred by individual i upon entering career j at time t. There is no saving or borrowing.[24] As is standard in the literature, I assume the career-specific idiosyncratic preference

[22] I do not need to take a stand on the time horizon T for estimation. See Online Appendix B for a detailed explanation of the estimation procedure.

[23] See Manso (2016), Dillon and Stanton (2017), Hincapié (2020), and Catherine (2022) for recent papers that explore the role of learning about entrepreneurial skills through experimentation in the tradition of Jovanovic (1982).

[24] Introducing an intertemporal budget constraint and modeling savings decisions would complicate the model to the point of intractability. In my model, the effects of initial wealth on mobility costs and en-

shock, $\epsilon_{i,j,t}$, is independent and identically distributed across individuals and over time and drawn from the Type I extreme value distribution with variance $\frac{\pi^2}{6}$. The scale parameter α determines the relative importance of expected log earnings in choosing a career.

To capture unobserved absolute and comparative advantages between individuals, I allow the earnings process in each career to flexibly depend on unobservable type. To capture heterogeneity in preferences, I allow key parameters of the utility function to vary by unobservable type. This is important in the context of entrepreneurship for two main reasons. First, a commonly cited reason for selection into entrepreneurship has to do with the value of being your own boss (Hurst and Pugsley, 2011, 2015). Such intrinsic motivation for entrepreneurship is captured by the type-specific amenities. Second, entrepreneurs are characterized by a higher tolerance to discomfort and disrupting activities (Levine and Rubinstein, 2016). This higher tolerance to discomfort is captured by type-specific mobility costs. I describe the earnings process, amenities, and mobility costs in subsections 4.2 and 4.3.

4.2 The Earnings Process

Earnings in career j are modeled as follows:

$$\begin{aligned}\ln(y_j(z_i, x_{i,t}, \mu_{i,j,t})) = r_j(z_i) + \sum_{j'=1}^{3} \beta^j_{j'}(z_i)\text{exper}_{i,j',t} + \beta^j_4(z_i)\text{exper}_{i,4,t} + \beta^j_5(z_i)\text{exper}_{i,5,t} \\ + \beta^j_6(z_i)(\sum_{j'=1}^{3}\text{exper}_{i,j',t})^2 + \beta^j_7(z_i)\text{exper}^2_{i,4,t} + \beta^j_8(z_i)\text{exper}^2_{i,5,t} + \mu_{i,j,t}\end{aligned} \tag{2}$$

where $r_j(z_i)$ represents the intercept in career j, $\{\text{exper}_{i,j',t}\}^3_{j'=1}$ denotes work experience accumulated by individual i in firm class j' up until time t, $\text{exper}_{i,4,t}$ denotes experience accumulated by individual i as an unincorporated entrepreneur up until time t, $\text{exper}_{i,5,t}$ denotes experience accumulated by individual i as an incorporated entrepreneur up until time t, and $\mu_{i,j,t}$ is the ex-post productivity shock. I assume individuals have no experience in any career upon entering the model.[25] $\mu_{i,j,t}$ is assumed to be normally distributed and i.i.d. across individuals over time with variance σ^2_j.

Equation (2) is flexible. It allows each career to have its own earnings process, characterized by different intercepts and different returns to various types of experience. It also

trepreneurial success are captured solely by the unobservable types. Mobility costs are specified in a reduced-form way to capture frictions that operate outside the model, such as startup costs and capital constraints. Evans and Jovanovic (1989), Holtz-Eakin et al. (1994a), Holtz-Eakin et al. (1994b), Hurst and Lusardi (2004), Cagetti and De Nardi (2006), Buera et al. (2011), and others discuss the role of liquidity constraints in entrepreneurship.

[25] From this point on, the process governing the evolution of the experience variables is a deterministic function of past actions: $\text{exper}_{i,j,t+1} = \text{exper}_{i,j,t} + a_{i,j,t}\ \forall j \in J$.

allows unobservable type to affect the earnings process in each career in two important ways. First, the career-specific intercepts vary by unobservable type. The introduction of such type fixed effects captures level effects associated with unobserved productivity differences across individuals. Second, the specification allows for the returns to various types of experience to depend on unobservable type. Allowing key parameters of the earnings process in each career to depend on unobservable type is crucial to allow the model to handle sorting on unobserved ability. Individuals may also have heterogeneous learning abilities and choose career paths accordingly.

This specification captures the key determinants of entrepreneurial success discussed in the introduction. I focus the discussion on the earnings process of incorporated entrepreneurs ($j = 5$). First, the specification allows for differences in innate entrepreneurial ability through the type-specific intercept $r_5(z_i)$. Second, the specification allows individuals to acquire skills in the labour market that are valuable in entrepreneurship. To capture the idea that experience in better firms might be more valuable in entrepreneurship, I allow the value of work experience to depend on the quality of the firm in which it has been acquired. For example, the value of one year of work experience in high-quality firms is given by the coefficient $\beta_3^5(z_i)$. I allow the rate at which individuals learn on the job to depend on their type to capture heterogeneous learning. Finally, the specification allows for learning-by-doing in entrepreneurship through the coefficients $\beta_5^5(z_i)$ and $\beta_8^5(z_i)$. I allow for the slope coefficient on entrepreneurial experience and the curvature to vary by type.

4.3 Amenities and Mobility Costs

Amenities are career-specific and enjoyed every period. To capture heterogeneity in preferences for entrepreneurship, I allow the value of amenities associated with unincorporated entrepreneurship and incorporated entrepreneurship to vary by unobservable type.

Individuals incur one-time mobility costs upon changing careers. Mobility costs are origin-destination specific, such that the cost of starting employment at a high-quality firm coming from employment at a medium-quality firm is not the same as the cost of starting employment at a high-quality firm coming from entrepreneurship. Similarly, the cost of entry into incorporated entrepreneurship coming from a low-quality firm is not the same as the cost of entry into incorporated entrepreneurship coming from a high-quality firm. This could be the case because of faster wealth accumulation in high-quality firms, for instance. To capture the idea that individuals who become entrepreneurs might have a higher tolerance to discomfort and disruption, I allow all entry costs into unincorporated entrepreneurship and incorporated entrepreneurship to vary by unobservable type. Mobility costs are fixed and depend on unobservable type and career of origin.[26]

The mobility costs are specified in a reduced-form way to fit transition patterns in the data. They are meant to capture mobility frictions that operate outside the model such as startup costs, search frictions, psychological costs, etc.[27] I assume it is costless to remain in the same career. I also assume the previous career choice of individuals upon entering the model is the same as their first observed career choice at age 25. As explained above, I use information on the first observed career choice of individuals to identify their unobservable type as opposed to mobility costs.

4.4 Optimal Career Choices

I now summarize the optimization problem of individuals. Additional mathematical details are in Online Appendix B.1. Letting β denote the common discount factor, the optimization problem of individual i at time t is given by:

$$\max_{\{a_{i,t},\ldots,a_{i,T}\}} \mathbb{E}_t \left[\sum_{b=0}^{T-t} \sum_{j=0}^{5} \beta^b a_{i,j,t+b} \left(u_j(z_i, x_{i,t+b}) + \epsilon_{i,j,t+b} \right) | z_i, x_{i,t}, \epsilon_{i,t} \right]$$

where the expectation is taken over future values of the idiosyncratic preference shocks conditional on all the information available at time t.

5 Estimation and Identification

In this section, I outline the estimation procedure and informally discuss identification. I provide complete details about the estimation procedure in Online Appendix B.

5.1 Estimation

I estimate the parameters of the model by maximum likelihood using a two-stage estimation procedure developed by Arcidiacono and Miller (2011). This two-stage estimation procedure has the advantage of being computationally light and it accommodates nonstationary data

[26]In unreported results, I have found that allowing mobility costs to additionally be a function of age makes little difference in terms of model fit.

[27]Indeed, all search frictions are folded into the idiosyncratic preference shocks and the mobility costs. One way to interpret the idiosyncratic preference shocks is as shocks to mobility costs, which could reflect job offers and exogenous job separations in a typical job ladder model. These shocks either increase or decrease the burden of choosing a career in a given year. For example, a large preference shock for non-employment can be thought of as a layoff shock, where the individual has no choice other than accept this outcome. The matrix of mobility costs is origin-destination specific which brings the model closer to a job ladder model in the tradition of Burdett-Mortensen, where the burden of changing occupations can depend on previous employment status.

generating processes.[28] The key idea is to exploit the finite dependence property of the model to derive a linear mapping between the conditional choice probabilities (CCPs) and the parameters of the utility function. Because CCPs can be recovered directly from the data, it is possible to estimate the parameters of the utility function without solving the full model.

A model is said to exhibit ρ-period finite dependence if it is possible to find two sequences of choices that lead to the same continuation values after ρ periods. In the context of my model, the effect on the future of a choice today occurs through two channels: human capital accumulation and mobility costs. It is possible to find two career paths that lead to the same continuation values at some point in the future because (a) there is no depreciation of career-specific human capital over time and (b) mobility costs only depend on last year's career choice, $a_{i,t-1}$. Consider the following career paths: (1) career j at time t, career $j^{'}$ at time $t+1$, and career $j^{''}$ at time $t+2$ and (2) career $j^{'}$ at time t, career j at time $t+1$, and career $j^{''}$ at time $t+2$. Both sequences lead to the same state at the beginning of period $t+3$. To see this, note that both career paths increase $\text{exper}_{i,j,t}$, $\text{exper}_{i,j',t}$, and $\text{exper}_{i,j'',t}$ by one unit and present individuals with the same menu of mobility costs at the beginning of time $t+3$ because the last career choice is $j^{''}$ in both cases.

In the first stage, I use an iterative procedure known as the Expectation-Maximization (EM) algorithm to obtain (1) estimates of the parameters governing the distribution of unobservable types, τ, (2) estimates of the parameters of the earnings equations, θ_Y, and (3) empirical estimates of the CCPs that vary non-parametrically by unobservable type.

In the second stage, I project the empirical estimates of the CCPs onto parameter space in a least-squares way to recover the parameters of the utility function, θ_U. Intuitively, these parameters are the ones that minimize the distance between the observed behavior of individuals in the data and the behavior of individuals that is predicted by the model.

5.2 Identification

I now informally discuss the variation in the data and assumptions that allow me to identify the parameters of the model.[29]

First, consider the identification of the parameters governing the distribution of unobservable types. The unobserved type, which affect earnings, amenities, and mobility costs, allows

[28] Nonstationarities arise naturally in the life cycle, for example through aging. For estimation, I do not need to make assumptions about payoff functions beyond the observed age range of individuals in the data and I do not need the take a stance on the time horizon of the model. One drawback of this estimation approach, however, is that it imposes limitations on the scope of policy interventions that can be simulated. See Arcidiacono and Miller (2019, 2020).

[29] Kasahara and Shimotsu (2009) discuss the non-parametric identification of finite mixtures in dynamic discrete choice models.

for the career choices and earnings of individuals to be correlated with each other and over time. As such, it allows the model to handle sorting on unobservables. A key assumption is that unobservable types are drawn from a discrete distribution with a small number of types. Unobservable types are identified using both persistence in earnings over time and persistence in career choices over time. For example, we can infer from someone who chooses to be an entrepreneur year after year that he is either good at it or that he particularly enjoys the amenities associated with this career. Within-person serial correlation in earnings residuals allows the EM algorithm to distinguish between these two possibilities. Unobservable types are also identified using cross sectional variation in baseline characteristics.

Second, consider the identification of the parameters of the earnings equations. These parameters are identified using both cross sectional and time series variation in earnings. For the sake of exposition, I discuss the identification of the returns to various types of experience in entrepreneurship. The returns to experience in entrepreneurship, which capture the importance of learning-by-doing in entrepreneurship, are identified by following individuals over time in entrepreneurship. The returns to various types of prior work experience in entrepreneurship are identified by comparing the baseline earnings of individuals that have different career histories before entry. Because these parameters are type-specific, they are identified by comparing individuals of the same type with one another. The key identifying assumption necessary to obtain unbiased estimates of the parameters of the earnings equations is that career choices are exogenous conditional on unobservable type and a vector of observable individual characteristics. In the model, two individuals with the same unobservable type have the same ex-ante probability of choosing each career path.

Finally, consider the identification of the parameters of the utility function. As is standard with these types of dynamic discrete choice models, I need to normalize the value of one career and the discount factor β to be able to identify the parameters of the utility function (Rust, 1994; Magnac and Thesmar, 2002). I set β equal to 0.9 throughout the estimation procedure. I choose non-employment as the reference career and normalize the value of amenities and entry costs associated with this career to zero. I set earnings in non-employment equal to \$10,400, which is the minimum income threshold used to define careers in Section 2.2.

Flow utility parameters are identified using observed career transitions. Specifically, the dependent variable in the second stage of the estimation procedure is a function of the empirical CCPs and can be interpreted as the minimum compensating differential an individual must receive to be willing to choose career path $\{a_{i,j',t} = 1, a_{i,j,t+1} = 1, a_{i,j'',t+2} = 1\}$ instead of $\{a_{i,j,t} = 1, a_{i,j',t+1} = 1, a_{i,j'',t+2} = 1\}$. The scale parameter is identified using variation in expected log earnings along these two career paths. Specifically, the correlation between the minimum compensating differential and the difference in expected log earnings along the two career paths pins down the scale parameter. Identification of the scale parameter requires an exclusion restriction. In my model, the number of years of experience an individual has in each career affects flow utility only through expected log earnings. Once we know how sensitive career choices are to expected log earnings, it is possible to pin down the career-specific amenities and mobility costs parameters. Accounting for expected log earnings differentials, the career-specific amenities and mobility costs parameters ensure that the minimum compensating differential that is predicted by the model matches the one implied by the empirical estimates of the CCPs.

6 Results and Model Fit

In this section, I present and discuss the results from the estimation. I focus on the parameters that are most relevant to understanding incorporated entrepreneurship and highlight the importance of unobserved heterogeneity. For the remainder of this section, I simply refer to incorporated entrepreneurship as entrepreneurship. All parameter estimates can be found in Online Appendix C. I discuss the fit of the model in Subsection 6.2 and sensitivity to various modelling choices in Online Appendix D.

6.1 Main Results

Earnings Profiles. Table 4 shows the potential earnings of individuals in each career at age 25 as a function of their unobservable type. This corresponds to the type-specific intercepts of the earnings equation in each career. As can be seen, there is substantial heterogeneity across individuals. Although certain types earn more than others in all careers, others have a comparative advantage in one career over others. It would therefore be incorrect to equate unobservable types with level differences in productivity, as is often assumed in fixed effects models. Both Type 1 and Type 5 individuals appear to have a comparative advantage in entrepreneurship at labour force entry. Type 1 individuals have the potential to earn nearly as much as entrepreneurs than as workers in high-quality firm at age 25. Type 5 individuals are, by far, the most successful entrepreneurs in the population at age 25.

In the model, there are two channels through which individuals acquire skills that are valuable in entrepreneurship: experience in entrepreneurship and work experience. I discuss their importance in turn.

Figure 3 describes what the parameters of the model pertaining to learning-by-doing imply for patterns of log earnings in each career. I plot the potential earnings of individuals in entrepreneurship and in the labour market as a function of their unobservable type, assuming no career changes. These earnings profiles are calculated using the parameter estimates reported in Tables C.3, C.5, and C.6 in Online Appendix C. The results confirm that Type 1 and Type 5 individuals have a comparative advantage in entrepreneurship over others. This comparative advantage persists and reinforces itself over the life cycle. Figure 3 shows that Type 1 and Type 5 individuals have higher earnings growth potential in entrepreneurship than in the labour market. On average, the earnings of Type 1 individuals grow by 10.85% annually in entrepreneurship over the first six years in this career. To interpret orders of magnitude, I note that their earnings in entrepreneurship grow about 1.85 times faster than their earnings as workers in high-quality firms and 2.52 times faster than their earnings in low-quality firms (which grow at an average annual rate of about 5.9% and 4.3% over the first six years, respectively). The high ability Type 5 individuals experience even higher earnings growth in entrepreneurship: their earnings grow at an average rate of 12.3% per year over the first six years in this career. In comparison, their earnings as workers in high-quality firms increase by about 9.65% per year, on average. These results tell us that learning-by-doing is an important channel through which individuals acquire skills that are valuable in entrepreneurship. However, this channel seems to be relevant only for those who have the potential to earn more as entrepreneurs than as workers at age 25. This can be seen clearly from the earnings profile of Type 2 individuals in entrepreneurship, which is essentially flat. The earnings profiles for Type 3 and Type 4 individuals look qualitatively similar to Type 2's and are available in Online Appendix Figure C.2.

Figure 4 shows expected log earnings in entrepreneurship as a function of prior work experience. I show the model implied earnings profiles for entrepreneurs with (1) five years of prior work experience in high-quality firms (diamond lines), (2) five years of prior work experience in low-quality firms (triangle lines), and (3) no prior work experience (dashed lines, similar to the black square lines in Figure 3). The solid black lines indicate baseline earnings in entrepreneurship at age 25. These earnings profiles tell us how valuable it is to accumulate work experience before starting a business. The main lesson that comes out of this examination is that there are heterogeneous returns to prior work experience in entrepreneurship. First, there is substantial heterogeneity across individuals, which could reflect something like heterogeneous learning abilities. Second, the value of prior work experience depends on the quality of the firm in which it has been acquired.

To see this, compare expected log earnings in entrepreneurship with five years of prior work experience to expected log earnings with no prior work experience. The most striking result concerns Type 1, who greatly benefits from prior work experience in high-quality firms before starting a business. For Type 1 individuals, five years of work experience in high-quality firms more than doubles their baseline earnings in entrepreneurship. Type 5 individuals also benefit from prior work experience in a high-quality firm but not to the same extent. Remarkably, the earnings potential of Type 1 individuals with five years of prior work experience in high-quality firms is comparable to the earnings potential of Type 5 individuals with a similar experience profile. Meanwhile, labour market experience appears to be of limited value in entrepreneurship for Type 2 and Type 3 individuals.

The parameter estimates reported in Online Appendix Tables C.3, C.4, and C.5 are also informative about the returns to entrepreneurship experience in the labour market. Again, we see substantial heterogeneity across individuals. Although experience in entrepreneurship is valuable in the labour market for Type 1 individuals, it is estimated to be of limited value for Type 5 individuals.

Career Choices by Type. To get a sense of the prevalence of the different types, I use the estimated posterior probabilities that individuals belong to each type and draw an unobservable type for each individual in the sample. I find that the majority of individuals belong to Type 2, Type 3, or Type 4. Only 9% of individuals are Type 1 and 10% of individuals are Type 5.

Table 5 describes the career choices of individuals as a function of their unobservable type. The most striking result from this table is that few individuals choose a career in entrepreneurship regardless of their type. In particular, only 1% of all individual-year observations for Type 1 individuals and 3% of all individual-year observations for Type 5 individuals are in entrepreneurship. Type 1 individuals are most likely to be found in non-employment and in low-quality firms. Type 2 are distributed across the three firm classes roughly evenly, with a small tilt towards low-quality firms. Type 3 are also found with a high probability in all firm classes, but with a small tilt towards medium- and high-quality firms. Type 4 are by far the most likely to be found in high-quality firms. Type 5 are the most likely to be found in incorporated entrepreneurship and they tend to be split between high-quality firms and low-quality firms otherwise. Online Appendix A.3 provides further characterization of unobservable types based on baseline individual characteristics, other entrepreneurial outcomes, and industry composition.

Amenities and Entry Costs. I now discuss estimates of the structural parameters of the utility function. Online Appendix Table C.1 reports the scale parameter and amenities. The estimated value of the scale parameter is 1.29, which is in the range of scale parameters typically found in the literature.[30] The amenities associated with employment in all firm classes are estimated to be positive relative to non-employment. Interestingly, the amenities

[30]For example, Traiberman (2019) estimates a scale parameter of 1.43 in the context of a dynamic model of occupational choice and Ransom (2022) estimates a scale parameter of 1.01 in the context of a dynamic model of migration decisions.

associated with entrepreneurship are estimated to be positive only for Type 1 and Type 5. For the remaining types, the amenities associated with entrepreneurship are either close to zero (Type 3) or prohibitively negative (Type 2 and Type 4).

To interpret orders of magnitude, I use the concept of willingness to pay to express amenity values in dollars, following Ransom (2022). I express willingness to pay as flow values and report these statistics for the two entrepreneurial types, Type 1 and Type 5.[31] Panel (a) in Figure 5 reports the willingness to pay for the amenities associated with entrepreneurship relative to the amenities of employment in low-quality firms (light grey) and employment in high-quality firms (dark grey). The amenities associated with entrepreneurship are worth about $12,000-$15,000 annually for Type 1 individuals and $9,400-$25,400 annually for Type 5, depending on the benchmark.

Online Appendix Table C.2 reports parameter estimates for the mobility costs. In general, the structure of mobility costs conforms with the transition patterns observed in Table 1. Importantly, we can see that the costs associated with moving back to employment in the labour market from entrepreneurship are quite high, which is part of the reason why few individuals choose a career in entrepreneurship. Moreover, we can see that the costs associated with entering entrepreneurship tend to be larger than the costs associated with moving between firm classes in the labour market.

To interpret orders of magnitude, I use the concept of willingness to accept to express mobility costs in dollars. Again, I express willingness to accept as flow values and report these statistics for the two entrepreneurial types, Type 1 and Type 5.[32] Panel (b) in Figure 5 shows the willingness to accept associated with a move from employment in low-quality firms to entrepreneurship (light grey) and employment in high-quality firms to entrepreneurship (dark grey). The estimated entry costs for entrepreneurship are very large. For Type 1 individuals, the willingness to accept for a move from low-quality firms to entrepreneurship is worth about $22,500 in additional income per year in perpetuity. For Type 5 individuals, the additional pay required to justify a move from low-quality firms to entrepreneurship, all else being equal, is about $28,000 per year in perpetuity. Coming from high-quality firms, we can see that the willingness to accept increases slightly for Type 1 individuals but decreases for Type 5 individuals. This could reflect faster wealth accumulation in high-quality firms

[31] Specifically, I ask: How much are individuals willing to pay every year to enjoy the amenities associated with a career in entrepreneurship instead of the amenities associated with employment in the labour market, assuming the pay is the same in both careers and there are no switching costs? See Online Appendix B.4 for calculation details.

[32] Specifically, I ask: Assuming everything else about utility stays the same, how much additional income should an individual receive every year to be just indifferent between staying employed in the labour market and paying the mobility costs required to move to entrepreneurship at time $t+1$? See Online Appendix B.4 for calculation details.

for Type 5 individuals which facilitates a transition into entrepreneurship.

In sum, the parameter estimates suggest that few individuals choose a career in entrepreneurship for various reasons. For Type 2, Type 3, and Type 4 individuals, entrepreneurship is not an attractive career option because (1) they have the potential to earn more as workers than as entrepreneurs and (2) they dislike the amenities associated with entrepreneurship. For Type 1 individuals, the main deterrents are the large estimated entry costs into this career. For Type 5 individuals, the main deterrents are two kinds of opportunity costs. First, the earnings of Type 5 individuals in high-quality firms dominate their earnings potential in entrepreneurship. Second, Type 5 individuals have low returns to entrepreneurship experience in the labour market, so any time spent in entrepreneurship is a forgone opportunity to accumulate skills that are valuable in the labour market.

6.2 Model Fit

I now discuss the fit of the model. Model comparisons are computed through forward simulation, using the structural parameter estimates presented above along with the empirical conditional choice probabilities, as in Arcidiacono et al. (2023). I provide more detail about the simulation procedure in Online Appendix C.1.

Online Appendix Table C.8 shows career choices over the life cycle. Panel (a) reports the observed fraction of individuals in each career at each age between 26 and 35. Panel (b) reports the same statistics using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of the period. Panel (c) uses fully simulated panel data. Overall, the model is well fitted along these dimensions. For employment in high-, medium-, and low-quality firms, the fully simulated data matches the initial levels and changes over the life cycle well. The model slightly overpredicts the share of incorporated entrepreneurs (by 2-5 percentage points in the fully simulated data), but is able to reproduce the life cycle trends in entrepreneurship. Panel (b) reveals that the prediction error for incorporated entrepreneurship is an issue primarily at age 26.

Table C.9 shows career transitions at age 30. For each origin-destination pair, it reports (1) the percentage of transitions from career of origin to destination career (row %) and (2) the percentage of observations in a destination career that comes from each career of origin (column %). Overall, most of the predicted frequencies are reasonably close to the empirical ones. In particular, the model is able to replicate the levels of persistence in career choices observed in the data (this can be seen by comparing the numbers on the diagonals). It also matches the cross-career transition patterns observed in the data reasonably well. Transitions into incorporated entrepreneurship are slightly overstated.

Earnings also appear to be well fitted, as can be seen in Table 2 (comparing the second and third rows). Here, differences in average log earnings across careers stem from (1) a non-random sorting of individual types across careers and (2) differences in estimated earnings processes across careers. The fully simulated sorting patterns of individuals and associated payoffs are broadly consistent with what we observe in the data. One exception is for incorporated entrepreneurship, where simulated earnings at age 30 are lower than what we observed in the data. Online Appendix Figure C.1 shows that this gap in average log earnings in incorporated entrepreneurship is roughly constant over the life cycle.

To better understand the small discrepancies between the full model simulations and the data, I explore the ability of the model to predict the career choices of individuals as a function of their assigned unobservable type. The main discrepancy is for Type 1 individuals, for whom the model is not able to fit the high fraction of observations in non-employment (54% in the data vs 36% in the model) and overpredicts the proportion of individuals that choose entrepreneurship. The model predictions are excellent for the other types at various points in the life cycle. See Online Appendix C.1 for an extended discussion of model fit.

7 Policy Simulations

Grants and subsidies are common tools used by governments to promote entrepreneurship. For example, the City of Montréal offers one-time $25,000 subsidies to local incorporated entrepreneurs if their business proposals meet certain conditions.[33] In Germany, the Hartz II labour market reform of 2003 established a new grant for entrepreneurs. The so-called Ich-AG grants ("Me Inc." in English) are specifically targeted to unemployed individuals to encourage transitions from unemployment to entrepreneurship. Typically, the objective of such policies is to increase the supply of entrepreneurs and foster job creation.

In this section, I evaluate the effectiveness of policies designed to promote entrepreneurship among early career individuals. Specifically, I consider the effects of an unanticipated one-time subsidy to choose entrepreneurship at age 30. Through model simulations, I evaluate the impulse response and report the short- and long-run impacts of the subsidy on the fraction of individuals who are entrepreneurs. I highlight selection and the heterogeneous effects of the subsidy across types.

I consider four versions of the subsidy, targeting different segments of the population. First, I consider a broad subsidy which is available to all unincorporated and incorporated entrepreneurs. Second, I consider a version of this subsidy which is only available to individuals who come from non-employment, inspired by the German subsidy mentioned above. Third, I consider a subsidy that is only available to incorporated entrepreneurs. Finally, I

[33] See https://pmemtl.com/en/services/financing/loans-and-subsidies, accessed on March 28, 2023.

consider a subsidy that is only available to incorporated entrepreneurs who come from employment at high-wage firms. The goal of this last policy is to attract individuals with higher entrepreneurial skills into incorporated entrepreneurship.

I simulate the effects of a 100% earnings subsidy in entrepreneurship, which is worth between \$20,000-\$50,000 depending on the individual. To simulate counterfactuals, I follow the same procedure as the one used to assess model fit described in Online Appendix C.1, but I impose different versions of the unanticipated one-time subsidy for entrepreneurship at age 30. For each policy counterfactual, I construct a synthetic panel dataset starting with real observations at age 25 and forward simulate career choices for 10 years (from age 26 to age 35). I then compare simulated careers with and without the policy intervention.

Some caution is warranted when interpreting the magnitude of the simulation results presented below. First, as discussed in the robustness appendix (Online Appendix D), the scale parameter is sensitive to the number of unobservable types and this parameter governs how people respond to income shocks. Second, I do not model the demand side, so general equilibrium effects are muted. Third, I only simulate the effects of unanticipated and temporary policy changes, thereby restricting the pathways through which interventions can exert their effects. For instance, individuals who anticipate a subsidy for entrepreneurship at age 30 might strategically plan ahead and adjust their career choices accordingly. There is no anticipatory response here because the policy comes as a complete surprise. Finally, as discussed in Subsection 6.2, the model slightly overpredicts the proportion of Type 1 individuals that choose entrepreneurship. In what follows, I report simulation results for the overall population, for the population excluding Type 1 individuals, and separately for each unobservable type.[34]

The results are presented in Table 6. For each policy, I report the change in the share of unincorporated entrepreneurs, incorporated entrepreneurs, and non-employed individuals in the year of the intervention and five years after the intervention (all in percentage points). I refer to the effect of the policy on individuals at age 30 as the short-run impact. The long-run impact refers to the effect five years after the policy intervention, when individuals are 35 years old.

Columns (1)-(3) in Panel (a) show the effects of a one-time subsidy to choose unincorporated or incorporated entrepreneurship at age 30. This subsidy is available to all. In the year of the intervention, this policy increases the share of unincorporated entrepreneurs in the population by 1.89 percentage points. The effect on unincorporated entrepreneurship is short-lived, however. Most of it is dissipated five years after the intervention. This pattern

[34] As a robustness check, Online Appendix Table C.17 presents simulation results where career choices are forward simulated starting at age 27 instead of age 26, given that the prediction error for Type 1 individuals is largest at age 26. The results are similar.

holds for all unobservable types.

Turning to the effect on incorporated entrepreneurship, we can see that the intervention increases the share of incorporated entrepreneurs by 1.04 percentage points in the year of the intervention and by 0.34 percentage points five years after. Looking at the effect of the policy separately by type, we can see that it is particularly effective in attracting Type 1 and Type 5 individuals towards incorporated entrepreneurship, although all types respond to some extent.

Columns (4)-(6) in Panel (a) show the effects of a one-time subsidy to choose unincorporated or incorporated entrepreneurship at age 30 which is only available to non-employed individuals. Overall, we see that this policy is largely ineffective at either increasing the supply of entrepreneurs or decreasing the fraction of individuals who are non-employed in the long-run. This aggregate effect, however, conceals non-negligible effects of the policy on Type 1 individuals, who are often found in non-employment. For Type 1 individuals, we see a 0.56 percentage points increase in the fraction of incorporated entrepreneurs five years after the intervention and a 0.46 percentage points reduction in the fraction non-employed five years after the intervention.

Columns (1)-(3) in Panel (b) show the effects of a one-time subsidy to choose incorporated entrepreneurship at age 30. This subsidy is available to all. In the short-run, this policy increases the fraction of individuals who choose incorporated entrepreneurship in the population by 1.16 percentage points. This policy is particularly successful at inducing a switch into incorporated entrepreneurship for Type 5 individuals. However, if the goal of the government is to attract individuals with high earnings potential in entrepreneurship, this untargeted subsidy seems costly to implement. This is because it also induces a large fraction of individuals with relatively low entrepreneurial skills to become incorporated entrepreneurs. Five years after the policy intervention, there is still a 0.86 percentage points increase in the fraction of Type 5 individuals in incorporated entrepreneurship relative to the baseline.

Columns (4)-(5) in Panel (b) show the effects of a one-time subsidy to choose incorporated entrepreneurship at age 30, which is only available to individuals who come from high-wage firms. The goal here is to target only individuals with higher entrepreneurial skills and hereby reduce the total cost of the policy. We can see that this policy is indeed successful at reducing take-up by a factor of five. The types that respond the most are the high ability Type 4 and Type 5. The response is of course more limited because the opportunity cost of leaving employment in a high-quality firm is high. Still, we can see that those who end up switching from Type 5 persist in this career for a few years. Both in the short-run and in the long-run, we see a 0.29 percentage points increase in the fraction of Type 5 individuals in incorporated entrepreneurship.

8 Conclusion

In this paper, I investigate both the mechanisms that drive entry into entrepreneurship and the determinants of entrepreneurial success. I use Canadian matched owner-employer-employee data to conduct my investigation. Empirically, I find that entrepreneurs who have previously worked in high-wage firms tend to do better. To explain these findings, I develop a dynamic Roy model of career choice that features heterogeneous firms, human capital accumulation, and unobserved heterogeneity across individuals. Using a computationally light two-stage estimation procedure, I recover parameters governing the returns to various types of experience in the labour market and in entrepreneurship, the non-pecuniary benefits associated with being a worker and an entrepreneur, and career-specific entry costs.

My results indicate that only a small fraction of the population has a comparative advantage in entrepreneurship at age 25. This subpopulation can be divided into two types: (1) individuals who can earn more as entrepreneurs because they have low earnings potential in the labour market at age 25 (the "subsistence" type) and (2) individuals who have high earnings potential in all careers at age 25 (the "transformational" type).

I provide evidence that the returns to various types of experience in entrepreneurship are heterogeneous and correlated with unobserved ability. In particular, I find that prior work experience is most valuable for "subsistence" entrepreneurs. Regarding the role of experience as an entrepreneur, I confirm recent empirical evidence that learning-by-doing is an important channel through which individuals acquire skills that are valuable in entrepreneurship. However, this channel seems to be relevant only for the two types mentioned above, who have a comparative advantage in entrepreneurship at labour force entry.

I use the estimated model to evaluate various policies that are designed to promote entrepreneurship. I find that income subsidies can induce the transformational type to pursue a career in entrepreneurship. However, if the goal of the government is to attract individuals with high-growth potential to entrepreneurship, then untargeted subsidies seem costly to implement. This is because it would also induce a large fraction of individuals with relatively low entrepreneurial skills to become entrepreneurs.

My finding that the main driver of entrepreneurial success seems to be either innate or acquired before age 25 warrants further investigation. The administrative dataset used in this paper is limited in that it does not include any information on education. Improving our understanding of the interaction between education and entrepreneurship would be important. For example, it would be interesting to know whether education (e.g., having an MBA or STEM degree) correlates with entrepreneurial success and why. More generally, future research could investigate what early life characteristics can help identify the transformational type, so that policy-makers can target them more efficiently.

In the absence of observable characteristics, I show that career choices and prior employment status can serve as useful filters. In particular, I show that a subsidy for entrepreneurship that is only available to people who come from high-wage firms narrows in on individuals with higher entrepreneurial skills.

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TABLE 1 – Career Transitions

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	89.6	4.4	2.5	0.3	0.7	2.5
Column %	89.0	5.6	4.3	8.7	9.3	11.0
Medium						
Row %	6.5	84.8	4.3	0.3	0.7	3.4
Column %	5.2	86.3	5.8	6.4	8.1	11.7
Low						
Row %	5.7	6.4	81.2	0.3	0.9	5.5
Column %	3.5	5.0	84.2	5.3	7.5	14.8
Incorp.						
Row %	3.4	1.3	1.1	86.5	0.6	7.1
Column %	0.1	0.0	0.1	66.8	0.3	0.9
Unincorp.						
Row %	7.0	4.9	5.0	3.1	65.9	14.1
Column %	0.4	0.4	0.5	5.5	59.2	3.9
Non-emp.						
Row %	8.6	9.6	14.1	1.2	5.1	61.4
Column %	1.9	2.7	5.1	7.3	15.6	57.8

Notes: This table describes the career transitions of individuals at age 30. It reports the percentage of transitions from career of origin at time $t-1$ to destination career at time t (row %) and the percentage of observations in a destination career at time t that comes from each career of origin at time $t-1$ (column %). "High" refers to worker in high-quality firms, "Medium" refers to worker in medium-quality firms, "Low" refers to worker in low-quality firms, "Incorp." refers to incorporated entrepreneur, "Unincorp." refers to unincorporated entrepreneur, and "Non-emp." refers to non-employed. See Section 2.2 for details about career definitions. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations of individuals at age 30 between 2001 and 2012 are used to calculate the statistics.

Table 2 – Summary Statistics

		Workers			Entrepreneurs	
	All	High	Medium	Low	Incorp.	Unincorp.
Log Earnings	10.67	10.92	10.65	10.35	10.63	10.17
	(0.56)	(0.52)	(0.49)	(0.49)	(0.66)	(0.62)
Log Earnings at Age 30	10.77	11.02	10.75	10.46	10.62	10.19
	(0.55)	(0.49)	(0.47)	(0.48)	(0.64)	(0.63)
Log Earnings at Age 30 (Simulated)	10.75	11.04	10.74	10.42	10.45	10.20
	(0.57)	(0.50)	(0.49)	(0.47)	(0.62)	(0.65)
Age	28.49	28.56	28.40	28.07	30.94	30.10
	(2.79)	(2.82)	(2.78)	(2.7)	(2.57)	(2.6)
Work Exper.	3.24	3.47	3.29	2.92	3.44	3.12
	(2.65)	(2.76)	(2.71)	(2.60)	(2.15)	(2.08)
- High	1.27	2.74	0.41	0.26	1.43	1.04
	(2.11)	(2.53)	(1.16)	(0.92)	(1.74)	(2.03)
- Medium	1.07	0.42	2.48	0.39	1.10	1.04
	(1.90)	(1.14)	(2.43)	(1.11)	(1.77)	(1.64)
- Low	0.90	0.31	0.41	2.27	0.91	1.04
	(1.70)	(0.92)	(1.08)	(2.33)	(1.60)	(1.57)
Incorp. Exper.	0.02	0.00	0.00	0.00	1.77	0.01
	(0.27)	(0.10)	(0.08)	(0.08)	(1.88)	(0.19)
Unincorp. Exper.	0.05	0.01	0.01	0.01	0.34	1.37
	(0.38)	(0.18)	(0.17)	(0.18)	(0.92)	(1.70)
High Income Area at 25	0.24	0.30	0.22	0.17	0.31	0.25
	(0.43)	(0.46)	(0.41)	(0.38)	(0.46)	(0.43)
Entrepreneurial Area at 25	0.24	0.26	0.24	0.23	0.38	0.29
	(0.43)	(0.44)	(0.42)	(0.42)	(0.48)	(0.46)
Large City at 25	0.31	0.32	0.31	0.28	0.29	0.33
	(0.46)	(0.47)	(0.46)	(0.45)	(0.45)	(0.47)
Number of individuals	721,730	382,455	356,180	328,115	14,465	36,790
Number of observations	4,906,785	1,777,295	1,445,080	1,211,805	44,240	87,550

Notes: This table summarizes the logarithm of annual earnings, age, experience profiles, and baseline characteristics of individuals in each career. It reports averages and standard deviations (in parentheses) for each variable. Statistics are calculated using all individual-year observations in the career described by the column header. The column header "All" pools all careers together. "High" refers to worker in high-quality firms, "Medium" refers to worker in medium-quality firms, "Low" refers to worker in low-quality firms, "Incorp." refers to incorporated entrepreneur, and "Unincorp." refers to unincorporated entrepreneur. There are 153,625 individuals in non-employment and 340,815 individual-year observations. See Section 2.2 for details about career definitions. Experience variables are equal to zero at age 25 and measured in years. I consider individuals to be living in a high income area at age 25 if the average annual earnings among all residents in their postal code at age 25 is in the top quartile of the distribution in the estimation sample. I consider individuals to be living in an entrepreneurial area at age 25 if the density of business owners in their postal code at age 25 is in the top quartile of the distribution in the estimation sample. Large city at 25 is an indicator variable for living in Toronto, Montreal, or Vancouver at age 25. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 are used to calculate the statistics. Simulated data is used to calculate the earnings statistics reported in the third row. See Online Appendix C.1 for details about model simulations.

Table 3 – First Spell in Incorporated Entrepreneurship

Origin	All	High			Medium			Low		
Age at Start	All	26-27	28-29	30+	26-27	28-29	30+	26-27	28-29	30+
Obs.										
Year 1	14,465	1,195	1,350	2,090	925	975	1,495	1,040	885	1,195
Survival Rate										
Year 2	0.84	0.83	0.85	0.82	0.85	0.86	0.84	0.83	0.86	0.87
Year 3	0.73	0.70	0.71	0.70	0.75	0.79	0.75	0.72	0.77	0.79
Year 4	0.65	0.60	0.65	0.63	0.68	0.70	0.65	0.64	0.67	0.71
Year 5	0.59	0.55	0.57	0.56	0.62	0.66	0.57	0.59	0.60	0.64
Year 6	0.56	0.50	0.55	0.52	0.58	0.63	0.53	0.55	0.56	0.58
Log Earnings										
Year 1	10.34	10.35	10.42	10.48	10.26	10.25	10.33	10.18	10.19	10.24
Year 2	10.70	10.75	10.82	10.89	10.66	10.67	10.74	10.52	10.56	10.62
Year 3	10.77	10.83	10.91	10.98	10.73	10.72	10.76	10.62	10.61	10.70
Year 4	10.82	10.87	10.98	10.99	10.81	10.81	10.87	10.67	10.71	10.71
Year 5	10.88	10.95	11.09	11.07	10.85	10.87	10.90	10.74	10.74	10.77
Year 6	10.92	11.03	11.06	11.09	10.90	10.95	10.87	10.78	10.78	10.78
Earnings Growth										
Year 1 to 6	1.23	1.42	1.43	1.37	1.34	1.48	1.19	1.21	1.13	1.12
	(2.35)	(2.02)	(2.28)	(2.43)	(2.23)	(1.83)	(1.94)	(4.30)	(1.37)	(1.80)

Notes: This table describes first spells in incorporated entrepreneurship. It reports survival rates and average log annual earnings in each year of the spell until Year 6. It also reports the average and standard deviation (in parentheses) of earnings growth for those who survive until Year 6. Statistics are calculated separately for different types of prior work experience. "All" pools all careers of origin together, "High" refers to individuals who come from employment in high-quality firms, "Medium" refers to individuals who come from employment in medium-quality firms, and "Low" refers to individuals who come from employment in low-quality firms. See Section 2.2 for details about career definitions. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 associated with a first spell in incorporated entrepreneurship are used to calculate the statistics.

Table 4 – Baseline Earnings in Each Career by Type

	Career				
	Work			Entrepreneurship	
Type	High	Medium	Low	Incorp.	Unincorp.
1	10.01	9.93	9.78	9.98	9.72
2	10.18	10.07	9.94	9.84	9.83
3	10.55	10.43	10.23	10.02	10.07
4	10.86	10.71	10.71	10.24	10.04
5	11.28	11.06	10.45	10.68	10.65

Notes: This table reports the potential earnings of individuals in each career at age 25 as a function of their unobservable type. This corresponds to the type-specific intercept in the earnings equation of each career. The intercepts are calculated using the parameter estimates reported in Tables C.3-C.7. "High" refers to worker in high-quality firms, "Medium" refers to worker in medium-quality firms, "Low" refers to worker in low-quality firms, "Incorp." refers to incorporated entrepreneur, and "Unincorp." refers to unincorporated entrepreneur. See Section 2.2 for details about career definitions. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model.

Table 5 – Career Choices by Type

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.07	0.10	0.24	0.01	0.05	0.54
2	0.21	0.25	0.29	0.33	0.00	0.02	0.12
3	0.32	0.36	0.37	0.20	0.01	0.02	0.04
4	0.28	0.55	0.31	0.09	0.02	0.02	0.02
5	0.10	0.38	0.15	0.40	0.03	0.02	0.03
Average		0.37	0.29	0.22	0.01	0.02	0.09

Notes: This table describes the observed career choices of individuals as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. I report the fraction of individual-year observations in each career by type. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model.

Table 6 – Short- and Long-Run Impacts of Subsidies on the Supply of Entrepreneurs

		Available to All			Available to Non-Employed Only		
Type	Age	Δ Uninc. (1)	Δ Inc. (2)	Δ Non-Emp (3)	Δ Uninc. (4)	Δ Inc. (5)	Δ Non-Emp (6)
All	30	1.89	1.04	-1.04	0.65	0.38	-0.68
	35	0.10	0.34	0.08	-0.01	0.17	0.00
No Type 1	30	1.79	0.99	-0.89	0.56	0.35	-0.59
	35	0.10	0.29	0.14	-0.02	0.13	0.05
Type 1	30	2.80	1.54	-2.4	1.54	0.68	-1.52
	35	0.14	0.88	-0.49	0.01	0.56	-0.46
Type 2	30	1.87	0.64	-0.99	0.62	0.31	-0.68
	35	0.10	0.21	0.11	0.00	0.18	0.02
Type 3	30	1.96	1.12	-0.89	0.69	0.42	-0.57
	35	0.09	0.43	0.00	-0.06	0.19	-0.05
Type 4	30	1.62	0.82	-0.57	0.33	0.19	-0.29
	35	0.13	0.20	0.33	0.02	0.03	0.16
Type 5	30	1.63	1.86	-1.73	0.70	0.73	-1.39
	35	-0.01	0.27	0.10	-0.03	0.08	0.07

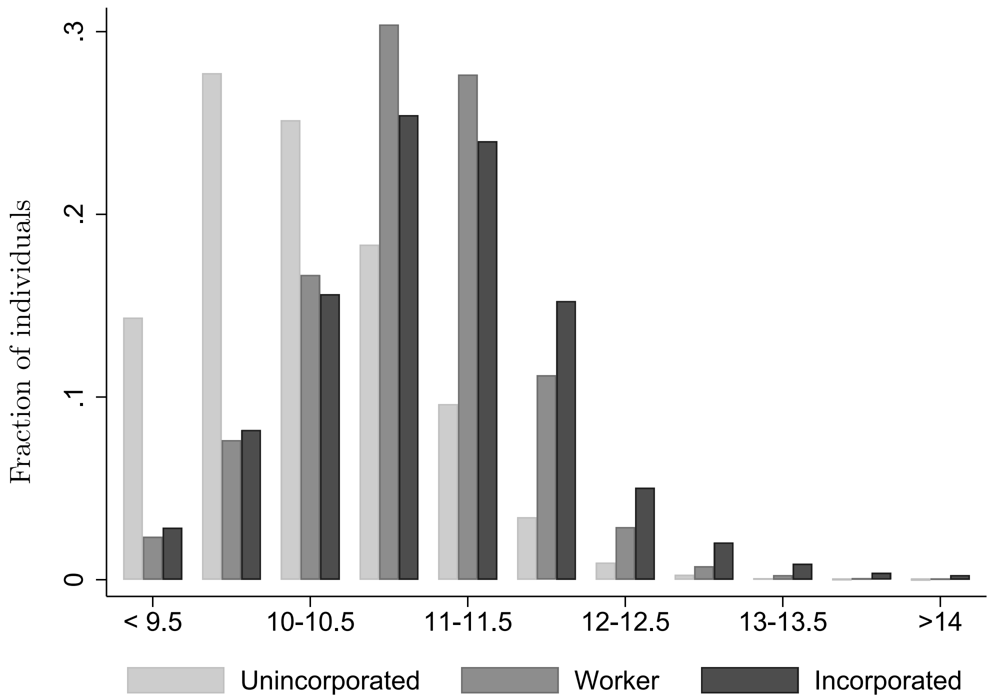
(a) One-Time Subsidy to Choose Unincorporated or Incorporated Entrepreneurship at Age 30

		Available to All			Available to High-Wage Only		
Type	Age	Δ Uninc. (1)	Δ Inc. (2)	Δ Non-Emp (3)	Δ Uninc. (4)	Δ Inc. (5)	Δ Non-Emp (6)
All	30	-0.14	1.16	-0.36	0.05	0.23	-0.03
	35	-0.02	0.21	0.02	-0.07	0.04	-0.01
No Type 1	30	-0.15	1.15	-0.37	0.04	0.25	-0.06
	35	-0.01	0.20	0.01	-0.06	0.05	-0.04
Type 1	30	-0.05	1.27	-0.24	0.19	0.07	0.21
	35	-0.04	0.29	0.10	-0.16	-0.01	0.29
Type 2	30	-0.09	0.70	-0.35	-0.03	0.12	-0.07
	35	0.15	0.00	0.03	-0.07	0.10	-0.07
Type 3	30	-0.15	1.30	-0.43	0.10	0.21	-0.10
	35	-0.08	0.25	-0.04	-0.10	-0.03	-0.12
Type 4	30	-0.08	0.92	-0.12	0.06	0.37	-0.05
	35	0.01	0.08	0.09	0.02	0.02	0.10
Type 5	30	-0.49	2.44	-1.04	-0.10	0.29	0.10
	35	-0.21	0.86	-0.13	-0.14	0.29	-0.16

(b) One-Time Subsidy to Choose Incorporated Entrepreneurship at Age 30

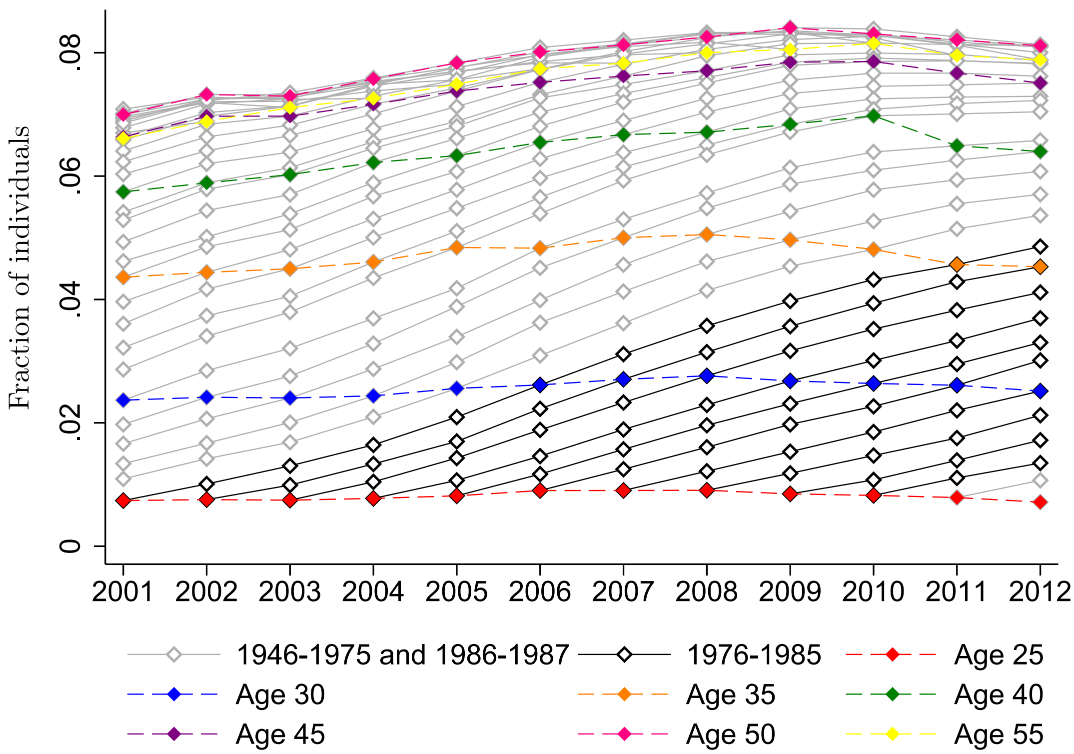
Notes: This table shows the effects of an unanticipated one-time 100% earnings subsidy to choose entrepreneurship at age 30. I report the change in the share of unincorporated entrepreneurs, incorporated entrepreneurs, and non-employed individuals in the year of the intervention and five years after the intervention (all in percentage points). I report these statistics for the overall population, for the population excluding Type 1 individuals, and separately for each unobservable type. I use simulated panel data to calculate the statistics. See Online Appendix C.1 for details about model simulations.

FIGURE 1 – Distribution of Annual Earnings



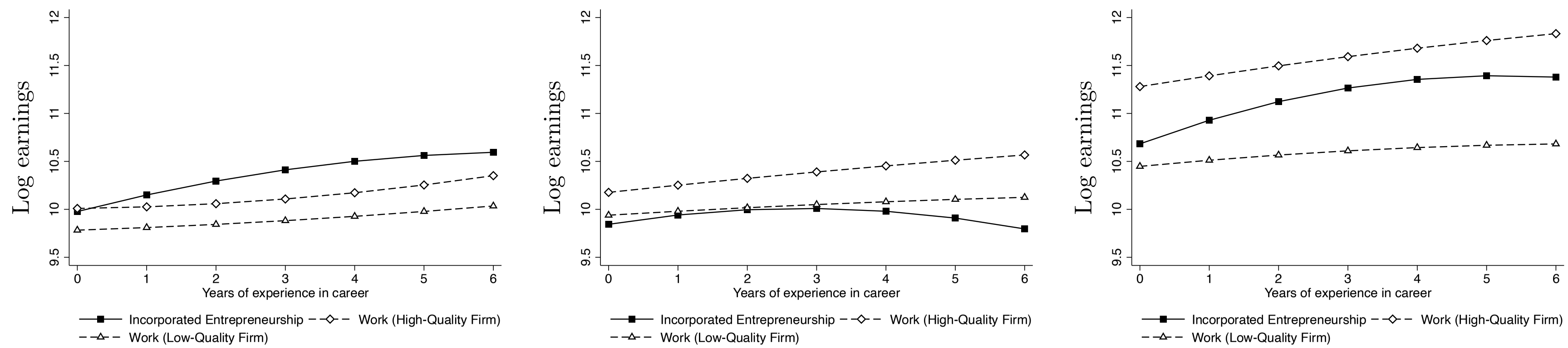
Notes: This figure shows the distribution of log annual earnings for unincorporated entrepreneurs (light grey), workers (grey), and incorporated entrepreneurs (dark grey) in 2012. The sample used includes all non-immigrant men age 25-55. Earnings are in CAD$2012. I use a broader definition of incorporated entrepreneurship which considers incorporated business income from all firms owned by the individual, not only start-up firms. Individuals are assigned to incorporated entrepreneurship if the incorporated business income they draw from their own firms is above $10,400. Individuals are assigned to unincorporated entrepreneurship if (1) they are not incorporated entrepreneurs and (2) they have a net unincorporated business income above $10,400. Individuals are considered to be workers if (1) they are not entrepreneurs and (2) they have employment income above $10,400. The annual earnings of workers is their total employment income, the annual earnings of incorporated entrepreneurs is their incorporated business income, and the annual earnings of unincorporated entrepreneurs is their unincorporated business income.

Figure 2 – Entrepreneurship Over the Life Cycle



Notes: This figure shows the fraction of incorporated entrepreneurs at each point in time between 2001 and 2012, cohort by cohort. The black lines indicate cohorts of individuals born between 1976 and 1985. The grey lines indicate other cohorts born 1946-1975 and 1986-1987. The red, blue, orange, green, purple, pink, and yellow lines highlight the fraction of incorporated entrepreneurs at age 25, 30, 35, 40, 45, 50, and 55, respectively. The sample used includes all non-immigrant men age 25-55. I use a broader definition of incorporated entrepreneurship which considers incorporated business income from all firms owned by the individual, not only start-up firms. Individuals are assigned to incorporated entrepreneurship if the incorporated business income they draw from their own firms is above $10,400.

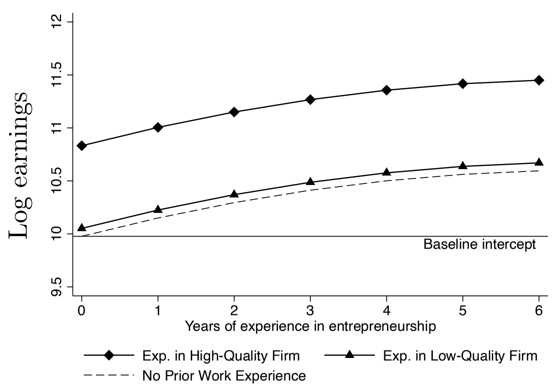
Figure 3 – Expected Log Earnings in Various Careers by Type



(a) Type 1 (b) Type 2 (b) Type 5

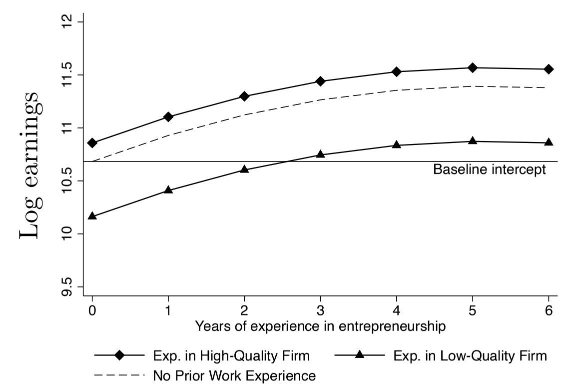
Notes: This figure describes what the parameters of the model pertaining to learning-by-doing imply for patterns of log earnings in various careers. It plots the expected log earnings of individuals in entrepreneurship and in the labour market as a function of their unobservable type and years of experience, assuming no career changes. Dashed diamond lines show expected log earnings as worker in high-quality firms, dashed triangle lines show expected log earnings as worker in low-quality firms, and solid black square lines show expected log earnings as incorporated entrepreneur. These earnings profiles are calculated using the parameter estimates reported in Tables C.3, C.5, and C.6 in Online Appendix C. See Section 2.2 for details about career definitions. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model.

Figure 4 – Heterogeneous Returns to Prior Work Experience in Entrepreneurship



(a) Type 1

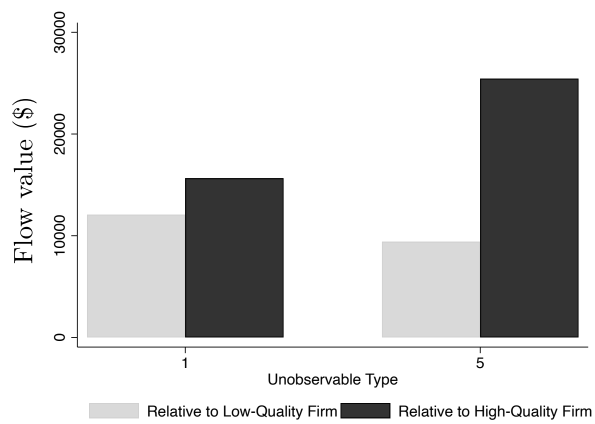
(b) Type 2



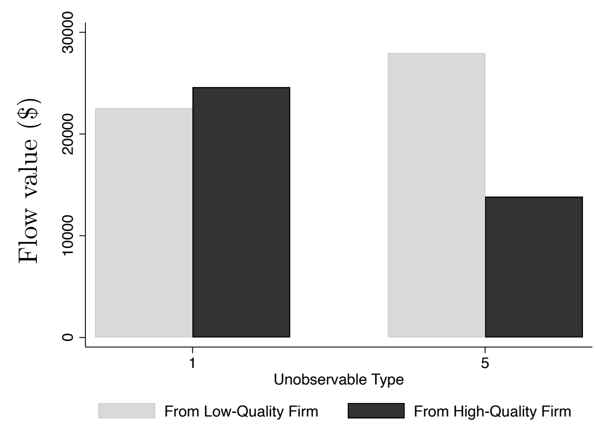
(b) Type 5

Notes: This figure shows expected log earnings in entrepreneurship as a function of unobservable type and prior work experience. It plots the model implied earnings profiles for incorporated entrepreneurs with (1) five years of prior work experience in high-quality firms (diamond lines), (2) five years of prior work experience in low-quality firms (triangle lines), and (3) no prior work experience (dashed lines). The solid black line indicates baseline earnings in incorporated entrepreneurship at age 25. These earnings profiles are calculated using the parameter estimates reported in Table C.6 in Online Appendix C. See Section 2.2 for details about career definitions. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model.

Figure 5 – Amenities and Entry Costs Associated With Entrepreneurship



(a) Amenities



(b) Entry Costs by Career of Origin

Notes: Panel (a) shows the willingness to pay for the amenities associated with incorporated entrepreneurship relative to the amenities of employment in low-quality firms (light grey) and employment in high-quality firms (dark grey). Panel (b) shows the willingness to accept to move from employment in low-quality firms to incorporated entrepreneurship (light grey) and employment in high-quality firms to entrepreneurship (dark grey). I report these statistics for the two types of individuals that have a comparative advantage in incorporated entrepreneurship: Type 1 and Type 5. The willingness to pay and willingness to accept are expressed as flow values (measured in dollars) and calculated using the parameter estimates reported in Table C.1 and C.2 in Online Appendix C. See Online Appendix B.4 for calculation details.

Online Appendix A Data and Descriptive Statistics

A.1 Sample Restrictions

I now provide complete details about the estimation sample. My analysis hinges on the ability to observe the career histories of entrepreneurs before they start their businesses. Because I only observe career histories between 2001 and 2012, I restrict my attention to individuals who start their careers during this sample period. Specifically, I estimate the model using individuals aged 25 or older that are born between 1976 and 1985. These are cohorts of individuals for which I observe right-truncated career histories starting at age 25.[35] I further restrict my attention to men only. Few women are entrepreneurs in the data and their career decisions early in the life cycle would require a different model that takes into account fertility decisions. I exclude immigrants because their background prior to arrival is unobserved and it is likely to be different than that of natives. I exclude individuals who work in firms with missing information on firm quality because I cannot characterize the type of work experience they acquire. For the main estimation sample, I also exclude individuals classified as workers who own and draw employment income from a non-startup firm in parallel. I exclude individuals who enter the agricultural sector in any given year because firms in this sector use a different set of tax forms which makes it difficult to compare with the rest of the economy. I also exclude individuals who enter the public sector in any given year because earnings in this sector are heavily regulated and organizations tend to be governmental agencies rather than firms.[36] I exclude individuals with missing postal code information at age 25 to construct initial conditions variables. I exclude individuals who appear in the data for less than three years and individuals with gaps in the middle of their panel. Finally, to form a homogeneous sample, I keep only individuals who are employed at age 25.[37] This leaves me with a sample of 721,730 individuals and 4,906,785 individual-year observations. I exclude observations from 2012 to estimate the model and use these observations only to evaluate out-of-sample fit. The model is therefore estimated using 4,283,785 individual-year observations.

[35] I follow individuals starting at age 25 to abstract from schooling decisions. A limitation of the Canadian matched owner-employer-employee data is that it does not include information on education. In unreported results, I have found that the results are similar if I follow individuals starting at age 24 or 26. I explain how I account for ex-ante heterogeneity in Section 4.

[36] The public sector is defined as educational services (NAICS code 61), health care and social assistance (NAICS code 62), and public administration (NAICS code 91).

[37] Individuals who are non-employed at age 25 have a very weak attachment to the labour force (about 80% of all individual-year observations for this group are in non-employment). My estimation sample is therefore not a random sample, and over-samples from the more educated population.

A.2 Additional Descriptive Statistics

Table A.2 shows the fraction of individuals in various careers between age 26 and 35 in the estimation sample. This table highlights the fact that very few individuals become entrepreneurs over the course of their career. The fraction of individuals who are entrepreneurs increases steadily over the life cycle, reaching about 3% for incorporated entrepreneurship and 3.5% for unincorporated entrepreneurship at age 35. The fraction of non-employed individuals increases from about 7% at age 26 to 9% at age 35. Unsurprisingly, the fraction of workers in the sample is large. However, this fraction decreases slightly with age. At age 26, about 92% of individuals in the sample are workers whereas, at age 35, 85% of individuals are workers. Interestingly, there is a clear shift in the distribution of workers across firm classes over the life cycle. Workers are more likely to be saddled in the lower rungs of the firm quality ladder early in their career. As can be seen, the fraction of individuals that work in high-quality firms increases steadily from about 35% at age 26 to 38% at age 35. In contrast, the fraction of individuals that work in medium- and low-quality firms decreases over the same age range. The largest decrease is seen in low-quality firms (from 27% at age 26 to 19% at age 35). Taken together, these patterns suggest that individuals climb the firm quality ladder over the life cycle.

Table 1 in the main text provides additional evidence that individuals climb the firm quality ladder over the course of their careers. Although workers tend to stay in the same firm class from one year to the next, those who move up the firm quality ladder are more likely to move up one rung at a time. Put differently, workers are more likely to transition into high-quality firms coming from medium-quality firms than from low-quality firms.[38] The reverse is also true: workers who move down the firm quality ladder tend to move down one rung at a time. Workers are more likely to transition into low-quality firms coming from medium-quality firms than from high-quality firms.

A.3 Further Characterization of Unobservable Types

Table A.5 summarizes the baseline characteristics of individuals at age 25 and additional entrepreneurship outcomes as a function of unobservable type. Looking at baseline characteristics, we can see that Type 4 and Type 5 individuals are more likely to come from high income areas at age 25 than the average. Type 5 individuals are also the most likely to come from entrepreneurial areas at age 25. In terms of initial city size, Type 4 individuals are the

[38] Consider individuals that are in low-quality firms at time $t-1$. The results in Table 1 in the main text show that they are about 1.12 ($6.4/5.7 = 1.12$) times more likely to move into medium-quality firms than into high-quality firms.

most likely to come from a large city at age 25 whereas Type 5 individuals are the least likely.

The last four columns of Table A.5 provide more information about entrepreneurship outcomes by type. As we've seen in Table 5 in the main text, Type 5 are the most likely to be found in incorporated entrepreneurship (3% of all individual-year observations are in this career for this type). We can see that they also spend more time in this career than any other type, 5% of them start at least one new firm during the panel, and they are about 2.5 times more likely to be serial entrepreneurs (i.e., start more than one new firm). Shaw and Sorensen (2019) find that serial entrepreneurs are more productive and have higher sales than other entrepreneurs. This is in line with my finding that Type 5 individuals have an absolute advantage in entrepreneurship.

Table A.6 describes the industry composition of workers as a function of unobservable type. Within each firm class, I report the fraction of individual-year observations in each 2-digit industry by type. We can see that Type 4 and Type 5 individuals are relatively more likely to work in high-skilled services industries, particularly "Finance and insurance" (NAICS 52), "Professional, scientific and technical services" (NAICS 54), and "Management of companies and enterprises" (NAICS 55). When they work in low-quality firms, Type 5 individuals are relatively more likely to work in manufacturing industries other than "Food and textile manufacturing" (NAICS 32 and 33) and less likely to work in "Accommodation and food services" (NAICS 72).

TABLE A.1 – Alternative Firm-Level Outcomes by Firm Class

	Employment		Revenue per employee		Payroll per employee		AKM Firm F.E.	
Firm Class	Unweighted (1)	Weighted (2)	Unweighted (3)	Weighted (4)	Unweighted (5)	Weighted (6)	Unweighted (7)	Weighted (8)
All	15.00	6,800	235,800	263,400	37,800	45,300	-0.21	-0.08
High	30.00	3,785	559,300	478,200	91,100	76,300	0.02	0.11
Medium	20.00	7,855	252,900	240,700	47,500	47,200	-0.13	-0.05
Low	10.00	8,045	166,100	141,200	24,700	24,900	-0.30	-0.24

Notes: Statistics are calculated using all firm-level observations in 2012 and are either unweighted or weighted by the number of employees, as indicated. The sample includes all observations with non-missing employment, payroll, and revenue. I exclude firms in the agricultural and public sectors. Firm classes are defined using quartiles of the average firm wage distribution. Specifically, I calculate average log payroll per employee at the firm level, taking out industry-year fixed effects. I then calculate quartiles weighting firms by their average employment over the entire firm panel. I classify firms as high-quality if they are in the top quartile, medium-quality if they are in the next quartile, and low-quality if they are below the median. Firm classes refer to permanent firm attributes so they remain unchanged over the entire panel. All dollar amounts are in CAD$2012. The AKM model decomposes the logarithm of annual earnings of workers into worker-specific and firm-specific pay components. I estimate the AKM model using all non-immigrant men age 20-55 and include year fixed effects and quadratic and cubic terms in age as time-varying covariates. I use only estimated firm effects from the largest connected to calculate averages reported in this table.

Table A.2 – Career Choices Over the Life Cycle

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.0	35.4	36.0	36.6	37.0	37.3	37.5	37.5	37.8	38.3
Medium	30.0	29.3	29.1	28.9	28.8	28.7	28.4	28.2	28.0	27.7
Low	27.4	25.4	24.0	22.8	21.8	21.0	20.4	19.8	19.2	18.8
Incorp.	0.2	0.4	0.7	1.0	1.3	1.6	1.9	2.3	2.5	2.7
Unincorp.	0.8	1.4	1.9	2.3	2.6	2.9	3.1	3.2	3.4	3.5
Non-emp.	6.6	8.1	8.4	8.4	8.4	8.5	8.6	9.0	9.1	9.1

Notes: This table describes the observed career choices of individuals over the life cycle. I report the fraction of individuals in each career by age. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 are used to calculate the statistics.

Table A.3 – Cross-Sectional Returns to Various Types of Experience in Entrepreneurship

	(1)	(2)
Work exper.	0.023	
	(0.008)	
Work exper. (high)		0.054
		(0.008)
Work exper. (medium)		0.018
		(0.008)
Work exper. (low)		-0.01
		(0.008)
Work exper. (sq)	0.00	-0.001
	(0.001)	(0.001)
Incorp. exper.	0.220	0.221
	(0.005)	(0.004)
Incorp. exper. (sq)	-0.019	-0.020
	(0.001)	(0.001)
Unincorp. exper.	0.047	0.046
	(0.012)	(0.012)
Unincorp. exper. (sq)	-0.004	-0.004
	(0.002)	(0.002)
Intercept	10.280	10.281
	(0.016)	(0.016)
Mean, dep. var.	10.63	10.63
Adjusted R-squared	0.11	0.13
Number of ind.	14,465	14,465
Number of obs.	44,240	44,240

Notes: This table reports OLS estimates of the returns to various types of experience (measured in years) in entrepreneurship. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations in incorporated entrepreneurship between 2001 and 2012 are included. "High" refers to experience in high-quality firms, "Medium" refers to experience in medium-quality firms, "Low" refers to experience in low-quality firms, "Incorp." refers to experience in incorporated entrepreneurship, and "Unincorp." refers to experience in unincorporated entrepreneurship. See Section 2.2 for details about career definitions. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses.

Table A.4 – First Spell in Incorporated Entrepreneurship (Balanced Sample)

Origin	All	High			Medium			Low		
Age at Start	All	26-27	28-29	30+	26-27	28-29	30+	26-27	28-29	30+
Obs.										
Year 1	2,010	260	240	115	250	215	100	250	150	85
Survival Rate										
Year 2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Year 3	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Year 4	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Year 5	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Year 6	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Log Earnings										
Year 1	10.37	10.41	10.49	10.54	10.30	10.26	10.33	10.29	10.22	10.27
Year 2	10.80	10.89	10.98	10.98	10.80	10.77	10.81	10.63	10.64	10.71
Year 3	10.86	10.95	11.03	11.00	10.84	10.85	10.87	10.70	10.70	10.80
Year 4	10.88	11.00	11.02	10.97	10.87	10.88	10.92	10.72	10.76	10.82
Year 5	10.92	11.02	11.09	11.03	10.88	10.92	10.92	10.75	10.82	10.84
Year 6	10.92	11.03	11.06	11.09	10.90	10.95	10.87	10.78	10.78	10.78
Earnings Growth										
Year 1 to 6	1.23	1.42	1.43	1.37	1.34	1.48	1.19	1.21	1.13	1.12
	(2.35)	(2.02)	(2.28)	(2.43)	(2.23)	(1.83)	(1.94)	(4.30)	(1.37)	(1.80)

Notes: This table describes first spells in incorporated entrepreneurship for a balanced sample of entrepreneurs that survive until Year 6. It reports survival rates and average log annual earnings in each year of the spell from Year 1 to Year 6. It also reports the average and standard deviation (in parentheses) of earnings growth from Year 1 to Year 6. Statistics are calculated separately for different types of prior work experience. "All" pools all careers of origin together, "High" refers to individuals who come from employment in high-quality firms, "Medium" refers to individuals who come from employment in medium-quality firms, and "Low" refers to individuals who come from employment in low-quality firms. See Section 2.2 for details about career definitions. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 associated with a first spell in incorporated entrepreneurship are used to calculate the statistics.

Table A.5 – Baseline Characteristics and Entrepreneurship Outcomes by Type

Type	Baseline Characteristics					Entrepreneurship Outcomes			
	Rich Area	Entrep. Area	Large City	Med. City	Small City	Years Incorp.	Incorp. Spell	Startup	Serial
1	0.19	0.23	0.32	0.23	0.31	0.05	0.01	0.02	0.0006
2	0.14	0.20	0.30	0.24	0.32	0.02	0.01	0.01	0.0003
3	0.17	0.23	0.30	0.26	0.31	0.05	0.02	0.02	0.0006
4	0.37	0.28	0.33	0.30	0.26	0.10	0.03	0.04	0.0012
5	0.44	0.34	0.24	0.29	0.31	0.17	0.05	0.05	0.0017
Average	0.25	0.25	0.30	0.26	0.30	0.06	0.02	0.02	0.0007

Notes: This table summarizes the baseline characteristics of individuals at age 25 and additional entrepreneurship outcomes as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. I report the average of the variable listed in the column header separately for each type. "Rich Area" is an indicator for living in a high income area at age 25. I consider individuals to be living in a high income area at age 25 if the average annual earnings among all residents in their postal code at age 25 is in the top quartile of the distribution in the estimation sample. "Entrep. Area" is an indicator for living in an entrepreneurial area at age 25. I consider individuals to be living in an entrepreneurial area at age 25 if the density of business owners in their postal code at age 25 is in the top quartile of the distribution in the estimation sample. "Large City" is an indicator for living in Toronto, Montreal, or Vancouver at age 25. "Med. City" is an indicator for living in a medium-sized city (e.g., Ottawa, Calgary, Halifax) at age 25. "Small City" is an indicator for living in a city with a population smaller than 350K in the 2006 Census. "Years Incorp." denotes the total number of years in incorporated entrepreneurship during the panel. "Incorp. Spell" is an indicator for having at least one spell in incorporated entrepreneurship during the panel. "Startup" is an indicator for starting at least one new firm during the panel. "Serial" is an indicator for starting more than one new firm during the panel. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. Averages are calculated using one observation per individual. Number of individuals: 721,730.

TABLE A.6 – Industry Composition by Type

	2-digit NAICS Code																	
	23	31	32	33	41	44	45	48	49	51	52	53	54	55	56	71	72	81
Type 1																		
High	0.18	0.04	0.03	0.04	0.05	0.10	0.03	0.05	0.01	0.04	0.03	0.03	0.07	0.09	0.08	0.03	0.08	0.03
Medium	0.15	0.03	0.05	0.09	0.07	0.10	0.03	0.03	0.02	0.02	0.04	0.02	0.05	0.04	0.08	0.03	0.11	0.04
Low	0.11	0.01	0.04	0.08	0.06	0.09	0.06	0.03	0.01	0.01	0.02	0.02	0.05	0.04	0.16	0.02	0.14	0.05
Type 2																		
High	0.16	0.04	0.03	0.04	0.06	0.11	0.04	0.06	0.01	0.04	0.03	0.03	0.07	0.09	0.06	0.03	0.06	0.03
Medium	0.14	0.03	0.06	0.10	0.08	0.11	0.03	0.03	0.03	0.02	0.05	0.02	0.05	0.05	0.06	0.02	0.09	0.05
Low	0.10	0.01	0.05	0.09	0.07	0.10	0.07	0.02	0.01	0.01	0.03	0.02	0.04	0.05	0.13	0.02	0.12	0.05
Type 3																		
High	0.16	0.04	0.05	0.06	0.07	0.09	0.03	0.07	0.01	0.04	0.04	0.02	0.09	0.10	0.05	0.02	0.02	0.04
Medium	0.15	0.02	0.08	0.14	0.10	0.08	0.01	0.03	0.03	0.02	0.07	0.01	0.06	0.06	0.05	0.01	0.03	0.06
Low	0.12	0.01	0.06	0.14	0.09	0.09	0.04	0.02	0.01	0.01	0.05	0.02	0.06	0.06	0.10	0.02	0.06	0.05
Type 4																		
High	0.19	0.03	0.05	0.09	0.07	0.05	0.01	0.06	0.00	0.03	0.05	0.02	0.14	0.12	0.04	0.01	0.01	0.03
Medium	0.16	0.01	0.07	0.19	0.11	0.04	0.01	0.03	0.03	0.02	0.10	0.01	0.09	0.06	0.04	0.01	0.01	0.04
Low	0.13	0.01	0.04	0.12	0.10	0.09	0.04	0.02	0.01	0.02	0.09	0.02	0.09	0.10	0.06	0.01	0.03	0.03
Type 5																		
High	0.18	0.01	0.06	0.06	0.08	0.04	0.00	0.05	0.00	0.02	0.08	0.03	0.16	0.14	0.05	0.01	0.00	0.03
Medium	0.13	0.01	0.05	0.19	0.10	0.04	0.01	0.01	0.01	0.01	0.21	0.01	0.09	0.06	0.04	0.01	0.01	0.02
Low	0.10	0.01	0.08	0.18	0.10	0.10	0.04	0.02	0.01	0.01	0.05	0.02	0.06	0.08	0.07	0.01	0.04	0.05

Notes: This table describes the industry breakdown of workers as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. Within each firm class, I report the fraction of individual-year observations in each 2-digit industry by type. "High" refers to worker in high-quality firms, "Medium" refers to worker in medium-quality firms, "Low" refers to worker in low-quality firms. Industry codes are: 23 = Construction, 31-33 = Manufacturing, 41 = Wholesale trade, 44-45 = Retail trade, 48-49 = Transporation and warehousing, 51-56 = High-skilled services, 71 = Arts, entertainment, and recreation, 72= Accommodation and food services, 81 = Other services (except public administration). See Section 2.2 for details about career definitions. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model.

Online Appendix B Model and Estimation Details

In this section, I explain in detail the two-stage estimator used to estimate the parameters of the model. The estimation procedure exploits the finite dependence property of the model and follows the two-stage estimator developed in Section 6 of Arcidiacono and Miller (2011).

B.1 Optimization

In what follows, I index by z any function or variable that depends on unobservable type, z_i. Let $\bar{V}_z(x_{i,t})$ denote the ex-ante (or integrated) value function. This function is defined as the expected discounted value of lifetime utility, before $\epsilon_{i,t}$ is realized, conditional on behaving according to the optimal decision rule:

$$\bar{V}_z(x_{i,t}) = \mathbb{E}_t\left[\sum_{b=0}^{T-t}\sum_{j=0}^{5}\beta^b a^*_{i,j,t+b}\left(u_{j,z}(x_{i,t+b}) + \epsilon_{i,j,t+b}\right)|z_i, x_{i,t}\right]$$

where $\{a^*_{i,t}, ..., a^*_{i,T}\}$ denotes the optimal decision rule.

To discuss the solution to the optimization problem of individuals, it is convenient to define the conditional ex-ante value function associated with career choice j at time t:

$$v_{j,z}(x_{i,t}) = u_{j,z}(x_{i,t}) + \beta\mathbb{E}_t[\bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j,t}))] \tag{3}$$

where $x_{i,t+1}(x_{i,t}, a_{i,j,t})$ denotes individual i's vector of observable individual characteristics at time $t+1$ conditional on choosing career j at time t. The conditional ex-ante value function captures the two channels through which career choices affect lifetime utility: through today's flow utility, $u_{j,z}(x_{i,t})$, and through the resulting expected value of lifetime utility tomorrow, $\beta\mathbb{E}_t[\bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j,t}))]$, the continuation value.

Since the career-specific idiosyncratic preference shocks are drawn from the Type I extreme value distribution, there is a closed form solution for the conditional choice probability (CCP) of optimally choosing career j at time t:

$$p_{j,z}(x_{i,t}) = \frac{\exp(v_{j,z}(x_{i,t}))}{\sum_{j=0}^{5}\exp(v_{j,z}(x_{i,t}))} \tag{4}$$

Standard logit derivations imply a key relationship between the ex-ante value function, $\bar{V}_z(x_{i,t})$, the conditional ex-ante value function, $v_{j,z}(x_{i,t})$, and the CCPs, $p_{j,z}(x_{i,t})$:

$$\bar{V}_z(x_{i,t}) = v_{j,z}(x_{i,t}) - \ln(p_{j,z}(x_{i,t})) + \gamma \tag{5}$$

where γ denotes Euler's constant.[39] This relationship holds for any $j \in J$. As I show below, this relationship is key to derive a linear mapping between the CCPs and the parameters of the utility function.

B.2 The First Stage

The likelihood of the observed data for individual i can be written as a finite mixture of likelihoods:

$$\mathbb{L}_i(\tau, \theta_Y, \theta_U) = \sum_{z=1}^{Z} \tau_{z|x_{i,0}} (\prod_{t=1}^{T} \prod_{j=0}^{5} [p_{j,z}(x_{i,t}; \theta_Y, \theta_U) f_{j,z}(y_{i,t}|x_{i,t}; \theta_Y)]^{a_{i,j,t}})$$

where $\tau_{z|x_{i,0}}$ is the probability individual i belongs to type z given his first observed career choice at age 25 and baseline characteristics, $p_{j,z}(x_{i,t}; \theta_Y, \theta_U)$ denotes the conditional choice probability of optimally choosing career j given the parameters of the model, $f_{j,z}(y_{i,t}|x_{i,t}; \theta_Y)$ is the conditional density of earnings in career j, and $a_{i,j,t}$ is an action variable that is equal to 1 if individual i chooses career j at time t and is equal to 0 otherwise.

Arcidiacono and Jones (2003) show that the log-likelihood of the observed data can be written as:

$$\begin{aligned} \mathbb{l}(\tau, \theta_Y, \theta_U) = & \sum_{i=1}^{N} \sum_{z=1}^{Z} \sum_{t=1}^{T} \sum_{j=0}^{5} q_{i,z} a_{i,j,t} \ln(p_{j,z}(x_{i,t}; \theta_Y, \theta_U)) \\ & + \sum_{i=1}^{N} \sum_{z=1}^{Z} \sum_{t=1}^{T} \sum_{j=0}^{5} q_{i,z} a_{i,j,t} \ln(f_{j,z}(y_{i,t}|x_{i,t}; \theta_Y)) \\ & + \sum_{i=1}^{N} \sum_{z=1}^{Z} q_{i,z} \ln(\tau_{z|x_{i,0}}) - \sum_{i=1}^{N} \sum_{z=1}^{Z} q_{i,z} \ln(q_{i,z}) \end{aligned} \tag{6}$$

where $q_{i,z}$ denotes the posterior probability individual i belongs to type z:

$$q_{i,z} = \frac{\tau_{z|x_{i,0}} (\prod_{t=1}^{T} \prod_{j=0}^{5} [p_{j,z}(x_{i,t}; \theta_Y, \theta_U) f_{j,z}(y_{i,t}|x_{i,t}; \theta_Y)]^{a_{i,j,t}})}{\sum_{z=1}^{Z} \tau_{z|x_{i,0}} (\prod_{t=1}^{T} \prod_{j=0}^{5} [p_{j,z}(x_{i,t}; \theta_Y, \theta_U) f_{j,z}(y_{i,t}|x_{i,t}; \theta_Y)]^{a_{i,j,t}})} \tag{7}$$

[39] To derive equation (5), take the log of equation (4) and use the following expression for the ex-ante value function:

$$\bar{V}_z(x_{i,t}) = \ln(\sum_{j=0}^{5} \exp(v_{j,z}(x_{i,t}))) + \gamma$$

Intuitively, the posterior probability individual i belongs to type z is equal to the fraction of the likelihood for individual i that comes from type z.

Instead of using the structural CCPs given by (4) to obtain estimates of θ_U directly, I pursue a two-stage approach proposed by Arcidiacono and Miller (2011) in which I find empirical estimates of the CCPs in the first stage and use them to recover estimates of θ_U in the second stage. The maximization problem of the first stage reduces to:

$$\begin{aligned}\{\hat{\tau}, \hat{\theta}_Y, \hat{p}\} = \underset{\tau,\theta_Y,p}{\operatorname{argmax}} & \sum_{i=1}^{N}\sum_{z=1}^{Z}\sum_{t=1}^{T}\sum_{j=0}^{5} q_{i,z} a_{i,j,t} \ln(p_{j,z}(x_{i,t})) \\ & + \sum_{i=1}^{N}\sum_{z=1}^{Z}\sum_{t=1}^{T}\sum_{j=0}^{5} q_{i,z} a_{i,j,t} \ln(f_{j,z}(y_{i,t}|x_{i,t};\theta_Y)) \\ & + \sum_{i=1}^{N}\sum_{z=1}^{Z} q_{i,z} \ln(\tau_{z|x_{i,0}}) - \sum_{i=1}^{N}\sum_{z=1}^{Z} q_{i,z} \ln(q_{i,z})\end{aligned} \tag{8}$$

As suggested by Arcidiacono and Jones (2003) and Arcidiacono and Miller (2011), I carry out this maximization problem in stages using the Expectation-Maximization (EM) algorithm. The EM algorithm proceeds in two steps. At the expectation step, the posterior probability individual i belongs to type z, $q_{i,z}$, is calculated given the data and the structure of the model using equation (7). At the maximization step, the posterior probabilities that each individual belongs to each unobservable type are taken as given and used as weights to obtain maximum likelihood estimates of $\{\tau, \theta_Y, p\}$. Note that, taking $q_{i,z}$ as given, the log-likelihood function in equation (8) is the sum of three components: a component associated with choices, a component associated with earnings, and a component associated with the probability that an individual belongs to each unobservable type given his first observed career choices at age 25 and other baseline characteristics. Because it is additively separable, consistent estimates of τ, θ_Y, and p can be obtained separately. The algorithm is easy to implement in practice because it amounts to iterating on a set of weighted OLS regressions. I now describe the EM algorithm in more detail.

The expectation step consists of updating the estimates of $q_{i,z}$ using equation (7). Specifically, at the $(m+1)^{th}$ iteration of the algorithm, I obtain a new estimate of $q_{i,z}$ as follows:

$$\hat{q}_{i,z}^{m+1} = \frac{\hat{\tau}_{z|x_{i,0}}^{m}\left(\prod_{t=1}^{T}\prod_{j=0}^{5}[\hat{p}_{j,z}^{m}(x_{i,t}) f_{j,z}(y_{i,t}|x_{i,t};\hat{\theta}_Y^{m})]^{a_{i,j,t}}\right)}{\sum_{z=1}^{Z}\hat{\tau}_{z|x_{i,0}}^{m}\left(\prod_{t=1}^{T}\prod_{j=0}^{5}[\hat{p}_{j,z}^{m}(x_{i,t}) f_{j,z}(y_{i,t}|x_{i,t};\hat{\theta}_Y^{m})]^{a_{i,j,t}}\right)} \tag{9}$$

The maximization step consists of finding estimates of τ, θ_Y, and p that solve equation (8), taking $\hat{q}_{i,z}$ as given.

Maximizing (8) with respect to τ gives:

$$\hat{\tau}^{m+1}_{z|x_{i,0}} = \frac{\sum_{i=1}^{N} \hat{q}^{m+1}_{i,z} \mathbb{1}\{x_{i,0} = x\}}{\sum_{i=1}^{N} \mathbb{1}\{x_{i,0} = x\}} \tag{10}$$

which implies that the probability individual i belongs to type z given his baseline characteristics is equal to the average of the posterior probabilities among all individuals with the same baseline characteristics. As a reminder, I allow the probability that an individual belongs to each type to depend on first observed career choice at age 25 and three baseline characteristics which are intended to capture a combination of initial wealth and initial learning opportunities about entrepreneurship: (1) an indicator for living in a high income area at age 25, (2) an indicator for living in an entrepreneurial area at age 25, and (3) four indicator variables capturing initial city size.

Maximizing (8) with respect to θ_Y gives:

$$\hat{\theta}^{m+1}_{Y} = \underset{\theta_Y}{\text{argmax}} \sum_{i=1}^{N} \sum_{z=1}^{Z} \sum_{t=1}^{T} \sum_{j=0}^{5} \hat{q}^{m+1}_{i,z} a_{i,j,t} \ln(f_{j,z}(y_{i,t}|x_{i,t}, \theta_Y)) \tag{11}$$

which amounts to obtaining OLS estimates of the parameters of the earnings equations taking the unobserved heterogeneity as given and using $\{\hat{q}^{m+1}_{i,z}\}_{i \in I}$ as population weights.

Finally, maximizing (8) with respect to $p_{j,z}$ gives:

$$\hat{p}^{m+1}_{j,z}(x_{i,t}) = \frac{\sum_{i=1}^{N} a_{i,j,t} \hat{q}^{m+1}_{i,z} \mathbb{1}\{x_{i,t} = x\}}{\sum_{i=1}^{N} \hat{q}^{m+1}_{i,z} \mathbb{1}\{x_{i,t} = x\}} \tag{12}$$

which is equivalent to the non-parametric empirical likelihood where $\{\hat{q}^{m+1}_{i,z}\}_{i \in I}$ are used as population weights. In practice, to avoid empty cells and small bin problems in calculating (12), I use flexible linear probability models to smooth the empirical estimates of the CCPs across the state space, as in Traiberman (2019). For each career option $j \in J$, I estimate a separate linear probability model for every possible combination of last year's career choice and unobservable type. In total, I run 180 regressions to obtain the empirical estimates of the CCPs.[40] In each regression, I include a constant term, and linear and quadratic terms of the number of years of experience an individual has in each career. The upside of this approach is that it allows me to obtain estimates of the CCPs that are flexible in a reasonable amount of computation time. The downside of this approach is that it does not impose the restriction that the predicted CCPs lie between 0 and 1. To deal with fitted values that lie outside this range and keep the likelihood well behaved numerically, I bound fitted values

[40] There are six career options, six possible career choices last period, and 5 unobservable types.

between 10^{-7} and $1 - 10^{-7}$. In practice, less than 4% of all fitted values are affected by this ad-hoc adjustment and the ones that are affected are all extremely close to 0 and 1.

B.3 The Second Stage

I now describe how I recover estimates of the parameters of the utility function using only empirical estimates of the CCPs and the parameters of the earnings equations.

I start by taking differences in conditional ex-ante value functions. As shown by Hotz and Miller (1993), there exists a simple one-to-one mapping between the CCPs and the conditional ex-ante value functions:

$$\ln\left(\frac{p_{j,z}(x_{i,t})}{p_{j',z}(x_{i,t})}\right) = v_{j,z}(x_{i,t}) - v_{j',z}(x_{i,t}) \tag{13}$$

Using equation (3) to replace for the conditional ex-ante value functions in equation (13), I obtain the following equation:

$$\begin{aligned}\ln\left(\frac{p_{j,z}(x_{i,t})}{p_{j',z}(x_{i,t})}\right) &= u_{j,z}(x_{i,t}) - u_{j',z}(x_{i,t}) \\ &\quad + \beta\left(\mathbb{E}_t[\bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j,t}))] - \mathbb{E}_t[\bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j',t}))]\right)\end{aligned} \tag{14}$$

At this point, it would be possible to estimate all the parameters of the utility function if I could calculate the difference in expected ex-ante value functions. From the first stage of the estimation procedure, I have empirical estimates of the CCPs which allow me to construct the left hand side of equation (14). I can also calculate the difference in expected log earnings between career j and j', which enters linearly on the right hand side of equation (14), using the estimated parameters of the earnings equations. However, the richness of the state space makes it prohibitively costly to calculate the ex-ante value functions using backward induction. I employ recent advances in the estimation of dynamic discrete choice models to address this issue.

First, I replace the difference in expected ex-ante value functions with the sum of its realization and forecasting error, as in Scott (2013) and Kalouptsidi et al. (2021):

$$\begin{aligned}\ln\left(\frac{p_{j,z}(x_{i,t})}{p_{j',z}(x_{i,t})}\right) &= u_{j,z}(x_{i,t}) - u_{j',z}(x_{i,t}) \\ &\quad + \beta\left(\bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j,t}))] - \bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j',t}))\right) \\ &\quad + \beta(\eta_{i,j,z,t+1} - \eta_{i,j',z,t+1})\end{aligned} \tag{15}$$

where $\eta_{i,j,z,t+1}$ is the forecasting error:

$$\eta_{i,j,z,t+1} \equiv \mathbb{E}_t[\bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j,t}))] - \bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j,t}))$$

The key idea behind this approach is that the forecasting error of individuals is mean uncorrelated with any information available at time t because individuals have rational expectations. From an econometrician's perspective, the forecasting error of individuals can be seen as an error term in equation (15) that is orthogonal to the difference in flow utilities at time t.

To deal with the issue that I cannot calculate the ex-ante value functions using backward induction, I exploit the finite dependence property of the model. Arcidiacono and Miller (2011) show that it is possible to calculate the difference in ex-ante value functions using only first stage estimates if the model exhibits finite dependence. They say that a model exhibits ρ-period finite dependence if it is possible to find two sequences of choices that lead to the same continuation values after ρ periods. In the context of my model, the effect on the future of a choice today occurs through two channels: human capital accumulation and mobility costs. It is possible to find two career paths that lead to the same continuation values at some point in the future because (a) there is no depreciation of career-specific human capital over time and (b) mobility costs only depend on last year's career choice, $a_{i,t-1}$. Consider the following career paths: (1) career j at time t, career $j^{'}$ at time $t+1$, and career $j^{''}$ at time $t+2$ and (2) career $j^{'}$ at time t, career j at time $t+1$, and career $j^{''}$ at time $t+2$. Both of them lead to the same state at the beginning of period $t+3$. To see this, note that both career paths increase $\text{exper}_{i,j,t}$, $\text{exper}_{i,j^{'},t}$, and $\text{exper}_{i,j^{''},t}$ by one unit and present individuals with the same menu of mobility costs at the beginning of time $t+3$ because the last career choice is $j^{''}$ in both cases.

Using equation (5), we can telescope equation (15) two periods in the future along two career paths that exhibit finite dependence ($\{j, j^{'}, j^{''}\}$ and $\{j^{'}, j, j^{''}\}$) to get rid of the continuation values:

$$\begin{aligned}
&\ln\left(\frac{p_{j,z}(x_{i,t})}{p_{j^{'},z}(x_{i,t})}\right) + \beta \ln\left(\frac{p_{j^{'},z}(x_{i,t+1}(x_{i,t}, a_{i,j,t}))}{p_{j,z}(x_{i,t+1}(x_{i,t}, a_{i,j^{'},t}))}\right) + \beta^2 \ln\left(\frac{p_{j^{''},z}(x_{i,t+2}(x_{i,t}, a_{i,j,t}, a_{i,j^{'},t+1}))}{p_{j^{''},z}(x_{i,t+2}(x_{i,t}, a_{i,j^{'},t}, a_{i,j,t+1}))}\right) \\
&= u_{j,z}(x_{i,t}) - u_{j^{'},z}(x_{i,t}) \\
&+ \beta[u_{j^{'},z}(x_{i,t+1}(x_{i,t}, a_{i,j,t})) - u_{j,z}(x_{i,t+1}(x_{i,t}, a_{i,j^{'},t}))] \\
&+ \beta^2[u_{j^{''},z}(x_{i,t+2}(x_{i,t}, a_{i,j,t}, a_{i,j^{'},t+1})) - u_{j^{''},z}(x_{i,t+2}(x_{i,t}, a_{i,j^{'},t}, a_{i,j,t+1}))] \\
&+ \beta(\eta_{i,j,z,t+1} - \eta_{i,j^{'},z,t+1}) + \beta^2(\eta_{i,j,j^{'},z,t+2} - \eta_{i,j^{'},j,z,t+2})
\end{aligned} \tag{16}$$

where $\eta_{i,j,j',z,t+2}$ is the two periods ahead forecasting error.[41] Equation (16) has an intuitive interpretation: the left hand side is equal to the minimum compensating differential an individual must receive at time t to be willing to choose career path $\{j', j, j''\}$ instead of $\{j, j', j''\}$.

To construct equation (16), I need to pick two sequence of choices that exhibit finite dependence. There are many ways to go about doing this. In practice, I forward simulate a sequence of choices $\{j, j', j''\}_{i,t}$ that is specific to each observation in the data in the spirit of Hotz et al. (1994). To do so, I use the empirical CCPs associated with unobservable type z_i and vector of observable characteristics $x_{i,t}$ to form a cumulative distribution function and draw a first action j in the sequence. I then update the state space assuming action j was taken at time t and use the empirical CCPs associated with z_i and $x_{i,t+1}(x_{i,t}, a_{i,j,t})$ to form a new cumulative distribution function and draw the second action j' in the sequence. I proceed in a similar fashion to draw the third action in the sequence. This gives me a specific sequence of choices $\{j, j', j''\}_{i,t}$ for each individual-year observation. Based on the discussion above, I switch the ordering of the first two choices in the sequence to form a counterfactual sequence that exhibit finite dependence: $\{j', j, j''\}_{i,t}^{\textbf{Counterfactual}}$.

Taking these sequences as given, equation (16) can be constructed and estimated easily because it is linear in the parameters of the utility function. Empirical estimates of the CCPs are used to construct the left hand side variable and differences in expected log earnings along the two career paths (calculated using estimates of the parameters of the earnings equations) appear on the right hand side as a regressor.

B.4 Interpreting the Value of Amenities and Mobility Costs

In this subsection, I explain how I calculate the willingness to pay for career-specific amenities and the willingness to accept to move from one career to another.

As in Ransom (2022), I use the concept of willingness to pay to express amenity values in dollars. The willingness to pay formula below answers the following question: "*How much is an individual willing to pay every year to receive the amenities associated with career B instead of the amenities associated with career A, assuming the pay is the same in both careers and there is no switching cost?*"

$$\alpha \ln(y) + \phi_A = \alpha \ln(y - \text{WTP}) + \phi_B$$

[41]The two periods ahead forecasting error is defined as:

$$\eta_{i,j,j',z,t+2} \equiv \mathbb{E}_{t+1}[\bar{V}_z(x_{i,t+2}(x_{i,t}, a_{i,j,t}, a_{i,j',t+1}))] - \bar{V}_z(x_{i,t+2}(x_{i,t}, a_{i,j,t}, a_{i,j',t+1}))$$

which gives us

$$\frac{\text{WTP}}{y} = 1 - \exp\left(\frac{\phi_A - \phi_B}{\alpha}\right)$$

I use the concept of willingness to accept to express mobility costs in dollars. The willingness to accept formula below answers the following question: "*Assuming everything else about utility stays the same, how much additional income should an individual receive in career B every year to be just indifferent between (a) staying in career A and (b) paying the mobility costs to move to career B at time* $t+1$*?*".

$$\sum_{t=1}^{T} \beta^t \alpha \ln(y) = \sum_{t=1}^{T} \beta^t \alpha \ln(y + \text{WTA}) - \beta \psi_{A \to B}$$

where $\psi_{A \to B}$ denotes the utility cost of moving from career A to career B. Simplifying, we get

$$\frac{\text{WTA}}{y} = \exp\left(\frac{\psi_{A \to B}}{\alpha} \frac{(1-\beta)}{(1-\beta^T)}\right) - 1$$

We can therefore express willingness to pay for amenities and willingness to accept for mobility costs as a fraction of flow earnings using the parameter estimates reported in Table C.1 and C.2 in Online Appendix C. To obtain a dollar value, we need to multiply these fractions by some measure of baseline earnings y. I use baseline earnings in low-quality firms from Table 4 for this purpose. That is, I multiply the fraction by $\exp(9.78)$ for Type 1 and $\exp(10.45)$ for Type 5.

Online Appendix C Parameter Estimates and Model Fit

C.1 Model Fit: Procedure and Additional Results

Procedure. I proceed as follows to forward simulate career choices. I construct a synthetic panel dataset starting with real observations at age 25 and forward simulate career choices for 10 years (from age 26 to age 35). For each individual in the sample, I record their initial conditions and the posterior probabilities that they belong to each type. Using the estimated posterior probabilities, I form a cumulative distribution function and draw an unobservable type. Using the estimated model parameters and empirical CCPs, I then calculate the conditional ex-ante value function associated with each career, taking unobservable types and observed state variables as given.[42] Specifically, I calculate $v_{j,z}(x_{i,t}) - v_{j',z}(x_{i,t})$ using Equation (16):

$$\begin{aligned}
&v_{j,z}(x_{i,t}) - v_{j',z}(x_{i,t}) \\
&= u_{j,z}(x_{i,t}) - u_{j',z}(x_{i,t}) \\
&+ \beta[u_{j',z}(x_{i,t+1}(x_{i,t}, a_{i,j,t})) - u_{j,z}(x_{i,t+1}(x_{i,t}, a_{i,j',t}))] \\
&+ \beta^2[u_{j'',z}(x_{i,t+2}(x_{i,t}, a_{i,j,t}, a_{i,j',t+1})) - u_{j'',z}(x_{i,t+2}(x_{i,t}, a_{i,j',t}, a_{i,j,t+1}))] \\
&- \beta \ln(\frac{p_{j',z}(x_{i,t+1}(x_{i,t}, a_{i,j,t}))}{p_{j,z}(x_{i,t+1}(x_{i,t}, a_{i,j',t}))}) - \beta^2 \ln(\frac{p_{j'',z}(x_{i,t+2}(x_{i,t}, a_{i,j,t}, a_{i,j',t+1}))}{p_{j'',z}(x_{i,t+2}(x_{i,t}, a_{i,j',t}, a_{i,j,t+1}))})
\end{aligned}$$

I then draw idiosyncratic preference shocks and compute optimal action. Individual i's payoff at time t is equal to his expected log earnings in the chosen career plus an ex-post productivity shock drawn from a career-specific normal distribution. I then update the state space and repeat $T = 10$ times. Given the large sample size of 721,730 individuals, I perform this forward simulation once for each individual in the estimation sample.

Additional Results. To assess out-of-sample fit, I take data from 2012, which I purposely set aside and left out of the estimation sample, and compare observed career choices in that year to the ones predicted by the model taking as given the observable characteristics of individuals at the beginning of 2012.

Table C.10 shows out-of-sample comparisons between career choices in 2012 and predicted career choices in that year, again as a function of age. The out-of-sample fit along that dimension is good. Table C.11 shows out-of-sample comparisons between observed career

[42] The vector of observed state variables includes the number of years of experience they have in each career and a set of indicator variables that identify their previous career choice. I take as given the first observed career choice at age 25 to predict choices at age 26.

transitions in 2012 and predicted career transitions in that year, pooling all ages this time. We can see that the model slightly overpredicts exit from entrepreneurship, but again most of the predicted transition rates are close to the ones observed in the data.

I explore the ability of the model to predict the career choices of individuals as a function of their assigned unobservable type in Table C.12. I find that the model does a good job at predicting career choices along that dimension as well. The main discrepancy is for Type 1 individuals, for whom the model is not able to fit the high fraction of observations in non-employment (54% in the data vs 36% in the model) and overpredicts the proportion of individuals that choose entrepreneurship. Table C.13-C.16 reveals that the prediction error for Type 1 individuals is an issue primarily at age 26, when people are at a clean slate in terms of state variables. The model predictions are excellent for the other types at various points in the life cycle.

Table C.1 – Parameters of the Utility Function: Scale Parameter and Amenities

Scale Parameter	1.29
	(0.07)
Amenities	
High-Quality Firms	1.07
	(0.11)
Medium-Quality Firms	1.94
	(0.09)
Low-Quality Firms	2.38
	(0.08)
Unincorporated	
Type 1	-2.16
	(0.22)
Type 2, Relative to Type 1	0.32
	(0.26)
Type 3, Relative to Type 1	1.14
	(0.29)
Type 4, Relative to Type 1	1.42
	(0.30)
Type 5, Relative to Type 1	0.69
	(0.84)
Incorporated	
Type 1	3.86
	(2.16)
Type 2, Relative to Type 1	-8.01
	(2.30)
Type 3, Relative to Type 1	-3.46
	(2.23)
Type 4, Relative to Type 1	-11.40
	(2.23)
Type 5, Relative to Type 1	-1.07
	(2.43)

Notes: This table reports structural parameter estimates for the scale parameter α and career-specific amenities from the dynamic discrete choice model detailed in Section 4. See Online Appendix B for estimation details. The value of amenities associated with non-employment is normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 721,730. Number of observations: 4,283,785. Standard errors clustered at the individual level are in parentheses.

Table C.2 – Parameters of the Utility Function: Mobility Costs

	Destination													
	Work			Incorporated					Unincorporated					
					Relative to Type 1					Relative to Type 1				
Origin	High	Medium	Low	Type 1	Type 2	Type 3	Type 4	Type 5	Type 1	Type 2	Type 3	Type 4	Type 5
High	0.00	-2.37	-2.34	-10.44	5.27	7.23	7.47	6.41	-2.02	0.73	0.13	1.00	-1.34
		(0.01)	(0.01)	(0.34)	(0.38)	(0.35)	(0.35)	(0.37)	(0.05)	(0.05)	(0.06)	(0.06)	(0.13)
Medium	-2.61	0.00	-2.33	-11.42	5.98	8.61	4.26	8.32	-1.96	0.32	0.42	0.20	-3.97
	(0.01)		(0.01)	(0.40)	(0.44)	(0.41)	(0.41)	(0.44)	(0.04)	(0.04)	(0.05)	(0.05)	(0.18)
Low	-2.89	-2.63	0.00	-9.84	6.33	7.30	6.22	2.74	-1.67	0.13	0.02	-0.07	-2.11
	(0.01)	(0.01)		(0.36)	(0.37)	(0.37)	(0.37)	(0.40)	(0.03)	(0.04)	(0.05)	(0.05)	(0.13)
Incorporated	-3.72	-6.75	-3.70	0.00	0.00	0.00	0.00	0.00	-0.40	-2.94	-2.43	-1.91	-6.75
	(0.09)	(0.11)	(0.10)						(0.63)	(0.66)	(0.64)	(0.63)	(0.70)
Unincorporated	-3.54	-3.47	-3.29	-8.53	4.90	5.89	4.57	4.93	0.00	0.00	0.00	0.00	0.00
	(0.03)	(0.03)	(0.03)	(0.34)	(0.36)	(0.35)	(0.34)	(0.43)					
Non-Employed	-3.14	-2.83	-2.87	-11.23	7.63	8.27	6.71	7.39	-1.93	0.39	0.34	-0.55	-1.46
	(0.01)	(0.01)	(0.01)	(0.32)	(0.34)	(0.33)	(0.33)	(0.36)	(0.03)	(0.04)	(0.05)	(0.06)	(0.13)

Notes: This table reports structural parameter estimates for the mobility costs from the dynamic discrete choice model detailed in Section 4. See Online Appendix B for estimation details. The value of mobility costs associated with non-employment are normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 721,730. Number of observations: 4,283,785. Standard errors clustered at the individual level are in parentheses.

TABLE C.3 – Parameters of the Earnings Equations: High-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.009	0.077	0.088	0.104	0.116
	(0.004)	(0.001)	(0.001)	(0.000)	(0.001)
Exper. Med.	-0.026	0.078	0.066	0.077	0.083
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Exper. Low	-0.023	0.048	0.056	0.092	-0.038
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Total Work Exper. (sq)	0.008	-0.002	-0.004	-0.005	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.095	0.283	-0.044	0.063	0.280
	(0.023)	(0.011)	(0.011)	(0.008)	(0.037)
Exper. Unincorp. (sq)	0.006	-0.042	0.017	-0.006	-0.055
	(0.007)	(0.003)	(0.003)	(0.003)	(0.008)
Exper. Incorp.	0.465	0.179	0.044	0.124	-0.025
	(0.082)	(0.031)	(0.038)	(0.019)	(0.030)
Exper. Incorp. (sq)	-0.037	-0.027	-0.01	-0.019	0.018
	(0.015)	(0.007)	(0.011)	(0.005)	(0.009)
Intercept relative to type 1	0	0.168	0.542	0.854	1.271
		(0.003)	(0.003)	(0.003)	(0.004)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 10.009 (s.e. 0.003). Mean, dependent variable : 10.90. Number of individuals: 368,350. Number of observations: 1,545,780. Adjusted R-squared: 0.54.

Table C.4 – Parameters of the Earnings Equations: Medium-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	-0.016	0.083	0.087	0.122	0.181
	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)
Exper. Med.	-0.016	0.070	0.076	0.092	0.128
	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)
Exper. Low	-0.022	0.044	0.056	0.107	-0.035
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Total Work Exper. (sq)	0.008	-0.003	-0.004	-0.005	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.077	0.206	-0.011	0.033	0.129
	(0.017)	(0.011)	(0.010)	(0.011)	(0.064)
Exper. Unincorp. (sq)	-0.004	-0.022	0.004	0.002	-0.065
	(0.004)	(0.003)	(0.003)	(0.003)	(0.022)
Exper. Incorp.	0.1	0.218	-0.108	0.01	-0.058
	(0.090)	(0.035)	(0.027)	(0.023)	(0.109)
Exper. Incorp. (sq)	-0.056	-0.046	0.024	0.004	0.07
	(0.028)	(0.008)	(0.006)	(0.006)	(0.063)
Intercept relative to type 1	0	0.140	0.504	0.785	1.127
		(0.002)	(0.002)	(0.002)	(0.004)

Notes: This table reports structural parameter estimates for the earnings process in medium-quality firms from the dynamic discrete choice model detailed in Section 4. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.928 (s.e. 0.002). Mean, dependent variable: 10.63. Number of individuals: 342,700. Number of observations: 1,271,945. Adjusted R-squared: 0.54.

Table C.5 – Parameters of the Earnings Equations: Low-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.038	0.053	0.111	0.107	0.282
	(0.002)	(0.001)	(0.001)	(0.001)	(0.005)
Exper. Med.	0.025	0.049	0.093	0.084	0.248
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Exper. Low	0.024	0.043	0.084	0.123	0.069
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Work Exper. (sq)	0.003	-0.002	-0.005	-0.006	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.169	-0.019	0.067	0.001	-0.217
	(0.012)	(0.014)	(0.010)	(0.017)	(0.043)
Exper. Unincorp. (sq)	-0.019	0.015	-0.004	-0.006	0.02
	(0.003)	(0.005)	(0.003)	(0.005)	(0.015)
Exper. Incorp.	0.260	0.108	-0.029	-0.028	-0.029
	(0.070)	(0.035)	(0.025)	(0.039)	(0.042)
Exper. Incorp. (sq)	-0.035	-0.025	0.003	0.004	0.013
	(0.012)	(0.010)	(0.006)	(0.011)	(0.010)
Intercept relative to type 1	0	0.156	0.450	0.931	0.665
		(0.002)	(0.002)	(0.002)	(0.002)

Notes: This table reports structural parameter estimates for the earnings process in low-quality firms from the dynamic discrete choice model detailed in Section 4. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.783 (s.e. 0.001). Mean, dependent variable: 10.34. Number of individuals: 318,075. Number of observations: 1,073,500. Adjusted R-squared: 0.53.

Table C.6 – Parameters of the Earnings Equations: Incorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.221	0.034	0.019	0.065	0.035
	(0.037)	(0.019)	(0.011)	(0.009)	(0.017)
Exper. Med.	0.087	0.027	0.020	0.045	0.056
	(0.034)	(0.018)	(0.012)	(0.009)	(0.018)
Exper. Low	0.065	0.014	0.038	0.080	-0.104
	(0.033)	(0.018)	(0.011)	(0.010)	(0.016)
Total Work Exper. (sq)	-0.010	0	0.001	-0.003	0
	(0.005)	(0.002)	(0.001)	(0.001)	(0.002)
Exper. Unincorp.	0.002	0.064	0.148	0.099	0.197
	(0.032)	(0.029)	(0.015)	(0.013)	(0.024)
Exper. Unincorp. (sq)	-0.008	-0.015	-0.019	-0.012	-0.022
	(0.008)	(0.008)	(0.003)	(0.003)	(0.005)
Exper. Incorp.	0.187	0.118	0.193	0.259	0.272
	(0.012)	(0.013)	(0.008)	(0.006)	(0.009)
Exper. Incorp. (sq)	-0.014	-0.021	-0.025	-0.028	-0.026
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Intercept relative to type 1	0	-0.133	0.041	0.260	0.706
		(0.053)	(0.046)	(0.047)	(0.053)

Notes: This table reports structural parameter estimates for the earnings process in incorporated entrepreneurship from the dynamic discrete choice model detailed in Section 4. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.977 (s.e. 0.044). Mean, dependent variable: 10.61. Number of individuals: 11,790. Number of observations: 33,965. Adjusted R-squared: 0.35.

Table C.7 – Parameters of the Earnings Equations: Unincorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.079	0.003	-0.036	0.029	0.050
	(0.012)	(0.007)	(0.007)	(0.009)	(0.017)
Exper. Med.	0.039	0.002	-0.061	0.054	0.033
	(0.011)	(0.007)	(0.006)	(0.009)	(0.018)
Exper. Low	0.037	-0.016	-0.056	0.034	-0.063
	(0.011)	(0.007)	(0.006)	(0.010)	(0.017)
Total Work Exper. (sq)	-0.006	0.001	0.005	-0.004	-0.004
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Exper. Unincorp.	0.121	0.168	0.200	0.307	0.373
	(0.005)	(0.006)	(0.004)	(0.007)	(0.012)
Exper. Unincorp. (sq)	-0.013	-0.028	-0.017	-0.037	-0.037
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Exper. Incorp.	0.064	0.037	-0.027	-0.116	0.122
	(0.074)	(0.043)	(0.059)	(0.064)	(0.218)
Exper. Incorp. (sq)	-0.016	-0.007	0.005	0.022	-0.056
	(0.016)	(0.008)	(0.022)	(0.020)	(0.045)
Intercept relative to type 1	0	0.108	0.352	0.321	0.933
		(0.016)	(0.017)	(0.020)	(0.034)

Notes: This table reports structural parameter estimates for the earnings process in unincorporated entrepreneurship from the dynamic discrete choice model detailed in Section 4. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.718 (s.e. 0.014). Mean, dependent variable: 10.16. Number of individuals: 31,680. Number of observations: 71,475. Adjusted R-squared: 0.31.

Table C.8 – Model Fit: Career Choices Over the Life Cycle

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.0	35.4	36.0	36.6	37.0	37.3	37.5	37.5	37.8	38.3
Medium	30.0	29.3	29.1	28.9	28.8	28.7	28.4	28.2	28.0	27.7
Low	27.4	25.4	24.0	22.8	21.8	21.0	20.4	19.8	19.2	18.8
Incorp.	0.2	0.4	0.7	1.0	1.3	1.6	1.9	2.3	2.5	2.7
Unincorp.	0.8	1.4	1.9	2.3	2.6	2.9	3.1	3.2	3.4	3.5
Non-emp.	6.6	8.1	8.4	8.4	8.4	8.5	8.6	9.0	9.1	9.1

(a) Data

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.3	36.0	35.9	36.3	36.2	36.4	36.6	37.1	38.3	39.2
Medium	29.5	29.8	29.3	29.0	29.0	28.1	28.2	27.8	27.7	28.0
Low	25.5	25.4	23.2	21.2	19.1	19.0	18.8	20.4	19.9	19.1
Incorp.	2.6	0.8	1.2	1.9	3.0	3.4	3.4	3.1	3.0	2.9
Unincorp.	0.8	1.3	1.7	2.0	2.6	4.2	4.2	3.9	3.6	3.2
Non-emp.	6.3	6.8	8.6	9.6	10.2	9.0	8.7	7.7	7.5	7.5

(b) One-Period Ahead Model Prediction

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.3	34.9	34.4	33.9	33.3	32.7	32.1	32.6	34.0	36.0
Medium	29.5	28.9	28.2	27.5	26.9	25.8	25.1	24.0	23.7	23.9
Low	25.6	23.8	22.7	21.0	18.7	17.1	16.5	17.4	17.8	17.9
Incorp.	2.5	3.1	3.9	5.0	6.9	8.3	9.2	9.0	8.2	7.0
Unincorp.	0.8	1.5	2.0	2.4	3.0	4.6	5.2	5.4	5.1	4.7
Non-emp.	6.2	7.8	8.9	10.2	11.4	11.5	12.0	11.6	11.2	10.6

(c) Full Model Simulation

Notes: This table describes the observed [Panel (a)], predicted [Panel (b)] and fully simulated [Panel (c)] career choices of individuals over the life cycle. I report the fraction of individuals in each career by age. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 are used to calculate the statistics. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of the period. I use fully simulated data to calculate the statistics reported in Panel (c). See Online Appendix C.1 for details about model simulations.

Table C.9 – Model Fit: Career Transitions

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	89.6	4.4	2.5	0.3	0.7	2.5
Column %	89.0	5.6	4.3	8.7	9.3	11.0
Medium						
Row %	6.5	84.8	4.3	0.3	0.7	3.4
Column %	5.2	86.3	5.8	6.4	8.1	11.7
Low						
Row %	5.7	6.4	81.2	0.3	0.9	5.5
Column %	3.5	5.0	84.2	5.3	7.5	14.8
Incorp.						
Row %	3.4	1.3	1.1	86.5	0.6	7.1
Column %	0.1	0.0	0.1	66.8	0.3	0.9
Unincorp.						
Row %	7.0	4.9	5.0	3.1	65.9	14.1
Column %	0.4	0.4	0.5	5.5	59.2	3.9
Non-emp.						
Row %	8.6	9.6	14.1	1.2	5.1	61.4
Column %	1.9	2.7	5.1	7.3	15.6	57.8

(a) Data

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	85.9	4.7	2.9	1.4	1.1	4.1
Column %	87.6	6.0	5.2	6.7	12.4	12.2
Medium						
Row %	6.5	81.6	4.5	1.6	0.9	5.0
Column %	5.4	83.4	6.6	6.4	8.5	12.0
Low						
Row %	5.1	5.9	71.7	4.9	1.1	11.3
Column %	3.2	4.6	80.6	15.0	8.0	20.8
Incorp.						
Row %	1.8	6.1	2.5	83.4	1.0	5.2
Column %	0.3	1.1	0.7	61.0	1.6	2.3
Unincorp.						
Row %	6.8	6.3	5.2	6.9	57.2	17.7
Column %	0.5	0.6	0.7	2.4	46.4	3.7
Non-emp.						
Row %	10.1	11.4	11.4	5.7	6.7	54.7
Column %	3.1	4.3	6.2	8.5	23.0	49.0

(b) Full Model Simulation

Notes: This table describes the career transitions of individuals at age 30 in the data [Panel (a)] and full model simulations [Panel (b)]. For each panel, it reports the percentage of transitions from career of origin at time $t-1$ to destination career at time t (row %) and the percentage of observations in a destination career at time t that comes from each career of origin at time $t-1$ (column %). See Section 2.2 for details about career definitions. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations of individuals at age 30 between 2001 and 2012 are used to calculate the statistics. I use fully simulated data to calculate the statistics reported in Panel (b). See Online Appendix C.1 for details about model simulations.

Table C.10 – Out-of-Sample Fit: Career Choices Over the Life Cycle

	Age									
	27	28	29	30	31	32	33	34	35	36
High	36.0	36.5	36.7	37.0	37.2	37.9	37.4	37.2	38.1	38.4
Medium	27.7	27.7	27.4	27.6	27.7	27.7	28.2	28.9	27.7	27.9
Low	26.4	25.0	23.7	22.5	21.8	21.2	20.4	19.5	19.1	18.1
Incorp.	0.5	0.8	1.0	1.3	1.7	1.9	2.3	2.8	2.8	3.0
Unincorp.	1.4	1.8	2.2	2.5	2.7	2.9	3.2	3.3	3.4	3.5
Non-emp.	8.0	8.2	8.9	9.0	8.8	8.6	8.5	8.4	8.9	9.1

(a) Data (2012)

	Age									
	27	28	29	30	31	32	33	34	35	36
High	38.0	37.3	36.5	36.0	36.0	36.5	37.1	38.2	39.1	40.4
Medium	28.9	28.0	27.3	27.6	27.3	27.1	27.4	28.0	28.1	28.3
Low	24.8	23.0	21.3	19.6	19.4	19.3	20.9	20.0	19.3	18.4
Incorp.	0.8	1.3	2.1	3.0	3.4	3.5	3.0	3.1	3.1	2.7
Unincorp.	1.2	1.6	1.9	2.5	4.0	4.2	3.7	3.4	3.2	2.9
Non-emp.	6.4	8.8	11.0	11.4	9.9	9.3	7.9	7.3	7.3	7.3

(b) One-Period Ahead Model Prediction (2012)

Notes: This table describes the observed [Panel (a)] and predicted [Panel (b)] career choices of individuals over the life cycle. I report the fraction of individuals in each career by age. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. Only observations from year 2012 are used to calculate the statistics. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of 2012. See Online Appendix C.1 for details about model simulations.

Table C.11 – Out-of-Sample Fit: Career Transitions

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	88.7	4.3	2.5	0.4	0.7	3.5
Column %	90.2	5.8	4.2	9.0	9.6	15.2
Medium						
Row %	6.5	83.3	4.4	0.3	0.8	4.6
Column %	5.1	87.2	5.8	5.4	9.1	15.6
Low						
Row %	5.4	6.2	78.7	0.3	1.1	8.3
Column %	3.6	5.5	87.5	5.0	10.3	23.7
Incorp.						
Row %	2.8	1.4	1.1	84.2	0.7	9.7
Column %	0.1	0.1	0.1	72.5	0.4	1.6
Unincorp.						
Row %	5.8	4.4	4.7	3.1	64.4	17.6
Column %	0.4	0.4	0.5	4.8	64.0	5.2
Non-emp.						
Row %	5.3	6.0	9.5	1.2	3.8	74.1
Column %	0.6	1.0	1.9	3.3	6.7	38.6

(a) Data (2012)

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	88.4	3.6	2.4	1.0	1.1	3.4
Column %	91.4	5.0	4.5	15.2	15.3	15.3
Medium						
Row %	5.2	83.2	4.3	1.2	1.6	4.5
Column %	4.0	88.1	6.2	13.0	15.8	15.3
Low						
Row %	5.0	5.2	78.3	2.1	1.7	7.9
Column %	3.0	4.2	85.3	17.5	12.7	20.1
Incorp.						
Row %	4.7	10.6	3.3	69.9	2.0	9.5
Column %	0.2	0.6	0.2	41.4	1.1	1.7
Unincorp.						
Row %	7.8	7.9	6.4	6.4	52.3	19.2
Column %	0.5	0.7	0.8	6.2	46.1	5.6
Non-emp.						
Row %	6.1	6.9	11.1	3.3	4.8	67.8
Column %	0.9	1.3	2.9	6.9	9.0	42.0

(b) Model (2012)

Notes: This table describes the career transitions of individuals at age 30 for year 2012 in the data [Panel (a)] and model simulations [Panel (b)]. For each panel, it reports the percentage of transitions from career of origin at time $t-1$ to destination career at time t (row %) and the percentage of observations in a destination career at time t that comes from each career of origin at time $t-1$ (column %). See Section 2.2 for details about career definitions. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations of individuals at age 30 in year 2012 are used to calculate the statistics. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of 2012. See Online Appendix C.1 for details about model simulations.

Table C.12 – Model Fit: Career Choices by Type

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.07	0.10	0.24	0.01	0.05	0.54
2	0.21	0.25	0.29	0.33	0.00	0.02	0.12
3	0.32	0.36	0.37	0.20	0.01	0.02	0.04
4	0.28	0.55	0.31	0.09	0.02	0.02	0.02
5	0.10	0.38	0.15	0.40	0.03	0.02	0.03
Average		0.37	0.29	0.22	0.01	0.02	0.09

(a) Data

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.09	0.13	0.30	0.07	0.05	0.36
2	0.21	0.24	0.29	0.33	0.01	0.02	0.10
3	0.32	0.34	0.35	0.21	0.02	0.02	0.05
4	0.28	0.55	0.31	0.09	0.01	0.02	0.03
5	0.10	0.36	0.15	0.37	0.04	0.02	0.05
Average		0.36	0.29	0.22	0.02	0.02	0.08

(b) One-Period Ahead Model Prediction

Notes: This table describes the observed [Panel (a)] and simulated [Panel (b)] career choices of individuals as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. I report the fraction of individual-year observations in each career by type. The sample used to estimate the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of the period. See Online Appendix C.1 for details about model simulations.

Table C.13 – Model Fit: Career Choices by Type Age 26

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.10	0.17	0.24	0.01	0.01	0.47
2	0.21	0.21	0.27	0.40	0.00	0.01	0.12
3	0.32	0.35	0.37	0.25	0.00	0.01	0.02
4	0.28	0.54	0.34	0.10	0.00	0.01	0.01
5	0.10	0.41	0.14	0.43	0.01	0.01	0.01
Average		0.36	0.30	0.25	0.00	0.01	0.08

(a) Data

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.11	0.14	0.26	0.23	0.01	0.24
2	0.21	0.22	0.29	0.37	0.00	0.01	0.12
3	0.32	0.33	0.36	0.27	0.00	0.01	0.03
4	0.28	0.53	0.34	0.11	0.00	0.01	0.01
5	0.10	0.40	0.13	0.43	0.01	0.00	0.03
Average		0.35	0.29	0.26	0.03	0.01	0.06

(b) One-Period Ahead Model Prediction

Notes: This table describes the observed [Panel (a)] and simulated [Panel (b)] career choices of individuals as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. I report the fraction of individual-year observations in each career by type. The sample used to estimate the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of the period. See Online Appendix C.1 for details about model simulations.

Table C.14 – Model Fit: Career Choices by Type Age 29

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.05	0.06	0.24	0.01	0.05	0.59
2	0.21	0.26	0.31	0.31	0.00	0.02	0.10
3	0.32	0.37	0.37	0.20	0.01	0.02	0.03
4	0.28	0.56	0.31	0.08	0.02	0.02	0.01
5	0.10	0.37	0.14	0.42	0.03	0.02	0.03
Average		0.37	0.29	0.21	0.01	0.02	0.09

(a) Data

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.07	0.10	0.28	0.05	0.05	0.45
2	0.21	0.25	0.31	0.32	0.01	0.02	0.10
3	0.32	0.35	0.36	0.20	0.02	0.02	0.06
4	0.28	0.55	0.31	0.07	0.01	0.02	0.04
5	0.10	0.35	0.14	0.39	0.04	0.02	0.06
Average		0.36	0.29	0.21	0.02	0.02	0.10

(b) One-Period Ahead Model Prediction

Notes: This table describes the observed [Panel (a)] and predicted [Panel (b)] career choices of individuals as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. I report the fraction of individual-year observations in each career by type. The sample used to estimate the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of the period. See Online Appendix C.1 for details about model simulations.

Table C.15 – Model Fit: Career Choices by Type Age 32

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.06	0.08	0.26	0.02	0.08	0.50
2	0.21	0.26	0.30	0.28	0.01	0.02	0.13
3	0.32	0.36	0.36	0.18	0.01	0.03	0.05
4	0.28	0.56	0.29	0.08	0.03	0.02	0.02
5	0.10	0.34	0.15	0.39	0.05	0.03	0.05
Average		0.38	0.29	0.20	0.02	0.03	0.09

(a) Data

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.06	0.09	0.24	0.05	0.09	0.47
2	0.21	0.25	0.29	0.29	0.02	0.05	0.09
3	0.32	0.35	0.34	0.17	0.03	0.05	0.06
4	0.28	0.55	0.29	0.09	0.02	0.02	0.03
5	0.10	0.33	0.16	0.31	0.08	0.05	0.06
Average		0.37	0.28	0.19	0.03	0.04	0.09

(b) One-Period Ahead Model Prediction

Notes: This table describes the observed [Panel (a)] and predicted [Panel (b)] career choices of individuals as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. I report the fraction of individual-year observations in each career by type. The sample used to estimate the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of the period. See Online Appendix C.1 for details about model simulations.

Table C.16 – Model Fit: Career Choices by Type Age 35

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.14	0.13	0.24	0.03	0.09	0.38
2	0.21	0.26	0.26	0.29	0.01	0.03	0.15
3	0.32	0.36	0.35	0.16	0.02	0.04	0.08
4	0.28	0.55	0.27	0.10	0.04	0.02	0.03
5	0.10	0.38	0.21	0.24	0.06	0.04	0.07
Average		0.38	0.28	0.18	0.03	0.03	0.10

(a) Data

		Career					
		Workers			Entrepreneurs		
Type	Share of pop.	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
1	0.09	0.22	0.23	0.23	0.03	0.07	0.22
2	0.21	0.28	0.23	0.33	0.01	0.04	0.11
3	0.32	0.35	0.34	0.17	0.03	0.03	0.07
4	0.28	0.57	0.27	0.10	0.03	0.01	0.02
5	0.10	0.37	0.23	0.22	0.07	0.06	0.06
Average		0.39	0.28	0.19	0.03	0.03	0.07

(b) One-Period Ahead Model Prediction

Notes: This table describes the observed [Panel (a)] and predicted [Panel (b)] career choices of individuals as a function of unobservable type. To assign types to individuals, I use the estimated posterior probabilities that they belong to each type and draw an unobservable type. I report the fraction of individual-year observations in each career by type. The sample used to estimate the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The statistics reported in Panel (b) are calculated using one-period ahead model predictions, taking as given the observable characteristics of individuals at the beginning of the period. See Online Appendix C.1 for details about model simulations.

Table C.17 – Impacts of Subsidies on the Supply of Entrepreneurs (Robustness)

		Available to All			Available to Non-Employed Only		
Type	Age	Δ Uninc. (1)	Δ Inc. (2)	Δ Non-Emp (3)	Δ Uninc. (4)	Δ Inc. (5)	Δ Non-Emp (6)
All	30	1.93	0.96	-0.95	0.65	0.32	-0.58
	35	0.27	0.27	0.12	0.13	0.09	0.03
No Type 1	30	1.76	0.93	-0.76	0.50	0.31	-0.47
	35	0.25	0.22	0.12	0.11	0.06	0.01
Type 1	30	3.55	1.23	-2.68	2.04	0.44	-1.53
	35	0.51	0.72	0.17	0.33	0.36	0.19
Type 2	30	1.85	0.62	-0.72	0.58	0.28	-0.40
	35	0.13	0.09	0.17	-0.03	0.06	0.07
Type 3	30	2.02	1.02	-0.95	0.74	0.34	-0.68
	35	0.41	0.31	-0.04	0.23	0.07	-0.09
Type 4	30	1.51	0.68	-0.37	0.19	0.07	-0.10
	35	0.20	0.16	0.35	0.07	-0.01	0.18
Type 5	30	1.50	2.17	-1.51	0.55	1.02	-1.18
	35	0.12	0.41	-0.23	0.09	0.25	-0.28

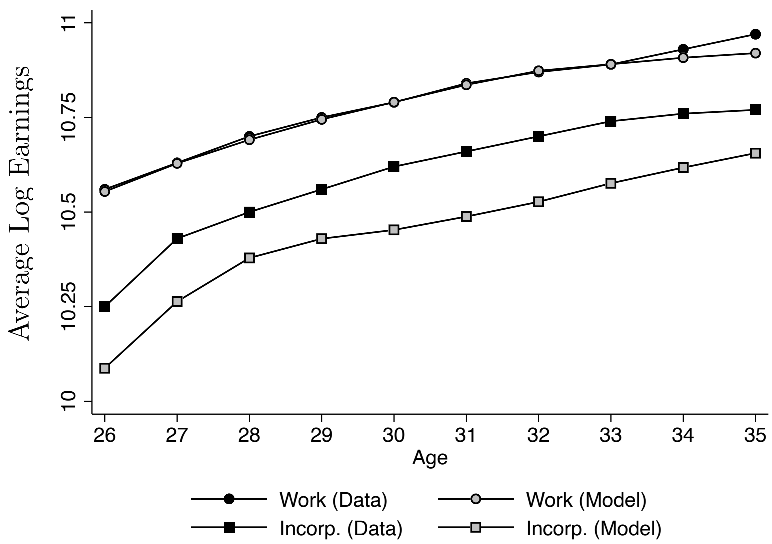
(a) One-Time Subsidy to Choose Unincorporated or Incorporated Entrepreneurship at Age 30

		Available to All			Available to High-Wage Only		
Type	Age	Δ Uninc. (1)	Δ Inc. (2)	Δ Non-Emp (3)	Δ Uninc. (4)	Δ Inc. (5)	Δ Non-Emp (6)
All	30	-0.16	1.21	-0.41	-0.03	0.19	-0.05
	35	0.01	0.25	0.08	0.01	0.04	0.07
No Type 1	30	-0.16	1.17	-0.37	-0.04	0.20	0.01
	35	0.00	0.23	0.10	-0.01	0.04	0.08
Type 1	30	-0.19	1.59	-0.83	0.06	0.15	-0.55
	35	0.13	0.42	-0.03	0.13	0.04	0.04
Type 2	30	-0.02	0.78	-0.19	-0.04	0.01	0.17
	35	0.06	0.07	0.32	-0.13	-0.09	0.19
Type 3	30	-0.15	1.28	-0.45	0.06	0.06	-0.05
	35	0.02	0.26	0.02	0.02	0.08	-0.04
Type 4	30	-0.16	0.88	-0.23	-0.11	0.30	-0.01
	35	0.03	0.09	0.09	0.06	0.05	0.12
Type 5	30	-0.49	2.66	-0.95	-0.11	0.74	-0.11
	35	-0.28	0.99	-0.13	-0.02	0.17	0.09

(b) One-Time Subsidy to Choose Incorporated Entrepreneurship at Age 30

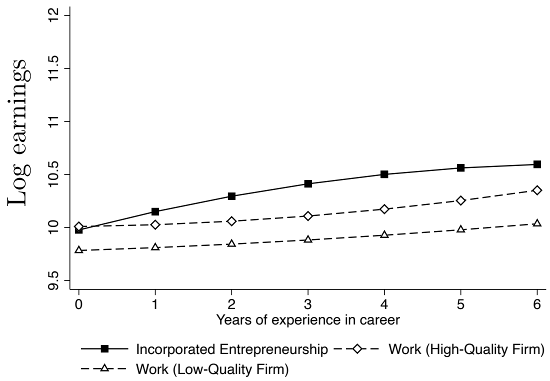
Notes: This table shows the effects of an unanticipated one-time 100% earnings subsidy to choose entrepreneurship at age 30. I report the change in the share of unincorporated entrepreneurs, incorporated entrepreneurs, and non-employed individuals in the year of the intervention and five years after the intervention (all in percentage points). I report these statistics for the overall population, for the population excluding Type 1 individuals, and separately for each unobservable type. I use simulated panel data starting simulations at age 27 to calculate the statistics. See Online Appendix C.1 for details about model simulations.

Figure C.1 – Model Fit: Earnings Over the Life Cycle

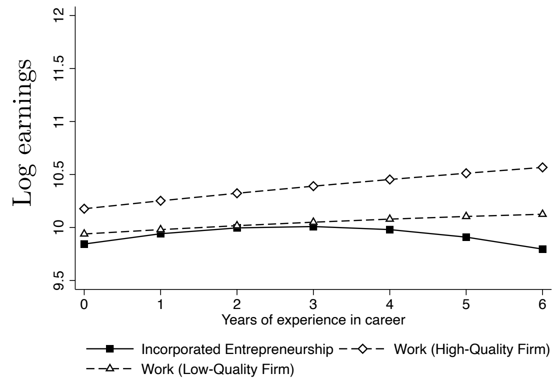


Notes: This figure describes the observed and fully simulated earnings of individuals over the life cycle. I report the average log earnings of workers and incorporated entrepreneurs by age. The sample used to calculate the black lines is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 are used to calculate the statistics. I use fully simulated data to calculate the statistics reported in the grey lines. See Online Appendix C.1 for details about model simulations.

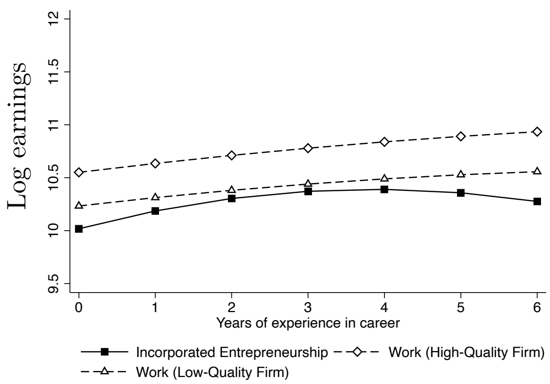
Figure C.2 – Expected Log Earnings in Various Careers by Type



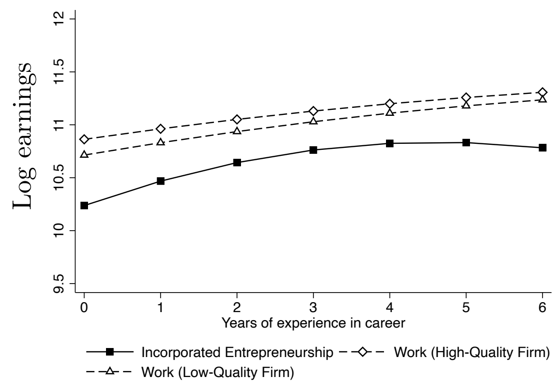
(a) Type 1



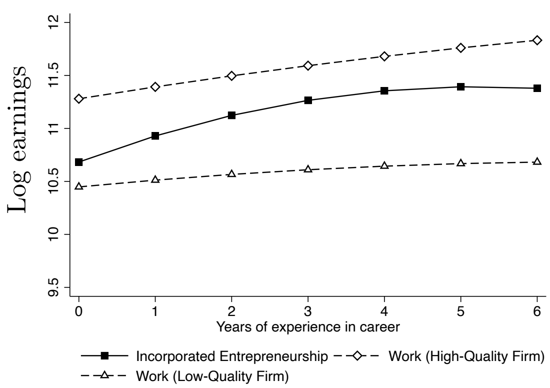
(b) Type 2



(c) Type 3



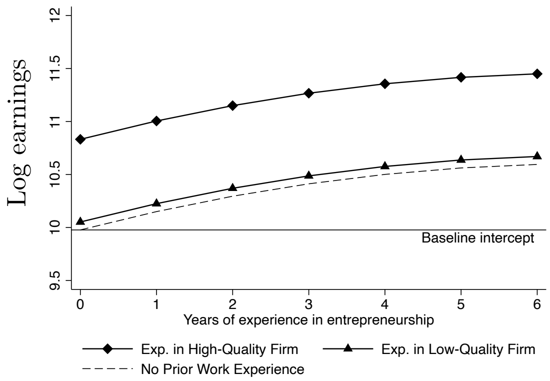
(d) Type 4



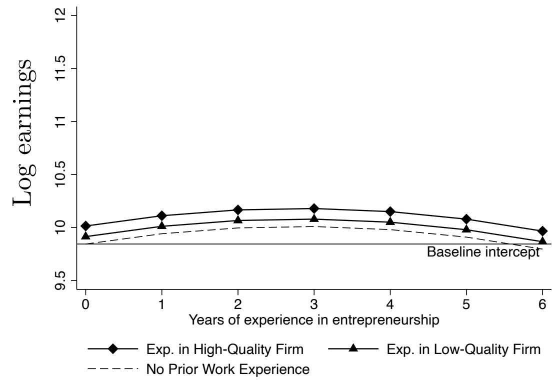
(e) Type 5

Notes: This figure describes what the parameters of the model pertaining to learning-by-doing imply for patterns of log earnings in various careers. It plots the expected log earnings of individuals in entrepreneurship and in the labour market as a function of their unobservable type and years of experience, assuming no career changes. Dashed diamond lines show expected log earnings as worker in high-quality firms, dashed triangle lines show expected log earnings as worker in low-quality firms, and solid black square lines show expected log earnings as incorporated entrepreneur. These earnings profiles are calculated using the parameter estimates reported in Tables C.3, C.5, and C.6 in Online Appendix C. See Section 2.2 for details about career definitions. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model.

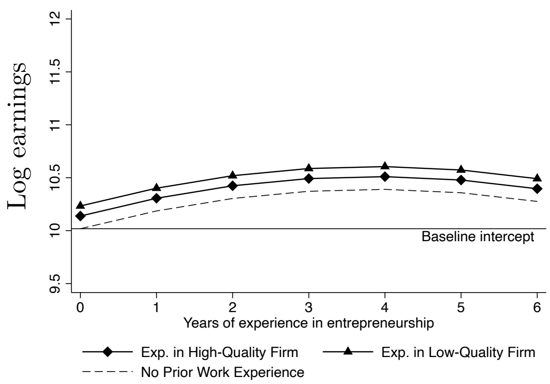
Figure C.3 – Heterogeneous Returns to Prior Work Experience in Entrepreneurship



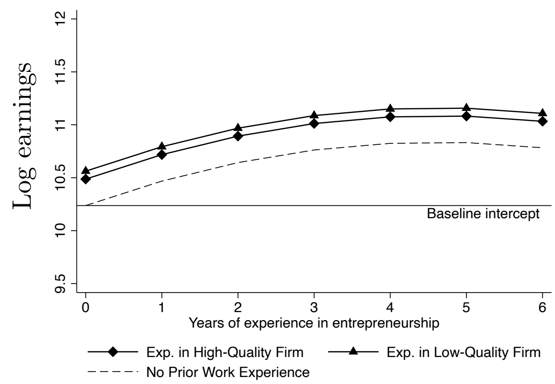
(a) Type 1



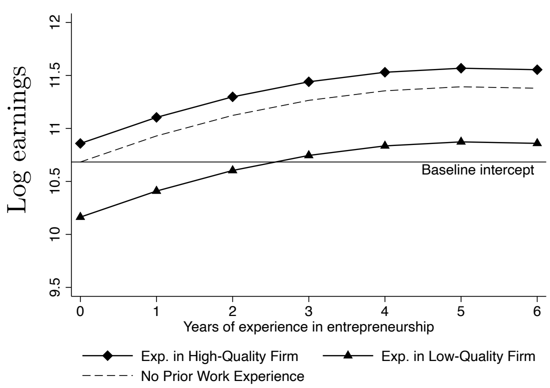
(b) Type 2



(c) Type 3



(d) Type 4



(e) Type 5

Notes: This figure shows expected log earnings in entrepreneurship as a function of unobservable type and prior work experience. It plots the model implied earnings profiles for incorporated entrepreneurs with (1) five years of prior work experience in high-quality firms (diamond lines), (2) five years of prior work experience in low-quality firms (triangle lines), and (3) no prior work experience (dashed lines). The solid black line indicates baseline earnings in incorporated entrepreneurship at age 25. These earnings profiles are calculated using the parameter estimates reported in Table C.6 in Online Appendix C. See Section 2.2 for details about career definitions. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model.

Online Appendix D Robustness

I now discuss sensitivity to various modelling choices. For each alternative model specification, I completely reestimate the model using the estimation procedure outlined in Online Appendix B and perform full model simulations to assess model fit following the procedure outlined in Subsection 6.2. Online Appendix D.1-D.3 report all parameter estimates and in-sample model fit for three such alternative specifications.

First, I explore how sensitive the results are to the number of unobservable types. In Online Appendix D.1, I report the results from a version of the main model with three unobservable types instead of five. I find that the model with three unobservable types fits the data adequately in sample. In unreported results, I also estimated a version of the main model with four unobservable types and six unobservable types. These alternative model specifications also fit the data reasonably well in sample. In fact, a log-likelihood based model selection criterion such as the Bayesian Information Criterion indicates that the number of types one should use is larger than what I can handle computationally.[43] With this said, my preferred specification among them is the model with five unobservable types because it fits the data better along several key dimensions. Regarding the parameter estimates, one notable pattern that emerges from this sensitivity analysis is that the scale parameter seems to decrease with the number of unobservable types. For instance, Table D.1 shows that the scale parameter with three unobservable types is 3.22 compared to 1.29 in the main model with five types. The scale parameter governs individuals' responsiveness to earnings differentials and preference shocks. All else equal, a smaller value of the scale parameter implies that career decisions are more sensitive to preference shocks and less to income shocks. This parameter plays an important role in the policy simulations where I simulate the effects of income subsidies, so exact magnitudes should be interpreted with caution. As mentioned in the main text, the estimated scale parameter for the main model with five unobservable types is close to what others have found in the literature.

Second, I report parameter estimates and model fit for a simpler model with homogeneous firms (no firm quality ladder) and homogeneous returns to experience across unobservable types. The results are in Online Appendix D.2. Unsurprisingly, given the importance of unobserved heterogeneity documented in Subsection 6.1, I find that this simpler model doesn't fit the data as well as the main model with heterogeneous firms and heterogeneous returns to prior work experience across types.

Finally, I report parameter estimates and model fit for the main model with five unobserv-

[43] $\text{BIC} = k \ln(N) - 2 \times \text{loglikelihood}$, where k is the number of model parameters and N is the number of observations.

able types, but using an alternative definition of entrepreneurship. Specifically, I construct a new panel dataset following the same procedure outlined in Subsection 2.2, but including non-startup firms in the definition of incorporated entrepreneurship. The results are in Online Appendix D.3. Overall, the sample changes only slightly and the results are similar to the main results.

For the main estimation sample, remember that I assign individuals to incorporated entrepreneurship if the incorporated business income they draw from their own start-up firms is above $10,400, regardless of the earnings they derive from other sources. About 8% of individual-year observations categorized under incorporated entrepreneurship exhibit employment income that exceeds incorporated business income. In unreported results, I drop these observations from the sample and reestimate the earnings functions found in Table A.3 and Table C.6 (taking unobservable types as given from post-estimation data). The parameter estimates are very similar.

D.1 Full Model with Three Unobservable Types Instead of Five

Table D.1 – Parameters of the Utility Function (3 Types): Scale Parameter and Amenities

Scale Parameter	3.217 (0.072)
Amenities	
High-Quality Firms	-4.569 (0.119)
Medium-Quality Firms	-2.967 (0.094)
Low-Quality Firms	-1.152 (0.069)
Unincorporated	
Type 1	-4.849 (0.140)
Type 2, Relative to Type 1	-0.440 (0.164)
Type 3, Relative to Type 1	2.958 (0.330)
Incorporated	
Type 1	-0.344 (0.822)
Type 2, Relative to Type 1	-5.964 (0.890)
Type 3, Relative to Type 1	-3.390 (0.904)

Notes: This table reports structural parameter estimates for the scale parameter α and career-specific amenities from the dynamic discrete choice model detailed in Section 4, but with three unobservable types instead of five. See Online Appendix B for estimation details. The value of amenities associated with non-employment is normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 721,730. Number of observations: 4,283,785. Standard errors clustered at the individual level are in parentheses.

TABLE D.2 – Parameters of the Utility Function (3 Types): Mobility Costs

	Destination								
	Work			Incorporated			Unincorporated		
					Relative to Type 1			Relative to Type 1	
Origin	High	Medium	Low	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
High	0	-2.460	-2.301	-4.870	2.335	1.863	-1.773	0.389	-0.598
		(0.007)	(0.007)	(0.144)	(0.150)	(0.154)	(0.028)	(0.031)	(0.056)
Medium	-2.498	0	-2.206	-4.478	2.192	0.334	-1.786	0.398	-0.913
	(0.007)		(0.007)	(0.119)	(0.126)	(0.133)	(0.024)	(0.029)	(0.057)
Low	-2.807	-2.667	0	-3.985	1.413	0.066	-1.680	0.026	-1.266
	(0.007)	(0.007)		(0.128)	(0.132)	(0.139)	(0.022)	(0.026)	(0.062)
Incorporated	-3.832	-4.869	-3.775	0	0	0	-2.933	0.423	-2.786
	(0.071)	(0.078)	(0.078)				(0.140)	(0.178)	(0.183)
Unincorporated	-3.515	-3.716	-3.012	-3.575	1.011	0.079	0	0	0
	(0.026)	(0.031)	(0.023)	(0.131)	(0.149)	(0.161)			
Non-Employed	-3.361	-3.134	-2.511	-4.386	1.849	0.468	-1.920	0.138	-1.138
	(0.012)	(0.011)	(0.011)	(0.115)	(0.124)	(0.134)	(0.022)	(0.030)	(0.055)

Notes: This table reports structural parameter estimates for the mobility costs from the dynamic discrete choice model detailed in Section 4, but with three unobservable types instead of five. See Online Appendix B for estimation details. The value of mobility costs associated with non-employment are normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 721,730. Number of observations: 4,283,785. Standard errors clustered at the individual level are in parentheses.

TABLE D.3 – Parameters of the Earnings Equations (3 Types): High-Quality Firms

	Type 1	Type 2	Type 3
Exper. High	0.049	0.098	0.106
	(0.001)	(0.000)	(0.001)
Exper. Med.	0.048	0.070	0.070
	(0.001)	(0.001)	(0.001)
Exper. Low	0.023	0.034	0.033
	(0.001)	(0.001)	(0.001)
Total Work Exper. (sq)	0.001	-0.005	-0.005
	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.067	0.092	0.096
	(0.014)	(0.008)	(0.013)
Exper. Unincorp. (sq)	0.006	-0.006	-0.019
	(0.005)	(0.002)	(0.004)
Exper. Incorp.	0.207	0.103	0.121
	(0.050)	(0.021)	(0.020)
Exper. Incorp. (sq)	-0.008	-0.019	-0.014
	(0.012)	(0.006)	(0.006)
Intercept relative to type 1	0	0.458	0.934
		(0.002)	(0.002)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with three unobservable types instead of five. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 10.109 (s.e. 0.002). Mean, dependent variable : 10.90. Number of individuals: 368,350. Number of observations: 1,545,780. Adjusted R-squared: 0.51.

Table D.4 – Parameters of the Earnings Equations (3 Types): Medium-Quality Firms

	Type 1	Type 2	Type 3
Exper. High	0.054	0.097	0.140
	(0.001)	(0.001)	(0.001)
Exper. Med.	0.041	0.082	0.104
	(0.001)	(0.000)	(0.001)
Exper. Low	0.025	0.034	0.052
	(0.001)	(0.001)	(0.001)
Total Work Exper. (sq)	0.000	-0.004	-0.005
	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.089	0.066	0.064
	(0.012)	(0.008)	(0.017)
Exper. Unincorp. (sq)	-0.005	-0.006	-0.008
	(0.003)	(0.002)	(0.005)
Exper. Incorp.	0.055	0.048	0.078
	(0.051)	(0.022)	(0.041)
Exper. Incorp. (sq)	0	-0.008	-0.006
	(0.013)	(0.006)	(0.007)
Intercept relative to type 1	0	0.441	0.845
		(0.002)	(0.002)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with three unobservable types instead of five. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.989 (s.e. 0.001). Mean, dependent variable: 10.63. Number of individuals: 342,700. Number of observations: 1,271,945. Adjusted R-squared: 0.51.

Table D.5 – Parameters of the Earnings Equations (3 Types): Low-Quality Firms

	Type 1	Type 2	Type 3
Exper. High	0.061	0.108	0.153
	(0.001)	(0.001)	(0.002)
Exper. Med.	0.052	0.086	0.133
	(0.001)	(0.001)	(0.002)
Exper. Low	0.044	0.076	0.089
	(0.001)	(0.001)	(0.001)
Total Work Exper. (sq)	-0.001	-0.005	-0.005
	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.129	0.027	0.02
	(0.010)	(0.010)	(0.020)
Exper. Unincorp. (sq)	-0.016	0.006	-0.006
	(0.002)	(0.003)	(0.006)
Exper. Incorp.	0.137	-0.016	0.023
	(0.032)	(0.025)	(0.035)
Exper. Incorp. (sq)	-0.021	0.002	-0.004
	(0.007)	(0.006)	(0.009)
Intercept relative to type 1	0	0.392	0.832
		(0.001)	(0.002)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with three unobservable types instead of five. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.830 (s.e. 0.001). Mean, dependent variable: 10.34. Number of individuals: 318,075. Number of observations: 1,073,500. Adjusted R-squared: 0.51.

Table D.6 – Parameters of the Earnings Equations (3 Types): Incorporated

	Type 1	Type 2	Type 3
Exper. High	0.038	0.019	0.027
	(0.020)	(0.010)	(0.011)
Exper. Med.	0.019	0.011	0.005
	(0.020)	(0.010)	(0.011)
Exper. Low	0.029	0.008	-0.014
	(0.020)	(0.010)	(0.011)
Total Work Exper. (sq)	-0.003	0.003	0
	(0.003)	(0.001)	(0.001)
Exper. Unincorp.	0.110	0.087	0.105
	(0.027)	(0.014)	(0.015)
Exper. Unincorp. (sq)	-0.013	-0.009	-0.010
	(0.007)	(0.003)	(0.003)
Exper. Incorp.	0.164	0.186	0.272
	(0.010)	(0.007)	(0.006)
Exper. Incorp. (sq)	-0.015	-0.021	-0.028
	(0.002)	(0.001)	(0.001)
Intercept relative to type 1	0	0.060	0.556
		(0.033)	(0.037)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with three unobservable types instead of five. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.970 (s.e. 0.031). Mean, dependent variable: 10.61. Number of individuals: 11,790. Number of observations: 33,965. Adjusted R-squared: 0.32.

Table D.7 – Parameters of the Earnings Equations (3 Types): Unincorporated

	Type 1	Type 2	Type 3
Exper. High	0.064	0.001	0.006
	(0.008)	(0.006)	(0.011)
Exper. Med.	0.040	-0.003	-0.012
	(0.008)	(0.005)	(0.011)
Exper. Low	0.024	-0.011	-0.019
	(0.008)	(0.005)	(0.012)
Total Work Exper. (sq)	-0.005	0.001	0
	(0.001)	(0.001)	(0.001)
Exper. Unincorp.	0.139	0.191	0.368
	(0.005)	(0.004)	(0.007)
Exper. Unincorp. (sq)	-0.016	-0.018	-0.035
	(0.001)	(0.001)	(0.001)
Exper. Incorp.	0.122	-0.094	0.083
	(0.044)	(0.043)	(0.104)
Exper. Incorp. (sq)	-0.018	0.019	-0.035
	(0.008)	(0.014)	(0.024)
Intercept relative to type 1	0	0.200	0.578
		(0.013)	(0.022)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with three unobservable types instead of five. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.749 (s.e. 0.011). Mean, dependent variable: 10.16. Number of individuals: 31,680. Number of observations: 71,475. Adjusted R-squared: 0.29.

TABLE D.8 – Model Fit (3 Types): Career Choices Over the Life Cycle

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.0	35.4	36.0	36.6	37.0	37.3	37.5	37.5	37.8	38.3
Medium	30.0	29.3	29.1	28.9	28.8	28.7	28.4	28.2	28.0	27.7
Low	27.4	25.4	24.0	22.8	21.8	21.0	20.4	19.8	19.2	18.8
Incorp.	0.2	0.4	0.7	1.0	1.3	1.6	1.9	2.3	2.5	2.7
Unincorp.	0.8	1.4	1.9	2.3	2.6	2.9	3.1	3.2	3.4	3.5
Non-emp.	6.6	8.1	8.4	8.4	8.4	8.5	8.6	9.0	9.1	9.1

(a) Data

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.0	35.0	34.9	34.7	34.0	32.7	31.8	31.1	31.5	32.2
Medium	29.9	28.9	28.2	27.6	26.6	25.3	23.9	23.3	23.6	23.6
Low	26.9	24.4	22.7	21.6	19.6	18.0	17.1	18.5	19.3	20.0
Incorp.	0.4	0.7	1.0	1.6	3.5	4.8	5.9	6.7	6.8	6.1
Unincorp.	0.9	1.8	2.4	2.8	3.4	5.0	6.0	5.4	4.6	3.8
Non-emp.	6.8	9.3	10.7	11.8	12.9	14.1	15.3	14.9	14.3	14.3

(b) Model

Notes: This table describes the observed [Panel (a)] and simulated [Panel (b)] career choices of individuals over the life cycle. I report the fraction of individuals in each career by age. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 are used to calculate the statistics. I use simulated data to calculate the statistics reported in Panel (b). See Online Appendix On details about model simulations. The model used to perform the simulations is as detailed in Section 4, but with three unobservable types instead of five.

Table D.9 – Model Fit (3 Types): Career Transitions

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	89.6	4.4	2.5	0.3	0.7	2.5
Column %	89.0	5.6	4.3	8.7	9.3	11.0
Medium						
Row %	6.5	84.8	4.3	0.3	0.7	3.4
Column %	5.2	86.3	5.8	6.4	8.1	11.7
Low						
Row %	5.7	6.4	81.2	0.3	0.9	5.5
Column %	3.5	5.0	84.2	5.3	7.5	14.8
Incorp.						
Row %	3.4	1.3	1.1	86.5	0.6	7.1
Column %	0.1	0.0	0.1	66.8	0.3	0.9
Unincorp.						
Row %	7.0	4.9	5.0	3.1	65.9	14.1
Column %	0.4	0.4	0.5	5.5	59.2	3.9
Non-emp.						
Row %	8.6	9.6	14.1	1.2	5.1	61.4
Column %	1.9	2.7	5.1	7.3	15.6	57.8

(a) Data

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	86.8	4.5	2.7	1.3	1.2	3.5
Column %	88.6	5.9	4.8	13.2	11.9	9.5
Medium						
Row %	6.4	82.0	4.5	0.5	1.3	5.3
Column %	5.2	84.9	6.4	3.8	10.4	11.4
Low						
Row %	5.4	5.8	73.9	5.2	1.4	8.4
Column %	3.4	4.7	81.1	32.2	8.7	14.0
Incorp.						
Row %	2.6	1.5	2.3	82.9	1.2	9.5
Column %	0.1	0.1	0.2	39.0	0.6	1.2
Unincorp.						
Row %	4.8	5.1	4.2	4.6	62.4	18.8
Column %	0.4	0.5	0.6	3.6	50.6	4.0
Non-emp.						
Row %	6.4	8.8	11.6	2.4	5.2	65.6
Column %	2.2	3.9	7.0	8.2	17.8	59.9

(b) Model

Notes: This table describes the career transitions of individuals at age 30 in the data [Panel (a)] and model simulations [Panel (b)]. For each panel, it reports the percentage of transitions from career of origin at time $t-1$ to destination career at time t (row %) and the percentage of observations in a destination career at time t that comes from each career of origin at time $t-1$ (column %). See Section 2.2 for details about career definitions. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations of individuals at age 30 between 2001 and 2012 are used to calculate the statistics. I use simulated data to calculate the statistics reported in Panel (b). See Online Appendix C.1 for details about model simulations. The model used to perform the simulations is as detailed in Section 4, but with three unobservable types instead of five.

D.2 Simpler Model with Homogeneous Firms and Homogeneous Returns to Experience Across Types

Table D.10 – Parameters of the Utility Function (Simpler Model): Scale Parameter and Amenities

Scale Parameter	6.410
	(0.091)
Amenities	
Work	-3.185
	(0.092)
Unincorporated	
Type 1	-5.551
	(0.215)
Type 2, Relative to Type 1	-2.344
	(0.224)
Type 3, Relative to Type 1	-1.262
	(0.278)
Type 4, Relative to Type 1	-2.084
	(0.277)
Type 5, Relative to Type 1	1.108
	(0.684)
Incorporated	
Type 1	9.873
	(2.141)
Type 2, Relative to Type 1	-20.476
	(2.196)
Type 3, Relative to Type 1	-13.481
	(2.263)
Type 4, Relative to Type 1	-18.197
	(2.158)
Type 5, Relative to Type 1	-12.877
	(2.222)

Notes: This table reports structural parameter estimates for the scale parameter α and career-specific amenities from the dynamic discrete choice model detailed in Section 4, but with homogeneous firms (only one firm class) and homogeneous returns to experience across the five unobservable types. See Online Appendix B for estimation details. The value of amenities associated with non-employment is normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 721,730. Number of observations: 4,283,785. Standard errors clustered at the individual level are in parentheses.

Table D.11 – Parameters of the Utility Function (Simpler Model): Mobility Costs

	Destination										
	Work	Incorporated					Unincorporated				
			Relative to Type 1					Relative to Type 1			
Origin	All	Type 1	Type 2	Type 3	Type 4	Type 5	Type 1	Type 2	Type 3	Type 4	Type 5
Work	0	-6.959	4.477	1.008	4.643	3.331	-2.226	1.387	-0.804	1.123	-1.315
		(0.299)	(0.305)	(0.323)	(0.305)	(0.314)	(0.032)	(0.034)	(0.042)	(0.038)	(0.089)
Incorporated	-2.948	0	0	0	0	0	-2.770	0.246	0.686	0.227	-5.350
	(0.086)						(0.263)	(0.368)	(0.299)	(0.271)	(0.371)
Unincorporated	-2.648	-5.759	2.759	0.660	3.275	1.645	0	0	0	0	0
	(0.024)	(0.299)	(0.328)	(0.332)	(0.305)	(0.416)					
Non-Employed	-1.783	-6.855	4.511	-1.273	4.474	1.679	-2.179	0.897	-1.351	0.588	-2.562
	(0.007)	(0.312)	(0.323)	(0.385)	(0.318)	(0.364)	(0.034)	(0.039)	(0.066)	(0.043)	(0.168)

Notes: This table reports structural parameter estimates for the mobility costs from the dynamic discrete choice model detailed in Section 4, but with homogeneous firms (only one firm class) and homogeneous returns to experience across the five unobservable types. See Online Appendix B for estimation details. The value of mobility costs associated with non-employment are normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 721,730. Number of observations: 4,283,785. Standard errors clustered at the individual level are in parentheses.

Table D.12 – Parameters of the Earnings Equations (Simpler Model): Work (Any Firm Class)

	Type Invariant	Type 1	Type 2	Type 3	Type 4	Type 5
Total Work Exper.	0.086					
	(0.000)					
Total Work Exper. (sq)	-0.004					
	(0.000)					
Exper. Unincorp.	0.117					
	(0.004)					
Exper. Unincorp. (sq)	-0.014					
	(0.001)					
Exper. Incorp.	0.080					
	(0.010)					
Exper. Incorp. (sq)	-0.010					
	(0.002)					
Intercept relative to type 1		0	0.107	0.532	0.905	1.388
			(0.001)	(0.001)	(0.001)	(0.002)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with homogeneous firms and homogeneous returns to work experience across types. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.829 (s.e. 0.001). Mean, dependent variable : 10.66. Number of individuals: 721,730. Number of observations: 3,891,225. Adjusted R-squared: 0.59.

Table D.13 – Parameters of the Earnings Equations (Simpler Model): Incorporated

	Type Invariant	Type 1	Type 2	Type 3	Type 4	Type 5
Total Work Exper.	0.017					
	(0.007)					
Total Work Exper. (sq)	0.001					
	(0.001)					
Exper. Unincorp.	0.133					
	(0.010)					
Exper. Unincorp. (sq)	-0.020					
	(0.002)					
Exper. Incorp.	0.218					
	(0.005)					
Exper. Incorp. (sq)	-0.023					
	(0.001)					
Intercept relative to type 1		0	-0.243	0.329	0.216	0.876
			(0.016)	(0.014)	(0.014)	(0.016)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with homogeneous firms and homogeneous returns to work experience across types. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.924 (s.e. 0.017). Mean, dependent variable: 10.61. Number of individuals: 11,790. Number of observations: 33,965. Adjusted R-squared: 0.35.

Table D.14 – Parameters of the Earnings Equations (Simpler Model): Unincorporated

	Type Invariant	Type 1	Type 2	Type 3	Type 4	Type 5
Total Work Exper.	-0.007 (0.004)					
Total Work Exper. (sq)	0.001 (0.001)					
Exper. Unincorp.	0.186 (0.003)					
Exper. Unincorp. (sq)	-0.019 (0.001)					
Exper. Incorp.	0.047 (0.038)					
Exper. Incorp. (sq)	-0.014 (0.009)					
Intercept relative to type 1		0	0 (0.005)	0.424 (0.006)	0.248 (0.006)	1.190 (0.013)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but with homogeneous firms and homogeneous returns to work experience across types. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.731 (s.e. 0.007). Mean, dependent variable: 10.16. Number of individuals: 31,680. Number of observations: 71,475. Adjusted R-squared: 0.32.

Table D.15 – Model Fit (Simpler Model): Career Choices Over the Life Cycle

	Age									
	26	27	28	29	30	31	32	33	34	35
Work	92.4	90.1	89.1	88.3	87.6	87.0	86.3	85.5	85.0	84.8
Incorp.	0.2	0.4	0.7	1.0	1.3	1.6	1.9	2.3	2.5	2.7
Unincorp.	0.8	1.4	1.9	2.3	2.6	2.9	3.1	3.2	3.4	3.5
Non-emp.	6.6	8.1	8.4	8.4	8.4	8.5	8.6	9.0	9.1	9.1

(a) Data

	Age									
	26	27	28	29	30	31	32	33	34	35
Work	91.5	87.5	83.3	79.9	77.2	74.7	73.0	74.4	74.4	75.2
Incorp.	1.9	1.5	2.9	4.2	4.9	5.3	5.9	6.1	6.7	6.3
Unincorp.	0.8	1.6	2.2	3.0	3.8	4.3	4.3	4.0	3.5	3.4
Non-emp.	5.9	9.5	11.6	13.0	14.1	15.7	16.8	15.5	15.4	15.1

(b) Model

Notes: This table describes the observed [Panel (a)] and simulated [Panel (b)] career choices of individuals over the life cycle. I report the fraction of individuals in each career by age. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 are used to calculate the statistics. I use simulated data to calculate the statistics reported in Panel (b). See Online Appendix C.1 details about model simulations. The model used to perform the simulations is as detailed in Section 4, but with homogeneous firms (only one firm class) and homogeneous returns to experience across the five unobservable types.

Table D.16 – Model Fit (Simpler Model): Career Transitions

Career at time $t-1$	Career at time t: Workers			
	Workers	Entrepreneurs		
	All	Incorp.	Unincorp.	Non-emp.
Work				
Row %	95.4	0.3	0.8	3.6
Column %	96.6	20.4	24.9	37.5
Incorp.				
Row %	5.8	86.5	0.6	7.1
Column %	0.1	66.8	0.3	0.9
Unincorp.				
Row %	16.9	3.1	65.9	14.1
Column %	0.4	5.5	59.2	3.9
Non-emp.				
Row %	32.3	1.2	5.1	61.4
Column %	3.0	7.3	15.6	57.8

(a) Data

Career at time $t-1$	Career at time t: Workers			
	Workers	Entrepreneurs		
	All	Incorp.	Unincorp.	Non-emp.
Work				
Row %	92.0	0.8	1.8	5.3
Column %	95.3	13.3	38.2	30.2
Incorp.				
Row %	8.8	80.5	1.1	9.6
Column %	0.5	68.9	1.2	2.8
Unincorp.				
Row %	17.3	6.3	55.8	20.6
Column %	0.7	3.8	43.2	4.3
Non-emp.				
Row %	21.3	5.2	5.1	68.3
Column %	3.6	14.0	17.4	62.7

(b) Model

Notes: This table describes the career transitions of individuals at age 30 in the data [Panel (a)] and model simulations [Panel (b)]. For each panel, it reports the percentage of transitions from career of origin at time $t-1$ to destination career at time t (row %) and the percentage of observations in a destination career at time t that comes from each career of origin at time $t-1$ (column %). See Section 2.2 for details about career definitions. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations of individuals at age 30 between 2001 and 2012 are used to calculate the statistics. I use simulated data to calculate the statistics reported in Panel (b). See Online Appendix C.1 for details about model simulations. The model used to perform the simulations is as detailed in Section 4, but with homogeneous firms (only one firm class) and homogeneous returns to experience across the five unobservable types.

D.3 Alternative Definition of Entrepreneurship

Table D.17 – Parameters of the Utility Function (Alt. Def.): Scale Parameter and Amenities

Scale Parameter	1.693
	(0.062)
Amenities	
High-Quality Firms	-0.858
	(0.098)
Medium-Quality Firms	0.082
	(0.082)
Low-Quality Firms	0.575
	(0.072)
Unincorporated	
Type 1	-3.220
	(0.185)
Type 2, Relative to Type 1	-0.21
	(0.226)
Type 3, Relative to Type 1	0.578
	(0.268)
Type 4, Relative to Type 1	1.280
	(0.276)
Type 5, Relative to Type 1	1.711
	(0.801)
Incorporated	
Type 1	0.118
	(1.237)
Type 2, Relative to Type 1	-5.438
	(1.420)
Type 3, Relative to Type 1	-2.09
	(1.307)
Type 4, Relative to Type 1	-7.914
	(1.324)
Type 5, Relative to Type 1	3.777
	(1.652)

Notes: This table reports structural parameter estimates for the scale parameter α and career-specific amenities from the dynamic discrete choice model detailed in Section 4, but using an alternative definition of entrepreneurship that includes non-start up firms. See Online Appendix B for estimation details. The value of amenities associated with non-employment is normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 719,555. Number of observations: 4,274,720. Standard errors clustered at the individual level are in parentheses.

Table D.18 – Parameters of the Utility Function (Alt. Def.): Mobility Costs

	Destination													
	Work			Incorporated					Unincorporated					
					Relative to Type 1					Relative to Type 1				
Origin	High	Medium	Low	Type 1	Type 2	Type 3	Type 4	Type 5	Type 1	Type 2	Type 3	Type 4	Type 5
High	0	-2.363 (0.010)	-2.258 (0.010)	-5.953 (0.193)	0.102 (0.268)	3.087 (0.203)	3.510 (0.203)	2.152 (0.237)	-1.908 (0.040)	0.588 (0.048)	-0.04 (0.052)	0.878 (0.053)	-1.052 (0.114)
Medium	-2.610 (0.010)	0	-2.244 (0.009)	-6.655 (0.241)	0.641 (0.287)	3.906 (0.260)	1.352 (0.257)	3.231 (0.295)	-1.892 (0.030)	0.225 (0.038)	0.372 (0.044)	0.131 (0.045)	-2.854 (0.156)
Low	-2.885 (0.010)	-2.627 (0.008)	0	-5.616 (0.224)	1.640 (0.244)	3.499 (0.229)	2.917 (0.229)	-0.971 (0.271)	-1.685 (0.026)	0.161 (0.033)	0.045 (0.042)	-0.137 (0.051)	-2.021 (0.121)
Incorporated	-3.956 (0.077)	-6.252 (0.096)	-4.157 (0.086)	0	0	0	0	0	-3.305 (0.330)	-1.390 (0.421)	0.378 (0.357)	0.062 (0.348)	-2.904 (0.423)
Unincorporated	-3.589 (0.029)	-3.454 (0.030)	-3.284 (0.030)	-4.601 (0.181)	0.125 (0.236)	2.088 (0.209)	1.394 (0.200)	1.065 (0.280)	0	0	0	0	0
Non-Employed	-3.365 (0.013)	-3.033 (0.011)	-2.569 (0.011)	-5.684 (0.164)	1.378 (0.198)	3.047 (0.178)	2.026 (0.183)	1.764 (0.230)	-1.802 (0.023)	0.134 (0.031)	0.137 (0.042)	-1.010 (0.059)	-1.323 (0.121)

Notes: This table reports structural parameter estimates for the mobility costs from the dynamic discrete choice model detailed in Section 4n alternative, but using a definition of entrepreneurship that includes non-start up firms. See Online Appendix B for estimation details. The value of mobility costs associated with non-employment are normalized to zero. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. Number of individuals: 719,555. Number of observations: 4,274,720. Standard errors clustered at the individual level are in parentheses.

Table D.19 – Parameters of the Earnings Equations (Alt. Def.): High-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.014	0.076	0.087	0.104	0.114
	(0.004)	(0.001)	(0.001)	(0.000)	(0.001)
Exper. Med.	-0.030	0.080	0.065	0.077	0.082
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Exper. Low	-0.016	0.045	0.057	0.096	-0.034
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Total Work Exper. (sq)	0.008	-0.002	-0.004	-0.005	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.087	0.277	-0.051	0.076	0.268
	(0.023)	(0.011)	(0.012)	(0.008)	(0.038)
Exper. Unincorp. (sq)	0.006	-0.041	0.020	-0.009	-0.052
	(0.007)	(0.003)	(0.003)	(0.003)	(0.009)
Exper. Incorp.	0.318	0.165	0.049	0.115	0.017
	(0.099)	(0.027)	(0.036)	(0.015)	(0.033)
Exper. Incorp. (sq)	-0.004	-0.020	-0.008	-0.013	0.009
	(0.019)	(0.006)	(0.009)	(0.004)	(0.009)
Intercept relative to type 1	0	0.179	0.544	0.844	1.257
		(0.003)	(0.003)	(0.003)	(0.003)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but usin alternativeng a definition of entrepreneurship that includes non-start up firms. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 10.007 (s.e. 0.003). Mean, dependent variable : 10.90. Number of individuals: 367,745. Number of observations: 1,542,235. Adjusted R-squared: 0.54.

Table D.20 – Parameters of the Earnings Equations (Alt. Def.): Medium-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0	0.084	0.085	0.122	0.175
	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)
Exper. Med.	-0.028	0.075	0.074	0.092	0.126
	(0.002)	(0.001)	(0.000)	(0.000)	(0.002)
Exper. Low	-0.006	0.044	0.056	0.111	-0.032
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Total Work Exper. (sq)	0.007	-0.003	-0.004	-0.005	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.083	0.196	-0.018	0.040	0.175
	(0.018)	(0.011)	(0.011)	(0.011)	(0.064)
Exper. Unincorp. (sq)	-0.007	-0.022	0.007	0	-0.079
	(0.005)	(0.003)	(0.003)	(0.003)	(0.021)
Exper. Incorp.	0.122	0.232	-0.104	-0.01	0.032
	(0.082)	(0.030)	(0.026)	(0.020)	(0.088)
Exper. Incorp. (sq)	-0.041	-0.042	0.019	0.010	0.045
	(0.028)	(0.007)	(0.006)	(0.005)	(0.047)
Intercept relative to type 1	0	0.161	0.513	0.781	1.120
		(0.002)	(0.002)	(0.002)	(0.004)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but usin alternativeng a definition of entrepreneurship that includes non-start up firms. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.922 (s.e. 0.002). Mean, dependent variable: 10.63. Number of individuals: 341,680. Number of observations: 1,266,325. Adjusted R-squared: 0.54.

Table D.21 – Parameters of the Earnings Equations (Alt. Def.): Low-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.043	0.053	0.109	0.105	0.271
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)
Exper. Med.	0.020	0.053	0.091	0.083	0.241
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Exper. Low	0.025	0.045	0.084	0.125	0.069
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Work Exper. (sq)	0.003	-0.002	-0.005	-0.006	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exper. Unincorp.	0.169	-0.008	0.059	0.01	-0.214
	(0.012)	(0.014)	(0.010)	(0.017)	(0.042)
Exper. Unincorp. (sq)	-0.019	0.013	-0.004	-0.007	0.018
	(0.003)	(0.005)	(0.003)	(0.005)	(0.014)
Exper. Incorp.	0.148	0.131	-0.056	-0.036	-0.01
	(0.040)	(0.034)	(0.021)	(0.032)	(0.030)
Exper. Incorp. (sq)	-0.018	-0.029	0.013	0.013	0.013
	(0.008)	(0.009)	(0.004)	(0.007)	(0.007)
Intercept relative to type 1	0	0.164	0.456	0.932	0.679
		(0.001)	(0.002)	(0.002)	(0.002)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but usin alternativeng a definition of entrepreneurship that includes non-start up firms. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.782 (s.e. 0.001). Mean, dependent variable: 10.34. Number of individuals: 317,180. Number of observations: 1,068,505. Adjusted R-squared: 0.53.

Table D.22 – Parameters of the Earnings Equations (Alt. Def.): Incorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.200	0.035	0.032	0.050	0.008
	(0.033)	(0.018)	(0.011)	(0.009)	(0.016)
Exper. Med.	0.080	0.019	0.034	0.033	0.021
	(0.030)	(0.017)	(0.012)	(0.009)	(0.017)
Exper. Low	0.046	0.004	0.058	0.084	-0.125
	(0.029)	(0.017)	(0.011)	(0.009)	(0.016)
Total Work Exper. (sq)	-0.008	0.001	-0.001	-0.002	0.003
	(0.004)	(0.002)	(0.001)	(0.001)	(0.002)
Exper. Unincorp.	0.049	0.113	0.138	0.081	0.200
	(0.030)	(0.028)	(0.014)	(0.012)	(0.025)
Exper. Unincorp. (sq)	-0.012	-0.024	-0.018	-0.007	-0.022
	(0.007)	(0.007)	(0.003)	(0.003)	(0.006)
Exper. Incorp.	0.186	0.127	0.192	0.255	0.272
	(0.010)	(0.013)	(0.007)	(0.006)	(0.008)
Exper. Incorp. (sq)	-0.015	-0.023	-0.024	-0.028	-0.026
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Intercept relative to type 1	0	-0.111	0.025	0.288	0.771
		(0.047)	(0.040)	(0.040)	(0.047)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but usin alternativeng a definition of entrepreneurship that includes non-start up firms. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.972 (s.e. 0.038). Mean, dependent variable: 10.62. Number of individuals: 13,175. Number of observations: 38,670. Adjusted R-squared: 0.36.

TABLE D.23 – Parameters of the Earnings Equations (Alt. Def.): Unincorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.078	0.01	-0.037	0.021	0.027
	(0.012)	(0.007)	(0.007)	(0.009)	(0.018)
Exper. Med.	0.035	0.011	-0.064	0.049	0.01
	(0.011)	(0.007)	(0.006)	(0.009)	(0.019)
Exper. Low	0.033	-0.009	-0.054	0.025	-0.076
	(0.011)	(0.007)	(0.006)	(0.010)	(0.018)
Total Work Exper. (sq)	-0.005	0	0.005	-0.003	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Exper. Unincorp.	0.118	0.174	0.196	0.305	0.388
	(0.005)	(0.006)	(0.004)	(0.007)	(0.012)
Exper. Unincorp. (sq)	-0.013	-0.029	-0.017	-0.035	-0.039
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Exper. Incorp.	0.121	-0.03	0.024	-0.063	0.208
	(0.051)	(0.064)	(0.048)	(0.048)	(0.173)
Exper. Incorp. (sq)	-0.024	0.025	-0.017	0.003	-0.075
	(0.009)	(0.022)	(0.013)	(0.013)	(0.037)
Intercept relative to type 1	0	0.101	0.353	0.335	0.971
		(0.016)	(0.017)	(0.020)	(0.035)

Notes: This table reports structural parameter estimates for the earnings process in high-quality firms from the dynamic discrete choice model detailed in Section 4, but usin alternativeng a definition of entrepreneurship that includes non-start up firms. See Online Appendix B for estimation details. The sample used to estimate the parameters of the model is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2011 are used to estimate the model. The dependent variable is the logarithm of annual earnings. Standard errors clustered at the individual level are in parentheses. Type 1 intercept/constant term: 9.717 (s.e. 0.013). Mean, dependent variable: 10.16. Number of individuals: 31,700. Number of observations: 71,520. Adjusted R-squared: 0.31.

Table D.24 – Model Fit (Alt. Def.): Career Choices Over the Life Cycle

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.0	35.4	36.0	36.6	37.0	37.3	37.5	37.5	37.8	38.3
Medium	30.0	29.3	29.1	28.9	28.8	28.7	28.4	28.2	28.0	27.7
Low	27.4	25.4	24.0	22.8	21.8	21.0	20.4	19.8	19.2	18.8
Incorp.	0.2	0.4	0.7	1.0	1.3	1.6	1.9	2.3	2.5	2.7
Unincorp.	0.8	1.4	1.9	2.3	2.6	2.9	3.1	3.2	3.4	3.5
Non-emp.	6.6	8.1	8.4	8.4	8.4	8.5	8.6	9.0	9.1	9.1

(a) Data

	Age									
	26	27	28	29	30	31	32	33	34	35
High	35.4	35.0	34.2	33.6	32.9	32.0	31.4	31.5	32.9	34.4
Medium	29.0	28.2	27.4	26.8	26.1	24.5	23.6	23.0	22.7	22.9
Low	24.9	22.8	21.1	19.2	17.5	16.3	15.6	16.3	16.8	17.2
Incorp.	3.5	3.9	4.7	6.0	7.7	9.1	9.9	9.7	8.9	7.9
Unincorp.	0.8	1.6	2.1	2.6	3.2	4.9	5.8	5.9	5.6	5.1
Non-emp.	6.4	8.4	10.4	11.7	12.6	13.1	13.8	13.6	13.1	12.5

(b) Model

Notes: This table describes the observed [Panel (a)] and simulated [Panel (b)] career choices of individuals over the life cycle. I report the fraction of individuals in each career by age. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations between 2001 and 2012 are used to calculate the statistics. I use simulated data to calculate the statistics reported in Panel (b). See Online Appendix C.1 details about model simulations. The model used to perform the simulations is as detailed in Section 4, but using n alternativea definition of entrepreneurship that includes non-start up firms.

Table D.25 – Model Fit (Alt. Def.): Career Transitions

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	89.6	4.4	2.5	0.3	0.7	2.5
Column %	89.0	5.6	4.3	8.7	9.3	11.0
Medium						
Row %	6.5	84.8	4.3	0.3	0.7	3.4
Column %	5.2	86.3	5.8	6.4	8.1	11.7
Low						
Row %	5.7	6.4	81.2	0.3	0.9	5.5
Column %	3.5	5.0	84.2	5.3	7.5	14.8
Incorp.						
Row %	3.4	1.3	1.1	86.5	0.6	7.1
Column %	0.1	0.0	0.1	66.8	0.3	0.9
Unincorp.						
Row %	7.0	4.9	5.0	3.1	65.9	14.1
Column %	0.4	0.4	0.5	5.5	59.2	3.9
Non-emp.						
Row %	8.6	9.6	14.1	1.2	5.1	61.4
Column %	1.9	2.7	5.1	7.3	15.6	57.8

(a) Data

	Career at time t					
	Workers			Entrepreneurs		
Career at time $t-1$	High	Medium	Low	Incorp.	Unincorp.	Non-emp.
High						
Row %	85.2	4.7	2.7	1.8	1.1	4.4
Column %	87.2	6.0	5.3	8.0	11.5	11.7
Medium						
Row %	6.4	81.5	4.3	1.6	1.0	5.2
Column %	5.2	83.9	6.6	5.4	8.0	11.1
Low						
Row %	5.9	6.2	70.9	3.7	1.4	11.9
Column %	3.4	4.6	78.1	9.2	8.3	18.1
Incorp.						
Row %	1.8	2.1	3.8	86.3	1.5	4.6
Column %	0.3	0.5	1.3	66.8	2.7	2.2
Unincorp.						
Row %	5.8	5.3	4.8	6.4	58.6	19.1
Column %	0.5	0.5	0.7	2.1	47.0	3.9
Non-emp.						
Row %	9.3	9.9	12.0	5.6	6.2	57.0
Column %	3.3	4.4	8.1	8.6	22.4	52.9

(b) Model

Notes: This table describes the career transitions of individuals at age 30 in the data [Panel (a)] and model simulations [Panel (b)]. For each panel, it reports the percentage of transitions from career of origin at time $t-1$ to destination career at time t (row %) and the percentage of observations in a destination career at time t that comes from each career of origin at time $t-1$ (column %). See Section 2.2 for details about career definitions. The sample used in Panel (a) is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations of individuals at age 30 between 2001 and 2012 are used to calculate the statistics. I use simulated data to calculate the statistics reported in Panel (b). See Online Appendix C.1 for details about model simulations. The model used to perform the simulations is as detailed in Section 4n alternative, but using a definition of entrepreneurship that includes non-start up firms.