Entrepreneurial Heterogeneity, Financial Development, and Business Cycle Dynamics

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Abstract. This paper studies how financial development impacts business cycles through entrepreneurial composition. Using Argentine microdata, I show that self-employed entrepreneurs are concentrated in lower income quintiles with countercyclical population shares, while employer entrepreneurs are concentrated in higher quintiles with procyclical shares. To interpret these patterns, I develop a dynamic occupational choice model with aggregate risk in which endogenous sorting creates a compositional channel for macroeconomic fluctuations. In the model, financial development raises aggregate output volatility by 10 percent, as the reallocation toward the more shock-sensitive employer sector outweighs the decline in volatility within entrepreneurial groups. The results highlight a potential trade-off: while financial development improves long-run outcomes, it may also lead to short-run instability.

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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 concentrated in lower income quintiles, while the majority of employer entrepreneurs reside in higher income quintiles. 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.

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 models a pure credit expansion, holding the volatility of aggregate shocks fixed.[2] The quantitative results show that financial development raises long-run output and productivity while reducing volatility within sectors. Yet, at the aggregate level, volatility rises in the model. The reason is that the compositional shift toward the high-volatility employer sector outweighs the stabilizing within-sector effects. For example, an increase in the external credit-to-GDP ratio from 0 to 2 raises output volatility by about 10 percent. Overall, the analysis highlights that financial development reallocates business cycle risk by shifting resources toward 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) and Quadrini (2000)) and has explored how individual characteristics shape the choice to become an entrepreneur versus a wage worker

[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.

(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) and 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 (2012) 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 (2023). 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 (2020) 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 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*.

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

[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 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	2,446	1,906	4,060
Median	0	1,975	1,391	3,074
P20	0	957	604	1,481
P80	339	3,499	2,763	5,716
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.

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 (1,906 pesos) is not only significantly lower than that of employers but also falls below the average for workers (2,446 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.

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 (4,060 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 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 (1,481 pesos) is higher than the median income for a self-employed (1,391 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.

Table 2: Income Composition of Population Groups

Income Group	Unemployed	Workers	Self-employed	Employers
Low income	0.97	0.54	0.70	0.33
High income	0.03	0.46	0.30	0.67

Note: Each column sums to 1. Values show the fraction of each population group that falls into the low income group (first 3 quintiles) or high income group (top 2 quintiles).

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 across low-income and high-income categories. Self-employed individuals are heavily concentrated in the low-income group (bottom three quintiles), where 70% of them are found, suggesting a prevalence of necessity-driven entrepreneurship. In contrast, employers are predominantly in the high-income group (top two quintiles), which contains two-thirds of all employer entrepreneurs. This pattern points to opportunity-driven entrepreneurship at the top of the distribution. 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 0.74. 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.

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. Moments using the U.S. data is taken from Kwark and Ma (2020).

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). Second, 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. Finally, 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 may choose to 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, Y_t. 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. The household then observes its current skills and, based on its predetermined occupation for period t, engages in production. Income is then realized: 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, $(1 + r_t^a)a_t$. 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. After this decision, the outcome of labor market shocks is revealed. These could be job offers or separations, which depend on the household's occupation in period t. Based on this new information, the household makes its occupational choice for the upcoming period, $t + 1$.

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

[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.

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.

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.

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

where $\phi_t \geq 1$. 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

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

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

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

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.

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

where $\bar{\phi}$ is the steady-state 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 $\rho_{z,\phi}$.

Household Problem

The household's problem can be formulated as a dynamic programming problem. The idiosyncratic state for a household at the beginning of a period is given by its assets, skills, and its predetermined occupation for that period, $s = (a, z_w, z_m)$. The aggregate state of the economy is $S = (\Lambda, Z, \phi)$.

Given the timing, it is useful to define two value functions. Let $v^o(s, S)$ be the occupation-specific value function at the beginning of period t, where the occupation is denoted by o. Let $\tilde{V}^o(s', S')$ be the occupation-specific continuation value at the end of period t, after the consumption-saving decision has been made but before the occupational choice for $t+1$ is made.

At the beginning of the period, the household's occupation o is known. Production occurs, income is realized, and the household makes its consumption-saving decision. The value function of occupation o, $v^o(s, S)$, is therefore written as:

$$v^o(s, S) = \max_{c,a'} \left\{ \frac{c^{1-\gamma} - 1}{1-\gamma} + \beta \mathbb{E}[\tilde{V}^o(s', S')|s, S] \right\}, \tag{12}$$

subject to the budget constraint:

$$c + a' = \text{inc}^o(s, S) + (1 + r(S))a, \tag{13}$$

$$a' \geq 0. \tag{14}$$

Here, $inc^o(s, S)$ is the income generated from the predetermined occupation o. 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 $\pi^o(s, S)$, 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.

The expectation $\mathbb{E}[.]$ is taken over the realization of next period's skill and aggregate state S. After the consumption-saving decision, the household learns the outcome of the labor market shocks and makes its occupational choice for the next period, o'. The continuation value, $\tilde{V}^o(s', S')$, depends on the household's occupation in the current period, o, as this determines the probabilities of receiving job offers or separations. For an individual who was unemployed in period t (i.e. $o = u$), the continuation value is:

$$\tilde{V}^u(s', S') = \left[p^u(S) v^w(s', S') + (1 - p^u(S)) \max_{o' \in \{u, se, em\}} \{ v^{o'}(s', S') + \varepsilon(o') \} \right]. \tag{15}$$

The first term represents the value of receiving a job offer and becoming a worker with a probability $p^u(S)$. The second term represents the value of not receiving an offer, where the household must choose from the restricted set of occupations $o' \in \{u, se, em\}$. The variable, $\varepsilon(o')$, is drawn from a Type-I Extreme Value distribution.[7] The inclusion of this shock means the occupational choice is probabilistic. This allows the value function to be differentiable with respect to the aggregate state variables.

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

$$\tilde{V}^w(s', S') = \left[p^w(S) v^u(s', S') + (1 - p^w(S)) \max_{o' \in \{u, w, se, em\}} \{ V^{o'}(s', S') + \varepsilon(o') \} \right], \tag{16}$$

where the second term is the expected value of choosing from the full set of occupations. For a household that is a self-employed or an employer entrepreneur, $o \in \{se, em\}$, they receive a job offer with a probability $p^o(S)$. If an offer is received, the agent can either choose to be a worker or continue as their current type of entrepreneur. If an offer is not received, the agent can continue to operate their business as its current type, exit to

[7] Smoothing parameter that controls the discrete choice probabilities is set to 0.05, which is a standard value in the literature.

unemployment, or switch their type of entrepreneurship. Their value function is

$$\tilde{V}^o(s', S') = \left[p^o(S) \max_{o_1' \in \{w, o\}} \{ v^{o_1'}(s', S') + \varepsilon(o_1') \} + (1 - p^o(S)) \max_{o_2' \in \{u, se, em\}} \{ v^{o_2'}(s', S') + \varepsilon(o_2') \} \right], \tag{17}$$

where $o = se, em$ and o_1' and o_2' represent sets of occupational choices to entrepreneurs with and without job offers, respectively.

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 over the individual state space. 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

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

and defining aggregate labor:

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

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:

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

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

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.[8]

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 $\{c(s,S), a'(s,S), o(s,S), t_m(s,S), l(s,S), k(s,S)\}$, 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;

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

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 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.

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 aggregate business cycle moments as much as possible. First, I externally calibrate a subset of parameters based on standard values in the literature. Second, I internally calibrate the remaining parameters in two stages. In the first stage, I

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
$\bar{\phi}$	Steady-state collateral constraint	1.42
$\underline{b}$	Unemployed income	0.001

target moments in the stationary equilibrium, calibrating parameters that primarily affect steady-state outcomes. 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 comes from two main sources. Micro-level moments on occupational choice and income distribution are calculated using the Argentinian Permanent Household Survey (EPH) from 2004Q1 to 2015Q4. Aggregate business cycle moments are from the International Financial Statistics (IFS) database.

External Calibration

Table 4 presents values that are externally calibrated. The risk aversion parameter, γ, in the utility function is set to a value of 2, which is a standard value used in the literature. Then, I set the annualized world interest rate to 2% and use the discount factor β to clear the capital market, 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 of the corporate production, α, to 0.32, a standard value in the literature. The manager, capital, and labor shares in the entrepreneur production (ν, η, θ) are set to 0.2, 0.32, and 0.48, respectively, based on the parameters outlined by Guner et al. (2008). The quarterly capital depreciation rate is set to 0.025, which is a standard value in the literature. Finally, I set the collateral constraint parameter of entrepreneurs in steady-state, $\bar{\phi}$, to 1.42 following the value used for a similar parameter in Herreño and Ocampo (2023).

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 12 parameters calibrated to match 12 empirical moments. While all parameters impact all moments jointly, it is helpful to identify which parameters have the greatest influence on specific targets. There are 8 parameters governing the idiosyncratic productivity processes, which are crucial for matching occupational structure. The two productivity processes, z_w and z_m, are discretized into a finite-state Markov chain using a Tauchen method. The persistence parameters, ρ_w and ρ_m, and the correlation coefficient, $\rho_{w,m}$, are targeted to match the relative average incomes across three occupations (worker/employer, self-employed/worker, and self-employed/employer). The standard deviations of the innovations to these processes, σ_w and σ_m, are targeted to match the variance of log incomes for workers and for entrepreneurs. Then, the fixed cost of production, κ, and the long-run means of productivity processes, μ_w and μ_m, are used to target the population shares of workers, self-employed, and employer entrepreneurs.

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

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

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 $\tilde{p}$ 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 aggregate output, Y_t, from its steady-state value, $\bar{Y}$. The sensitivity of these probabilities to the business cycle is governed by a

Table 5: **Internally Calibrated Parameters**

Parameter	Description	Value
Stationary Equilibrium		
ρ_w	Persistence of working abilities	0.61
σ_w	Standard deviation of working abilities	0.62
ρ_m	Persistence of managerial abilities	0.90
σ_m	Standard deviation of managerial abilities	0.90
$\rho_{w,m}$	Correlation between working and managing	0.19
μ_w	Shift parameter of working abilities	-0.30
μ_m	Shift parameter of managerial abilities	-1.09
κ	Fixed cost of production	1.16
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	0.26
p^{em}	Job-finding rate of employers	0.32
Aggregate Parameters		
ρ_Z	Persistence of TFP shock	0.76
σ_Z	Standard deviation of TFP shock	0.02
ρ_ϕ	Persistence of financial shock	0.74
σ_ϕ	Standard deviation of financial shock	0.11
$\rho_{z,\phi}$	Correlation between TFP and financial shock	0.51
ψ	Labor market parameter	1.34

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

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 parameters governing the two idiosyncratic skill processes show a distinct difference. The managerial skill process is both more persistent ($\rho_m = 0.90$ vs. $\rho_w = 0.61$) and significantly more volatile ($\sigma_m = 0.90$ vs. $\sigma_w = 0.62$). This specification is necessary for the model to generate the higher income variance observed among entrepreneurs compared to workers. The innovations to the two skills are also moderately and positively correlated ($\rho_{w,m} = 0.19$). Despite a more negative shift parameter of managerial abilities ($\mu_m = -1.09$), the high persistence and variance of the managerial skill process result in a substantially higher unconditional mean for managerial ability compared to worker ability (4.86 vs. 1.04).

The model also includes several parameters related to various frictions. The fixed cost for employer entrepreneurs, κ, is calibrated to 1.16, a significant value representing approximately 31% of the average employer's income. 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 0.32, and lower for the self-employed ($p^{se} = 0.26$).

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 0.76 and its standard deviation, σ_Z, is 0.02. 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 much more volatile 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 1.34. This implies that a 1% increase in aggregate output above its steady state leads to a 0.3 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 successfully matches the income distribution both within and across occupations. The targeted variances of log income for workers and entrepreneurs capture the empirical

Table 6: **Calibration Results**

Moment	Data	Model
Stationary Equilibrium		
Population shares		
Unemployed	0.10	0.10
Self-employed	0.17	0.16
Workers	0.69	0.70
Employers	0.04	0.04
Average income of X to the average income of Y		
Self-employed/workers	0.78	0.77
Workers/employers	0.60	0.61
Self-employed/employers	0.47	0.47
Variance of log income of workers	0.69	0.69
Variance of log income of entrepreneurs	0.94	0.94
Transition into employment from X		
Unemployed	0.42	0.42
Workers	0.89	0.89
Self-employed	0.20	0.20
Employers	0.10	0.10
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: Composition of Entrepreneurs**

Moment	Data	Model
Low-Income (1st-3rd quintiles)		
Share of self-employed	0.70	0.64
Share of employers	0.33	0.35
High-Income (4th-5th quintiles)		
Share of self-employed	0.30	0.36
Share of employers	0.67	0.65

finding that income is more dispersed among entrepreneurs than among workers.

The model also replicates the occupational composition of the economy. The calibrated population shares of entrepreneurs exactly match the empirical counterpart while the population shares of self-employed and workers almost exactly match the empirical moments. Furthermore, the model matches the average income ranking across these groups (employers $>$ workers $>$ self-employed), with the calibrated income ratios aligning well with the data. The model also successfully matches all moments related to aggregate dynamics.

To externally validate the model, I compare key untargeted moments from the simulation with the data. Table 7 shows that the model successfully replicates the composition of the entrepreneurial pool at both the low (bottom 3 quintiles) and high (top 2 quintiles) ends of the income distribution, even though these moments were not directly targeted. In the data, the 70% of self-employed entrepreneurs is situated in the low-income group, where only a third of employers reside in the low-income group. The model generates shares of self-employed and employers of 64% and 35%, respectively. On the other hand, 36% of self-employed entrepreneurs are in the high-income group whereas 63% of employers are located in the high-income group. In the model, these shares are 36% for self-employed and 65% for employers, which are very close to the data.

This result demonstrates 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 through external labor hiring. Only individuals with a combination of high managerial ability and sufficient wealth, which are correlated with high income, can profitably overcome this barrier. This mechanism endogenously generates an economy where necessity-driven self-employment is the dominant form of entrepreneurship for the low-income population, while opportunity-driven employer entrepreneurship becomes much more prevalent among high-income individuals.

It must be noted that the model, consistent with the data, still predicts that one-third of employers are located in the low-income group. This occurs because idiosyncratic shocks to managerial abilities are persistent. For a small subset of individuals, such as the recently unemployed with sufficient wealth and managerial productivity but low working abilities, it remains optimal to choose employer entrepreneurship since they are more likely to overcome the fixed cost. However, their resulting income after paying the fixed cost remains low. Conversely, some self-employed entrepreneurs optimally choose to continue their self-employment because their managerial abilities are not sufficiently high relative to their working abilities.

Table 8: Occupational Transition Rates

	Data	**Model**		**Data**	**Model**		**Data**	**Model**		**Data**	**Model**
$U \to U$	0.37	0.23	$U \to W^*$	0.42	0.42	$U \to Se$	0.19	0.31	$U \to Em$	0.01	0.03
$W \to U$	0.04	0.09	$W \to W^*$	0.89	0.89	$W \to Se$	0.06	0.02	$W \to Em$	0.01	0.01
$Se \to U$	0.08	0.06	$Se \to W^*$	0.20	0.19	$Se \to Se$	0.64	0.68	$Se \to Em$	0.08	0.06
$Em \to U$	0.02	0.05	$Em \to W^*$	0.10	0.10	$Em \to Se$	0.26	0.44	$Em \to Em$	0.62	0.41

Note: Values represent quarter-to-quarter transition probabilities between occupational states. An asterisk (*) 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 only calibrated to match the moments related to the worker state (denoted by asterisks), yet it captures the general patterns of mobility reasonably well.

However, the model has some notable deviations from the data. For instance, the model overstates the exit rate from employer entrepreneurship (48% in the data vs. 59% in the model) as well as the transition from employer to self-employed (26% in the data vs. 44% in the model). Furthermore, the model generates a higher job separation rate relative to the data (4% in the data vs. 9% in the model). This particular discrepancy arises because the calibration of the separation rate was disciplined by the persistence of the worker state ($W \to W$) rather than the direct transition into unemployment from being a worker.

Nonetheless, the model captures a high degree of persistence for the self-employed, a rate of 68% that is close to the 64% in the data. The model also captures the higher switch rates among unemployed individuals and towards employers from self-employed.

5 Aggregate Dynamics with Occupational Heterogeneity

Now that the model has been calibrated and validated against the Argentinian data, this section uses the model as a laboratory to explore its properties and answer the paper's main research question: what are the business cycle implications of financial development policies?

First, I show that the model not only matches many of the aggregate business cycle statistics but also successfully replicates the dynamics of the population shares and aggregate occupational incomes across the different groups. I then analyze the model's baseline transmission mechanisms by examining the impulse responses to the aggregate shocks. With the validated model, I investigate the business cycle consequences of broad-based financial development, modeled by varying the steady-state collateral constraint, $\bar{\phi}$. I find that the relationship between financial development and business cycle volatility is generally 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

Table 9: Business Cycle Statistics: Model vs. Data

	Relative Std. Dev.		Correlation w/ Output	
	Data	Model	Data	Model
Aggregate variables				
Output	1.00*	1.00*	1.00	1.00
Consumption	1.09	0.52	0.95	0.86
Investment	2.39	2.11	0.96	0.94
Population shares				
Unemployed	0.22	0.14	-0.85	-0.99
Worker	0.24*	0.24*	0.86	0.94
Self-Employed	0.11	0.15	-0.66	-0.89
Employer	0.07	0.06	0.70*	0.70*
Occupational incomes				
Unemployed	3.14	3.67	0.43	0.54
Worker	1.61	1.15	0.73	0.99
Self-employed	0.85	0.58	0.73	0.63
Employer	3.27	3.48	0.51	0.83

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 2015Q4. An asterisk (*) indicates a moment that was explicitly targeted during the model's calibration.

consumption that is about half as volatile as output (a ratio of 0.52). 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. [9]

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 counter-cyclical, while the shares of workers and employers are procyclical. The model's correlations are quantitatively close to the data, particularly for the untargeted unemployed (-0.99 in the model vs. -0.85 in the data) and self-

[9] Other papers, such as Hong (2023), 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.

employed (-0.89 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 strong 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.[10]

5.2 Impulse Response Analysis

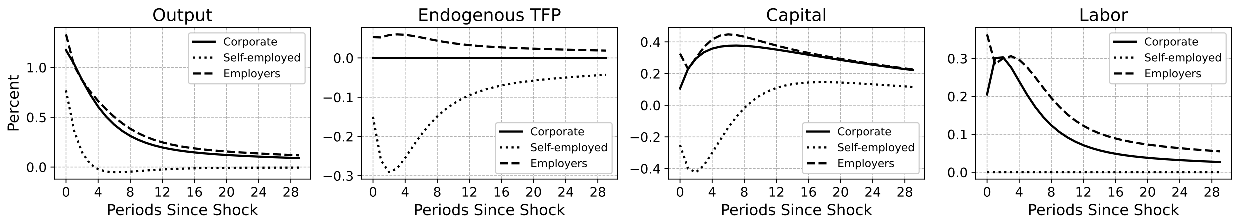
This section analyzes the model's dynamic properties by examining the impulse responses to a one percent positive shock to aggregate productivity (Z_t) and financial shock (ϕ_t). To highlight the role of entrepreneurial heterogeneity, the analysis focuses on the differential responses of the corporate, self-employed, and employer sectors.[11] Unless otherwise noted, all variables are shown as percent deviations from their steady-state values.

The top panel of Figure 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 over 1% on impact. In contrast, the response of the self-employed sector is much more muted and transitory.

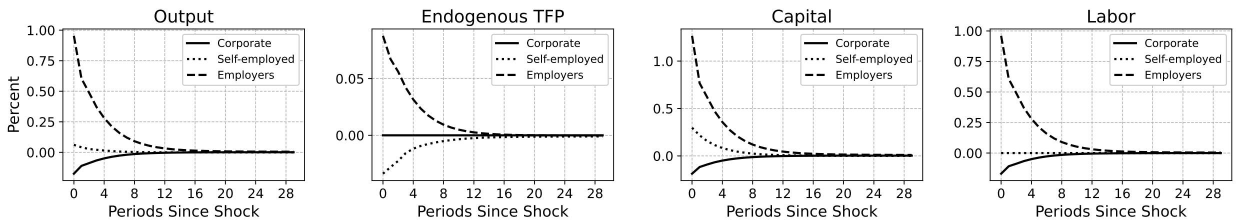
The underlying factor responses reveal the mechanisms driving these heterogeneous output dynamics. The endogenous TFP of the self-employed sector actually declines,

[10] In the appendix, I perform sensitivity analysis with respect to key parameters.

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



(a) TFP Shock



(b) Financial Shock

Figure 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.

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 bottom panel of Figure 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% 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.

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 steady-state composition of the entrepreneurial sector 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); Buera et al. (2011)). However, the implications of such policies for business-cycle volatility 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 (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.(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.

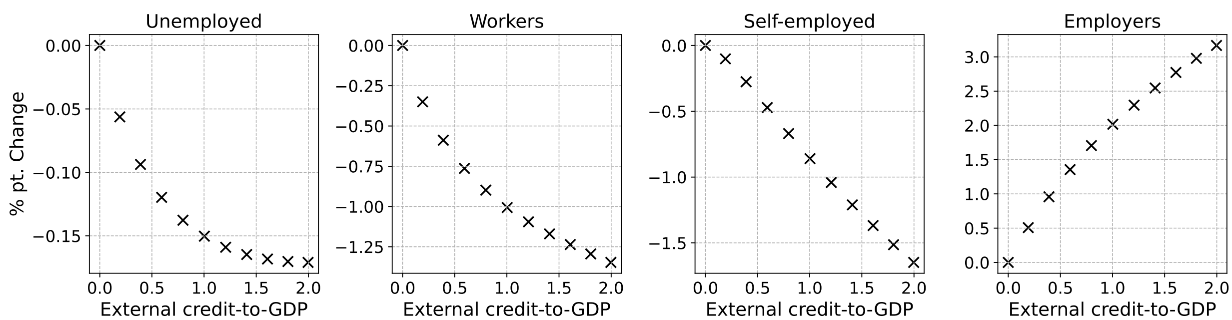


Figure 2: Impact of Financial Development: Steady-State Population Shares

Note: The figure plots the deviation of the steady-state population share for each occupation across values of the collateral constraint parameter. The y-axis shows the change in percentage points relative to the completely self-financed economy.

Given the focus on occupational heterogeneity, I first examine how financial development alters the long-run distribution of the population. Figure 2 plots the change in the steady-state population share of each occupation as a function of the external credit-to-GDP ratio. The most pronounced result is a reallocation away from self-employment and toward employer entrepreneurship. As financial constraints are relaxed, the share of self-employed entrepreneurs falls by about 1.8 percentage points, while the share of employers rises by more than 3 percentage points. This demonstrates that financial development does not merely increase the number of entrepreneurs; it facilitates a compositional shift from smaller-scale self-employment to larger, more volatile 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 1.25 percentage points, while the unemployed share decreases by about 0.15 percentage points. This reflects that as financial development raises the returns to becoming an employer, individuals at the margin with sufficient wealth and managerial ability transition out of wage work or unemployment into employer entrepreneurship.

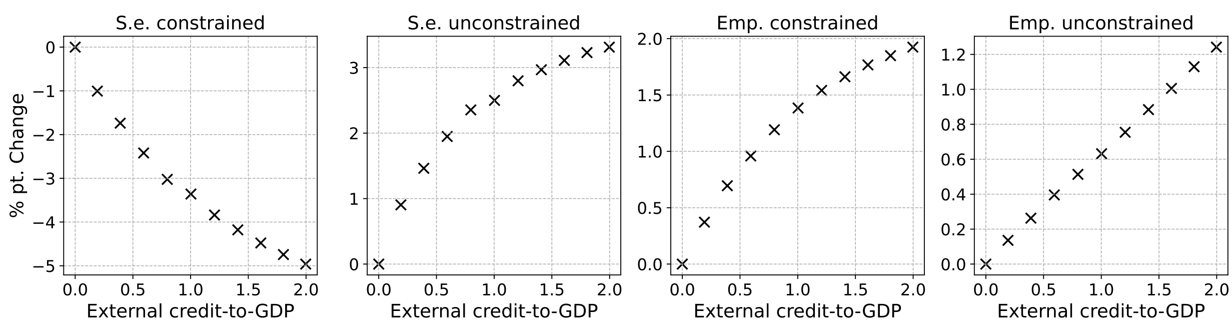


Figure 3: Impact of Financial Development: Constrained and Unconstrained Shares

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.

To further understand the population shifts, I decompose the entrepreneurial population into financially constrained and unconstrained subgroups. Figure 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 5 percentage points while the shares of unconstrained self-employed and both types of employers increase monotonically.

Interestingly, the share of constrained employer entrepreneurs rise. This highlights a subtle dynamic: 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.

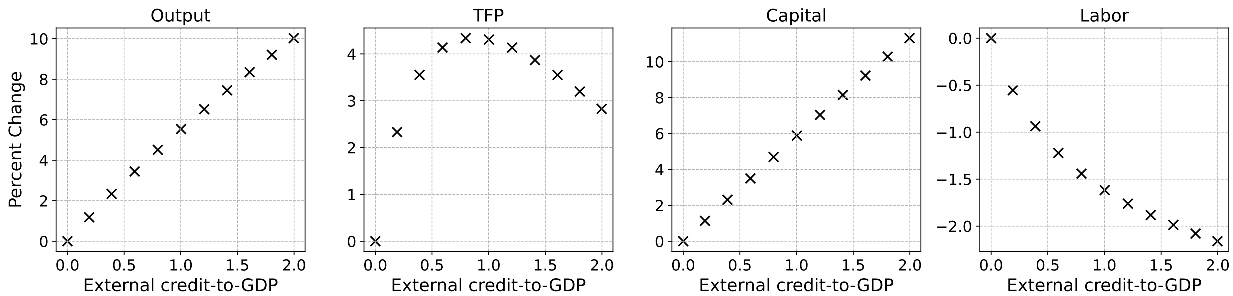


Figure 4: Impact of Financial Development: Steady-State Supply-side Aggregates

Note: The figure plots the percent deviation of steady-state aggregate output, TFP (sum of self-employed and employer TFP), capital, and labor as a function of external credit-to-GDP. Deviations are calculated as percent changes relative to $\phi_a = 1$.

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 percentage points, implying that improved access to credit does reduce the number of financially constrained entrepreneurs.

Next, I turn to steady-state supply-side aggregates: output, TFP, capital, and labor. Figure 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, increasing by more than 10 percent. Aggregate labor, by contrast, declines modestly, reflecting the shrinking share of workers in the occupational distribution.

TFP exhibits a non-monotonic pattern. It rises to a peak of just above 4 percent when the external credit-to-GDP ratio is around 1, but the rate of increase tapers off thereafter. This behavior reflects the way aggregate TFP is constructed as the sum of self-employed and employer TFP. On the one hand, self-employed TFP falls slightly: although misallocation within the self-employed sector improves, many relatively productive self-employed exit into employer entrepreneurship, lowering the aggregate. On the other hand, employer TFP rises as more marginal entrepreneurs enter and scale up. The combination generates a mild decline in overall TFP at higher levels of financial development, though it remains well above the self-financed benchmark.

Taken together, these results are consistent with the broader literature: output gains

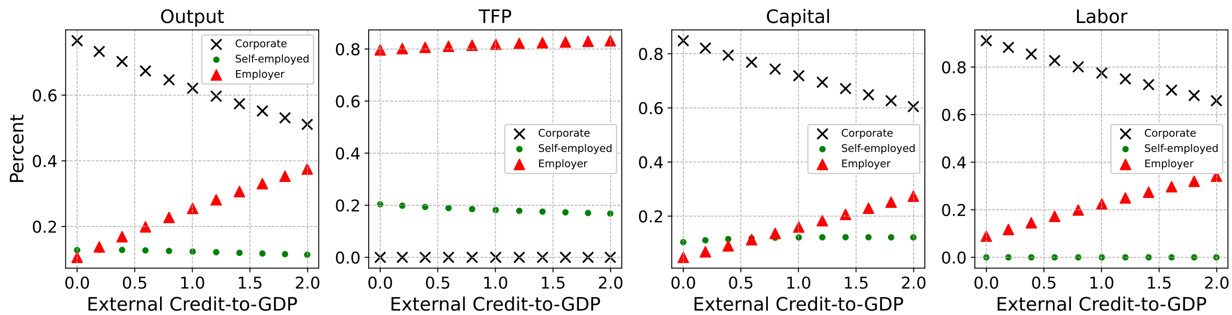


Figure 5: Impact of Financial Development: Sectoral Shares

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.

are driven primarily by capital deepening and rising employer productivity, while aggregate labor supply falls as workers transition into entrepreneurship. The joint effect is a sizable increase in steady-state output, even in the presence of declining labor input and modestly flattening TFP growth at higher levels of financial development.

Having established the aggregate steady-state effects of financial development, I now decompose output, capital, and labor into the corporate sector, self-employed entrepreneurs, and employer entrepreneurs. Figure 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 changes only 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 rises to above 20 percent, while their share of labor approaches 40 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

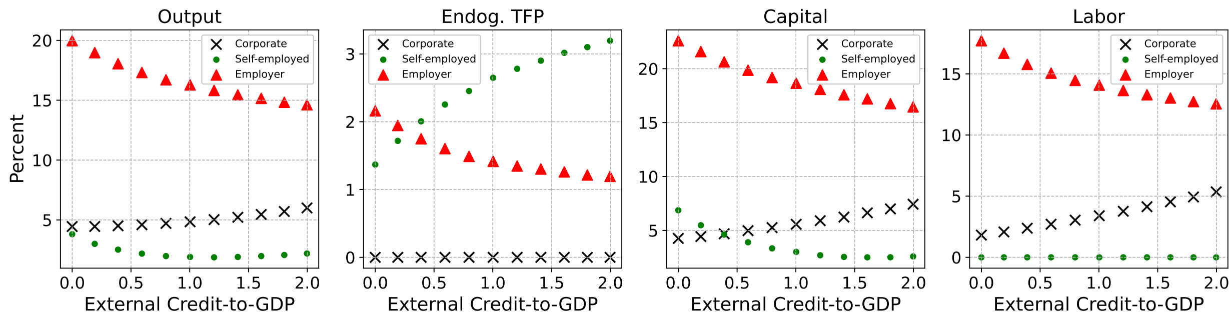


Figure 6: Impact of Financial Development: Sectoral Volatility

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.

reaches 2, however, the employer share rises to almost 40 percent, while the corporate share falls to around 50 percent. Self-employed shares decline only slightly and remain relatively stable.

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 the second-moment properties of the model. Figure 6 plots sectoral volatilities—measured as standard deviations—for output, factor inputs, and endogenous TFP. These results show that financial development not only reshapes the distribution of resources but also changes how volatility is borne across sectors.

The main finding is that entrepreneurial sectors become less volatile as collateral constraints are relaxed. Employer output volatility declines by nearly 5 percentage points (from 20 percent to under 15 percent), while self-employed output volatility falls by about 2 percentage points (from 5 percent to around 3 percent).

This stabilization arises because improved credit access, together with the accumulation of wealth among employers, enables them to smooth production more effectively in response to shocks. As entrepreneurs operate larger firms and are wealthier in the aggregate, they are better able to smooth shocks. Their greater scale also dampens the sensitivity of capital and labor decisions to aggregate fluctuations, making production more stable overall. Employer TFP volatility likewise declines, potentially reflecting reduced entry–exit dynamics as the sector matures and stabilizes, even though some misallocation persists due to the continued presence of constrained entrants.

For the self-employed, factor volatilities decline, but their TFP volatility increases. This stems from greater fluctuations in their population share, as relaxed credit constraints make entry and exit more frequent. Even so, their overall output volatility falls modestly, by less than 2 percentage points. In contrast, the corporate sector becomes the residual adjuster: as entrepreneurial sectors smooth their responses, corporates absorb a larger share of aggregate shocks, reflecting the reallocation of resources from corporates to employers. Consequently, the volatility of corporate capital, labor, and output all rise.

In sum, financial development reduces volatility within entrepreneurial sectors by providing better credit access and enabling smoother adjustment. Yet this stabilization does not reduce aggregate risk exposure. Employers remain the most volatile sector, and as resources shift toward them, the composition effect dominates the stabilization effect. This explains why, despite lower within-sector volatilities, aggregate volatility can rise as financial development deepens.

So far, I have highlighted that although within-sector volatilities decline with financial development, employers remain the most volatile sector. Because their steady-state share rises, aggregate volatility increases. I now quantify this 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

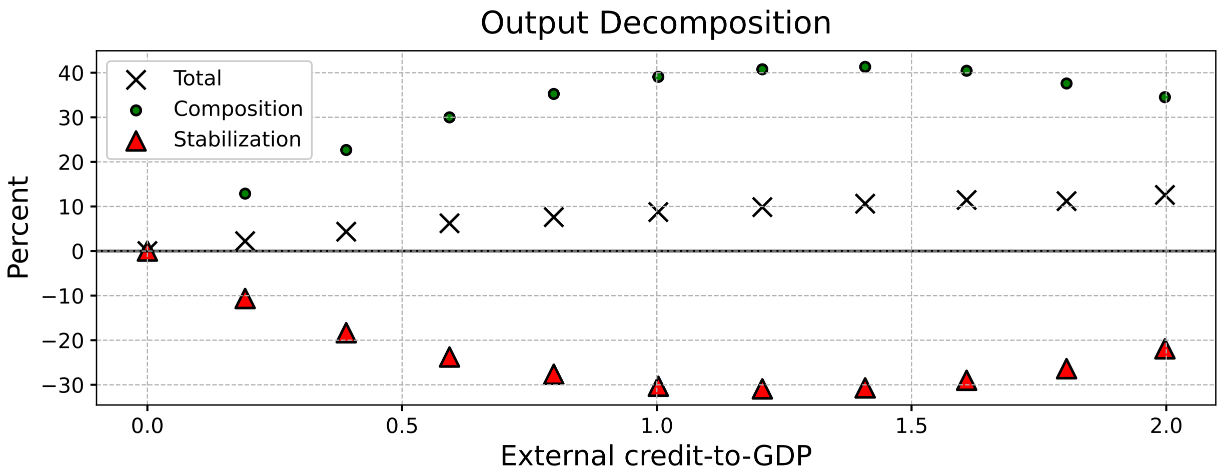


Figure 7: Impact of Financial Development: Output Volatility

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).

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:

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

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.[12] Figure 7 plots the results. The black crosses denote the total change in output variance, while green dots capture the composition effect and red triangles the stabilization effect. The decomposition makes clear that financial development produces two opposing forces: composition effects push volatility up, while stabilization effects pull it down. Counterfactual exercises highlight the im-

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

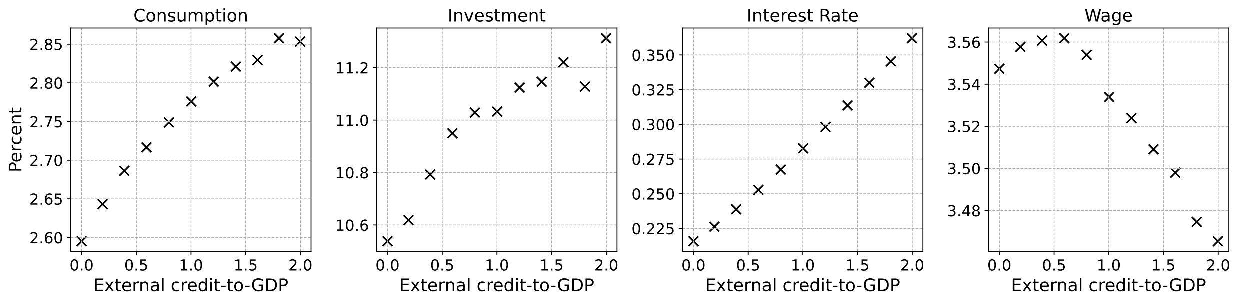


Figure 8: Impact of Financial Development: Quantities and Prices Volatility

Note: The figure plots the standard deviations of aggregate consumption, investment, the interest rate, and wages for different levels of financial development.

portance of endogenous occupational choices. Without changes in population shares, the model would predict that total variance falls by roughly 30 percent. By contrast, with only compositional changes, aggregate variance would rise by nearly 40 percent. Ultimately, when both channels operate, the composition effect dominates, and aggregate output volatility rises by more than 10 percent as credit-to-GDP reaches 2.

The figure also reveals nonlinear dynamics. At low levels of financial development, both the composition and stabilization effects rise sharply, reflecting large adjustments in steady-state shares and within-sector variances. As development deepens further, the stabilization effect flattens while the composition effect accelerates, producing diminishing stabilization benefits alongside compounding exposure to employer volatility. This pattern implies that the initial impact of financial development on volatility is large, but its marginal effect declines as credit-to-GDP continues to grow.

This decomposition underscores a broader trade-off. On 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, which are key variables that directly affect household welfare and macroeconomic stability.

Figure 8 plots the change in the standard deviations of aggregate consumption, investment, interest rates, and wages as the economy's external credit-to-GDP ratio increases.

The results show that, much like output, volatility rises in most aggregates as financial development deepens.

Consumption volatility increases modestly, rising from 2.6 percent in the self-financed economy to roughly 2.85 percent at high levels of financial development. Investment volatility follows a similar pattern but with a larger magnitude, climbing from just under 10.5 percent to over 11 percent. Interest rate volatility also exhibits a sharp increase, rising from 0.23 percent to more than 0.35 percent, reflecting greater sensitivity of capital markets to shocks as credit expands. In contrast, wage volatility remains relatively stable 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 lower within-sector volatilities. 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 contri-

Figure 9: 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.

butions.

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

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. Figure 9 plots the resulting contributions. The decomposition highlights a clear reallocation of business-cycle risk as financial development progresses. In particular, the contribution of employer entrepreneurs to output volatility rises steadily, from around 0.3 at low levels of credit-to-GDP to over 0.8 as financial markets deepen.

Consumption volatility, by contrast, remains largely stable in terms of ranking. Workers continue to be the dominant source of aggregate consumption volatility across all levels of financial development due to their large population share and the relatively smooth nature of consumption compared to income. Even as entrepreneurship expands, its impact on consumption volatility remains limited, with most of the aggregate variation driven instead by rising interest-rate volatility.

Investment volatility reveals a more complex dynamic. At low levels of financial development, 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 dramatically 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, self-employed entrepreneurs are disproportionately concentrated in the lower end of the income distribution; and second, the share of self-employed entrepreneurs moves countercyclically with GDP.

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 both the distributional and cyclical features of entrepreneurship observed in the data and captures endogenous sorting across occupations by wealth and ability. Quantitative experiments reveal that financial development tends to make business cycles more volatile. Looser credit constraints raise long-run output and efficiency but simultaneously increase volatility by reallocating activity toward employer entrepreneurs, who operate larger firms and respond more strongly to aggregate shocks.

These findings underscore a trade-off between long-run growth and short-run stability. Policies that expand access to credit may deliver higher steady-state output, 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. Future work could relax the pure credit expansion assumption by allowing financial development to alter the volatility of financial shocks, as is likely when credit deepening is accompanied by macroprudential reforms.

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A Computational Appendix

The baseline model contains multiple idiosyncratic productivity shocks, an aggregate shock, and discrete choice at the household level. The general steps to solve the model is as follows:

1. Solve for the stationary equilibrium.

   (a) Guess the level of interest rate, r_{ss}.

   (b) Find factor prices (U, W) from corporate first-order conditions.

   (c) Given prices, solve the household problem, which is solved using a value function iteration with a linear spline to evaluate the value function off the grid points. The asset grid is set from 0.001 to 300. The number of asset grid points is 100. Increasing the number of grid points did not substantially change the results. In order to capture the high degree of nonlinearity at the lower end of the grid, I include more grid points towards the bottom of grid. There are 7 grid points in the managerial productivity shock, another 7 grid points for worker productivity, and 4 occupations. In total, there are 19,600 individual state space.

   (d) Given the solution to the household problem, simulate the distribution as in Young (2010).

   (e) Check that equation (19) holds.

2. Linearize the model with only respect to aggregate shocks

   (a) Jacobian is calculated by taking automatic differentiations

   (b) Use the dimension reduction techniques from Bayer and Luetticke (2020) to make the model computationally feasible. Using this technique reduces the number of state variables from 19,602 (19,600 individual states plus an aggregate shock, and aggregate capital) to 238 (100 asset grids plus 7 managerial productivity (persistent component) plus 7 working productivity (persistent component) plus 85 states for copulas plus aggregate capital and productivity). The number of control variables decline from 19,612 to 46.

3. Solve the linearized model using Klein's method.

A.0.1 Details on Solving the Model

There are two infinite dimensional objects in the model that need to be approximated, which are the value functions and the distribution of households over the idiosyncratic states. Value functions are approximated by a linear spline. I first calculate the prices in the steady state and turn off all aggregate shocks. In this step, the conditional expectations for the value functions are only taken with respect to idiosyncratic shocks. Given that the value function can be approximated with a linear spline, one can maximize each value functions on the RHS using Brent's method. And then the household's equilibrium dynamics with aggregate shocks can be characterized by the above set of equations, where $s = (a, z_w, z_m, o)$ are idiosyncratic state variables while $S = (Z, \phi, \Lambda)$ will be aggregate state variables.

The high dimensionality of this system makes the computation nearly infeasible. Therefore, I pursue a dimension reduction technique as Bayer and Luetticke (2020) for the distribution of households. To reduce the dimension of the value function, compression algorithm is used. To be more specific, I write the value function as some form of sparse polynomial expansions around its stationary equilibrium values.

$$v_t(s) = \bar{v}(s) + g_v(s; \theta_v^s), \tag{A1}$$

where g_v is the discrete cosine transformation of the stationary equilibrium of the value function. I shrink all but the largest elements without losing too much information. That is, I only keep the nodes of the value function where it is most informative in response to aggregate shocks. For more technical details, I refer the readers to Bayer and Luetticke (2020).

The second infinite dimensional object in the model to be approximated is the distribution of the idiosyncratic state. This is done with a histogram method as in Young

(2010). Let $a'(s,S)$ be the savings function for the household's that maximizes their value functions. Then the distribution over households can be summarized by a transition matrix Q, where each element $Q_{i,i'}$ is the probability that a type i will be type i'. This can be obtained by

$$Q_{i,i'} = \mathbb{P}[(a^{i'} = a_j, \epsilon^{i'} = \epsilon_s, \theta^{i'} = \theta_k)|(a^i, \epsilon^i, \theta^i)] \tag{A2}$$

$$= w_{ij}\mathbb{P}(\epsilon_s, \theta_k|\epsilon^i\theta^i) \tag{A3}$$

In the case of the stationary equilibrium, the steady state distribution over households is a histogram $\Lambda(s)$ that satisfies the following condition:

$$\Lambda = Q\Lambda \tag{A4}$$

With aggregate shocks, the equilibrium dynamic must satisfy the following:

$$\Lambda' = Q\Lambda \tag{A5}$$

where Q is generated by the savings function $a'(s,S)$.

Furthermore, there needs to be equations that describe the aggregate capital stock, and aggregate shocks. They are

$$\int a_i d\Lambda = K, \tag{A6}$$

$$\int z_{wi} d\Lambda = L^c + L^{em} \tag{A7}$$

$$\log Z' = (1-\rho_z)\log \bar{Z} + \rho_z \log Z + \varepsilon'_z, \tag{A8}$$

$$\log \phi' = (1-\rho_\phi)\log \bar{\phi} + \rho_\phi \log \phi + \varepsilon'_\phi, \tag{A9}$$

$$Y^c = Z(K^c)^\alpha (L^c)^\alpha, \tag{A10}$$

$$Y = Y^c + \int y(s) d\Lambda_{em,se}(s), \tag{A11}$$

$$W = Z(1-\alpha)(K^c/L^c)^\alpha, \tag{A12}$$

$$U = Z\alpha(K^c/L^c)^{(1-\alpha)}, \tag{A13}$$

$$I = K' - (1-\delta)K, \tag{A14}$$

$$C = \int c(s) d\Lambda, \tag{A15}$$

$$K = K^c + \int k(s) d\Lambda_{se,em}, \tag{A16}$$

$$\int z_w(s) d\Lambda_w = L^c + \int n_d(s) d\Lambda_{em}, \tag{A17}$$

This completes the minimum number of equations in order to fully characterize the equilibrium dynamics in my model.

Given the distribution and the value functions, all other auxiliary aggregate variables can be calculated from the value functions (and its resulting savings/consumption functions) and the resulting distribution.

The equilibrium dynamic can be represented by a set of nonlinear equations (shown above) which then can be written as:

$$\mathbb{E}_t F(X, X', Y, Y') = 0, \tag{A18}$$

where Y is the set of control variables (such as value functions or aggregate output), and X is the set of state variables (such as the distribution Λ). Thus, linearizing the model with respect to aggregate shocks gives the following linear dynamic system.

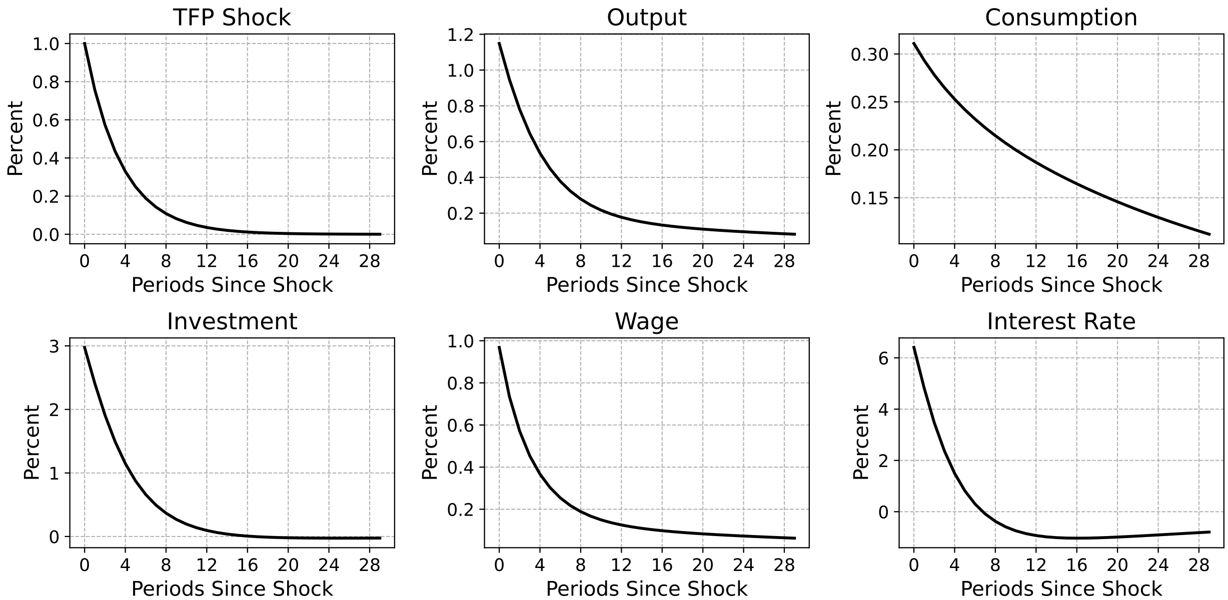
$$X' = H_x X + \eta \epsilon', \tag{A19}$$

$$Y = G_x X, \tag{A20}$$

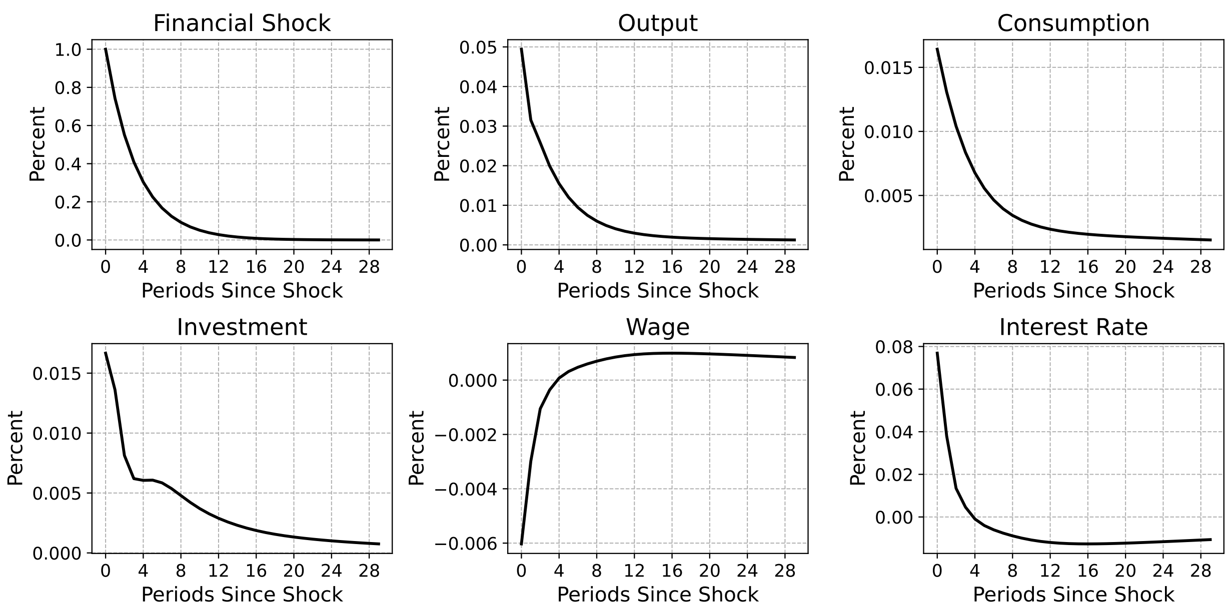
which then can simulate the model, calculate second moments, and perform impulse response analysis.

B Additional Impulse Response

In response to TFP shocks, output, consumption, investment, wages, and interest rates all respond similarly to the representative-agent economy. Output increases by slightly more than 1% due to general equilibrium amplifications. Consumption responds much less than output, while investment responds three times as much as output. Both wages



(a) TFP Shock



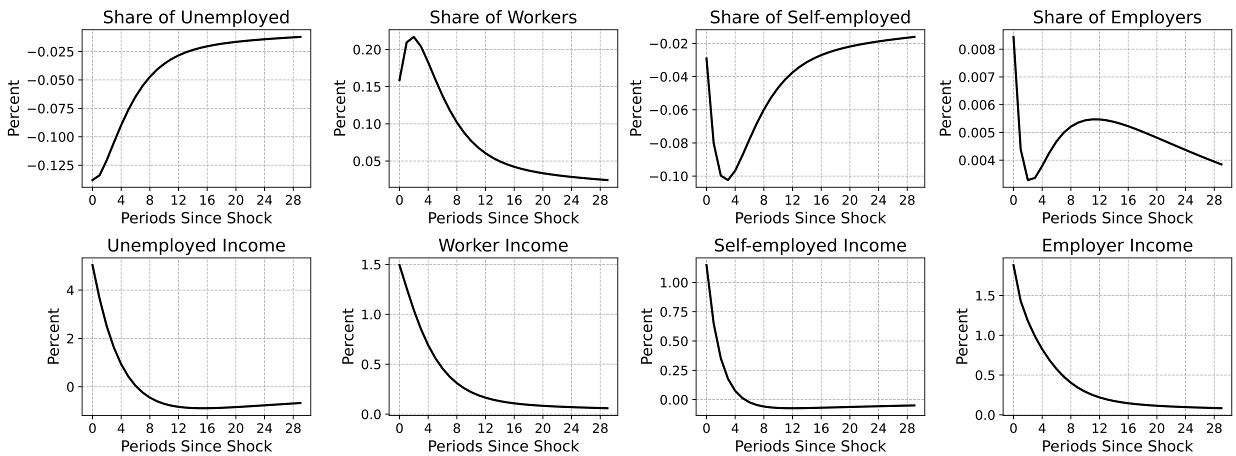
(b) Financial Shock

Figure 10: Impulse Response Analysis - Aggregate Variables

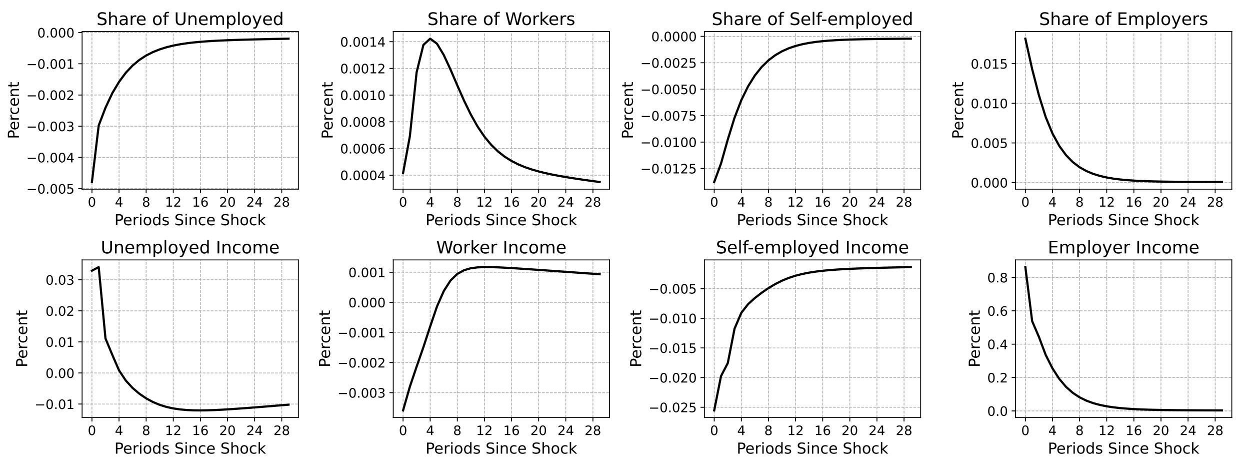
Note: These figures show the impulse response of aggregate variables and prices to a one percent positive shock. All variables except interest rate are in percent deviations from the steady state.

and interest rates rise following productivity shocks.

For financial shocks, output, consumption, and investment all increase on impact, though the aggregate effects are minimal because these shocks directly affect only a small share of the population. Since financial shocks typically impact entrepreneurial capital demand, they reallocate resources from the corporate sector to entrepreneurs. This reallocation ultimately leads to a rise in interest rates and a slight decline in wages.



(a) TFP Shock



(b) Financial Shock

Figure 11: Impulse Response Analysis - Population Dynamics

Note: These figures show the impulse response of population shares and group-level incomes to a one percent positive shock. All variables are in percent deviations from the steady state except for population shares, which are in percentage point deviations.

Figure 11 plots population shares and aggregate incomes for each occupation in response to two aggregate shocks, shown in separate panels. When exogenous TFP rises, this increases the share of both workers and employers. The rise in the share of workers occur due to higher wage rates and the rise in the share of employers occur from increased profits relative to other occupations. Conversely, due to labor market dynamics, the shares of unemployed and self-employed individuals decline. The share of employers also falls slightly after the initial shock impact, as employer-entrepreneurs with higher labor productivity shift to employment. However, these shares quickly recover as marginal entrepreneurs enter the market, then decline again as many entrepreneurs cannot continue paying fixed costs when the productivity shock's impact returns to zero.

Regarding occupational-level income, unemployed individuals experience the largest income increase, though this primarily reflects their initially low baseline income near zero. The income response is largest for the unemployed, followed by employers, then workers, and finally the self-employed.

For financial shocks, there is an increase in the shares of both employers and workers, similar to the productivity shock case. Essentially, a positive financial shock improves aggregate output, although the effect is much smaller than in the TFP shock case. Nevertheless, due to rising aggregate output, job-finding probabilities and job-offer rates increase for unemployed and self-employed individuals, leading many of them toward employment. Due to the decline in wage rates, worker income falls slightly, while employer and unemployed incomes rise modestly.

C Sensitivity Analysis: Second Moments

Table 10 presents a sensitivity analysis of the model's second moment properties. The "Baseline" column reports the moments from the main calibration in the paper. The subsequent columns show results from changing a single parameter or shock structure relative to the baseline. "Low κ" and "High κ" refer to a 50% decrease and 100% increase in the fixed cost of employer entrepreneurship, respectively. "Low ψ" and "High ψ" refer to a 50% decrease and 100% increase in the labor market cyclicality parameter, respectively. The final two columns report results when only one of the two aggregate shocks is active.

First, altering the fixed cost parameter κ significantly affects the distribution of entrepreneurs. The low-κ economy leads to a lower share of self-employed entrepreneurs

Table 10: Sensitivity Analysis: Alternative Calibrations

	Baseline	**Low** κ	**High** κ	**Low** ψ	**High** ψ
Panel A: Steady-State Population Shares (%)					
Unemployed	0.09	0.09	0.09	0.09	0.09
Workers	0.70	0.70	0.70	0.70	0.70
Self-employed	0.17	0.15	0.18	0.17	0.17
Employers	0.04	0.06	0.02	0.04	0.04
Panel B: Business Cycle Volatility (Relative Std. Dev. to Output)					
Consumption	0.52	0.52	0.53	0.48	0.64
Investment	2.13	2.17	2.09	2.21	1.91
Worker Share	0.11	0.24	0.25	0.10	0.54
Self-emp. Share	0.11	0.16	0.15	0.09	0.33
Employer Share	0.07	0.06	0.04	0.07	0.05
Self-emp. Income	0.57	0.57	0.66	0.77	0.8
Employer Income	3.50	3.10	4.13	3.73	3.06
Panel C: Correlation with GDP					
Consumption	0.85	0.85	0.84	0.82	0.91
Investment	0.96	0.94	0.94	0.95	0.93
Worker Share	0.94	0.94	0.93	0.92	0.95
Self-emp. Share	-0.89	-0.89	-0.88	-0.82	-0.92
Employer Share	0.70	0.68	0.68	0.72	0.6
Self-emp. Income	0.57	0.48	0.76	0.88	-0.53
Employer Income	0.84	0.85	0.83	0.83	0.86

Notes: This table reports key moments from the model under seven different calibrations. The "Baseline" column reports the moments from the main calibration in the paper. The subsequent columns show results from changing a single parameter or shock structure relative to the baseline. "Low κ" and "High κ" refer to a 50% decrease and 100% increase in the fixed cost of employer entrepreneurship, respectively. "Low ψ" and "High ψ" refer to a 50% decrease and 100% increase in the labor market cyclicality parameter, respectively. The final two columns report results when only one of the two aggregate shocks is active.

and a higher share of employer entrepreneurs due to the reduced barrier to entry. Conversely, the high-κ economy produces a lower share of employer entrepreneurs and a higher share of self-employed entrepreneurs. The unemployed and worker population shares remain relatively stable across these variations. For the final four columns, the steady-state values remain unchanged because these scenarios only modify the aggregate shock structure rather than structural parameters.

Turning to business cycle volatilities, the results across different economies are largely comparable, with some notable exceptions in the third panel. When the labor market responds more strongly to GDP changes (high ψ) or when only financial shocks are present, the self-employed population share reacts much more strongly to GDP fluctuations. This creates larger swings in the share of subsistence entrepreneurs, ultimately leading to countercyclical patterns in group-level incomes for this category of workers.