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Prior Work Experience and Entrepreneurship: The Careers of Young Entrepreneurs

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DISCUSSION PAPER SERIES

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McGill University and IZA

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ABSTRACT

Prior Work Experience and Entrepreneurship: The Careers of Young Entrepreneurs*

I investigate the mechanisms that drive sorting into entrepreneurship and entrepreneurial success among young individuals. I use Canadian matched owner-employer-employee data to conduct my investigation. Empirically, older entrepreneurs and 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 employers, human capital accumulation, and unobserved heterogeneity across individuals. Among other things, I find that prior work experience is particularly valuable for “subsistence” entrepreneurs. I use the estimated model to evaluate policies designed to promote entrepreneurship.

JEL Classification: J24, J31, J62, L26

Keywords: entrepreneurship, human capital, firm heterogeneity, career choice, dynamic Roy model, unobserved heterogeneity

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1 INTRODUCTION

In this paper, I investigate the mechanisms that drive sorting into entrepreneurship and entrepreneurial success among young individuals. 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 about entrepreneurship. I find that only a small fraction of individuals become entrepreneurs. The fraction increases over the life cycle, but stays low. At age 35, 3% of individuals are incorporated entrepreneurs and 3.5% are unincorporated entrepreneurs. Empirically, it is important to make a distinction between the two types of entrepreneurs (Levine and Rubinstein, 2016). I find that unincorporated entrepreneurship pays less than paid employment on average and, based on observed career transitions, it appears to be a closer substitute to non-employment and employment in low-wage firms. Incorporated entrepreneurs, in contrast, earn more than workers on average and are likely to stay in entrepreneurship from one year to the next. This finding challenges the idea that most entrepreneurship spells are short lived.

The type of work experience individuals acquire before starting a business appears to be important. Older entrepreneurs and 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 be explained by human capital accumulation. 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. Alternatively, these patterns could be explained by a non-random sorting of individuals across careers and dynamic selection. Perhaps individuals with high innate ability are more likely to be employed at high-wage firms and do better in entrepreneurship if they decide to start a business. There is indeed evidence that incorporated entrepreneurs are different at age 25: they are more likely to come from high-income neighbourhoods and more entrepreneurial neighbourhoods.

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. The model accounts for unobserved heterogeneity across individuals, human capital accumulation, and endogenous career choices over time. 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. 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.

The model is particularly flexible on the human capital side and captures three key determinants of entrepreneurial success. 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 which 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.¹ 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. Finally, there is learning-by-doing in entrepreneurship. 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. The model allows for this possibility.

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

Again, there are two channels in the model through which individuals acquire skills that are valuable in entrepreneurship: experience in entrepreneurship and work experience. 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 types mentioned above, who have a comparative advantage in entrepreneurship at labour force entry. For the vast majority of the population, the 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

¹The hypothesis is that firm productivity is partly driven by knowledge, and that knowledge is fundamentally non-appropriable ([Arrow, 1962](#)). Workers internalize some of their employer’s knowledge because they are intimately involved in the production process. If such knowledge spillovers exist, we would expect the costs associated with entering a firm to depend on its quality. See, for example, the market for jobs model of [Rosen \(1972\)](#). In my model, employers of different quality offer different amenities and have different costs of entry.

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

the subsistence type. For these individuals, five years of work experience in high-quality firms more than doubles their baseline earnings in entrepreneurship. 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.

My investigation is important for two reasons. First, I recover parameters that may be of interest in their own right, such as those of the earnings equations. Economists have long recognized that workers acquire human capital through on-the-job training and learning-by-doing, and that their stock of human capital affects their productivity and earning capacity (e.g. Becker, 1964; Rosen, 1972; Killingsworth, 1982; Shaw, 1989). Similarly, business owners bring with them a stock of human capital, which has been partly acquired through employment in the labour market and prior business ownership. 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). However, our understanding of the returns to various types of experience in entrepreneurship is limited (Goetz et al., 2016). The lack of evidence on the value of prior work experience in entrepreneurship can be explained by (1) the fact that datasets linking business owners to their previous career histories are rare and (2) the selection issues inherent to this work.³ The unique administrative dataset and structural approach used in this paper allow me to provide some of the first estimates of the returns to prior work experience in entrepreneurship.

Second, the results can inform policy-makers tasked with increasing the quantity and quality entrepreneurs in the economy. Evaluating the effectiveness of policies designed to promote successful entrepreneurship is challenging because there is tremendous heterogeneity across entrepreneurs. 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).⁴ Policies may therefore increase the supply of entrepreneurs in the econ-

³The selection issues are analogous to the ones researchers face when estimating the returns of schooling in a Mincer equation. See Card (1999), Heckman et al. (2006), and Belzil (2007) for useful surveys of the literature devoted to estimating returns to schooling. Belzil (2007) focuses specifically on the use of dynamic structural models in this context.

⁴Non-pecuniary benefits are thought to play an important role in the decision to become an entrepreneur (Hurst

omy without attracting individuals with high-growth potential in entrepreneurship (Schoar, 2010). The challenge is to identify which type of individual is most likely to respond to a given policy. I use the estimated model to evaluate the effectiveness of various subsidies designed to promote entrepreneurship among early career individuals. I highlight selection and the heterogeneous effects of the subsidies across types.

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 nascent literature in entrepreneurship 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 literature by considering heterogeneity in the returns to experience across types.⁵ Such heterogeneity is key to understanding which policies can promote entrepreneurial success. I provide the first evidence that the returns to various types of experience in entrepreneurship are heterogeneous and correlated with unobserved ability. In particular, I show that prior work experience is particularly valuable in entrepreneurship for the subsistence type. I also provide the first evidence that learning-by-doing in entrepreneurship is mostly relevant for those who have a comparative advantage in entrepreneurship at labour force entry.

Another distinguishing feature of my model is that it accounts for the presence of heterogeneous employers in the labour market. Firm heterogeneity is a pervasive feature of the labour market and the firm a worker matches with matters for earnings outcomes (e.g., Abowd et al., 1999; Oreopoulos et al., 2012; Card et al., 2018; Bonhomme et al., 2019). A number of recent empirical papers 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 is positively correlated with the average education of co-workers, firm-specific components of earnings growth, and firm size. 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. I also show that the costs of switching into entrepreneurship depend on a worker’s position on the firm quality ladder.

The remainder of the paper proceeds as follows. I present the data in Section 2 and provide some

and Pugsley, 2011, 2015).

⁵Belzil 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.

new stylized facts about entrepreneurship in Section 3. I present the model in Section 4. In Section 5, I discuss the estimation procedure and identification. I present the results and discuss model fit and sensitivity to various modelling choices in Section 6. I discuss policy simulations in Section 7. I conclude in Section 8.

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, similar to Form 1040 in the U.S.). These individual tax returns are merged to firm records of employment remuneration (Form T4, similar to Form W-2 in the U.S.). Additional information on firms comes from corporate income tax returns (Form T2, similar to Form 1120 in the U.S.) 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.

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.⁶ 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. 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.

⁶This incorporated business income measure corresponds to the "draw" in [Hamilton \(2000\)](#).

1. *Incorporated Entrepreneurship.* I assign individuals to incorporated entrepreneurship if the incorporated business income they draw from their own start-up firms is above \$10,400.⁷ In a robustness check, I consider a broader definition of incorporated entrepreneurship which considers incorporated business income from all firms owned by the individual, not only start-up firms.

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.⁸ 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. 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 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. This is a robust finding in the empirical literature on entrepreneurship (e.g., [Evans and Leighton, 1989](#); [Hamilton, 2000](#); [Hurst and Pugsley, 2011](#)). In contrast, incorporated entrepreneurs tend to earn more than workers. As we can see, the higher mean earnings among incorporated entrepreneurs is accounted for by changes over the entire distribution. As [Levine and Rubinstein \(2016\)](#) argue, entrepreneurs with high-growth potential tend to start incorporated businesses.⁹

2.3 Definition of the Firm Quality Ladder

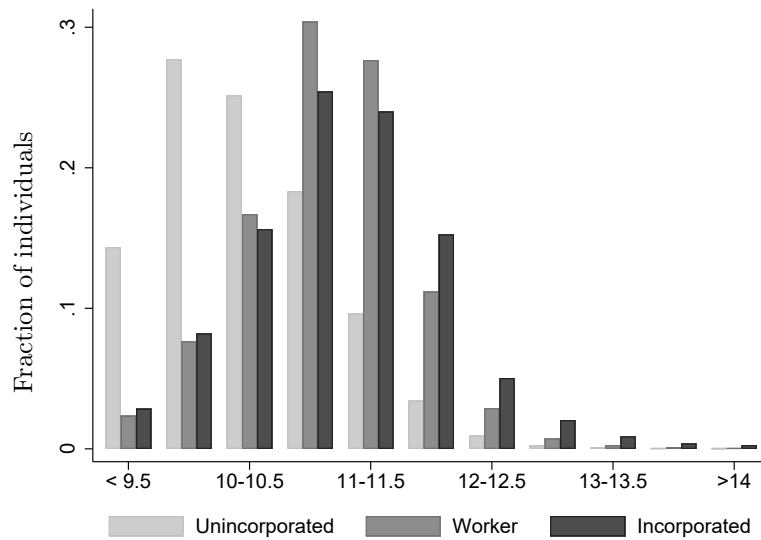
I assign firms to one of three classes: high-, medium-, or low-quality. These classes are defined using quartiles of the average firm wage distribution, as in [Oreopoulos et al. \(2012\)](#) and [Haltiwanger et al. \(2018\)](#). Specifically, I calculate average log payroll per employee at the firm level, taking out

⁷I 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. [Song et al. \(2018\)](#) use a similar minimum threshold for analogous reasons.

⁸I observe most individuals who are unemployed or out of the labour force because individuals need to file a T1 to claim benefits in Canada.

⁹Two 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.

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. 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.

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.

I consider three classes of firms for two main reasons. First, using only a small number of classes reduces the dimension of the state space in the structural model and facilitates the estimation. Second, reducing the dimensionality of firm heterogeneity increases statistical power and ensures that measurement error is not exacerbated.

In principle, I could have used alternative measures of firm quality to classify firms. As I show in Table A.13, 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 very 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), I find that firm size is only weakly correlated with firm wage and labour productivity.

2.4 Sample Restrictions

I now describe 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 25.¹² I further restrict my attention to men only. Very 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

¹⁰Industries are defined using two-digit NAICS codes.

¹¹In 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). The AKM model decomposes the logarithm of annual earnings of workers into worker-specific and firm-specific pay components. 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. Furthermore, a restrictive exogenous mobility assumption is required to interpret the AKM firm fixed effects as capturing differential firm quality. Such an assumption is inconsistent with the dynamic Roy model that I bring to the data.

¹²I 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.

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.¹³ 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 25.¹⁴ 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

I now present descriptive statistics and some new stylized facts about entrepreneurship.

Figure 2 shows the fraction of individuals in various careers between age 26 and 36. Panel (a) focuses on entrepreneurs. The dashed line represents unincorporated entrepreneurs and the solid line represents incorporated entrepreneurs. This figure 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 3% for incorporated entrepreneurship and 3.5% for unincorporated entrepreneurship at age 36.¹⁵

Panel (b) plots the fraction of individuals who are workers between age 26 and 36. 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 36, 84% 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 36. 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 18% at age 36). Taken together, these patterns suggest that individuals climb the firm quality ladder over the life cycle.

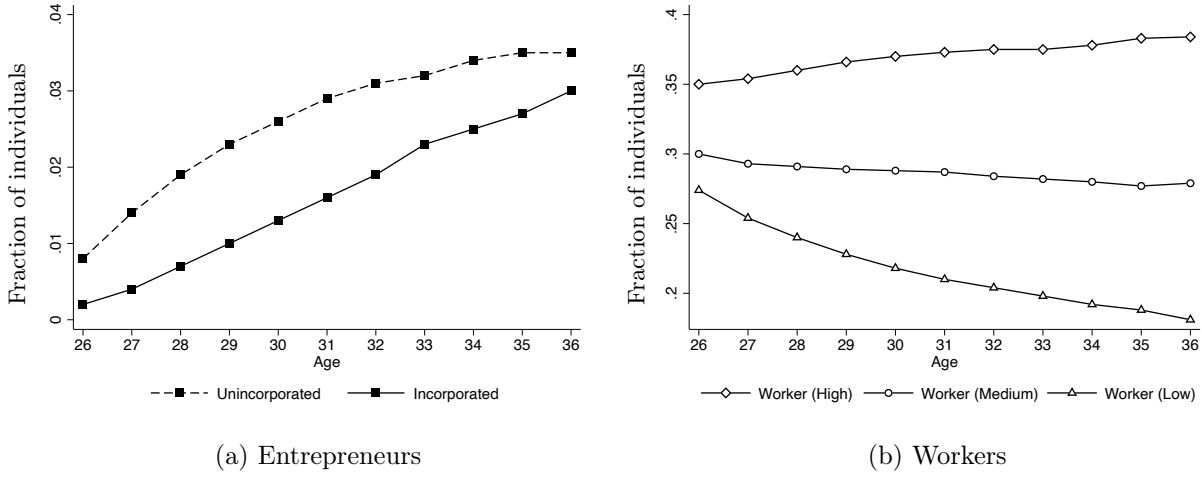
Table 1 describes the types of career transitions observed in the data. For each origin-destination pair, it reports (1) the percentage of transitions from career of origin to destination career (row %) and (2) the percentage of observations in a destination career that comes from each career

¹³The public sector is defined as educational services (NAICS code 61), health care and social assistance (NAICS code 62), and public administration (NAICS code 91).

¹⁴Individuals 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). This restriction also excludes a few individuals who are already entrepreneurs at age 25.

¹⁵The fraction of individuals who are entrepreneurs converges to about 7.8% for incorporated entrepreneurs and 6.7% for unincorporated entrepreneurs around age 50.

FIGURE 2 – Career Choices Over the Life Cycle



Notes: This figure shows the career choices of individuals over the life cycle. It reports the fraction of individuals in the sample in various careers at each age between 26 and 36. The fraction of non-employed individuals increases from about 7% at age 26 to 9% at age 36 (see Table A.8). 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 are used to calculate the statistics.

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.¹⁶ 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.

Turning to the career transitions of workers, Table 1 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.¹⁷ 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

¹⁶Of all the individuals that transition into entrepreneurship from low-quality firms, 25% ($0.3/(0.3 + 0.9)$) of them become incorporated entrepreneurs. In contrast, 30% of individuals that transition into entrepreneurship from high- or medium-quality firms become incorporated entrepreneurs.

¹⁷Consider individuals that are in low-quality firms at time $t - 1$. The results in Table 1 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.

TABLE 1 – Career Transitions

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

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.

from high-quality firms.

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 very 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 main estimation sample. The average log earnings in the sample is 10.67. In the labour market, average log earnings increase monotonically with

TABLE 2 – Summary Statistics

	All	Workers			Entrepreneurs	
		High	Medium	Low	Incorp.	Unincorp.
Log Earnings	10.67 (0.56)	10.92 (0.52)	10.65 (0.49)	10.35 (0.49)	10.63 (0.66)	10.17 (0.62)
Log Earnings at Age 30	10.77 (0.55)	11.02 (0.49)	10.75 (0.47)	10.46 (0.48)	10.62 (0.64)	10.19 (0.63)
Log Earnings at Age 30 (Simulated)	10.75 (0.57)	11.04 (0.50)	10.74 (0.49)	10.42 (0.47)	10.45 (0.62)	10.20 (0.65)
Age	28.49 (2.79)	28.56 (2.82)	28.40 (2.78)	28.07 (2.7)	30.94 (2.57)	30.10 (2.6)
Work Exper.	3.24 (2.65)	3.47 (2.76)	3.29 (2.71)	2.92 (2.60)	3.44 (2.15)	3.12 (2.08)
- High	1.27 (2.11)	2.74 (2.53)	0.41 (1.16)	0.26 (0.92)	1.43 (1.74)	1.04 (2.03)
- Medium	1.07 (1.90)	0.42 (1.14)	2.48 (2.43)	0.39 (1.11)	1.10 (1.77)	1.04 (1.64)
- Low	0.90 (1.70)	0.31 (0.92)	0.41 (1.08)	2.27 (2.33)	0.91 (1.60)	1.04 (1.57)
Incorp. Exper.	0.02 (0.27)	0.00 (0.10)	0.00 (0.08)	0.00 (0.08)	1.77 (1.88)	0.01 (0.19)
Unincorp. Exper.	0.05 (0.38)	0.01 (0.18)	0.01 (0.17)	0.01 (0.18)	0.34 (0.92)	1.37 (1.70)
High Income Area at 25	0.24 (0.43)	0.30 (0.46)	0.22 (0.41)	0.17 (0.38)	0.31 (0.46)	0.25 (0.43)
Entrepreneurial Area at 25	0.24 (0.43)	0.26 (0.44)	0.24 (0.42)	0.23 (0.42)	0.38 (0.48)	0.29 (0.46)
Large City at 25	0.31 (0.46)	0.32 (0.47)	0.31 (0.46)	0.28 (0.45)	0.29 (0.45)	0.33 (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 Section 6.2 for details about model simulations.

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).¹⁸ 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.¹⁹ I also find that earnings profiles in incorporated entrepreneurship are steep: average earnings increase by about 78% between Year 1 and Year 6.²⁰

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 profitable businesses.²¹ We can also see that the

¹⁸I 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.

¹⁹84% 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 ($0.84^5 = 0.42$).

²⁰Average earnings in Year 1 are about 37,500 = $\exp(10.34 + \frac{0.62^2}{2})$ compared to 67,000 = $\exp(10.92 + \frac{0.62^2}{2})$ in Year 6 (0.62 is the standard deviation of log earnings in both years).

²¹Comparing individuals who enter incorporated entrepreneurship for the first time from high-quality firms at age

type of prior work experience matters. Individuals who come from better firms earn more in Year 1 and have steeper earnings profiles.²² Appendix Table A.14 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.

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.

²²Consider 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 $\left(\frac{\exp(10.48 + \frac{0.67^2}{2})}{\exp(10.24 + \frac{0.60^2}{2})} = 1.33\right)$. The earnings gap between these two groups of entrepreneurs widens over time spent in incorporated entrepreneurship.

TABLE 3 – First Spell in Incorporated Entrepreneurship

Origin	All	High			Medium			Low			Uninc.		
		26-27	28-29	30+	26-27	28-29	30+	26-27	28-29	30+	26-27	28-29	30+
Age at Start	All												
Obs.	14,465	1,195	1,350	2,090	925	975	1,495	1,040	885	1,195	170	640	1,455
Survival Rate													
Year 1	0.84	0.83	0.85	0.82	0.85	0.86	0.84	0.83	0.86	0.87	0.83	0.85	0.84
Year 2	0.73	0.70	0.71	0.70	0.75	0.79	0.75	0.72	0.77	0.79	0.72	0.74	0.75
Year 3	0.65	0.60	0.65	0.63	0.68	0.70	0.65	0.64	0.67	0.71	0.63	0.68	0.69
Year 4	0.59	0.55	0.57	0.56	0.62	0.66	0.57	0.59	0.60	0.64	0.59	0.64	0.62
Year 5	0.56	0.50	0.55	0.52	0.58	0.63	0.53	0.55	0.56	0.58	0.57	0.61	0.59
Log Earnings													
Year 1	10.34	10.35	10.42	10.48	10.26	10.25	10.33	10.18	10.19	10.24	10.46	10.48	10.47
Year 2	10.70	10.75	10.82	10.89	10.66	10.67	10.74	10.52	10.56	10.62	10.65	10.72	10.71
Year 3	10.77	10.83	10.91	10.98	10.73	10.72	10.76	10.62	10.61	10.70	10.72	10.79	10.76
Year 4	10.82	10.87	10.98	10.99	10.81	10.81	10.87	10.67	10.71	10.71	10.80	10.81	10.74
Year 5	10.88	10.95	11.09	11.07	10.85	10.87	10.90	10.74	10.74	10.77	10.83	10.86	10.86
Year 6	10.92	11.03	11.06	11.09	10.90	10.95	10.87	10.78	10.78	10.78	10.93	10.92	10.81

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. 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, "Low" refers to individuals who come from employment in low-quality firms, and "Uninc." refers to individuals who come from unincorporated entrepreneurship. 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.

4 THE MODEL

In this section, I develop a dynamic Roy model of career choice that flexibly incorporates various mechanisms driving entry into entrepreneurial careers 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.²³ 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.²⁴ 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 very demanding in terms of identification and estimation, I limit the number of unobservable types in the population to five.²⁵

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

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.²⁶ 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

²³This way of accounting for unobserved heterogeneity is based on the seminal work of Heckman and Singer (1984) and Keane and Wolpin (1997).

²⁴I 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.

²⁵In Appendix 4, I report parameter estimates and model fit for a model with three unobservable types instead of five.

²⁶See 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).

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 :

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

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.²⁷ As is standard in the literature, I assume the career-specific idiosyncratic preference 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. I describe the earnings process, amenities, and mobility costs in Subsection 4.2 and 4.3.

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.

4.2 The Earnings Process

Earnings in career j are modeled as follows:

$$\begin{aligned} \ln(y_j(z_i, x_{i,t}, \mu_{i,j,t})) = & r_j(z_i) + \sum_{j'=1}^3 \beta_{j'}^j(z_i) \text{exper}_{i,j',t} + \beta_4^j(z_i) \text{exper}_{i,4,t} + \beta_5^j(z_i) \text{exper}_{i,5,t} \\ & + \beta_6^j(z_i) \left(\sum_{j'=1}^3 \text{exper}_{i,j',t} \right)^2 + \beta_7^j(z_i) \text{exper}_{i,4,t}^2 + \beta_8^j(z_i) \text{exper}_{i,5,t}^2 + \mu_{i,j,t} \end{aligned} \quad (2)$$

²⁷Introducing an intertemporal budget constraint and modeling savings decisions would greatly complicate the model to the point of intractability. In my model, the effects of initial wealth on mobility costs and entrepreneurial 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.

where $r_j(z_i)$ represents the intercept in career j , $\{\text{exper}_{i,j',t}\}_{j'=1}^3$ 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.²⁸ $\mu_{i,j,t}$ is assumed to be normally distributed and i.i.d. across individuals over time with variance σ_j^2 .

Equation (2) is very 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 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. I allow the curvature of the earnings process in each career to depend on the total number of years of work experience, the number of years of experience as an unincorporated entrepreneur, and the number of years of experience as an incorporated entrepreneur. The curvature parameters are also allowed to vary by unobservable type.

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.

There are two sources of mobility frictions operating through the earnings equations. First, career-specific human capital is not fully transferable across careers. Second, unobservable type differentially affects the earnings process in each career so individuals have persistent unobserved comparative advantages across careers. I now describe the mobility frictions that operate outside the earnings equations.

²⁸From this point on, the process governing the evolution of the experience variables is a deterministic function of past actions: $\text{exper}_{i,j,t+1} = \text{exper}_{i,j,t} + a_{i,j,t} \forall j \in J$.

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 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.²⁹

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 earnings equations such as startup costs, search frictions, psychological costs, etc.³⁰ 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.

The value of amenities and entry costs associated with non-employment are normalized to zero.

4.4 Optimal Career Choices

I now describe the optimization problem of individuals. Letting β denote the common discount factor, the optimization problem of individual i at time t is given by:

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

where the expectation is taken over future values of the idiosyncratic preference shocks conditional on all the information available at time t . Let $\{a_{i,t}^*, \dots, a_{i,T}^*\}$ denote the optimal decision rule.

²⁹In unreported results, I have found that allowing mobility costs to additionally be a function of age makes little difference in terms of model fit.

³⁰Indeed, 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 really 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.

For the remainder of the paper, 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:

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

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 :

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

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, $\beta \mathbb{E}_t[\bar{V}_z(x_{i,t+1}(x_{i,t}, a_{i,j,t}))]$.

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 of optimally choosing career j at time t :

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

Standard logit derivations also 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 conditional choice probability, $p_{j,z}(x_{i,t})$:

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

where γ denotes Euler's constant.³¹ This relationship holds for any $j \in J$. As I show in Appendix 1, this relationship is key to derive a linear mapping between the conditional choice probabilities and the parameters of the utility function.

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 Appendix 1.

³¹To derive equation (5), take the log of equation (4) and use the following expression for the ex-ante value function:

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

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 models that have a large state space. The key idea is to exploit the finite dependence property of the model to derive a linear mapping between the conditional choice probabilities and the parameters of the utility function. Because conditional choice probabilities 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 conditional choice probabilities that vary non-parametrically by unobservable type.

In the second stage, I project the type-specific empirical estimates of the conditional choice probabilities 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.³²

First, consider the identification of the parameters governing the distribution of unobservable types. The unobserved type, which affect earnings, amenities, and mobility costs, 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. A key assumption is that unobservable types are drawn from a discrete distribution with a small number of types. Unobservable types are

³²[Kasahara and Shimotsu \(2009\)](#) discuss the non-parametric identification of finite mixtures in dynamic discrete choice models.

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 conditional choice probabilities. Loosely, the fraction of individuals who stay in career j from one year to the next relative to transition rates from career j to non-employment identifies amenities in career j relative to non-employment. Transition rates from career j to career j' relative to transition rates from career j to career j'' identifies mobility costs.

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 Appendix 2. I discuss the fit of the model and sensitivity to various modelling choices in Subsection 6.2.

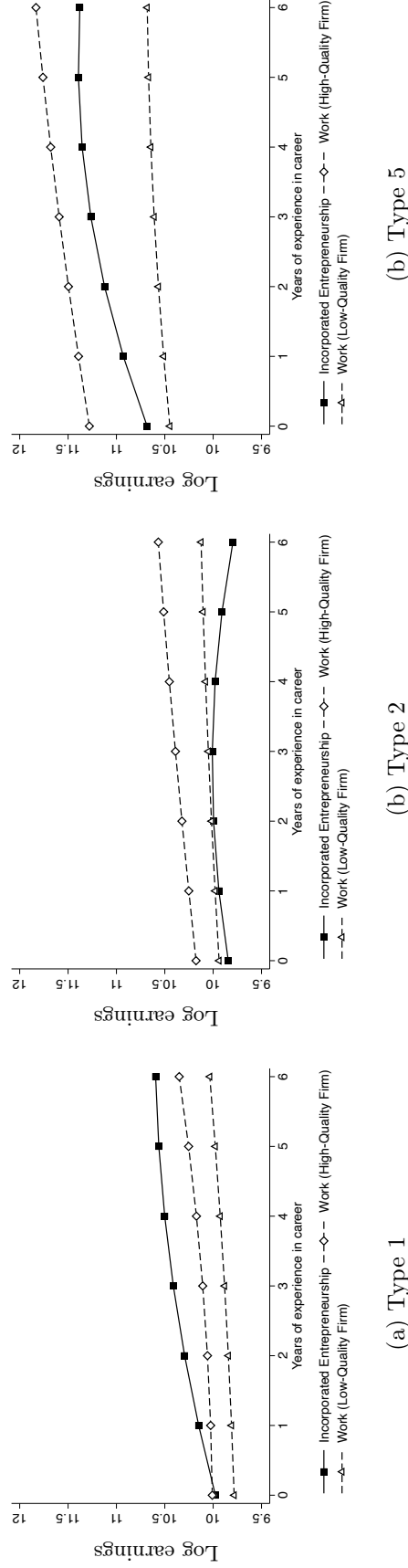
6.1 Main Results

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 (e.g., Type 5), 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 A.3, A.5, and A.6 in Appendix 2. 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. As we’ve seen in Table 4, both types have the potential to earn more as entrepreneurs than as workers at labour force entry. Figure 3 shows that Type 1 and Type 5 individuals also 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

FIGURE 3 – Expected Log Earnings in Various Careers by Type



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 A.3, A.5, and A.6 in Appendix 2. 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 4 – Baseline Earnings in Each Career by Type

Type	Career				
	Work			Entrepreneurship	
	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

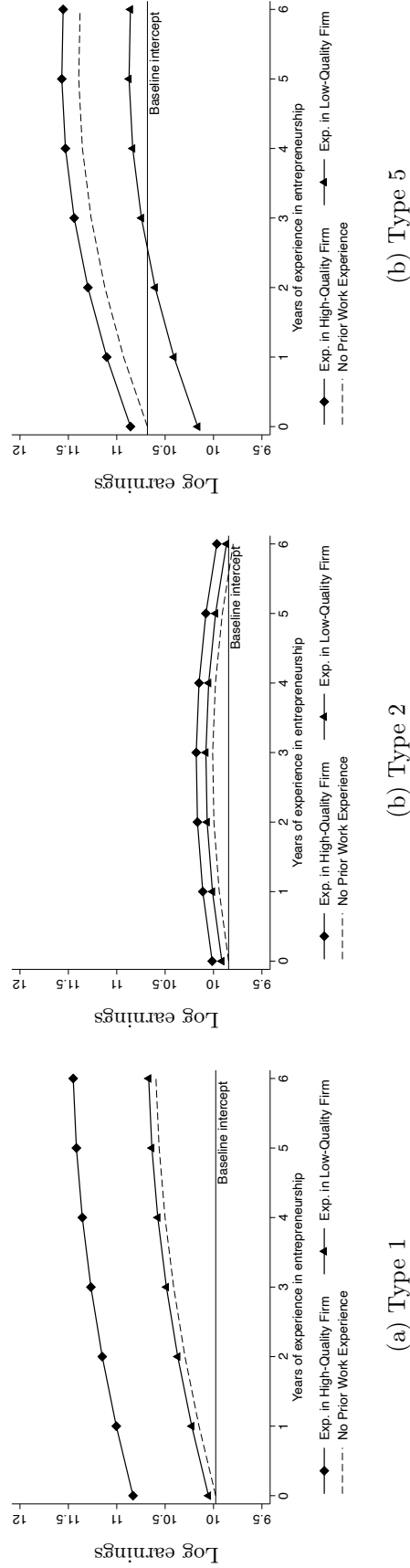
Notes: This table reports the potential earnings of individuals in each career at age 25 as a function of their unobservable type. This corresponds to the type-specific intercept in the earnings equation of each career (equation (2)). The intercepts are calculated using the parameter estimates reported in Tables A.3-A.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.

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 Appendix Figure A.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

FIGURE 4 – Heterogeneous Returns to Prior Work Experience in Entrepreneurship



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 A.6 in Appendix 2. 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

Type	Share of pop.	Career					
		Workers			Entrepreneurs		
		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.

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. In some sense, these results are consistent with Lazear (2005)’s theory that individuals must have a balanced set of skills to be successful in entrepreneurship. Type 1 individuals, who lack innate entrepreneurial skills compared to Type 5, can acquire those skills in the labour market by working in high-quality firms. Experience in low-quality firms is of limited value in entrepreneurship for Type 1 individuals and is estimated to decrease the baseline earnings of Type 5 individuals in entrepreneurship.

The parameter estimates reported in Appendix Tables A.3, A.4, and A.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. As we’ve seen, only two types of individuals have a comparative advantage in entrepreneurship: Type 1 and Type 5. Both types have high earnings growth potential in entrepreneurship. To get a sense of how prevalent these types are in the sample, 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 very 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. This is despite the fact that both types have the potential to earn more in entrepreneurship than in the labour market. 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. To understand why individuals who have a comparative advantage in entrepreneurship seldom choose to become entrepreneurs in practice, I turn to the parameters of the utility function.

Amenities and Entry Costs. I now discuss estimates of the structural parameters of the utility function. Table A.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.³³ The amenities associated with employment in all firm classes are estimated to be positive relative to non-employment. Comparing across firm classes, we can see that employment in high-quality firms is associated with a lower amenity value than employment in low-quality firms. Interestingly, the amenities 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). 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?* I express willingness to pay as flow values (measured in dollars) and report these statistics for the two entrepreneurial types, Type 1 and Type 5.³⁴

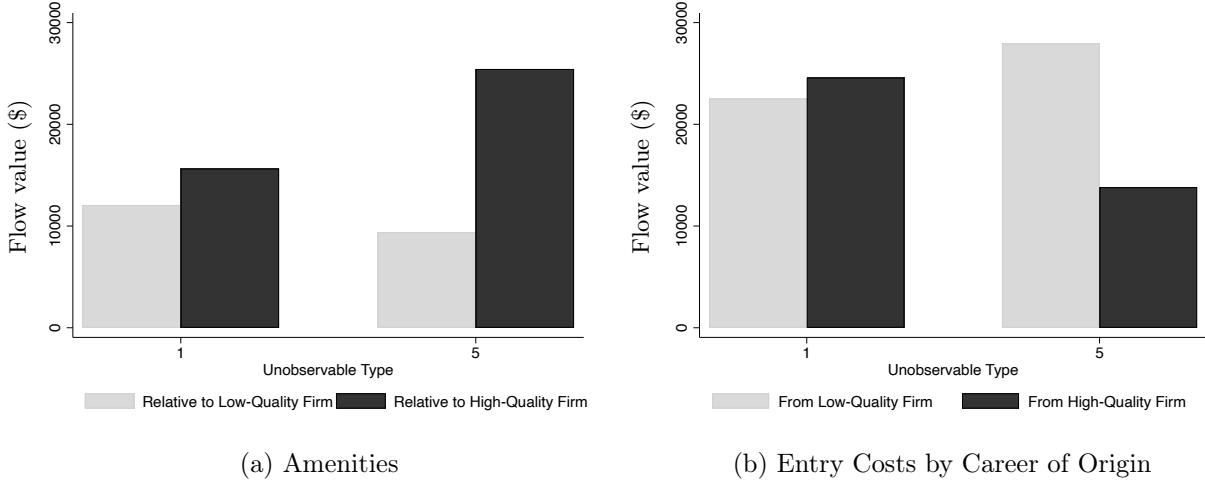
Panel (a) in Figure 5 reports the willingness to pay for the amenities associated with entrepreneurship relative to the amenities of employment in low-quality firms (light grey) and employment in high-quality firms (dark grey). The amenities associated with entrepreneurship are worth about \$12,000-\$15,000 annually for Type 1 individuals and \$9,400-\$25,400 annually for Type 5, depending on the benchmark.

Table A.2 reports parameter estimates for the mobility costs. In the labour market, we can see that the costs associated with entering high-quality firms are higher for individuals coming from low-quality firms than from medium-quality firms. Moreover, the costs of moving to high-quality firms are higher than the costs of moving to medium-quality firms for individuals coming from low-quality

³³For 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.

³⁴See Appendix 1 for calculation details.

FIGURE 5 – Amenities and Entry Costs Associated With Entrepreneurship



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 A.1 and A.2 in Appendix 2. See Appendix 1 for calculation details.

firms. 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.

Turning to the costs associated with entering entrepreneurship, we can see that they tend to be larger than the costs associated with moving between firm classes in the labour market. The costs are particularly large for Type 1 and Type 5 individuals. To interpret orders of magnitude, I use the concept of willingness to accept to express mobility costs in dollars. 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 $t + 1$?* Again, I express willingness to accept as flow values (measured in dollars) and report these statistics for the two entrepreneurial types, Type 1 and Type 5.³⁵

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 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. 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. Coming from high-quality firms, we can see that the willingness to accept increases slightly

³⁵See Appendix 1 for calculation details.

for Type 1 individuals but decreases to about \$14,000 for Type 5 individuals. This could reflect faster wealth accumulation in high-quality firms for Type 5 individuals which facilitates a transition into entrepreneurship. Ignoring earnings differences between careers, the path of least resistance to entrepreneurship for Type 5 individuals appears to be from high-quality firms since the willingness to pay for the amenities exceeds the compensation needed to bear the mobility costs.

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.

Further Characterization of Unobservable Types. Table 6 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 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 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 6 provide more information about entrepreneurship outcomes by type. As we’ve seen in Table 5, 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.

6.2 Model Fit and Sensitivity

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 CCPs, as in Arcidiacono et al. (2016).

I assess both in-sample and out-of-sample fit. To assess in-sample fit, 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 proceed as follows. 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.

TABLE 6 – Further Characterization of Unobservable Types

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.

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.³⁶ 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. 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. I follow the same procedure as described above to predict choices, taking as given observable characteristics at the beginning of 2012.

Table A.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 and Panel (b) reports the same statistics calculated using model simulated data. Overall, the model is well fitted along these dimensions. For employment in high-, medium-, and low-quality firms, the 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), but is able to reproduce the life cycle trends in entrepreneurship. Table A.9 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 is just as good.

Table A.10 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. Table A.11 shows out-of-sample comparisons between observed career 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 very 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 A.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 very high fraction of observations in non-employment (54% in the data vs 36% in the model).

Finally, earnings 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

³⁶The 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.

sorting of individual types across careers and (2) differences in estimated earnings processes across careers. The predicted sorting patterns of individuals and associated payoffs are broadly consistent with what we observe in the data. One notable exception is for incorporated entrepreneurship, where simulated earnings at age 30 are lower than what we observed in the data. Appendix Figure A.1 shows that this gap in average log earnings in incorporated entrepreneurship is roughly constant over the life cycle. This gap can be explained by the larger proportion of Type 1 individuals that choose incorporated entrepreneurship in the model compared to the data, as documented in Table A.12.

Sensitivity Analysis. I now discuss sensitivity to various modelling choices. For each alternative model specification, I completely reestimate the model using the estimation procedure outlined in Appendix 1 and perform model simulations to assess model fit following the procedure outlined in Subsection 6.2. Appendix 4-6 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 Appendix 4, 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.³⁷ 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 A.15 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 that follows where I simulate the effects of income subsidies, so exact magnitudes should be interpreted with caution. As mentioned above, 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 Appendix 5. 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 unobservable

³⁷BIC = $k \ln(N) - 2 \times \text{loglikelihood}$, where k is the number of model parameters and N is the number of observations.

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 Appendix 6. Overall, the sample changes only slightly and the results are similar to the main results.

7 POLICY SIMULATIONS

Grants and subsidies are common tools used by governments to promote entrepreneurship. For example, the City of Montréal offers one-time CAD\$25,000 subsidies to local incorporated entrepreneurs if their business proposals meet certain conditions.³⁸ 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 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% subsidy in entrepreneurship, which is worth between \$20,000-\$50,000 depending on the individual.³⁹ To simulate counterfactuals, I follow the same procedure as the one used to assess in sample model fit described in Subsection 6.2, 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.

The results are presented in Table 7. 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 report these statistics for the population overall and separately for each unobservable type. I refer to the effect

³⁸See <https://pmemtl.com/en/services/financing/loans-and-subsidies>, accessed on March 28, 2023.

³⁹To give a sense of magnitude, such a subsidy is comparable to the flow value of the entry costs into entrepreneurship for Type 1 and Type 5 individuals (see Figure 5).

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. I note that some caution is in order when interpreting the magnitude of the results. First, I do not model the demand side, so general equilibrium effects are muted. Second, as discussed in the previous section, the scale parameter is sensitive to the number of unobservable types and this parameter governs how people respond to income shocks.

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 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. Again, this is in the spirit of the German subsidy mentioned above. 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. We can see that 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 (i.e., job creators), this untar-geted subsidy is 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

TABLE 7 – Short- and Long-Run Impacts of One-Time Subsidies on the Supply of Entrepreneurs

Type	Age	Available to All			Available to Non-Employed Only		
		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	0.1	0.34	0.08	-0.01	0.17	0
Type 1	30	2.8	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	0.1	0.21	0.11	0	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	-0.06	0.19	-0.05
Type 4	30	1.62	0.82	-0.57	0.33	0.19	-0.29
	35	0.13	0.2	0.33	0.02	0.03	0.16
Type 5	30	1.63	1.86	-1.73	0.7	0.73	-1.39
	35	-0.01	0.27	0.1	-0.03	0.08	0.07

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

Type	Age	Available to All			Available to High-Wage Only		
		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
Type 1	30	-0.05	1.27	-0.24	0.19	0.07	0.21
	35	-0.04	0.29	0.1	-0.16	-0.01	0.29
Type 2	30	-0.09	0.7	-0.35	-0.03	0.12	-0.07
	35	0.15	0	0.03	-0.07	0.1	-0.07
Type 3	30	-0.15	1.3	-0.43	0.1	0.21	-0.1
	35	-0.08	0.25	-0.04	-0.1	-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	0.1
Type 5	30	-0.49	2.44	-1.04	-0.1	0.29	0.1
	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% 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 population overall and separately for each unobservable type. I use simulated data to calculate the statistics. See Section 6.2 for details about model simulations.

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. Overall, this policy appears to be more cost effective than the untargeted subsidy to choose incorporated entrepreneurship.

8 CONCLUSION

In this paper, I investigate the mechanisms that drive sorting into entrepreneurship and entrepreneurial success among young individuals. I use Canadian matched owner-employer-employee data to conduct my investigation. Empirically, I find that older entrepreneurs and 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 employers, 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 labour force entry. This subpopulation can be divided into two types: (1) individuals who earn more as entrepreneurs because they have low earnings potential in the labour market (the “subsistence” type) and (2) individuals who have high earnings potential in all careers (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.

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.

I use the estimated model to evaluate various policies that are designed to promote entrepreneur-

ship. 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 earnings potential towards entrepreneurship (i.e., job creators), an untargeted subsidy would be costly. 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 Canadian matched owner-employer-employee dataset used in this paper is limited in that it does not include any information on education. It would be interesting to know whether education (e.g., having an MBA or STEM degree) correlates with the transformational type. More generally, future research could investigate what early life characteristics can help identify the transformational type, so that policymakers 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 is more cost effective. This is because it narrows in on individuals with higher entrepreneurial skills.

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APPENDIX 1 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 \(2011\)](#).

A.1.1 The First Stage

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

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

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:

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

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

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

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 conditional choice probabilities 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 conditional choice probabilities 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:

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

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:

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

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:

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

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 entrepreneur-

ship: (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:

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

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

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

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

which is equivalent to the non-parametric empirical likelihood where $\{\hat{q}_{i,z}^{m+1}\}_{i \in I}$ 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 conditional choice probabilities 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 conditional choice probabilities.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 conditional choice probabilities that are very flexible in a reasonable amount of computation time. The downside of this approach is that it does not impose the restriction that the predicted conditional choice probabilities 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 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.

A.1.2 The Second Stage

I now describe how I recover estimates of the parameters of the utility function using only empirical estimates of the conditional choice probabilities 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 conditional choice probabilities and the conditional ex-ante value functions:

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

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

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

the following equation:

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

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 conditional choice probabilities 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 [Kalouptside et al. \(2021\)](#):

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

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: $\{j', j, j''\}_{i,t}^{\text{Counterfactual}}$.

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 conditional choice probabilities 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.

⁴¹The two periods ahead forecasting error is defined as:

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

A.1.3 Interpreting the value of amenities and mobility costs

In this section, 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.

Amenities. 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?*”

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

which gives us

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

Mobility Costs. 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 $t + 1$?*”.

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

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

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

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 A.1](#) and [A.2](#) in [Appendix 2](#). 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.

APPENDIX 2 PARAMETER ESTIMATES AND MODEL FIT

TABLE A.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 Appendix 1 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 parenthesis.

TABLE A.2 – Parameters of the Utility Function: Mobility Costs

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

Notes: This table reports structural parameter estimates for the mobility costs from the dynamic discrete choice model detailed in Section 4. See Appendix 1 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 parenthesis.

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

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

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

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.038 (0.002)	0.053 (0.001)	0.111 (0.001)	0.107 (0.001)	0.282 (0.005)
Exper. Med.	0.025 (0.002)	0.049 (0.001)	0.093 (0.001)	0.084 (0.001)	0.248 (0.003)
Exper. Low	0.024 (0.001)	0.043 (0.001)	0.084 (0.001)	0.123 (0.001)	0.069 (0.001)
Total Work Exper. (sq)	0.003 (0.000)	-0.002 (0.000)	-0.005 (0.000)	-0.006 (0.000)	-0.005 (0.000)
Exper. Unincorp.	0.169 (0.012)	-0.019 (0.014)	0.067 (0.010)	0.001 (0.017)	-0.217 (0.043)
Exper. Unincorp. (sq)	-0.019 (0.003)	0.015 (0.005)	-0.004 (0.003)	-0.006 (0.005)	0.02 (0.015)
Exper. Incorp.	0.260 (0.070)	0.108 (0.035)	-0.029 (0.025)	-0.028 (0.039)	-0.029 (0.042)
Exper. Incorp. (sq)	-0.035 (0.012)	-0.025 (0.010)	0.003 (0.006)	0.004 (0.011)	0.013 (0.010)
Intercept relative to type 1	0	0.156 (0.002)	0.450 (0.002)	0.931 (0.002)	0.665 (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 Appendix 1 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 A.6 – Parameters of the Earnings Equations: Incorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.221 (0.037)	0.034 (0.019)	0.019 (0.011)	0.065 (0.009)	0.035 (0.017)
Exper. Med.	0.087 (0.034)	0.027 (0.018)	0.020 (0.012)	0.045 (0.009)	0.056 (0.018)
Exper. Low	0.065 (0.033)	0.014 (0.018)	0.038 (0.011)	0.080 (0.010)	-0.104 (0.016)
Total Work Exper. (sq)	-0.010 (0.005)	0 (0.002)	0.001 (0.001)	-0.003 (0.001)	0 (0.002)
Exper. Unincorp.	0.002 (0.032)	0.064 (0.029)	0.148 (0.015)	0.099 (0.013)	0.197 (0.024)
Exper. Unincorp. (sq)	-0.008 (0.008)	-0.015 (0.008)	-0.019 (0.003)	-0.012 (0.003)	-0.022 (0.005)
Exper. Incorp.	0.187 (0.012)	0.118 (0.013)	0.193 (0.008)	0.259 (0.006)	0.272 (0.009)
Exper. Incorp. (sq)	-0.014 (0.002)	-0.021 (0.003)	-0.025 (0.001)	-0.028 (0.001)	-0.026 (0.002)
Intercept relative to type 1	0	-0.133 (0.053)	0.041 (0.046)	0.260 (0.047)	0.706 (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 Appendix 1 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 A.7 – Parameters of the Earnings Equations: Unincorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.079 (0.012)	0.003 (0.007)	-0.036 (0.007)	0.029 (0.009)	0.050 (0.017)
Exper. Med.	0.039 (0.011)	0.002 (0.007)	-0.061 (0.006)	0.054 (0.009)	0.033 (0.018)
Exper. Low	0.037 (0.011)	-0.016 (0.007)	-0.056 (0.006)	0.034 (0.010)	-0.063 (0.017)
Total Work Exper. (sq)	-0.006 (0.002)	0.001 (0.001)	0.005 (0.001)	-0.004 (0.001)	-0.004 (0.002)
Exper. Unincorp.	0.121 (0.005)	0.168 (0.006)	0.200 (0.004)	0.307 (0.007)	0.373 (0.012)
Exper. Unincorp. (sq)	-0.013 (0.001)	-0.028 (0.002)	-0.017 (0.001)	-0.037 (0.001)	-0.037 (0.002)
Exper. Incorp.	0.064 (0.074)	0.037 (0.043)	-0.027 (0.059)	-0.116 (0.064)	0.122 (0.218)
Exper. Incorp. (sq)	-0.016 (0.016)	-0.007 (0.008)	0.005 (0.022)	0.022 (0.020)	-0.056 (0.045)
Intercept relative to type 1	0	0.108 (0.016)	0.352 (0.017)	0.321 (0.020)	0.933 (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 Appendix 1 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 A.8 – In-Sample 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	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

(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 Section 6.2 for details about model simulations.

TABLE A.9 – 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) Model (2012)

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. Only observations from year 2012 are used to calculate the statistics. I use simulated data to calculate the statistics reported in Panel (b). See Section 6.2 for details about model simulations.

TABLE A.10 – In-Sample Fit: Career Transitions

Career at time $t - 1$		Career at time t				
		Workers			Entrepreneurs	
		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 $t - 1$		Career at time t				
		Workers			Entrepreneurs	
		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) 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 Section 6.2 for details about model simulations.

TABLE A.11 – Out-of-Sample Fit: Career Transitions

Career at time $t - 1$		Career at time t					
		Workers			Entrepreneurs		Non-emp.
		High	Medium	Low	Incorp.	Unincorp.	
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 $t - 1$		Career at time t					
		Workers			Entrepreneurs		Non-emp.
		High	Medium	Low	Incorp.	Unincorp.	
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. I use simulated data to calculate the statistics reported in Panel (b). See Section 6.2 for details about model simulations.

TABLE A.12 – In-Sample Fit: Career Choices by Type

Type	Share of pop.	Career					
		Workers			Entrepreneurs		Non-emp.
		High	Medium	Low	Incorp.	Unincorp.	
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

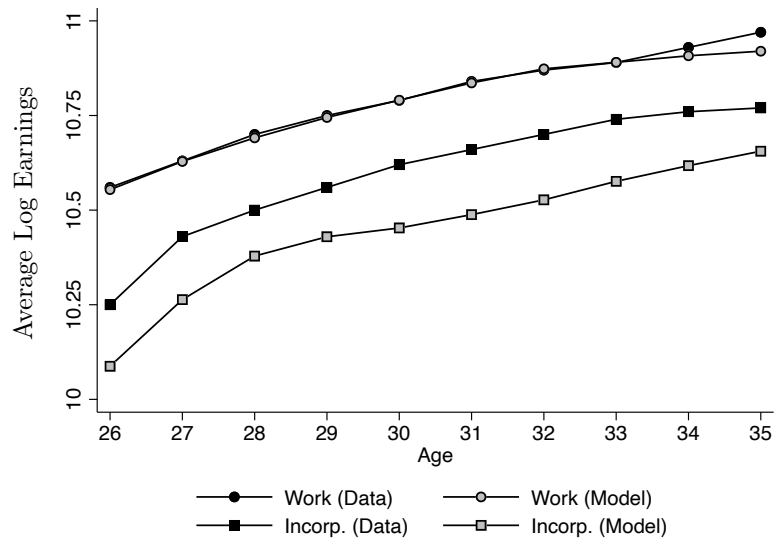
(a) Data

Type	Share of pop.	Career					
		Workers			Entrepreneurs		Non-emp.
		High	Medium	Low	Incorp.	Unincorp.	
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) Model

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. I use simulated data to calculate the statistics reported in Panel (b). See Section 6.2 for details about model simulations.

FIGURE A.1 – In-Sample Fit: Earnings Over the Life Cycle



Notes: This figure describes the observed and 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 simulated data to calculate the statistics reported in the grey lines. See Section 6.2 for details about model simulations.

APPENDIX 3 SUPPLEMENTAL TABLES AND FIGURES

TABLE A.13 – Alternative Firm-Level Outcomes by Firm Class

Firm Class	Employment		Revenue per employee		Payroll per employee		AKM Firm F.E.	
	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

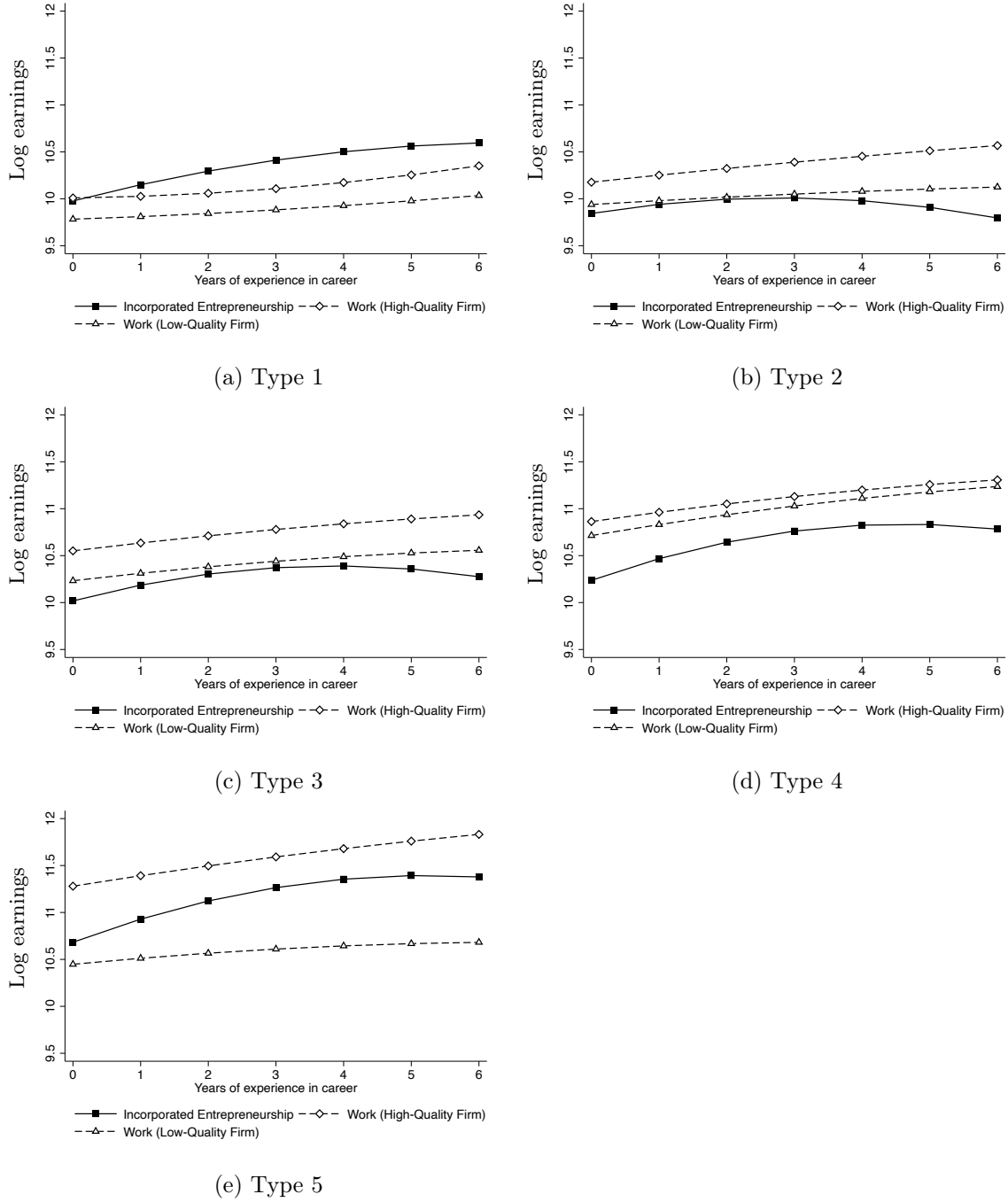
Notes: Statistics are calculated using all firm-level observations in 2012 and are either unweighted or weighted by the number of employees, as indicated. The sample includes all observations with non-missing employment, payroll, and revenue. I exclude firms in the agricultural and public sectors. Firm 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.14 – 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 (0.005)	0.221 (0.004)
Incorp. exper. (sq)	-0.019 (0.001)	-0.020 (0.001)
Unincorp. exper.	0.047 (0.012)	0.046 (0.012)
Unincorp. exper. (sq)	-0.004 (0.002)	-0.004 (0.002)
Intercept	10.280 (0.016)	10.281 (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

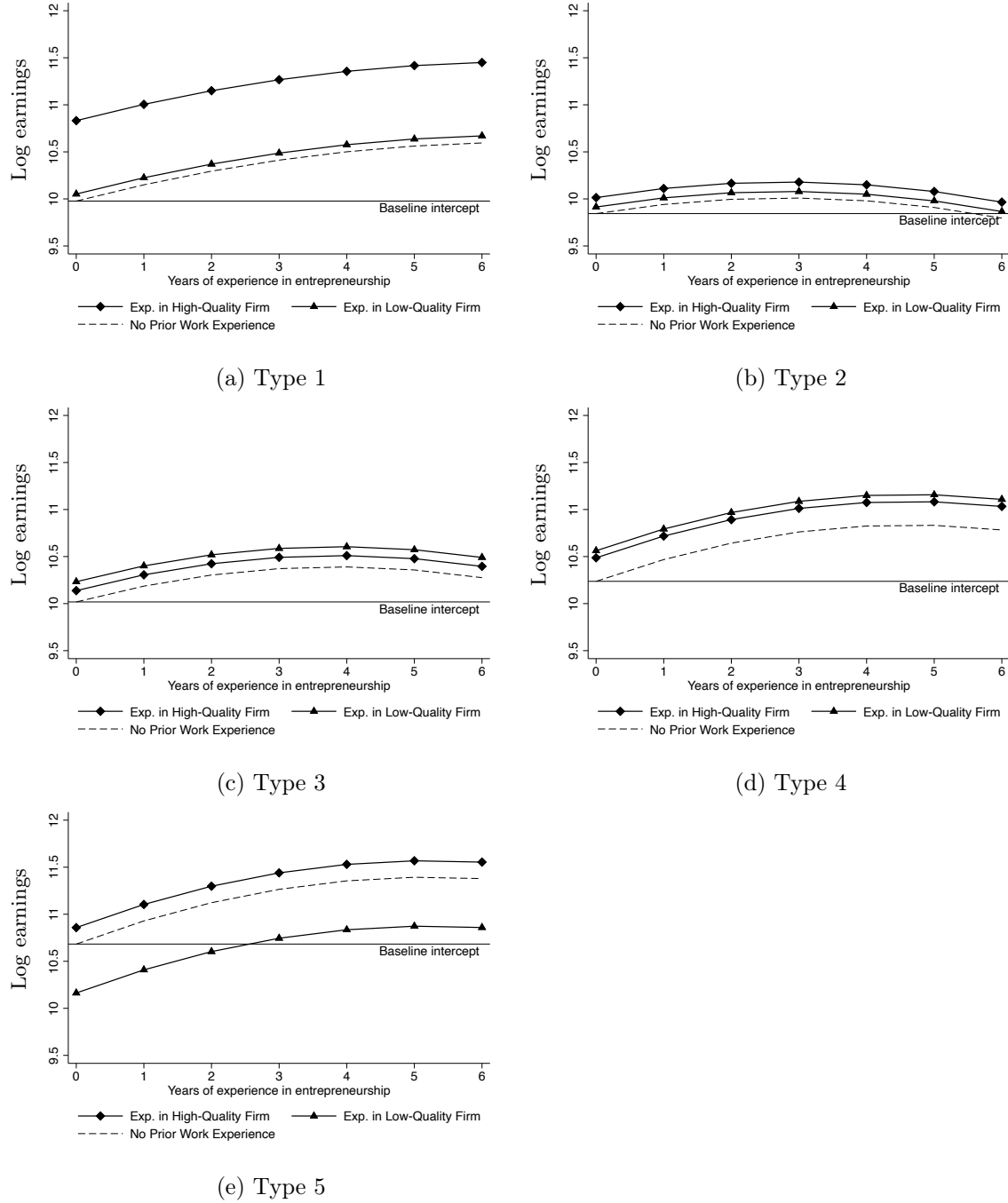
Notes: This table reports OLS estimates of the returns to various types of experience (measured in years) in entrepreneurship. The sample used is the main estimation sample described in Section 2.4, which focuses on non-immigrant men born between 1976 and 1985. All observations in incorporated entrepreneurship 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.

FIGURE A.2 – Expected Log Earnings in Various Careers by Type



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 A.3, A.5, and A.6 in Appendix 2. 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 A.3 – Heterogeneous Returns to Prior Work Experience in Entrepreneurship



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 A.6 in Appendix 2. 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.

APPENDIX 4 ROBUSTNESS: FULL MODEL WITH THREE UNOBSERVABLE TYPES INSTEAD OF FIVE

TABLE A.15 – 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 Appendix 1 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 parenthesis.

TABLE A.16 – Parameters of the Utility Function (3 Types): Mobility Costs

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

TABLE A.17 – Parameters of the Earnings Equations (3 Types): High-Quality Firms

	Type 1	Type 2	Type 3
Exper. High	0.049 (0.001)	0.098 (0.000)	0.106 (0.001)
Exper. Med.	0.048 (0.001)	0.070 (0.001)	0.070 (0.001)
Exper. Low	0.023 (0.001)	0.034 (0.001)	0.033 (0.001)
Total Work Exper. (sq)	0.001 (0.000)	-0.005 (0.000)	-0.005 (0.000)
Exper. Unincorp.	0.067 (0.014)	0.092 (0.008)	0.096 (0.013)
Exper. Unincorp. (sq)	0.006 (0.005)	-0.006 (0.002)	-0.019 (0.004)
Exper. Incorp.	0.207 (0.050)	0.103 (0.021)	0.121 (0.020)
Exper. Incorp. (sq)	-0.008 (0.012)	-0.019 (0.006)	-0.014 (0.006)
Intercept relative to type 1	0	0.458 (0.002)	0.934 (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 Appendix 1 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 A.18 – Parameters of the Earnings Equations (3 Types): Medium-Quality Firms

	Type 1	Type 2	Type 3
Exper. High	0.054 (0.001)	0.097 (0.001)	0.140 (0.001)
Exper. Med.	0.041 (0.001)	0.082 (0.000)	0.104 (0.001)
Exper. Low	0.025 (0.001)	0.034 (0.001)	0.052 (0.001)
Total Work Exper. (sq)	0.000 (0.000)	-0.004 (0.000)	-0.005 (0.000)
Exper. Unincorp.	0.089 (0.012)	0.066 (0.008)	0.064 (0.017)
Exper. Unincorp. (sq)	-0.005 (0.003)	-0.006 (0.002)	-0.008 (0.005)
Exper. Incorp.	0.055 (0.051)	0.048 (0.022)	0.078 (0.041)
Exper. Incorp. (sq)	0 (0.013)	-0.008 (0.006)	-0.006 (0.007)
Intercept relative to type 1	0	0.441 (0.002)	0.845 (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 Appendix 1 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 A.19 – Parameters of the Earnings Equations (3 Types): Low-Quality Firms

	Type 1	Type 2	Type 3
Exper. High	0.061 (0.001)	0.108 (0.001)	0.153 (0.002)
Exper. Med.	0.052 (0.001)	0.086 (0.001)	0.133 (0.002)
Exper. Low	0.044 (0.001)	0.076 (0.001)	0.089 (0.001)
Total Work Exper. (sq)	-0.001 (0.000)	-0.005 (0.000)	-0.005 (0.000)
Exper. Unincorp.	0.129 (0.010)	0.027 (0.010)	0.02 (0.020)
Exper. Unincorp. (sq)	-0.016 (0.002)	0.006 (0.003)	-0.006 (0.006)
Exper. Incorp.	0.137 (0.032)	-0.016 (0.025)	0.023 (0.035)
Exper. Incorp. (sq)	-0.021 (0.007)	0.002 (0.006)	-0.004 (0.009)
Intercept relative to type 1	0	0.392 (0.001)	0.832 (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 Appendix 1 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 A.20 – Parameters of the Earnings Equations (3 Types): Incorporated

	Type 1	Type 2	Type 3
Exper. High	0.038 (0.020)	0.019 (0.010)	0.027 (0.011)
Exper. Med.	0.019 (0.020)	0.011 (0.010)	0.005 (0.011)
Exper. Low	0.029 (0.020)	0.008 (0.010)	-0.014 (0.011)
Total Work Exper. (sq)	-0.003 (0.003)	0.003 (0.001)	0 (0.001)
Exper. Unincorp.	0.110 (0.027)	0.087 (0.014)	0.105 (0.015)
Exper. Unincorp. (sq)	-0.013 (0.007)	-0.009 (0.003)	-0.010 (0.003)
Exper. Incorp.	0.164 (0.010)	0.186 (0.007)	0.272 (0.006)
Exper. Incorp. (sq)	-0.015 (0.002)	-0.021 (0.001)	-0.028 (0.001)
Intercept relative to type 1	0	0.060 (0.033)	0.556 (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 Appendix 1 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 A.21 – Parameters of the Earnings Equations (3 Types): Unincorporated

	Type 1	Type 2	Type 3
Exper. High	0.064 (0.008)	0.001 (0.006)	0.006 (0.011)
Exper. Med.	0.040 (0.008)	-0.003 (0.005)	-0.012 (0.011)
Exper. Low	0.024 (0.008)	-0.011 (0.005)	-0.019 (0.012)
Total Work Exper. (sq)	-0.005 (0.001)	0.001 (0.001)	0 (0.001)
Exper. Unincorp.	0.139 (0.005)	0.191 (0.004)	0.368 (0.007)
Exper. Unincorp. (sq)	-0.016 (0.001)	-0.018 (0.001)	-0.035 (0.001)
Exper. Incorp.	0.122 (0.044)	-0.094 (0.043)	0.083 (0.104)
Exper. Incorp. (sq)	-0.018 (0.008)	0.019 (0.014)	-0.035 (0.024)
Intercept relative to type 1	0	0.200 (0.013)	0.578 (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 Appendix 1 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 A.22 – In-Sample 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 Section 6.2 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.

TABLE A.23 – In-Sample Fit (3 Types): Career Transitions

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

(a) Data

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

(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 Section 6.2 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.

**APPENDIX 5 ROBUSTNESS: SIMPLER MODEL WITH HOMOGENEOUS FIRMS AND
HOMOGENEOUS RETURNS TO EXPERIENCE ACROSS TYPES**

TABLE A.24 – 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 Appendix 1 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 parenthesis.

TABLE A.25 – Parameters of the Utility Function (Simpler Model): Mobility Costs

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

TABLE A.26 – 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 (0.001)	0.532 (0.001)	0.905 (0.001)	1.388 (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 Appendix 1 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 A.27 – 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 (0.016)	0.329 (0.014)	0.216 (0.014)	0.876 (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 Appendix 1 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 A.28 – 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 Appendix 1 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 A.29 – In-Sample 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 Section 6.2 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.

TABLE A.30 – In-Sample Fit (Simpler Model): Career Transitions

Career at time $t - 1$		Career at time t			
		Workers	Entrepreneurs		
			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	Entrepreneurs		
			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 Section 6.2 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.

APPENDIX 6 ROBUSTNESS: ALTERNATIVE DEFINITION OF ENTREPRENEURSHIP

TABLE A.31 – 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 Appendix 1 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 parenthesis.

TABLE A.32 – Parameters of the Utility Function (Alt. Def.): Mobility Costs

Origin	Destination									
	Work					Unincorporated				
	Incorporated					Relative to Type 1				
	High	Medium	Low	Type 1	Type 2	Type 3	Type 4	Type 5	Type 1	Type 2
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)
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)
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)
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)
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
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)
										-2.904 (0.423)
										0
										-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 Appendix 1 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 parenthesis.

TABLE A.33 – Parameters of the Earnings Equations (Alt. Def.): High-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.014 (0.004)	0.076 (0.001)	0.087 (0.001)	0.104 (0.000)	0.114 (0.001)
Exper. Med.	-0.030 (0.003)	0.080 (0.001)	0.065 (0.001)	0.077 (0.001)	0.082 (0.002)
Exper. Low	-0.016 (0.003)	0.045 (0.001)	0.057 (0.001)	0.096 (0.001)	-0.034 (0.002)
Total Work Exper. (sq)	0.008 (0.000)	-0.002 (0.000)	-0.004 (0.000)	-0.005 (0.000)	-0.004 (0.000)
Exper. Unincorp.	0.087 (0.023)	0.277 (0.011)	-0.051 (0.012)	0.076 (0.008)	0.268 (0.038)
Exper. Unincorp. (sq)	0.006 (0.007)	-0.041 (0.003)	0.020 (0.003)	-0.009 (0.003)	-0.052 (0.009)
Exper. Incorp.	0.318 (0.099)	0.165 (0.027)	0.049 (0.036)	0.115 (0.015)	0.017 (0.033)
Exper. Incorp. (sq)	-0.004 (0.019)	-0.020 (0.006)	-0.008 (0.009)	-0.013 (0.004)	0.009 (0.009)
Intercept relative to type 1	0	0.179 (0.003)	0.544 (0.003)	0.844 (0.003)	1.257 (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 using alternatively a definition of entrepreneurship that includes non-start up firms. See Appendix 1 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 A.34 – Parameters of the Earnings Equations (Alt. Def.): Medium-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0 (0.003)	0.084 (0.001)	0.085 (0.001)	0.122 (0.001)	0.175 (0.003)
Exper. Med.	-0.028 (0.002)	0.075 (0.001)	0.074 (0.000)	0.092 (0.000)	0.126 (0.002)
Exper. Low	-0.006 (0.002)	0.044 (0.001)	0.056 (0.001)	0.111 (0.001)	-0.032 (0.002)
Total Work Exper. (sq)	0.007 (0.000)	-0.003 (0.000)	-0.004 (0.000)	-0.005 (0.000)	-0.004 (0.000)
Exper. Unincorp.	0.083 (0.018)	0.196 (0.011)	-0.018 (0.011)	0.040 (0.011)	0.175 (0.064)
Exper. Unincorp. (sq)	-0.007 (0.005)	-0.022 (0.003)	0.007 (0.003)	0 (0.003)	-0.079 (0.021)
Exper. Incorp.	0.122 (0.082)	0.232 (0.030)	-0.104 (0.026)	-0.01 (0.020)	0.032 (0.088)
Exper. Incorp. (sq)	-0.041 (0.028)	-0.042 (0.007)	0.019 (0.006)	0.010 (0.005)	0.045 (0.047)
Intercept relative to type 1	0	0.161 (0.002)	0.513 (0.002)	0.781 (0.002)	1.120 (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 using alternatively a definition of entrepreneurship that includes non-start up firms. See Appendix 1 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 A.35 – Parameters of the Earnings Equations (Alt. Def.): Low-Quality Firms

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.043 (0.002)	0.053 (0.001)	0.109 (0.001)	0.105 (0.001)	0.271 (0.004)
Exper. Med.	0.020 (0.002)	0.053 (0.001)	0.091 (0.001)	0.083 (0.001)	0.241 (0.003)
Exper. Low	0.025 (0.001)	0.045 (0.001)	0.084 (0.001)	0.125 (0.001)	0.069 (0.001)
Total Work Exper. (sq)	0.003 (0.000)	-0.002 (0.000)	-0.005 (0.000)	-0.006 (0.000)	-0.005 (0.000)
Exper. Unincorp.	0.169 (0.012)	-0.008 (0.014)	0.059 (0.010)	0.01 (0.017)	-0.214 (0.042)
Exper. Unincorp. (sq)	-0.019 (0.003)	0.013 (0.005)	-0.004 (0.003)	-0.007 (0.005)	0.018 (0.014)
Exper. Incorp.	0.148 (0.040)	0.131 (0.034)	-0.056 (0.021)	-0.036 (0.032)	-0.01 (0.030)
Exper. Incorp. (sq)	-0.018 (0.008)	-0.029 (0.009)	0.013 (0.004)	0.013 (0.007)	0.013 (0.007)
Intercept relative to type 1	0	0.164 (0.001)	0.456 (0.002)	0.932 (0.002)	0.679 (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 using alternatively a definition of entrepreneurship that includes non-start up firms. See Appendix 1 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 A.36 – Parameters of the Earnings Equations (Alt. Def.): Incorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.200 (0.033)	0.035 (0.018)	0.032 (0.011)	0.050 (0.009)	0.008 (0.016)
Exper. Med.	0.080 (0.030)	0.019 (0.017)	0.034 (0.012)	0.033 (0.009)	0.021 (0.017)
Exper. Low	0.046 (0.029)	0.004 (0.017)	0.058 (0.011)	0.084 (0.009)	-0.125 (0.016)
Total Work Exper. (sq)	-0.008 (0.004)	0.001 (0.002)	-0.001 (0.001)	-0.002 (0.001)	0.003 (0.002)
Exper. Unincorp.	0.049 (0.030)	0.113 (0.028)	0.138 (0.014)	0.081 (0.012)	0.200 (0.025)
Exper. Unincorp. (sq)	-0.012 (0.007)	-0.024 (0.007)	-0.018 (0.003)	-0.007 (0.003)	-0.022 (0.006)
Exper. Incorp.	0.186 (0.010)	0.127 (0.013)	0.192 (0.007)	0.255 (0.006)	0.272 (0.008)
Exper. Incorp. (sq)	-0.015 (0.002)	-0.023 (0.003)	-0.024 (0.001)	-0.028 (0.001)	-0.026 (0.001)
Intercept relative to type 1	0	-0.111 (0.047)	0.025 (0.040)	0.288 (0.040)	0.771 (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 using alternatively a definition of entrepreneurship that includes non-start up firms. See Appendix 1 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 A.37 – Parameters of the Earnings Equations (Alt. Def.): Unincorporated

	Type 1	Type 2	Type 3	Type 4	Type 5
Exper. High	0.078 (0.012)	0.01 (0.007)	-0.037 (0.007)	0.021 (0.009)	0.027 (0.018)
Exper. Med.	0.035 (0.011)	0.011 (0.007)	-0.064 (0.006)	0.049 (0.009)	0.01 (0.019)
Exper. Low	0.033 (0.011)	-0.009 (0.007)	-0.054 (0.006)	0.025 (0.010)	-0.076 (0.018)
Total Work Exper. (sq)	-0.005 (0.002)	0 (0.001)	0.005 (0.001)	-0.003 (0.001)	-0.002 (0.002)
Exper. Unincorp.	0.118 (0.005)	0.174 (0.006)	0.196 (0.004)	0.305 (0.007)	0.388 (0.012)
Exper. Unincorp. (sq)	-0.013 (0.001)	-0.029 (0.002)	-0.017 (0.001)	-0.035 (0.001)	-0.039 (0.002)
Exper. Incorp.	0.121 (0.051)	-0.03 (0.064)	0.024 (0.048)	-0.063 (0.048)	0.208 (0.173)
Exper. Incorp. (sq)	-0.024 (0.009)	0.025 (0.022)	-0.017 (0.013)	0.003 (0.013)	-0.075 (0.037)
Intercept relative to type 1	0	0.101 (0.016)	0.353 (0.017)	0.335 (0.020)	0.971 (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 using alternatively a definition of entrepreneurship that includes non-start up firms. See Appendix 1 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 A.38 – In-Sample 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 Section 6.2 for details about model simulations. The model used to perform the simulations is as detailed in Section 4, but using an alternative definition of entrepreneurship that includes non-start up firms.

TABLE A.39 – In-Sample 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 Section 6.2 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.