Founders and Their Heterogeneous Firms*

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Abstract

Firm creation is at the heart of macroeconomic growth, but entrepreneurial outcomes are highly unequal. In this paper, we study the determinants of which entrants become large firms with macroeconomic importance. Using employer-employee-shareholder linked Canadian administrative data based on tax records, we find that workers with higher employment earnings are more likely both to enter entrepreneurship and to found larger firms with greater growth potential. We incorporate this link between founders' labor-market and entrepreneurial capacities into a quantitative model of endogenous occupational choice. In the presence of ex-ante heterogeneity, small business tax deductions induce negative selection by drawing lower-potential entrepreneurs into entry, largely offsetting their positive effects in alleviating financial frictions and generating a quantity-quality trade-off in the design of entrepreneurial policies.

JEL: E23, E24, E60, D24, J24, L26

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1. Introduction

Firm creation is at the heart of macroeconomic growth.[1] However, entrepreneurial outcomes are highly skewed: most new businesses fail, and among those that survive, only a small fraction accounts for the bulk of job creation and growth (Haltiwanger, 2022). What determines which entrants grow into firms of macroeconomic significance?

In this paper, we study the macroeconomic implications of firm creation, through the lens of founders and their decisions to start firms. We are motivated by a growing body of evidence showing that differences across firms at entry persist throughout the firm life cycle (e.g., Sedláček and Sterk, 2017; Sterk, Sedláček and Pugsley, 2021). If a substantial share of firm heterogeneity originates at entry, then understanding the characteristics and choices of founders becomes crucial for assessing how firm creation shapes aggregate outcomes.

To that end, we address three questions. First, conditional on entry, which individuals create successful firms? Second, along the extensive margin, who chooses to become an entrepreneur? Third, how do macroeconomic policies affect entrepreneurial selection, and how does this selection shape the aggregate effects of policy?

Using employer-employee-shareholder linked administrative data based on Canadian personal and corporate tax filings, we document a positive and persistent relationship between founders' labor-market outcomes and the subsequent performance of the firms they create. Founders with higher pre-entry employment income create firms that are larger at entry and exhibit stronger growth throughout their life cycle. These high-employment-income workers are also more likely to enter entrepreneurship.

We incorporate the link between labor-market and entrepreneurial capacities into a quantitative model of endogenous occupational choice. In the presence of ex-ante heterogeneity, size-based entrepreneurial policies such as small business tax deductions reduce aggregate output and productivity. Although these policies alleviate financial frictions, approximately three-quarters of these gains are offset by negative selection that encourages entry by lower-potential entrepreneurs. Our analysis therefore highlights a quality-quantity trade-off in entrepreneurial policy design.

[1] See, for example, Schumpeter (1934); Romer (1990); Aghion and Howitt (1992); Lucas (1978); Hopenhayn (1992).

Empirical evidence. Our main data source is the Canadian Employer Employee Dynamics Database (CEEDD) between 2001 and 2016, 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 complement these data with information on wealth from the Survey of Financial Security (SFS), a nationally representative survey of Canadian households from 1999 to the present.

We first document a positive and persistent relationship between founders' labor-market capacity and firms' outcomes. Within firm cohorts and controlling for founder characteristics, including wealth, startups founded by individuals with higher pre-entry employment income are more likely to survive their first five years. Conditional on survival, these firms begin with a larger size and grow more rapidly thereafter. The pattern holds across multiple measures of firm size: founders with higher pre-entry employment income create firms with greater employment, higher revenue, and larger assets.

To interpret these findings, we use a simple occupational-choice framework that highlights two potential channels. The first is a selection channel (Roy, 1951): individuals with higher employment income have a higher threshold of entering entrepreneurship, and therefore, those who do become entrepreneurs have higher expected payoffs from the startups. The second is a positive relationship between labor-market and entrepreneurial capacities. Under this channel, individuals who are more productive workers also tend to be more productive entrepreneurs and consequently create more successful firms.

Our second empirical finding provides evidence for the latter channel through the entrepreneurial selection schedule. Workers with higher employment income are more likely to become entrepreneurs. Among the workers below the 90th percentile of the employment-income distribution, approximately one in 200 enters entrepreneurship in the following year. By contrast, among workers in the top 1 percent of the employment-income distribution, approximately one in 40 becomes an entrepreneur, five times more likely than the remaining workers. Because high-income workers face greater opportunity costs of leaving paid employment, this pattern is difficult to reconcile with models in which labor-market and entrepreneurial capacities are uncorrelated and instead points to a positive relationship between the two.

Our third empirical result measures the importance of founder characteristics for firm heterogeneity. We extend the statistical framework of Sterk et al. (2021) to decompose the cross-sectional variation in firm size into ex-ante and ex-post components. We find that ex-ante heterogeneity accounts for approximately half of the variation in firm size among Canadian firms. Founder characteristics explain approximately 10% of the ex-ante heterogeneity, indicating that founder heterogeneity plays an empirically important role.

Taken together, these findings indicate that differences among founders shape both entrepreneurial selection and subsequent firm outcomes. As a result, policies that affect entry influence not only the quantity of entrepreneurship but also its composition. Our quantitative analysis incorporates both mechanisms and evaluates their macroeconomic importance.

Quantitative analysis. We develop a span-of-control model (Lucas, 1978) with endogenous occupational choice. Households choose between paid employment and entrepreneurship. Labor-market capacity determines workers' earnings, whereas the entrepreneurial capacity determines the ex-ante productivity of the firms entrepreneurs create. Consistent with the empirical findings, the two capacities are allowed to be correlated.

The model includes two additional features. First, firms have both ex-ante and ex-post heterogeneity. This distinction is important because policies affect entrepreneurial selection only to the extent that productive differences are present before entry. Second, there are financial frictions, which creates a role for policies.

The correlation between labor-market and entrepreneurial capacities—often assumed to be zero—is an important parameter that governs the aggregate costs of financial frictions. When the correlation is high, talent is concentrated. A talented entrepreneur, even if prevented from starting a business by financial constraints, still remains a productive worker, mitigating the aggregate costs of financial frictions. Calibrating the model to match the entrepreneurial selection schedule, we find a large positive correlation between labor-market and entrepreneurial capacities, implying substantial talent concentration in the Canadian economy and correspondingly smaller aggregate losses from financial frictions.

We use the model to study the macroeconomic effects of Canada's small business tax deductions. Although the policy relaxes financial constraints for incumbent firms, it also alters entrepreneurial selection. By subsidizing entry, it attracts marginal entrepreneurs with lower entrepreneurial capacity. These entrants leave paid employment, reducing the quality of the workforce available to incumbent firms and generating labor-market distortions. The resulting effects from the negative selection offset three-quarters of the gains associated with alleviating financial frictions. In general equilibrium, wages rise, further reducing aggregate output. Overall, we find that the small business tax deduction lowers aggregate output by approximately 0.5% and aggregate productivity by approximately 1%.

Our analysis highlights the importance of both the quantity and the quality of firm creation. When differences among firms are present at entry and persist over the life cycle, entrepreneurial selection becomes a key determinant of aggregate outcomes. Policies that target small businesses irrespective of productivity may, therefore, generate unintended distortions and reduce aggregate output and productivity.

Related literature. Our paper relates to four strands of the literature. First, we contribute to the literature on the macroeconomic importance of entrepreneurship (Quadrini, 2009; Salgado, 2020; Queiró, 2022; Leahy and Thapar, 2022; Morazzoni, 2024; De Haas, Sterk and Van Horen, 2022; Bhandari, Kass, May, McGrattan and Schulz, 2026, among others). Using comprehensive administrative data, we document the importance of entrepreneurs' labor-market outcomes for the quality of firm creation, as well as the persistence of these cross-firm differences.

Since macroeconomic policy shapes the entrepreneurial selection and shifts the composition of entrants, our analysis highlights that both the quality and quantity of entrepreneurship matter for the aggregate outcomes. Size-based entrepreneurial policies, such as small business tax deductions, may encourage the quantity of entrepreneurship at the cost of its quality, consistent with evidence on size-based policies (Guner, Ventura and Xu, 2008; Garicano, Lelarge and Van Reenen, 2016; Chen, Liu, Suárez Serrato and Xu, 2021).

Second, our paper contributes to the discussion on the determinants of heterogeneous firm growth. 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, Lasry, Lions and Moll, 2016) and aggregate growth.

Several key factors have been identified to drive firm heterogeneity, ranging from economic and institutional features (Guzman and Stern, 2020; Bai, Hsieh, Song and Wang, 2020; Akcigit, Alp and Peters, 2021; Basante and Simonovska, 2025), to employee characteristics (Ouimet and Zarutskie, 2014), intangible assets (Bhandari, Martellini and McGrattan, 2025), and firm capital structure (Guntin and Kochen, 2025; Boppart, Klenow, Laski and Li, 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, Félix, Karmakar and Sedlácek, 2025), and the spin-off effect of founders departing incumbent innovators (Baslandze and Vardishvili, 2025). We provide empirical evidence on the sources of ex-ante heterogeneity using new administrative data, and we uncover founders as a source of this heterogeneity. Moreover, we document a positive relationship between founders' labor-market and entrepreneurial productivity. This concentration of talent within a small subset of individuals create aggregate tradeoffs, which we characterize 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 individual's working and entrepreneurial capacities, as in Jovanovic (1994). We discipline the joint distribution using our rich micro data and find it to drive entrepreneurial selection and influence the aggregate costs of financial frictions.

Road map. The rest of the paper proceeds as follows. Section 2 describes data sources and variable construction. Section 3 presents our three main empirical findings: the link between founders' labor-market and entrepreneurial outcomes, the selection schedule of entrepreneurship, and the statistical importance of founder characteristics for firm heterogeneity. Section 4 presents our quantitative model of entrepreneurial choices. Section 5 analyzes the macroeconomic effects of small business tax deductions. Section 6 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, partnership, or trust). When the shareholder is not an individual, the ownership is traced through the ownership chain to identify the ultimate individual owner.[2] 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

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

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.1 provides details on the methodology and measures of fit.[3]

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

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.

Panel (a) of Table 1 presents descriptive statistics for new firms founded between 2001 and 2016, which represent 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, Roberts and Samuelson, 1988; Davis, Haltiwanger and Schuh, 1996), entrants in our sample are notably smaller than the average firm (12 employees), for which descriptive statistics are provided in Appendix Table A.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 A.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

[3] 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%.

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

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 provides 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 A.1b, founders are, on average, two years older and are 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.

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.

2.3. Founder characteristics of largest 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 A.2 alternatively ranks firms by their sizes after 10 years and reveals similar differences between the founders of 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 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' employment income outside of entrepreneurial spells, estimated using the Abowd, Kramarz and Margolis (1999) (AKM) model.[4] Among founders with multi-firm employment histories as non-owners, the average worker premium is 0.08 for founders of 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 an 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 A.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, we further study the role of founders in shaping firm heterogeneity.

3. Empirical Evidence

3.1. Illustrative theoretical framework

We begin with a simple model of entrepreneurial choice, in which individuals decide whether to work or start a business, and firm productivity depends on the founder's entrepreneurial

[4] 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.

capacity (Roy, 1951; Lucas, 1978). Despite its simplicity, the model generates testable predictions that guide our empirical analysis: on the relationship between founders' capacities and firm outcomes and the selection into entrepreneurship.

The model is static, and there is a unit mass of individuals indexed by $i \in [0, 1]$. Individuals are heterogeneous along two dimensions: working capacity, e, and entrepreneurial capacity, z.[5] These two capacities follow a jointly normal distribution

$$\begin{pmatrix} e \\ z \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ \mu_z \end{pmatrix}, \begin{pmatrix} \sigma_e^2 & \rho\sigma_e\sigma_z \\ \rho\sigma_e\sigma_z & \sigma_z^2 \end{pmatrix} \right). \tag{1}$$

The existing literature often assumes that the correlation between the working and entrepreneurial capacity, ρ, is zero (i.e., a single dimension of capacity) or one (e.g. Cagetti and De Nardi, 2009). By contrast, we allow for arbitrary values of $\rho \in [-1, 1]$. As we will show, ρ is an important parameter that governs entrepreneurial choices.

Individuals choose between paid employment and entrepreneurship. Workers earn labor income equal to $V^W(e, z) \equiv \exp(e)W$, where W denotes the equilibrium wage. Entrepreneurs operate a production technology given by $\exp(z)n^\theta$, where $\theta \in (0, 1)$ and n denotes labor demand. In this simple environment, entrepreneurial capacity directly determines firm productivity, implying entrepreneurship profits equal to $V^E(e, z) \equiv \max_n \exp(z)n^\theta - Wn$.

An individual chooses entrepreneurship whenever the value of entrepreneurship exceeds the value of paid employment, that is, whenever $V^E(e, z) \geq V^W(e, z)$. This condition holds when entrepreneurial capacity is sufficiently high relative to the working capacity. Define $\Delta(e, z) \equiv z - (1 - \theta)e$ as this difference. Then there exists an entry threshold $\bar{\Delta}$ such that entrepreneurship occurs if and only if

$$\Delta(e, z) \geq \bar{\Delta}(W) = \log W - c(\theta),$$

where $c(\theta) = (1 - \theta) \log(\theta^{\frac{\theta}{1-\theta}} - \theta^{\frac{1}{1-\theta}})$ is a constant that depends only on θ.

Appendix Section B details the solution to the model and the proofs of the two propositions. The toy model intentionally abstracts from other sources of firm heterogeneity unrelated to founders, as well as financial frictions and dynamic choices—all of which are

[5] Capacities are measured in efficiency units and represent effective labor supply.

incorporated in the quantitative model in Section 4. Our objective here is to understand an individual's entrepreneurial choice and study the determinants of startup success. The following two propositions summarize the model's main implications.

***Proposition* 1** (Predictive power of founder's working capacity)**.** *Conditional on entry, the expected z among entrants of type e is given by*

$$\mathbb{E}[z \mid entry,\, e] = \mu_z + \underbrace{\sigma_z\sqrt{1-\rho^2}\mathcal{M}(\alpha+\beta\cdot e)}_{selection\ channel} + \underbrace{\rho(\sigma_z/\sigma_e)\cdot e}_{correlation\ channel} \tag{2}$$

where $\mathcal{M}$ is the inverse Mills ratio,[6] $\alpha = \frac{\bar{\Delta}(W)-\mu_z}{\sigma_z\sqrt{1-\rho^2}}$ *and* $\beta = \frac{1-\theta-\rho\sigma_z/\sigma_e}{\sigma_z\sqrt{1-\rho^2}}$*; and $\mathbb{E}[z \mid entry,\, e]$ is strictly increasing in e if $\rho \geq 0$.*

Proposition 1 establishes that founder's labor-market capacity predicts firm productivity conditional on the entry. The inverse-Mills term in (2) reflects a selection effect: conditional on the entry decision, higher working-capacity entrepreneurs have higher expected entrepreneurial capacity, because the entry threshold is higher for them. This channel is present even when the working and entrepreneurial capacities are uncorrelated ($\rho = 0$). The last term captures the correlation channel: when $\rho > 0$, good workers tend to be good entrepreneurs, generating an additional positive relationship between the founder's working capacity and firm productivity.

The observed relationship between founders' labor-market ability and firm performance may therefore arise either from entrepreneurial selection or from an underlying concentration of abilities. The next proposition shows how selection into entrepreneurship differs across the capacity distribution.

***Proposition* 2** (Entrepreneurial selection)**.** *The conditional probability of entry for a given working capacity e is given by*

$$p_e(e) \equiv Pr(\Delta(e,z) \geq \bar{\Delta}(W) \mid e) = 1 - \Phi(\alpha + \beta e) \tag{3}$$

where $\alpha = \frac{\bar{\Delta}(W)-\mu_z}{\sigma_z\sqrt{1-\rho^2}}$ *and* $\beta = \frac{1-\theta-\rho\sigma_z/\sigma_e}{\sigma_z\sqrt{1-\rho^2}}$*; and $p_e(e)$ is strictly decreasing in e if $\rho \leq 0$ and strictly increasing in e if $\rho > (1-\theta)\sigma_e/\sigma_z$.*

[6] The function $\mathcal{M}(x) = \frac{\phi(x)}{1-\Phi(x)}$ is the upper hazard function of standard normal distribution, or the inverse Mills ratio. The inverse Mills ratio is strictly increasing in x.

Proposition 2 characterizes selection into entrepreneurship across the working capacity distribution. Individuals with high working capacity face a higher opportunity cost of entrepreneurship because they earn higher employment income. Absent sufficiently high expected entrepreneurial profits, such individuals find it optimal to remain workers. As a result, when $\rho \leq 0$, the probability of entrepreneurship declines with labor-market ability. By contrast, the probability of entrepreneurship increases with working capacity only when the correlation, ρ, is sufficiently positive. Therefore, Proposition 2 provides a way to distinguish between selection effects and an underlying correlation in capacities.

From model to data. Proposition 1 predicts that conditional on entry, founders with higher working capacity create more productive firms whenever working and entrepreneurial capacities are not negatively correlated. Our administrative tax data does not provide a direct measure of firm productivity because it contains limited information on firm capital. However, firm size is strictly increasing in productivity in our model and standard models of firm dynamics (e.g., Hopenhayn, 1992). We therefore test the prediction using firm size. To measure founder's working capacity, our main proxy is founder's pre-entry employment income. For the subset of entrepreneurs with two prior employment spells, we also construct a measure of worker premium based on the AKM (Abowd et al., 1999) decomposition.

The relationship between founders' working capacity and firm outcomes, however, does not by itself identify whether successful entrepreneurs are drawn from good workers because of selection, or because working and entrepreneurial capacities are positively correlated in the population. We then turn to Proposition 2, which generates an additional prediction on the extensive margin of entrepreneurship. In particular, an entrepreneurial selection schedule that increases with working ability provides evidence for a sufficiently positive correlation between working and entrepreneurial capacity, whereas a declining selection schedule is evidence for weak or negative correlation between the two dimensions of capacities.

Finally, the model builds on the premise that founder's entrepreneurial capacity shapes firm productivity. However, firms may not differ ex-ante at entry, and even when such ex-ante heterogeneity exists, it may not be driven by founders. To validate the structure of our theoretical framework, we conduct a statistical decomposition to quantify the importance of ex-ante firm heterogeneity and the extent this heterogeneity can be explained by founder characteristics, extending the methodology by Sterk et al. (2021).

3.2. Founder working capacity and firm heterogeneity

Empirical specification. To study the relationship between founder's working capacity and startup outcomes, we focus on the subset of firms created by first-time entrepreneurs, isolating, to the extent possible, founders' labor-market experience from entrepreneurial experience. We estimate local projections for firm j founded in year t:

$$y_{jh} = \delta_{ts} + \beta_h \text{Ent}_j + \Gamma' Z_j + \varepsilon_{jh}, \tag{4}$$

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 founders' capacity (detailed below) averaged at the firm level; Z_j is a vector of firm controls that include the average age of the founders, the number of founders, and their average pre-entry wealth measured one year before founding; and ε_{ih} is a random error. The founding year of each firm is normalized to $t = 0$ such that each 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.

The outcome variables of interest includes 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.

The explanatory variable, Ent_j, summarizes founders' working capacity at the firm level. Our main measure is the pre-entry average real employment income earned by founders of firm j, $\log \bar{w}_{jt-1}$, measured one year before the founding of the firm.

We construct an alternative measure of worker premium, θ_i, estimated using the AKM model:

$$y_{it} = \theta_i + \lambda_t + \psi_{j(i,t)} + \varepsilon_{it}, \tag{5}$$

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. Widely used in the macro-labor literature, identification of the worker fixed effect in the AKM model relies on entrepreneurs with at least two employment spells. We conduct robustness using the AKM worker premium as a direct measure of founder's working capacity, but since it covers a subset of entrepreneurs in our sample, we use pre-entry employment income as our main independent variable.

Results. Figure 1 reports the relationship between founders' pre-entry employment income and startup outcomes among entrepreneurs creating their first businesses. Panel (a) shows that founders with higher pre-entry employment income tend to create firms with higher employment at entry. This relationship is persistent throughout the ten-year horizon and gradually increases across most of the estimation horizons. Panel (b) further shows that founders' pre-entry employment income is positively associated with post-entry firm growth.

In terms of magnitude, a one-standard-deviation increase in log pre-entry employment income (4.9, corresponding 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. Although employment income is a flow variable, it exhibits a substantial economic correlation with the startup's employment stock.

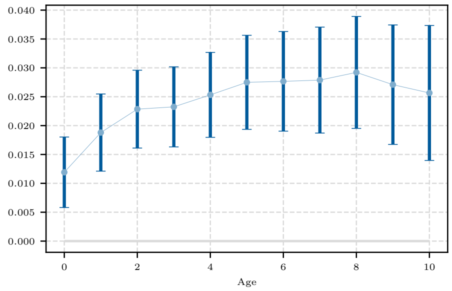
Figure 1 also shows that the positive relationship between founders' pre-entry employment income is robust across different measures of firm size. In addition to creating more jobs, higher-employment-income entrepreneurs also establish firms with greater assets and revenues. The positive associations are even stronger for asset and revenue than for employment, and remain equally persistent over time.

The results thus far indicate that, conditional on firm survival, there is a persistently positive relationship between founders' pre-entry employment income and firm size and growth. Panel (g) further shows that higher pre-entry employment income is correlated with a greater likelihood of firm survival. A one-standard-deviation increase in pre-entry employment income is associated with a 0.15 percentage point increase in the probability of surviving the first five years after entry.

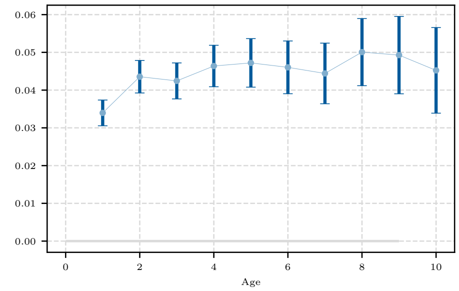
Consistent with the prediction of Proposition 1 in the illustrative model in Section

Figure 1: Founders' pre-entry employment income and entrepreneurial outcomes

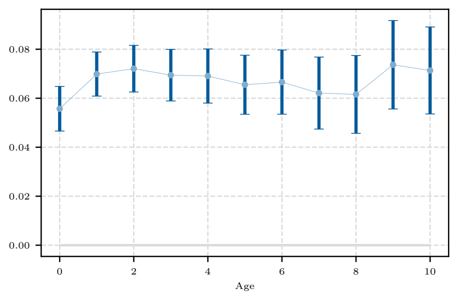
(a) Employment level



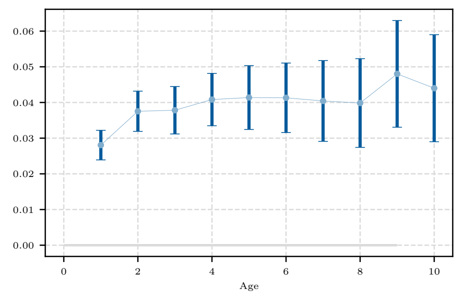
(b) Employment growth



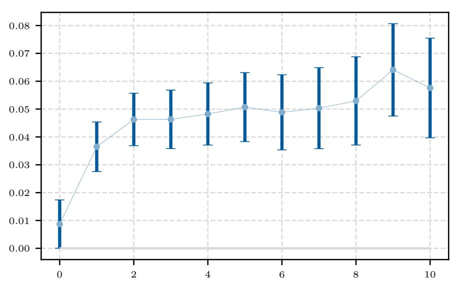
(c) Assets level



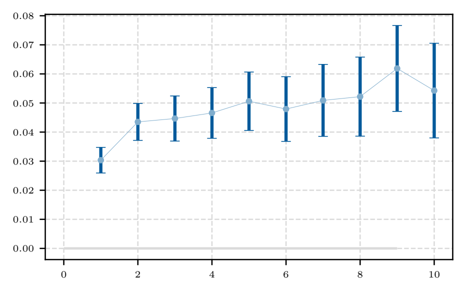
(d) Assets growth



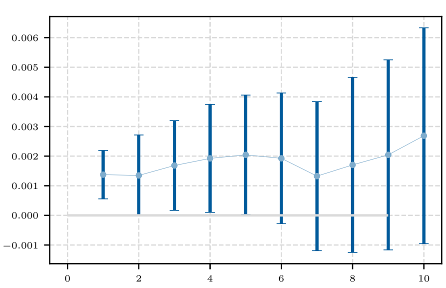
(e) Revenue level



(f) Revenue growth



(g) Survival



Notes: The left column report β_h of firm j for h years after the creation, estimated from $y_{jh} = \delta_{ts} + \beta_h \log \bar{w}_j + \Gamma' Z_j + \varepsilon_{jh}$, based on the sample of startups created by novice entrepreneurs, where y_{jh} is log firm employment, log real assets, log real revenue, and survival indicator, respectively; δ_{ts} is a firm-founding-year-by-sector fixed effect (sectors measured at the 4-digit NAICS level); $\log \bar{w}_j$ is the log average real employment of founders one year prior to founding; 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 right column reports β_h from estimating $\Delta_h \log s_{jh} = \delta_{ts} + \beta_h \log \bar{w}_j + \Gamma' Z_j + \gamma \log s_{j0} + \varepsilon_{jh}$, 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.

3.1, conditional on entry, founders' labor-market capacity persistently predicts the size and success of the firms. The predictive power may arise from two channels. First, a selection channel, individuals with higher employment income face a higher threshold for entering entrepreneurship, leading to stronger expected firm performance among those who choose to enter. Second, there may be a direct relationship between an individual's ability as a worker and their effectiveness as an entrepreneur. To distinguish between these mechanisms, we next test the model's prediction on entrepreneurial selection in Proposition 2.

3.3. Entrepreneurial selection

Figure 2 reports the share of workers who transition to entrepreneurship in the following year by percentile of current-year employment income. Workers are ranked within each year according to their employment income percentile. Entrepreneurial transition probabilities are rounded to three decimal places to comply with disclosure requirements.

We find that, on the extensive margin, workers with higher employment income are more likely to enter entrepreneurship. For most workers, the probability of transitioning into entrepreneurship is below 1%. In contrast, workers in the top 1% of employment income distribution have a 2.5% probability of becoming entrepreneurs in the following year, approximately 5 times higher than that of remaining workers.

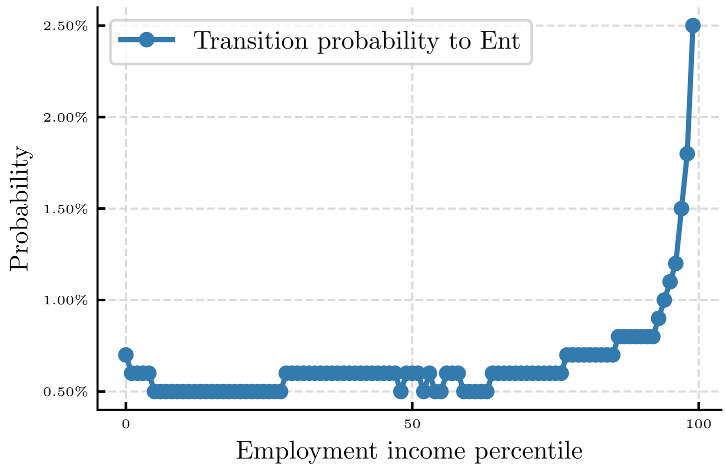
The entrepreneurial selection schedule is increasing in employment income, which indicates a positive relationship between labor-market capacity and entrepreneurial capacity. Absent such a positive correlation, high-income workers would face higher opportunity cost of leaving wage employment and would, therefore, be less likely to transition into entrepreneurship.

The upward slope of the entrepreneurial selection schedule provides evidence of a direct link between an individual's ability as a worker and their effectiveness as an entrepreneur. High-working-capacity workers are not only more likely to become entrepreneurs, but also more likely to establish successful firms.

3.4. Statistical importance of founders for ex-ante firm heterogeneity

Our theoretical and empirical framework thus far assume that a founder's entrepreneurial ability directly shapes the firm's productivity. This section verifies this assumption of the

Figure 2: 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. Employment income percentile is ranked for workers within each year. The probability of entrepreneurship is rounded to the nearest three decimal points.

connection between founder characteristics and firm outcome. We conduct a statistical decomposition on the sources of firm heterogeneity, extending the model by Sterk et al. (2021), who observes that the persistence of firm size provides information on the relative importance of ex-ante and ex-post heterogeneity. We further use the persistence of the *conditional* relationship between founders and firm size to assess not only the importance of ex-ante firm heterogeneity, but also the role of founder for ex-ante heterogeneity.

Statistical model Our statistical model includes both ex-ante and ex-post firm heterogeneity.[7] Let $n_{j,a}$ denote the employment of firm j at age a. Its process is specified by

$$\log n_{i,a} = \underbrace{u_{j,a} + v_{j,a}}_{\text{ex-ante component}} + \underbrace{w_{j,a} + z_{j,a}}_{\text{ex-post component}}, \tag{6}$$

[7]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 $\rho_u = 0$, $u_{i,-1} = v_{i,-1} = z_{ia} = \varepsilon_{ia} = 0$ yields Melitz (2003).

where

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

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.

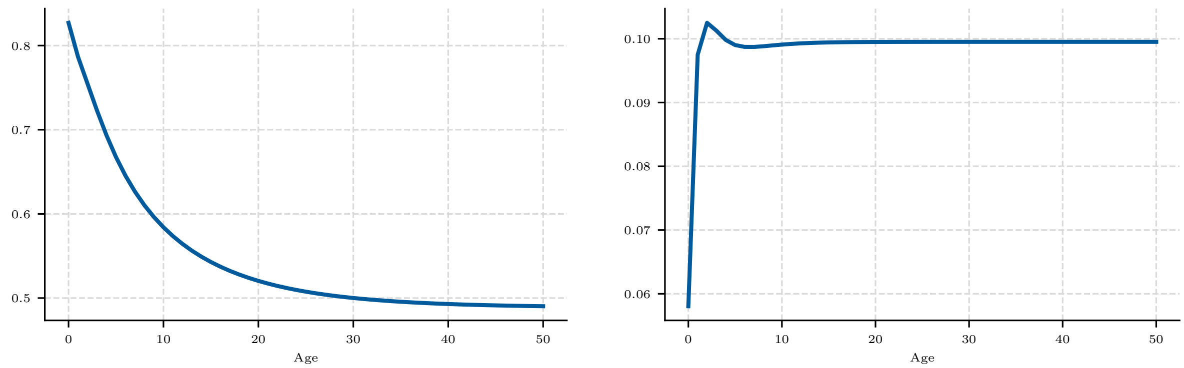
The ex-ante component, $u_{j,a} + v_{j,a}$, is driven by three key variables: $u_{j,-1}$ and $v_{j,-1}$ capture differences across firms at entry that diminish to zero over the life cycle; and θ_j captures permanent differences across firms that are present at entry. Sterk et al. (2021) assume $u_{j,-1}$, $v_{j,-1}$, and θ_j to be drawn at random. Motivated by our previous empirical results, we allow these variables to depend on observable founder characteristics, $\boldsymbol{X_j}$, in addition to unobserved shocks, $(\hat{\theta}_j, \hat{u}_j, \hat{v}_j)$.

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.

Decomposition Appendix Section C details the estimation.[8] 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 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

[8] 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 identifies $\boldsymbol{\beta_u}$, $\boldsymbol{\beta_\theta}$, 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 identifies ρ_u, ρ_v, ρ_w, $\sigma_{\hat{u}}$, $\sigma_{\hat{v}}$, $\sigma_{\hat{\theta}}$, σ_ϵ, and σ_z.

Figure 3: 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 (7) 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 (7) as a share of the sum of the first two terms.

a can be expressed as

$$\begin{aligned} \mathbb{V}\text{ar}\left(\log n_{j,a}\right) &= \underbrace{\mathbb{V}\text{ar}\left(\boldsymbol{X_j}\hat{\boldsymbol{\beta}}_{\boldsymbol{a}}\right)}_{\text{observed}} + \underbrace{\mathbb{V}\text{ar}\left(\hat{n}_{j,a}\right)}_{\text{unobserved}} \\ &= \underbrace{\mathbb{V}\text{ar}\left(\boldsymbol{X_j}\hat{\boldsymbol{\beta}}_{\boldsymbol{a}}\right)}_{\text{observed}} + \underbrace{\sigma^2_{\hat{u}}\rho_u^{2(a+1)} + \sigma^2_{\hat{\theta}}\left(\frac{1-\rho_u^{a+1}}{1-\rho_u}\right)^2 + \sigma^2_{\hat{v}}\rho_v^{2(a+1)}}_{\text{unobserved: ex-ante}} \quad \underbrace{+\,\sigma_{\varepsilon}\frac{1-\rho_w^{2(a+1)}}{1-\rho_w^2} + \sigma_z^2}_{\text{unobserved: ex-post}} \end{aligned} \tag{7}$$

where the second equality further separates the unobserved components into those driven by ex-ante shocks and those driven by ex-post shocks.[9]

Figure 3 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 (7) 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 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,

[9]Appendix Section C contains the derivation.

consistent with the US evidence on the substantial ex-ante differences across firms (Sterk et al., 2021).

Panel (b) in Figure 3 reports the share of ex-ante heterogeneity that are accounted for the six observable founder factors, computed as the first term in (7) 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 show that founders' labor-market capacity persistently predicts firm performance. This persistent relationship provides evidence that founders are a source of firm ex-ante heterogeneity, which generates permanent differences across firms that are present at firm creation. Furthermore, firm entry is not random. Workers with higher labor-market capacity are more likely to become entrepreneurs. The persistent nature of firm differences indicates that this entrepreneurial selection shapes the composition of firms and, consequently, influences aggregate outcomes.

Motivated by these findings, our quantitative analysis incorporates the link between founders and their heterogeneous firms into an occupational choice model, and studies the macroeconomic importance of entrepreneurial selection.

4. 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.

4.1. 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 entrepreneurial 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 labor 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 an earnings-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.[10]

4.1.1. 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 an entrepreneur. Households are heterogeneous in the working capacity, e_t, and the entrepreneurial capacity, z_t, which follow a joint AR(1) process

$$\begin{bmatrix} \log e_{t+1} \\ \log z_{t+1} \end{bmatrix} = \begin{bmatrix} \mu_e \\ \mu_z \end{bmatrix} + \begin{bmatrix} \rho_e & 0 \\ 0 & \rho_z \end{bmatrix} \begin{bmatrix} \log e_t \\ \log z_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{e,t+1} \\ \varepsilon_{z,t+1} \end{bmatrix}. \tag{8}$$

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

$$\begin{bmatrix} \varepsilon_{e,t+1} \\ \varepsilon_{z,t+1} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_e^2 & \rho_{ez}\,\sigma_e\sigma_z \\ \rho_{ez}\,\sigma_e\sigma_z & \sigma_z^2 \end{bmatrix} \right). \tag{9}$$

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

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

[10] 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

$$x_{it} \equiv w_t l_{it}$$

through wealth $a_{i,t}$ or borrowing $b_{i,t}$ units of one-period risk-free bonds at the rate r_t. The borrowing is subject to an earnings-based borrowing constraint (Lian and Ma, 2021; Drechsel, 2023):

$$b_{i,t} \leq \lambda \cdot \text{EBIT}_{i,t}, \tag{10}$$

where the earnings before interest and taxes (EBIT) is defined as $\text{EBIT}_{i,t} \equiv y_{i,t} - x_{i,t}$, and $\lambda < 1$ governs the degree of financial frictions. A firm's borrowing limit is tied to its flow earnings, and we impose that debt cannot exceed a firm's working capital needs, i.e. $b_{i,t} = \min\{x_{i,t}, \lambda \text{EBIT}_{i,t}\}$.

Every period, an entrepreneur receives firm profits, pays corporate taxes $\tau(\pi_{i,t})$, and repays debt with interest. Therefore, the wealth of entrepreneurs evolves according to

$$a_{i,t+1} = (1 + r_t)(a_{i,t} - (x_{i,t} - b_{i,t})) + (1 - \tau(\pi_{i,t}))\pi_{i,t} - c_{i,t}.$$

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

4.1.2. 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

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

where $l_{i,a}$ denotes the labor inputs. Firm productivity depends on an "ex-ante" component, $z_{i,t}$, and an "ex-post" component, $\eta_{i,t}$. The ex-ante heterogeneity $z_{i,t}$ is determined before firm creation, since it follows the founder's entrepreneurial capacity from (8). Once a worker transitions into entrepreneurship, we assume that their entrepreneurial capacity stays fixed at $z_{i,t}$ for 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 creates 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 (8).

4.1.3. 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.

4.2. Decision problems

This subsection analyzes the decision problem of workers and entrepreneurs.

4.2.1. Value function of workers

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

$$V_t^w(a,e,z) = \max\left\{ \underbrace{W_t^w(a,e,z) + \zeta_w}_{\text{remain a worker}},\ \underbrace{EW_t^f(a,e,z) + \zeta_{nf}}_{\text{become an entrepreneur}} \right\}, \tag{11}$$

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 (11), W^w, is the value of continuing as a worker and equals

$$\begin{aligned} W_t^w(a,e,z) =& \max_{c,a'} u(c) + \beta \cdot (1-\pi_d)\mathbb{E}_{e',z'|e,z}\left[V_{t+1}^w(a',e',z')\right] \\ \text{s.t. } & a' = (1+r)\cdot a + w \cdot e - c \\ & a' \geq 0. \end{aligned} \tag{12}$$

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 (11), EW^f, is the expected value of becoming an entrepreneur and equals

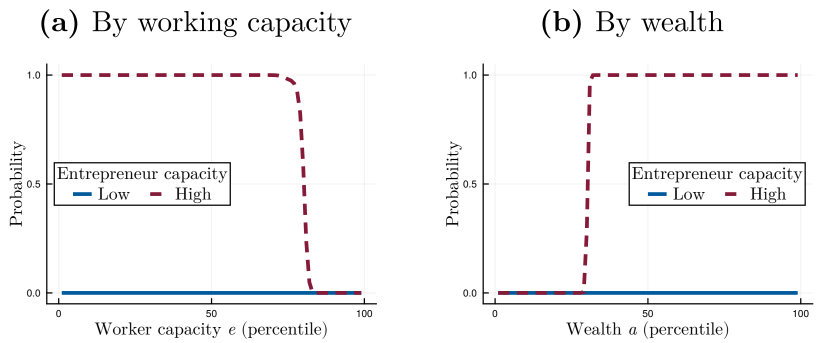
$$EW_t^f(a,e,z) = \mathbb{E}_{\eta\sim\mathcal{D}_0(\eta)}\left[W_{t+1}^f(a,e,z,\eta)\right], \tag{13}$$

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

$$\begin{aligned} W_t^f(a,e,z,\eta) =& \max_{c,a',k,l} u(c) + \beta(1-\pi_d)\mathbb{E}_{e',z',\eta'|e,z,\eta}\left[V_{t+1}^f(a',e,z,\eta')\right] \\ \text{s.t. } & a' = (1+r)\cdot(a-(wl-b)) + (1-\tau)\cdot(y - wl - rb) - c \\ & a' \geq 0. \end{aligned} \tag{14}$$

Entrepreneurs finance their firms' capital using wealth and borrowing from a risk-free one-period bond. They face a borrowing constraint specified in (10). Their wealth evolves as

Figure 4: 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).

unappreciated capital plus firm profits minus borrowing and interest repayment.

4.2.2. Policy function of workers

Before discussing our calibration strategy, we first discuss the policy functions of agents in our model. Figure 4 plots the occupational choice of workers, reporting the probability that a worker of a given type chooses to become an entrepreneur.

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.

4.2.3. 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

$$V_t^f(a,e,z,\eta) = \max\left\{ \underbrace{W_t^f(a,e,z,\eta)+\zeta_f}_{\text{continue managing current firm}}, \underbrace{EW_t^f(a,e,z)+\zeta_{nf}}_{\text{create new firm}}, \underbrace{EW_t^w(a,e,z)+\zeta_w}_{\text{become a worker}} \right\} \tag{15}$$

where $W^f(a,e,z,\eta)$, as in (14), denotes the value of continuing managing the current firm; $EW^f(a,e,z)$, as in (13), 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

$$EW_t^w(a,e,z) = \mathbb{E}_{e',z'|e,z}\left[V_{t+1}^w(a,e',z')\right], \tag{16}$$

where the joint distribution of (e',z') conditional on (e,z) is assumed to follow the joint AR(1) process specified in (8).

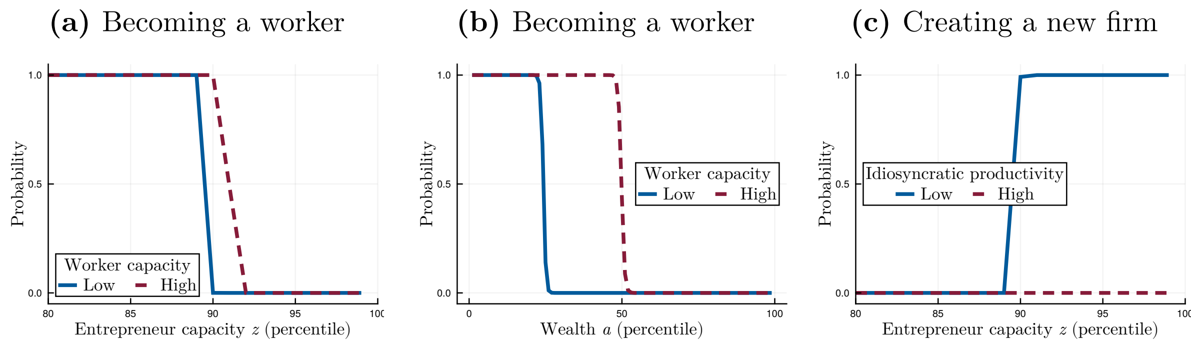
4.2.4. Policy function of entrepreneurs

Figure 5 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,

Figure 5: 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).

η, it is attractive for them to create a new firm.

4.3. 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 $\{\mathbf{p}_t^{w,\ w}(a,e,z), \mathbf{p}_t^{w,\ f}(a,e,z),\ \mathbf{c}_t^w(a,e,z),\ \mathbf{a}_t^{\prime w}(a,e,z)\}$ and $\{\mathbf{p}_t^{f,\ f}(a,e,z,\eta),\ \mathbf{p}_t^{f,\ nf}(a,e,z,\eta), \mathbf{c}_t^f(a,e,z,\eta),\ \mathbf{a}_t^{\prime w}(a,e,z,\eta), \mathbf{l}_t^f(a,e,z,\eta), \mathbf{k}_t^f(a,e,z,\eta), \mathbf{b}_t^f(a,e,z,\eta)\}$, 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 (11) and (15), respectively;

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

evolves as:

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

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

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

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

$$
\int e \cdot \mathcal{D}_t^w(a,e,z) dadedz = \int \mathbf{l}_t^f(a,e,z,\eta) \cdot \mathcal{D}_t^f(a,e,z,\eta)\ dadedzd\eta. \tag{17}
$$

4.4. Calibration

4.4.1. 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[11]. The 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.

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

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%

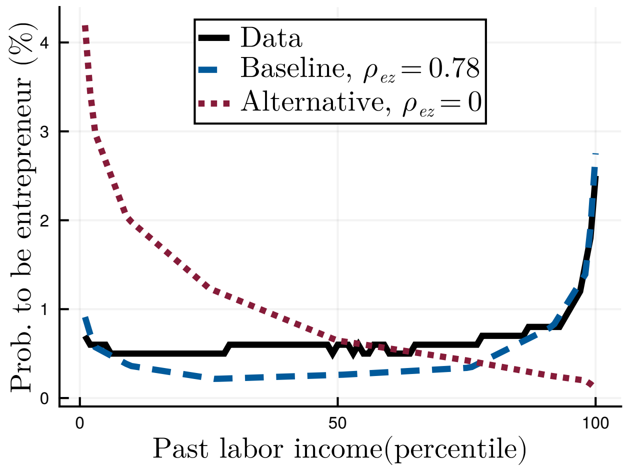
4.4.2. Internally calibrated parameters

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 6, 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

Figure 6: 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 aternative calibration of $\rho_{ez} = 0$. The empirical relationship from Figure 2 is repeated in solid black line.

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.

4.4.3. Talent concentration and the aggregate costs of financial frictions

The parameter $\rho_{e,z}$ governs the concentration of talent — whether the best entrepreneurs in an economy also tend to be the best workers — and is crucial for the aggregate costs of financial frictions.

To highlight this connection, Table 4 presents the steady-state aggregate outcomes across four counterfactual economies, varying the degree of financial frictions (λ) and the concentration of talent ($\rho_{e,z}$). A comparison between the first two economies 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.

As a benchmark, the first row in Table 4 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 (calculated as the geometric mean of firm productivity). Subsequent rows compare this benchmark to alternative economics.

Table 4: Aggregate outcomes in counterfactual economics

	Financial Frictions (λ)	**Correlated Capacities** ($\rho_{e,z}$)	**Output**	**Labor**	**Wage**	**Ent Share**	**TFP**
1	No	Yes	3.37	0.92	2.98	0.076	5.09
2	No	No	+3.30%	−0.44%	+3.74%	+1.47%	+0.90%
3	Yes	Yes	−0.31%	−5.46%	−43.20%	+3.68%	−3.49%
4	Yes	No	+1.13%	−2.08%	−45.26%	+2.78%	−5.19%

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 results, except for entrepreneur share, are presented as percentage deviations from the benchmark.

Talent distribution. The first two rows of Table 4 quantify the importance of the talent distribution. Without financial frictions, the entrepreneur share is higher when talent is more disperse ($\rho_{e,z} = 0$). High-entrepreneurial-capacity households are more likely to enter entrepreneurship, since a high entrepreneurial capacity no longer implies a high alternative wage income; and similarly, 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 3.3% 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.

Financial frictions. Comparing the first and third economies in Table 4 quantifies the costs of financial frictions, holding constant the talent distribution. These costs are substantial: output falls by 0.3% and aggregate TFP falls by 5% compared to the frictionless benchmark. Among operating firms, financial frictions slow capital accumulation, delaying firms reaching an optimal scale of production. Among 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.

Talent distribution and costs of financial frictions. To quantify how the aggregate costs of financial frictions vary with the underlying talent distribution, we use a "difference-in-differences" approach across the aforementioned economies, 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).

For economies with concentrated talent, as in our baseline calibration for the Canadian economy ($\rho_{e,z} = 0.63$), financial frictions reduce aggregate output only by -0.3%. The costs of financial frictions are substantially lower compared to those an economy with more dispersed talent ($\rho_{e,z} = 0$), where aggregate output decreases by -2.2%.

Why do the costs of financial frictions vary with the talent distribution? When talent is concentrated, a talented entrepreneur is likely to be a talented worker. While financial constraints may delay high-entrepreneurial-capacity individuals to start a business, they remain productive as high-working-capacity workers. Therefore, the aggregate costs of financial frictions are low. On the other hand, when talent is disperse, it becomes important to allocate households where they are most productive. Financial frictions are costly because they distort the efficient allocation.

Our analysis suggests that the calibration of the joint distribution on the working and entrepreneurial capacities is crucial for the aggregate costs of financial frictions, and we offer a calibration strategy that discipline this parameter with our data.

5. Macroeconomic Effects of Entrepreneurial Policy

We use the calibrated model to assess the macroeconomic impact of entrepreneurial policy. Our analysis focuses on Canada's Small Business Deduction (SBD), a commonly used size-based entrepreneurial policy which offers a reduced corporate tax rate for small businesses. This section provides background on the policy, quantifies its macroeconomic effects on productivity and output, and unpacks the transmission mechanism through life-cycle dynamics, entrepreneurial selection, and general-equilibrium effects.

5.1. Size-based entrepreneurial policy

First introduced in 1972, the Small Business Deduction (SBD) offers a reduced Federal corporate taxes rate to Canadian small businesses. SBD has undergone several changes since its introduction, including in the coverage of corporations, eligibility of deductible income, and the threshold of business income. As of 2025, Canadian businesses can claim up to CA\$0.5 million income for a rate of 9%, compared to an otherwise rate of 28% after abatement.

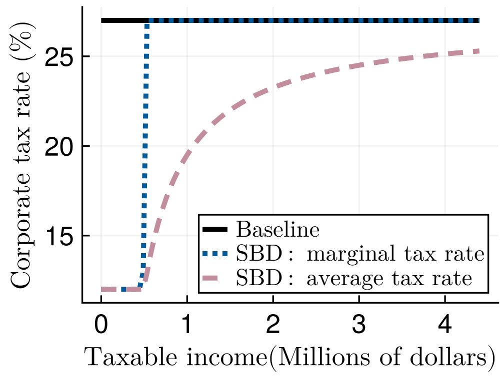
Size-based preferential tax treatment is prevalent in many countries beyond Canada, making for one of the most widely use forms of entrepreneurial policy.[12] Its merits remain actively debated in both policy and public discourse. Proponents argue that such policy encourages business dynamism by alleviating frictions disproportionally faced by small businesses, while critics argue that the policy leads to misallocation.[13] Given the widespread use, the macroeconomic implications of such policies warrant close study.

We use our quantitative model to study the macroeconomic effect of SBD. Figure 7 depicts the policy experiment. We set the baseline flat corporate tax rate to be 27% , which combines the net Federal tax rate after the general tax reduction of 15% and the median provincial higher tax rate of 12%. We set the SBD rate to be 12%, which combines the net marginal federal tax rate for SBD of 9% and the median provincial lower tax rate of 3%. The model cutoff for the taxable income for SBD is set to be 70th percentile of of firms by revenue, corresponding to the percentage of firms with taxable income below CA\$0.5 million

[12] Countries with preferential tax treatment for small businesses include Japan, Spain, Portugal, Slovakia (Reforms, 2020), China (Bai et al., 2020), France (Garicano et al., 2016), among others.

[13] For instance, Joe Oliver, former Finance Minister, stated in the 2015 Budget that "small businesses are critical to the health of the Canadian economy. [...] That is why we have worked so hard to support them over the years, and continue to do so. Small businesses across the country will be able to use these additional tax savings to fuel growth in capital and hire more people." In contrast, *The Globe and Mail*, a newspaper, commented that "The awkward reality for Mr. Oliver is that large companies are Canada's engines of growth, not small ones. The research is compelling. Large companies are more productive, hire more people, pay better wages, provide more stable employment, invest more in research and development, and are more likely to export. In other words, they do all the things governments should want businesses to do."

Figure 7: Tax schedule in the quantitative analysis



Notes: This figure shows tax schedule in the quantitative analysis. The black solid line represents the flat corporate tax rate of 27% in our baseline model. The dashed lines represent the marginal and average tax rates in our counterfactual analysis with the small business deductions (SBD), for which the model cutoff for the taxable income for SBD is set to be 70th percentile of firms by revenue.

in the data.

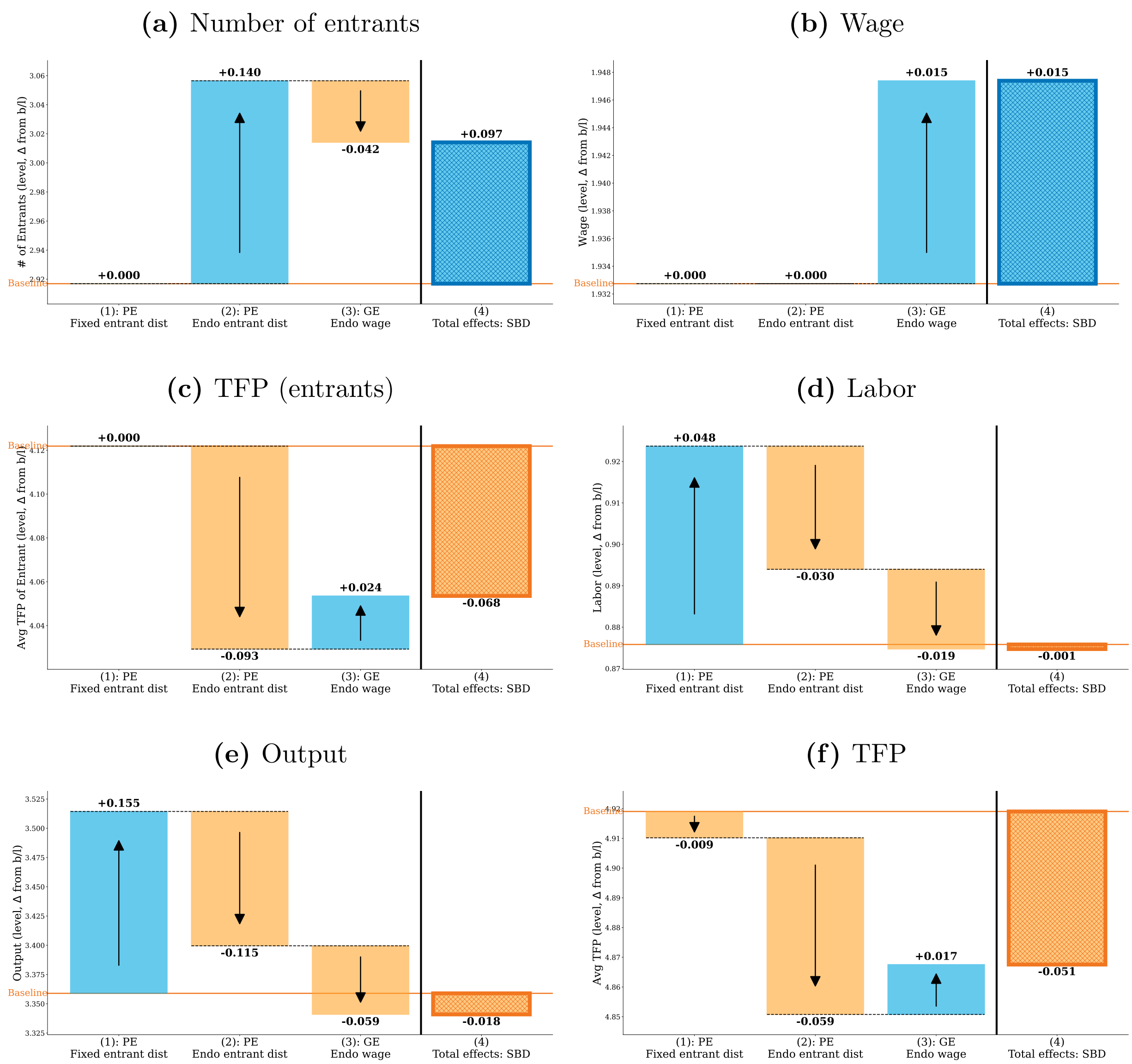
5.2. Macro effects of Small Business Deduction

The last columns of Figure 8 quantifies the macroeconomic effects of the SBD. Compared to the baseline economy without the SBD, the policy increases the share of entrepreneurs by 1% as intended, leading to a decline in labor supply and an increase in wages. However, aggregate output falls by 0.5% under the SBD, while aggregate productivity declines by 1%. Strikingly, small business deductions, designed to encourage entrepreneurship and improve productivity, lead to a decline in aggregate output and business dynamism.

Figure 8 further decomposes its transmission to understand the underlying cause. The baseline economy from Section 4 without the SBD serves as the benchmark, plotted as the horizontal orange line. Then, to the study the transmission of the SBD, we introduce three incremental changes.

The first change introduces the SBD into the baseline economy while holding the entrant distribution and wage fixed at their baseline levels. This experiment isolates the partial-equilibrium effect of the SBD on the life cycle of incumbent firms. In Figure 8, the results for this case are shown in the first set of bars, labeled "PE: Fixed entrant dist." By construction, the number of entrants and wage remain unchanged relative to the baseline. Since the SBD relaxes financial frictions, small incumbent firms that are financially constrained are able to hire more and produce more, which leads to higher aggregate labor and output,

Figure 8: The transmission of SBD



consistent with policymakers' intended effects. TFP declines slightly, since firms that would otherwise exit remain in operation. Overall, without affecting the entrant distribution, the SBD increases aggregate output by 4.5%.

Next, we allow the entrant distribution to adjust endogenously in response to the SBD. This experiment isolates the effects of the SBD on entrepreneurial selection. In Figure 8, the results are shown in the second set of bars, labeled "PE: Endo entrant dist." A lower tax rate for small businesses attracts greater entry, as shown in panel (a), but reduces the average quality of entrants, as reflected in decline in entrant TFP in panel (c). Since more households choose entrepreneurship, aggregate labor falls. Overall, the endogenous entry response reduces aggregate TFP by 2.3% and output by 3.3%, offsetting three-quarters of the positive effects of the SBD.

Lastly, we study the general-equilibrium effects of the policy by allowing wage to adjust endogenously. The results are reported in the third set of bars, labeled "GE: Endo wage." In general equilibrium, wage rises in response to the reduced labor supply, which slightly discourages entry and moderates the decline in TFP. However, the endogenous wage increase further reduces equilibrium labor and output, erasing the remaining positive effects of the policy. The total effects of the SBD, reported in the fourth set of bars, are lower output and lower productivity.

Our analysis suggests that both the quantity and quality of firm creation matter for macroeconomic outcomes. Size-based entrepreneurial policies can reduce output and productivity by attracting lower-potential entrants. In the presence of ex-ante firm heterogeneity, differences at entry tend to persist throughout the firm life cycle, making selection effects particularly important. As a result, macroeconomic policies that target small businesses irrespective of productivity may be costly and counterproductive.

6. Conclusion

Using longitudinal administrative data based on Canadian personal and corporate tax filings, we document two new facts about firm creation. Conditional on entry, founders' labor-market capacities have persistent relationship with firm performance. Moreover, entry is not random. Workers with higher employment income are more likely to become entrepreneurs.

Incorporating both facts in a quantitative model of occupational choice and firm dynamics, we find that firm heterogeneity is shaped by both the selection into entrepreneurship and post-entry life-cycle dynamics. Small business tax deduction, therefore, has limited effects at the aggregate level: Even though it helps firms grow faster by relaxing financial constraints, it worsens entrepreneurial selection, largely offsetting the positive effects. Our analysis highlights that for the macroeconomic outcomes, both the quantity and quality of firm creation are crucial.

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Online Appendices

A. Additional Details for the Empirical Analysis

A.1. 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, Goodman, Volz and Moore (2021), Ganong, Jones, Noel, Greig, Farrell and Wheat (2020) and Gauthier (2025). Our results are robust to both different specifications and predictive models.[14] We first estimate the regression

$$\log w_{it} = \alpha + \delta_{it} + \boldsymbol{\beta}' \boldsymbol{X_{it}} + \varepsilon_{it}, \tag{18}$$

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

[14] 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, Henriques, Krimmel and Sabelhaus (2016)'s reconciliation of wealth surveys and capitalized administrative income tax data.

variables.[15] Then, the wealth of i in year t is predicted as

$$\log \hat{w}_{it} = \hat{\alpha} + \hat{\delta}_t + \hat{\boldsymbol{\beta}}' \boldsymbol{X_{it}}, \tag{19}$$

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 are correctly imputed into the 90-100 group, with 70% of them classified above the 80th percentile by the methodology.

[15] 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.

A.2. Additional Tables and Figures

Table A.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 A.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.

B. Additional Details for the Theoretical Framework

This section derives the entry threshold in Section 3.1 and proves Propositions 1 and 2.

B.1. Entry threshold

An individual who becomes an entrepreneur solves

$$V^E(e,z) = \max_n \left\{\exp(z)n^\theta - Wn\right\}.$$

The first-order condition is

$$\theta \exp(z) n^{\theta-1} = W,$$

which implies the optimal labor demand

$$n^*(z) = \left(\frac{\theta \exp(z)}{W}\right)^{\frac{1}{1-\theta}}.$$

Substituting this choice into the entrepreneur's problem gives

$$V^E(e,z) = \left(\theta^{\frac{\theta}{1-\theta}} - \theta^{\frac{1}{1-\theta}}\right) \exp\left(\frac{z}{1-\theta}\right) W^{-\frac{\theta}{1-\theta}}.$$

Let

$$A(\theta) \equiv \theta^{\frac{\theta}{1-\theta}} - \theta^{\frac{1}{1-\theta}}.$$

Because the value of paid employment is $V^W(e,z) = \exp(e)W$, the entry condition $V^E(e,z) \geq V^W(e,z)$ is equivalent to

$$\log A(\theta) + \frac{z}{1-\theta} - \frac{\theta}{1-\theta}\log W \geq e + \log W.$$

Multiplying by $1-\theta$ and rearranging yields

$$z - (1-\theta)e \geq \log W - (1-\theta)\log A(\theta) \equiv \bar{\Delta}(W).$$

Hence, defining $\Delta(e,z) \equiv z - (1-\theta)e$, an individual chooses entrepreneurship if and only if $\Delta(e,z) \geq \bar{\Delta}(W)$.

B.2. Proof of Proposition 1

The joint normal distribution of (e,z) implies

$$z \mid e \sim \mathcal{N}\left(\mu_z + \rho\frac{\sigma_z}{\sigma_e}e,\ \sigma_z^2(1-\rho^2)\right).$$

Conditional on e, entry occurs when

$$z \geq \bar{\Delta}(W) + (1-\theta)e.$$

Standardizing this threshold using the conditional distribution of z gives

$$\frac{\bar{\Delta}(W) + (1-\theta)e - \mu_z - \rho(\sigma_z/\sigma_e)e}{\sigma_z\sqrt{1-\rho^2}} = \alpha + \beta e,$$

where

$$\alpha \equiv \frac{\bar{\Delta}(W) - \mu_z}{\sigma_z\sqrt{1-\rho^2}}, \qquad \beta \equiv \frac{1-\theta-\rho\sigma_z/\sigma_e}{\sigma_z\sqrt{1-\rho^2}}.$$

For a normally distributed variable, the mean of the upper tail is the conditional mean plus the conditional standard deviation times the upper hazard function $\mathcal{M}(x) = \phi(x)/(1-\Phi(x))$. Therefore,

$$\mathbb{E}[z \mid \text{entry},\ e] = \mu_z + \rho\frac{\sigma_z}{\sigma_e}e + \sigma_z\sqrt{1-\rho^2}\mathcal{M}(\alpha+\beta e).$$

This is equation (2).

It remains to show that the conditional mean is strictly increasing in e when $\rho \geq 0$. Differentiating gives

$$\frac{\partial}{\partial e}\mathbb{E}[z \mid \text{entry},\ e] = \rho\frac{\sigma_z}{\sigma_e} + \left(1-\theta-\rho\frac{\sigma_z}{\sigma_e}\right)\mathcal{M}'(\alpha+\beta e).$$

The upper hazard function satisfies $0 < \mathcal{M}'(x) < 1$ for all x. If $1-\theta-\rho\sigma_z/\sigma_e \geq 0$, the derivative is strictly positive because either the first term is positive or the second term is positive. If $1-\theta-\rho\sigma_z/\sigma_e < 0$, then

$$\frac{\partial}{\partial e}\mathbb{E}[z \mid \text{entry},\, e] > \rho\frac{\sigma_z}{\sigma_e} + \left(1-\theta-\rho\frac{\sigma_z}{\sigma_e}\right) = 1-\theta > 0.$$

Thus, $\mathbb{E}[z \mid \text{entry},\, e]$ is strictly increasing in e when $\rho \geq 0$.

B.3. Proof of Proposition 2

Using the same standardized threshold, the conditional probability of entry is

$$\begin{aligned} p_e(e) &\equiv \Pr\left(\Delta(e,z) \geq \bar{\Delta}(W) \mid e\right) \\ &= \Pr\left(z \geq \bar{\Delta}(W) + (1-\theta)e \mid e\right) \\ &= 1-\Phi(\alpha+\beta e), \end{aligned}$$

where α and β are defined as above. Differentiating with respect to e gives

$$p_e'(e) = -\phi(\alpha+\beta e)\beta.$$

Since $\phi(\cdot) > 0$, the sign of $p_e'(e)$ is the sign of $-\beta$. If $\rho \leq 0$, then

$$1-\theta-\rho\frac{\sigma_z}{\sigma_e} > 0,$$

so $\beta > 0$ and $p_e'(e) < 0$. The conditional probability of entry is therefore strictly decreasing in e. If instead

$$\rho > (1-\theta)\frac{\sigma_e}{\sigma_z},$$

then $\beta < 0$ and $p_e'(e) > 0$. The conditional probability of entry is therefore strictly increasing in e.

C. Additional Details for the Statistical Decomposition

This section provides details for the statistical decomposition in Section 3.4.

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

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 identifies $\boldsymbol{\beta_u}$, $\boldsymbol{\beta_\theta}$, 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 identifies ρ_u, ρ_v, ρ_w, $\sigma_{\hat{u}}$, $\sigma_{\hat{v}}$, $\sigma_{\hat{\theta}}$, σ_ϵ, and σ_z.

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

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

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).[16]

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 in terms of both the shape and the levels.

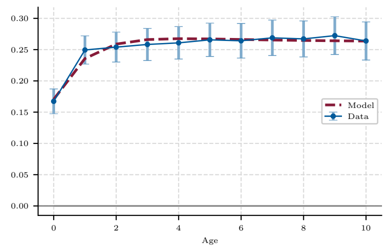
Local projection coefficients $\hat{\beta}_a$ helps to identify the $\boldsymbol{\beta}$'s since

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

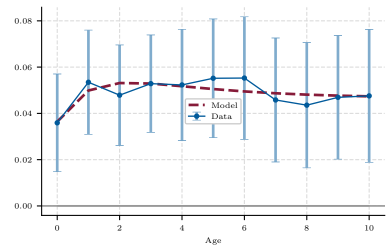
[16]To include the full sample of new firms in the estimation, the empirical specification here slightly differs from equation (4) in Section 3. Missing observations are populated with 0, with a separate indicator variable for each explanatory variable that equal 1 if the observation is missing and 0 otherwise.

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

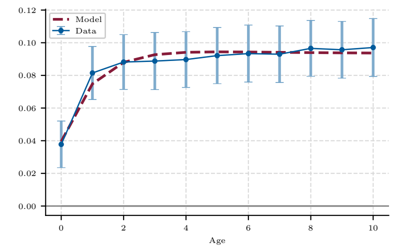
(a) Serial Ent



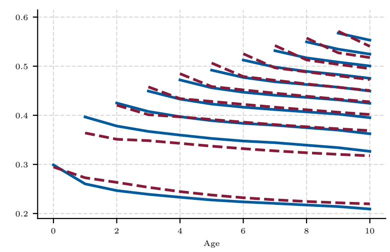
(b) Past profits



(c) Past emp income



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



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

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

C.3. Variance decomposition

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

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

which can expressed as

$$\begin{aligned}\mathbb{V}[\log n_{j,a}] =& \hat{\beta}_a^T \cdot \mathbb{V}[x_j] \cdot \hat{\beta}_a \\ & + \sigma_{\hat{u}}^2 \cdot \rho_u^{2(a+1)} + \sigma_{\hat{\theta}}^2 \cdot \left(\frac{1-\rho_u^{a+1}}{1-\rho_u} \right)^2 + \sigma_{\hat{v}}^2 \cdot \rho_v^{2(a+1)} \\ & + \sigma_\varepsilon^2 \cdot \frac{1-\rho_w^{2(a+1)}}{1-\rho_w^2} + \sigma_z^2. \end{aligned} \tag{20}$$

The importance of ex-ante heterogeneity relative to total heterogeneity is calculated as the sum of the first two rows in (20) 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 (20) as a share of the sum of the first two rows.