Entrepreneurship and Sources of Ex-ante Firm Heterogeneity*

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Abstract

We study how founders' human capital serves as a source of ex-ante firm heterogeneity. Using employer-employee-shareholder linked administrative data from Canada, we find that ex-ante firm heterogeneity accounts for half of total firm heterogeneity, and founder factors account for approximately 10% of this ex-ante heterogeneity. Founders' prior experience, both entrepreneurial profit for serial entrepreneurs and employment income for novice entrepreneurs, is positively associated with larger initial firm size and greater growth potential. Motivated by these findings, we develop a model of occupational choice featuring multidimensional talent, where selection into entrepreneurship shapes the ex-ante heterogeneity across firms. Using the model to evaluate the macroeconomic effects of small business tax deductions, we find that three-quarters of the positive effects from alleviating financial frictions are offset by the negative selection that draws in lower-potential entrepreneurs.

JEL: D22, D24, E23, E24, E60, G31, J24, L26, M13

Keywords: ex-ante heterogeneity, entrepreneurship, firm dynamics, financial frictions

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1. Introduction

Understanding the sources of firm heterogeneity is fundamental to the design of entrepreneurial policy. Growing evidence suggests that there are persistent differences across firms present since firm creation, highlighting the importance of "ex-ante" firm heterogeneity (Luttmer, 2011; Gabaix et al., 2016; Sterk et al., 2021). In the presence of such ex-ante heterogeneity, entrepreneurial policies that provide preferential treatment to small businesses may result in misallocation, as they fail to target firms with high growth potential. This paper studies how entrepreneurial choices and incentives shape this ex-ante firm heterogeneity, drive business dynamics, and ultimately influence aggregate output.

Using employer-employee-shareholder linked administrative data from Canada, we find that founder factors explain a significant share of ex-ante firm heterogeneity: ex-ante heterogeneity explains approximately half of overall size variation in Canadian firms, and founder characteristics explain 10% of this ex-ante heterogeneity. Moreoever, founders' human capital positively correlates with both initial firm size and subsequent growth potentials. The differences are economically significant and persist throughout firm life cycle.

Our quantitative model studies how the selection into entrepreneurship shapes business dynamics and aggregate output. We build a span-of-control model featuring financial frictions and correlated, multidimensional talent. This correlation drives occupational selection into entrepreneurship, which we discipline using empirical selection incidence probabilities. We find that the distribution of talent shapes long-run dynamism and growth.

Correlational evidence. Our main data source is the Canadian Employer Employee Dynamics Database (CEEDD), an employer-employee-shareholder matched, longitudinal data based on personal and corporate tax filings. The CEEDD covers the universe of Canadian firms and workers at annual frequency, providing information on business history since creation, business owners' personal history as workers and entrepreneurs, and histories and characteristics of their employees.

We document a positive and robust relationship between founder human capital and firm performance. Within firm cohorts and controlling for founder characteristics including their wealth, we find that startups created by a serial entrepreneur (who has previously founded

other firms) are 14% larger at birth, measured by employment, and grow 18% faster over the first 10 years. The positive relationship hold for different aspects of firm size, including employment, assets, and revenue.

Among both serial entrepreneurs and novice entrepreneurs, measures of their past experience further correlate startup performance. The initial size and growth potentials of startups rise with the past profits earned by serial entrepreneurs' past businesses and the past employment income earned by novice entrepreneurs. The positive relationship is highly persistent, lasting for at least 10 years. The predictive power of employment earnings and startup performance further suggest a correlation between working and entrepreneurial capacities.

Structural decomposition. Sterk et al. (2021) showed that the persistence of firm size differences from birth through the life cycle provides evidence on the importance of ex-ante firm heterogeneity. Our reduced-form analysis further documents a persistent *conditional* relationship between firm size and founder factors, which suggests an potentially important role of entrepreneurs in explaining firm heterogeneity.

Motivated by the correlational evidence, we decompose the variation in firm size using a statistical model that incorporates both ex-post and ex-ante firm heterogeneity, with ex-ante firm heterogeneity allowed to depend on observed founder factors and other unobserved factors. We find that ex-ante heterogeneity explains about half of overall variation in sizes of Canadian firms. Among the ex-ante heterogeneity, founder characteristics explain about 10% of the variation, substantially empirically.

Taken together, our empirical findings show that conditional on the decision to start a firm, founders and their experience are highly positively related to trajectory of the firm.

Quantitative analysis. To evaluate entrepreneurial policies, in addition to the intensive margin of which entrepreneurs create successful firms conditional on starting a business, we also need to understand the extensive margin of which individuals choose to become entrepreneurs. Our quantitative model incorporates both margins.

To study the selection into entrepreneurship, we build a span-of-control model (Lucas, 1978) with endogenous occupational choice, correlated working and entrepreneurial capacities, and financial frictions. Households make the occupational choice between working and

starting a business. The working capacity of an individual determines her labor income, whereas the entrepreneurial capacity drives the ex-ante heterogeneity in the productivity of the firm created. Consistent with our empirical findings that founders' past employment income is positively correlated with startup performance, we allow the working and entrepreneurial capacities to be correlated.

To calibrate the model, we show that this correlation is key to match the empirical pattern of the selection into entrepreneurship. As working capacity increases, the opportunity cost of starting a business increases, making it less attractive to switch to entrepreneurship. Without a sufficiently high correlation, the incidence probability of entrepreneurship decreases with wage. Empirically, however, we find that the incidence probability of entrepreneurship rises with past employment income, particularly for high-income workers, which pins down a positive and high value for the correlation.

For realism, our model incorporates both ex-ante and ex-post heterogeneity in considering policy tradeoffs. It also embeds financial frictions, to separate the learning of entrepreneurs from their financial conditions. Each of these features are calibrated using micro data.

We report three quantitative findings. First, talent concentration increases opportunity costs. Because entrepreneurial and working capacities are positively correlated, the economy faces a high opportunity cost for dynamism. When an individual starts a firm, the economy "sacrifices" a highly productive worker. If capacities were uncorrelated, output would be 3.6% higher due to better labor allocation.

Second, the costs of financial frictions are substantial, reducing output by 6% and TFP by 5%. Financial frictions affect the economy by slowing capital accumulation in existing firms, delaying market entry for talented but wealth-poor individuals, and forcing premature exits of incumbents following unlucky idiosyncratic shocks.

Finally, concentrated talent mitigates the costs of financial frictions. In our calibrated economy with correlated capacities, a person discouraged from starting a firm by financial constraints still contributes significantly as a high-productivity worker. In contrast, if capacities were uncorrelated, a discouraged entrepreneur would be a mediocre worker, making the macroeconomic loss from financial frictions even larger.

Literature. Our paper relates to four strands of the literature. First, we contribute to the literature on the macroeconomic importance of ex-ante firm heterogeneity. Seminal papers by Sedláček and Sterk (2017) and Sterk et al. (2021) document that early years of a firm have lasting impact on its trajectory over the life cycle. This "ex-ante" heterogeneity is important for explaining both the firm size distribution (Luttmer, 2011; Gabaix et al., 2016) and aggregate growth. Our paper provides empirical evidence on the importance of ex-ante heterogeneity using new administrative data, and we uncover founding entrepreneurs as the sources of this heterogeneity. Our findings suggest that attracting productive entrepreneurs to enter the market is key for driving aggregate growth and productivity.

Second, our paper contributes to the literature on the determinants of heterogeneous firm growth. Prior studies have identified several key drivers, ranging from economic and institutional features (Guzman and Stern, 2020; Basante and Simonovska, 2025), to employee characteristics (Ouimet and Zarutskie, 2014) and firm capital structure (Guntin and Kochen, 2025). Most related to our work is the role of founder characteristics, such as human capital (Queiró, 2022), concurrent ownership of multiple firms (De Vera et al., 2025), and the "spinoff" effect of founders departing incumbent innovators (Baslandze and Vardishvili, 2025). Leveraging comprehensive administrative data from Canada, we corroborate the significant impact of founder human capital on firm performance. Furthermore, we find a positive correlation between an individual's productivity as a worker and their productivity as an entrepreneur. This concentration of talent within a subset of individuals create aggregate tradeoffs, which we study quantitatively.

Third, our quantitative model builds upon the dynamic models of occupational choice pioneered by Lucas (1978). This class of models has been applied extensively to analyze social mobility and wealth distribution (Quadrini, 2000), effects of tax policies (Cagetti and De Nardi, 2009), interaction with financial constraints (Greenwood and Jovanovic, 1990; Boháček, 2006; Akyol and Athreya, 2009), entrepreneurial risk taking (Vereshchagina and Hopenhayn, 2009), among others. Guided by our empirical findings, we extend the model to allow for a correlation between an individuals' working and entrepreneurial capacities, as in Jovanovic (1994). This joint distribution, which we discipline using our rich micro data, drives entrepreneurial selection and shapes aggregate productivity and output.

Lastly, we contribute to the literature on the macroeconomic importance of entrepreneur-

ship (e.g., Quadrini, 2009; Salgado, 2020; Queiró, 2022; Morazzoni, 2021; De Haas et al., 2022; Bhandari et al., 2025; Leahy and Thapar, 2022, among others). Empirically, we provide evidence that founder characteristics serve as a source of ex-ante firm heterogeneity. Quantitatively, we show that the selection into entrepreneurship interacts with financial frictions to influence the macroeconomic outcomes in significant ways.

Road map. The rest of the paper proceeds as follows. Section 2 describes data sources and variable construction. Section 3 presents reduced-form evidence on positive relationship between founders' human capital and startups' size and growth. Section 4 conducts a structural decomposition to account for the importance of founder characteristics for ex-ante firm heterogeneity. Section 5 presents our quantitative model of entrepreneurial choices. Section 6 analyzes the macroeconomic outcomes of entrepreneurial selection and financial frictions. Section 7 concludes.

2. Data

2.1. Data sources

Our main data is the Canadian Employer Employee Dynamics Database (CEEDD) from 2001 to 2016, an employer-employee-shareholder matched, longitudinal data based on administrative data and tax filings. The CEEDD covers the universe of Canadian firms and workers at annual frequency, providing three dimensions of information relevant for our analysis.

First, at the firm level, the CEEDD contains information from the Canadian business registry, covering all incorporated businesses that submit corporate tax returns (Form T2) and unincorporated businesses with at least one employee that submit T4 statements of remuneration (Form T4) and payroll remittances (Form PD7). The dataset includes detailed firm characteristics (such as location, industry, and founding year) and financial information from income statement and balance sheet. It also contains information on both shareholders and employees.

Second, and important for our analysis, is information on firm ownership. Corporations are required to report all shareholders who hold 10% or more of in Form T2 Schedule 50. We have information on the anonymized identity of shareholder, the percent of shares held,

the type of the share (preferred or common), and the type of the shareholder (individual, corporation, parnership, or trust). When the shareholder is not an individual, the ownership is traced through the ownership chain to identify the ultimate individual owner.[1] Combining this ownership information with data on a firm's birth year recorded in the business registry allows us to identify a firm's founding shareholders and changes in ownership over a firm's life cycle.

Third, at the individual level, the CEEDD contains demographic data based on personal and family income tax filings (Form T1) and employer-reported earnings (T4 slips and Records of Employment). This includes data on an individual's age, gender, location, marital status, personal and family income, and employment and shareholding histories.

In addition, we obtain information on individuals' wealth from the Survey of Financial Security (SFS) produced by Statistic Canada. The SFS is a nationally representative survey of Canadian households from 1999 to the present. It contains approximately 12,000 households per wave, covering wealth, income, debts and demographic information. SFS respondents are linked to their records in the same tax data underlying the CEEDD. From these shared variables, we impute the wealth for each taxpayer in the CEEDD. Appendix A.2 provides details on the methodology and measures of fit.[2]

We focus on corporations, sole proprietorship, and partnership — the most common business structures in Canada representing more than 99% of the businesses in the CEEDD — and exclude non-profits and government agencies. The firm ownership data from T2 Schedule 50 is restrict to incorporated businesses. However, when considering the experience of a firm's founders, we use the full history of their working experience, including in both incorporated and unincorporated businesses.

2.2. Variables and descriptive statistics

Appendix Section A.1 provides definitions of firm- and individual-level variables used in our analysis. In this subsection, we define two key variables and provide descriptive statistics for new firms and their founders.

[1] Similar to methodologies developed by Peter (2025) and Kochen (2025).

[2] Our wealth imputation predicts the actual wealth with a R^2 of 0.44 and successfully classifies 26% of SFS individuals into correct wealth deciles, and 58% into a correct or adjoining decile. We note that this is a substantial improvement from assuming an individual's wealth decile is equivalent to an income decile, which has a correct classification ratio of 13%.

We define a firm's *birth year* as the earlier between its first reported year in the business registry, which is required for both unincorporated and incorporated business, and its incorporation year, which is available for incorporated business.

Table 1: Descriptive statistics on new businesses and founders

(a) New businesses

	Mean	**SD**	**Median**	**5th**	**95th**
Number of employees	3.9	10.1	2	1	11.8
Number of founders	1.6	0.8	1	1	3
Assets ($000)	226.3	2015.3	63.1	3.2	719.8
Revenue ($000)	327.1	1220.2	137.7	18.9	995.1
Number of New Firms					N=239925

(b) Founders

	Mean	**SD**	**Median**	**5th**	**95th**
Founder age (years)	45.2	11.1	45	27	64
Number of firms with shareholdings	1.7	2	1	1	4
Number of firms with direct shareholdings	1.4	1.1	1	1	3
Personal income ($000)	118.9	419.7	63	12.4	317.2
Personal employment income ($000)	79.4	262.5	45.6	3.5	205.9
Family income ($000)	185.9	451.8	116	29.8	477.5
Personal wealth ($000)	1521	12649.3	490.9	26.7	5026.7
Number of Founders					N=1580490

Panel (a) of Table 1 presents descriptive statistics for new firms founded between 2001 and 2016, which represents 13% of firms in our sample. At entry, these new firms employ an average of 4 workers but exhibit significant size heterogeneity, with a standard deviation of 10. Consistent with existing U.S. evidence (e.g., Dunne et al., 1988; Davis et al., 1996), entrants in our sample are notably smaller than the average firm (12 employees), for which descriptive statistics are provided in Appendix Table B.1a.

The average new firm holds approximately $370,000 in assets and generates $515,000 in revenue, representing 6% and 3%, respectively, of the corresponding averages for all firms in Table B.1a. On average, new entrants comprise approximately 4% of the firm population annually. The industry distribution of new firms mirrors that of overall Canadian firms, with the highest share of new firms concentrated in services and trade.

We define a firm's *founders* as individuals who have direct holdings of common or preferred shares during a firm's birth year. For each firm, the CEEDD traces its ultimate ownership to individuals by applying algorithms similar to Peter (2025) and Kochen (2025). Our baseline definition of founders requires direct ownership and excludes indirect ownership through corporate chains. This restriction ensures our sample more accurately captures individuals who maintain both "ownership of a business together with an active management role" (Quadrini, 2009). Our empirical results are robust to broad definition of founders that also includes indirect shareholdings.

Panel (b) of Table 1 provide descriptive statistics for firm founders, who represent approximately 7% of the individual-year observations. The vast majority of founders own only a single firm in a given year. Relative to the general population of workers (see Appendix Table B.1b, founders are, on average, two years older and characterized by significantly higher financial resources. Specifically, founders earn an average personal income of $79,000 and a family income of $139,000, nearly double those of the average worker. Furthermore, founders hold substantially more wealth, with mean personal wealth exceeding $1 million.

3. Correlational Evidence

This section provides empirical evidence on the connection between firm heterogeneity and founder characteristics. We first compare founder characteristics across the top 1% and non-top firms, and then document the positive connection between founders' human capital and firms' performance.

3.1. Founder characteristics of top 1% firms

As motivational evidence, Table 2 compares characteristics of founders who create the top 1% firms by asset size at entry with those who create the remaining non-top firms. Appendix Table B.2 alternatively ranks firms by their sizes after 10 years and reveals similar differences between founders for top and non-top firms.

Firms on average have 1.7 founders, with a standard deviation of 0.9. Top 1% firms have slightly larger founding teams, with an average of 1.9 founders per firm. The average founders is 41 years old, about two years older than the average worker and consistent

Table 2: Founder characteristics of top 1% and non-top firms

	Top 1%	**Bottom 99%**	**Total**
Number of founders	1.94	1.70	1.70
	(1.24)	(0.87)	(0.88)
Average founder age (years)	49.95	40.67	40.70
	(11.31)	(9.99)	(10.01)
Average share of founders who are serial entrepreneurs	0.78	0.27	0.27
	(0.36)	(0.40)	(0.41)
Average founder personal income ($mn)	1.24	0.10	0.10
	(3.54)	(0.31)	(0.38)
Average founder employment income ($mn)	0.90	0.07	0.08
	(4.03)	(0.23)	(0.33)
Average founder family income ($mn)	1.37	0.16	0.16
	(3.40)	(0.34)	(0.40)
Average founder wealth ($mn)	13.47	1.02	1.07
	(54.27)	(9.92)	(10.44)
Average founder AKM worker premium	1.00	0.08	0.08
	(1.15)	(0.69)	(0.70)

Notes: This table reports the average founder characteristics of the top 1%, bottom 99%, and all sample firms. Firms are ranked by real assets at entry. Standard deviations are reported in parenthesis.

with the US evidence that entrepreneurs tend to be middle-aged (Leahy and Thapar, 2022). Founders of the top firms are notably older, with a mean age of 50 and approximately 9 years older than founder of the non-top firms.

In addition to being older, founders of the top firms are also more experienced. Among all newly established firms, only 1 in 4 founders is a serial entrepreneur who has previously started another firm. In contrast, among the largest 1% firm at entry, 3 out of 4 founders have prior entrepreneurial experience.

The next four rows of Table 2 reveal stark differences in income and wealth between the founders of top 1% firms and those of non-top firms. In the year before starting a firm, the typical founder earns an annual income of $0.1 million, with 80% earned from employment. In contrast, founders of the largest 1% firm report significantly higher income, earning $1.2 million annually, with 72% from employment income. Founder wealth also shows a positive relationship with firm size at entry: founders of the top 1% firms have an average net worth of $54 million, compared to $10 million among founders of the remaining 99% firms.

The last row of Table 2 presents the individual-specific pay premium in founders' em-

ployment income outside of entrepreneurial spells, estimated using the Abowd et al. (1999) (AKM) model.[3] Among founders with multi-firm employment histories as non-owners, the average worker premium is 0.08 for founders in the bottom 99% firms and 1.15 for founders of firms in the top 1%. Since the estimates are expressed in log wage, these estimates imply that top-firm founders enjoy a individual-specific wage premium that more than triples that of founders of the remaining firms, which reflects their higher labor market quality even outside of entrepreneurship.

Overall, Table 2 and Appendix Table B.2 suggest that founder heterogeneity is highly correlated with a firm's initial size and subsequent growth. Founders of the top firms tend to be older, richer, more experienced, more capable as workers. As Sterk et al. (2021) highlight, these ex-ante heterogeneity of firms can be highly persistent, shaping firm outcomes throughout their life cycles. Therefore, the next subsection documents the relationship between founder characteristics and firm heterogeneity using local projections.

3.2. Founder human capital and firm heterogeneity

3.2.1. Empirical specification

Motivated by the founder heterogeneity observed in top and non-top firms, we now use local projections to study any correlation between founder human capital and startup performance. For firm j founded in year t, we estimate variants of:

$$y_{jh} = \delta_{ts} + \beta_h \text{Ent}_j + \Gamma' Z_j + \varepsilon_{jh}, \tag{1}$$

where y_{ih} is the firm outcome variable of interest, measured $h \geq 0$ years after firm entry; δ_{ts} is a firm-founding-year-by-sector fixed effect; Ent_j captures the characteristics of founders of firm j, detailed below; Z_j is a vector of firm controls that include the average age of the founders, the number of founders, and their average wealth one year prior to founding; and ε_{ih} is a random error. The founding year of each firm is normalized to $t = 0$ such that each

[3]The AKM model, widely used in the macro-labor literature, decomposes wage variation into worker-, firm-, and job-specific effects. We estimate $y_{it} = \theta_i + \lambda_t + \psi_{j(i,t)} + \varepsilon_{it}$, where y_{it} is the log real employment income of individual i in year t, θ_i is a worker fixed effect, λ_t is a year fixed effect, $\psi_{j(i,t)}$ is a firm fixed effect, and ε_{it} is a random error. The matching function, $j(i,t)$, maps worker i to their primary employer in year t. We exclude entrepreneurial spells and focus on the employment history. Therefore, the AKM regression is identified with workers have worked for more than one firm as a non-owners.

firm appears once per horizon h. Standard errors are clustered at the firm-founding-year-by-sector level. Sectors are defined at the 4-digit NAICS level.

For the outcome variables, we consider both the level and cumulative growth of firm size. The size of firm j in the h-th year after entry, s_{jh}, is measured along three related but distinct dimensions: log employment, log real assets, and log real revenue. All analyses compare firms founded in the same year and operating within the same industry. In addition to these main outcome variables of interest, we also study firm survival, which we can accurately measure because of the longitudinal nature of our data.

For the explanatory variable, Ent_j, we capture three aspects of founder experience. First, among all new firms, we measure whether a firm is founded by a serial entrepreneur who has previously owned another business. This information is summarized in an indicator variable at the firm level,

$$\mathbb{1}(\text{Serial Ent})_j \equiv \max_{i \in j} \mathbb{1}(\text{Serial Ent})_i, \tag{2}$$

which equals 1 if any founder i of firm j is a serial entrepreneur and 0 otherwise. As De Vera et al. (2025) document, serial entrepreneurship is a simple but effective measure of entrepreneurial experience.[4]

Second, we split the sample of new firms into those created by serial entrepreneurs and those created by novice entrepreneurs, and construct continuous measures of founder human capital for each subsample.

Among firms created by serial entrepreneurs, we measure the entrepreneurial capacity of founders with the profitability of their past businesses:

$$\log \bar{\Pi}_{jt-1} \quad \text{for } j \in \{j : \mathbb{1}(\text{Serial Ent})_j = 1\}, \tag{3}$$

where $\bar{\Pi}_{jt-1} = \frac{1}{N_j} \sum_{i \in j} \left(\sum_{k \in \mathcal{F}_i} \Pi_{kt-1} \right)$ captures the lagged average profits from all firms previously owned by the founders of firm j. For each founder i, $\mathcal{F}_i$ denotes the set of firms they owned before founding firm j, and Π_{kt-1} denotes the real gross profit (revenue minus cost of goods sold) of firm k in year $t-1$.

[4] Our measure of serial entrepreneurs focuses on the past entrepreneurial experience of a founder, whereas the main measure of serial entrepreneurs by De Vera et al. (2025) focuses on the portfolio aspect and is defined as individuals who own multiple businesses at the same time.

Among firms created by novice entrepreneurs, we measure the working capacity of founders with their employment income before starting a business:

$$\log \bar{w}_{jt-1} \text{ for } j \in \{j : \mathbb{1}(\text{Serial Ent})_j = 0\} \tag{4}$$

where $\bar{w}_{jt-1} = \frac{1}{N_j} \sum_{i \in j} w_{it-1}$ captures the average real employment income earned by the founders of firm j in the year before its founding.

3.2.2. Results

Figure 1 shows that experienced entrepreneurs tend to create firms that have larger initial sizes and higher growth potentials. Each point in the figure represents the point estimates from (1) using the serial entrepreneur indicator in (2) as the explanatory variable, along with the 95% confidence intervals.

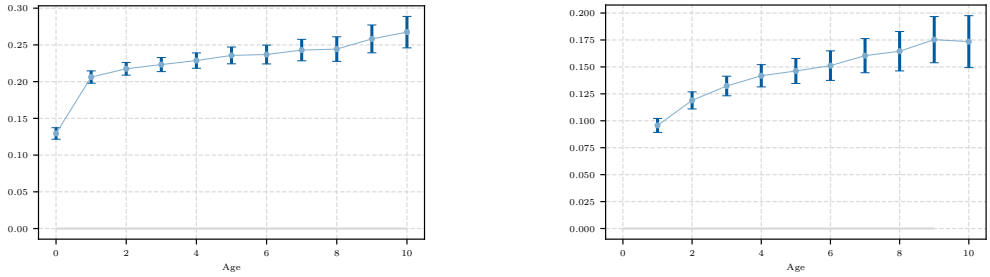
Panel (a) finds a positive correlation between firms' initial sizes and entrepreneurs' experience. Firms created by serial entrepreneurs are 14% bigger at entry than firms created by novice entrepreneurs. The differences in firm size are highly persistent and widen as firm age, reaching 27% by the tenth year. Panel (b) shows that the firms created by serial entrepreneurs are not just larger, they also tend to grow faster. The differences in firm growth are also highly persistent and widen with most of the estimation horizons. Over the first 10 years, firms created by serial entrepreneurs grow 18% faster than firms created by inexperienced entrepreneurs.

Appendix Figure B.1 shows that the positive relationship between founder experience is robust across different measure of firm size. In addition to creating firms with more employees, experience entrepreneurs also tend to create firms with more assets and revenues. The magnitude of the correlation is even larger when firm size is measured with assets and revenues.

Having studied the connection between firm heterogeneity and serial entrepreneurship, Figure 2 further investigates the relationship between firm outcomes and the intensity of founder experience.

The top row of Figure 2 focuses on the subset of firms with a serial entrepreneur as a founder. We measure the entrepreneurial capacities of serial entrepreneurs using their past

Figure 1: Serial entrepreneurship and the initial size and subsequent growth of firms



(a) Employment level **(b)** Employment growth

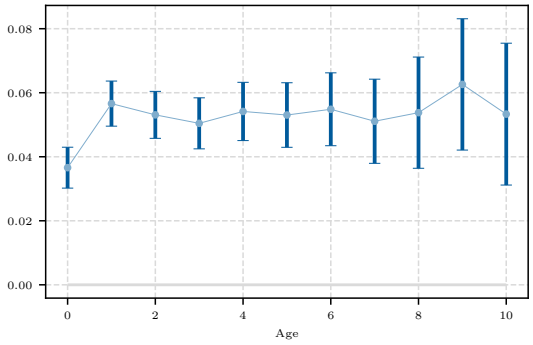
Notes: Panel (a) reports β_h of firm j for h years after the creation, estimated from the local projections $\log s_{jh} = \delta_{ts} + \beta_h \mathbb{1}(\text{Serial Ent})_j + \Gamma' Z_j + \varepsilon_{jh}$, where s_{jh} denotes firm employment; δ_{ts} is a firm-founding-year-by-sector fixed effect (sectors measured at the 4-digit NAICS level); $\mathbb{1}(\text{Serial Ent})_j$ is an indicator variable which equals 1 if any founder of firm j is a serial entrepreneur and 0 otherwise; Z_j is a vector of firm controls that include the average age of the founders, the number of founders, and their average wealth one year prior to founding; and ε_{ih} is a random error. Panel (b) reports β_h from estimating $\Delta_h \log s_{jh} = \delta_{ts} + \beta_h \log \mathbb{1}(\text{Serial Ent})_j + \Gamma' Z_j + \gamma \log s_{j0} + \varepsilon_{jh}$, where s_{j0} denotes firm employment at entry, and remaining variables are defined as above. Standard errors are clustered at the firm-founding-year-by-sector level. 95% confidence intervals are reported.

success: average profits of the businesses they owned in the year before creating the new firm, defined in equation (3). Panels (a) and (b) document that the profitability of founders' past businesses are positively correlated with the initial sizes and growth potentials of the new businesses that they create. In terms of economic magnitude, one standard deviation higher log past profits (2.4, which corresponds to $11 in 2010 Canadian dollars) is associated with 0.04% higher employment at entry and 0.05% higher cumulative growth by the tenth year. This relationship is highly persistent and remain positive throughout a ten-year horizon.

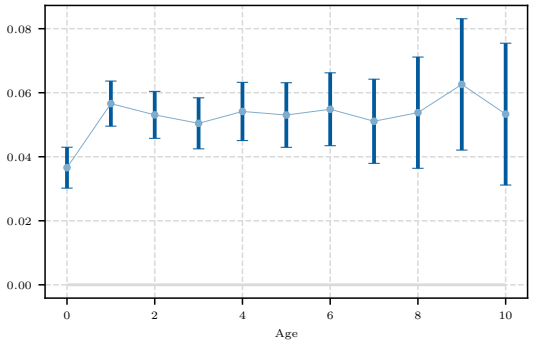
The bottom row of Figure 2 focuses on the subset of firms founded by novice entrepreneurs. Since the novice founders do not have entrepreneurial experience, we measure instead their working capacity using the average employment income in the year before entrepreneurship, defined in equation (4). Panels (c) and (d) document that founders' past employment income are positively correlated with the initial sizes and growth potentials of the new businesses that they create. One standard deviation higher log past employment income (4.9, which corresponds to $134 in 2010 Canadian dollars) is associated with 0.01% higher employment at entry and 0.05% higher cumulative growth by the tenth year. This relationship is similarly persistent, remaining positive throughout a ten-year horizon and gradually increasing for most of the estimation horizons.

Figure 2: Founder human capital and firm heterogeneity

A. Firms with serial founders: average profits of founders' past firms

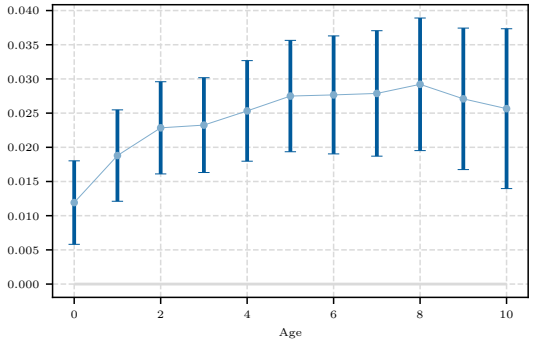


(a) Employment level

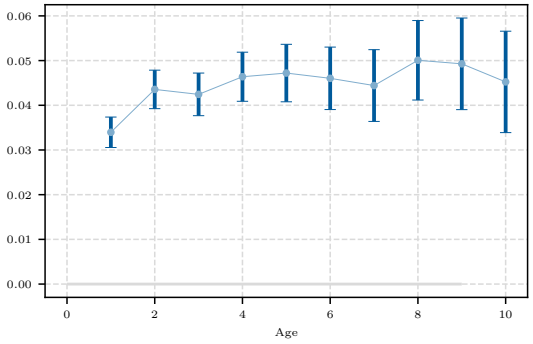


(b) Employment growth

B. Firms with only novice founders: average employment income of founders



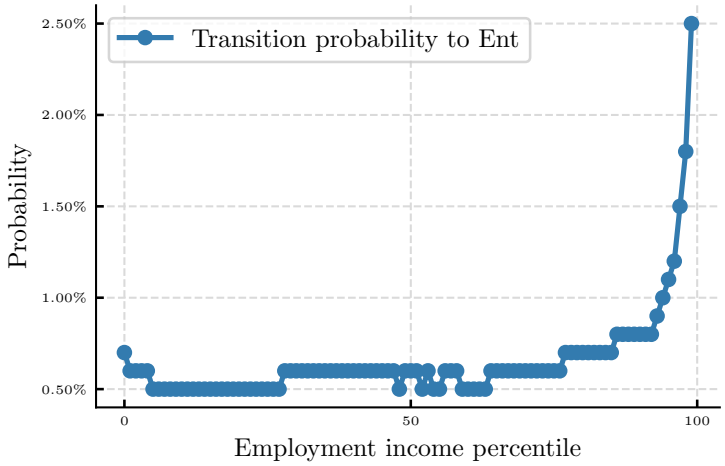
(c) Employment Level



(d) Employment Growth

Notes: Panel (a) reports, for firms with serial founders, β_h of firm j for h years after the creation, estimated from the local projections $\log s_{jh} = \delta_{ts} + \beta_h \log \bar{\Pi}_{jt-1} + \Gamma' Z_j + \varepsilon_{jh}$, where s_{jh} denotes firm employment; δ_{ts} is a firm-founding-year-by-sector fixed effect (sectors measured at the 4-digit NAICS level); $\log \bar{\Pi}_{jt-1}$ denotes lagged average profits from all firms previously owned by the founders of firm j; Z_j is a vector of firm controls that include the average age of the founders, the number of founders, and their average wealth one year prior to founding; and ε_{ih} is a random error. Panel (b) reports, for firms with serial founders, β_h from estimating $\Delta_h \log s_{jh} = \delta_{ts} + \beta_h \bar{\Pi}_{jt-1} + \Gamma' Z_j + \gamma \log s_{j0} + \varepsilon_{jh}$, where s_{j0} denotes firm employment at entry, and remaining variables are defined as above. Panel (c) reports, for firms with only novice founders, β_h of firm j for h years after the creation, estimated from the local projections $\log s_{jh} = \delta_{ts} + \beta_h \log \bar{w}_{jt-1} + \Gamma' Z_j + \varepsilon_{jh}$, where s_{jh} denotes firm employment; δ_{ts} is a firm-founding-year-by-sector fixed effect (sectors measured at the 4-digit NAICS level); $\log \bar{w}_{jt-1}$ denotes lagged average employment income of founders of firm j; Z_j is a vector of firm controls that include the average age of the founders, the number of founders, and their average wealth one year prior to founding; and ε_{ih} is a random error. Panel (d) reports, for firms with only novice founders, β_h from estimating $\Delta_h \log s_{jh} = \delta_{ts} + \beta_h \bar{w}_{jt-1} + \Gamma' Z_j + \gamma \log s_{j0} + \varepsilon_{jh}$, where s_{j0} denotes firm employment at entry, and remaining variables are defined as above. Standard errors are clustered at the firm-founding-year-by-sector level. 95% confidence intervals are reported.

Figure 3: Incidence probability of entrepreneurship by employment income



Notes: This figure reports the percentage of workers for a given employment income percentile who transition to entrepreneurship in the next year.

In addition to a positive connection between founder experience and firm scale, panels (c) and (d) also show that the working capacities of founders is positively correlated with their entrepreneurial capacities. This highlights a somewhat overlooked aspect in the design of entrepreneurial policies: productive entrepreneurs also tend to be productive workers, and so encouraging entrepreneurship comes with a nontrivial opportunity cost of lost labor.

In fact, Figure 3 highlights that at the aggregate level, as employment income rises, the average likelihood of entrepreneurship also rises. This suggests that the policies that influence the occupational choice of productive workers have macroeconomic importance — our quantitative model in Section 5, therefore, focuses on studying the forces behind this entrepreneurial selection.

4. Semi-structural Decomposition

Having documented the robust and positive relationship between founder characteristics and firm size, we now assess the extent that founders explain the "ex-ante" differences across firms. Our statistical model extends that by Sterk et al. (2021), who observe that high persistence of firm size is indicative of high levels of ex-ante heterogeneity. Our reduced-form evidence documents not only the unconditional persistence of firm size, but also the persistence of the *conditional* relationship between firm size and founder characteristics, which

points to an important role of founder characteristics in explaining ex-ante firm heterogeneity. The following analysis formalizes the intuition.

4.1. Statistical model

The objectives of the decomposition is to assess: how important is ex-ante heterogeneity; and how important are founder characteristics for ex-ante heterogeneity. We use a general statistical model that incorporates both ex-ante and ex-post firm heterogeneity.[5] Let $n_{j,a}$ denote the employment of firm j at age a. Its process is specified by

$$\log n_{i,a} = \underbrace{u_{j,a} + v_{j,a}}_{\text{ex-ante component}} + \underbrace{w_{j,a} + z_{j,a}}_{\text{ex-post component}}, \tag{5}$$

where

$$\begin{aligned}
&u_{j,a} = \rho_u u_{j,a-1} + \theta_j, && u_{j,-1} = \boldsymbol{X_j}\boldsymbol{\beta_u} + \hat{u}_{j,-1}, && \hat{u}_{j,-1} \sim \text{iid}(0, \sigma_u^2),\\
&&& \theta_j = \boldsymbol{X_j}\boldsymbol{\beta_\theta} + \hat{\theta}_{j,-1}, && \hat{\theta}_j \sim \text{iid}(0, \sigma_\theta^2),\\
&v_{j,a} = \rho_v v_{j,a-1}, && v_{j,-1} = \boldsymbol{X_j}\boldsymbol{\beta_v} + \hat{v}_{j,-1}, && \hat{v}_{j,-1} \sim \text{iid}(0, \sigma_v^2),\\
&w_{j,a} = \rho_w w_{j,a-1} + \varepsilon_{j,a}, && w_{j,-1} = 0, && \varepsilon_{j,a} \sim \text{iid}(0, \sigma_\varepsilon^2),\\
&z_{j,a} \sim \text{iid}(0, \sigma_z^2), &&&&
\end{aligned}$$

and persistence is assumed to be $|\rho_u| \leq 1$, $|\rho_v| \leq 1$, and $|\rho_w| \leq 1$. $\boldsymbol{X_j}$ denotes a vector of observable founder characteristics, assumed to be orthogonal to the unobservable shocks, $(\hat{\theta}_j, \hat{u}_j, \hat{v}_j)$, and shocks related to ex-post heterogeneity, (ε_j, z_{ia}). All shocks are drawn from distributions which are i.i.d. across time and across firms.

The ex-ante component, $u_{j,a} + v_{j,a}$, is driven by three key variables: $u_{j,-1}$ and $v_{j,-1}$ capture differences across firms at entry that diminish to zero over the life cycle; and θ_j captures permanent differences across firms that are present at entry. Motivated by our findings in Section 3, we allow these variables to depend on observable founder characteristics, $\boldsymbol{X_j}$, in addition to unobserved shocks, $(\hat{\theta}_j, \hat{u}_j, \hat{v}_j)$.

[5] The statistical model nests common models of firm dynamics. For instance, setting $\rho_u = \rho_v = \rho_w = 0$, $\theta_i = \mu_\theta$, and $u_{i,-1} = z_{ia} = 0$ yields Hopenhayn and Rogerson (1993); and setting $\rho_u = 0$, $u_{i,-1} = v_{i,-1} = z_{ia} = \varepsilon_{ia} = 0$.

The ex-post component, $w_{j,a} + z_{j,a}$, consists of a persistent shock ($w_{j,a}$) and a transitory shock ($z_{j,a}$). To differentiate from the ex-ante component, the expected profile of the ex-post component is zero and flat.

4.2. Estimation

We estimate the model using generalized methods of moments (GMM), targeting two sets of moments: the first being regression coefficients, $\hat{\beta}_a$, from projecting firm employment at each age to founder characteristics, which helps to identify $\boldsymbol{\beta_u}$, $\boldsymbol{\beta_\theta}$, and $\boldsymbol{\beta_v}$; and the second being the auto-covariance structure, $\mathbb{C}ov(\hat{n}_{j,a}, \hat{n}_{i,a+\Delta a})$, which helps to identify ρ_u, ρ_v, ρ_w, $\sigma_{\hat{u}}$, $\sigma_{\hat{v}}$, $\sigma_{\hat{\theta}}$, σ_ϵ, and σ_z. Appendix Section C details their analytical expressions and derivations.

For their empirical counterparts, we use the regression coefficients estimated from a variant of the local projection in Section 3 and the auto-covariances of log employment between the age 0 and 10 of new firms in our sample. In the local projection, we include the six variables that measure founder characteristics aggregated at the firm level. These consist of the three explanatory variables used in our baseline (the serial entrepreneur indicator, log average profits of founders' previous businesses, and log average employment income of founders) and the three control variables (average founder age, the number of founders, and log average wealth of founders).[6]

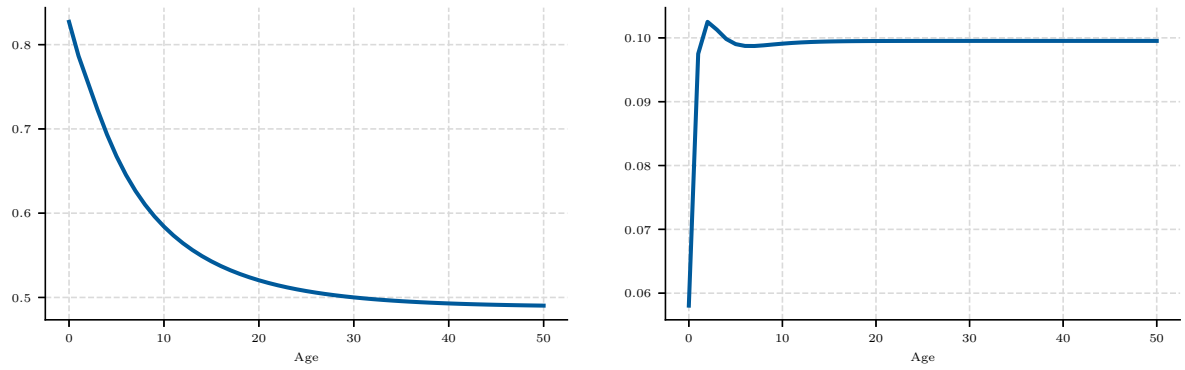
The estimated coefficients are reported in Appendix Table C.1. Appendix Figure C.1 reports the fit of the estimation. The top panel compares the model-generated regression coefficients in red with empirical regression coefficients in blue. All model moments fall within 95% confidence intervals of the empirical estimates which suggest a good fit of the estimation. Similarly, the bottom panel compares the model and empirical auto-covariance profiles of the unobserved factors, which suggests the estimation provide good fit both in terms of both the shape and the levels.

4.3. Decomposition

We use the estimated model to compute the importance of ex-ante heterogeneity and the importance of founder factors for ex-ante heterogeneity. Since the size of a firm at a given

[6]To include the full sample of new firms in the estimation, the empirical specification here slightly differs from equation (1) in Section 3. Missing observations are populated with 0, with a separate indicator variable for each explanatory variable that equal 1 if the observation is missing and 0 otherwise.

Figure 4: Variance decomposition and sources of ex-ante heterogeneity



(a) Ex-ante vs. overall heterogeneity **(b)** Founder factors vs. ex-ante heterogeneity

Notes: Panel (a) reports the the share of total firm heterogeneity that can be accounted for by ex-ante heterogeneity, computed as the first two terms in (6) as a fraction of the total variance. Panel (b) reports the share of ex-ante heterogeneity that are accounted for the six observable founder factors, computed as the first term in (6) as a share of the sum of the first two terms.

age is determined by observed factors related to founders, $\boldsymbol{X_j}$, and remaining unobserved factors that are orthogonal to founder factors, denoted $\hat{n}_{j,a}$, the total cross-sectional variance in firm size in an age cohort a can be expressed as

$$\begin{aligned}\mathbb{V}\text{ar}\left(\log n_{j,a}\right) &= \underbrace{\mathbb{V}\text{ar}\left(\boldsymbol{X_j}\hat{\boldsymbol{\beta}}_{\boldsymbol{a}}\right)}_{\text{observed}} + \underbrace{\mathbb{V}\text{ar}\left(\hat{n}_{j,a}\right)}_{\text{unobserved}} \\ &= \underbrace{\mathbb{V}\text{ar}\left(\boldsymbol{X_j}\hat{\boldsymbol{\beta}}_{\boldsymbol{a}}\right)}_{\text{observed}} + \underbrace{\sigma^2_{\hat{u}}\rho_u^{2(a+1)} + \sigma^2_{\hat{\theta}}\left(\frac{1-\rho_u^{a+1}}{1-\rho_u}\right)^2 + \sigma^2_{\hat{v}}\rho_v^{2(a+1)}}_{\text{unobserved: ex-ante}} + \underbrace{\sigma_\varepsilon \frac{1-\rho_w^{2(a+1)}}{1-\rho_w^2} + \sigma_z^2}_{\text{unobserved: ex-post}}\end{aligned} \tag{6}$$

where the second equality further separates the unobserved components into those driven by ex-ante shocks and those driven by ex-post shocks.[7]

Figure 4 decomposes the sources of firm heterogeneity for each firm age. Panel (a) reports the the share of total firm heterogeneity that can be accounted for by ex-ante heterogeneity, computed as the first two terms in (6) as a fraction of the total variance. At entry, ex-ante factors account for more than 80% of the total variation in firm size. As firms mature, the importance of transitory ex-ante factors diminishes, but the ex-ante factors

[7] Appendix Section C contains the derivation.

shaping the permanent differences across firms remain important. At the steady state, ex-ante heterogeneity accounts for approximately half of overall firm heterogeneity in Canada, consistent with the US evidence on the substantial ex-ante differences across firms (Sterk et al., 2021).

Panel (b) in Figure 4 reports the share of ex-ante heterogeneity that are accounted for the six observable founder factors, computed as the first term in (6) as a share of the sum of the first two terms. We find that founder factors are indeed empirically important: in the steady state, the six observed founder factors account for approximately 10% of the total ex-ante heterogeneity.

Our empirical results from reduced-form evidence and semi-structural estimation jointly present a coherent picture that conditional on starting a firm, founders' human capital is highly related to the performance of firms that they create. In particular, past employment income of founders predicts entrepreneurial success, implying a tradeoff between working productivity and entrepreneurial productivity.

In the next section, we evaluate the aggregate implications of entrepreneurial policy that shapes the incentives for entrepreneurship. The quantitative model focuses on the extensive margin on the selection into entrepreneurship, complementing the intensive margin that the empirical analysis has thus far focused on.

5. Quantitative Model

We study the selection into entrepreneurship through the lens of a span-of-control model (Lucas, 1978). It contains three key elements. First, motivated by our empirical findings, we allow households' working and entrepreneurial capacities to be correlated. Second, entrepreneurs operate their firms subject to financial frictions. Third, to understand how entrepreneurial selection interacts with financial frictions and entrepreneurial policy, we incorporate both ex-ante and ex-post firm heterogeneity.

5.1. Model environment

Time is discrete and infinite. There is no aggregate uncertainty. The economy consists of a continuum of households and firms. Households have heterogeneous working and en-

trepreneurial capacities and access to a one-period risk-free bond. They make occupational choices between workers and entrepreneurs, for which payoffs depend on the working and entrepreneurial capacities, respectively.

Firms, created and owned by entrepreneurs, produce the final good with capital and labor as inputs, taking the goods price and wage as given. The production technology features both ex-ante and ex-post heterogeneity in productivity, with the ex-ante heterogeneity determined by the founder's entrepreneurial capacity. Entrepreneurs finance the firm's working capital with wealth and borrowing and are subject to a capital-based borrowing constraint.

We consider a small open economy with a fixed interest rate and the wage endogenously determined by the labor market clearing condition.[8]

5.1.1. Households

Households maximize lifetime utility over consumption, $\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t)$, where $\beta \in (0,1)$ is the discount rate and $u(\cdot)$ is strictly increasing and concave. They make the occupational choice between becoming a worker or a entrepreneur. Households are heterogeneous in the working capacity, e_t, and the entrepreneurial capacity, z_t, which follow a joint AR(1) process

$$\begin{bmatrix} \log e_{t+1} \\ \log z_{t+1} \end{bmatrix} = \begin{bmatrix} \mu_e \\ \mu_z \end{bmatrix} + \begin{bmatrix} \rho_e & 0 \\ 0 & \rho_z \end{bmatrix} \begin{bmatrix} \log e_t \\ \log z_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{e,t+1} \\ \varepsilon_{z,t+1} \end{bmatrix}. \tag{7}$$

Motivated by our empirical findings on the correlation between employment income and entrepreneurial performance, we allow e_t and z_t to be correlated:

$$\begin{bmatrix} \varepsilon_{e,t+1} \\ \varepsilon_{z,t+1} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_e^2 & \rho_{ez}\,\sigma_e\sigma_z \\ \rho_{ez}\,\sigma_e\sigma_z & \sigma_z^2 \end{bmatrix} \right). \tag{8}$$

Financial markets are incomplete. Workers have access to saving through a one-period risk-free bond with the interest rate r, but are excluded from borrowing. Their wealth, $a_{i,t}$, evolves according to

$$a_{i,t+1} = (1+r) \cdot a_{i,t} + w_t e_{i,t} - c_{i,t},$$

[8] We focus on the labor market to study the allocation of human capital, the focus of our model.

where $w_t e_{i,t}$ represents the labor income, and they face the borrowing constraint

$$a_{i,t+1} \geq 0.$$

Entrepreneurs have the option to finance the firm's working capital k_{it} through wealth $a_{i,t}$ or borrowing $b_{i,t}$ units of one-period risk-free bonds at the rate r, so that

$$k_{i,t} = b_{i,t} + a_{i,t}.$$

However, they are subject to a borrowing constraint that depends on the net worth of the firm

$$(1 + r) \cdot b_{i,t} \leq \lambda(1 - \delta)k_{i,t} \tag{9}$$

where $\lambda < 1$ is a parameter that governs the degree of financial frictions. The wealth of entrepreneurs evolve according to

$$a_{i,t+1} = (1 - \delta)k_{i,t} - (1 + r)b_{i,t} + y_{i,t} - w_t l_{i,t} - c_{i,t}.$$

Lastly, households exit the economy with $\pi_d \in (0, 1)$ probability in each period.

5.1.2. Firms

Firms are owned and managed by entrepreneurs. They produce a final good and take the output price as given. The production function of a firm managed by entrepreneur i is

$$y_{i,t} = (\eta_{i,t} z_{i,t}) \cdot (k_{i,t}^{\alpha} \cdot l_{i,t}^{1-\alpha})^{\theta},$$

where $k_{i,a}$ and $l_{i,a}$ denote capital and labor inputs, respectively. $z_{i,t}$ is the ex-ante heterogeneity in firm productivity determined by the founder's entrepreneurial capacity drawn from the process specified in (7). Once a worker transitions into entrepreneurship, we assume that their entrepreneurial capacity stays fixed at $z_{i,t}$ for the life cycle of this entrepreneurial spell. In addition to the ex-ante heterogeneity, firms also face ex-post idiosyncratic productivity

shocks $\eta_{i,t}$, which evolves according to a log AR(1) process

$$\log \eta_{i,t+1} = \mu_\eta + \rho_\eta \log \eta_{i,t} + \varepsilon_{i,\eta,t+1}, \quad \text{where } \varepsilon_{\eta,i,t+1} \sim \mathcal{N}(0, \sigma_\eta^2).$$

At entry when a worker switches into entrepreneurship and create a new firm, the initial η is drawn from the initial distribution $\mathcal{D}_0(\eta)$. When an entrepreneur chooses to return to being a worker, the capacities (e, z) evolves according to the original AR(1) process in (7).

5.1.3. Timing

The timing in each period is as follows. First, idiosyncratic shocks to capacity (e, z) and η realize. New households who are born enter the economy as workers. Second, households make their occupation choices: those who are workers in the previous period make the choice between continuing being a worker or becoming an entrepreneur, and those who were entrepreneurs in the previous period make choices between three options: keep managing the same firm, creating a new firm, or becoming a worker. Then, firms produce and workers supply their labor. Lastly, death and exogenous firm exits occur.

We refer to households before making the occupational choices as *previous-period* workers or entrepreneurs, and households after making the choices as *current-period* workers or entrepreneurs.

5.2. Decision problems

This subsection analyzes the decision problem of workers and entrepreneurs.

5.2.1. Value function of workers

The value function of previous-period workers, who are making occupational choices in the current period, is given by

$$V_t^w(a, e, z) = \max \left\{ \underbrace{W_t^w(a, e, z) + \zeta_w}_{\text{remain a worker}}, \underbrace{EW_t^f(a, e, z) + \zeta_{nf}}_{\text{become an entrepreneur}} \right\}, \tag{10}$$

where the $W_t^w(a, e, z)$ denotes the value of continuing as a worker, and $EW_t^f(a, e, z)$ denotes the expected value of creating a new firm as an entrepreneur. ζ_w and ζ_f are i.i.d. extreme

value type I distributed with scale parameter ϑ.

The first component in (10), W^w, is the value of continuing as a worker and equals

$$\begin{aligned} W_t^w(a,e,z) = &\max_{c,a'} u(c) + \beta \cdot (1-\pi_d)\mathbb{E}_{e',z'|e,z}\left[V_{t+1}^w(a',e',z')\right] \\ \text{s.t. } & a' = (1+r)\cdot a + w\cdot e - c \\ & a' \geq 0. \end{aligned} \tag{11}$$

A worker inelastically supplies e units of labor drawn from the capacity distribution; consumes and saves through a risk-free one-period bond and is subject to a borrowing constraint.

The first component in (10), EW^f, is the expected value of becoming an entrepreneur and equals

$$EW_t^f(a,e,z) = \mathbb{E}_{\eta\sim\mathcal{D}_0(\eta)}\left[W_{t+1}^f(a,e,z,\eta)\right], \tag{12}$$

where $W^f(a,e,z,\eta)$ is the value function of entrepreneurs operating a new firm with idiosyncratic productivity η. This value is given by

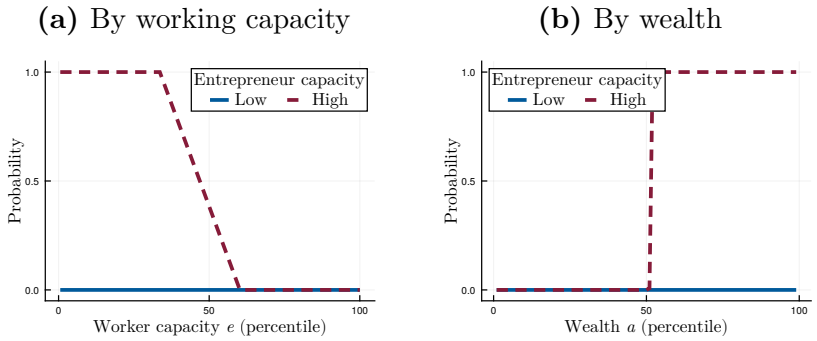
$$\begin{aligned} W_t^f(a,e,z,\eta) = &\max_{c,a',k,l} u(c) + \beta(1-\pi_d)\mathbb{E}_{e',z',\eta'|e,z,\eta}\left[V_{t+1}^f(a',e,z,\eta')\right] \\ \text{s.t. } & a' = (1+r)a - (\delta+r)k + (\eta z)(k^\alpha l^{1-\alpha})^\theta - wl - c \\ & k \leq \frac{a}{1-\lambda\frac{(1-\delta)}{(1+r)}} \\ & a' \geq 0. \end{aligned} \tag{13}$$

Entrepreneurs finance their firms' capital using wealth and borrowing from a risk-free one-period bond. They face a borrowing constraint specified in (9). Their wealth evolves as unappreciated capital plus firm profits minus borrowing and interest repayment.

5.2.2. Policy function of workers

Before discussing our calibration strategy, we first discuss the policy functions of agents in our model. Figure 5 plots the occupational choice of workers, reporting the probability that a worker of a given type chooses to become an entrepreneur.

Figure 5: Occupational choice of workers: Transition probability to entrepreneurs



Notes: Panel (a) plots the transition probability into entrepreneurs of workers with median-level wealth. The dashed red line represents workers with high entrepreneurial capacity (75th percentile of z), and the solid blue line represents workers with low entrepreneurial capacity (25th percentile of z). Panel (b) plots the transition probability into entrepreneurs of workers with median-level working capacity. The dashed red line represents workers with high entrepreneurial capacity (75th percentile of e), and the solid blue line represents workers with low entrepreneurial capacity (25th percentile of e).

In panel (a), the dashed red line shows that the probability of workers to become entrepreneurs decreases with their working capacity. As the working capacity rises, the opportunity cost of entrepreneurship also rises because of workers will have to forgo higher wage income. The blue line shows that the decision is trivial for workers with low entrepreneurial capacity, who will never enter entrepreneurship since their firms are unlikely to be profitable.

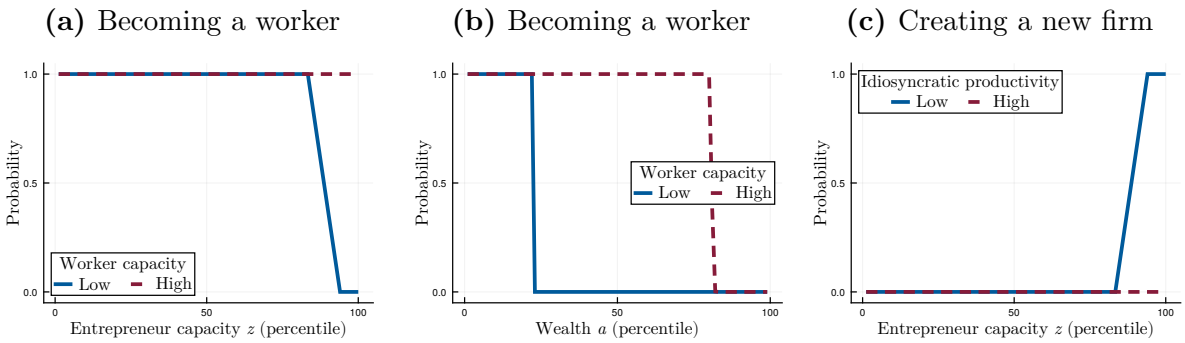
Panel (b) demonstrates how financial frictions affect the workers' occupational choice. Even among workers with high entrepreneurial capacity, represented by the dashed red line, those who do not possess sufficient wealth do not choose to pursue entrepreneurship because of the financial frictions.

5.2.3. Value function of entrepreneurs

Now, we turn to the decision problem of previous-period entrepreneurs, who are making the occupational choices in the current period. Their value function is

$$V_t^f(a,e,z,\eta) = \max\left\{ \underbrace{W_t^f(a,e,z,\eta)+\zeta_f}_{\text{continue managing current firm}}, \underbrace{EW_t^f(a,e,z)+\zeta_{nf}}_{\text{create new firm}}, \underbrace{EW_t^w(a,e,z)+\zeta_w}_{\text{become a worker}} \right\} \tag{14}$$

Figure 6: Occupational choice of entrepreneurs



Notes: Panel (a) plots the transition probability into workers of entrepreneurs with median-level wealth. The dashed red line represents workers with high working capacity (75th percentile of z), and the solid blue line represents workers with low working capacity (25th percentile of z). Panel (b) plots the transition probability into workers of entrepreneurs with median-level entrepreneurial capacity. The dashed red line represents workers with high working capacity (75th percentile of e), and the solid blue line represents workers with low working capacity (25th percentile of e). Panel (c) plots the transition probability into creating a new firm of entrepreneurs with median-level wealth and capacities. The dashed red line represents entrepreneurs with high idiosyncratic productivity (75th percentile of η), and the solid blue line represents workers with low idiosyncratic productivity (25th percentile of η).

where $W^f(a, e, z, \eta)$, as in (13), denotes the value of continuing managing the current firm; $EW^f(a, e, z)$, as in (12), denotes the expected value of operating a new firm as an entrepreneur; and $EW^w(a, e, z)$ denotes the expected value of becoming a worker and equals

$$EW_t^w(a, e, z) = \mathbb{E}_{e', z'|e,z}\left[V_{t+1}^w(a, e', z')\right], \tag{15}$$

where the joint distribution of (e', z') conditional on (e, z) is assumed to follow the joint AR(1) process specified in (7).

5.2.4. Policy function of entrepreneurs

Figure 6 demonstrates the policy function of entrepreneurs. Panel (a) shows that the probability of an entrepreneurs to transition back to working decreases with their entrepreneurial capacity. When the entrepreneurial capacity is high, the ex-ante productivity of the entrepreneur's firm is high, making it more likely to exceed the wage that the entrepreneur would earn as a worker.

Panel (b) demonstrates how financial frictions affect the occupational choice of entrepreneurs. When the wealth is low and the borrowing constraint binds, entrepreneurs

choose to close the firm and return to working. Among entrepreneurs with identical entrepreneurial capacity, those with higher working capacity requires a higher wealth threshold to remain in entrepreneurship because the outside option of simply earning high wage income is attractive.

Panel (c) reports the transition probability of an entrepreneur to close the current firm and create a new firm. The blue line shows that for entrepreneurs who have high entrepreneurial capacity, but are unlucky in the draw of the ex-post idiosyncratic productivity, η, it is attractive for them to create a new firm.

5.3. Equilibrium

The equilibrium is a collection of aggregate prices $\{w_t\}$, distribution of acting workers and entrepreneurs $\{\mathcal{D}_t^w(e,z,a), \mathcal{D}_t^f(e,z,a,\eta)\}$, value functions $\{V_t^w(a,e,z),\ V_t^f(a,e,z,\eta)\}$, and policy functions of workers and entrepreneurs $\{\mathbf{p}_t^{w,\ w}(a,e,z), \mathbf{p}_t^{w,\ f}(a,e,z),\ \mathbf{c}_t^w(a,e,z),\ \mathbf{a}_t'^w(a,e,z)\}$ and $\{\mathbf{p}_t^{f,\ f}(a,e,z,\eta),\ \mathbf{p}_t^{f,\ nf}(a,e,z,\eta), \mathbf{c}_t^f(a,e,z,\eta),\ \mathbf{a}_t'^w(a,e,z,\eta), \mathbf{l}_t^f(a,e,z,\eta), \mathbf{k}_t^f(a,e,z,\eta), \mathbf{b}_t^f(a,e,z,\eta)\}$, such that:

1. given the path of aggregate wage $\{w_t\}$, the policy functions and value functions solve the workers and entrepreneurs' decision problem specified in (10) and (14), respectively;

2. given the policy functions, the distribution of current-period workers and entrepreneurs evolves as:

$$\begin{aligned}
\mathcal{D}_t^w(a,e,z) =& \mathbf{p}_t^{w,\ w}(a,e,z) \times \left[\hat{\mathcal{D}}_t^w(a,e,z) + \pi_d \cdot \mathcal{D}^{\text{entrant}}(a,e,z)\right] + \\
& \int \mathbf{p}_t^{f,\ w}(a,e,z,\eta) \times \hat{\mathcal{D}}_t^f(a,e,z,\eta) da de dz d\eta \\
\mathcal{D}_t^f(a,e,z,\eta) =& \mathbf{p}_t^{w,\ f}(a,e,z) \times \left[\hat{\mathcal{D}}_t^w(a,e,z) + \pi_d \cdot \mathcal{D}^{\text{entrant}}(a,e,z)\right] + \\
& \int \mathbf{p}_t^{f,\ f}(a,e,z,\eta) \times \hat{\mathcal{D}}_t^f(a,e,z,\eta) da de dz d\eta + \\
& \mathcal{D}_0(\eta) \int \mathbf{p}_t^{f,\ nf}(a,e,z,\tilde{\eta}) \times \hat{\mathcal{D}}_t^f(a,e,z,\tilde{\eta}) da de dz d\tilde{\eta}
\end{aligned}$$

Table 3: Calibrated parameters

(a) Calibrated parameter values

Externally Calibrated Parameter		Value
β	Discount factor	0.96
r	Risk-free interest rate	0.04
δ	Depreciation rate	0.10
π_d	Exogenous exit probability	1/43
α	Capital share	0.30
θ	Returns to scale	0.85
ϑ	Scale of taste shocks	0.01
Internally Calibrated Parameter		**Value**
Financial friction		
λ	Borrowing limit	0.90
Ex-post productivity process		
ρ_η	Persistence	0.52
σ_η	Std. dev. of innovations	0.10
Working and entrepreneurial capacity process		
ρ_e	Working capacity, persistence	0.85
σ_e	—, Std. dev. of innovations	0.32
ρ_z	Entrepreneurial capacity, persistence	0.83
σ_z	—, Std. dev. of innovations	0.03
ρ_{ez}	Correlation between the two capacities	0.78

(b) Target moments used in calibration

Moment	Data	Model
Firms' financing		
Average leverage ratio	0.35	0.36
Within-firm variation of log-revenue		
Autocorrelation	0.52	0.52
Standard deviation	0.83	0.83
Dynamics of workers' log-income		
Autocorrelation	0.85	0.85
Standard deviation	0.61	0.61
Selection into entrepreneurship		
Share of entrepreneurs in population	10%	9%
Worker-to-entrepreneur transition rate, average	0.7%	0.4%
—, workers with top 1% income	2.5%	2.8%

where the distribution of surviving previous-period workers and entrepreneurs is

$$\hat{\mathcal{D}}_t^w(a,e,z) \equiv (1-\pi_d)\int \Gamma(e,z|e^-,z^-)\mathbb{1}[\mathbf{a}'^w_{t-1}(a^-,e^-,z^-)=a]\cdot\mathcal{D}^w_{t-1}(a^-,e^-,z^-)da^-de^-dz^-$$

$$\hat{\mathcal{D}}_t^f(a,e,z,\eta) \equiv (1-\pi_d)\int \Gamma(\eta|\eta^-)\mathbb{1}[\mathbf{a}'^f_{t-1}(a^-,e^-,z^-,\eta^-)=a]\mathcal{D}^f_{t-1}(a^-,e^-,z^-,\eta^-)da^-de^-dz^-d\eta^-$$

3. given the distribution and the policy functions, the aggregate prices should clear the labor market:

$$\int e\cdot\mathcal{D}^w_t(a,e,z)dadedz = \int \mathbf{l}^f_t(a,e,z,\eta)\cdot\mathcal{D}^f_t(a,e,z,\eta)\ dadedzd\eta. \tag{16}$$

5.4. Calibration

5.4.1. Externally calibrated parameters

We assume log utility, $u(c)=\log c$, and set the discount factor to $\beta=0.96$. The risk-free interest rate is $r=4\%$ and the depreciation rate is $\delta=0.10$. Households face an exogenous exit probability of $\pi_d=1/43$, matching an average working life of 43 years in Canada[9]. The

[9]A typical Canadian worker enters the labor market at the age of 22 and retire at 65 years old.

production technology is parameterized by $\alpha = 0.3$ and $\theta = 0.85$. Finally, we set the scale of the i.i.d. extreme-value preference shocks to $\vartheta = 0.01$, which is small enough to have negligible effects on model outcomes while ensuring numerical smoothness. The top panel of Table 3a summarizes the parameter values.

5.4.2. Internally calibrated parameters

We calibrate the remaining parameters internally by matching a set of empirical moments that discipline the model's key mechanisms. The calibrated parameters are reported in the bottom panel of Table 3a, and the targeted moments are reported in Table 3b.

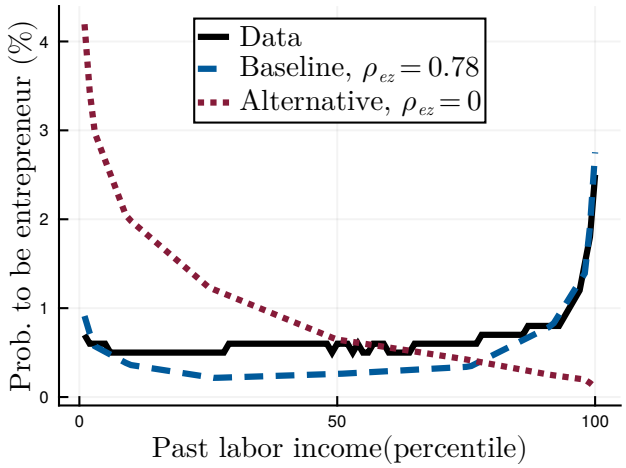
The borrowing-limit parameter λ is chosen to match the average leverage ratio reported in Kermani and Ma (2022). The ex-post productivity process (ρ_η, σ_η) governs ex-post firm heterogeneity, and we set these parameters to match the persistence and volatility of log firm revenues after removing firm fixed effects. On the household side, we discipline the working-capacity process (ρ_e, σ_e) using the persistence and volatility of workers' employment income. We then choose the entrepreneurial-capacity parameters to match key moments of entrepreneurial selection: we set σ_z to match the share of entrepreneurs in the population and ρ_z to match the average worker-to-entrepreneur transition rate.

A key parameter in our calibration is the correlation between working and entrepreneurial capacities, ρ_{ez}. As shown in Figure 7, this correlation is central for generating the empirical selection schedule into entrepreneurship conditional on workers' previous employment income. In the data, the probability of entry rises with prior employment income, particularly among top earners. When ρ_{ez} is low, the model predicts a selection schedule that is nearly flat or even declining in income. We therefore calibrate ρ_{ez} to match the worker-to-entrepreneur transition probability among individuals in the top 1% of the income distribution.

6. Ex-ante Heterogeneity, Entrepreneurial Selection, and the Costs of Financial Frictions

As in Lucas (1978) and Hopenhayn (1992), the competitive equilibrium without any frictions will be efficient. However, the presence financial frictions creates distortions that tend to disproportionally affect new entrants. In this section, we use our calibrated model to

Figure 7: The role of ρ_{ez} in shaping the selection of entrepreneurship



Notes: This figure reports the relationship between selection incidence probability into entrepreneurship and past employment income for two different calibrations of ρ_{ez}. The dashed blue line reports the relationship under the baseline calibration of $\rho_{ez} = 0.78$. The dashed red line reports the relationship under an laternative calibration of $\rho_{ez} = 0$. The empirical relationship from Figure 3 is repeated in solid black line.

examine how the interaction between the underlying talent distribution and the selection of entrepreneurship shapes the costs of financial frictions. Finally, we evaluate the aggregate consequences on business dynamism and long-run growth.

Table 4 presents the steady-state aggregate outcomes across four counterfactual economies, where the third economy represents the baseline model discussed in Section 5. By comparing the first two economies, we isolate the effects of the talent distribution while muting financial frictions. A comparison of the first and third economies reveals the impact of financial frictions while holding the underlying talent distribution constant. Finally, the comparison between the last two economies captures the interaction between financial frictions and the talent distribution.

6.1. The distribution of talent and the entrepreneurial selection

The first two rows of Table 4 quantify the importance of the talent distribution. As a benchmark, the first row reports a frictionless economy ($\lambda = \infty$) with all other parameters held constant. We report the steady-state levels of aggregate output, capital, labor, wage, the share of entrepreneurs, and TFP, where the latter is calculated as the geometric mean of firm productivity, which includes both the ex-ante and ex-post components.

In the second row, we compare this benchmark to an alternative frictionless economy

Table 4: Aggregate outcomes in counterfactual economics

	Financial Frictions	Correlated Capacities	Output	Capital	Labor	Wage	Ent Share	TFP
1	No	Yes	0.932	1.698	0.874	0.635	0.117	0.883
2	No	No	+3.61%	+3.61%	−0.84%	+4.45%	+3.07%	+3.19%
3	Yes	Yes	−6.14%	−9.89%	+2.61%	−8.75%	−2.31%	−5.17%
4	Yes	No	−3.42%	−7.61%	+2.23%	−5.64%	−0.16%	−2.80%

Notes: This table reports the steady-state aggregate outcomes for four counterfactual economies. Aggregate outcomes include aggregate output, capital, labor, wage, the share of entrepreneurs, and TFP, where the latter is calculated as the geometric mean of firm productivity. The aggregate outcomes in the benchmark economy in the first row with no financial frictions ($\lambda = \infty$) and correlated capacities ($\rho_{ez} = 0.78$) is reported in levels. The steady-state aggregate variables in the remaining economies are reported as percentage differences compared to their counterparts in the benchmark economy. The levels of the steady-state values are reported in Appendix Table D.1

where working capacity is uncorrelated with entrepreneurial capacity ($\rho_{e,z} = 0$). The results, except for entrepreneur share, are presented as percentage deviations from the benchmark.

At the micro level, two mutually reinforcing forces lead to a higher entrepreneur share. First, high-entrepreneurial-capacity households are more likely to enter entrepreneurship because a high entrepreneurial capacity no longer implies a high alternative wage income. Second, low-labor-productivity households are more likely to enter entrepreneurship, since they are no longer hindered by low entrepreneurial productivity. Because the occupational choice is mutually exclusive (i.e., creating a firm necessitates the loss of a worker), the zero-correlation structure reduces the likelihood of "sacrificing" a highly productive worker to gain an entrepreneur. This improved dynamism results in a steady-state output that is 3.6% higher than in the benchmark economy characterized by positive talent correlation.

The comparison between these two economies highlight the aggregate importance of the talent distribution. As documented in Section 3, talent tends to be concentrated: a productive entrepreneur is often a productive worker. This concentration imposes a high opportunity cost on the economy, which is alleviated when the correlation is muted.

6.2. The costs of financial frictions

Holding the talent distribution constant, we compare the first and third economies in Table 4 to quantify the costs of financial frictions. These costs are substantial: output falls by 6%

lower and aggregate TFP by 5% compared to the frictionless benchmark.

Financial frictions slow growth and productivity through three channels. Within operating firms, these frictions act as a drag on capital accumulation, slowing the transition toward an optimal scale of production. For potential entrants, financial constraints force high-entrepreneurial-capacity households to delay business creation in favor of wage labor, as they must first accumulate sufficient wealth to finance initial capital. Finally, these frictions induce talented entrepreneurs to exit the market prematurely following unfavorable idiosyncratic shocks because of an inability to finance the working capital.

It should be noted that while our model accounts for general equilibrium in the labor market, we abstract from it in the goods market. This is a reasonable assumption for a small open economy like Canada, though it implies the existence of potential moderating forces not captured here.

6.3. The interaction between the talent distribution and financial frictions

Finally, we quantify how the aggregate costs of financial frictions depend on the underlying talent distribution. To do so, we use a "difference-in-differences" approach across the four economies presented in Table 4, comparing the costs of financial frictions under a positively correlated talent distribution (Economy 1 vs. Economy 3) against those under an uncorrelated distribution (Economy 2 vs. Economy 4). This comparison allows us to isolate how the talent distribution either amplifies or mutes the macroeconomic costs of financial frictions. To facilitate the comparison, we report the levels of the aggregate outcomes in Appendix Table D.1.

For economies with positively correlated working and entrepreneurial capacities (our baseline), financial frictions reduce aggregate output by 6.1% and TFP by 5.2%. These costs are higher for economics with uncorrelated capacities: financial frictions reduce output by 6.7% and TFP by 5.8% respectively.

Why do the costs of financial frictions vary? The difference arise because talent is rivaled: an individual must choose to be either a wage worker or an entrepreneur. Financial frictions distort this selection by delaying the transition into entrepreneurship. In an economy where talent is positively correlated, these distortions are partially mitigated: although a constrained individual may be prevented from founding a high-productivity firm, they remain

a highly productive worker and contribute to aggregate output. Therefore, the concentration of talent serves to moderate the aggregate costs of financial frictions.

This interaction suggests that for entrepreneurial policies to effectively support small businesses, they must be designed with a precise understanding of the underlying talent distribution.

7. Conclusion

This paper demonstrates that entrepreneurs shape the pre-determined differences between firms that persist throughout their life cycles. Because of this ex-ante heterogeneity, attracting high-talent individuals to creating new businesses is essential for long-run dynamism and growth.

However, entrepreneurial policies face a fundamental trade-off: every new entrepreneur is a lost productive worker. Our analysis shows that the macroeconomic impact of entrepreneurship hinges on the concentration of talent. This yields two key policy insights. First, size-based incentives are often sub-optimal because they fail to target firms with high growth potential. Second, as the correlation between multi-dimensional talents increases, the aggregate costs of early-stage financial frictions decrease. Ultimately, mapping the distribution of talent is critical for designing optimal entrepreneurial policy.

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Online Appendices

A. Data Description

A.1. Variable construction

A.2. Measure of wealth

We use the Survey of Financial Security, produced by Statistics Canada, to estimate and control for household wealth, as described in Section 2. Throughout, we use waves of the SFS that overlap with our CEEDD sample. Wealth is defined as the sum of assets (deposits, stocks and shares, mutual funds, registered savings accounts and real estate) and subtract debts (mortgages, lines of credit, credit cards, auto loans, student loans and installment debt). The variables from the CEEDD used for wealth imputation include: age; family and individual total income (both pre- and post- taxes and benefits); investment and interest income; capital gains income; province of residence; and year. We censor wealth to be at least $1 for households.

Our imputation methodology uses a population-weighted regression to predict the wealth of an individual. We do so following a 'correlation approach' similar to Bricker et al. (2021), Ganong et al. (2020) and Gauthier (2025). Our results are robust to both different specifications and predictive models.[10] We first estimate the regression

$$\log w_{it} = \alpha + \delta_{it} + \boldsymbol{\beta}' \boldsymbol{X_{it}} + \varepsilon_{it}, \tag{17}$$

where α is a constant, δ_{it} is an indicator variable for the year of observation of i, and X_{it} is a vector of individual-level variables, containing transformations of the aforementioned

[10] Our method is close to, and informed by, Statistics Canada's enhancement of SFS tail wealth inequality estimates with inference from income tax data in Gauthier (2025); Ganong et al. (2020)'s inference of total liquid wealth; and the flexible 'correlation' method preferred by Bricker et al. (2021) to augment the U.S. Survey of Consumer Finances. It is also closely related to the stricter capitalization methods seen in, for example, Saez and Zucman (2016) and to Bricker et al. (2016)'s reconciliation of wealth surveys and capitalized administrative income tax data.

variables.[11] Then, the wealth of i in year t is predicted as

$$\log \hat{w}_{it} = \hat{\alpha} + \hat{\delta}_t + \hat{\boldsymbol{\beta}}' \boldsymbol{X_{it}}, \tag{18}$$

where the year effect $\hat{\delta}_t$ is interpolated with a polynomial for non-survey years in the CEEDD.

The imputation methodology has a high regression fit, with R^2 of 0.44. Compared to using income group alone to infer wealth, the imputation methodology delivers substantial improvements in wealth prediction: 26% are correctly classified into respective wealth deciles, with 58% correct or in an adjoining decile (44% are classified in the correct quintile). For comparison, using income group alone to infer wealth achieves 13% and 37%, respectively.

The method is especially successful in the upper tail of the wealth distribution, where entrepreneurs are more prevalent: 50% of the households in the top decile is correctly imputed into the 90-100 group, with 70% of them classified above the 80th percentile by the methodology.

[11] These individual variables include: province; indicators for age groups (5-year groups from 20 to 75, inclusive, and 75+); family income (log income, an indicator for positive income, indicators for income deciles, the interaction between income deciles and log income, and the interaction between income deciles and age groups); individual investment income including interest income (log investment income and an indicator for positive investment income); and capital gains (log capital gains, indicators for zero, non-zero, and top 5th quantile group). Most individuals enter only one wave in our sample.

B. Additional Details for the Correlational Evidence

Table B.1: Descriptive statistics on businesses and workers

(a) Businesses

	Mean	**SD**	**Median**	**5th**	**95th**
Firm age (years)	12.3	10.7	9	1	33
Number of employees	13	348.2	2.9	0.7	36.4
Assets ($000)	8499.5	1400000	218.2	9	4623.3
Revenue ($000)	2667	100000	313.4	11.9	5883.7
Number of Firms					N=1897975

(b) Workers

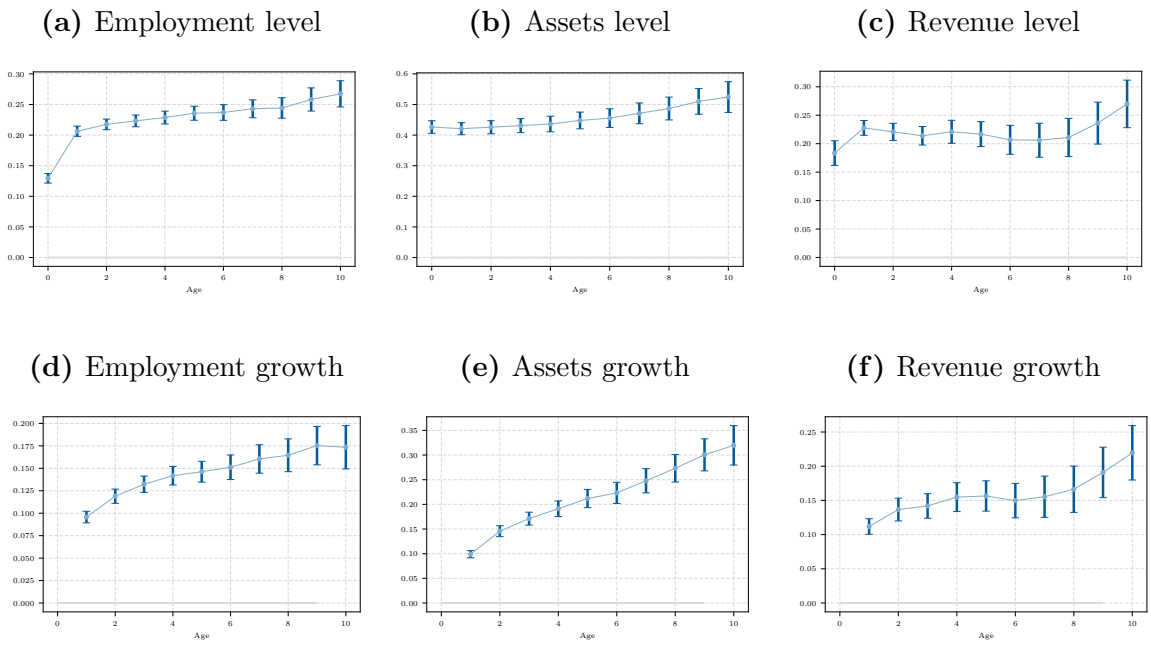
	Mean	**SD**	**Median**	**5th**	**95th**
Worker age (years)	40	13.8	40	19	62
Number of employers	1.4	0.8	1	1	3
Personal income ($000)	48.9	135.7	36.8	4.5	117.6
Personal employment income ($000)	41.6	79.2	31.5	1.8	105.7
Family income ($000)	98.7	162.9	78.5	15.6	225.8
Personal wealth ($000)	509.6	3528.5	199.6	5.4	1855.3
Number of Workers					N=26531515

Table B.2: Founder characteristics of top 1% and non-top firms: alternative size measure

	Top 1%	**Bottom 99%**	**Total**
Number of founders	1.86	1.73	1.73
	(1.36)	(0.89)	(0.89)
Average founder age	48.90	40.21	40.22
	(10.81)	(9.53)	(9.53)
Average share of founders who are serial entrepreneurs	0.78	0.22	0.22
	(0.38)	(0.37)	(0.37)
Average founder personal income ($mn)	2.06	0.09	0.09
	(5.90)	(0.35)	(0.42)
Average founder employment income ($mn)	1.23	0.07	0.07
	(2.60)	(0.24)	(0.26)
Average founder family income ($mn)	2.15	0.15	0.15
	(5.04)	(0.38)	(0.43)
Average founder wealth ($mn)	18.80	0.98	1.00
	(53.95)	(10.07)	(10.28)
Average founder AKM worker premium	1.17	0.19	0.19
	(1.20)	(0.71)	(0.71)

Notes: This table reports the average founder characteristics of the top 1%, bottom 99%, and all sample firms. Firms are ranked by real assets at year 10. Standard deviations are reported in parenthesis.

Figure B.1: Serial entrepreneurship and the initial size and subsequent growth of firms



Notes: Panels (a)–(c) report β_h of firm j for h years after the creation, estimated from the local projections $\log s_{jh} = \delta_{ts} + \beta_h \mathbb{1}(\text{Serial Ent})_j + \Gamma' Z_j + \varepsilon_{jh}$, where s_{jh} denotes firm employment in panel (a), real assets in panel (b) and real revenue in panel (c); δ_{ts} is a firm-founding-year-by-sector fixed effect (sectors measured at the 4-digit NAICS level); $\mathbb{1}(\text{Serial Ent})_j$ is an indicator variable which equals 1 if any founder of firm j is a serial entrepreneur and 0 otherwise; Z_j is a vector of firm controls that include the average age of the founders, the number of founders, and their average wealth one year prior to founding; and ε_{ih} is a random error. Panels (d)—(e) reports β_h from estimating $\Delta_h \log s_{jh} = \delta_{ts} + \beta_h \log \mathbb{1}(\text{Serial Ent})_j + \Gamma' Z_j + \gamma \log s_{j0} + \varepsilon_{jh}$, where variables are defined as above, and s_{j0} denotes firm size at entry. Standard errors are clustered at the firm-founding-year-by-sector level. 95% confidence intervals are reported.

C. Additional Details for the Structural Decomposition

This section provides details for the structural decomposition in Section 4

C.1. Derivation

The firm size process can be expressed as

$$\begin{aligned}
\log n_{j,a} =& \rho_u^{a+1} u_{j,-1} + \theta_i \cdot \frac{1-\rho_u^{a+1}}{1-\rho_u} + \rho_v^{a+1} v_{j,-1} + \sum_{\tau=0}^{a} \rho_w^{\tau} \epsilon_{j,a-\tau} + z_{j,a} \\
=& x_i^T \cdot \left(\beta_u \cdot \rho_u^{a+1} + \beta_\theta \frac{1-\rho_u^{a+1}}{1-\rho_u} + \beta_v \rho_v^{a+1} \right) \\
&+ \rho_u^{a+1} \hat{u}_{j,-1} + \hat{\theta}_i \cdot \frac{1-\rho_u^{a+1}}{1-\rho_u} + \rho_v^{a+1} \hat{v}_{j,-1} + \sum_{\tau=0}^{a} \rho_w^{\tau} \epsilon_{j,a-\tau} + z_{j,a} \\
\equiv& x_i \cdot \hat{\beta}_a + \hat{n}_{j,a},
\end{aligned}$$

where

$$\begin{aligned}
\hat{\beta}_a \equiv& \beta_u \cdot \rho_u^{a+1} + \beta_\theta \frac{1-\rho_u^{a+1}}{1-\rho_u} + \beta_v \rho_v^{a+1} \\
\hat{n}_{j,a} \equiv& \rho_u^{a+1} \hat{u}_{j,-1} + \hat{\theta}_i \cdot \frac{1-\rho_u^{a+1}}{1-\rho_u} + \rho_v^{a+1} \hat{v}_{j,-1} + \sum_{\tau=0}^{a} \rho_w^{\tau} \epsilon_{j,a-\tau} + z_{j,a},
\end{aligned}$$

and it can be shown that $x_i \perp \hat{n}_{j,a}$.

C.2. Details for the identification

Local projection coefficients $\hat{\beta}_a$ helps to identify the $\boldsymbol{\beta}$'s since

$$\hat{\beta}_a = \beta_u \cdot \rho_u^{a+1} + \beta_\theta \frac{1-\rho_u^{a+1}}{1-\rho_u} + \beta_v \rho_v^{a+1}$$

The auto-covariance structure of firm employment helps to identify the remaining parameters, ρ_u, ρ_v, ρ_w, $\sigma_{\hat{u}}$, $\sigma_{\hat{v}}$, $\sigma_{\hat{\theta}}$, σ_ϵ, and σ_z since

$$\begin{aligned}\mathbb{C}ov(\hat{n}_{j,a}, \hat{n}_{j,a+\Delta a}) =& \sigma^2_{\hat{u}} \cdot \rho_u^{2(a+1)+\Delta a} + \sigma^2_{\hat{\theta}} \cdot \left(\frac{1-\rho_u^{a+1}}{1-\rho_u} \cdot \frac{1-\rho_u^{a+\Delta a+1}}{1-\rho_u} \right) + \sigma^2_{\hat{v}} \cdot \rho_v^{2(a+1)+\Delta a} \\ &+ \sigma^2_{\varepsilon} \cdot \rho_w^{\Delta a} \cdot \frac{1-\rho_w^{2(a+1)}}{1-\rho_w^2} + \sigma^2_z \cdot \mathbb{1}_{\Delta a=0}\end{aligned}$$

Table C.1: Estimated parameters for the statistical model

Factor	β_θ	β_u	β_v
$\mathbb{1}$(Serial Ent)	0.1582	-0.0471	0.0436
$\log \bar{w}_{jt-1}$	0.0563	-0.0647	0.0127
$\log \bar{\Pi}_{jt-1}$	0.0281	-0.0380	0.0330
Average founder	-0.0040	-0.0169	0.0157
Number of founders	0.0443	-0.0001	0.0181
Log average lagged founder wealth	0.0055	-0.0035	-0.0011

Parameter	Estimate
ρ_u	0.3977
ρ_v	0.7107
ρ_w	0.9518
σ_θ	0.3438
σ_u	0.4907
σ_v	0.4100
σ_ε	0.1838
σ_z	0.1406

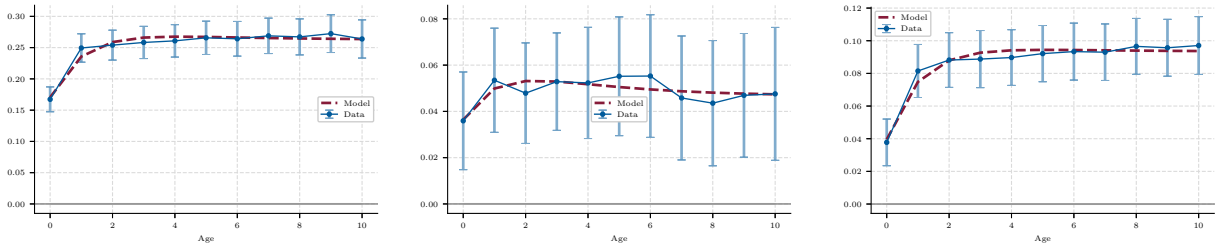
C.3. Variance decomposition

Since $x_j \perp \hat{n}_{j,a}$, the overall variance of $\log n_{j,a}$ can be decomposed as

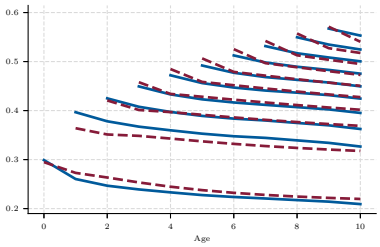
$$\mathbb{V}[\log n_{j,a}] = \mathbb{V}[x_i \cdot \hat{\beta}_a] + \mathbb{V}[\hat{n}_{j,a}],$$

Figure C.1: Estimation fit: data and model moments

(a) Serial Ent **(b)** Past profits **(c)** Past emp income



(d) $\text{Cov}(\log n_{ja}, \log n_{j,a+\Delta a})$



which can expressed as

$$\begin{aligned}\mathbb{V}[\log n_{j,a}] =& \hat{\beta}_a^T \cdot \mathbb{V}[x_j] \cdot \hat{\beta}_a \\ &+ \sigma^2_{\hat{u}} \cdot \rho_u^{2(a+1)} + \sigma^2_{\hat{\theta}} \cdot \left(\frac{1-\rho_u^{a+1}}{1-\rho_u}\right)^2 + \sigma^2_{\hat{v}} \cdot \rho_v^{2(a+1)} \\ &+ \sigma^2_{\varepsilon} \cdot \frac{1-\rho_w^{2(a+1)}}{1-\rho_w^2} + \sigma^2_z. \end{aligned} \tag{19}$$

The importance of ex-ante heterogeneity relative to total heterogeneity is calculated as the sum of the first two rows in (19) as a share of the total variance.

The importance of founder characteristics in accounting for ex-ante heterogeneity is calculated as the first row in (19) as a share of the sum of the first tow rows.

D. Additional Details for the Quantitative Model

Table D.1: Aggregate outcomes in counterfactual economics (reported in levels)

	Financial Frictions	**Correlated Capacities**	**Output**	**Capital**	**Labor**	**Wage**	**Ent Share**	**TFP**
1	No	Yes	0.932	1.698	0.874	0.635	0.117	0.883
2	No	No	0.966	1.760	0.866	0.664	0.148	0.911
3	Yes	Yes	0.877	1.538	0.897	0.582	0.094	0.838
4	Yes	No	0.901	1.573	0.893	0.600	0.115	0.858