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Entrepreneurial heterogeneity, financial development, and business cycle dynamics

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ABSTRACT

This paper studies how financial development affects business cycles through entrepreneurial composition. Using Argentine microdata, I show that self-employed entrepreneurs are concentrated below the median of the income distribution and have countercyclical population shares, while employer entrepreneurs are concentrated above the median and have procyclical shares. Motivated by these patterns, I develop a dynamic occupational choice model with aggregate risk in which endogenous sorting across occupations shapes macroeconomic fluctuations. In the calibrated model, financial development raises aggregate output volatility by 8 percent because relaxing collateral constraints shifts economic activity toward employer entrepreneurs, who are more sensitive to aggregate shocks. These findings show that while financial development raises long-run output, it may also increase short-run instability.

1. Introduction

Entrepreneurship plays a vital role in economic development, yet these activities are far from homogeneous, with a diverse range of entrepreneurs operating at different scales and facing unique challenges. While a large body of literature has studied the long-run effects of financial development policies on aggregate output and productivity, its impact on short-run macroeconomic stability is less understood. This paper addresses this gap by investigating the business cycle consequences of financial development in an economy with entrepreneurial heterogeneity.

I show that financial development can generate a trade-off between long-run outcomes and short-run stability. While improved access to credit enhances the steady-state of the economy, it simultaneously amplifies business cycle volatility through an endogenous compositional shift in entrepreneurial activity. Specifically, financial deepening encourages a reallocation from self-employed subsistence entrepreneurs toward employer entrepreneurs who operate larger firms and respond more aggressively to aggregate shocks. This compositional change increases the economy's sensitivity to business cycle fluctuations, creating larger volatility in the aggregate.

The analysis is motivated by two empirical facts documented using microdata from Argentina's Household Survey (EPH). First, entrepreneurial composition varies systematically across the income distribution: self-employed entrepreneurs are disproportionately concentrated below the median, while the majority of employer entrepreneurs reside above the median. Second, the aggregate share of entrepreneurs exhibits strong countercyclical behavior, driven primarily by the countercyclical population share of self-employed entrepreneurs. These patterns suggest that response of entrepreneurs to business cycles are heterogeneous across types.

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To formalize these insights, I develop a dynamic general equilibrium model with occupational choice, entrepreneurial heterogeneity, and aggregate risk. The framework incorporates three key mechanisms that generate realistic patterns of entrepreneurial sorting and cyclical behavior. First, labor market frictions create barriers to employment transitions, giving rise to a class of necessity-driven entrepreneurs, primarily self-employed, who use entrepreneurship as insurance against unemployment risk. Second, I distinguish between self-employed and employer entrepreneurs through endogenous labor hiring decisions and fixed operating costs, which naturally sort individuals by wealth and productivity. Third, correlated aggregate productivity and financial shocks generate business cycle fluctuations that affect both production technologies and credit market conditions.

The model is calibrated to match key features of the Argentinian economy, including cross-sectional income inequality and the distribution of individuals across occupational categories. The quantitative framework successfully replicates the cyclicality of population shares and aggregate income dynamics across occupational groups observed in the microdata. Importantly, the model generates endogenous heterogeneity in shock transmission: employer entrepreneurs exhibit larger responses to both productivity and financial shocks compared to the self-employed group.

Next, I conduct a counterfactual experiment that models financial development as a loosening of collateral constraints. This setup captures a pure credit expansion, holding the volatility of aggregate shocks fixed.[2] Because the model allows occupational choices and equilibrium prices (wages and interest rates) to adjust endogenously, it captures general equilibrium feedbacks that a purely reduced-form empirical exercise cannot recover. The quantitative results show that financial development raises long-run output but also increases aggregate volatility. For example, an increase in the external credit-to-GDP ratio from 0 to 2 raises output volatility by more than 8 percent. The mechanism is driven by a compositional shift in the exposure to the business cycle: relaxing collateral constraints reallocates output, capital, and labor toward employer entrepreneurs, who operate at larger scale, hire external labor, and respond more strongly to aggregate shocks. Although financial development dampens output volatility within the employer sector, employers remain the most volatile sector throughout the experiment. As a result, the rising aggregate weight of employer entrepreneurs dominates this sectoral stabilization and increases aggregate volatility. Overall, the analysis highlights that financial development raises long-run output while reallocating aggregate risk towards larger, more shock-sensitive entrepreneurs.

This paper builds upon and contributes to several strands of literature at the intersection of entrepreneurship, financial frictions, and business cycles. First, this paper draws from the literature on entrepreneurship and occupational choice. This research has established that financial constraints significantly impact entrepreneurial entry and outcomes (Evans and Jovanovic, 1989; Quadrini, 2000) and has explored how individual characteristics shape the choice to become an entrepreneur versus a wage worker (Lucas, 1978), with important consequences for wealth and income inequality (Cagetti and De Nardi, 2006).

Second, I contribute to the literature studying the aggregate consequences of misallocation and financial frictions. A key theme in this work is that improving allocative efficiency through financial development can lead to substantial gains in productivity and output (Midrigan and Xu, 2014; Hsieh and Klenow, 2009). Consequently, a large body of research has analyzed the steady-state effects of policies that ease financial constraints, such as broad financial reforms as in Buera et al. (2011) or microfinance programs as in Buera et al. (2021) and Herreño and Ocampo (2023). This paper extends this analysis by focusing on the business cycle implications of such policies, moving beyond a purely steady state perspective.

Third, the paper is closely related to an active literature on subsistence entrepreneurship, informality, and labor market frictions in developing economies. This work emphasizes that many entrepreneurs are driven by necessity rather than opportunity. Several studies, such as Poschke (2013) and Feng and Ren (2023), have explored how factors like education or labor market frictions, such as Donovan et al. (2023), Finamor (2025) and Herreño and Ocampo (2023), give rise to a large class of low-income, self-employed individuals. These "necessity" entrepreneurs often act as a substitute for formal unemployment insurance as noted by Jaar (2026). Papers such as McKiernan (2021) study how the presence of informal sectors interact with public policies in complex ways. Furthermore, Bosch and Maloney (2010) and Loayza and Rigolini (2011) have documented countercyclicality of self-employment in emerging markets. While some structural models have explored the business cycle implications of informality (see Finkelstein-Shapiro (2014), Restrepo-Echavarria (2014), Horvath (2018) and Fernández and Meza (2015)), these have typically been in representative-agent frameworks. My contribution is to analyze these dynamics in a setting with uninsurable idiosyncratic risk and rich household heterogeneity.

Perhaps most closely, this paper extends the frameworks of Herreño and Ocampo (2023) and Allub and Erosa (2019). I build on the former by incorporating labor market frictions to "push" poor households into entrepreneurship. I build on the latter by differentiating between self-employed and employer entrepreneurs to generate an endogenous sorting of rich and poor entrepreneurs. My primary contribution is to integrate these two frameworks and introduce aggregate risk to study the business cycle dynamics that were outside the scope of those papers. While Kwark and Ma (2021) also studies entrepreneurship with aggregate risk, my model features a household problem that includes these crucial labor market frictions and entrepreneurial heterogeneity.

Finally, the paper contributes methodologically by applying state-of-the-art computational techniques for solving heterogeneous-agent models with aggregate shocks. Following the approach pioneered by Reiter (2009) and further extended by Bayer and Luetticke (2020), I use a combination of non-linear methods for the stationary equilibrium and linearize the model only with respect to aggregate shocks. To the best of my knowledge, this is the first paper to apply the Reiter's method to a model of occupational choice to study the business cycle impacts of financial development.

The outline of the paper is as follows: Section 2 presents the empirical evidence on entrepreneur heterogeneity. Section 3 presents a heterogeneous-agent model with occupational choice and labor market frictions with aggregate shocks. Section 4 presents the solution method used to solve the model and the calibration strategy. Section 5 discusses quantitative results. Section 6 concludes.

[2] In practice, however, episodes of financial deepening often coincide with regulatory and institutional reforms that directly affect the volatility of shocks themselves. Nonetheless, this exercise provides a useful and stylized counterfactual.

Table 1
Summary statistics.

	Unemployed	Workers	Self-employed	Employer
Income share	0.01	0.77	0.15	0.07
Population share	0.10	0.69	0.17	0.04
Income Share/Population share	0.10	1.12	0.88	1.75
Mean	317	2446	1906	4060
Median	0	1975	1391	3074
P20	0	957	604	1481
P80	339	3499	2763	5716
Gini	0.53	0.56	0.53	0.55

Note: These are time-averaged statistics from 2004Q1 to 2015Q2. The first two rows are in percentages, P20 and P80 imply 20th and 80th percentiles. Mean, median, P20, and P80 are real monthly income deflated by the GDP deflator, which are in units of Argentine peso.

2. Empirical evidence on entrepreneur heterogeneity

In this section, I provide the empirical motivation for the model by documenting two key features of entrepreneurship using an Argentine dataset. First, I show that the composition of entrepreneurs differs systematically across the income distribution, with shares of self-employed entrepreneurs declining as income rises. This pattern is consistent with Herreño and Ocampo (2023), who document a U-shaped relationship between entrepreneurship and income in economies with large share of self-employment. Second, consistent with a broad literature (e.g., Bosch and Maloney (2010); Loayza and Rigolini (2011)), I find that the aggregate share of entrepreneurs is countercyclical. This dynamic is driven primarily by self-employed entrepreneurs, who constitute the majority of entrepreneurs and have lower average incomes than their employer counterparts. Together, these facts underscore the importance of distinguishing between self-employed and employer entrepreneurs to capture key distributional patterns and aggregate dynamics.

Data description and summary statistics

The microdata for this analysis is from the Encuesta Permanente de Hogares (Permanent Household Survey, or EPH), conducted by the National Institute of Statistics and Censuses (INDEC) of Argentina. I selected this dataset for two reasons. First, Argentina has a significant prevalence of self-employed entrepreneurs, the focal point of this study. Second, the EPH has been available quarterly since 2004, providing a rich, high-frequency dataset that is ideal for business cycle analysis, in contrast to the annual data common in other individual-level surveys.[3]

This study focuses on the period from 2004Q1 to 2015Q2 to account for methodological revisions to the EPH post-2015. Data for 2007Q3 is absent due to an EPH staff strike; where necessary, I linearly interpolate this data point. The survey provides comprehensive data on individual characteristics related to employment, occupation, and income. This analysis relies on a few key variables to classify individuals. The variable, *CAT_OCUP*, identifies a person's primary occupation as an employee, a self-employed entrepreneur, or an employer entrepreneur. To identify unemployed individuals, I use the variable *PP10A*, which records how long an individual has been looking for a job. Total income is measured using variable *P47T*. This variable should be interpreted as reported monthly individual income: it includes income from the respondent's main occupation as well as other labor and non-labor income sources. Appendix A.1 and A.2 provide additional details on variable construction and related measurement issues.

Finally, data on aggregate variables such as GDP and consumption come from the International Monetary Fund's (IMF) International Financial Statistics (IFS) database. All aggregate series are logged and linearly filtered. The results are robust to alternative filtering methods.

Table 1 presents summary statistics on the income distribution across the four occupational states. The first three rows highlight significant disparities in population and income shares. While workers constitute the majority of both the population (69%) and total income (77%), the unemployed represent a sizable 10% of the population but capture a negligible 1% of income, with a median income of zero.

The primary focus of this paper is the heterogeneity within entrepreneurs (third and fourth columns), which makes up 21% of the population. The data reveals two distinct types of entrepreneurs, a distinction made clear by comparing their income shares relative to their population shares.

First, there are the self-employed, who are numerous but have low average earnings. This group makes up the vast majority of entrepreneurs (17% of the total population), yet their share of total income (15%) is smaller than their population share. Their average income (1906 pesos) is not only significantly lower than that of employers but also falls below the average for workers (2446 pesos). This suggests that many individuals in this group enter self-employment out of necessity rather than for high-growth opportunities, a finding consistent with the literature on subsistence entrepreneurship.

[3] While the EPH data extends back to 1998, available biannually until 2003, this study excludes the pre-2004 data due to inconsistencies in survey frequency. The main results are robust to including the pre-2004 data.

Table 2
Composition of occupations across income groups.

Income group	Unemployed	Workers	Self-employed	Employers
Below median	0.96	0.43	0.61	0.25
Above median	0.04	0.57	0.39	0.75

Note: Each column sums to one. Entries report the share of individuals in each occupational group whose total individual income is below or above the sample median.

Table 3
Population share and GDP.

	$\rho(Y,U)$	$\rho(Y,W)$	$\rho(Y,E)$	$\rho(Y,Se)$	$\rho(Y,Em)$
United States	–	0.76	0.24	–	–
Argentina	−0.85	0.86	−0.32	−0.66	0.70

Note: $\rho(Y,X)$ denotes correlation of variable X with respect to Y, where Y is GDP, U is the population share of unemployed, E is the population share of entrepreneurs (self-employed and employers combined), Se is the population share of self-employed, Em is the population share of employers. The correlations reported for the United States are from Kwark and Ma (2021).

In contrast, there are employer entrepreneurs. This group is small, making up only 4% of the population, but command a disproportionately large 7% share of total income. Their mean income (4060 pesos) is more than double that of the self-employed. The Gini coefficients are similar across all groups, suggesting that income inequality within each occupation is comparable. However, the 20th and 80th percentiles (P20 and P80) provide insights into the lower and upper ends of the income distribution and also reveal a large income disparity between the entrepreneurial types: the 20th percentile of income for an employer (1481 pesos) is higher than the median income for a self-employed (1391 pesos).

This sharp divide between numerous, low-income self-employed individuals and a small cohort of high-income employers is the central empirical fact motivating the baseline model's distinction between the two groups.

To highlight the compositional heterogeneity at the heart of this paper, I examine entrepreneurial sorting by income level. Table 2 shows the distribution of each occupational group below and above median income. More than 60% of self-employed entrepreneurs are located below the median, consistent with the view that self-employment is often associated with lower-income, necessity-oriented activity. By contrast, employer entrepreneurs are concentrated in the upper half of the income distribution: 75% of employers are above the median. This pattern suggests that employer entrepreneurship is more closely associated with higher-income, opportunity-oriented activity. The same compositional pattern emerges when using finer income disaggregations or alternative income thresholds. Capturing this compositional shift is one of the primary goals of this paper.

While the previous table focuses on the time-averaged shares of entrepreneurs across the income distribution, Table 3 presents how the population shares of occupations behave with respect to GDP across time. This presents an intriguing insight into the relationship between GDP and the population shares of entrepreneurs and workers in both the United States and Argentina. In both economies, the population share of workers are highly procyclical with respect to GDP. In the US, the correlation is 0.76 and in Argentina, the correlation is 0.86. Also, the population share of unemployed is countercyclical with respect to GDP in Argentina. There exists a large contrast between the US and Argentina when it comes to population dynamics of entrepreneurs: the population share of entrepreneurs is slightly procyclical in the US (0.24), but countercyclical in Argentina (−0.32). When the entrepreneurial group is decomposed into self-employed and employers, it can be seen that the main driver of negative correlation in Argentina is driven by self-employed entrepreneurs. This indicates that, during economic downturns, individuals turn to self-employed entrepreneurship out of necessity. However, the population share of employer entrepreneurs is highly procyclical. During economic booms, individuals may find it more optimal or less difficult to start their own businesses. The empirical findings highlight the importance of modeling occupational choice with entrepreneur heterogeneity, aggregate dynamics, and its role in shaping business cycles.

3. Baseline model

This section develops a dynamic general equilibrium model of occupational choice. The framework is designed to be quantitatively consistent with the two key empirical facts documented above: the composition of entrepreneurs across the income distribution and the cyclicality of their population shares.

To achieve this, the model incorporates labor market frictions to create a "push" factor into entrepreneurship out of necessity following Herreño and Ocampo (2023). The model explicitly distinguishes between self-employed and employer entrepreneurs using a similar approach as Allub and Erosa (2019). As noted in the original papers, these features are crucial for matching income and wealth inequalities within and across occupations. Furthermore, the model introduces aggregate productivity and financial shocks that drive the economy's dynamics, which allows one to study how population dynamics influence aggregate fluctuations.

Time is discrete, and the horizon is infinite. There is a continuum of infinitely-lived households normalized to a unit measure. At the beginning of each period, households with an asset level (a) observe their skills as a worker (z_w) and as a manager (z_m). Each household is subject to uninsurable idiosyncratic shocks to their skills. Each period, households operate in one of four occupational

states: unemployed (u), worker (w), self-employed entrepreneur (se), or employer entrepreneur (em). Households cannot always freely choose their preferred occupation due to labor market frictions that does not always guarantee employment (becoming a worker).

The choices available to a household at the beginning of each period depend on the realization of labor market shocks. These frictions are represented by occupation-specific probabilities of receiving job offers or being separated from a job. An unemployed agent receives a job offer with probability, p^u. If an offer is received, they become a worker. If no offer arrives, they must choose between remaining unemployed or starting a business as a self-employed or employer entrepreneur. For a worker, they face an exogenous probability of separation, p^w, which forces them into unemployment. They may also choose to quit and become an entrepreneur (self-employed or employer) any time. A self-employed or an employer entrepreneur can choose to continue their business, or they can transition to being a worker if they receive a job offer with some exogenous probabilities p^{se} and p^{em}. They may also choose to abandon their business and become unemployed.

To capture realistic business cycle dynamics, the probabilities governing labor market transitions are modeled as a function of aggregate output of the previous period, Y_{-1}. During economic expansions when output is high, the job-finding rate increases while the job-separation rate falls, ensuring the model generates a tighter labor market in booms and a looser one in recessions, consistent with the data. Finally, employer entrepreneur hires external labor but for self-employed entrepreneurs, labor inputs must come from their own. Employers pay a fixed cost denoted by κ. Given their occupation choice, households choose their amount of final goods consumption (c) and decide how much to save with a real return denoted by r.

To summarize the timing of events, a household begins period t with assets (a_t) carried over from the previous period. At the start of the period, the household observes its current skills and the outcome of labor market shocks, which could be either job offers or separations that depends on their occupation in the prior period. Based on this information and after observing aggregate state of the economy, the household makes its occupational choice for the current period. Following this choice, production and income realization occur based on the chosen occupation: unemployed agents receive a small, fixed amount,[4] workers earn wage income, and entrepreneurs earn profits. The household also receives the gross return on its past savings, $(1 + r_t)a_t$. With all income for the period realized, the household makes its consumption-saving decision, consuming c_t and choosing savings a_{t+1} for the next period.

Preferences

Households derive utility from the consumption of a final good, denoted by c_t. Individuals maximize the expected utility of the form

$$U(c_t) = \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma} - 1}{1-\gamma}\right], \tag{1}$$

where β is the discount factor between 0 and 1, and γ denotes the parameter that relates to the household's risk aversion.

Evolution of idiosyncratic skills

At time t, a household's skills as a worker and an entrepreneur are determined by their labor productivity z_{wt} and managerial/entrepreneurial[5] abilities z_{mt}. Each skill is composed of a fixed component, μ_j, which determines the long-run mean of the skill, and a persistent stochastic component, x_{jt}. The skill level is given by:

$$z_{jt} = \exp(\mu_j + x_{jt}), \quad j = w, m. \tag{2}$$

The stochastic component, x_{jt}, follows a mean-zero AR(1) process.

$$x_{jt+1} = \rho_j x_{jt} + \epsilon_{jt+1}, \quad j = w, m, \tag{3}$$

where ρ_j is the persistence parameter and ϵ_{jt+1} is the innovation term of the productivity. The innovations, ϵ_{wt+1} and ϵ_{mt+1}, are drawn from a bivariate Normal distribution with a mean of zero, standard deviations σ_w and σ_m, and the correlation coefficient, ρ_{wm}.

Technology

Production in the economy takes place in two sectors: a corporate sector and a heterogeneous entrepreneurial sector. The corporate sector is standard, consisting of a representative firm that behaves competitively, taking the market wage and rental rate as given to choose its optimal capital and labor inputs. The entrepreneurial sector is populated by a continuum of agents who also take factor prices as given. A key feature of this model is the distinction between two types of entrepreneurs, which is determined by their labor input choices. Self-employed entrepreneurs split their time between working and managing, while employer entrepreneurs hire external labor and focus their time on managerial tasks.

[4] This can be interpreted as home production or transfers.

[5] I use managerial skills and entrepreneurial abilities interchangeably throughout the rest of the text.

Corporate Production The corporate sector produces final goods that can either be used for consumption or investment using a constant-returns-to-scale Cobb–Douglas production technology:

$$Y_t^c(K_t^c, L_t^c, Z_t) = Z_t K_t^{c,\alpha} L_t^{c,1-\alpha}, \tag{4}$$

where K_t^c and L_t^c denote capital and labor used in the corporate production. α is the share of capital used and is bounded between 0 and 1. Z_t is the exogenous aggregate productivity.

Entrepreneurial Production Following Lucas (1978) and Allub and Erosa (2019), entrepreneurs' production uses three inputs: managerial ability, labor, and capital. There are no markets for managerial ability, so entrepreneurs must only use their own manager skills as input. The total effective managerial input is determined by the level of managerial skill z_m and time devoted to managing their businesses t_m. The production function of an entrepreneur can be written as follows:

$$Y^o(m_t, k_t, n_t; Z_t) = Z_t m_t^{\nu} k_t^{\eta} n_t^{\theta}, \quad o \in \{se, em\} \tag{5}$$

where $\nu+\eta+\theta = 1$ and $m_t = t_{mt} z_{mt}$ represents effective managerial supply. Likewise, k_t represents capital inputs for an entrepreneur, and n_t denotes effective units of labor input. The time allocation decision is used to differentiate two types of entrepreneurship. An entrepreneur's own labor input is written as $(1 - t_m)z_w$. The total effective labor input, n_t, is the sum of labor supplied by the entrepreneur and any external labor hired, l_t:

$$n_t = (1 - t_{mt})z_{wt} + l_t. \tag{6}$$

Based on these choices, I define the two entrepreneurial types as follows: self-employed entrepreneurs do not hire external labor, which implies $l_t = 0$. They choose their optimal time allocation, $t_{mt} \in [0, 1]$, to split between managing and working in their own firm. On the other hand, employer entrepreneurs hire external labor ($l_t > 0$). I make the simplifying assumption that they are "pure managers", meaning they dedicate their entire time endowment to management $t_{mt} = 1$ and provide no direct labor input themselves.[6]

Finally, both types of entrepreneurs face a collateral constraint of the following form.

$$k_t \le \phi_t a_t, \tag{7}$$

where $\phi_t \ge 1$. The functional form of this constraint is standard in the literature on financial frictions and entrepreneurship, such as Buera et al. (2015). The parameter ϕ_t captures the degree of financial development in the economy, with $\phi_t = 1$ representing pure self-financing and $\phi_t = \infty$ representing a perfect credit market. The steady state value of this parameter, $\bar{\phi}$, describes the long-run level of financial development, consistent with the literature studying misallocation over long horizons. One of the key departures in this paper is that I allow the degree of financial friction to vary over the business cycle. I model ϕ_t as a stochastic, time-varying process. This captures the idea of financial shocks, which affect firms' ability to borrow. A large body of literature has shown this shock to be a significant driver of business cycles, such as Jermann and Quadrini (2012) and Kiyotaki and Moore (1997).

Given the market wage and interest rate (W_t, r_t), the profit maximization problem for a self-employed entrepreneur with idiosyncratic state variables (a_t, z_{wt}, z_{mt}) can be written as

$$\pi^{se}(a_t, z_{wt}, z_{mt}; Z_t) = \max_{t_{mt}, k_t} Z_t (z_{mt} t_{mt})^{\nu} k_t^{\eta} ((1 - t_{mt}) z_{wt})^{\theta} - (r_t + \delta) k_t, \tag{8}$$

subject to (7). For a self-employed entrepreneur, their only choice is how much time they spend on managerial activities and the amount of capital input. For an employer entrepreneur, their profit maximization problem can be written as

$$\pi^{em}(a_t, z_{wt}, z_{mt}; Z_t, \kappa_t) = \max_{k_t, l_t} Z_t z_{mt}^{\nu} k_t^{\eta} l_t^{\theta} - (r_t + \delta) k_t - W_t l_t - \kappa, \tag{9}$$

subject to (7). Employer entrepreneurs must not only choose capital and time spent on managing, but they also decide how many workers to hire. Finally, κ denotes the fixed cost of production for an employer entrepreneur.

Aggregate Shocks Aggregate fluctuations in this economy are driven by an aggregate productivity shock, Z_t, and a financial shock, ϕ_t, which affects the tightness of the collateral constraint. The log of aggregate productivity, $\ln Z_t$, follows AR(1) process:

$$\ln Z_{t+1} = \rho_z \ln Z_t + \varepsilon_{z,t+1}. \tag{10}$$

Here, ρ_z is the persistence, and ε_{zt} is the innovation term that follows a normal distribution with a standard deviation σ_z. Similarly, financial shock also follows an AR(1) process in logs.

$$\ln \phi_{t+1} = (1 - \rho_\phi) \ln \bar{\phi} + \rho_\phi \ln \phi_t + \varepsilon_{\phi,t+1}, \tag{11}$$

where $\bar{\phi}$ is the long-run level of financial development, ρ_ϕ is the persistence of financial shocks, and the innovation term, $\varepsilon_{\phi,t}$, follows a normal distribution with a standard deviation σ_ϕ. I further assume that the two shocks are correlated, which is represented by $\rho_{z,\phi}$.

[6] The main quantitative results are robust to allowing employers to choose t_{mt} endogenously.

Household problem

The household's problem can be formulated as a dynamic programming problem. At the beginning of a period, the household enters with assets and observes its current skills. Let $s = (a, z_w, z_m)$ denote the household's individual state, where a is assets, z_w is worker productivity, and z_m is managerial ability. In addition, the household enters the period with a lagged occupation $o \in \{u, w, se, em\}$ which is the occupation chosen in the previous period. This lagged occupation determines the type of labor market shocks faced by households at the beginning of period t. After the labor market shock is realized, the household chooses its current occupation j, production takes place, and realizes income. The aggregate state of the economy is $S = (\Lambda^-, Z, \phi, Y_{-1})$, where Λ^- is the beginning-of-period distribution of households, Z is aggregate productivity, ϕ is the financial condition of the economy, and Y_{-1} is the aggregate output in the previous period that determines the state of the labor market today.

Given the timing, it is useful to define two value functions. Let $\tilde{V}^o(s, S)$ be the beginning-of-period value for a household whose occupation in the previous period was o. Furthermore, let $v^j(s, S)$ denote the value of choosing occupation j in the current period, after the aggregate state has been realized and the feasible set of occupations is known. The current occupation j determines current income and, through the budget constraint, the household's consumption-saving decision. It also becomes the household's lagged occupation in the next period.

Consider first a household that was unemployed in the previous period, $(o = u)$. At the beginning of the current period, the household receives a job offer with probability $p^u(S)$.[7] If the offer arrives, the household becomes a worker in the current period. If no offer arrives, the household cannot choose wage work and must choose among unemployment, self-employment, and employer entrepreneurship. Therefore, the beginning-of-period value for households who were unemployed last period can be written as:

$$\tilde{V}^u(s, S) = \left[p^u(S) v^w(s, S) + (1 - p^u(S)) \max_{j \in \{u, se, em\}} \{ v^j(s, S) + \varepsilon(j) \} \right]. \tag{12}$$

The first term is the value of receiving a job offer and working in the current period. The second term is the value of not receiving an offer, in which case the household chooses from the restricted set of feasible occupations. The term $\varepsilon(j)$ is an occupation-specific preference shock drawn from a Type-I Extreme Value distribution.[8] The inclusion of this shock means that occupational choice is probabilistic. This allows the value function to be differentiable with respect to the aggregate state variables.

For a household that was a worker in the previous period, $(o = w)$, it faces an exogenous separation shock with probability $p^w(S)$. If the household is separated, the agent is forced into unemployment in the current period and receives the value $v^u(s, S)$. If the household is not separated, the agent can continue as a worker or switch to any other occupation. The value function can be written as:

$$\tilde{V}^w(s, S) = \left[p^w(S) v^u(s, S) + (1 - p^w(S)) \max_{j \in \{u, w, se, em\}} \{ V^j(s, S) + \varepsilon(j) \} \right], \tag{13}$$

where the second term is the expected value of choosing from the full set of occupations.

For a household that was self-employed or an employer entrepreneur in the previous period, $o \in \{se, em\}$, the household receives a job offer with probability $p^o(S)$. If an offer is received, the agent can either choose to be a worker or continue as the same type of entrepreneur. If an offer is not received, the agent can continue to operate the business as its current type, exit to unemployment, or switch entrepreneurial type. The value function is

$$\tilde{V}^o(s, S) = \left[p^o(S) \max_{j_1 \in \{w, o\}} \{ v^{j_1}(s, S) + \varepsilon(j_1) \} + (1 - p^o(S)) \max_{j_2 \in \{u, se, em\}} \{ v^{j_2}(s, S) + \varepsilon(j_2) \} \right], \tag{14}$$

where $o \in \{se, em\}$ and j_1 and j_2 represent the sets of occupational choices available to entrepreneurs with and without job offers, respectively.

After facing their labor market shocks at the beginning of the period and observing the aggregate state of the economy, households choose their current occupation j. For a given occupation j, the value function is written as:

$$v^j(s, S) = \max_{c, a'} \left\{ \frac{c^{1-\gamma} - 1}{1 - \gamma} + \beta \mathbb{E}[\tilde{V}^j(s', S') | s, S] \right\}, \tag{15}$$

subject to the budget constraint:

$$c + a' = \text{inc}^j(s, S) + (1 + r(S))a, \tag{16}$$

$$a' \geq 0. \tag{17}$$

Here, $inc^j(s, S)$ is the income generated from the current occupation choice j. Unemployed agents receive a small fixed amount $\underline{b}$. Workers earn wage income which depends on the market wage rate and their labor productivity, $W(S)z_w$. Entrepreneurs earn profits $\pi^j(s, S)$, which depend on their occupation and skill. In addition, the household receives the gross return $(1 + r(S))a$ on assets carried into the period. Finally, the expectation $\mathbb{E}[.]$ is taken over the realization of next period's skill and aggregate state S, which depend on their current occupation.

[7] In the quantitative implementation, labor-market probabilities are functions of lagged aggregate output, which is known at the beginning of the period before current production takes place. For notational simplicity, I write these probabilities as functions of the aggregate state S.

[8] The smoothing parameter that controls the discrete-choice probabilities is set to 0.015, which is a standard value in the literature.

3.1. Market clearing and recursive competitive equilibrium

Aggregate consumption (C_t) and output (Y_t) are the sum of their individual and sectoral components.

$$C_t = \int c_{it} d\Lambda_t, \tag{18}$$

$$Y_t = Y_t^c + Y_t^{se} + Y_t^{em}, \tag{19}$$

where Y_t^c is the output of the corporate sector, and Y_t^{se} and Y_t^{em} are the aggregate outputs of self-employed and employers, respectively. $d\Lambda_t$ is the distribution of households after occupational choices are realized. Y_t^{se} and Y_t^{em} are obtained by integrating the output of individual entrepreneurs over their respective distributions, $d\Lambda_t^{se}$ and $d\Lambda_t^{em}$. This can be written as

$$Y_t^{se} = \int y_{it}^{se} d\Lambda_t^{se}, \quad Y_t^{em} = \int y_{it}^{em} d\Lambda_t^{em}. \tag{20}$$

Aggregate capital is defined as

$$K_t = K_t^c + \int k_{it}^{se} d\Lambda_t^{se} + \int k_{it}^{em} d\Lambda_t^{em} = K_t^c + K_t^{se} + K_t^{em}, \tag{21}$$

I define L_t as the total labor demanded by the corporate sector and employer entrepreneurs:

$$L_t = L_t^c + \int l_{it} d\Lambda_t^{em} = L_t^c + L_t^{em}. \tag{22}$$

Self-employed labor is used internally within self-employed firms and is not traded in the market. Finally, in the model with household heterogeneity and financial frictions, the aggregate productivity of entrepreneurial sectors is made up of exogenous component, Z_t, and an endogenous component, A_t. The endogenous component captures the sector's allocative efficiency, which is determined by the degree of misallocation and the joint distribution of skills, assets, and choices of households. I define and measure the endogenous productivity as follows:

$$A_t^{se} = Y_t^{se} / (Z_t (K_t^{se})^{\eta}), \tag{23}$$

$$A_t^{em} = Y_t^{em} / (Z_t (K_t^{em})^{\eta} (L_t^{em})^{\theta}). \tag{24}$$

In equilibrium, the labor demanded by the corporate sector and employer entrepreneurs must equal the labor supplied by workers. Similarly, the amount of capital demanded by the corporate sector and entrepreneurs must equal the savings done by households.

$$\int z_{wt} d\Lambda_t^w = L_t, \tag{25}$$

$$\int a_{it} d\Lambda_t = K_t, \tag{26}$$

The above market clearing conditions lead to the final goods market clearing condition, which can be stated as follows:

$$C_t + I_t = Y_t - \kappa \int d\Lambda_t^{em}, \tag{27}$$

where the aggregate investment I_t is defined as $K_{t+1} - (1-\delta)K_t$. The last term is the deadweight loss that stems from the fixed cost of production for households that choose to be employer entrepreneurs.[9]

A *recursive competitive equilibrium* for this economy is given by a set of pricing functions $\{W(S), r(S)\}$, corporate capital and labor decisions $\{K^c(S), L^c(S)\}$, households' policy functions $\{c(s,S), a'(s,S), j(s,S), t_m(s,S), l(s,S), k(s,S)\}$, value functions $v(s,S)$, and law of motion for the distribution $\Gamma(.)$ such that the following conditions hold:

1. Households maximize their value functions by choosing policy functions and their choices of occupations given prices;
2. Corporate firms maximize profit by choosing capital and labor given prices;
3. Labor market, capital market, and goods market clear;
4. Aggregate law of motion is generated by savings decisions by households.

4. Solution method and calibration

This section outlines the computational strategy used to solve the model and the calibration procedure used to discipline its parameters.

4.1. Solution method

The model features both rich household heterogeneity and aggregate shocks, making it computationally complex. A standard method for solving such models is the algorithm proposed by Krusell and Smith (1998), which involves simulating the economy to

[9] While there is also home production income from unemployed households, they are negligible in the aggregate and is thus ignored.

Table 4
Externally calibrated parameters.

Parameter	Description	Value
γ	Risk aversion	2
β	Discount factor	0.98
α	Capital share in corporate production	0.32
ν	Managerial share in entrepreneur production	0.20
η	Capital share in entrepreneur production	0.32
θ	Labor share in entrepreneur production	0.48
δ	Capital depreciation rate	0.025
$\underline{b}$	Unemployed income	0.001
ρ_w	Persistence of working abilities	0.96
σ_w	S.d. of worker ability innovations	0.13

approximate the law of motion for the distribution of wealth. However, this simulation-based approach is computationally intensive and can become infeasible when multiple shocks or a large state space are present.

Given that the paper's focus is on business cycle properties, I follow the perturbation approach recommended by Reiter (2009). This method involves first solving the non-linear model in the stationary equilibrium (without aggregate shocks) and then linearizing the equilibrium dynamics with respect to the aggregate shocks. As shown by Bayer and Luetticke (2020) and others, this approach provides a good balance of accuracy and computational speed for analyzing business cycle questions. Specifically, I solve the household's problem using value function iteration on a discretized state space and then linearize the full system to compute second moments. Appendix C provides details on how the model is solved and simulated.

4.2. Calibration

The calibration is done in two separate steps. The goal is to match occupation-level statistics from the data, as well as key aggregate business cycle moments. First, I externally calibrate a subset of parameters based on standard values in the literature and estimates from the worker income process. Second, I internally calibrate the remaining parameters in two stages. In the first stage, I target moments in the stationary equilibrium, calibrating parameters that primarily affect outcomes in the steady state. In the second stage, using the linearized model, I calibrate the parameters governing the aggregate shock processes to match key business cycle moments. The data for this procedure come from two main sources. Micro-level moments on occupational choice and income distribution are calculated using Argentina's Permanent Household Survey (EPH) from 2004Q1 to 2015Q2. Aggregate business cycle moments are from the International Financial Statistics (IFS) database.

External calibration

Table 4 presents the externally calibrated parameters. The risk aversion parameter, γ, is set to 2, a standard value in the literature. I set the annualized world interest rate to 2% and choose the discount factor, β, so that the stationary equilibrium is consistent with this interest rate, which leads to a value of about 0.98. Production parameters are also chosen to be consistent with the previous literature. I set the capital share in corporate production, α, to 0.32. The managerial, capital, and labor shares in entrepreneurial production, (ν, η, θ), are set to 0.20, 0.32, and 0.48, respectively, based on the parameters in Guner et al. (2008). The quarterly capital depreciation rate is set to 0.025, which is a standard value in the literature. Finally, I estimate the persistence and innovation standard deviation of worker ability to match the income process of workers in the microdata, which are $\rho_w = 0.96$ and $\sigma_w = 0.13$, respectively. Appendix A.3 provides details on the estimation procedure.

Internal calibration

I internally calibrate the remaining parameters in two stages. First, I calibrate parameters that primarily affect the stationary equilibrium. Second, using the linearized model, I calibrate the parameters governing the aggregate shock processes to match key business cycle moments.

For the stationary equilibrium, there are 11 parameters calibrated to match 12 empirical moments. While all parameters affect all moments jointly, it is helpful to identify which parameters have the greatest influence on specific targets. Five parameters related to the idiosyncratic productivity processes remain to be calibrated. The productivity processes, z_w and z_m, are discretized into a finite-state Markov chain using the Tauchen method. The persistence parameter of managerial ability, ρ_m, and the correlation coefficient, $\rho_{w,m}$, are disciplined primarily by the relative average incomes across occupations: worker/employer, self-employed/worker, and self-employed/employer. The standard deviation of innovations to managerial ability, σ_m, is targeted to match the variance of log income for entrepreneurs. The fixed cost of production, κ, and the long-run means of the productivity processes, μ_w and μ_m, are used to target the population shares of workers, self-employed entrepreneurs, and employer entrepreneurs. Furthermore, I set the steady state collateral constraint parameter, $\bar{\phi}$, to match an external credit-to-GDP ratio of 25%.

Finally, I assume that the labor market processes, p^j follow a logistic distribution. This is expressed as

$$p^j(Y_{t-1}) = \frac{\exp(\psi^j(\ln Y_{t-1} - \ln \bar{Y}) + \tilde{p}^j)}{1 + \exp(\psi(\ln Y_{t-1} - \ln \bar{Y}) + \tilde{p}^j)}, \tag{28}$$

Table 5
Internally calibrated parameters.

Parameter	Description	Value
Stationary equilibrium		
ρ_m	Persistence of managerial abilities	0.92
σ_m	S.d. of managerial ability innovations	0.60
$\rho_{w,m}$	Correlation between working and managing	0.75
μ_w	Shift parameter of working abilities	0.30
μ_m	Shift parameter of managerial abilities	0.13
κ	Fixed cost of production	0.07
$\bar{\phi}$	Collateral constraint parameter	1.24
p^u	Job-finding rate of unemployed	0.43
p^w	Job-separation rate of workers	0.09
p^{se}	Job-finding rate of self-employed	0.22
p^{em}	Job-finding rate of employers	0.36
Aggregate parameters		
ρ_Z	Persistence of TFP shock	0.71
σ_Z	S.d. of TFP shock	0.03
ρ_ϕ	Persistence of financial shock	0.89
σ_ϕ	S.d. of financial shock	0.08
$\rho_{z,\phi}$	Correlation between TFP and financial shock	0.67
ψ	Labor market parameter	1.54

Note: This table lists parameter values that are chosen to match the moments in Table 6.

where $j = u, w, se, em$ and $\tilde{p}^j$ governs the steady-state level of the probability for each occupation j. The four steady-state level parameters, $\tilde{p}^j$, are then internally calibrated to match key moments of occupational flows in the data. While I estimate 'pp in practice, I report p^j for easier interpretations.

I capture the cyclical nature of the labor market in a parsimonious way. The labor market probabilities depend on the log-deviations of lagged aggregate output, Y_{t-1}, from its steady-state value, $\bar{Y}$. The sensitivity of these probabilities to the business cycle is governed by a single parameter, $\psi > 0$. I assume that all job-finding/offer probabilities move together with the business cycle, and the job-separation probability moves countercyclically. This implies that $\psi^u = \psi^{se} = \psi^{em} = \psi$ and $\psi^w = -\psi$.

After linearizing the model with respect to aggregate shocks, there are 6 parameters chosen to match 6 moments from aggregate dynamics. The persistence and standard deviation of TFP shock, ρ_z and σ_z, are chosen to match the serial correlation and standard deviation of aggregate output. The persistence and standard deviation of financial shock, ρ_ϕ and σ_ϕ, are chosen to match the serial correlation and standard deviation of income of entrepreneurs (including both employers and self-employed). The correlation of the shock $\rho_{z,\phi}$ to match the cyclicality of employer shares, and ψ is used to match the standard deviation of the population share of workers.

Table 5 presents the resulting parameter values from the internal calibration. The persistence of managerial ability is high, with $\rho_m = 0.92$. The innovation standard deviation of managerial ability is much larger than that of worker ability, with $\sigma_m = 0.60$ compared to $\sigma_w = 0.13$. This higher dispersion helps the model generate the higher income variance observed among entrepreneurs. The innovations to the two skill processes are also highly and positively correlated, with $\rho_{w,m} = 0.75$. Although the shift parameter for worker ability is higher than that for managerial ability, the larger dispersion of managerial ability generates a thick upper tail, which is important for matching the income of employer entrepreneurs.

The model also includes several parameters related to various frictions. The fixed cost for employer entrepreneurs, κ, is calibrated to 0.07, which represents approximately 16% of total employer output. In terms of the labor market frictions, the job-finding rates are highest for unemployed individuals with the value of 43 percent, followed by employers with the value of 0.36, and lower for the self-employed ($p^{se} = 0.22$).

Finally, the parameters for the aggregate TFP shock process are calibrated to match the business cycle properties of the Argentinian GDP. The persistence of the shock, ρ_Z, is estimated to be 0.71 and its standard deviation, σ_Z, is 0.03. These values are consistent with estimates for aggregate productivity shocks in the representative-agent business cycle literature. After calibration, I find that the financial shock is much more volatile and persistent than the TFP shock. The innovations to the two shocks are found to be strongly and positively correlated. The parameter governing the cyclicality of the labor market, ψ, is estimated to be 1.54. This implies that a 1% increase in aggregate output above its steady state leads to a 0.4 percentage point increase in the job-finding probability for an unemployed individual.

Table 6 presents the targeted moments and compares the model's performance to the data. The results are organized into two panels: moments related to the stationary equilibrium and moments related to aggregate dynamics. Overall, the model does a very good job of capturing the key features of the data. In the stationary equilibrium, the model matches the population shares across occupations, the average income ratios across occupations, and the income dispersion among entrepreneurs.

The model also replicates the occupational composition of the economy. The calibrated population shares of unemployed individuals, workers, self-employed entrepreneurs, and employer entrepreneurs closely match their empirical counterparts. Furthermore, the model matches the average income ranking across these groups, with employers earning more than workers and workers earning more than the self-employed. The calibrated income ratios also align well with the data. The model also successfully matches the targeted moments related to aggregate dynamics.

Table 6
Calibration results.

Moment	Data	Model
Stationary equilibrium		
Population shares		
Unemployed	0.10	0.09
Self-employed	0.17	0.18
Workers	0.69	0.70
Employers	0.04	0.03
Average income of X to the average income of Y		
Self-employed/workers	0.78	0.77
Workers/employers	0.60	0.60
Self-employed/employers	0.47	0.46
Variance of log income of entrepreneurs	0.94	0.94
Transition into employment from X		
Unemployed	0.42	0.43
Workers	0.89	0.90
Self-employed	0.20	0.18
Employers	0.10	0.11
External credit-to-GDP ratio	0.25	0.25
Aggregate dynamics		
Serial correlation of output	0.83	0.83
Standard deviation of output	0.05	0.05
Serial correlation of entrepreneur income	0.69	0.69
Standard deviation of entrepreneur income	0.07	0.07
Correlation of employer share with GDP	0.70	0.70
Standard deviations of worker share	0.01	0.01

Table 7
Untargeted moments.

Moment	Data	Model
Income shares		
Unemployed	0.01	0.01
Workers	0.77	0.79
Self-employed	0.15	0.15
Employers	0.07	0.05
Composition of entrepreneurs		
Below median		
Share of self-employed	0.61	0.64
Share of employers	0.25	0.20
Above median		
Share of self-employed	0.39	0.36
Share of employers	0.75	0.80

To externally validate the model, I compare key untargeted moments from the simulation with the data, as shown in Table 7. I focus on two sets of statistics. First, I compare the income shares held by each occupation. These moments are closely matched by the model. Second, I show that the model successfully replicates the sorting of entrepreneurial types across the income distribution, even though these moments were not directly targeted.

In the data, 61% of self-employed entrepreneurs are below the median income, whereas only 25% of employers are below the median. The model generates corresponding shares of 64% and 20%, respectively. Conversely, 39% of self-employed entrepreneurs are above the median, whereas 75% of employers are above the median. In the model, these shares are 36% for self-employed entrepreneurs and 80% for employers, which are close to the data.

This result indicates that the model's core sorting mechanisms are working as intended. The fixed cost, κ, acts as a significant barrier to entry into employer entrepreneurship, while the self-employed face limitations in scaling because they cannot hire external labor. Only individuals with a combination of high managerial ability and sufficient wealth, both of which are correlated with high income, can profitably overcome this barrier. This mechanism endogenously generates an economy in which necessity-driven self-employment is more prevalent below the median of the income distribution, while opportunity-driven employer entrepreneurship is more prevalent above the median.

It is important to note that the model, consistent with the data, still predicts that some employers are located below the median of the income distribution. This occurs because idiosyncratic shocks to managerial ability are persistent. For a small subset of individuals, such as those with sufficient wealth and managerial productivity but low worker ability, it remains optimal to choose employer entrepreneurship because they are more likely to overcome the fixed cost. However, their income after paying the fixed cost can remain relatively low. Conversely, some self-employed entrepreneurs optimally continue in self-employment because their managerial ability is not sufficiently high relative to their worker ability.

Table 8
Occupational transition rates.

	Data	Model		Data	Model		Data	Model		Data	Model
$U \to U$	0.37	0.20	$U \to W$[a]	0.42	0.43	$U \to Se$	0.19	0.35	$U \to Em$	0.01	0.02
$W \to U$	0.04	0.09	$W \to W$[a]	0.89	0.90	$W \to Se$	0.06	0.01	$W \to Em$	0.01	0.00
$Se \to U$	0.08	0.04	$Se \to W$[a]	0.20	0.18	$Se \to Se$	0.64	0.75	$Se \to Em$	0.08	0.03
$Em \to U$	0.02	0.02	$Em \to W$[a]	0.10	0.11	$Em \to Se$	0.26	0.20	$Em \to Em$	0.62	0.67

Note: Values represent quarter-to-quarter transition probabilities between occupational states.
[a] Indicates a moment that was explicitly targeted during the model's calibration.

Table 9
Business cycle statistics: Model vs. Data.

	Relative Std. Dev.		Correlation w/ Output	
	Data	Model	Data	Model
Aggregate variables				
Output	1.00[a]	1.00[a]	1.00	1.00
Consumption	1.09	0.54	0.95	0.79
Investment	2.39	2.95	0.96	0.94
Population shares				
Unemployed	0.22	0.12	−0.85	−0.91
Worker	0.24[a]	0.24[a]	0.86	0.74
Self-Employed	0.11	0.20	−0.66	−0.65
Employer	0.07	0.09	0.70[a]	0.70[a]
Occupational incomes				
Unemployed	3.14	4.30	0.43	0.59
Worker	1.61	1.19	0.73	0.99
Self-employed	0.85	1.04	0.73	0.23
Employer	3.27	4.87	0.51	0.82

Note: All variables, except population shares, are logged. Standard deviations are expressed relative to the standard deviation of output. All variables are linearly filtered in the data while the model reports theoretical moments. Data moments are calculated using quarterly Argentinian data from 2004Q1 to 2015Q2.
[a] Indicates a moment that was explicitly targeted during the model's calibration.

Next, I evaluate the model's performance on the quarterly occupational transition rates shown in Table 8. The model was calibrated only to match the moments related to transitions into, or persistence in, wage employment, which are denoted by asterisks. Despite not targeting the remaining transition rates directly, the model captures the general patterns of occupational mobility reasonably well.

However, there are some notable deviations. Quantitatively, the model understates the persistence of unemployment, with 20% of unemployed individuals remaining unemployed in the model compared to 37% in the data. It also overstates entry into self-employment from unemployment, with a transition rate of 35% in the model compared to 19% in the data. Furthermore, the model generates a higher job-separation rate from wage employment than in the data, with $W \to U$ equal to 9% in the model compared to 4% in the data. This discrepancy arises because the calibration of the separation rate is disciplined by the persistence of the worker state, $W \to W$, rather than by the direct transition from wage employment into unemployment.

Nonetheless, the model replicates the fact that wage employment and both types of entrepreneurship are persistent in the data. In particular, the model generates high persistence among workers and employer entrepreneurs, and it captures broad occupational mobility patterns despite not directly targeting most of the transition rates.

5. Aggregate dynamics with occupational heterogeneity

With the model calibrated and validated on Argentinian data, this section uses it as a laboratory to address the paper's central question: what are the business cycle implications of financial development policies? This question cannot be answered with reduced-form evidence alone. Financial development is structural: it alters entry, scale, and hiring decisions and shifts equilibrium wages and returns in general equilibrium. Because these behavioral and price responses are endogenous, the mapping from credit conditions to aggregate dynamics is not policy invariant (Lucas critique). A quantitatively disciplined model is therefore needed to run the relevant counterfactual and to separate within-sector stabilization from the composition (and covariance) effects created by reallocating activity toward employer entrepreneurs.

I begin by showing that the model matches key aggregate business cycle statistics and replicates the observed dynamics of population shares and occupational incomes across groups. I then study the model's baseline transmission mechanisms using impulse responses to the aggregate shocks. Finally, with the validated framework, I analyze the business cycle consequences of broad-based financial development by varying the steady state collateral constraint, $\bar{\phi}$. The main finding is that the relationship between financial development and aggregate volatility is positive.

5.1. Second moments

I now evaluate the model's ability to replicate key business cycle statistics from the data, as shown in Table 9. The table is organized into three panels: aggregate variables, population shares, and occupational total incomes.

The model successfully captures the high volatility of investment relative to output, a standard feature of business cycles. However, it does not generate the "excess consumption volatility" commonly observed in emerging markets. In the data, consumption is slightly more volatile than output (a ratio of 1.09), whereas the model produces consumption that is about half as volatile as output (a ratio of 0.54). Resolving this well-known puzzle is beyond the scope of this paper's central research questions. The discrepancy likely stems from the model's shock structure; as argued by Aguiar and Gopinath (2007), a more persistent TFP shock that behaves like a permanent income shock would be needed to generate a stronger consumption response.[10]

The model performs well in matching the cyclical patterns of occupational shares and incomes, even though most of these moments were not directly targeted. In terms of population shares, the model correctly generates that the shares of unemployed and self-employed individuals are countercyclical, while the shares of workers and employers are procyclical. The model's correlations are quantitatively close to the data, particularly for the untargeted unemployed (−0.91 in the model vs. −0.85 in the data) and self-employed (−0.65 in the model vs. −0.66 in the data) groups. This success is driven by the model's realistic labor market frictions, where an economic boom (and the associated rise in wages) endogenously pulls individuals out of unemployment and self-employment and into wage work or to pursue employer entrepreneurship.

In terms of aggregate occupational incomes, the model captures the key volatility rankings. Consistent with the data, employer and unemployed incomes are the most volatile, while self-employed income is the most stable. The model also generates the procyclicality of incomes for all productive groups. These endogenous dynamics are a key strength of the framework: even though all entrepreneurs face the same aggregate shocks, their heterogeneous production structures and financial constraints cause them to respond differently. Overall, the model provides a good qualitative and quantitative match to the second moment properties of the Argentinian data, capturing the key relative volatilities and cyclical patterns that are central to the paper's mechanism.[11]

5.2. Impulse response analysis

This section analyzes the model's dynamic properties by examining the impulse responses to a one percent positive shock to aggregate productivity (Z_t) and financial shock (ϕ_t). To highlight the role of entrepreneurial heterogeneity, the analysis focuses on the differential responses of the corporate, self-employed, and employer sectors.[12] Unless otherwise noted, all variables are shown as percent deviations from their steady state values.

The top panel of Fig. 1 shows the impulse responses to a positive TFP shock. As the shock hits, output rises across all three production sectors, but the responses differ significantly in magnitude and persistence. The corporate and employer sectors experience a strong and persistent increase in output, rising by 1% on impact. In contrast, while the response of the self-employed sector rises by more than 1 percent on impact, it is much more transitory, even turning negative after two quarters.

The underlying factor responses reveal the mechanisms driving these heterogeneous output dynamics. The endogenous TFP of the self-employed sector actually declines, counteracting the direct effect of the aggregate TFP shock. This is driven by the nature of "necessity" entrepreneurship that characterizes this group. The productivity boom makes wage work a more attractive outside option (due to higher wages and job-finding rates), leading to an overall lower share of self-employed entrepreneurs. Those with high working abilities become employees, while those with strong managerial skills become employers. This compositional shift lowers the productivity of the remaining self-employed.

In contrast, the endogenous TFP of the employer sector rises moderately. This reflects the "opportunity-driven" nature of this group. The favorable economic conditions create profitable opportunities, allowing high-quality entrepreneurs to enter and scale up their operations. These divergent TFP responses, combined with a larger increase in capital and labor for employers, explain the differential output dynamics between the two sectors. The factor responses further highlight this mechanism: capital and labor demand from the corporate and employer sectors rise persistently, while capital demand from the self-employed sector falls after two quarters.

The bottom panel of Fig. 1 shows the responses to a positive financial shock (a loosening of the collateral constraint). The transmission mechanism of this shock is fundamentally different. It has no direct effect on the corporate sector, but instead operates by relaxing the borrowing constraints of entrepreneurs.

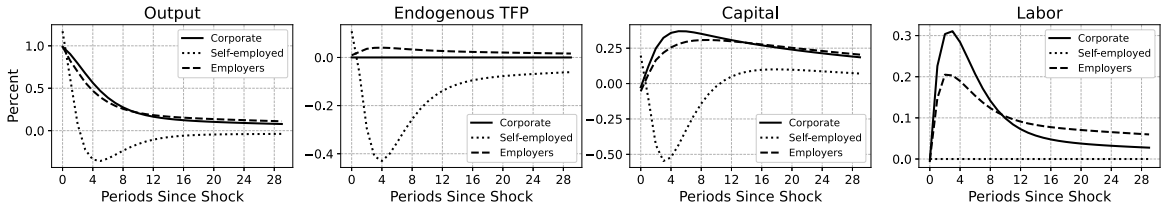
The results show that the employer sector is the primary beneficiary and transmitter of the financial shock. Employer output rises by approximately 1.2% on impact, driven by a substantial increase in both capital and labor inputs. The self-employed sector is unable to translate the positive financial shock into a large output gain due to its smaller scale and more limited use of capital (from lack of external labor), ultimately leading to a slight decline of endogenous productivity. Thus, the financial shock is propagated to the rest of the economy primarily through the higher capital and labor decisions of employer entrepreneurs, which causes a reallocation of capital and labor away from the corporate sector.[13]

[10] Other papers, such as Hong (2026), find that higher MPCs in emerging markets contribute to excess consumption volatility. However, I do not pursue this due to data limitations on household-level consumption.

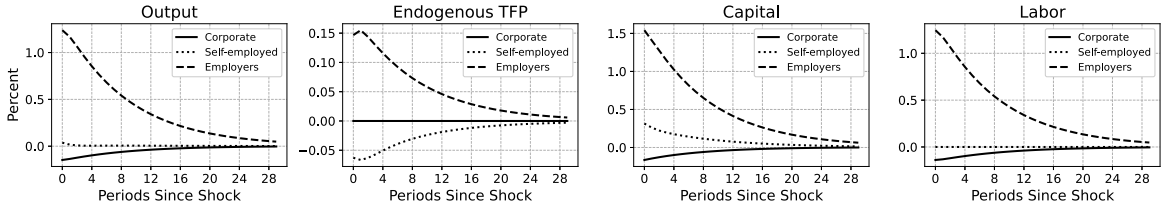
[11] Appendix E presents a sensitivity analysis with respect to key parameters.

[12] The impulse responses for other key variables, such as aggregate quantities and population shares, are presented in the appendix.

[13] Appendix D presents additional impulse responses of aggregate variables, population shares, and group-level incomes to these shocks.



(a) TFP Shock.



(b) Financial Shock.

Fig. 1. Impulse response analysis.
Note: These figures show the impulse response of sectoral output, endogenous TFP, capital, and labor to a unit positive shock. All variables are in percent deviations from the steady state.

This analysis highlights a key finding: the two entrepreneurial sectors respond to the same aggregate shocks differently. The self-employed sector's response is dampened by the higher switch rate towards better opportunities in response to TFP shocks and limited by its scale in response to financial shocks. The employer sector, in contrast, is able to leverage its larger scale and access to hired labor to amplify both types of shocks. This differential propagation mechanism is central to the paper's main result. Financial development alters the composition of the entrepreneurial sector in the steady state and shifts the economy's weight from the less responsive self-employed to the more responsive employers, which fundamentally changes the economy's aggregate volatility.

5.3. Financial development and business cycles

I now use the validated model to conduct the main counterfactual analysis on the relationship between financial development and aggregate dynamics. A large body of literature has shown that in steady state models, financial development improves resource allocation, leading to higher aggregate TFP, output, and welfare (e.g., Buera et al. (2015, 2011)). However, the implications of such policies for business cycles are less well understood. This section contributes by analyzing these dynamic consequences, moving beyond a purely steady state focus.

It is important to emphasize that the quantitative experiments in this paper isolate the effects of a pure credit expansion. In practice, episodes of financial deepening are rarely so simple. Historical evidence shows that credit booms without improvements in prudential regulation or institutional quality are often linked to heightened volatility and financial fragility (e.g., Ranciere et al. (2006) and Reinhart and Rogoff (2009)).

By contrast, the reductions in macroeconomic volatility observed in cross-country data generally arise when credit deepening occurs alongside broader regulatory reforms and institutional strengthening (e.g., Denizer et al. (2002) and Cerutti et al. (2017)). The model intends to capture a specific scenario of financial development: one in which access to credit expands, but the structure and volatility of aggregate shocks remain unchanged.

Formally, financial development is represented by an increase in the steady-state value of the collateral constraint parameter, $\bar{\phi}$. I re-solve the stationary equilibrium for values of $\bar{\phi}$ ranging from 1 to 3 and then linearize around the new steady states to compute business-cycle moments. The analysis first considers steady-state outcomes and then turns to second-moment properties.

Given the focus on occupational heterogeneity, I first examine how financial development alters the long-run distribution of the population. Fig. 2 plots the change in the population share of each occupation as a function of the external credit-to-GDP ratio. The figure shows that financial development increases entrepreneurship overall, but its effects differ across entrepreneurial types. The response of self-employment is non-monotonic. At very low levels of financial development, the self-employed share rises slightly, by less than 0.1 percentage points. This initial increase reflects the fact that small relaxations of borrowing constraints allow some households to operate small-scale businesses without hiring outside labor or paying the fixed cost required for employer entrepreneurship. As financial development deepens, however, the employer margin becomes more attractive, and productive self-employed entrepreneurs can scale up, hire labor, and become employers. As a result, when the external credit-to-GDP ratio reaches 2, the self-employed share is about 1.6 percentage points below its level in the self-financed economy. By contrast, the share of employer entrepreneurs rises monotonically, increasing by more than 4 percentage points, as individuals with high managerial abilities gain access to more capital and the return to operating larger firms increases. Thus, financial development does not simply

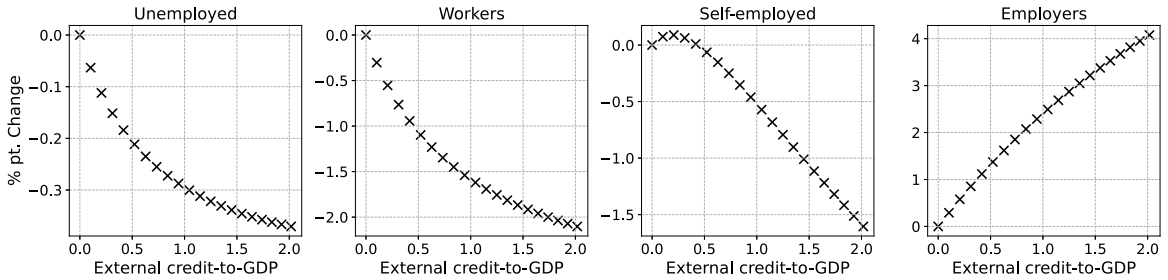


Fig. 2. Long-run impact of financial development: Population shares.
Note: The figure plots the deviation of the steady-state population share for each occupation across values of the collateral constraint parameter. The x-axis shows the external credit-to-GDP ratios implied by each value of the collateral constraint parameter. The y-axis shows the change in percentage points relative to the completely self-financed economy.

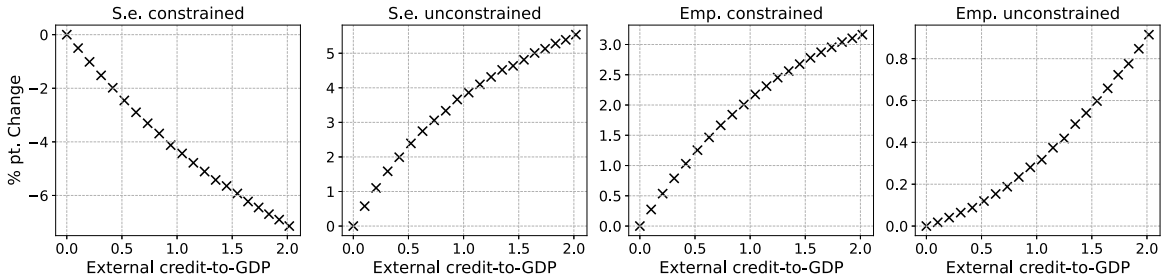


Fig. 3. Long-run impact of financial development: Constrained and unconstrained shares.
Note: The figure plots the deviation of the steady-state population share for each entrepreneurial subgroup. The y-axis shows the change in percentage points relative to the self-financed economy.

increase the number of entrepreneurs; it reallocates entrepreneurial activity from small-scale self-employment toward larger-scale employer entrepreneurship.

The shares of workers and the unemployed also decline as entrepreneurship becomes a more attractive outside option. The worker share falls by more than 2 percentage points, while the unemployed share decreases by about 0.35 percentage points. This reflects that, as financial development raises the return to entrepreneurial activity, individuals at the margin with sufficient wealth and managerial ability transition out of wage work or unemployment into entrepreneurship, especially employer entrepreneurship.

To further understand the population shifts, I decompose the entrepreneurial population into financially constrained and unconstrained subgroups. Fig. 3 plots the change in population shares for each subgroup. The primary effect of financial development is a broad reallocation away from constrained self-employment toward all other entrepreneurial categories. As the collateral constraint loosens, the share of constrained self-employed individuals falls sharply by roughly 7 percentage points while the shares of unconstrained self-employed and both types of employers increase monotonically.

Interestingly, the share of constrained employer entrepreneurs rises because financial development enables the most productive self-employed to transition into employer entrepreneurship. However, as they are often individuals with relatively low wealth, they immediately become financially constrained in their new roles. This finding reveals that financial development not only shifts the composition across types but also alters the nature of financial constraints within them. Lastly, it must be noted that in the aggregate, the total share of constrained entrepreneurs declines by about 3.9 percentage points, implying that improved access to credit does reduce the number of financially constrained entrepreneurs.

Next, I turn to long-run supply-side aggregates: output, TFP, capital, and labor. Fig. 4 plots their percentage deviations relative to the completely self-financed economy. Consistent with the literature, both output and capital rise strongly with financial development, both increasing by approximately 6 percent.

The response of aggregate labor is less direct because financial development affects both labor demand and occupational sorting. On the one hand, higher wages and increased labor demand by employer entrepreneurs tend to expand labor supply. On the other hand, higher returns to entrepreneurship, together with reduced labor demand from the corporate sector, put downward pressure on total labor supply. In equilibrium, the second force modestly dominates, so aggregate labor declines slightly. This decline is consistent with the shrinking share of workers in the occupational distribution.

TFP also rises by more than 12 percent but displays a moderate degree of curvature. This behavior reflects the way aggregate TFP is constructed as the sum of endogenous TFPs across entrepreneurial sectors. Self-employed TFP falls slightly: although misallocation within the self-employed sector improves, many relatively productive self-employed entrepreneurs exit into employer entrepreneurship, lowering the aggregate productivity of the remaining self-employed sector. On the other hand, employer TFP rises

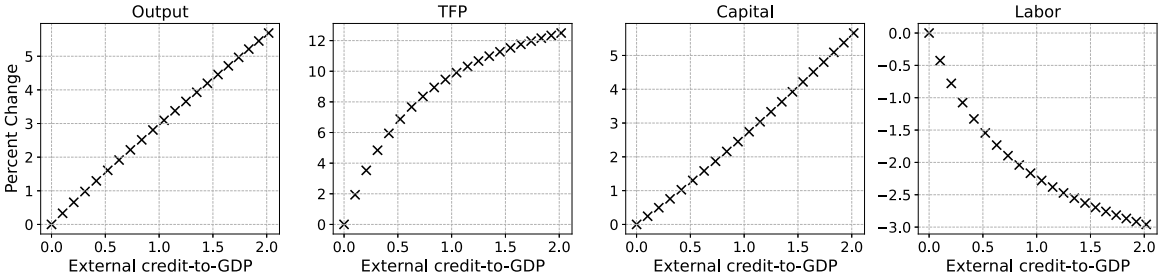


Fig. 4. Long-run impact of financial development: Supply-side aggregates.
Note: The figure plots the percent deviation of steady-state aggregate output, TFP (sum of endogenous TFPs across sectors), capital, and labor as a function of external credit-to-GDP. Deviations are calculated as percent changes relative to $\bar{\phi} = 1$.

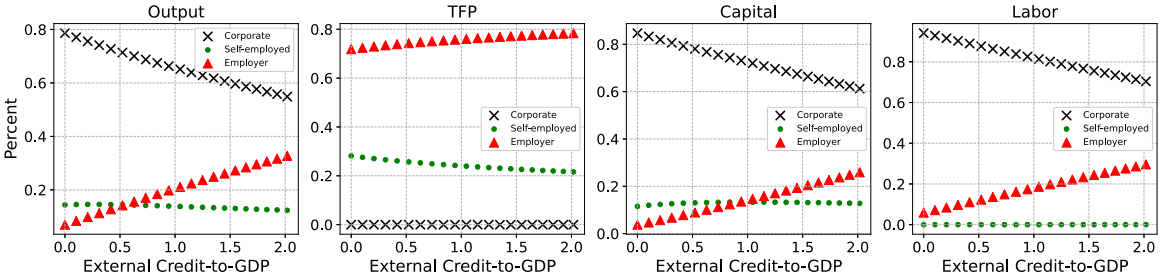


Fig. 5. Long-run impact of financial development: Sectoral shares.
Note: The figure plots the steady-state shares of the corporate sector, self-employed, and employer entrepreneurs in output, TFP, capital, and labor as a function of external credit-to-GDP.

as more entrepreneurs enter and scale up. The combination generates mild curvature in overall TFP, although it continues to rises monotonically.[14]

Having established the aggregate steady state effects of financial development, I now decompose the output, capital, and labor into the corporate sector, self-employed entrepreneurs, and employer entrepreneurs. Fig. 5 shows that the shift in shares towards the employer sector, whose share of output rises dramatically as resources are reallocated toward larger-scale entrepreneurship.

In terms of TFP, the employer sector accounts for the vast majority of measured productivity, and its share increases modestly with financial development. For factors of production, the patterns differ. Among the self-employed, even though population shares decline somewhat, their capital share remains relatively flat, and by construction they do not employ outside labor. By contrast, there is a substantial reallocation of both capital and labor from the corporate sector to employers. The employer share of capital and labor rises to almost 30 percent, with corporate shares falling by comparable amounts.

This reallocation translates into a dramatic change in output composition. In a fully self-financed economy, the corporate sector produces nearly 80 percent of total output while employers account for less than 10 percent. When the external credit-to-GDP ratio reaches 2, however, the employer share rises to over 30 percent, while the corporate share falls to 55 percent. Self-employed shares decline only slightly and remain relatively stable, from 14 to 12 percent.

Overall, these results highlight the central mechanism of the model: financial development encourages a reallocation of resources from corporate firms toward employer entrepreneurship, amplifying the role of high-scale entrepreneurs in driving aggregate outcomes. This sectoral shift is one of the key channels through which improved access to credit shapes business cycle dynamics.

Having documented how financial development reallocates resources across sectors, I now turn to analyzing the second moments of the model. Fig. 6 plots sectoral volatilities, measured as standard deviations, for output, factor inputs, and endogenous TFP. The figure shows that financial development not only changes where production takes place, but also changes how aggregate risk is transmitted across sectors.

I first consider endogenous TFP and factor inputs. Endogenous TFP is less volatile than output in both entrepreneurial sectors, but its response differs sharply across them. For employer entrepreneurs, endogenous TFP volatility declines steadily as collateral constraints are relaxed. By contrast, self-employed endogenous TFP volatility rises. This increase reflects changes in selection into self-employment as financial development deepens: some relatively productive self-employed entrepreneurs transition into employer entrepreneurship, while more marginal entrepreneurs remain in or enter self-employment. As a result, the composition of the self-employed sector becomes more sensitive to aggregate conditions. The corporate sector has no endogenous TFP component by construction, so its measured endogenous TFP volatility is zero.

[14] Appendix B presents additional steady state results on welfare, factor prices, labor market outcomes, and the TFP decomposition.

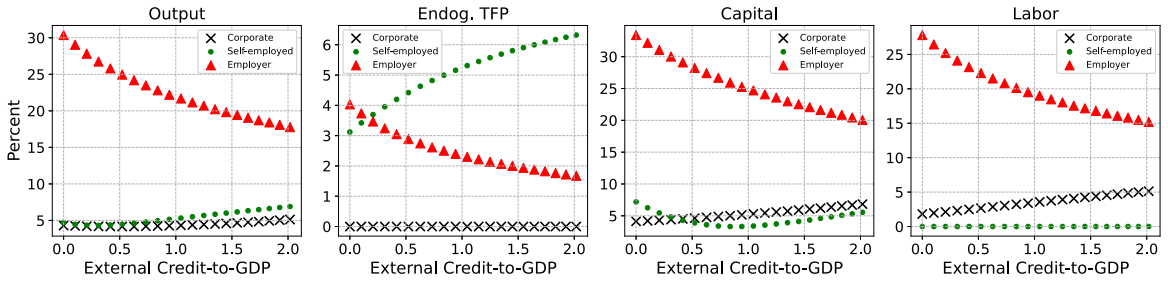


Fig. 6. Impact of financial development: Sectoral volatility.
Note: The figure plots the standard deviations of output, factor inputs, and endogenous TFP for the corporate sector, self-employed entrepreneurs, and employer entrepreneurs. All volatilities are expressed as percentages.

The factor responses reinforce the central role of employer entrepreneurship. Employer capital and labor are much more volatile than the corresponding inputs in the corporate and self-employed sectors, reflecting employers' use of hired labor and their stronger exposure to aggregate productivity and financial shocks. However, employer input volatility declines substantially with financial development. This stabilization reflects improved access to credit and greater wealth accumulation among employer entrepreneurs, which allow them to adjust production more smoothly in response to aggregate shocks. As employers rely less heavily on binding collateral constraints, their capital and labor choices become less sensitive to fluctuations in aggregate conditions. By contrast, the volatility of corporate factor inputs rises as the corporate sector absorbs more of the general equilibrium adjustment in wages and interest rates. For the self-employed, capital volatility remains relatively low and non-monotonic, while hired labor is zero by construction.

These factor inputs and endogenous TFP patterns translate into different volatility responses across sectoral outputs. Employer output remains by far the most volatile sector throughout the experiment, but its volatility declines sharply as financial development deepens, falling from about 31 percent in the self-financed economy to about 17 percent when external credit-to-GDP reaches 2. Self-employed output volatility rises moderately, from about 5 percent to about 7 percent, largely reflecting the increase in endogenous TFP volatility in the self-employed sector. Corporate output volatility increases only modestly and remains relatively low.

In sum, Fig. 6 shows that financial development dampens output volatility in the employer sector, and that this decline is quantitatively much larger than the moderate increase in self-employed output volatility. However, this sectoral stabilization does not imply a decline in aggregate risk exposure. Employers remain much more volatile than the corporate and self-employed sectors throughout the experiment, even after their volatility declines. Since financial development also reallocates output, capital, and labor toward employer entrepreneurs, the aggregate economy becomes more exposed to this shock-sensitive sector. The composition effect can therefore dominate the stabilization of employer-sector volatility, helping to explain why aggregate output volatility rises even though employer-sector volatility falls.

I quantify these forces more directly through a variance decomposition. Log-linearized aggregate output can be written as

$$\hat{Y}_t = \theta_c \hat{Y}_t^c + \theta_{se} \hat{Y}_t^{se} + \theta_{em} \hat{Y}_t^{em}, \tag{29}$$

where θ_j denotes the steady-state output share of sector $j \in c, se, em$. The variance of aggregate output is then

$$var(\hat{Y}_t) = \sum_j \theta_j^2 var(\hat{Y}_t^j) + \sum_{j \neq k} \theta_j \theta_k cov(\hat{Y}_t^j, \hat{Y}_t^k). \tag{30}$$

This expression shows that aggregate volatility depends both on within-sector volatilities and output shares across sectors. Let $var_0(\hat{Y}_t)$ denote the variance in the self-financed economy. For a given level of financial development i, the change in variance relative to self-financed economy is

$$\Delta_i var(\hat{Y}_t) = var_i(\hat{Y}_t) - var_0(\hat{Y}_t). \tag{31}$$

I decompose this change into a composition effect and a stabilization effect:

$$\Delta_i var(\hat{Y}_t) = \underbrace{(var_i(\hat{Y}_t) - var_{i'}(\hat{Y}_t))}_{\text{Composition effect}} - \underbrace{(var_{i'}(\hat{Y}_t) - var_0(\hat{Y}_t))}_{\text{Stabilization effect}}, \tag{32}$$

where $var_{i'}(\hat{Y}_t)$ is the counterfactual variance obtained by holding sectoral shares fixed at the baseline while allowing only variances to adjust.[15] Fig. 7 plots the results. The black crosses denote the total change in aggregate output variance, while the green dots capture the composition effect and the red triangles capture the stabilization effect. The decomposition shows that financial development generates two opposing forces. The composition effect raises aggregate volatility by reallocating output toward the employer sector, which remains the most volatile sector throughout the experiment. The stabilization effect works in the opposite

[15] This is defined as $var(\hat{Y}_t) = \sum_j (\theta_j^o)^2 var(\hat{Y}_t^j) + \sum_{j \neq k} \theta_j^0 \theta_k^0 cov(\hat{Y}_t^j, \hat{Y}_t^k)$.

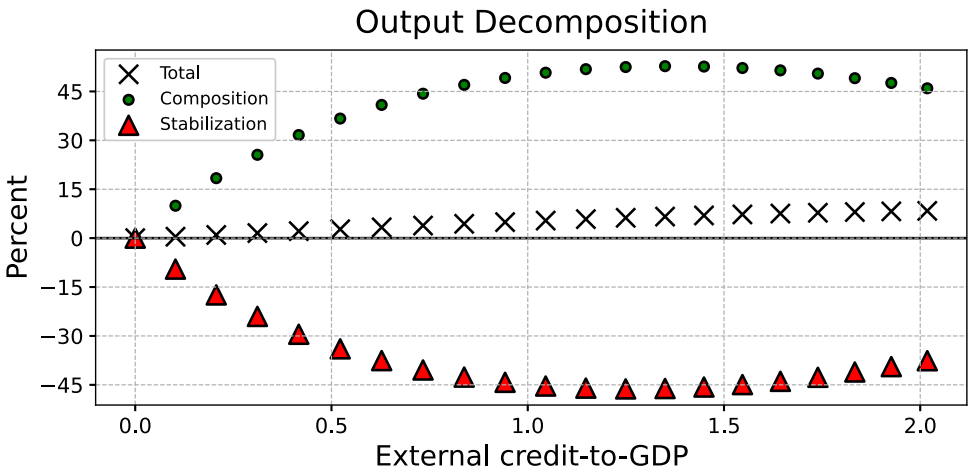


Fig. 7. Impact of financial development: Output volatility.
Note: The figure decomposes the percentage change in the variance deviation of aggregate output relative to the self-financed economy ($\phi = 1$). Black crosses denote the total variance change, green dots the composition effect (arising from changes in steady-state output shares), and red triangles the stabilization effect (arising from changes in within-sector variances).

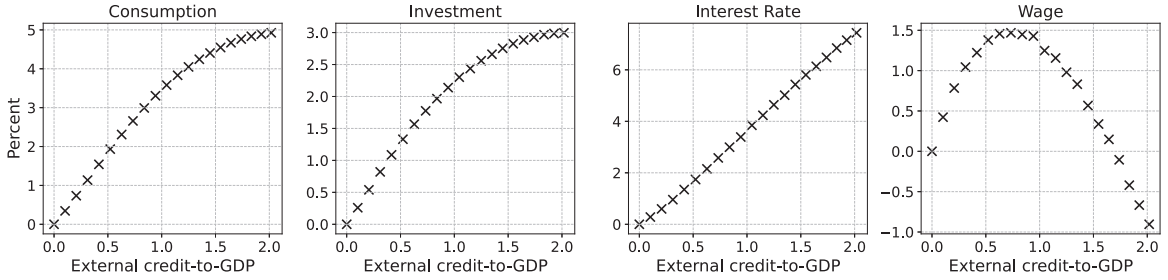


Fig. 8. Impact of financial development: Quantities and prices volatility.
Note: The figure plots changes in volatility relative to the self-financed economy. For consumption, investment, and wages, the y-axis reports the percent change in the standard deviation. For the interest rate, the y-axis reports the percentage-point change in its standard deviation.

direction: holding sectoral output shares fixed at their baseline values, changes in sectoral second moments would reduce aggregate variance, primarily because employer sector output volatility declines substantially with financial development.

Quantitatively, the stabilization effect is large. If sectoral output shares were held fixed, the model would predict that aggregate output variance falls by as much as 46 percent. However, the composition effect is even larger, increasing aggregate variance by more than 52 percent at intermediate levels of financial development. When both channels operate, the composition effect dominates, and aggregate output variance rises by more than 8 percent when external credit-to-GDP reaches 2.

The figure also reveals nonlinear dynamics. At low levels of financial development, both the positive composition effect and the negative stabilization effect increase sharply in absolute value. This reflects large adjustments in both steady state sectoral shares and sectoral second moments as the economy moves away from the self-financing benchmark. As financial development deepens further, both effects flatten and eventually weaken. The stabilization effect becomes smaller in absolute value because the decline in employer sector volatility is partly offset by modest increases in volatility in the corporate and self-employed sectors. At the same time, the composition effect remains positive because employer entrepreneurs continue to account for a rising share of economic activity and remain the most volatile sector. As a result, the total effect on aggregate output variance remains positive even though the stabilizing force from employer sector volatility is quantitatively important.

This decomposition underscores a broader trade-off. On the one hand, financial development improves allocative efficiency and raises steady state output and TFP. On the other hand, it reallocates resources toward the most volatile sector, amplifying aggregate business cycle risk. To fully assess these dynamics, however, it is not enough to focus only on output volatility. I next examine how financial development shapes the volatility of consumption, investment, and prices.

Fig. 8 shows how the volatility of aggregate consumption, investment, the interest rate, and wages changes as the economy's external credit-to-GDP ratio rises. Consistent with the results for output, volatility increases for most aggregate variables as financial development deepens. Consumption volatility rises by about 5 percent relative to the self-financed economy, while investment volatility increases by about 3 percent. Interest-rate volatility rises more sharply, increasing by more than 7 percentage points, reflecting the greater sensitivity of capital-market conditions as credit expands. By contrast, wage volatility remains relatively stable

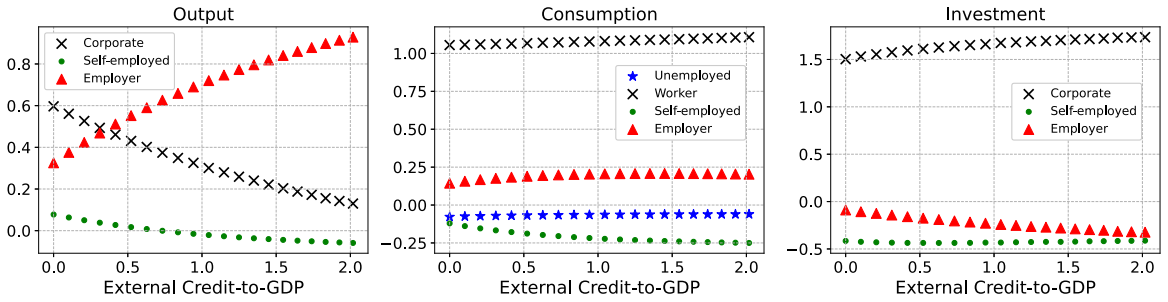


Fig. 9. Short-run impact of financial development: Variance contribution by group.
Notes: The figure plots the percentage contribution of each component to the variance of the corresponding aggregate variable as a function of the external credit-to-GDP. The components for the output and investment decompositions are the three production sectors. The components for the consumption decomposition are the four household types.

and follows a non-monotonic pattern. As labor demand becomes more concentrated in the employer sector, it initially amplifies wage fluctuations but later stabilizes as employers accumulate wealth and scale, making their labor demand less sensitive to aggregate shocks.

The previous decomposition separated aggregate output volatility into composition and stabilization effects, clarifying why volatility rises with financial development despite the stabilization of employer-sector output volatility. While this analysis explains the mechanism, it does not reveal which groups within the economy bear responsibility for volatility in different aggregates, which is crucial in identifying the source of aggregate risk. For instance, volatility driven primarily by employers has very different implications than volatility borne by workers, since their income sources, labor market dynamics, and exposure to financial constraints differ. To address this, I turn to a complementary decomposition that attributes the variance of output, consumption, and investment to their underlying group-level components. For any aggregate variable, $\hat{X}_t$, its variance can be expressed as a share-weighted sum of its components.

$$var(\hat{X}_t) = \sum_j \theta_j cov(\hat{X}_t, \hat{X}_t^j), \tag{33}$$

where θ_j is the steady-state share of component j, $\hat{X}_t$ denotes the log-linearized variable. Dividing both sides by the variance of $\hat{X}$, I can decompose the total variance into contributions.

$$1 = \sum_j \theta_j \frac{cov(\hat{X}_t, \hat{X}_t^j)}{var(\hat{X}_t)} = \sum_j \theta_j \beta_j. \tag{34}$$

Here, β_j is the "beta" of the component's volatility with respect to the aggregate's volatility. The term, $\theta_j \beta_j$, represents the total percentage contribution of component j to the aggregate variance. I apply this decomposition to aggregate output, consumption, and investment. Fig. 9 plots the resulting variance contributions. The output decomposition reinforces the main composition channel. As financial development deepens, the employer sector accounts for a steadily larger share of aggregate output volatility. Its contribution rises from around 0.3 in the self-financed economy to more than 0.9 when external credit-to-GDP reaches 2. At the same time, the corporate contribution declines sharply, while the contribution of self-employment remains small and eventually turns slightly negative. Thus, aggregate output fluctuations become increasingly tied to the employer sector as credit constraints are relaxed.

The consumption decomposition shows a different pattern. Workers remain the dominant source of aggregate consumption volatility at all levels of financial development, mainly because they account for the largest share of the population. Their contribution exceeds one because the unemployed and self-employed components contribute negatively to aggregate consumption variance. These negative contributions do not mean that these groups have negative volatility; rather, their aggregate consumption components covary negatively with aggregate consumption. This reflects the countercyclical nature of unemployment and self-employment: during downturns, individuals are more likely to move into unemployment or necessity-driven self-employment. As financial development deepens, the negative contributions of these groups become larger in magnitude, while the employer contribution rises modestly. However, these changes remain quantitatively limited relative to the output decomposition.

Investment volatility reveals a more complex dynamic. Entrepreneurial investment contributes negatively to aggregate investment volatility. This arises because a transitory positive financial shock leads to an immediate boom in entrepreneurs' capital accumulation, followed by sharp disinvestment as forward-looking entrepreneurs anticipate tighter future credit conditions. Despite this negative correlation, the overall magnitude of employers' contribution rises with financial development, indicating that entrepreneurial investment decisions become increasingly important for aggregate fluctuations.

In summary, this section highlights that looser credit constraints shift the economy toward employer entrepreneurship. Because this sector is more exposed to aggregate shocks, the result is heightened macroeconomic volatility.

6. Conclusion

This paper examines how entrepreneurial heterogeneity shapes macroeconomic dynamics. Using microdata from Argentina, I document two key facts. First, entrepreneurial types differ systematically across the income distribution: self-employed entrepreneurs are disproportionately concentrated below the median, while employer entrepreneurs are concentrated above the median. Second, these groups move differently over the business cycle. The population share of self-employed entrepreneurs is countercyclical, while the employer share is procyclical.

Motivated by these patterns, I develop a dynamic general equilibrium model with occupational choice, financial and labor market frictions, and aggregate shocks. The model replicates the distributional and cyclical features of entrepreneurship observed in the data and captures endogenous sorting across occupations by wealth and ability. Quantitative experiments show that financial development raises long-run output but also increases aggregate volatility. The mechanism operates through occupational composition. Relaxing collateral constraints shifts economic activity toward employer entrepreneurs, who operate larger firms and remain more exposed to aggregate shocks. Although financial development dampens output volatility within the employer sector, employers remain the most volatile sector, and their rising aggregate weight increases the economy's exposure to business cycle risk.

These findings underscore a trade-off between long-run growth and short-run stability. Policies that expand access to credit delivers higher output in the long-run, but they can also amplify business cycle fluctuations unless accompanied by complementary structural reforms that dampen volatility. More broadly, the analysis highlights the importance of explicitly accounting for heterogeneity within the entrepreneurial sector when evaluating the macroeconomic consequences of financial development.

Declaration of Generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author used ChatGPT for code de-bugging, plotting assistance, and proofreading. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Declaration of competing interest

The author declares that he has no relevant or material financial interests that relate to the research described in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2026.105459.

Data availability

Data will be made available on request.

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