Wasted on the Young? Aging and Entrepreneurial Activity, Opportunity, and Skill

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Abstract

Population aging is transforming the age structure of advanced economies, yet evidence on how that structure relates to new venture creation remains thin at the macroeconomic level. This paper provides such evidence for 59 countries over 2002–2017, linking population age structure with Global Entrepreneurship Monitor measures of early-stage entrepreneurial activity and of the perceptions that entrepreneurship theory ties to entry. A simple life-cycle framework distinguishes three channels: the age-specific perceptions of a population's members, the shorter horizon over which older workers can recoup entry costs, and the economic conditions that aging alters for young and old alike. Countries with younger working-age populations start more businesses yet report less entrepreneurial skill. They perceive more opportunity, but macroeconomic conditions fully explain the advantage, and fear of failure varies little with age structure. Once all three perceptions are held constant, age structure no longer predicts established business ownership. It still predicts new entry. The evidence suggests that aging reduces entry through channels that perceptions do not register: the shortening horizon over which a venture can pay off, or the economic environment that aging brings with it.

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1. Introduction

Advanced economies are aging at an unprecedented pace, and their rates of new business formation have been declining for decades (Decker, Haltiwanger, Jarmin, and Miranda, 2014). If entrepreneurial vitality is an endowment of the young, aging societies face a demographic headwind that few startup policies can easily offset. Whether that is so depends on how age shapes entrepreneurship, a question with a long pedigree in entrepreneurship research. The decision to start a venture depends on the interplay between individual characteristics, such as perceived opportunity and entrepreneurial skill, and the broader economic environment in which potential entrepreneurs operate (Shane and Venkataraman, 2000; Arenius and Minniti, 2005; Lazear, 2004; Stenholm, Acs, and Wuebker, 2013). At the individual level the role of age is increasingly well documented: the propensity to enter entrepreneurship varies systematically over the life cycle, typically peaking in early-to-mid career (Levesque and Minniti, 2006, 2011; Parker, 2018), though the relationship is far from uniform across entrepreneur types and cohorts (Kautonen, Down, and Minniti, 2014; Zhang and Acs, 2018). Recent syntheses of this literature by Lévesque, Stephan, Kautonen, and Bakker (2026) and Syed, Singh, Ahmad, and Butt (2024) are organized almost entirely around the individual entrepreneur's age. Less is known about how the age composition of an entire population shapes aggregate entrepreneurial activity and the perceptual factors associated with it. Individual-level research supplies the mechanisms that select people into new ventures. Studying those mechanisms across whole populations tests whether they are visible in aggregate data, and whether the wages and returns that aging shifts for everyone matter alongside them. That is the contribution of this paper.

The gap between individual-level evidence and aggregate outcomes is consequential. Policymakers increasingly ask whether demographic change will erode entrepreneurial dynamism (Lévesque et al., 2026; Kautonen et al., 2014), and the aggregate stakes are real: declines in business creation have been documented across developed economies (Decker, Haltiwanger, Jarmin, and Miranda, 2016; Cao, Salameh, Seki, and St-Amant, 2017; Bijnens and Konings, 2020), and models of firm demographics assign slowing population growth a central role in that decline (Karahan, Pugsley, and Şahin, 2024; Hopenhayn, Neira, and Singhania, 2022). Proposed channels range from life-cycle risk-taking (Kopecky, 2017) to demographic pressure on wages and returns that raises the macroeconomic cost of starting up (Lim, 2026). Rising life expectancy may itself link the individual and aggregate levels. For example, Wickstrøm, Klyver, and Cheraghi-Madsen (2022) show that societal increases in lifespan shift the peak age of entrepreneurial entry later, suggesting that population-level demographic change reshapes the psychology of individual entry decisions. But cross-country evidence on which of these channels operate remains scarce. Does aging reduce entrepreneurship because fewer people are at the "right age" to start a business, an age at which people see more opportunities, fear failure less, and have more years left to recoup an entry cost (a compositional channel)? Or does it alter the macroeconomic environment, shifting wages, returns to capital, and labor market conditions in ways that discourage entry for individuals of all ages (a macro-structural channel)?

Disentangling these channels matters because they carry different policy implications. If the relationship is primarily compositional, then aging economies face a headwind that can only be offset by raising entry rates among older cohorts. If macro-structural forces dominate, then policies addressing the business environment (financing, regulation, education) may be more effective. Prior work has made progress on this question. Levesque and Minniti (2011) show theoretically that population age composition should affect aggregate entrepreneurship through life-cycle entry profiles. Bönte, Falck, and Heblich (2009) find that the age structure of German regions predicts regional startup rates. Liang, Wang, and Lazear (2018) develop a model in which demographic structure shapes the opportunity to acquire entrepreneurial skills and test it using Global Entrepreneurship Monitor (GEM) data. What existing work has not examined is whether the perceptual underpinnings of entrepreneurial entry, specifically perceived opportunity, self-assessed skill, and fear of failure, are themselves correlated with population age structure. If they are, this would point to compositional channels operating through individual perceptions; if they are not, the relationship would more plausibly run through channels that leave no trace in perception data, whether macro-structural forces or the life-cycle time horizon itself.

This paper addresses this gap. I investigate the relationship between population age structure and both entrepreneurial activity and entrepreneurial perceptions across 59 countries over the period 2002–2017, combining data from the GEM Adult Population Survey, the United Nations World Population Prospects, and the Penn World Tables. To estimate how the full age distribution relates to the outcomes of interest, I employ the Fair and Domínguez (1991) approach, which allows the entire population age distribution, not just one or two summary age shares, to enter the analysis flexibly, so that the full shape of the age–entrepreneurship relationship can be estimated.

Two findings line up with life-cycle theory. Early-stage entrepreneurial activity (TEA) is significantly higher in countries with larger young working-age populations (ages 15–39) and lower in countries with older populations. Self-reported entrepreneurial skill runs the other way: older populations report more of it, consistent with skills accumulating over the working life.

The perceptual evidence, however, poses a puzzle for accounts that attribute the entry advantage of young populations to the characteristics of young individuals. Perceived opportunity does track demographics in the raw data, but the relationship disappears once macroeconomic conditions are held constant: younger populations perceive more opportunity because of the economies they live in, not because of their age composition. The demographic gradient in fear of failure is weak. And the demographic effect on TEA itself persists after controlling for skill, opportunity, and fear of failure alike, suggesting that life-cycle forces such as the shrinking horizon over which entrepreneurial returns can be realized operate beyond what either individual perceptions or observed economic conditions capture. A contrast between the flow and the stock of entrepreneurship reinforces this reading. The demographic gradient in established business ownership is fully explained by perceptual variables, while the gradient in new entry is not.

This study makes three contributions to the entrepreneurship literature. First, I provide systematic evidence that population age structure is significantly associated with entrepreneurial activity at the country level, extending the work of Levesque and Minniti (2011) and Liang et al. (2018) to a broader set of outcomes and to the full age distribution. Second, I link demographic structure to entrepreneurial cognition by testing whether the perceptual antecedents of entry (opportunity, skill, and fear of failure) vary with population age composition. The finding that skill tracks demographics robustly while opportunity is mediated by macroeconomic conditions helps adjudicate between competing theoretical accounts. Third, I show that the demographic gradient in early-stage activity is not fully explained by either perceptual or macroeconomic variables, pointing to life-cycle forces that operate alongside compositional and structural macroeconomic channels rather than behavioral ones.

The remainder of the paper is organized as follows. Section 2 develops a theoretical framework drawing on life-cycle models of entrepreneurial entry and derives five testable hypotheses. Section 3 describes the data and empirical methodology. Section 4 presents results. Section 5 discusses the findings in light of the theoretical framework, and Section 6 concludes with policy implications and directions for future research.

2. Theoretical Background and Hypotheses

Entrepreneurship research has long recognized that the decision to create a new venture is shaped by the interplay between opportunities in the environment and the characteristics of the individuals who perceive and act upon them (Shane and Venkataraman, 2000). A substantial body of work has examined how individual attributes, including human capital, cognitive perceptions, and risk preferences, vary over the life cycle and affect entrepreneurial entry (Levesque and Minniti, 2006; Kautonen et al., 2014; Bohlmann, Rauch, and Zacher, 2017; Kautonen, Kibler, and Minniti, 2017). A more recent line of inquiry extends this logic from the individual to the aggregate level, asking how the age composition of a population shapes entrepreneurial activity across economies (Levesque and Minniti, 2011; Bönte et al., 2009; Liang et al., 2018; Lévesque et al., 2026). This paper sits at this intersection, investigating how population age structure relates to both the rate of early-stage entrepreneurial activity and the perceptual underpinnings (perceived opportunity, self-assessed skill, and fear of failure) that entrepreneurship theory identifies as proximate determinants of entry.

In this section, I review relevant theory and prior evidence to develop a set of testable hypotheses. I first present a simple formal framework that captures the key trade-offs facing potential entrepreneurs at different ages. I then use this framework to derive predictions about how population age structure should relate to aggregate entrepreneurial activity and perceptions, organizing the discussion around three channels: *perceptual-compositional* channels, in which population age structure shifts the distribution of the perceptions that drive entry (accumulated skill, perceived opportunity, fear of failure); a *non-perceptual time-horizon* channel, in which the shrinking window over which entrepreneurial returns can be realized changes the entry calculus without changing perceptions; and *macro-structural* channels, in which age structure alters wages, returns, and the broader economic environment facing individuals of all ages. These channels generate distinct, and in some cases competing, predictions, which I test empirically in Sections 3 and 4.

2.1. A Simple Framework

To fix ideas, I outline a stylized model of the entrepreneurial entry decision that captures the essential trade-offs between age, skill, and time horizon. The framework draws on Levesque and Minniti (2006) and Lazear (2004), and is intentionally simple: it serves to organize the theoretical channels and generate testable predictions rather than to be estimated directly. The main text presents only the entry condition and its aggregate implication; Appendix A contains the primitives and derivation.

Consider an individual of age a who will exit the labor force at age T, choosing each period between wage employment and entrepreneurship. Three ingredients shape that choice. Both wages and entrepreneurial profits increase with an accumulated skill $s(a)$, with skill rewarded more strongly in wage work than in entrepreneurship, consistent with the slower earnings growth of the self-employed documented by Hamilton (2000). Skill itself accumulates with experience (Lazear, 2004), and I assume it does so at a diminishing rate. Finally, entrepreneurial profits scale with a talent draw θ, known to the individual, and entry requires paying a fixed cost C. An individual enters when the expected discounted value of entrepreneurial profits over the remaining career exceeds the value of foregone wages plus the entry cost. This condition reduces to a talent threshold:

$$\theta > \underbrace{\frac{\omega \cdot \bar{s}(a)^{\alpha}}{A \cdot s(a)^{\gamma}}}_{\substack{\text{Skill-adjusted} \\ \text{opportunity cost}}} + \underbrace{\frac{C}{\mathcal{A}(a) \cdot A \cdot s(a)^{\gamma}}}_{\substack{\text{Amortized} \\ \text{entry cost}}} \equiv \theta^*(a) \tag{1}$$

where ω is the market wage rate, A is the productivity of entrepreneurial ventures, α and γ govern returns to skill in wage work and entrepreneurship respectively, $\bar{s}(a)$ is the average skill level over remaining wage-work years, and $\mathcal{A}(a)$ is an annuity factor that shrinks as retirement approaches. The probability of entry at age a is $\Pr(\theta > \theta^*(a))$, and the aggregate rate of early-stage entrepreneurial activity in an economy with age distribution $\{p_j\}$ is:

$$\text{TEA} = \sum_j p_j \cdot \Pr\big(\theta > \theta^*(a_j)\big) \tag{2}$$

Key predictions. The threshold $\theta^*(a)$ moves with age through three forces, illustrated in Figure 1.

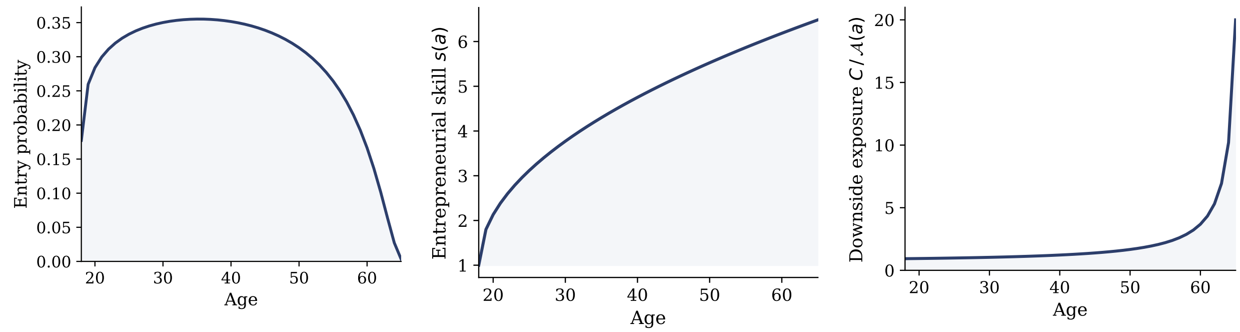
Time horizon. As retirement approaches, the annuity factor $\mathcal{A}(a)$ shrinks and the amortized entry cost rises: the same fixed investment must be recouped over fewer working years. Holding skill constant, entry falls with age. This is the mechanism emphasized by Levesque and Minniti (2006), and it operates independently of ability or opportunity. Wickstrøm et al. (2022) provide societal-level support: increases in life expectancy shift the peak of entrepreneurial entry toward later ages, consistent with a longer planning horizon lowering the effective threshold.

Skill accumulation. Early in the career, accumulating skill lifts entry. A young worker's profits are earned at current skill while the wages forgone reflect the rising path ahead, and the fixed entry cost weighs heavily against low-skill profits; both handicaps fade as skill accumulates. If skill raises the wage faster than it raises profits ($\gamma < \alpha$, a condition I maintain throughout), the opportunity cost of leaving wage work levels off in mid-career, and the shrinking horizon then dominates. The net result is the hump-shaped entry profile in Panel (a), peaking in early-to-mid career.

Downside exposure. The cost of failure (losing the entry cost C) looms larger as remaining earnings capacity shrinks. This exposure, proportional to $C/\mathcal{A}(a)$, is roughly flat through mid-career and rises sharply near retirement (Panel (c)), giving older workers a reason to report greater fear of failure.

Figure 1: *Illustrative model predictions over the life cycle*

(a) *Entry probability* **(b)** *Entrepreneurial skill* **(c)** *Downside exposure*



Notes: Illustrative predictions from the framework in Section 2.1. Panel (a): entry probability as a function of age, showing the hump shape generated by the interaction of skill accumulation and time-horizon effects. Panel (b): entrepreneurial skill $s(a)$, increasing and concave in age. Panel (c): downside exposure $C/\mathcal{A}(a)$, increasing with age as the remaining career shortens. Parameter values are reported in Appendix A.

2.2. From Individual Age to Population Age Structure

The individual-level framework above motivates the central question of this paper: does population age structure affect aggregate entrepreneurial activity, and if so, through which channels? Following Levesque and Minniti (2011) and Liang et al. (2018), I first distinguish compositional from macro-structural mechanisms, and then split compositional channels by whether they leave a trace in perception data, which yields the three channels introduced above.

Compositional effects arise when the age distribution of a population interacts with the life-cycle profile of entrepreneurial entry. Equation (2) shows how: if entry probability peaks in early-to-mid career, countries with larger shares of young working-age adults will exhibit higher rates of early-stage entrepreneurship simply because more individuals are at the age where entry is most likely. This channel requires only that individual-level age–entry profiles are similar across countries and that population age structure varies. Evidence for such compositional effects has been documented in country-level (Lamotte and Colovic, 2013) and regional data (Bönte et al., 2009).

Macro-structural effects arise when shifts in population age structure alter economic conditions that affect entrepreneurial incentives for individuals of *all* ages. In the framework above, these operate through the "environmental" parameters ω (wages) and A (venture productivity). Demographic change is known to affect aggregate wages and rates of return to capital (Gagnon, Johannsen, and Lopez-Salido, 2016). Karahan et al. (2024) show that declining labor force growth reduces firm entry by lowering the labor supply available to new firms. In the framework above, the only channel for scarcer labor is a higher ω, which raises θ^* at every age. Hopenhayn et al. (2022) reach a similar conclusion in general equilibrium: slower population growth mechanically lowers firm entry rates and ages the firm distribution. Demographic structure may also shape the institutional and cultural environment that conditions entry (Stenholm et al., 2013; Lévesque et al., 2026), in ways captured by A and C.

Separating these mechanisms empirically requires care, because all three predict higher entrepreneurship in younger populations. The distinction I exploit runs through perceptions. *Perceptual-compositional* channels should be visible in the perceptual data: younger populations should exhibit the perceptual profile of their constituent individuals (higher perceived opportunity, lower accumulated skill, and perhaps lower fear of failure), and holding these perceptions constant should absorb the demographic gradient in entry. Two channels, however, predict a gradient that survives perception controls. Macro-structural forces operate through ω and A rather than through any individual attribute. And the time-horizon mechanism, while compositional, is invisible to perception measures: a shrinking annuity factor changes the entry calculus without changing what individuals believe about their opportunities, their skills, or their fears. Observed macroeconomic conditions partially proxy for the former, so a demographic effect on entry that persists net of both perceptions and macroeconomic controls points to the time-horizon channel, unmeasured macro-structural forces, or both. One caveat bounds this inference: the three GEM items do not exhaust individual attributes, so a surviving gradient could also reflect compositional differences in traits the survey does not measure, such as risk tolerance or innovativeness. The test aims to separate what the measured perceptions capture from what they do not. It identifies the residual as non-perceptual, not as non-compositional. This distinction motivates the empirical strategy below.

2.3. Hypotheses

Drawing on the framework above, I develop the following hypotheses regarding the relationship between population age structure and entrepreneurial outcomes at the country level.

The most direct prediction is compositional: if entry probability peaks in early-to-mid career, countries with more individuals near that peak will exhibit higher rates of early-stage activity, by the aggregation logic of Equation (2). Micro-level evidence places the entry peak in the late twenties to mid-thirties (Liang et al., 2018; Levesque and Minniti, 2011), and aggregate evidence points the same way (Lamotte and Colovic, 2013; Bönte et al., 2009):

H1: *Countries with larger young working-age populations (ages 15–39) exhibit higher rates of early-stage entrepreneurial activity, while countries with larger older populations exhibit lower rates.*

Entrepreneurial skill accumulates through experience: prior ownership and work experience improve opportunity identification and the competencies needed to run a venture (Baron, 2006; Lazear, 2004; Ucbasaran, Westhead, and Wright, 2009). Countries with older populations, where more individuals have had time to accumulate that experience, should therefore report higher skill levels (Panel (b) of Figure 1). The GEM measure is self-assessed, and self-assessed skill is itself among the strongest predictors of entry across countries (Koellinger, Minniti, and Schade, 2007). Three individual-level findings cut the other way: Liang et al. (2018) propose that younger populations offer greater *opportunity* for skill acquisition through rank effects,[1] feasibility beliefs appear to peak in young adulthood (Minola, Criaco, and Obschonka, 2016), and in GEM microdata self-assessed skill itself declines with age (Bohlmann et al., 2017). None, however, should reverse the relationship between population age and the accumulated *stock* of skill:

H2: *Self-reported entrepreneurial skill is higher in countries with older populations.*

Younger individuals may also be more alert to opportunities. Cognitive flexibility and creativity decline with age (Kaufman and Horn, 1996; Ryan, Sattler, and Lopez, 2000; Acemoglu, Akcigit, and Celik, 2014), focus on opportunities narrows as remaining time shortens (Gielnik, Zacher, and Frese, 2012), and Liang et al. (2018) model an "advantages of youth" factor (idea generation and the capacity to break with past products and methods) that is strongest among the young. Perceived opportunity is also among the most robust predictors of entry across countries (Arenius and Minniti, 2005). If these individual-level patterns aggregate to the country level, younger populations should report more opportunity. The formal framework is deliberately agnostic here. The entry condition depends on talent, skill, and the economic environment, but not on a separate perception of whether opportunities exist. That agnosticism is what makes H3 an informative test, since a robust demographic gradient in perceived opportunity would point to compositional forces the model does not impose:

H3: *Perceived entrepreneurial opportunity is higher in countries with younger working-age populations.*

[1] Since there are fewer cohorts ahead blocking young workers, they are given more opportunity to accumulate skills (e.g., management experience) at earlier ages.

The framework does speak directly to the cost of failure. Downside exposure $C/\mathcal{A}(a)$ rises sharply as workers approach retirement (Panel (c) of Figure 1). Fear of failure suppresses entry in ways that vary with national context (Wennberg, Pathak, and Autio, 2013), and reported fear plausibly reflects this exposure (Cacciotti, Hayton, Mitchell, and Giazitzoglu, 2016; Kopecky, 2017). If the population's age composition determines how many individuals face high downside exposure, then:

H4: *Fear of failure is higher in countries with older populations.*

Finally, the framework identifies channels that leave no trace in perception data. The market wage ω and venture productivity A shift the entry threshold at every age without altering skill, opportunity perceptions, or fear of failure, and the time-horizon mechanism changes the entry calculus without changing beliefs. Age-graded social norms may operate similarly. Kautonen, Tornikoski, and Kibler (2011) find that permissive age norms raise late-career entry intentions, with only part of the effect running through perceptions of the kind the GEM measures, and Gielnik, Zacher, and Wang (2018) show in longitudinal data that younger individuals are more likely to turn an identified opportunity into an intention to pursue it. In the GEM conceptual model, by contrast, country conditions affect entrepreneurial activity precisely through opportunity and skill perceptions (Levie and Autio, 2008). Whether perceptions fully mediate the demographic gradient in entry is therefore a discriminating test:

H5: *The relationship between population age structure and early-stage entrepreneurial activity persists after controlling for perceived opportunity, self-reported skill, and fear of failure.*

An auxiliary prediction sharpens this test. The threshold $\theta^*(a)$ governs the *flow* of new entry, a decision taken at the horizon-sensitive margin: the time-horizon and macro-structural terms enter at the moment of entry. The *stock* of established owners is a different object. It is a survivorship-selected cross-section, filtered through years of exit decisions (Wennberg, Wiklund, DeTienne, and Cardon, 2010), and the owners who remain are those whose skill and perceived opportunities have kept their ventures viable; their current perceptions summarize the selection that built the stock. One might object that the stock, as accumulated past flow, should inherit the flow's non-perceptual imprint. But that imprint decays, as horizon conditions at long-past entry dates matter for today's stock only through who survived, and survival is what current skill and opportunity perceptions capture. Perceptual variables should therefore mediate the demographic gradient in established ownership more completely than the gradient in new entry. I examine this contrast alongside H5.

Table 1 summarizes the hypotheses, the channel each reflects, and where each is tested later in the paper. Support for H1 and H2 would confirm that the basic life-cycle mechanics of the framework operate at the country level. H3 and H4 test whether the perceptual mechanisms emphasized in individual-level research aggregate. H5 discriminates between the two, as full mediation by perceptions would favor perceptual-compositional explanations, while persistence would point to the time-horizon channel and macro-structural forces operating beyond individual cognition.

Table 1: *Summary of hypotheses*

	Prediction	Channel	Test
H1	Larger young working-age (15–39) shares are associated with higher early-stage activity	Compositional (perceptual and time-horizon)	Table 4; Figure 2; Appendix C
H2	Older populations report higher entrepreneurial skill	Perceptual-compositional	Table 5; Figure 3
H3	Younger populations perceive more opportunity	Perceptual-compositional	Table 5; Figure 3
H4	Older populations report more fear of failure	Perceptual-compositional	Table 5; Figure 3
H5	Demographic gradient in early-stage activity survives perception controls	Non-perceptual (time-horizon and/or macro-structural)	Table 4, cols. (3)–(4); contrast with ownership, Appendix D.1

3. Data and Methodology

Publicly available data on entrepreneurial activity and perception come from the Global Entrepreneurship Monitor (GEM) (Reynolds, Bosma, Autio, Hunt, De Bono, Servais, Lopez-Garcia, and Chin, 2005). The GEM has conducted annual surveys since 2000 in a large and growing number of countries; as many as 115 economies have been surveyed to date. Its adult population survey (APS) is the source for national statistics on entrepreneurial behavior and opinions. My primary activity measure is *total early-stage entrepreneurial activity* (TEA): the share of the 18–64 population engaged in nascent entrepreneurial activity (early activity that has not yet paid wages for over three months) plus those involved in a new business (a firm that has paid wages for 3 to 42 months). The GEM also records whether activity is opportunity- or necessity-driven.[2] The two types of entrant differ in

[2]Opportunity-based TEA counts early-stage activity whose founders report pursuing a business opportunity rather than having no better options for work, under GEM's pre-2019 motive classification. Fairlie and Fossen (2018) treat this self-report as subjective and define necessity from prior unemployment instead.

age and in growth orientation (Block and Wagner, 2010; Fairlie and Fossen, 2018) and may respond differently to population age structure. I use three perception measures as well: perceived entrepreneurial opportunity,[3] self-reported entrepreneurial skill,[4] and fear of failure.[5]

In addition to the national averages from the APS, the GEM surveys regional experts on entrepreneurial conditions within economies. I use these National Expert Survey (NES) variables to control for institutional and environmental factors. Twelve conditions are surveyed, spanning entrepreneurial finance, government policies and programs, entrepreneurial education, R&D transfer, internal market dynamics and openness, cultural and social norms, and physical and commercial infrastructure. These provide a more precise way of comparing country-specific factors that may be missed by broader macroeconomic controls.

Demographic data come from the United Nations *World Population Prospects* (UN, 2019), which provide age-specific population counts from age 0 to 100. From these I construct population shares covering the entire age distribution, not just the working-age population on which GEM statistics are measured; the construction and the rationale for including young and old dependents are described below.

Finally, I merge data from the Penn World Tables (PWT) (Feenstra, Inklaar, and Timmer, 2015), which provide macroeconomic controls capturing the economic incentives for business creation in each country-year. I use data on output, employment, hours worked, human capital, prices of capital, and internal rates of return, as well as a dummy for the global financial crisis (2008–2010). The merged dataset is an unbalanced panel of 59 countries over 2002–2017. For some countries the GEM has only a few years of data, but the average panel with all controls spans 9.1 years. I report summary statistics for all outcomes and controls in Table 2 for the sample where all variables are present. Specifications that omit the NES variables have a slightly larger sample (about 10 years for the average panel) with little difference in summary statistics.

To estimate the relationship between the full population age distribution and outcomes of interest, I use the Fair and Domínguez (1991) polynomial specification, applied to cross-country panels by Higgins (1998). Aksoy, Basso, Smith, and Grasl (2019) instead enter the age shares directly in a shorter OECD panel with fewer age groups. The restriction matters here because population shares in adjacent age groups are highly correlated, making it impractical to include many age shares as separate regressors. The Fair-Dominguez approach addresses this by assuming that the age-specific coefficients lie on a low-order

[3]Percent yes to: *In the next 6 months there will be good opportunities for starting a business in the area where you live?*

[4]Percent yes to: *You have the knowledge, skill, and experience required to start a new business?*

[5]Percent yes to: *Fear of failure would prevent you from starting a new business?*

Table 2: *Descriptive Statistics*

	Mean	SD	Min	Max
GEM Outcome Variables				
Total Early Stage Entrepreneurship (TEA)	10.25	6.25	1.40	40.34
TEA: Opportunity Based	7.51	4.50	0.81	29.57
Current Business Owner	16.17	7.56	4.24	49.72
Recent Business Exit	2.75	2.05	0.38	15.02
Entrepreneurial Opportunity	38.60	15.15	2.85	81.30
Entrepreneurial Skill	46.28	12.67	8.65	82.29
Fear of Failure	39.54	8.92	17.08	72.35
PWT Macroeconomic Controls				
Output Growth	3.32	5.28	-17.09	31.93
Employment Growth	1.15	2.06	-15.06	13.10
Human Capital Growth	0.69	0.56	-0.69	3.72
Growth Average Hours	-0.35	1.06	-6.09	8.59
Global Fin. Crisis	0.17	0.37	0.00	1.00
Price Capital formation	67.81	20.29	27.90	145.84
Price Capital Services	90.21	37.22	24.54	282.29
Internal Rate of Return	8.94	4.32	1.00	23.36
GEM NES Variables				
Financing	2.61	0.44	1.57	4.08
Governmental support and policies	2.60	0.47	1.53	3.96
Taxes & Bureaucracy	2.42	0.59	1.32	4.27
Cultural/Social Norms	2.83	0.52	1.62	4.59
Govt. Programs	2.69	0.46	1.20	3.75
School Entre. Educ.	2.07	0.37	1.28	3.43
Post-School Entre. Educ.	2.85	0.34	1.89	3.86
R&D Transfer	2.47	0.37	1.64	3.73
Infrastructure	3.10	0.36	2.08	4.21
Internal Market Dynamics	2.95	0.52	1.78	4.40
Internal Market Openness	2.65	0.35	1.84	3.73
Physical Infrastructure	3.84	0.46	2.10	4.82

Statistics reported for the 2002–2017 sample used in the full regressions below, where all variables are present. The full specification uses an unbalanced panel of 59 countries with N=537 and an average panel length of 9.1 years. NES refers to variables from the GEM national expert survey and are averages of expert responses on a scale of 1 (low) to 5 (high). GEM entrepreneurial activity variables are percentages of working-age adults.

polynomial, reducing the problem from estimating J parameters to estimating a small number of polynomial coefficients. Starting from:

$$y_{i,t} = \phi X_{i,t} + \sum_{j=1}^{J} \alpha_j p_{j,i,t} + \mu_i + \mu_t + \epsilon_{i,t} \tag{3}$$

where $p_{j,i,t}$ is the share of population in group j in country i at time t, two assumptions provide joint estimation of the age-specific effects α_j:

$$\sum_{j=1}^{J} \alpha_j = 0 \tag{4}$$

$$\alpha_j = \delta_0 + \delta_1 j + \delta_2 j^2 + \delta_3 j^3 \tag{5}$$

The first assumption normalizes effects to sum to zero, making them jointly estimable alongside the regression constant. The second assumes a smooth polynomial relationship between age group and effect size. I use a third-order (cubic) polynomial, which allows for up to two turning points in the age profile and is flexible enough to capture the hump-shaped patterns predicted by the theoretical framework while avoiding overfitting.[6] Substituting these assumptions into Equation 3 yields three constructed demographic predictors (see Appendix B for the derivation):

$$\begin{aligned} D_{1,it} &= \left(\sum_{j=1}^{J} j \, p_{j,it} - (1/J) \sum_{j=1}^{J} j \right), \\ D_{2,it} &= \left(\sum_{j=1}^{J} j^2 \, p_{j,it} - (1/J) \sum_{j=1}^{J} j^2 \right), \\ D_{3,it} &= \left(\sum_{j=1}^{J} j^3 \, p_{j,it} - (1/J) \sum_{j=1}^{J} j^3 \right). \end{aligned} \tag{6}$$

The estimated coefficients on D1–D3 are the polynomial parameters $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ of Equation (5). Loosely, D1, the linear term, captures whether the overall relationship tilts toward young or old populations; D2, the quadratic term, its curvature; and D3, the cubic term, lets that curvature change sign across the age range, which permits a second turning point and, in the profiles estimated here, mostly appears as asymmetry between the young and old tails. None is the effect of any particular age group. The quantities of interest are the implied age-specific effects $\hat{\alpha}_j$, which I recover from these estimates using Equation (5) and

[6] Higher-order polynomials produce qualitatively similar results but with greater instability in the tails. Second-order polynomials are too restrictive to capture the asymmetric profiles observed for several outcomes.

plot with confidence intervals computed via the delta method, a standard approximation for the sampling variance of nonlinear functions of estimated coefficients. The estimating equation is:

$$y_{i,t} = \delta D_{i,t} + \phi X_{i,t} + \mu_i + \mu_t + \epsilon_{i,t} \tag{7}$$

where $y_{i,t}$ is an outcome of interest, $D_{i,t}$ is the vector of three demographic predictors, and $X_{i,t}$ is a vector of additional controls.

I construct age groups covering the entire population distribution: ages 0–9, twelve five-year groups from 10–14 through 65–69, and 70 and above, yielding $J = 14$ groups. While GEM statistics are measured on the working-age population (18–64), including non-working-age groups is motivated by the macro-structural channels discussed in Section 2.2: young dependents and retirees do not start businesses themselves,[7] but shifts in their population shares affect family structure, labor supply, aggregate savings, and the institutional environment in ways that may influence entrepreneurial incentives for working-age adults (Thébaud, 2016; Cacciotti, Hayton, Mitchell, and Allen, 2020; Kopecky, 2017). The sum-to-zero assumption in Equation (4) ensures that effects are identified relative to a population-weighted average rather than to any particular omitted group.

I estimate Equation (7) for two sets of outcomes. *Activity outcomes* include total early-stage entrepreneurial activity (TEA) and opportunity-based TEA, which directly test H1. *Perception outcomes* include perceived opportunity, self-reported skill, and fear of failure, which test H2–H4. Controls enter in four steps: (1) demographic predictors and year fixed effects only; (2) macroeconomic controls from the PWT (growth rates of output, employment, human capital, and average hours worked; a global financial crisis dummy for 2008–2010; prices of capital services and formation; and the internal rate of return);[8] (3) the perception variables, except where one is the outcome; and (4) the twelve NES institutional variables. The TEA specifications that add perception controls in step (3) constitute the test of H5; as a contrast, I estimate the same build-up for established business ownership in Appendix D.1. Country effects μ_i are estimated with a random effects (RE) estimator, which uses both cross-country and within-country variation rather than discarding cross-country differences as fixed effects would; the choice matters here because demographic structure varies primarily across countries over the sample period. A Hausman test, which asks whether RE and fixed effects estimates differ systematically (a signal that the RE assumptions fail), does not reject RE ($p = 0.885$). Fixed effects results are reported in Appendix E and corroborate the main findings.

[7] Old-age entrepreneurs may be an interesting phenomenon as populations age, but the GEM data used here are not suited to studying it.

[8] I use growth rates rather than levels, as these may better capture the forward-looking opportunities relevant to nascent entrepreneurs. Results are qualitatively unchanged with levels.

Table 3 reports pairwise correlations among the outcomes, the perception measures, and the demographic predictors. The three predictors are near-collinear in this sample (pairwise correlations of 0.99–1.00), and their correlations with any outcome are not informative about the implied age profile, which depends on the three coefficients jointly; this is why the analysis below interprets the recovered profiles rather than the individual coefficients.

Table 3: *Correlation Matrix*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. TEA	1.00								
2. TEA (Opp.)	0.96***	1.00							
3. Own Business	0.77***	0.74***	1.00						
4. Opportunity	0.57***	0.58***	0.56***	1.00					
5. Skill	0.64***	0.61***	0.65***	0.71***	1.00				
6. Fear of Failure	-0.19***	-0.18***	0.11**	0.04	0.14***	1.00			
7. D1	-0.67***	-0.59***	-0.48***	-0.49***	-0.52***	0.33***	1.00		
8. D2	-0.65***	-0.58***	-0.47***	-0.47***	-0.50***	0.33***	1.00***	1.00	
9. D3	-0.63***	-0.57***	-0.46***	-0.45***	-0.49***	0.32***	0.99***	1.00***	1.00

Pairwise correlations, listwise deletion, over the 2002–2017 sample. Column numbers refer to the numbered rows. $*p < 0.10, **p < 0.05, ***p < 0.01$.

4. Results

I now present results for country-year estimations of Equation 7, first for entrepreneurial activity (H1) and then for the perception outcomes (H2–H4). The closest antecedent is Lamotte and Colovic (2013), who use earlier GEM data and find positive effects of age shares 0–34 and negative effects above 35. Their specification required a separate regression for each population age share, while mine estimates the full profile jointly. The distinction matters: adjacent age shares are highly correlated, and with long-run aging trends non-adjacent shares are negatively correlated, so a positive coefficient on, say, the 18–24 share in a separate regression may capture that group's effect or variation coming through its negative relationship with older shares.

I present regression results as a progressive build-up, adding controls sequentially to show how the demographic relationship evolves with conditioning. The quantities of interest remain the implied age-specific effects $\hat{\alpha}_j$, plotted in the figures that follow.

4.1. Population Age Structure and Entrepreneurial Activity

Table 4 presents the results for TEA, the direct test of H1, as a progressive build-up of controls. Column (1) includes only the demographic predictors and year fixed effects. The demographic predictors are jointly highly significant ($p < 0.001$), but the individual coefficients are not well estimated. Adding macroeconomic controls in column (2) leaves the joint significance unchanged. In column (3), I add the perception variables (self-reported skill, opportunity, and fear of failure). Skill and opportunity are both strong positive predictors of TEA, and their inclusion sharpens the demographic coefficients: all three demographic predictors become individually significant (D1 and D2 at the 1% level, D3 at 5%). The demographic predictors remain jointly significant ($p = 0.001$) even after conditioning on all three perceptual variables, consistent with H5. The addition of NES institutional controls in column (4) attenuates the individual coefficients somewhat but does not change the joint significance ($p = 0.001$). Among the NES variables (not reported, to conserve space), cultural and social norms around entrepreneurship and post-schooling entrepreneurial education have positive and statistically significant effects for opportunity-based TEA.

That the individual demographic coefficients sharpen after conditioning on perceptions is itself informative: without holding constant the offsetting effects of skill and opportunity, the raw demographic relationship with TEA is partially obscured. The unconditional age profiles (presented in Appendix D.5) show a strong positive effect concentrated among very young populations, likely reflecting the correlation between young age structure and developing-economy characteristics. Conditioning on macroeconomic variables and perceptions reveals the hump-shaped profile predicted by the theoretical framework.

The implied age effects from the full specification are plotted in Figure 2. These 14 age-specific parameters are recovered from the regression coefficients using Equation (5), with 95% confidence bands estimated via the delta method. I plot coefficients for both the NES and non-NES specifications, with the more conservative confidence intervals shown. Consistent with H1, there is a strong hump-shaped correlation between age structure and early-stage entry, with positive effects for ages 15–39 and negative effects for ages 50 and above. Established business ownership behaves differently: its unconditional demographic gradient is significant ($p < 0.001$) but is fully absorbed once perception variables are added ($p = 0.65$; Appendix D.1), in sharp contrast to TEA, where demographics survive the same controls. This is the stock-flow contrast anticipated in Section 2.3 (Fonseca and Parker, 2019). Opportunity-based TEA shows a similar pattern to overall TEA but with somewhat smaller point estimates and a negative effect for very young dependents. One candidate explanation is that households with young children favor self-employment chosen for its flexibility

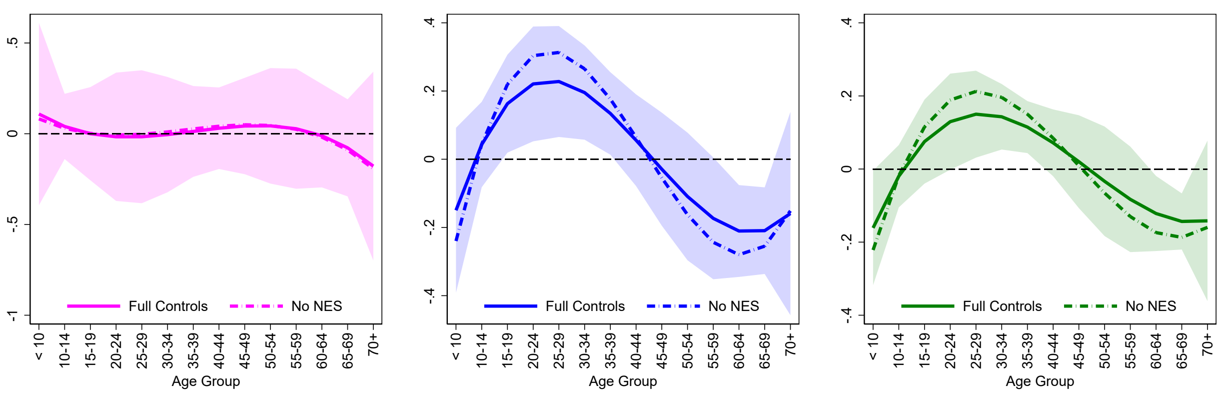
Table 4: *Population Age Structure and Early-Stage Entrepreneurial Activity: Model Build-Up (tests H1, H5)*

	TEA				TEA (Opportunity)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D1	-0.15	0.14	0.48^{***}	0.33^{**}	-0.03	0.09	0.33^{***}	0.23^{*}
	(0.15)	(0.24)	(0.17)	(0.17)	(0.13)	(0.19)	(0.12)	(0.13)
D2	0.08	-0.26	-0.72^{***}	-0.49^{*}	-0.04	-0.15	-0.46^{**}	-0.31
	(0.24)	(0.38)	(0.27)	(0.27)	(0.21)	(0.31)	(0.20)	(0.22)
D3	-0.00	0.11	0.29^{**}	0.19	0.04	0.05	0.17^{*}	0.11
	(0.11)	(0.17)	(0.12)	(0.13)	(0.10)	(0.14)	(0.09)	(0.10)
Skill			0.22^{***}	0.22^{***}			0.15^{***}	0.16^{***}
			(0.03)	(0.03)			(0.02)	(0.02)
Opportunity			0.06^{***}	0.06^{***}			0.06^{***}	0.05^{***}
			(0.02)	(0.02)			(0.01)	(0.02)
Fear of Failure			-0.02	-0.04			-0.03	-0.04
			(0.04)	(0.04)			(0.03)	(0.03)
D1-D3 Joint p	0.000	0.000	.001	.001	0.000	0.000	.001	.003
Macro Controls		✓	✓	✓		✓	✓	✓
Perceptions			✓	✓			✓	✓
NES				✓				✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Country RE	✓	✓	✓	✓	✓	✓	✓	✓
R2	0.06	0.13	0.31	0.32	0.08	0.16	0.35	0.35
N	797	589	589	537	797	589	589	537

Dependent variables are TEA and opportunity-based TEA, in percent of adults 18–64. All specifications include year fixed effects and country random effects. Standard errors, clustered by country, in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$. *Macro controls include growth rates of output, employment, human capital, and average hours; a global financial crisis dummy; prices of capital services and formation; and the internal rate of return. NES refers to the twelve GEM national expert survey variables.* R^2 *is the within-country* R^2 *from the RE estimator and need not increase as regressors are added.*

(Thébaud, 2016). The time demands and downside risk of an opportunity-driven venture may also weigh more heavily on such households, though separating these mechanisms is a task for individual-level data rather than country aggregates. Given the 0.96 correlation between the two activity measures (Table 3), the opportunity-based results are best read as a robustness parallel rather than an independent test of H1. Whether aging also shifts the composition of entry between opportunity- and necessity-motivated activity is a distinct question; the short answer parallels H3.[9]

Figure 2: *Implied age effects on entrepreneurial behavior*



(a) *Own Business* **(b)** *TEA* **(c)** *TEA (Opportunity)*

Notes: Age specific coefficients calculated using regression coefficients for full specification in Table 4. Shaded areas are 95% confidence intervals calculated using the delta method.

The framework makes no prediction about business exit, but exit offers a check on one alternative reading of H1: that high entry in young populations simply reflects churn by inexperienced entrants. Appendix D.4 examines the GEM measure of recent business exit using the same specification. Exit rates are lowest precisely where entry is highest (economies with large shares aged 30–34), so young economies experience more entry without more churn, though the exit profile poses its own puzzle when set against the skill results below.

The country-level analysis of entrepreneurial entry is consistent with H1: long-run demographic trends that shrink younger working-age groups and increase shares of late-career workers and old-age dependents are associated with lower levels of early-stage

[9]Defining the opportunity share of early-stage activity as the ratio of opportunity-based TEA to total TEA, the share exhibits a significant unconditional demographic gradient ($p < 0.001$ jointly; in a simple-shares specification, a one percentage point larger population share aged 55 and above is associated with a 0.49 percentage point higher opportunity share), which is fully absorbed by macroeconomic controls ($p = 0.16$; simple shares $p = 0.45$). A modest gradient re-emerges only conditional on the perception levels ($p = 0.012$), with no individually significant coefficients. Like perceived opportunity itself, the opportunity mix appears to track the economic environment rather than age composition.

activity. Nor is the relationship an artifact of comparing rich old countries with poor young ones: the demographic predictors remain jointly significant within both OECD and non-OECD subsamples in the unconditional and macro-controlled specifications (Appendix D.3). To unpack this relationship, I next ask whether similar age patterns are present in the perceived entrepreneurial opportunities, skills, and fears (H2–H4). If perceptual variables are themselves correlated with demographics, this would point to compositional channels; if they are not, it would suggest that the demographic-entrepreneurship relationship operates through other forces.

4.2. Age Structure and Opportunity, Skill, and Fear of Failure

Table 5 presents D1–D3 coefficients for skill, opportunity, and fear of failure, both unconditionally (odd columns) and with the full set of macroeconomic and perceptual controls (even columns).

Table 5: *Population Age Structure and Entrepreneurial Perceptions: Raw and Controlled (tests H2–H4)*

	Skill		Opportunity		Fear of Failure	
	(1)	(2)	(3)	(4)	(5)	(6)
D1	-0.86**	-1.89***	0.58	0.83	-0.15	-0.19
	(0.37)	(0.55)	(0.64)	(0.87)	(0.36)	(0.61)
D2	1.29**	2.82***	-1.29	-1.48	0.25	0.09
	(0.64)	(0.87)	(1.14)	(1.44)	(0.63)	(0.99)
D3	-0.58*	-1.20***	0.64	0.68	-0.09	0.04
	(0.30)	(0.38)	(0.54)	(0.64)	(0.30)	(0.44)
D1-D3 Joint p	0.000	0.000	0.000	.227	0.000	.016
Macro + Other Perc.		✓		✓		✓
Year	✓	✓	✓	✓	✓	✓
Country RE	✓	✓	✓	✓	✓	✓
R2	0.73	0.26	0.52	0.33	0.75	0.24
N	797	589	797	589	797	589

Dependent variables are the percent of adults 18–64 reporting entrepreneurial skill, perceived opportunity, and fear of failure. Odd columns include only D1–D3 and year fixed effects; even columns add macroeconomic controls and the other perception variables. All specifications include country random effects. Standard errors, clustered by country, in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$. *$R^2$ is the within-country R^2 from the RE estimator and need not increase as regressors are added.*

The comparison between raw and controlled specifications reveals an important pattern. All three perceptual variables show jointly significant demographic relationships in the unconditional specification ($p < 0.001$ for all three). However, the results diverge sharply once macroeconomic conditions are accounted for. Skill remains strongly significant ($p <$

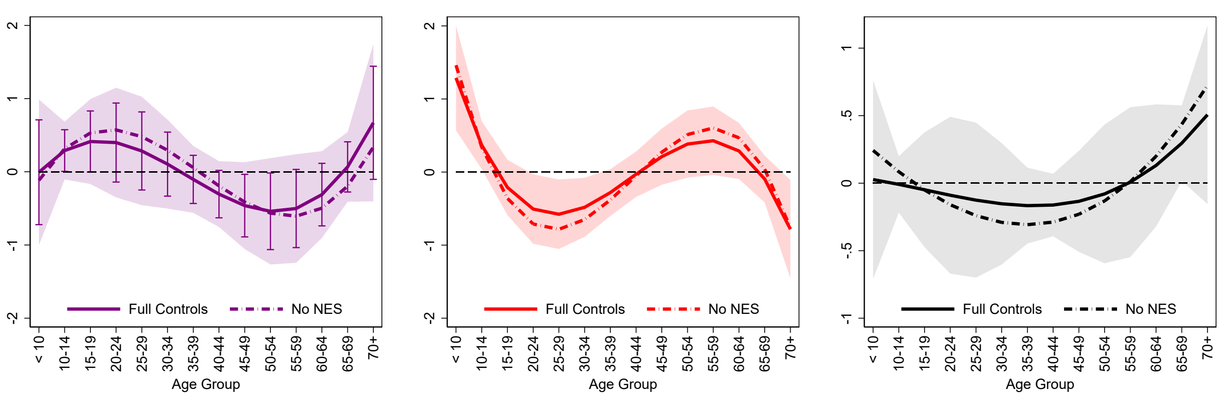
0.001), with both individual coefficients and joint tests robust to the inclusion of controls. This is consistent with H2: the relationship between age structure and entrepreneurial skill reflects genuine life-cycle skill accumulation that is not an artifact of correlated economic conditions.

Perceived opportunity tells a different story. The unconditional relationship is jointly significant ($p < 0.001$), with point estimates suggesting higher opportunity perceptions in younger populations. However, this relationship is fully absorbed by macroeconomic controls ($p = 0.227$): H3 holds only unconditionally, a mediation pattern that Section 5 interprets. Fear of failure shows an intermediate pattern, remaining weakly significant with controls ($p = 0.016$) but with no individually significant coefficients, providing weak support for H4.

In Figure 3, I plot the age-specific coefficients from the controlled specifications. Skill shows a strong inverted pattern relative to TEA, with low values for young populations and high values for old. Opportunity is not significant at any age at the 95% level in the controlled specification; I include the 85% intervals for reference, which show the qualitative shape predicted by theory (higher for young, lower for old) but without statistical confidence. Fear of failure is relatively flat across the age distribution.

Figure 3: *Implied age effects on entrepreneurial opportunity and skill*

(a) *Entrepreneurial Opportunity* **(b)** *Entrepreneurial Skill* **(c)** *Fear of Failure*



Notes: Age specific coefficients calculated using regression coefficients for full specification in Table 5. Shaded areas are 95% confidence intervals calculated using the delta method. Panel (a) includes 85% confidence intervals in brackets for reference.

While these are self-reported skills rather than measured ability, self-assessments correlate reasonably well with actual ability (Ackerman, Beier, and Bowen, 2002), though GEM-based evidence suggests they also embed a healthy dose of overconfidence (Koellinger et al., 2007). The inverted skill profile bears directly on the rank-effects model of Liang et al. (2018), in which younger populations offer more opportunity to acquire entrepreneurial skill; Section 5 takes up that adjudication.

Fear of failure is relatively flat across the age distribution, showing weak positive effects only where old-age dependent shares are large. The downside-exposure mechanism of the framework predicted stronger effects among late-career workers themselves, and finds little support there.

5. Discussion

The results confirm the basic life-cycle mechanics of the framework while undermining explanations that locate the demographic gradient in the characteristics of young individuals. In this section, I summarize the evidence for each hypothesis, discuss what the overall pattern implies for the relative importance of the three channels developed in Section 2.2, and consider the implications for theory and policy.

5.1. Summary of Hypothesis Tests

Table 6: *Summary of hypothesis tests*

	Prediction	Verdict	Key evidence
H1	Larger young working-age shares are associated with higher early-stage activity	Supported	Jointly significant in every specification ($p \leq 0.003$); hump-shaped age profile (Figure 2); robust to simple shares (Appendix C)
H2	Older populations report higher skill	Supported	$p < 0.001$ with full controls; age profile the mirror image of TEA (Figure 3)
H3	Younger populations perceive more opportunity	Supported only unconditionally; fully mediated by macroeconomic conditions	$p < 0.001$ raw; $p = 0.227$ with macroeconomic controls
H4	Older populations report more fear of failure	Weakly supported; gradient appears among retiree shares, not late-career workers	$p = 0.016$ with controls; near-flat profile, modest effect among retiree-heavy populations
H5	Demographic gradient in early-stage activity survives perception controls	Supported	$p = 0.001$ with all three perceptions; established-ownership gradient fully mediated by perceptions (Appendix D.1, $p = 0.65$)

Table 6 summarizes the verdicts; two require comment. The H3 verdict is a mediation result, not a null. Demographics are jointly highly significant for perceived opportunity on their own ($p < 0.001$), with higher perceived opportunity in younger populations, but the relationship is fully absorbed by macroeconomic controls. Younger populations do perceive more opportunity; they appear to do so because of the economies they live in (growth rates, labor market conditions, capital costs) rather than because of their age composition. H4 earns only weak support: the demographic predictors are jointly significant for fear of failure with controls, but no individual coefficient is, and the implied age profile is nearly flat, with a modest positive effect where old-age dependent shares are large. One reading is that rising life expectancy raises the burden of financing old-age consumption, making late-career losses costlier (Kopecky, 2017), but the profile gives that mechanism little traction among working-age shares. The GEM fear measure also captures personal and social dimensions beyond the financial exposure the framework models (Cacciotti et al., 2020), which may dilute the predicted gradient. For H5, adding the perception variables raises model fit substantially (R^2 rises from 0.13 to 0.31) but does not eliminate the demographic effect; a perception-by-perception decomposition (Appendix D.2) shows that skill does nearly all of that work, with opportunity and fear adding little.

5.2. The Puzzle: High Entry, Low Skill, No Opportunity

The combination of these findings creates a puzzle for standard accounts of the age-entrepreneurship relationship. In these accounts, younger populations have higher entrepreneurship because younger individuals possess some combination of greater perceived opportunity, higher risk tolerance, and more innovative ideas. The evidence here tells a more nuanced story. Young economies do have higher TEA (H1), but they report *lower* entrepreneurial skill (H2), their higher perceived opportunity is fully explained by macroeconomic conditions (H3), and they exhibit at most a weak fear-of-failure advantage (H4). Moreover, business exit rates are lowest in these same young economies (Appendix D.4), suggesting that the higher entry rate is not driven by inexperienced churning.

This pattern is difficult to reconcile with accounts that attribute the entry advantage of young populations to superior individual endowments. If young populations entered more because their members were better equipped (more alert to opportunity, less afraid to fail), the perceptual correlates of entry should remain significant after conditioning on economic circumstances. Instead, the only perceptual variable that retains a demographic gradient after controls is skill, and young economies have more entrepreneurs despite reporting less of it. Within the framework this is no contradiction: skill rises monotonically with age while entry peaks in early-to-mid career, so populations concentrated near the peak report less skill than older ones. But the pattern does rule out explanations in which young populations enter because they are better equipped. The mediation of opportunity perceptions is particularly telling. What appears to be an age-related advantage in opportunity recognition may instead be a reflection of the economic environment rather than of age-specific cognition.

Three classes of explanation remain consistent with the evidence. First, the *time-horizon* mechanism of Levesque and Minniti (2006) does not require young workers to perceive more opportunities or have more skill. It operates through the shrinking net present value of entrepreneurial investments as workers age, a channel that would not show up in survey measures of opportunity, skill, or fear, but would generate higher entry among younger populations. The annuity factor $\mathcal{A}(a)$ in the framework captures this mechanism, and it is consistent with both the entry results and the perception findings. Second, *macro-structural* channels, where demographic change affects wages, rates of return, and labor market conditions (Karahan et al., 2024; Gagnon et al., 2016; Hopenhayn et al., 2022), can generate the observed pattern. The mediation of opportunity perceptions by macroeconomic controls, and the support for H5, are consistent with such channels being operative. Third, these two mechanisms may be complementary: macro-structural forces shift the economic environment (affecting opportunity perceptions among other things), while the time-horizon effect operates independently through the life-cycle calculus of individual entry decisions. A fourth possibility cannot be fully excluded: compositional differences in attributes the GEM items do not measure, such as risk tolerance or innovativeness, would also survive the perception controls. This is why I characterize the residual as non-perceptual rather than non-compositional.

5.3. Implications for Theory

These findings contribute to the theoretical understanding of the age-entrepreneurship relationship in several ways. Lévesque et al. (2026) synthesize research on the age of the individual entrepreneur; among the avenues they leave open is why "aging regions may follow distinct entrepreneurial trajectories," and they close by noting that numerous countries face significant shifts in their populations' age composition. The present study addresses this gap by showing that the basic life-cycle predictions of the framework, which draws on Levesque and Minniti (2006) and Lazear (2004), hold at the country level, extending individual-level findings to the aggregate. The mediation of H3 by macroeconomic conditions and the weak support for H4, combined with the support for H5, suggest that the mechanisms linking demographics to entrepreneurship operate largely outside the measured perceptions: through the time-horizon channel, through macro-structural forces, or both. Perceived age norms offer one concrete example of a channel the GEM items miss: social expectations about what people of a given age should do shape entry intentions among older workers even conditional on self-assessed skill (Kautonen et al., 2011), and no skill, opportunity, or fear question would record them.

This has implications for how we think about the work of Liang et al. (2018), whose rank-effects model predicts that younger populations afford greater opportunity for entrepreneurial skill acquisition. While the country-level evidence does not rule out their channel (the net effect of age on skill in their framework is ambiguous), the absence of a demographic gradient in perceived opportunity suggests that the advantages of youth their model posits, idea generation and novel thinking, are not visible at the country level. The contrast with individual-level evidence that feasibility beliefs peak in young adulthood (Minola et al., 2016) underlines the compositional point: the country-level skill gradient reflects the stock of accumulated experience, not the confidence of any particular age group. The evidence is more consistent with models where the time-horizon effect and aggregate economic conditions jointly drive the age-entrepreneurship relationship, and where the role of individual perceptions is secondary.

It is also worth noting that the age profile of early-stage activity documented here (peaking in the late twenties to mid-thirties) describes *entry* into entrepreneurship, not entrepreneurial *success*. Azoulay, Jones, Kim, and Miranda (2020) show that the average age of founders of high-growth firms in the United States is 45, and a meta-analysis by Zhao, O'Connor, Wu, and Lumpkin (2021) finds that age has a weak positive relationship with overall entrepreneurial success, with stronger effects for older cohorts. Together these suggest that while entry peaks young, the most successful ventures are started by middle-aged entrepreneurs with accumulated experience. This distinction reinforces the interpretation that demographic effects on TEA reflect the time-horizon incentive to enter rather than a young-age advantage in entrepreneurial ability.

The distinction between the stock of self-employment and the flow of new ventures is also relevant here, and it maps onto the auxiliary prediction developed in Section 2.3. Fonseca and Parker (2019) document that self-employment rates among older workers are substantial and increasing with age across countries, and late-career entry is real, if motivated more by quality of life than by income (Kautonen et al., 2017). My finding that established business ownership and early-stage entry respond differently to demographics is consistent with their evidence, but the build-up analysis (Appendix D.1) adds a nuance. The demographic gradient in business ownership is itself significant unconditionally ($p < 0.001$), but is fully mediated by skill and opportunity perceptions: once these are controlled for, the relationship disappears ($p = 0.65$). For early-stage activity, by contrast, demographic effects persist through all controls ($p = 0.001$). This contrast suggests that the stock of existing businesses relates to demographics through the perceptions of the owners it has selected, while the flow of new entry is additionally shaped by forces that operate independently of individual perceptions. Population aging may therefore reduce the flow of new entrants through channels that policies targeting individual perceptions alone cannot address.

5.4. Implications for Policy

These results carry practical implications for policymakers in aging economies concerned about entrepreneurial dynamism. If demographic effects on entrepreneurship were primarily compositional, the policy response would focus on raising entry rates among older cohorts, for instance through programs targeting older nascent entrepreneurs. The evidence here suggests that such efforts may face headwinds, since the time-horizon mechanism operates independently of policy-amenable perceptions. However, Fonseca and Parker (2019) caution that self-employment among older workers is disproportionately part-time and may reflect necessity rather than opportunity entrepreneurship, suggesting that simply encouraging more older self-employment may not produce the high-growth ventures that drive dynamism.

The support for non-perceptual channels points instead toward policies that address the economic environment: reducing entry costs (the parameter C in the framework), improving financing conditions, and ensuring that labor market institutions do not disproportionately discourage new firm creation as populations age. The significant role of cultural and social norms around entrepreneurship, found in the NES controls for opportunity-based TEA, further suggests that the broader institutional environment may be at least as important as the demographic composition of the workforce.

6. Conclusion

This paper investigates how population age structure relates to entrepreneurial activity and perceptions across 59 countries. The central finding is that demographics are significantly associated with early-stage entrepreneurship, but not in the ways that accounts based on individual endowments would predict. Young working-age populations are associated with higher rates of new venture creation, yet these same populations report lower entrepreneurial skill and no independent advantage in perceived opportunity. Demographic effects on TEA persist even after controlling for the perceptual variables such accounts emphasize, consistent with channels that operate through the economic environment or life-cycle incentives rather than solely through the characteristics of individual entrepreneurs.

Several limitations should be noted. The analysis is correlational; causal identification would require exogenous shifts in demographics that are difficult to isolate at this level of aggregation. The GEM perception measures are self-reported and may capture their constructs with error (Cacciotti et al., 2020); if so, their ability to absorb the demographic effect on TEA is attenuated, potentially overstating the importance of residual (non-perceptual) channels in the mediation analysis. The design also cannot separate age effects from cohort effects, which individual-level evidence suggests can matter (Zhang and Acs, 2018). The estimates are also country-level associations: they support claims about population composition, not about the behavior of any individual, and projecting aggregate gradients onto individuals would risk ecological fallacy. Finally, the sample covers 2002–2017: a clean pre-COVID window that avoids a methodological break in GEM's motivation classification after 2018, but one that does not capture the most recent demographic trends.

These limitations point to research opportunities. Understanding which specific economic conditions drive the demographic gradient in opportunity perceptions could inform targeted policy responses. The contrast between the stock of business ownership and the flow of entry deserves theoretical development in models that explicitly distinguish entry from persistence. And micro-level data linking individual demographics, perceptions, and entry decisions within the same framework could separate the compositional and structural channels that this aggregate analysis can only distinguish indirectly.

For policymakers in aging economies, the results offer a cautionary note. As argued in Section 5, structural levers (entry costs, financing conditions, cultural norms) are likely to be more effective than interventions aimed at individual perceptions, though the robust link between demographics and skill perceptions suggests that supporting skill development across the life cycle retains value. Entrepreneurial vitality, on this evidence, is not so much wasted on the young as priced by forces that perceptions do not register: the shortening horizon, and the economic environment that aging brings with it. Sustaining dynamism will depend on making entry cheaper, not just on making older workers more confident.

References

Acemoglu, D., U. Akcigit, and M. A. Celik (2014). Young, restless and creative: Openness to disruption and creative innovations. Technical report, National Bureau of Economic Research.

Ackerman, P. L., M. E. Beier, and K. R. Bowen (2002). What we really know about our abilities and our knowledge. *Personality and individual differences 33*(4), 587–605.

Aksoy, Y., H. S. Basso, R. P. Smith, and T. Grasl (2019). Demographic structure and macroeconomic trends. *American Economic Journal: Macroeconomics 11*(1), 193–222.

Arenius, P. and M. Minniti (2005). Perceptual variables and nascent entrepreneurship. *Small Business Economics 24*(3), 233–247.

Azoulay, P., B. F. Jones, J. D. Kim, and J. Miranda (2020). Age and high-growth entrepreneurship. *American Economic Review: Insights 2*(1), 65–82.

Baron, R. A. (2006). Opportunity recognition as pattern recognition: How entrepreneurs "connect the dots" to identify new business opportunities. *Academy of Management Perspectives 20*(1), 104–119.

Bijnens, G. and J. Konings (2020). Declining business dynamism in belgium. *Small Business Economics 54*(4), 1201–1239.

Block, J. H. and M. Wagner (2010). Necessity and opportunity entrepreneurs in germany: Characteristics and earnings differentials. *Schmalenbach Business Review 62*(2), 154–174.

Bohlmann, C., A. Rauch, and H. Zacher (2017). A lifespan perspective on entrepreneurship: Perceived opportunities and skills explain the negative association between age and entrepreneurial activity. *Frontiers in psychology 8*, 2015.

Bönte, W., O. Falck, and S. Heblich (2009). The impact of regional age structure on entrepreneurship. *Economic Geography 85*(3), 269–287.

Cacciotti, G., J. C. Hayton, J. R. Mitchell, and D. G. Allen (2020). Entrepreneurial fear of failure: Scale development and validation. *Journal of Business Venturing 35*(5), 106041.

Cacciotti, G., J. C. Hayton, J. R. Mitchell, and A. Giazitzoglu (2016). A reconceptualization of fear of failure in entrepreneurship. *Journal of Business Venturing 31*(3), 302–325.

Cao, S., M. Salameh, M. Seki, and P. St-Amant (2017). Trends in firm entry and new entrepreneurship in canada. *Canadian Public Policy 43*(3), 202–220.

Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda (2014). The secular decline in business dynamism in the US. Working paper, University of Maryland.

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2016). Declining business dynamism: What we know and the way forward. *American Economic Review 106*(5), 203–07.

Fair, R. C. and K. M. Domínguez (1991). Effects of the changing us age distribution on macroeconomic equations. *The American Economic Review 81*(5), 1276–1294.

Fairlie, R. W. and F. M. Fossen (2018). Opportunity versus necessity entrepreneurship: Two components of business creation. Technical Report DP11258, IZA Institute of Labor Economics.

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015). The next generation of the penn world table. *American Economic Review 105*(10), 3150–3182.

Fonseca, R. and S. C. Parker (2019). Entrepreneurship among older workers: International evidence. In M. Backman, C. Karlsson, and O. Kekezi (Eds.), *Handbook of Research on Entrepreneurship and Aging*, pp. 23–45. Edward Elgar.

Gagnon, E., B. K. Johannsen, and D. Lopez-Salido (2016). Understanding the new normal: The role of demographics.

Gielnik, M. M., H. Zacher, and M. Frese (2012). Focus on opportunities as a mediator of the relationship between business owners' age and venture growth. *Journal of Business Venturing 27*(1), 127–142.

Gielnik, M. M., H. Zacher, and M. Wang (2018). Age in the entrepreneurial process: The role of future time perspective and prior entrepreneurial experience. *Journal of Applied Psychology 103*(10), 1067–1085.

Hamilton, B. H. (2000). Does entrepreneurship pay? an empirical analysis of the returns to self-employment. *Journal of Political Economy 108*(3), 604–631.

Higgins, M. (1998). Demography, national savings, and international capital flows. *International Economic Review 39*(2), 343–369.

Hopenhayn, H., J. Neira, and R. Singhania (2022). From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share. *Econometrica 90*(4), 1879–1914.

Karahan, F., B. Pugsley, and A. Şahin (2024). Demographic origins of the start-up deficit. *American Economic Review 114*(7), 1986–2023.

Kaufman, A. S. and J. L. Horn (1996). Age changes on tests of fluid and crystallized ability for women and men on the kaufman adolescent and adult intelligence test (kait) at ages 17–94 years. *Archives of clinical neuropsychology 11*(2), 97–121.

Kautonen, T., S. Down, and M. Minniti (2014). Ageing and entrepreneurial preferences. *Small Business Economics 42*(3), 579–594.

Kautonen, T., E. Kibler, and M. Minniti (2017). Late-career entrepreneurship, income and quality of life. *Journal of Business Venturing 32*(3), 318–333.

Kautonen, T., E. T. Tornikoski, and E. Kibler (2011). Entrepreneurial intentions in the third age: the impact of perceived age norms. *Small Business Economics 37*(2), 219–234.

Koellinger, P., M. Minniti, and C. Schade (2007). "I think I can, I think I can": Overconfidence and entrepreneurial behavior. *Journal of Economic Psychology 28*(4), 502–527.

Kopecky, J. (2017). An aging dynamo: demographic change and the decline of entrepreneurial activity in the united states. *Available at SSRN 2907198*.

Lamotte, O. and A. Colovic (2013). Do demographics influence aggregate entrepreneurship? *Applied Economics Letters 20*(13), 1206–1210.

Lazear, E. P. (2004). Balanced skills and entrepreneurship. *American Economic Review 94*(2), 208–211.

Levesque, M. and M. Minniti (2006). The effect of aging on entrepreneurial behavior. *Journal of business venturing 21*(2), 177–194.

Levesque, M. and M. Minniti (2011). Age matters: How demographics influence aggregate entrepreneurship. *Strategic Entrepreneurship Journal 5*(3), 269–284.

Lévesque, M., U. Stephan, T. Kautonen, and R. Bakker (2026). Entrepreneurship, age, and the lifespan: Taking stock and avenues for future research. *Journal of Business Venturing 41*(1), 106548.

Levie, J. and E. Autio (2008). A theoretical grounding and test of the GEM model. *Small Business Economics 31*(3), 235–263.

Liang, J., H. Wang, and E. P. Lazear (2018). Demographics and entrepreneurship. *Journal of Political Economy 126*(S1), S140–S196.

Lim, T. (2026). Demographic change and entrepreneurship: General equilibrium implications for economic dynamism. *Economic Modelling*, 107595.

Minola, T., G. Criaco, and M. Obschonka (2016). Age, culture, and self-employment motivation. *Small Business Economics 46*(2), 187–213.

Parker, S. C. (2018). *The Economics of Entrepreneurship* (2nd ed.). Cambridge University Press.

Reynolds, P., N. Bosma, E. Autio, S. Hunt, N. De Bono, I. Servais, P. Lopez-Garcia, and N. Chin (2005). Global entrepreneurship monitor: Data collection design and implementation 1998–2003. *Small Business Economics 24*(3), 205–231.

Ryan, J. J., J. M. Sattler, and S. J. Lopez (2000). Age effects on wechsler adult intelligence scale-iii subtests. *Archives of clinical neuropsychology 15*(4), 311–317.

Shane, S. and S. Venkataraman (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review 25*(1), 217–226.

Stenholm, P., Z. J. Acs, and R. J. Wuebker (2013). Exploring country-level institutional arrangements on the rate and type of entrepreneurial activity. *Journal of Business Venturing 28*(1), 176–193.

Syed, R. T., D. Singh, N. Ahmad, and I. Butt (2024). Age and entrepreneurship: Mapping the scientific coverage and future research directions. *International Entrepreneurship and Management Journal 20*(2), 1451–1486.

Thébaud, S. (2016). Passing up the job: The role of gendered organizations and families in the entrepreneurial career process. *Entrepreneurship Theory and Practice 40*(2), 269–287.

Ucbasaran, D., P. Westhead, and M. Wright (2009). The extent and nature of opportunity identification by experienced entrepreneurs. *Journal of Business Venturing 24*(2), 99–115.

UN (2019). World population prospects. *Department of Economic and Social Affairs, Population Division (2019) Online Edition. Rev. 1.*

Wennberg, K., S. Pathak, and E. Autio (2013). How culture moulds the effects of self-efficacy and fear of failure on entrepreneurship. *Entrepreneurship & Regional Development 25*(9-10), 756–780.

Wennberg, K., J. Wiklund, D. R. DeTienne, and M. S. Cardon (2010). Reconceptualizing entrepreneurial exit: Divergent exit routes and their drivers. *Journal of Business Venturing 25*(4), 361–375.

Wickstrøm, K. A., K. Klyver, and M. Cheraghi-Madsen (2022). Age effect on entry to entrepreneurship: Embedded in life expectancy. *Small Business Economics 58*(1), 57–76.

Zhang, T. and Z. Acs (2018). Age and entrepreneurship: nuances from entrepreneur types and generation effects. *Small Business Economics 51*(4), 773–809.

Zhao, H., G. O'Connor, J. Wu, and G. T. Lumpkin (2021). Age and entrepreneurial career success: A review and a meta-analysis. *Journal of Business Venturing 36*(1), 106007.

A. Model Details and Parameterization

The framework in Section 2.1 builds on the following primitives. Wage employment pays

$$w(a) = \omega \cdot s(a)^{\alpha} \tag{8}$$

where ω is the market wage rate and $\alpha \in (0, 1)$ governs returns to skill in wage work. Entrepreneurship generates per-period profits

$$\pi(a) = A \cdot s(a)^{\gamma} \cdot \theta \tag{9}$$

where A captures the productivity of entrepreneurial ventures, $\gamma \in (0, 1)$ governs returns to skill in entrepreneurship, and θ is the individual's entrepreneurial talent, drawn from a known distribution. Entrepreneurial skill accumulates with experience (Lazear, 2004), and I assume it does so at a diminishing rate:

$$s(a) = s_0 + \lambda \cdot a^{\eta} \tag{10}$$

where s_0 is initial skill, λ is the rate of skill acquisition, and $\eta \in (0, 1)$. An individual enters entrepreneurship at age a if the expected present value of entrepreneurial profits over the remaining career exceeds the present value of foregone wages plus a fixed entry cost C:

$$\underbrace{E_{\theta}\left[\sum_{t=0}^{T-a} \beta^{t}\, \pi(a)\right]}_{\text{PV of entrepreneurial profits}} - \underbrace{\sum_{t=0}^{T-a} \beta^{t}\, w(a+t)}_{\text{PV of foregone wages}} > C \tag{11}$$

where β is the discount factor. Defining the annuity factor $\mathcal{A}(a) \equiv \frac{1-\beta^{T-a+1}}{1-\beta}$ and letting $\bar{s}(a)$ denote the average skill level over the remaining wage-work years, the condition reduces to the threshold in Equation (1) of the main text.[10]

Figure 1 uses the following illustrative parameterization: working life from age 18 to $T = 65$; discount factor $\beta = 0.96$; initial skill $s_0 = 1$; skill accumulation parameters $\lambda = 0.8$ and $\eta = 0.5$; returns to skill $\alpha = 0.60$ in wage work and $\gamma = 0.35$ in entrepreneurship,

[10]Two simplifications are involved. First, profits are earned at the skill held at entry, with no skill growth during the entrepreneurial spell. This simplification is what handicaps young entrants, whose forgone wages embed the skill growth ahead of them while their profits do not, and it generates the rising segment of the entry profile in Panel (a) of Figure 1. Allowing profits to grow with skill during the spell removes the hump under the parameterization below; I read the simplification as a stand-in for the frictions that handicap young entrants in practice, such as limited collateral or the lack of a track record. Second, replacing the discounted stream of age-varying wages with the average $\bar{s}(a)$ is exact only for a discount-weighted mean, so Equation (1) should be read as an approximation.

satisfying the maintained condition $\gamma < \alpha$; wage rate $\omega = 1$; venture productivity $A = 1.8$; entry cost $C = 20$; and talent θ distributed lognormally with location 0 and scale 0.7. Under this parameterization, entry probability peaks in the early thirties. The hump in Panel (a) requires a positive entry cost, skill that grows with experience, and the fixed-profit simplification of the preceding footnote. The remaining assumptions shape it rather than create it: the condition $\gamma < \alpha$ places the peak in early-to-mid career, and relaxing it to $\gamma = \alpha$ moves the peak to age 40; concave accumulation deepens the hump and pulls the peak earlier, and linear accumulation moves it to the mid-thirties.

B. Construction of the Demographic Predictors

The demographic predictors follow Fair and Domínguez (1991). Starting from Equation 3, substitute the polynomial assumption of Equation (5):

$$y_{i,t} = \phi X_{i,t} + \sum_{j=1}^{J} \left[(\delta_0 + \delta_1 j + \delta_2 j^2 + \delta_3 j^3) p_{j,i,t} \right] + \mu_i + \mu_t + \epsilon_{i,t} \tag{12}$$

Because population shares sum to one, $\sum_j \delta_0 p_{j,i,t} = \delta_0$. Imposing the sum-to-zero assumption of Equation (4) then pins down the constant:

$$\delta_0 = -\frac{1}{J} \left[\delta_1 \sum_j j + \delta_2 \sum_j j^2 + \delta_3 \sum_j j^3 \right]$$

Substituting δ_0 back into Equation 12 and rearranging terms yields:

$$y_{i,t} = \phi X_{i,t} + \delta_1 \sum_{j=1}^{J} \left(p_{j,i,t}\, j - \frac{\sum_j j}{J} \right) + \delta_2 \sum_{j=1}^{J} \left(p_{j,i,t}\, j^2 - \frac{\sum_j j^2}{J} \right) + \delta_3 \sum_{j=1}^{J} \left(p_{j,i,t}\, j^3 - \frac{\sum_j j^3}{J} \right) + \mu_i + \mu_t + \epsilon_{i,t} \tag{13}$$

The terms in parentheses are the demographic predictors D_1–D_3 described in the text; their coefficients estimate the linear, squared, and cubic terms of the polynomial, with the regression constant implicitly defined by the sum-to-zero assumption. The approach requires estimating three parameters rather than fourteen, avoids the instability that collinearity among adjacent age shares produces when many shares enter a regression separately, and identifies the implied age effects relative to a population-weighted average. It does not dictate where turning points in the age profile occur, but the cubic limits their number to two.

C. Robustness: Simple Population Shares

The demographic predictors D_1–D_3 are polynomial parameters whose individual coefficients lack a direct interpretation. To verify that the main findings are not an artifact of the polynomial specification, I replicate the analysis using two simple, directly interpretable population shares: the share of the population aged 15–39 and the share aged 55 and above. These correspond roughly to the positive and negative regions of the implied age profiles in the main results.

Table 7 reports these estimates. The core finding is robust: a one percentage point increase in the share aged 15–39 is associated with a 0.49 percentage point increase in TEA ($p < 0.01$) and a 0.31 percentage point increase in opportunity-based TEA ($p < 0.01$). Business ownership shows no significant relationship, consistent with the polynomial results. Among the perception outcomes, the signs on the share aged 15–39 are directionally consistent with the main results—negative for skill and fear of failure, positive for opportunity—but are not statistically significant, consistent with the weak aggregate relationships found in the polynomial specification.

The simple-shares approach cannot capture the nonlinear age profiles that the polynomial method reveals (for example, the inverted-U shape of the skill–age relationship in Figure 3), which is precisely its limitation and the motivation for the Fair and Domínguez (1991) methodology. However, the fact that the main activity results replicate with this transparent specification provides confidence that the polynomial approach is not driving the findings.

Table 7: *Robustness: Simple Population Shares*

	Activity			Perceptions		
	(1) TEA	(2) TEA (Opp.)	(3) Own Bus.	(4) Skill	(5) Opport.	(6) Fear
Share 15-39 (%)	0.49^{***}	0.31^{***}	0.17	-0.45	0.24	-0.41
	(0.15)	(0.11)	(0.25)	(0.38)	(0.57)	(0.56)
Share 55+ (%)	0.01	0.02	-0.01	-0.35	-0.30	0.17
	(0.11)	(0.08)	(0.17)	(0.29)	(0.39)	(0.35)
Year	✓	✓	✓	✓	✓	✓
Country RE	✓	✓	✓	✓	✓	✓
R2	0.32	0.35	0.31	0.22	0.32	0.23
N	589	589	589	589	589	589

Standard errors clustered by country, $*p < 0.10, **p < 0.05, ***p < 0.01$. All specifications include macroeconomic controls, year fixed effects, and country random effects, matching the baseline specification in the main text.

D. Additional Results

D.1. Established Business Ownership

Table 8 reports the relationship between population age structure and established business ownership. The demographic predictors are jointly significant in the unconditional specification ($p < 0.001$) and with macroeconomic controls ($p = 0.003$), but this relationship disappears entirely once perceptual variables are added ($p = 0.65$). This contrasts sharply with the TEA results in Table 4, where demographic effects persist through all controls; Section 5 interprets the contrast.

Table 8: *Population Age Structure and Established Business Ownership*

	Established Business Ownership			
	(1)	(2)	(3)	(4)
D1	-0.55*	-0.56	-0.11	-0.14
	(0.29)	(0.47)	(0.33)	(0.36)
D2	0.77	0.78	0.19	0.23
	(0.50)	(0.72)	(0.52)	(0.56)
D3	-0.32	-0.33	-0.10	-0.11
	(0.23)	(0.31)	(0.23)	(0.24)
Skill			0.26***	0.26***
			(0.04)	(0.05)
Opportunity			0.07***	0.07***
			(0.02)	(0.02)
Fear of Failure			0.00	-0.03
			(0.04)	(0.04)
D1-D3 Joint p	0.000	.003	.65	.672
Macro Controls		✓	✓	✓
Perceptions			✓	✓
NES				✓
Year	✓	✓	✓	✓
Country RE	✓	✓	✓	✓
R2	0.39	0.11	0.30	0.34
N	797	589	589	537

Dependent variable is the share of adults 18–64 owning an established business (older than 42 months). Specifications mirror the build-up in Table 4: country random effects with year fixed effects throughout. Standard errors clustered by country, $*p < 0.10, **p < 0.05, ***p < 0.01$.

D.2. Perception-by-Perception Mediation of the TEA Gradient

Table 9 decomposes the H5 test by adding each perception variable separately to the TEA specification. All columns include the macroeconomic controls, so the decomposition isolates the perceptions. Relative to the pre-perception baseline (column 1), adding skill alone raises R^2 from 0.13 to 0.29 (column 2), nearly all of the improvement achieved by all three perceptions together (0.31, column 5). Opportunity alone raises R^2 to 0.21, and fear of failure adds essentially nothing. The demographic predictors remain jointly significant in every column: the perceptions improve fit, but none of them, alone or together, absorbs the demographic gradient.

Table 9: *Perception-by-Perception Mediation of the TEA–Demographics Relationship*

	Total Early-Stage Entrepreneurship (TEA)				
	(1)	(2)	(3)	(4)	(5)
D1	0.14	0.54***	0.11	0.14	0.48***
	(0.24)	(0.18)	(0.22)	(0.24)	(0.17)
D2	-0.26	-0.82***	-0.19	-0.27	-0.72***
	(0.38)	(0.28)	(0.34)	(0.38)	(0.27)
D3	0.11	0.33***	0.07	0.11	0.29**
	(0.17)	(0.13)	(0.15)	(0.17)	(0.12)
Skill		0.25***			0.22***
		(0.03)			(0.03)
Opportunity			0.11***		0.06***
			(0.02)		(0.02)
Fear of Failure				-0.02	-0.02
				(0.04)	(0.04)
D1-D3 Joint p	0	0	.001	0	.001
Perception Controls		Skill	Opp.	Fear	All
Year	✓	✓	✓	✓	✓
Country RE	✓	✓	✓	✓	✓
R2	0.13	0.29	0.21	0.13	0.31
N	589	589	589	589	589

Dependent variable is TEA (percent of adults 18–64). All columns include the demographic predictors, macroeconomic controls, year fixed effects, and country random effects; columns (2)–(5) add the indicated perception variables. R^2 is the within-country R^2 from the RE estimator. Standard errors clustered by country, $*p < 0.10, **p < 0.05, ***p < 0.01$.

D.3. Development-Group Split

A natural concern with cross-country demographic variation is that it proxies for development: young populations are concentrated in developing economies, which differ from advanced economies in many ways beyond age structure. The macroeconomic controls and the fixed-effects robustness in Appendix E address this in part; Table 10 confronts it directly by estimating the TEA build-up separately within OECD and non-OECD subsamples, with membership classified as of 2017.

The demographic relationship is not a between-group artifact. The demographic predictors are jointly significant within both subsamples, unconditionally ($p < 0.001$ in each) and with macroeconomic controls ($p = 0.005$ OECD; $p < 0.001$ non-OECD). The perception-augmented specification that tests H5 retains joint significance in the non-OECD group ($p = 0.001$), while within the OECD it weakens to marginal significance ($p = 0.064$) with the same sign pattern as the pooled estimates. The weaker within-OECD result is unsurprising: splitting the sample halves the demographic variation available, and OECD age structures are compressed relative to the full panel. The pooled estimates remain the basis for H5; the split establishes that the underlying association is present within development groups rather than an artifact of comparing rich old countries with poor young ones.

Table 10: *TEA and Age Structure Within Development Groups*

	OECD			Non-OECD		
	(1)	(2)	(3)	(4)	(5)	(6)
D1	0.41	0.20	0.26	-0.29	-1.84**	0.30
	(0.26)	(0.25)	(0.18)	(0.20)	(0.79)	(0.41)
D2	-0.51	-0.16	-0.26	0.28	2.87**	-0.17
	(0.38)	(0.38)	(0.29)	(0.35)	(1.28)	(0.63)
D3	0.16	-0.00	0.06	-0.08	-1.25**	-0.03
	(0.16)	(0.17)	(0.14)	(0.16)	(0.56)	(0.27)
Skill			0.14***			0.39***
			(0.03)			(0.06)
Opportunity			0.05***			0.08*
			(0.02)			(0.05)
Fear of Failure			-0.02			-0.07
			(0.04)			(0.10)
D1-D3 Joint p	0.000	0.005	0.064	0.000	0.000	0.001
Macro Controls		✓	✓		✓	✓
Perceptions			✓			✓
Year	✓	✓	✓	✓	✓	✓
Country RE	✓	✓	✓	✓	✓	✓
R2	0.30	0.32	0.44	0.01	0.00	0.25
Countries	34	34	34	68	25	25
N	407	381	381	390	208	208

Dependent variable is TEA (percent of adults 18–64). OECD membership as of 2017 (34 members appear in the sample; Lithuania, which joined in 2018, is classified as non-OECD). Columns mirror the build-up in Table 4: columns (1) and (4) include the demographic predictors and year fixed effects only; (2) and (5) add macroeconomic controls; (3) and (6) add the perception variables. Country random effects throughout. Standard errors, clustered by country, in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$.

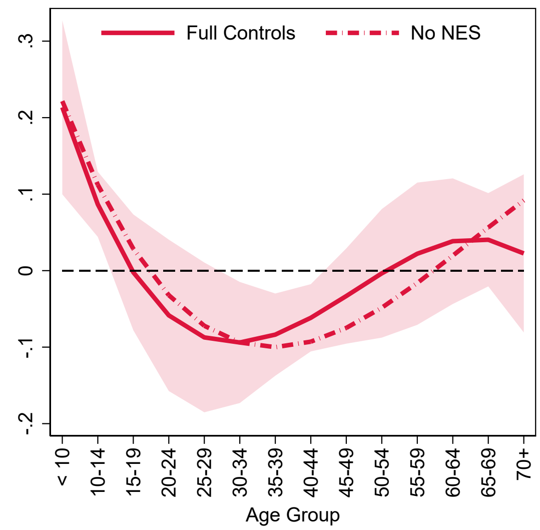
D.4. Business Exit

The GEM surveys contain a question on recent business exit within the last 12 months. Figure 4 reports estimates of Equation 7 with the exit share as the outcome, alongside the implied age profile. Exit rates are lowest in economies with large early-to-middle working-age populations, with positive effects among young and old dependents. The lowest exit effect is for the 30–34 share, which is also the age share most strongly associated with entry. There is thus no evidence that young economies experience both high entry and high churn; if anything, they see lower exit. Using United States data, Decker et al. (2014) document a long-run decline in new business entry with no change in exit rates, and Karahan et al. (2024) suggest that demographic forces may be consistent with both facts. The age profile of exits does create an additional puzzle when set against the skill results: the population age groups associated with the lowest exit rates are also those associated with the lowest self-reported entrepreneurial skill.

The most striking feature of the exit profile is the spike associated with large population shares aged 0–14. One explanation is that family obligations push individuals out of entrepreneurship; however, Thébaud (2016) finds that family obligations tend to pull women into self-employment in search of flexibility, which cuts against this reading. For years after 2006, GEM surveys ask about reasons for exit, including personal or family obligations. Replicating the estimations using the share of exits citing this reason as the outcome reveals no correlation across the age profile. Several macro-structural explanations remain possible; for example, higher fertility (which increases the young-dependent share) may reduce investment in human capital, increasing business exits.

Figure 4: *Population Age and Business Exit*

	Exit Last 12 Months	
	(1)	(2)
D1	-0.15	-0.19**
	(0.10)	(0.09)
D2	0.15	0.24*
	(0.15)	(0.15)
D3	-0.04	-0.09
	(0.07)	(0.06)
D1-D3 Joint p	0.000	0.000
NES		✓
Year	✓	✓
Country RE	✓	✓
R2	0.35	0.38
N	589	537

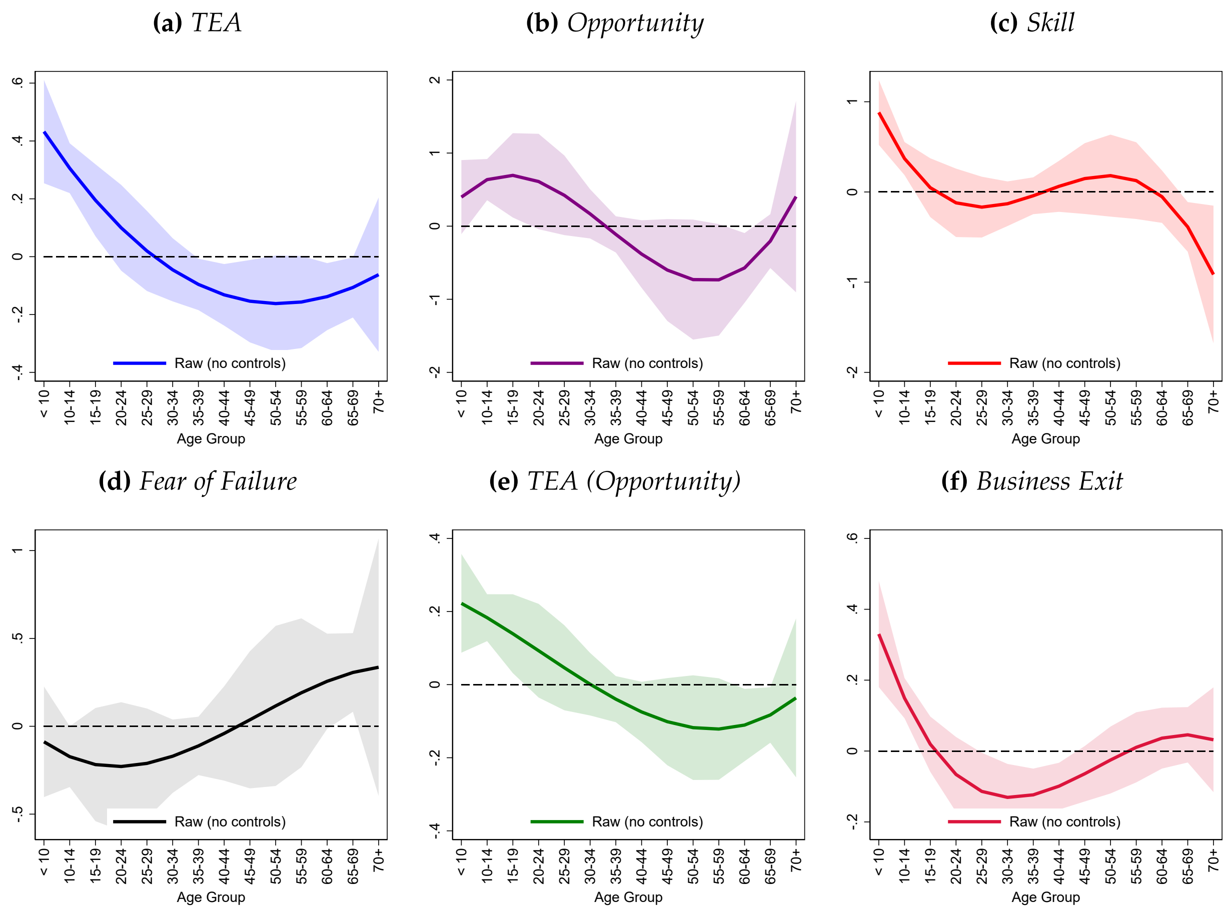


Notes: Left panel reports coefficients on the demographic predictors from Equation 7, with the share of adults 18–64 reporting a business exit in the past 12 months as the dependent variable. Both columns include macroeconomic controls, year fixed effects, and country random effects; column (2) adds the twelve NES variables. Standard errors, clustered by country, in parentheses; $*p < 0.10, **p < 0.05, ***p < 0.01$. *Right panel plots the implied age-specific effects with 95% confidence intervals calculated using the delta method.*

D.5. Unconditional Age Profiles

Figures 5a–5d present the implied age-specific effects from unconditional specifications that include only the demographic predictors D1–D3 and year fixed effects, without macroeconomic or perceptual controls. Comparing these to the controlled profiles in the main text illustrates the role of conditioning variables. For perceived opportunity, the unconditional profile shows a significant positive effect for young populations that disappears with macroeconomic controls (see Table 5), suggesting that the demographic gradient in opportunity perceptions operates through the economic environment. For skill, the profile is similar in shape across specifications, consistent with a direct link between age structure and skill accumulation. The TEA profiles shift from a strong positive effect concentrated among very young ages in the unconditional specification to the hump shape in the controlled specification, reflecting the partial confound between young age structure and developing-economy characteristics.

Figure 5: *Unconditional implied age effects (D1–D3 and year FE only)*



Notes: Age-specific coefficients from regressions including only D1–D3 and year fixed effects (no macroeconomic or perceptual controls). Shaded areas are 95% confidence intervals calculated using the delta method. Compare to controlled specifications in the main text.

E. Country Fixed Effects Robustness

The baseline results use a random effects estimator, motivated by the fact that demographic structure varies primarily across countries and a Hausman test that fails to reject RE consistency ($p = 0.885$). Table 11 and Table 12 replicate the main build-up analysis using country fixed effects instead.

The FE results confirm and sharpen the main findings. For TEA, the demographic predictors are not jointly significant in the unconditional or macro-only specifications ($p = 0.274$ and 0.329), reflecting the limited within-country variation in age structure over the sample period. However, once perception variables are added, demographics become jointly significant ($p = 0.011$) with individual coefficients that are larger in magnitude than the RE estimates. This is a suppressor pattern: controlling for the perception variables strengthens rather than weakens the demographic association, because within countries the offsetting effects of skill and opportunity perceptions mask the underlying demographic relationship with TEA. Once these are held constant, the residual demographic signal emerges clearly, reinforcing the support for H5.

For perceptions, FE results show that skill retains a significant demographic gradient with controls ($p = 0.044$), while opportunity is insignificant throughout ($p > 0.2$) and fear of failure remains weakly significant ($p = 0.027$). These patterns are consistent with the RE results and confirm that the key findings are not driven by cross-sectional confounds.

Table 11: *Country Fixed Effects: TEA Build-Up*

	TEA (Country Fixed Effects)			
	(1)	(2)	(3)	(4)
D1	0.26	0.58^{*}	0.81^{***}	0.73^{***}
	(0.23)	(0.32)	(0.23)	(0.24)
D2	-0.47	-0.86^{*}	-1.19^{***}	-1.11^{***}
	(0.33)	(0.48)	(0.36)	(0.41)
D3	0.23^{*}	0.37^{*}	0.50^{***}	0.47^{**}
	(0.14)	(0.21)	(0.16)	(0.19)
Skill			0.20^{***}	0.20^{***}
			(0.04)	(0.04)
Opportunity			0.05^{**}	0.06^{**}
			(0.02)	(0.02)
Fear of Failure			-0.01	-0.02
			(0.04)	(0.04)
D1-D3 Joint p	.274	.329	.011	.029
Macro Controls		✓	✓	✓
Perceptions			✓	✓
NES				✓
Year	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
R2	0.08	0.16	0.32	0.34
N	797	589	589	537

Standard errors clustered by country, $*p < 0.10, **p < 0.05, ***p < 0.01$. Specifications mirror Table 4 but with country fixed effects instead of random effects.

Table 12: *Country Fixed Effects: Perceptions Build-Up*

	Skill		Opportunity		Fear of Failure	
	(1)	(2)	(3)	(4)	(5)	(6)
D1	-0.76	-1.66**	1.38	1.97*	-1.20*	-0.99
	(0.50)	(0.63)	(0.86)	(1.08)	(0.63)	(0.76)
D2	1.25	2.65***	-2.55*	-3.41*	1.61	1.02
	(0.78)	(0.97)	(1.42)	(1.74)	(1.02)	(1.25)
D3	-0.57	-1.13***	1.20*	1.56*	-0.60	-0.28
	(0.35)	(0.42)	(0.65)	(0.79)	(0.47)	(0.58)
D1-D3 Joint p	.44	.044	.218	.247	.018	.027
Macro + Other Perc.		✓		✓		✓
Year	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
R2	0.73	0.27	0.52	0.34	0.76	0.26
N	797	589	797	589	797	589

Standard errors clustered by country, $*p < 0.10, **p < 0.05, ***p < 0.01$. *Specifications mirror Table 5 but with country fixed effects instead of random effects.*