Collateral Scarcity and Bad Credit Booms*

Joseba Martinez — LBS & CEPR
Fatih Ozturk — OECD
Pau Rabanal — IMF
Filiz Unsal — OECD

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Abstract

We study, both theoretically and empirically, the role of collateral scarcity as a driver of bad credit booms. In our model, entrepreneurs with private information about the quality of their project borrow in a frictional credit market from banks that use collateral as a screening device. During episodes of high productivity or low interest rates, the demand for loans increases, increasing the aggregate collateral demand. When collateral supply does not rise sufficiently in response, banks relax credit standards by offering low collateral contracts that attract low-quality borrowers, resulting in a bad boom. We show that such booms are constrained inefficient, creating scope for welfare-improving policy that mitigates the fall in collateralization and dampens the rise in credit. Using firm-level data, we find empirical support for the main predictions of the model: i) collateral requirements fall disproportionately for low-productivity, low-information borrowers during bad booms, and ii) the value of collateral assets relative to economic activity falls in bad booms, especially for high-quality borrowers.

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1 Introduction

Credit is vital for economic development and growth. However, history teaches that rapid credit expansions present a vexing challenge: some, but not all, credit booms culminate in costly financial distress and crises. The average cumulative output loss in a banking crisis is around 20% over an average crisis duration of two years, according to the database of Laeven and Valencia (2020), and we only obtain certainty about whether a boom is "good" or "bad" (Gorton and Ordoñez (2019)) once those costs have materialized. Distinguishing beneficial credit expansions from potentially destabilizing ones and designing policy interventions that can effectively prevent or mitigate harmful credit booms is a central focus for policymakers seeking to balance growth with financial stability.

In this paper, we provide theoretical and empirical support for a new diagnosis of the causes of bad credit booms: we argue that booms turn bad when collateral becomes scarce relative to productive firms' desired investment levels, because collateral scarcity reduces banks' ability to screen out bad borrowers using collateral. Our contribution complements existing theories, which emphasize collateral values as amplifiers of business cycles (Bernanke et al. (1999), Kiyotaki and Moore (1997)), or the nexus between collateral and information production (Gorton and Ordoñez (2014), Asriyan et al. (2021)) as the cause of harmful expansions.

Our theory has two essential features: asymmetric information about borrower quality and a frictional credit market where banks use collateral in contracts to screen borrowers. The model describes a small open economy populated by bankers and entrepreneurs that can be good or bad, with positive or negative net present value projects. Bankers face an adverse selection problem because they lend to entrepreneurs without knowing their types. Consequently, they optimally design a contract that screens bad projects by asking for collateral. The ability to separate good from bad projects depends on the value of the collateral that each entrepreneur has. In particular, bankers can easily separate good and bad entrepreneurs if the collateral value relative to the desired credit amount for good entrepreneurs is high. However, if the relative value of collateral is low, separation through collateral becomes less desirable for bankers. As a result, they might choose to relax credit standards and start lending to bad entrepreneurs.

The model delivers parameter restrictions under which credit booms with relaxed credit standards emerge in equilibrium, specifically when the price of collateral responds relatively weakly to aggregate shocks, or new credit lines respond strongly.

Empirically, credit booms are episodes of sharp increases in lending to the private sector and economic activity, often followed by large contractions[1]. Moreover, there is evidence that credit growth during these booms is a strong *predictor* of recessions and lower future returns.[2] Moreover, there is evidence indicating that credit standards are relaxed during these booms, assigning cheaper credit to riskier projects and worsening the allocation of credit.[3] We show that credit booms simulated using our theoretical model are consistent with these well-documented stylized facts.

We analyze the policy implications using a parameterized version of the model. In particular, we compare the private sector equilibrium with a constrained planner and find that if credit standards fluctuate, the constrained planner and equilibrium allocations are different during credit booms: the planner chooses to dampen the increase in credit and the decrease in credit spreads. In our parameterization, the consumption-equivalent welfare gain of moving from the competitive equilibrium to the constrained optimum is approximately one-third of the gain from eliminating asymmetric information.

The inefficiency in our model stems from bankers' optimal decision to issue new credit lines because they do not internalize the impact on the value of collateral per credit line. This inefficiency can be decomposed into direct and price effects. First, bankers do not take into account that by creating a credit line, the value of collateral per credit line decreases for a given value of collateral. Second, they do not take into account the effect of their decision on the equilibrium collateral price. We show that a nonlinear tax on credit lines that depends on credit market tightness can generate almost 90% of the welfare increase of going from the decentralized to the planner's solution.

Our empirical analysis provides evidence on how credit booms turn bad, with disproportionate reductions in collateralization requirements for loans to low-productivity borrowers. We examine

[1]See Gourinchas et al. (2001), Mendoza and Terrones (2008), Mendoza and Terrones (2012), Gorton and Ordoñez (2019), Laeven and Valencia (2020)

[2]See Schularick and Taylor (2012) and López-Salido et al. (2017).

[3]See Asea and Blomberg (1998), Jimenez et al. (2006), Dell'Ariccia et al. (2012), Greenwood and Hanson (2013).

this mechanism in two empirical settings using firm-level difference-in-differences analysis around the credit expansion preceding the Global Financial Crisis (GFC). The first setting studies Spanish firms, and the second a cross-country sample of firms in Central and Eastern Europe and Central Asia. In common with many other countries worldwide, these countries experienced large credit booms in the run-up to the GFC, driven by global factors that manifested as low domestic interest rates and high capital inflows (Miranda-Agrippino and Rey (2022)).

First, we analyze Spanish firm-level ORBIS data using a diff-in-diff approach and show that in the years preceding the GFC, collateral standards, defined as total credit relative to tangible firm assets, fell disproportionately for the least productive firms within sectors. Credit markets in Spain, a prototypical bad boom country, exhibited the mechanism of a bad boom predicted by our model in the run-up to the GFC.

We find a consistent result employing the same empirical methodology in a different setting, using firm-level survey data from the World Bank/EBRD Business Environment and Enterprise Performance Survey (BEEPS) in 28 Central and Eastern European and Central Asian countries. Consistent with the Spanish evidence, we find that during the credit boom prior to the GFC, low-productivity firms were significantly more likely to receive collateral-free loans, especially among low-information firms where collateral is particularly crucial for screening borrower quality. Importantly, this effect is significant only in countries that experienced a bad credit boom, identified ex-post by indicators such as high non-performing loans, high fiscal cost of bailouts, and IMF interventions.

Lastly, we examine the collateral scarcity channel using BEEPS data. We find that aggregate collateral values (collateral assets relative to aggregate sales) fall during bad credit booms, especially for high-productivity firms. We do not find the same effect in good boom economies, supporting our hypothesis that collateral scarcity for high-quality borrowers underpins the relaxation of lending standards characteristic of bad booms.

Related Literature. This paper contributes to the empirical and theoretical literature that studies credit booms, and in particular, focuses on why some expansions are "bad". Contributions include Gourinchas et al. (2001), Mendoza and Terrones (2008), Mendoza and Terrones (2012), Greenwood and Hanson (2013), Gorton and Ordoñez (2019), López-Salido et al. (2017), Neuhann (2019), Coimbra and Rey (2023), Fouliard et al. (2023), Müller and Verner (2023) and Krishnamurthy and Muir (2025). Our paper is also related to papers including Jimenez et al. (2006), Berger et al. (2011), and Ioannidou et al. (2022) that specifically study the role of collateral in alleviating asymmetric information in credit markets, and how that role changes in response to aggregate fluctuations and shocks.

Moreover, this paper belongs to the literature that proposes models with information frictions where credit contracts are endogenous and credit standards fluctuate over time. These articles include Dell'Ariccia and Marquez (2006), Martin (2008), Gorton and Ordoñez (2014), Hu (2022), Figueroa and Leukhina (2018), Gorton and Ordoñez (2019), Asriyan et al. (2021), Ozdenoren et al. (2023), Farboodi and Kondor (2023), and Fishman et al. (2024). Our work is particularly related to Asriyan et al. (2021), which studies the role that collateral shocks play in causing inefficient credit expansions. In their setting, collateralization is a substitute for information production, and collateral booms cause information depletion, and consequently, the financing of bad projects. We do not study information production and instead focus on asymmetric information and how banks' ability to use collateral as a screening device changes as a function of the economy's aggregate state. The scope of our empirical analysis is also different since they study the effect of collateral shocks on information production in the context of listed US firms. We study collateralization standards and collateral scarcity using data on overall business assets and listed and unlisted firms of all sizes.

More broadly, our model is related to articles in which the value of collateral plays a crucial role in amplifying economic fluctuations, including Kiyotaki and Moore (1997), Bernanke et al. (1999), Lorenzoni (2008), and Mendoza (2010). In these models, the price of collateral amplifies macroeconomic shocks for a particular level of credit standards, which are summarized by the collateral constraint parameter related to moral hazard friction in credit markets. In our model, credit contracts are a function of the aggregate state of the economy, and the total value of collateral plays a role when banks decide to relax or tighten standards.

The remainder of the paper is divided as follows. Section 2 describes the model. Section 3 contains our main theoretical results and simulations of credit booms. Section 4 discusses the optimal policy derived from the constrained planner problem. Section 5 presents empirical evidence for our findings, and Section 6 concludes.

2 Model

The model describes a small open economy populated by entrepreneurs and bankers that interact in a frictional credit market. We describe these agents in the following.

2.1 Entrepreneurs

There is a representative family composed of a unit mass of entrepreneurs that use capital to produce a homogeneous perishable final good, the numeraire. Each entrepreneur i can produce the quantity y_{it} in time t using the following technology:

$$f(A_{it}, k_{it}, p_{it}) = \begin{cases} A_{it}k_{it}^{\alpha} & \text{with prob. } p_{it} \\ 0 & \text{with prob. } 1 - p_{it} \end{cases}$$

Entrepreneurs have access to a decreasing returns to scale technology in capital k_{it}, with capital-output elasticity $0 < \alpha < 1$. The technology produces a positive amount only when the project is successful, which happens with probability p_{it} in any time t. The technology is subject to productivity shocks A_{it} that follow an exogenously given stochastic process.

Entrepreneurs can be good or bad every year t. A good entrepreneur has a productivity level A_{gt} and a constant success productivity p_g, whereas a bad one has productivity and a success probability A_{bt} and p_b. We assume that good entrepreneurs have higher expected productivity, that is, $p_g A_{gt} > p_b A_{bt}$ for all t. Bad entrepreneurs have riskier projects with lower success probability ($p_b < p_g$) but higher return conditional on success ($A_{gt} < A_{bt}$). For simplicity, we assume that $A_{gt} = A_t$ and $A_{bt} = \mu A_t$ where $1 < \mu < p_g/p_b$, and A_t is a random variable that follows the process,

$$\log(A_t) = \rho \log(A_{t-1}) + \sigma_a \varepsilon_{at} \qquad \rho \in (0, 1)$$

We assume that an entrepreneur's type is i.i.d. across time, with any entrepreneur having a probability χ of being good at any time t. By the law of large numbers, χ is also the proportion of good entrepreneurs.

Entrepreneurs need capital to produce goods and, therefore, an active credit line to produce every year. The credit market is subject to search frictions. Every entrepreneur without a credit line searches for a banker and finds one with probability $\lambda^e(\theta_t)$, where $\lambda' > 0$ and

$$\theta_t \equiv \frac{F_t}{1 - N_t}$$

denotes credit market tightness, defined as the ratio of the measure of bankers looking for entrepreneurs (F_t) and the number of entrepreneurs looking for credit ($1 - N_t$).

Once an entrepreneur and a banker meet, they must agree on a credit contract for the credit line to become active. An entrepreneur's type is private information. Bankers offer credit contracts to maximize profits, which, where possible, implies distinguishing between the two types. The contract, described in detail below, is a one-period agreement specifying the loan amount, interest rate, and collateral requirement. We assume that there is a non-perishable good that we call land, l_t, that trades at a price q_t and is used as a saving vehicle and collateral asset.

We assume perfect consumption insurance among entrepreneurs in the same family. A representative family makes the consumption-saving decision, and every entrepreneur consumes the same amount. The family saves in land l_t, distributed within a period to entrepreneurs who need it to collateralize loans. Entrepreneurs matched with a banker receive a menu of one-period loan contracts and choose one. If the chosen contract requires pledging collateral, the entrepreneur asks the household for the required land. The household distributes the total collateral value $q_t l_t$ among the entrepreneurs who request it. The family's utility maximization problem is given by:

$$\begin{aligned} &\max_{\{c_t, l_{t+1}\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \phi l_t \right\} \\ &\text{s.t.} \\ &c_t + q_t l_{t+1} = \left[\chi \pi_{gt} + (1-\chi)\pi_{bt}\right] N_t + q_t l_t + T_t \end{aligned} \tag{1}$$

$$N_{t+1} = \left[\chi p_g + (1-\chi)p_b\right] N_t + \lambda^e(\theta_t)(1-N_t)$$

The family chooses consumption and land savings to maximize a time-separable utility function in consumption and land subject to two constraints. The first is the budget constraint that equalizes consumption (c_t) and savings in land ($q_t l_{t+1}$) with the resources the family has: profits from production ($[\chi\pi_{gt} + (1-\chi)\pi_{bt}] N_t$), land holdings from the previous period ($q_t l_t$) and lump-sum transfers (T_t). The second constraint is the law of motion of active credit lines (N_t). Credit lines at $t+1$ are a function of the new credit lines created at time t ($\lambda^e(\theta_t)(1-N_t)$), and the number of existing credit lines that survive from the previous period, $[\chi p_g + (1-\chi)p_b] N_t$)). The latter expression implies that a credit relationship ends when a project fails.

2.2 Bankers

A continuum of bankers can be in a credit relationship (active) or not (idle). The value function of an idle banker is given by,

$$V_t = \max\left\{-\kappa + \lambda^f(\theta_t)\mathbb{E}_t\left\{\Lambda_{t,t+1}\left[\chi J^g_{t+1} + (1-\chi)J^b_{t+1}\right]\right\}, 0\right\} \tag{2}$$

An idle banker can remain so and get zero value, represented by the second term in the max, or they can decide to search for an entrepreneur. In that case, the banker pays a search cost κ, and with probability $\lambda^f(\theta_t)$ finds an entrepreneur and starts a credit relationship. The value of starting a credit line with a good (bad) entrepreneur is given by J^g_{t+1} (J^b_{t+1}). Future profits are discounted by the stochastic discount factor for the representative family, $\Lambda_{t,t+1}$.

The value of an active banker is J^g_t or J^b_t depending on the quality of the time-t match. The value function is

$$J^i_t = \Pi_{it} + \mathbb{E}_t\left\{\Lambda_{t,t+1}\left[p_i\left(\chi J^g_{t+1} + (1-\chi)J^b_{t+1}\right) + (1-p_i)V_{t+1}\right]\right\}, \tag{3}$$

for $i \in \{g, b\}$, where Π_{it} denotes the banker's expected profit.The continuation value depends on whether the project succeeds (with probability p_i) or fails ($1-p_i$). If the project fails, the banker starts the next period idle, but continues with the credit line if it succeeds. We assume free entry into banking and, therefore, the value of being idle satisfies $V_t = 0$.

2.3 Credit Contract

In each period, entrepreneurs and bankers in a credit relationship sign a one-period credit contract that specifies the loan size (k_t), interest rate (r_t^k), and collateral (b_t). The contract gives bankers the expected profit

$$\Pi_{it} = p_i r_{it}^k k_{it} + (1 - p_i) b_{it} - r_t^* k_{it} - \psi(A_t, r_t^*) \mathbb{1}_{\{k_{it}>0\}} \quad \text{for} \quad i \in \{g, b\}, \tag{4}$$

where $p_i r_{it}^k k_{it}$ represents the expected interest income and $(1 - p_i) b_{it}$ the expected recovery of collateral if the project fails. The third term $r_t^* k_{it}$ denotes the interest cost. We assume that bankers get funds from international lenders at an interest rate r_t^* that follows an exogenous stochastic process given by

$$\log(r_t^*) = (1 - \rho_r) \log(\bar{r}^*) + \rho_r \log(r_{t-1}^*) + \sigma_r \varepsilon_{rt}. \quad \rho_r \in (0, 1)$$

Lastly, the fourth term $\psi(A_t, r_t^*) \mathbb{1}_{\{k_{it}>0\}}$ is a fixed intermediation cost that bankers pay only if they provide capital to entrepreneurs. The fixed cost can be scaled by the aggregate shocks in the economy, A_t and r_t^*. Note that we are allowing bankers to offer contracts conditional on the type $i \in \{g, b\}$. As we will discuss in our analysis, when collateral levels are high enough, bankers optimally offer two contracts in equilibrium, one for good entrepreneurs $(r_{gt}^k, b_{gt}, k_{gt})$ and another for bad ones $(r_{bt}^k, b_{bt}, k_{bt})$.

The expected profits entrepreneurs get from the credit contract are given by,

$$\pi_{it} = p_i \left(A_{it} k_{it}^{\alpha} - r_{it}^k k_{it} \right) - (1 - p_i) b_{it} \quad \text{for} \quad i \in \{g, b\}$$

The entrepreneur's project succeeds with probability p_i, in which case the payoff is the value of production minus interest payments. The project fails and the entrepreneur loses the collateral pledged in the contract with complementary probability $1 - p_i$.

We assume that bankers make entrepreneurs a take-it-or-leave-it offer without knowing the type of borrower they are dealing with. Assuming that the entrepreneur has a collateral value equal to $\tilde{b}$, the banker offers a contract that solves the following problem (we omit time subscripts to save notation):

$$\max_{k_g, r_g^k, b_g, k_b, r_b^k, b_b} \quad \chi \mathbb{1}_{\{k_g>0\}} \left(p_g r_g^k k_g + (1-p_g) b_g - r^* k_g - \psi(A_t, r_t^*) \right) + (1-\chi) \mathbb{1}_{\{k_b>0\}} \left(p_b r_b^k k_b + (1-p_b) b_b - r^* k_b - \psi(A_t, r_t^*) \right)$$

s.t.

$$\left[p_b \left(A_b k_b^\alpha - r_b^k k_b \right) - (1-p_b) b_b \right] \mathbb{1}_{\{k_b>0\}} \geq \left[p_b \left(A_b k_g^\alpha - r_g^k k_g \right) - (1-p_b) b_g \right] \mathbb{1}_{\{k_g>0\}} \tag{5}$$

$$\left[p_g \left(A_g k_g^\alpha - r_g^k k_g \right) - (1-p_g) b_g \right] \mathbb{1}_{\{k_g>0\}} \geq \left[p_g \left(A_g k_b^\alpha - r_b^k k_b \right) - (1-p_g) b_b \right] \mathbb{1}_{\{k_b>0\}} \tag{6}$$

$$\left[p_g \left(A_g k_g^\alpha - r_g^k k_g \right) - (1-p_g) b_g - \gamma \pi_g^* \right] \mathbb{1}_{\{k_g>0\}} \geq 0 \tag{7}$$

$$\left[p_b \left(A_b k_b^\alpha - r_b^k k_b \right) - (1-p_b) b_b - \gamma \pi_b^* \right] \mathbb{1}_{\{k_b>0\}} \geq 0 \tag{8}$$

$$\mathbb{1}_{\{k_g>0\}} b_g \geq 0 \qquad \mathbb{1}_{\{k_g>0\}} (b_g - \tilde{b}) \leq 0 \tag{9}$$

$$\mathbb{1}_{\{k_b>0\}} b_b \geq 0 \qquad \mathbb{1}_{\{k_b>0\}} (b_b - \tilde{b}) \leq 0 \tag{10}$$

Bankers offer a menu of contracts subject to (i) incentive compatibility constraints (5) and (6), (ii) participation constraints (7) and (8), and (iii) constraints on the amount of collateral pledged, included in inequalities (9) and (10), which require that the collateral requirements are positive and feasible. The incentive compatibility constraints guarantee that good and bad entrepreneurs do not want to mimic each other. Participation constraints require that entrepreneurs be willing to accept the contract, since they imply that the benefit of accepting the deal exceeds the outside option. These outside options are given by $\gamma \pi_g^*$ and $\gamma \pi_b^*$ for good and bad entrepreneurs, where $\gamma \in (0,1)$ is a parameter and π_g^* and π_b^* are the profits entrepreneurs would achieve if they had all the bargaining power in a symmetric information case. In other words,

$$\pi_i^* = \max_{k_i} \left\{ p_i A_i (k_i)^\alpha - r^* k_i - \psi(A, r^*) \mathbb{1}_{\{k_i>0\}} \right\} \quad i \in \{g, b\}$$

The parameter γ allows us to modulate entrepreneurs' bargaining power. Given that we are not interested in studying the typical congestion inefficiency that arises in any search model, we will set γ to eliminate that inefficiency in the non-stochastic steady state of the model.[4]

Lastly, note that the banker might decide to offer a pooling contract for very low levels of collateral. However, given that we will focus our quantitative analysis for collateral values where this type of equilibrium does not exist, we skip the discussion of this type of contract in this section.

2.4 Equilibrium

Given an initial state N_0 and a sequence $\{A_t, r_t^*\}_{t=0}^{\infty}$, an equilibrium is a sequence of prices $\{q_t\}_{t=0}^{\infty}$, credit contracts $\left\{k_{gt}, r_{gt}^k, b_{gt}, k_{bt}, r_{bt}^k, b_{bt}\right\}_{t=0}^{\infty}$ and allocations $\{Y_t, C_t, N_{t+1}, \theta_t, l_t\}_{t=0}^{\infty}$, such that:

1. C_t, l_{t+1}, N_{t+1} solve households' problem every period
2. $k_{gt}, r_{gt}^k, b_{gt}, k_{bt}, r_{bt}^k, b_{bt}$ is a solution to the contract problem
3. θ_t is consistent with banker's problem and the free entry condition
4. Markets clear

$$
\begin{aligned}
Y_t = {} & C_t + r_t^* \left(\chi k_{gt} + (1-\chi) k_{bt}\right) N_t + \left(\chi \mathbb{1}_{\{k_{gt}>0\}} + (1-\chi)\mathbb{1}_{\{k_{bt}>0\}}\right) \psi N_t \\
& + \kappa \theta_t (1 - N_t) \\
l_t = {} & \bar{l}
\end{aligned}
$$

where $\bar{l}$ is a fixed supply of land.

3 Collateral Scarcity and Bad Credit Booms

In this Section, we study the link between collateral scarcity and inefficient credit expansions. To do so, we start by characterizing the credit contract banks offer as a function of the economy's

[4] One way to microfound this outside option would be to incorporate a second stage in the bargaining process where the entrepreneur can make a counter-offer with probability γ and before the counter-offer is made, nature moves and reveals entrepreneurs' types to bankers.

aggregate state. We then simulate a parameterized version of the model to study the properties of credit booms generated by the model.

In our analysis, we will assume that bad projects have a negative expected net present value at optimal scale (net of the fixed cost of intermediation). Hence, under symmetric information, it is optimal not to fund bad projects:

$$0 = \text{argmax}_k \left\{ p_b A_b (k)^\alpha - r^* k - \psi(A, r^*) \mathbb{1}_{\{k>0\}} \right\},$$

which implies that the first best expected profit for a bad entrepreneur (π_b^*) is just zero every period.

Although bad projects generate an expected loss to the banker, under certain conditions, bankers might optimally decide to fund them. The reason is that providing funds to these projects is a potentially profitable strategy to deal with the adverse selection problem bankers face. The next proposition describing the solution of the credit contract shows that lending to bad entrepreneurs can happen when the value of collateral that entrepreneurs have is lower than a certain threshold that depends on aggregate shocks.

Proposition 1. *If the incentive compatibility constraint of good entrepreneurs (6) is slack, the separating contract bankers offer satisfies the following (where we are omitting time subscripts),*

1. *If* $\tilde{b} \geq \bar{b}_1 \equiv \frac{p_g}{p_g - p_b} \left[p_b(\mu - 1) A \left(\frac{\alpha p_g A}{r^*} \right)^{\frac{\alpha}{1-\alpha}} + \frac{p_b}{p_g} \gamma \pi_g^* \right]$*, then bad entrepreneurs do not get credit* ($k_b = 0$)*, and*

$$k_g = k_g^* \equiv \left(\frac{\alpha p_g A}{r^*} \right)^{\frac{1}{1-\alpha}}$$

$$b_g = \bar{b}_1$$

$$r_g^k = \left(A k_g^\alpha - \frac{1 - p_g}{p_g} b_g - \frac{\gamma \pi_g^*}{p_g} \right) \frac{1}{k_g}$$

2. *If* $\bar{b}_2 \leq \tilde{b} < \bar{b}_1$ *then only good entrepreneurs get credit but less than the optimal allocation,*

$$k_g = \left(\frac{\left(\frac{p_g - p_b}{p_g} \right) \tilde{b} - \frac{p_b \gamma \pi_g^*}{p_g}}{p_b (\mu - 1) A} \right)^{\frac{1}{\alpha}}$$

$$
\begin{aligned}
b_g &= \tilde{b} \\
r_g^k &= \left(A k_g^\alpha - \frac{1-p_g}{p_g} b_g - \frac{\gamma \pi_g^*}{p_g} \right) \frac{1}{k_g}
\end{aligned}
$$

in this case $\bar{b}_2 = \bar{b}_2(A, r^*)$ *is the value of collateral that makes bankers indifferent between lending only to good entrepreneurs and lending to both good and bad.*

3. *If* $\tilde{b} < \bar{b}_2$ *then bankers relax credit standards and good and bad entrepreneurs get credit. Good entrepreneurs get,*

$$
\begin{aligned}
k_g &= \left(\frac{\left[\chi p_g - (1-\chi)(\mu - 1) p_b\right] \alpha A}{r^* \chi} \right)^{\frac{1}{\alpha}} \\
b_g &= \tilde{b} \\
r_g^k &= \left(A k_g^\alpha - \frac{1-p_g}{p_g} b_g - \frac{\gamma \pi_g^*}{p_g} \right) \frac{1}{k_g}
\end{aligned}
$$

and the contract for bad entrepreneurs is,

$$
\begin{aligned}
k_b &= \left(\frac{\alpha p_b \mu A}{r^*} \right)^{\frac{1}{1-\alpha}} \\
b_b &= 0 \\
r_b^k &= \left[p_b \mu A k_b^\alpha - p_b(\mu - 1) A k_g^\alpha + \frac{p_g - p_b}{p_g} \tilde{b} - \frac{p_b \gamma \pi_g^*}{p_g} \right] \frac{1}{p_b k_b}
\end{aligned}
$$

Proof. See Appendix A. □

Proposition 1 establishes that the type of contract that bankers offer in equilibrium depends on the amount of collateral every entrepreneur has, $\tilde{b}$, and the thresholds $\bar{b}_1$ and $\bar{b}_2$ which in turn are functions of the exogenous states of the model (A, r^*). In the equilibria characterized by Proposition 1, only good entrepreneurs use land holding as collateral: bad entrepreneurs do not pledge collateral when they get credit. It follows that good entrepreneurs always have collateral of value $\tilde{b} = \frac{ql}{\chi N}$, which is the total value of collateral over the number of good entrepreneurs with a credit line.

The proposition defines three different separating contracts. In the first contract, the banker can attain the first-best allocation: provide credit to good entrepreneurs only and allocate the optimal amount of capital. In the second, the banker manages to provide credit to good entrepreneurs only, but it is costly to separate good and bad because good entrepreneurs operate at a suboptimal scale. In other words, in this second case, the first-best capital allocation does not satisfy the incentive compatibility constraint for bad entrepreneurs, given the amount of collateral available:

$$p_b \left[A_b (k_g^*)^\alpha - r_g^k k_g^* \right] - (1 - p_b) \frac{ql}{\chi N} > 0,$$

which implies that bad entrepreneurs would mimic good ones if this contract was offered. Hence, the banker decides to reduce the amount lent to good entrepreneurs to satisfy this constraint, which implies that in this second case, credit k_g satisfies

$$p_b \left[A_b (k_g)^\alpha - r_g^k k_g \right] - (1 - p_b) \frac{ql}{\chi N} = 0.$$

The third contract entails a relaxation of credit standards. In this case, bankers cross-subsidize bad entrepreneurs so that they do not mimic good ones. They do this by providing credit without asking for collateral, so that bad entrepreneurs prefer it over the contract targeted to good entrepreneurs. This cross-subsidization allows the banker to provide more capital to good entrepreneurs. Mathematically, by combining the incentive compatibility constraint for bad entrepreneurs (that is binding in this case) with the participation constraint for the good, we get

$$p_b \left[(A_b - A_g) k_g^\alpha \uparrow + \gamma \frac{\pi_g^*}{p_g} \right] - \frac{p_g - p_b}{p_g} \frac{ql}{\chi N} = \pi_b \uparrow$$

This condition guarantees that bad entrepreneurs do not want to mimic good ones. From this expression, we can infer that by increasing the profit of bad entrepreneurs π_b, the banker can increase the credit to good entrepreneurs for a given amount of collateral.

The decision of what contract bankers offer depends on comparing the collateral value with the thresholds $\bar{b}_1$ and $\bar{b}_2$. It can be shown that both $\bar{b}_1$ and $\bar{b}_2$ are increasing (decreasing) functions of A (r^*).[5] This implies that, for a given value of collateral available $ql/\chi N$, a positive shock to productivity or a reduction in r^* can make bankers change credit contracts from type 1 to type 2 (because of an increase in $\bar{b}_1$) or from type 2 to type 3 contracts (because of an increase in $\bar{b}_2$). As we will see in our quantitative example, it is the switch to the type 3 equilibrium that typically occurs during a credit boom. These booms happen when bankers offer type 1 or 2 separating contracts and there is a sudden increase in productivity (or a decrease in international interest rates) that generates a jump in $\bar{b}_2$, moving the economy from an equilibrium where $\bar{b}_2 \leq ql/\chi N$ to another where $\bar{b}_2 > ql/\chi N$. This change in credit standards results in a large increase in credit, since, at the new equilibrium, both types of entrepreneurs receive credit.

In the previous analysis, we implicitly held the total amount of collateral available in the economy constant. However, the price of collateral and the amount of credit lines change due to aggregate shocks; therefore, $ql/\chi N$ also changes. Under certain parameterizations, an increase in productivity can trigger an increase in $ql/\chi N$ that exceeds that of $\bar{b}_2$. If that is the case, bankers will not relax credit standards as a consequence of a positive productivity shock; on the contrary, credit standards may fall in response to *negative* productivity shocks.

The question of which parameterization of the model is more plausible is ultimately empirical. The evidence presented by (inter alia) Mendoza and Terrones (2008) and Gorton and Ordoñez (2014), suggests that positive productivity (or world interest rate) shocks are common precursors of credit booms. We can infer the necessary conditions for the model to be consistent with this empirical evidence: the switch from type 2 to type 3 contracts happens because bankers find it profitable to relax the incentive compatibility constraint for bad entrepreneurs; hence, one necessary condition to have booms with a switch to type 3 contracts is that the benefit from relaxing that constraint is higher when A is high or r^* is low. In other words, the model needs a Lagrange multiplier related to the constraint that is increasing in A or decreasing in r^*. This multiplier under the type 2 contract is given by,

$$\xi = \frac{p_g \chi}{p_b(\mu - 1)} - \frac{\chi r^* k_g^{1-\alpha}}{\alpha p_b(\mu - 1) A}$$

[5] $\bar{b}_1$ is defined in proposition 1 and is always increasing (decreasing) in A (r^*). There is no closed form solution of $\bar{b}_2$, but it is increasing in A and decreasing in r^* under general parameter values.

Inspecting the above expression, it is straightforward to show that to satisfy $\partial\xi/\partial A > 0$ and $\partial\xi/\partial r^* < 0$, two conditions must be satisfied:

$$\frac{d\log(k_g)}{d\log(A)} < \frac{1}{1-\alpha} \tag{11}$$

$$-\frac{d\log(k_g)}{d\log(r^*)} < \frac{1}{1-\alpha} \tag{12}$$

Inequalities (11) and (12) determine an upper bound on the increase in credit to good entrepreneurs in response to shocks that increase output. In particular, they state that credit to good projects in the type 2 separating contract has to increase by less than what the first best allocation would increase. Given that in this contract k_g is an increasing function of the value of collateral $ql/\chi N$, conditions (11) and (12) also impose an upper bound on how much $ql/\chi N$ can increase in a boom. Hence, parameterizations where q does not increase much in response to aggregate shocks or where N increases quickly during booms are good candidates to generate credit booms that are accompanied by a relaxation of credit standards.

In the next section, we present a numerical example to show the properties of credit booms generated in this model.

3.1 Credit Boom Simulations

We now turn to studying the properties of credit booms in our model using a numerical example. We assume a constant returns to scale matching function given by

$$M(F_t, 1-N_t) = \bar{m}F_t^{\nu}(1-N_t)^{1-\nu},$$

for parameters $\bar{m} > 0$ and $\nu \in (0,1)$. This matching function implies that $\lambda^e(\theta_t) = \bar{m}\theta_t^{\nu}$ and $\lambda^f(\theta_t) = \bar{m}\theta_t^{\nu-1}$. Moreover, in order to ensure that bad projects have negative net present value in equilibrium we scale the intermediation cost by the productivity level and assume $\psi = \bar{\psi}A^{1/(1-\alpha)}$ and we parameterize $\bar{\psi}$ so that $\pi_b^* = 0$ in equilibrium.

The parameter values we use in this example are summarized in Table A8. The economy is parameterized to generate credit booms with changes in credit standards. As discussed in the previous section, a condition for the model to generate such "bad" booms is that the price of land does not respond too much to aggregate shocks that raise the optimal project scale. The price of land in equilibrium is given by the following equation that comes from the first-order conditions of the household,

$$q_t = \phi C_t^{\sigma} + \beta \mathbb{E}_t \left\{ \Lambda_{t,t+1} q_{t+1} \right\} \tag{13}$$

Hence, we parametrize the risk aversion parameter σ to discipline the increase in collateral prices during booms. In an alternative, "good boom" parameterization, we set σ to a higher value. The utility parameter ϕ is chosen to generate a steady-state collateral value consistent with a first-best allocation at the non-stochastic steady state (contracts are type 1 at steady state, so $k_g = k_g^*$ and $k_b = 0$). Lastly, the parameter γ that affects the outside option for entrepreneurs and defines their bargaining power is set such that the search friction distortion is zero at steady state (the Hosios (1990) condition holds in the context of this model). We parameterize γ so that the equilibrium non-stochastic steady state is the same as the stationary solution of a constrained planner problem where the planner cannot affect the way credit contracts are written.

To study credit booms generated by the competitive equilibrium of the model we simulate the model for 10,000 periods and compute log total credit in the economy every period. We then HP-detrend the series (with an HP parameter equal to 100), compute its standard deviation and, following Mendoza and Terrones (2008), define a credit boom as an episode during which total credit it 1.65 standard deviations above steady state. We then analyze relevant variables around these credit booms by plotting time windows showing the average evolution of key variables before, during and after booms. The top row of Figure 1 shows what happens to GDP, consumption and the credit market during a typical credit boom. The solid red lines in the figure show the log HP detrended series of GDP (panel A), consumption (panel B), credit (panel C) and market tightness (panel D) during the credit boom peak and seven years before and after the peak. In these events, there is a rapid increase in credit and market tightness reflecting the fact that many bankers are looking for entrepreneurs to issue credit lines. As Figure 1 shows, during these events there are large, rapid increases in GDP and consumption. This is primarily because our simulated credit booms are caused by positive productivity shocks and low international interest rates, consistent with empirical evidence (for example Mendoza and Terrones (2008), Gorton and Ordoñez (2019), and Krishnamurthy and Muir (2025)).

The bottom row of Figure 1 illustrates changes in micro and macro measures of credit standards during credit booms. Consistent with empirical evidence (Asea and Blomberg (1998) and Jimenez et al. (2006)), panel E shows a decrease in the aggregate collateral-to-credit ratio that is related to the sharp increase in credit (panel C) that results from the relaxation of standards. Similarly, aggregate collateral relative to GDP (panel F) decreases in a bad credit boom, a prediction that we will verify in the empirical analysis of Section 5. Panel H shows a decrease in the (quantity-weighted) proportion of loans with collateral, which comes about when bankers extend credit without collateral to bad entrepreneurs. Lastly, note that under this parameterization, model-generated credit booms show a decrease in lending spreads (panel G), the difference between the lending rate and the international interest rate. This spread reduction follows from our assumption of diminishing marginal returns in production. During a credit boom, bankers can increase credit to good entrepreneurs, but given decreasing marginal returns, the marginal productivity of capital decreases and, as a consequence, bankers are forced to reduce the lending interest rate to good entrepreneurs so that the participation constraint is satisfied and the credit contract is still profitable to the borrower.

Figure 1 also shows (dashed green lines) the dynamics of all variables for the alternative parameterization of the model with $\sigma = 0.85$, where we feed identical shocks to A and r^* as in the baseline simulation. With a higher value of σ, collateral prices respond more to aggregate shocks, and the economy does not experience *bad* credit booms in response to the simulated productivity and interest rate shocks. The two economies generate similar dynamics for consumption (panel C), but both credit (panel C) and GDP (panel A) increase by less in good than in bad booms. The aggregate collateral/credit ratio decreases in good booms but by less. Interestingly, credit spreads respond similarly in magnitude during good and bad booms, although changes occur more gradually in good booms. Our model simulation is therefore consistent with the finding of Krishnamurthy and Muir (2025) that an increase in credit spreads alone is not a predictor of booms ending in crises but that the interaction between credit growth and spreads is informative.

3.2 Discussion

This section outlines the key findings of our theory. We find that variation in aggregate collateral availability, relative to investment demand, as a function of the aggregate state of the economy, is a determinant of whether credit booms are efficient (we will study *constrained* efficiency in the next section). When good entrepreneurs have too little collateral relative to the desired investment levels, banks react by offering contracts that attract unprofitable borrowers, allowing them to lend more to good borrowers for the same amount of collateral.

The most salient differences between good and bad booms are in collateral value relative to GDP (panel F) and in the share of uncollateralized credit (panel H). In the good boom parameterization, the economy (by definition) does not switch to an equilibrium in which bad borrowers are extended credit, so there is no change in the share of collateralized lending. This suggests that focusing on lending standards for the lowest quality borrowers is a more useful metric for diagnosing bad booms than aggregate measures. In practice, however, it is not obvious how this diagnostic tool would be used since, by definition, the quality of the borrower is hidden from the bankers (and the social planner). Most interestingly, in the good boom, the collateral/GDP ratio is roughly unchanged, suggesting that this is a reasonable metric for the collateral scarcity channel at the heart of efficiency losses in our model. In Section 5, we present empirical evidence that supports the finding that collateral scarcity and collateralization standards for low-quality borrowers are important metrics in diagnosing the quality of a credit boom.

These results rely on the assumption that banks are not able to produce information on borrowers, such that asymmetric information remains. Asriyan et al. (2021) studies an economy in which collateral use and information production are substitutes and finds that collateral *abundance* can be the cause of bad credit booms. Our work is complementary because these two mechanisms can coexist. After all, asymmetric information might remain an issue even in settings in which the technology for information production is efficient and public credit registries are available (see, for example, Albertazzi et al. (2025)).

Search friction in credit markets is an important feature of the model because the gradual formation (and dissolution) of matches is the mechanism of propagation of aggregate shocks.

Moreover, search is a natural market mechanism in which to embed the bargaining problem between bankers and entrepreneurs, which enables the existence of separating equilibria in which negative NPV projects are funded in equilibrium. It is less clear that random search is the best model of credit line formation, but given that we parameterize our model to ensure that the Hosios condition is satisfied, the effects that we find are not the result of congestion externalities unrelated to the forces we are principally interested in.

We make two simplifying assumptions that we believe are not central to the result. First, our model assumes frictionless reallocation of collateral among entrepreneurs. While this assumption greatly simplifies aggregation and analysis, introducing frictions would likely reinforce our findings. Specifically, collateral misallocation would amplify credit misallocation, as collateral would remain inefficiently allocated to bad entrepreneurs, leaving good entrepreneurs with a smaller share of collateral in equilibrium. Second, we assume free entry into the banking sector, which has significant implications, since the bank capital structure interacts with risk taking (Dell'Ariccia et al. (2014)). We abstract from this important consideration to focus on the novel implications of our theory.

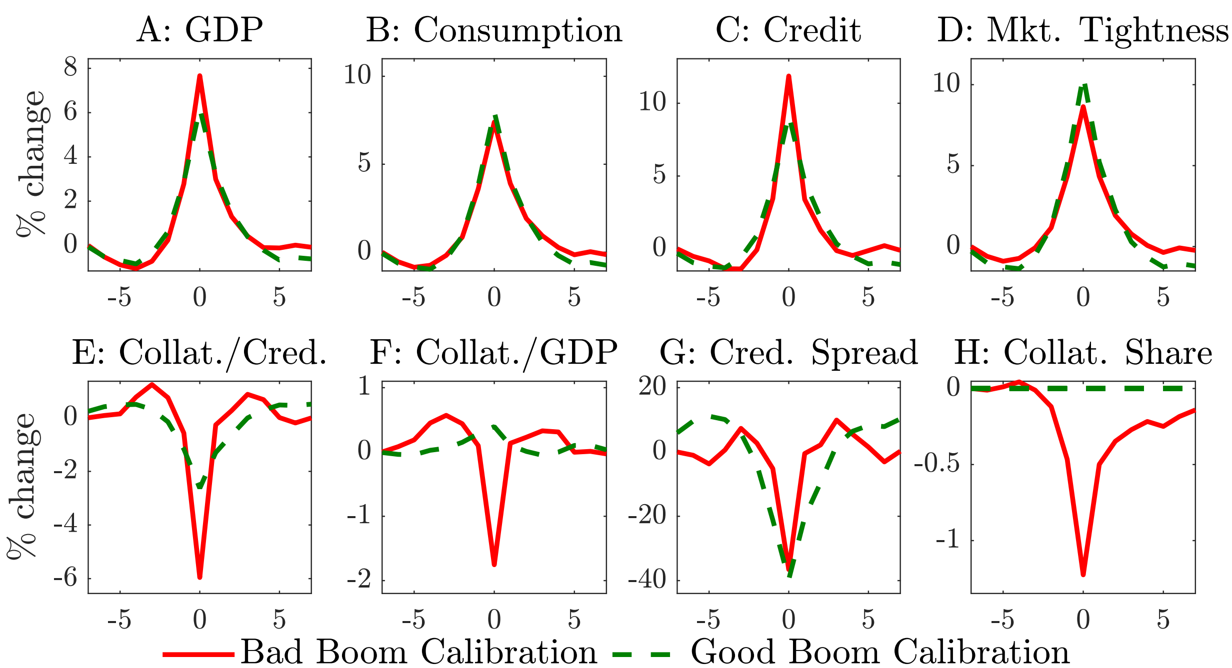
The analysis in this section shows that the model can generate dynamics consistent with the stylized facts highlighted by the rich literature that studies credit booms, and with the novel empirical evidence of Section 5. The model can generate periods with above-trend economic activity and credit, and a change in credit standards with lower collateralization and lending spreads. Are these credit booms efficient, or is there room for policy? The following section addresses this question.

4 Policy

We first consider a constrained-planner problem to determine whether there is room for economic policy to improve welfare. The constrained planner maximizes household utility but cannot modify how credit contracts or prices are determined in equilibrium. The planner's problem is:

$$\max_{\{C_t^*, F_t^*, N_{t+1}^*\}} \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \beta^t \frac{(C_t^*)^{1-\sigma}}{1-\sigma} + \phi \bar{l} \right\}$$

Figure 1: Model Credit Booms - Bad and Good Booms



This figure shows the dynamics around model-simulated credit booms. The model is run for 10,000 periods; a boom is any episode in which the HP–detrended ($\lambda = 100$) log level of total credit rises at least 1.65 standard deviations above its steady state. For every boom we align the peak at $t = 0$ and plot the average path for each variable from seven years before to seven years after. Top row (A–D): GDP, consumption, total credit, and credit-market tightness. Bottom row (E–H): collateral-to-credit ratio, collateral-to-GDP ratio, lending spread, and share of collateralized loans. Solid red lines show the baseline parameterization that produces "bad" booms ; dashed green lines show the alternative parameterization that produces "good" booms (see Table A8).

s.t.

$$C_t^* = \Psi_t\left(\frac{q_t\bar{l}}{\chi N_t^*}\right)N_t^* - \kappa F_t^* \tag{14}$$

$$N_{t+1}^* = [\chi p_g + (1-\chi)p_b]\,N_t^* + \bar{m}\,(F_t^*)^{\nu}\,(1-N_t^*)^{1-\nu} \tag{15}$$

$$q_t = \phi\,(C_t^*)^{\sigma} + \mathbb{E}_t\left\{\beta\left(\frac{C_{t+1}^*}{C_t^*}\right)^{-\sigma} q_{t+1}\right\} \tag{16}$$

where $\Psi_t\left(\frac{q_t\bar{l}}{\chi N_t^*}\right)$ is the total expected value added generated in a credit contract, that is,

$$\Psi_t = \chi\,(\pi_{gt} + \Pi_{gt}) + (1-\chi)\,(\pi_{bt} + \Pi_{bt})$$

Ψ_t is a function of exogenous states of the economy, but also of the amount of collateral every good entrepreneur holds, $\frac{q_t\bar{l}}{\chi N_t^*}$. In fact, the higher the amount of collateral, the closer the contract is to the first-best allocation and therefore the higher the expected income that the credit relationship generates, which implies $\Psi_t' \geq 0$. Furthermore, notice that if the economy is already in the first-best allocation (type 1 contract), more collateral will not affect the income generated in the credit contract, or $\Psi_t' = 0$.

As expressed in the problem, the planner chooses aggregate consumption, bankers looking for credit (F_t^*) and credit relationships (N_{t+1}^*) to maximize welfare subject to the resource constraint (14), the law of motion of credit lines (15) and the price of collateral (16). The solution to this problem can be summarized in the following expression.

$$\frac{\kappa}{\lambda^f(\theta_t^*)} = \mathbb{E}_t\left\{\underbrace{\tilde{\Lambda}_{t,t+1}}_{\substack{\text{Pecuniary}\\ \text{externality}}}\left[\underbrace{\nu\Psi_{t+1} - (1-\nu)\kappa\theta_{t+1}^*}_{\text{Search Friction}}\underbrace{-\nu\Psi_{t+1}'\frac{q_{t+1}\bar{l}}{\chi N_{t+1}}}_{\substack{\text{Credit lines}\\ \text{inefficiency}}} + \frac{\bar{p}\kappa}{\lambda^f(\theta_{t+1}^*)}\right]\right\} \tag{17}$$

where,

$$\tilde{\Lambda}_{t,t+1} = \beta\left(\frac{C_{t+1}^*}{C_t^*}\right)^{-\sigma}\frac{1-\Psi_t' q_t'\bar{l}}{1-\Psi_{t+1}' q_{t+1}'\bar{l}}$$

$$q_t' = \frac{\partial q_t}{\partial C_t^*}.$$

Equation (17) looks similar to the equilibrium condition (18) with three important differences that highlight different sources of inefficiency. First, future expected profits for bankers $\chi \Pi_{gt+1} + (1-\chi)\Pi_{bt+1}$ are replaced by the term $\nu \Psi_{t+1} - (1-\nu)\kappa \theta_{t+1}^*$ in the planner problem. This difference is related to the typical congestion inefficiency in any model with search frictions. Bankers, when they decide to spend resources to find entrepreneurs in equilibrium, care only about their expected income and not the total expected income of the match. In addition, bankers do not internalize the congestion they generate when they search for new credit lines. As our focus is not on this source of inefficiency, we parameterize the entrepreneur's bargaining power (parameter γ) such that this distortion is eliminated in the steady state. As a consequence, the importance of this distortion is minor in our quantitative results.

The second difference between the planner's solution and equilibrium is the stochastic discount factor. The stochastic discount factor of the planner incorporates a financial externality related to the decision of paying a fixed cost κ and searching for entrepreneurs. In particular, this decision affects current and future collateral prices, which might, in turn, impact current and future levels of income.

Regarding the impact on current levels of income, increasing search intensity can reduce current income because paying a fixed cost today generates a drop in current consumption levels, which in turn reduces the price of collateral (q_t) today. If the economy is away from the first-best allocation and $\Psi_t' > 0$, then this reduction in q_t decreases aggregate income. This effect is summarized by the term $\Psi_t' q_t' \bar{l}$ in the stochastic discount factor of the planner.

Consider the effect of this pecuniary externality on future levels of income. Deciding to increase credit lines today can increase future collateral prices, which might increase aggregate future income if $\Psi_{t+1}' > 0$. The reason is that an increase in the number of credit lines tomorrow increases future consumption and, hence, the collateral price. As a consequence, if the economy is expected to be below the first best tomorrow $\Psi_{t+1}' > 0$, increasing search intensity today has a positive impact on income tomorrow. This effect is summarized by the term $\Psi_{t+1}' q_{t+1}' \bar{l}$ in the stochastic discount factor. Hence, in principle, the pecuniary externality has an ambiguous impact on the incentives to issue more credit lines after positive aggregate shocks. On the one hand, the effect on current income tends to dampen the incentives to increase the search intensity. In contrast, the impact on future income magnifies the response of market tightness θ_t compared to equilibrium. However, when the economy is below the first-best allocation and $\Psi'_t > 0$, the effect through current income tends to dominate. The reason is that since aggregate shocks are stationary and revert to their means, there is a set of future values of exogenous shocks for which $\Psi'_{t+1} = 0$, which in turn reduces the expected value of $\Psi'_{t+1} q'_{t+1} \bar{l}$ and the overall importance of the pecuniary externality effect through future income. Consequently, our quantitative results indicate that overall the pecuniary externality makes the planner want to reduce the issue of new credit lines during booms relative to the laissez-faire equilibrium.

The third source of inefficiency is summarized by the term $-\nu \Psi'_{t+1} \frac{q_{t+1}\bar{l}}{\chi N_{t+1}}$. In the decentralized equilibrium, market tightness and the number of active credit lines are given by,

$$\frac{\kappa}{\lambda^f(\theta_t)} = \mathbb{E}_t \left\{ \Lambda_{t,t+1} \left[\chi \Pi_{gt+1} + (1-\chi)\Pi_{bt+1} + \frac{\bar{p}\kappa}{\lambda^f(\theta_{t+1})} \right] \right\} \tag{18}$$

$$N_{t+1} = [\chi p_g + (1-\chi)p_b] N_t + \lambda^e(\theta_t)(1-N_t) \tag{19}$$

where $\bar{p} \equiv \chi p_g + (1-\chi)p_b$. The additional term is present in the planner's solution but absent in the equilibrium condition (18). The difference stems from the fact that, in equilibrium, bankers do not internalize that by creating new credit lines, they reduce the overall value of collateral available for every line. Recall that the collateral good entrepreneurs use in equilibrium is given by $ql/\chi N$. Hence, an increase in N_{t+1} reduces $q_{t+1}\bar{l}/\chi N_{t+1}$ for a given future price of collateral, which reduces future aggregate income if $\Psi'_{t+1} > 0$. Therefore, this effect reduces the planner's incentives to increase credit after increases in productivity or sudden reductions in international interest rates.

In summary, we have shown room for welfare-improving economic policy. The planner internalizes the negative effect of an increase in search intensity on the collateral value per credit line $ql/\chi N$. As a consequence, they optimally decide to dampen the increase in credit as a consequence of positive aggregate shocks compared to the laissez-faire equilibrium when the economy is away from the first-best allocation and $\Psi'_t > 0$, or the planner expects $\Psi'_{t+1} > 0$ in some future aggregate states. In that sense, the optimal policy is activated only when the economy is inefficient.[6]

We can also study the dynamics of constrained first-best credit booms, shown by the dashed blue lines in Figure 2, which plots simulated credit booms for the competitive equilibrium of our baseline, "bad boom", parameterization (solid red lines) and in the constrained first-best (dashed blue lines). Panel A shows that the expansion in GDP is muted in the planner's solution relative to laissez-faire, but consumption (panel B) is similar. This indicates that entrepreneurs' income does not change even though GDP is lower because there are fewer bad projects under the optimal policy. Moreover, the figure also shows a lower increase in credit (panel C) and market tightness (panel D) with the optimal policy.

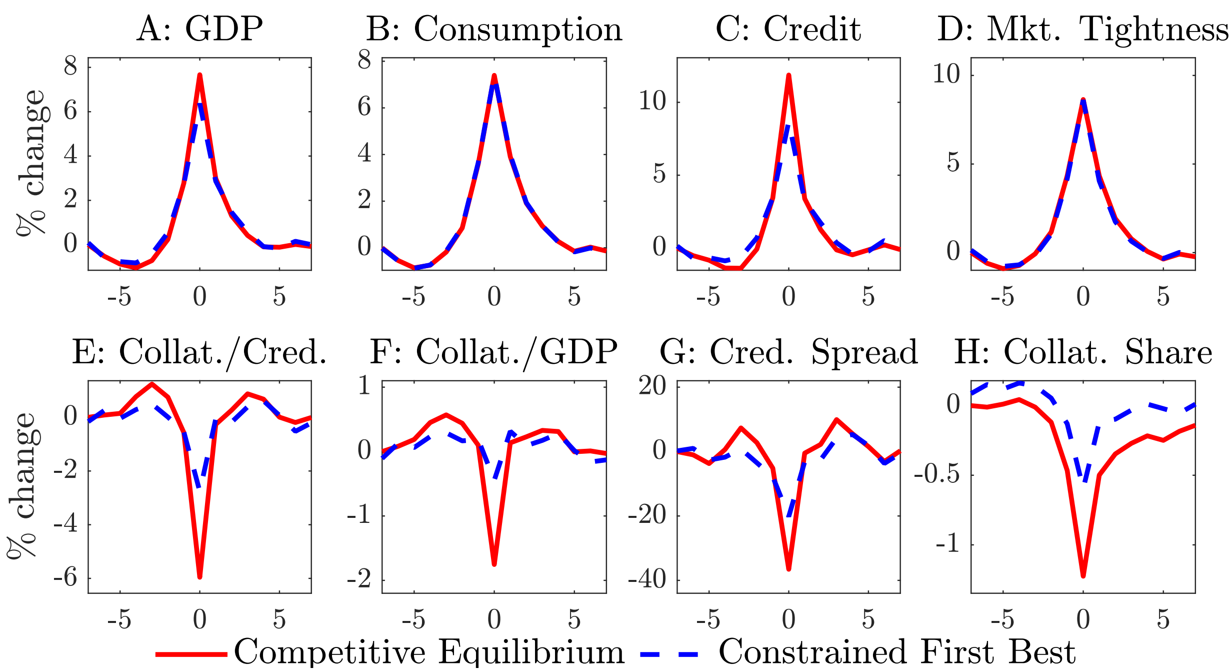
The bottom row of Figure 2 shows the aggregate effects of the differences in the equilibrium credit contracts. In particular, the drop in the collateral over total credit (panel E) is considerably reduced under the optimal policy, and the collateral relative to GDP (collateral scarcity) is muted (panel F). On average, there are fewer booms with changes in credit standards and a relaxation of collateral requirements. As such, there is a milder drop in the proportion of loans with collateral (panel H), indicating a less aggressive relaxation of credit standards overall. Moreover, lending spreads decrease by less with the optimal policy (panel G).

Welfare We have shown that optimal policy can have a meaningful effect on the economy's behavior around credit booms. We now evaluate the welfare gains of following the optimal policy. To do so, we compute the average welfare gain of being in a world with the optimal policy in consumption-equivalent units from a simulation of 10,000 periods. To benchmark the welfare gains from the optimal policy, we also compute the welfare gain associated with eliminating asymmetric information frictions (but keeping search frictions).

In our example parameterization, the welfare gain of the optimal policy is 0.07%: an entrepreneur in a world with the optimal policy in place is willing to give up 0.07% of her consumption to maintain that optimal policy and avoid living in a world without it. Under the same

[6]This result is shown in Figure A6a. The figure compares the impulse response function to a positive productivity shock that moves the economy from a first-best allocation to a situation where $\Psi'_t > 0$. We can see that the planner decides to reduce the increase in credit and market tightness, which in turn increases collateral per credit line compared to equilibrium. The response to an interest rate shock (Figure A6b) has similar properties.

Figure 2: Model Credit Booms - Competitive Equilibrium and Constrained First Best



This figure shows the dynamics around model-simulated credit booms. The model is run for 10,000 periods; a boom is any episode in which the HP–detrended ($\lambda = 100$) log level of total credit rises at least 1.65 standard deviations above its steady state. For every boom we align the peak at $t = 0$ and plot the average path for each variable from seven years before to seven years after. Top row (A–D): GDP, consumption, total credit, and credit-market tightness. Bottom row (E–H): collateral-to-credit ratio, collateral-to-GDP ratio, lending spread, and share of collateralized loans. Solid red lines show the baseline parameterization (see Table A8) that produces "bad" booms; dotted blue lines show the constrained first-best.

parameterization, the welfare gain from eliminating information frictions is 0.25% of consumption. This numerical example suggests that the welfare gains from eliminating inefficient credit booms are significant, at least relative to a salient credit market friction such as asymmetric information.

Simpler Macro-Prudential Policy We can show that this optimal policy can be reasonably well approximated with a state-dependent tax on the issuance of credit lines. In fact, we show that a state-dependent tax that increases search costs during booms can generate welfare gains similar to those of the optimal policy. To do so, we solve for the equilibrium incorporating a tax $\tau_t \geq 0$ that can increase the search cost from κ to $\kappa(1+\tau_t)$. The income generated from this tax is then rebated back to entrepreneurs. We assume that,

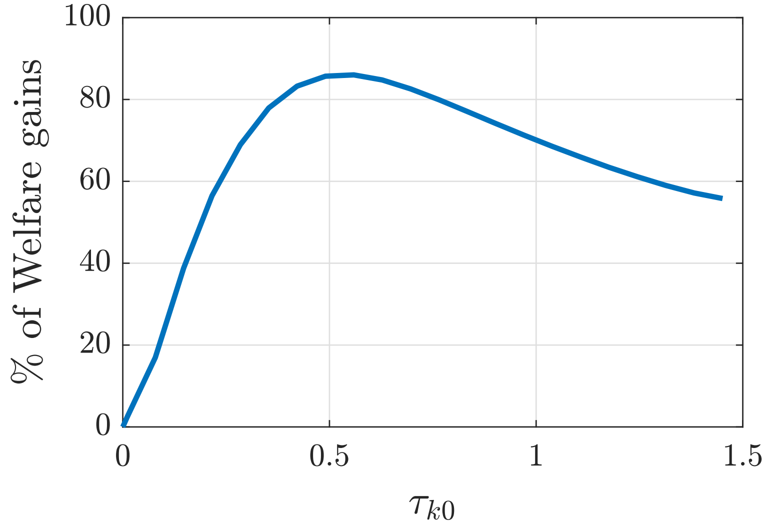
$$\tau(\theta_t) = \tau_0 \max\{\theta_t - \theta_{ss}, 0\}$$

where $\tau_0 \geq 0$ and θ_{ss} is market tightness at the non-stochastic steady state. Hence, this tax is only implemented if market tightness is above steady-state levels, in which the tax is increasing in market tightness. With this policy in place, the equilibrium condition for θ_t satisfies,

$$\frac{\kappa\left(1+\tau(\theta_t)\right)}{\lambda^f(\theta_t)} = \mathbb{E}_t\left\{\Lambda_{t,t+1}\left[\chi\Pi_{gt+1} + (1-\chi)\Pi_{bt+1} + \frac{\bar{p}\kappa\left(1+\tau(\theta_{t+1})\right)}{\lambda^f\left(\theta_{t+1}\right)}\right]\right\} \tag{20}$$

Even though there is not a direct mapping between equations (17) and (20), we can compare the welfare gains from implementing the tax with that of the optimal policy. With that aim, we solve the equilibrium with the tax for different values for τ_0 and compute the welfare gain in consumption equivalent units. The results are summarized in figure 3. We see that when the parameter τ_0 is around 0.5, welfare gains are 0.06%, almost 86% of the welfare gains achieved by the optimal policy. Hence, we can conclude from this section that, conditional on having an economy that faces credit booms with a relaxation of credit standards, there is room for simple macro-prudential policy with significant welfare gains.

Figure 3: Welfare gain of macro-prudential policy relative to constrained first-best



Welfare gains from a simple macro-prudential tax on credit lines. The line shows the fraction of the welfare gain (in consumption-equivalent terms) achieved by the tax, relative to the fully optimal policy, as a function of the tax $\tau_{\kappa 0}$.

5 Supporting Evidence

In this section, we provide evidence for two key predictions of our model: the way credit booms turn bad is a reduction in collateralization standards for low-quality borrowers, and collateral scarcity is a telltale sign of a bad credit boom.

We test these predictions in two empirical settings using firm-level difference-in-differences analysis around the credit expansion preceding the Global Financial Crisis (GFC). The first setting studies Spanish firms, and the second a cross-country sample of firms in Central and Eastern Europe and Central Asia. The countries in our sample experienced large credit booms in the run-up to the GFC, driven by global factors that manifested as low domestic interest rates and high capital inflows. Informed by the evidence on the global financial cycle presented in Miranda-Agrippino and Rey (2022), we use post-2002 as the reference time period for the start of the global credit boom.

5.1 Data

5.1.1 ORBIS

ORBIS is the largest cross-country firm-level database, widely used because it offers granular and harmonized firm-level data across countries. It provides detailed balance sheet and income statement information for millions of firms worldwide, encompassing all industries and including both private and public firms. ORBIS captures a diverse cross-section of firms across industries and offers a highly representative sample of the average European firm. Notably, firms with fewer than 250 employees constitute a significant portion of the dataset. These firms predominantly rely on bank financing and exhibit limited access to alternative funding sources. This reliance improves the precision of our analysis of the collateral channel, enabling a more robust identification of its effects. Specifically, we leverage this feature of the data to examine how changes in interest rates—through their influence on collateral requirements—affect firms differentially according to their productivity levels. The empirical analysis focuses on Spain, a country that presents several advantages for our purposes. First, ORBIS provides consistent coverage of Spanish firms from 2000 to 2009, enabling a longitudinal analysis. Second, Spain experienced a pronounced credit expansion in the years preceding the Global Financial Crisis (GFC), offering a rich context to explore how collateral constraints interact with firm-level productivity during this period. Table A5 shows summary statistics for the BEEPS data.

5.1.2 BEEPS

The Business Environment and Enterprise Performance Survey (BEEPS) is a joint initiative of the European Bank for Reconstruction and Development (EBRD) and the World Bank, aimed at assessing the business environment and enterprise performance in transition economies in Central and Eastern Europe, the former Soviet Union, and Turkey. The BEEPS collects cross-sections of firm-level data through structured interviews with managers and owners of enterprises in the manufacturing and services sectors. The survey covers a wide range of topics, including firm characteristics and access to finance. Stratified sampling ensures representation across firm size, industry, and region. We use three waves of data (2002, 2005, 2009) to study the evolution of collateral requirements and collateral relative to sales during the credit boom leading up to the GFC. We use three survey waves in our empirical analysis because the questionnaire and variable definitions for our variables of interest are consistent across these waves (see Appendix Table A4 for details), but differ substantially or are missing in earlier and later waves. As part of the analysis, we estimate the effects of interest in good and bad boom sub-samples. Our classification of credit boom episodes into good or bad is presented in Appendix Table A7. We examine the sensitivity of our main empirical findings by reestimating all the main effects using a leave-one-out and an add-one-in approach. These results are presented in Appendix C.1 and our results are robust to these two checks.

5.2 Empirical specifications

In this section, we present the empirical specifications to identify the effects of a credit boom on variables of interest.

5.2.1 Effects on collateral requirements

To identify the effect of the credit boom on collateral requirements, we estimate the following specification using ordinary least squares (OLS), with firm-level data from the Spanish sample of the ORBIS data:

$$\log \frac{\text{TFA}_{ist}}{\text{Bank Credit}_{ist}} = \beta \text{Low-Prod}_i \times D_{\text{Year}>2002} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{21}$$

and a similar specification using BEEPS data:

$$\text{Collateral}_{isct} = \beta \text{Low-Prod}_{isct} \times D_{\text{Year}>2002} + \delta_{sct} + \gamma' X_{isc} + \varepsilon_{isct}. \tag{22}$$

In equation 21, $\frac{\text{TFA}_{ist}}{\text{Bank Credit}_{ist}}$ is the ratio of tangible fixed assets to the sum of short- and long-term financial debt, which we interpret as a measure of the extent to which firm i's credit is collateralized, since collateral consists primarily of tangible fixed assets. $D_{\text{Year}>2002}$ is a dummy that takes a value of one for years after 2002. The variable Low-Prod$_{ist}$ is a dummy that takes a value of one if firm i's productivity is below sector s median productivity in 2002, where productivity is defined as value added divided by the number of employees. The control variables are firm and sector-by-time fixed effects. Including sector-by-by-time fixed effects and therefore using within-sector, cross-firm variation to identify the effect of interest is particularly important given the finding in Müller and Verner (2023) that credit reallocation towards non-tradable sectors is an indication of a harmful credit expansion.[7] In addition to the baseline specification, we assess the validity of the parallel trends assumption, a key identifying condition for our difference-in-differences approach. Specifically, the identification strategy relies on the assumption that, prior to the onset of the credit boom, firms with high and low productivity followed similar trends in collateral requirements. To evaluate this assumption, we estimate the following event-study specification:

$$\log \frac{\text{TFA}_{ist}}{\text{Bank Credit}_{ist}} = \sum_{2000}^{2007} \beta_t \text{Low-Prod}_i \times D_{\text{Year}=t} + \alpha_i + \delta_{st} + \epsilon_{ist}. \tag{23}$$

Equation 23 implements a dynamic difference-in-differences approach, allowing the interaction coefficients β_t to capture the year-by-year differential evolution of collateral requirements between low- and high-productivity firms. A lack of significant pre-trend differences would support the validity of the parallel trends assumption underlying our empirical strategy.

In Equation 22, the dependent variable Collateral_{isct} is an indicator taking the value one if firm i in sector s in country c at time t was required to post collateral for its most recent loan, and zero otherwise, so we are estimating a linear probability model. The variable Low-Prod_{isct} is a dummy that takes a value of one if the firm's productivity is below the median productivity of its respective sector, where productivity is defined as sales divided by the number of employees. The control variables are sector-by-country-by-time fixed effects and firm-level controls (sector and categorical variables indicating whether i) the firm is small, medium, or large; ii) the firm is state or privately owned; and iii) the population size of the city where the firm is located). We include these firm-level controls instead of firm fixed effects, as BEEPS is not a panel data set. Since we are interested in studying environments where asymmetric information is likely present, we also estimate a specification in which we include the interaction $\text{Low-Prod}_{isct} \times \text{High-Info}_{isct} \times D_{\text{Year}>2002}$, where High-Info_{isct} is a dummy that takes the value of one if the

[7] As a further check, our results are robust to dropping the construction sector, which is the principal driver of credit growth for Spain in the Müller and Verner (2023) data.

firm's financial accounts are audited by an external auditor, which we interpret as implying that lenders face less asymmetric information when they lend to those firms. Since our BEEPS sample data begin in 2002, we cannot check for pre-trend equivalence in this setting. As a robustness check in Appendix C.2 we present an alternative empirical specification for which we can add one additional pre-treatment year (1999) and the results are consistent with the finding presented in the main text.

5.2.2 Effects on collateral scarcity

Panel F of Figure 1 shows that the model predicts that the most salient difference between good and bad booms is the aggregate dynamics of collateral value relative to GDP. To examine the prediction that collateral-to-GDP falls (becomes scarce) during bad booms but not good booms, we estimate the following regression using BEEPS data:

$$\log\left(\text{Assets/Sales}\right)_{jct} = \beta \text{High-Prod}_{jct} \times D_{\text{Year}>2002} + \gamma' X_{jct} + \delta_c + \varepsilon_{jct}, \tag{24}$$

where the dependent variable $\log\left(\text{Assets/Sales}\right)_{jct}$ is the (log) ratio of the sum of assets over the sum of sales for above and below median productivity firms in each country c at time t. For each country-time cell, we therefore have two observations, for the aggregate $\log\left(\text{Assets/Sales}\right)$ summing across above and below median productivity firms. It is important to note that the measure of assets reported in BEEPS is not book value, but the estimated current replacement value of firms' productive tangible assets, so this variable provides contemporaneous information on the market value of collateralizable assets. A measure of value added at the country-firm type cell level is unavailable, so we use sales as a proxy. The variable High-Prod_{jct} is a dummy that takes a value of one for observations corresponding to high productivity aggregates in each country. In this specification, we estimate the treatment effect on the high-productivity part of the economy, because the theory predicts that collateral scarcity affecting high-productivity firms is the cause of bad credit booms. $D_{\text{Year}>2002}$ is a dummy that takes a value of one for years after 2002. The regression includes country fixed effects. Informed by our theory, we also add the share of audited firms in each country-firm-group cell as a control, conjecturing that this will absorb some of the variation in informational asymmetries across countries. And, given that Müller and Verner (2023) have shown the importance of non-tradeable sectors in driving bad credit booms, we add a control for the share of tradable firms (defined as firms in the manufacturing and mining/extraction sectors).

5.3 Results

5.3.1 Effects on collateral requirements

Figure 4 plots the median $\frac{\text{TFA}_{ist}}{\text{Bank Credit}_{ist}}$ for firms with above- and below-median within-sector productivity in 2002. At the onset of the period, collateral requirements are higher for low-productivity firms. However, during the credit boom, this pattern reverses, with collateral requirements for low-productivity firms falling below those for their high-productivity counterparts. During the bad credit boom in Spain, consistent with our theory's predictions, collateral requirements were disproportionately lowered for the low-productivity firms.

Table 1 provides formal empirical evidence consistent with the patterns illustrated in Figure 4. Specifically, it reports the estimation results of Equation 21. In all columns, the estimated coefficient on the interaction term, β, is negative and highly significant. This suggests that collateral requirements declines more for low-productivity firms relative to their high-productivity counterparts during the credit boom.

Column 3 presents our baseline specification, which includes both firm and industry-time fixed effects. Based on the estimate, during the credit boom period, collateral requirements decreases by 2.9% more for low-productivity firms compared to high-productivity firms. The remaining columns provide a series of robustness checks. Column 1 excludes firm fixed effects. The positive coefficient on the low-productivity dummy suggests that, prior to the credit boom, low-productivity firms were required to post more collateral than high-productivity firms for an equivalent amount of credit. Column 2, which omits industry-time fixed effects, yields a negative coefficient on the credit boom dummy, indicating a general reduction in collateral requirements during the boom. Column 4 excludes firms in the construction sector (NACE Rev.2 codes 41–43). This exclusion serves to ensure that our results are not driven by construction sector-specific dynamics that may have influenced collateral requirements during the credit boom. The results remain robust to this exclusion.

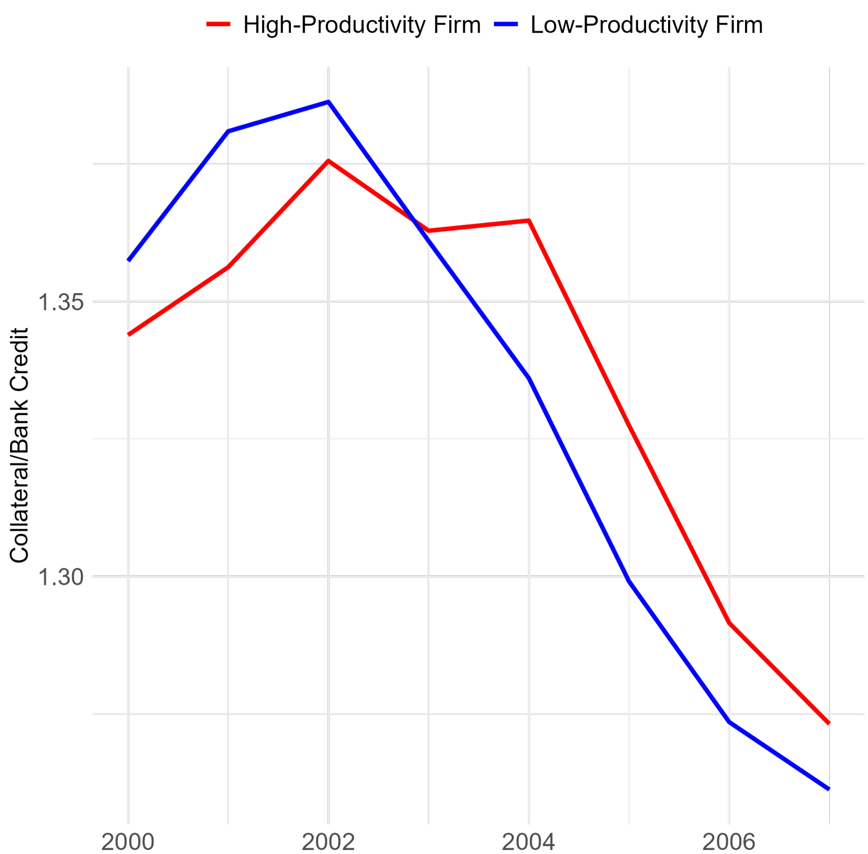


Figure 4: Collateral requirements by productivity

This figure plots the average $\frac{\text{TFA}_{ist}}{\text{Bank Credit}_{ist}}$ ratio for Spanish firms with above (red line) and below (blue line) median sectoral productivity (defined as value added divided by the number of employees) in 2002. $\frac{\text{TFA}_{ist}}{\text{Bank Credit}_{ist}}$ is the ratio of tangible fixed assets to the sum of short- and long-term financial debt. Source: ORBIS.

Table 1: Impact of Credit Booms on Collateral Requirements by Firm Productivity

Dependent variable:	*Collateral required (log)*			
	(1)	(2)	(3)	(4) Exc Construction
Low-Prod	0.0144			
	(0.0629)			
$D_{Year>2002}$		-0.0181		
		(0.0187)		
Low-Prod × $D_{Year>2002}$	-0.0262**	-0.0295***	-0.0291***	-0.0369***
	(0.0102)	(0.00982)	(0.00974)	(0.0105)
Firm FE	No	Yes	Yes	Yes
Year-Industry FE	Yes	No	Yes	Yes
Observations	458628	458601	458601	373456
R^2	0.0436	0.706	0.708	0.694

Notes: This table reports OLS estimates of the following model:

$$\ln \frac{\text{Collateral}_{ist}}{\text{Bank Credit}_{ist}} = \beta \text{Low-Prod}_i \times D_{\text{Year}>2002} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{25}$$

where i stands for firm i working sector s at time t. The dependent variable in this analysis is the Collateral Requirement at the firm level, defined as the ratio of Collateral to Bank Credit. Collateral refers to the Tangible Fixed Assets as recorded in the Orbis database, while Bank Credit is the total of both Long- and Short-Term Financial Debt, as recorded in Orbis. The variable `Low-Prod` is a dummy variable that takes a value of 1 if the firm's productivity in 2002 is below the median productivity of its respective sector in 2002. Labor productivity is calculated as Value Added divided by the Number of Employees. Additionally, $D_{\text{Year}>2002}$ is a dummy variable that takes the value of 1 if the year is greater than 2002. Standard errors are presented in parentheses below the coefficient estimates. Robust standard errors are clustered at the industry level.
****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*

Figure 5 plots the estimates of time varying regression coefficients of the model in Equation 23 relative to the year 2002, with confidence intervals of a 95% confidence level. For the period 2000 and 2001, the coefficients are not statistically different from zero, but the coefficients become negative and significant at 5% level during the credit boom years from 2004 to 2007. This provides further support for the causal interpretation of our results.[8] The difference between the estimates in the good and bad boom sub-samples are consistent with the model dynamics shown in Panel F of Figure 1.

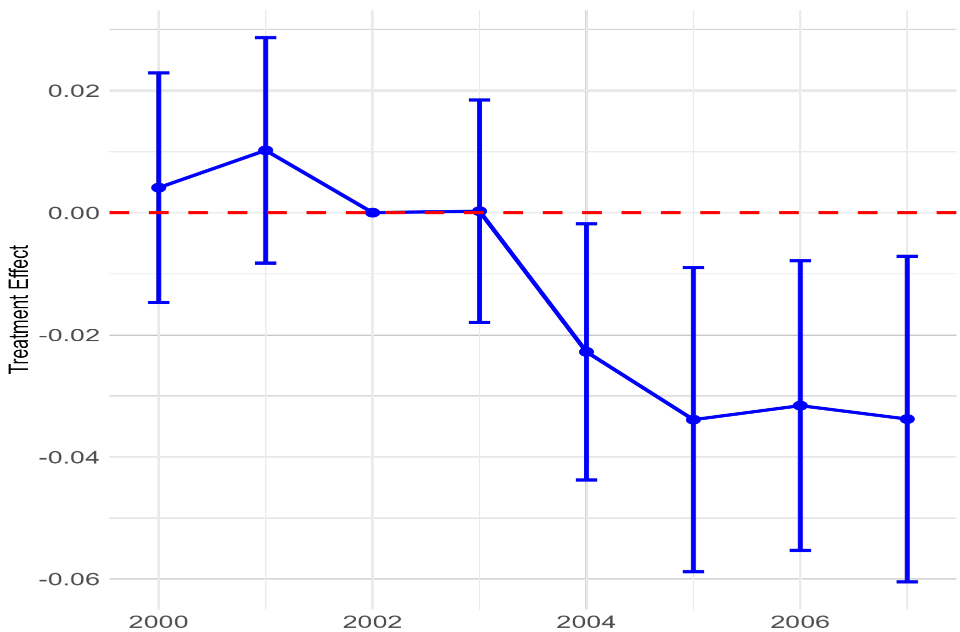


Figure 5: Impact of credit boom on collateral requirements by productivity

Notes: This figure plots the coefficient estimates $\hat{\beta}_t$ of the following model:

$$\ln \frac{\text{Collateral}_{ist}}{\text{Bank Credit}_{ist}} = \sum_{2000}^{2007} \beta_t \, \text{Low-Prod}_i \times D_{\text{Year}=t} + \alpha_i + \delta_{st} + \epsilon_{ist}$$

$\hat{\beta}_t$ is time-varying treatment effect of credit boom on collateral requirement. Vertical bars correspond to 95% confidence intervals. The terms $D_{\text{Year}=t}$ are year dummies for t = 2000 to 2007. The year 2002 is the reference year. The dependent variable is the firm-level collateral requirement, defined as the ratio of collateral to bank credit. Collateral is measured as Tangible Fixed Assets from the Orbis database, and Bank Credit refers to the sum of Long- and Short-Term Financial Debt. The variable `Low-Prod` is a binary indicator equal to 1 if the firm's 2002 labor productivity falls below the sectoral median. Labor productivity is defined as Value Added per Employee. Firm fixed effects are included. Industry-Time fixed effects are based on two-digit NACE Rev.2 codes. Robust standard errors are clustered at the industry level.

[8] These results are also presented in Table A9 in the Appendix for reference.

Table 2 presents the results of estimating Equation 22 using BEEPS data. The first column shows the main effect in the full sample. Collateral requirements (probability of collateral being posted) for low-productivity firms fall by approximately 5.6 percentage points relative to high-productivity firms following the credit boom shock. In the second column, we add an interaction with an indicator (High-Info) of whether a firm has its financial accounts audited externally, which we interpret as making lending less subject to asymmetric information. The reduction in collateral standards in the credit boom is not uniform across firms: relative collateral requirements (probability of collateral being posted) for low-productivity, low-information firms fall by 11.1% , whereas these decreases are less pronounced for low-productivity, high-information firms, as indicated by the positive triple interaction term of 9.72%. Additional specifications for these effect are presented as robustness checks in Appendix Table A10. Columns 3 and 4 show that the significance of this finding is driven by countries that experienced a bad credit boom. Collateral requirements for low-productivity, low-information firms fall by 12.8% in the bad boom subsample, whereas the point estimate is closer to zero and insignificant in the good boom subsample. Appendix Figures A7-A10 present leave-one-out and add-one-in robustness checks of our bad boom classification for columns 3 and 4. We re-estimate these two specifications, first leaving one bad (good) boom country out at a time, and then adding in one good (bad) country to the bad (good) sub-sample. The finding of a decrease in collateral relative to economic activity in bad boom economies is robust to these two checks, as is the null finding in the good boom economies. As an additional robustness check, we present an alternative specification in Appendix C.2, for which we are able to add one additional pre- and post-treatment year from the BEEPS survey. The results are consistent with the finding that credit standards for low-productivity borrowers are relaxed during bad credit booms.

Overall, our results support the model prediction that, in a bad credit boom, collateralization standards fall disproportionately for lower quality, lower information borrowers.

5.3.2 Effects on collateral scarcity

Table 3 presents the estimation results for Equation 24 using BEEPS data in the bad and good boom country sub-samples. Column 1 shows that assets/sales falls in the bad boom economies,

Table 2: Impact of Credit Boom on Collateral Requirements

Dependent variable:	*Collateral required (0/1)*			
	(1) Full sample	(2) Full sample	(3) Bad boom	(4) Good boom
Low-Prod × $D_{\text{Year}>2002}$	-0.0568***	-0.111***	-0.128***	-0.0576
	(0.0215)	(0.0306)	(0.0349)	(0.0591)
Low-Prod × High-Info × $D_{\text{Year}>2002}$		0.0972**	0.122**	0.0461
		(0.0395)	(0.0467)	(0.0718)
Firm Controls	Yes	Yes	Yes	Yes
Country-Industry-Time FE	Yes	Yes	Yes	Yes
Observations	9037	9037	6322	2715
R2	0.138	0.138	0.147	0.114

Notes: This table reports OLS estimates from difference-in-differences regressions evaluating the change in collateral requirements during credit booms. The dependent variable is an indicator of whether collateral was required for the firm's most recent loan. $D_{Year>2002}$ indicates the period after 2002. *Low-Prod* is an indicator equal to one if the firm's labor productivity (sales per employee) is below the median. *High-Info* is an indicator equal to one if the firm's accounts are externally audited. Columns (3) and (4) split the sample into countries experiencing bad and good credit booms, respectively, and column (5) estimates the triple interaction with a dummy equal to 1 for bad boom countries. Firm controls (employment indicator, industry, size of city where firm is based, firm's legal status) are included but not reported. Robust standard errors are clustered at the country-industry level.
****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*

by approximately 2% for low-productivity firms, and by an additional 1% for high-productivity firms (the total effect is 3% with a p-value of 0.015). As a robustness check, column 3 adds country-year fixed effects and confirms the finding that assets/sales falls disproportionately for high-productivity firms. In contrast, we do not find any evidence of the collateral scarcity channel in the good boom subsample in either specification in columns 2 and 4 (albeit the sample size is significantly smaller because there are fewer good boom economies in our dataset). Figures A11-A14 in the appendix present leave-one-out and add-one-in robustness checks of our bad boom classification for columns 1 and 2. The finding of a decrease in collateral relative to economic activity in bad boom economies is robust to these two checks, as is the null finding in the good boom economies.

Overall our findings point to the existence of a collateral scarcity channel that affects bad but not good boom economies, consistent our theoretical predictions.

Table 3: Impact of Credit Boom on Collateral Scarcity

Dependent variable:	*Assets/Sales (log)*			
	(1) Bad Boom	(2) Good Boom	(3) Bad Boom	(4) Good Boom
$D_{\text{Year}>2002}$	-1.997*	-1.770		
	(1.108)	(1.128)		
High-Prod $\times$ $D_{\text{Year}>2002}$	-0.986**	0.573	-0.830**	-0.101
	(0.410)	(0.464)	(0.351)	(0.463)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Country-Year FE	No	No	Yes	Yes
Observations	110	44	110	44
R2	0.484	0.353	0.971	0.970

Notes: This table reports OLS estimates from difference-in-differences regressions evaluating the change in (log) Assets/Sales during credit booms. $D_{Year>2002}$ is a dummy equal to 1 for years after 2002. *High-Prod* is an indicator equal to 1 if the firm has above-median labor productivity (sales per employee) within sector. The interaction *High-Prod* $\times$ $D_{Year>2002}$ captures the differential change in assets/sales for high-productivity firms after the shock. Column (1) and (2) report results for the country aggregate regressions, for bad and good booms, respectively. Columns (3) and (4) report results for the productivity group within country aggregate regressions (the aggregate asset/sales for high and low productivity firms within each country, so there are 2 observations per country-year), for bad and good boom subsamples, respectively. All regressions include country fixed effects and controls (average audited firm share and the share of firms in tradable sectors). Robust standard errors are clustered at the country level.
****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*

6 Conclusion

We proposed a model that can generate credit booms that are consistent with empirical evidence on the macro and micro characteristics of these episodes, and also with empirical evidence on the differences between good and bad booms. Our theory makes a novel prediction: credit booms turn bad, in the sense that banks lower credit standards and lend to bad borrowers, when collateral becomes scarce relative to economic activity.

We verify two predictions of the model in two different settings, using a diff-in-diff model with the run-up to the GFC as our treatment. As predicted by the theory, collateral standards fall disproportionately for bad borrowers during bad booms. And, during bad but not good booms, collateral value falls relative to economic activity. Together, our model and empirical evidence provide a new diagnostic metric for policy-makers seeking to differentiate in real time between good and bad credit booms.

Our findings complement the existing literature on the interactions between collateral and bad credit booms. The important connection between information production and collateral values is better understood thanks to the work of Gorton and Ordoñez (2014) and Asriyan et al. (2021), among others. Both theory and empirical evidence suggest that an excess of a specific form of collateral – real estate – is a leading culprit of bad credit booms. Our analysis can be understood as relevant to situations in which information production is either infeasible or in which all possible information has been produced. And, even in the presence of a real estate boom, there is no guarantee that the most productive firms in the economy are also those that are blessed with abundant collateral. In such settings, our analysis suggests that collateral scarcity can lead to constrained inefficient credit booms.

In our theory, good or bad booms are distinguished by the response of asset prices, which we model as an asset in fixed, positive net-supply that is priced using the representative household's stochastic discount factor. A fruitful direction for future research is to integrate into settings such as ours a richer model of the determination of collateral values, which would allow for deeper analysis of the institutional and other factors that mediate the relationship between collateral values and the credit cycle.

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Appendices

A Proof of Proposition 1

Assuming that the incentive compatibility constraint for good entrepreneurs is slack, the problem to solve is the following

$$\max_{k_g,r_g^k,b_g,k_b,r_b^k,b_b} \quad \chi \mathbb{1}_{\{k_g>0\}} \left(p_g r_g^k k_g + (1-p_g)b_g - r^* k_g - \psi(A_t, r_t^*)\right)$$
$$+ (1-\chi)\mathbb{1}_{\{k_b>0\}} \left(p_b r_b^k k_b + (1-p_b)b_b - r^* k_b - \psi(A_t, r_t^*)\right)$$

s.t.

$$\left[p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)b_b\right]\mathbb{1}_{\{k_b>0\}} \geq \left[p_b\left(A_b k_g^\alpha - r_g^k k_g\right) - (1-p_b)b_g\right]\mathbb{1}_{\{k_g>0\}} \tag{26}$$

$$\left[p_g\left(A_g k_g^\alpha - r_g^k k_g\right) - (1-p_g)b_g - \gamma\pi_g^*\right]\mathbb{1}_{\{k_g>0\}} \geq 0 \tag{27}$$

$$\left[p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)b_b\right]\mathbb{1}_{\{k_b>0\}} \geq 0 \tag{28}$$

$$\mathbb{1}_{\{k_g>0\}}b_g \geq 0 \qquad \mathbb{1}_{\{k_g>0\}}(b_g - \tilde{b}) \leq 0 \tag{29}$$

$$\mathbb{1}_{\{k_b>0\}}b_b \geq 0 \qquad \mathbb{1}_{\{k_b>0\}}(b_b - \tilde{b}) \leq 0 \tag{30}$$

where we are incorporating the assumption that the outside option for bad entrepreneurs is zero, $\pi_b^* = 0$.

The first and second types of contract happen when only good entrepreneurs get credit, hence $\{k_b, r_b^k, b_b\} = \{0,0,0\}$. Hence, for these types of contract the problem is the following,

$$\max_{k_g,r_g^k,b_g} \quad \chi\left(p_g r_g^k k_g + (1-p_g)b_g - r^* k_g - \psi(A_t, r_t^*)\right)$$

s.t.

$$0 \geq p_b\left[A_b(k_g)^\alpha - r_g^k k_g\right] - (1-p_b)b_g \tag{31}$$

$$p_g\left[A_g(k_g)^\alpha - r_g^k k_g\right] - (1-p_g)b_g \geq \gamma\pi_g^* \tag{32}$$

$$b_g \leq \tilde{b} \tag{33}$$

$$b_g \geq 0 \tag{34}$$

The first order condition with respect to r_g^k yields,

$$\chi + \eta_1 \frac{p_b}{p_g} = \eta_2 \tag{35}$$

where η_1 and η_2 are weakly positive Lagrange multipliers related to constraints (31) and (32), respectively. Note that this equation already reveals that $\eta_2 > 0$ and, therefore, the participation constraint (32) is binding. Now getting the FOC with respect to k_g and using (35) we get,

$$\eta_1 = \frac{\alpha p_g A_g k_g^{\alpha-1} - r^*}{\alpha p_b (A_b - A_g) k_g^{\alpha-1}} \chi \tag{36}$$

Taking derivatives with respect to b_g and using (35) yields,

$$\frac{p_g - p_b}{p_g} \eta_1 + \theta_2 - \theta_1 = 0 \tag{37}$$

Where θ_1 and θ_2 are the Lagrange multipliers of constraints (33) and (34) respectively. Notice that, given that $\eta_1 \geq 0$, from the last expression we can infer that $\theta_2 = 0$. In other words, the banker finds it optimal to ask for collateral and $b_g > 0$. Now the first order conditions define two different contracts. The first one is when collateral level $\tilde{b}$ is high and constraint (33) is slack. In that case $\eta_1 = \theta_1 = 0$ and the amount lent is the first best one. This amount can be obtained from (36):

$$k_g = \left(\frac{\alpha p_g A_g}{r^*} \right)^{\frac{1}{1-\alpha}}$$

Also, using the binding constraint (32) and (31) we know that the collateral asked is,

$$b_g \geq \frac{p_g}{p_g - p_b} \left[p_b (A_b - A_g) \left(\frac{\alpha p_g A}{r^*} \right)^{\frac{\alpha}{1-\alpha}} + \frac{p_b}{p_g} \gamma \pi_g^* \right] \equiv \bar{b}_1$$

Hence, in principle, any level of collateral satisfying the previous condition will maximize bankers profits. However, if we incorporated an infinitesimal cost of recovering the collateral after default, the banker would choose the minimum b_g possible and the previous equation would hold with equality. As a consequence, we assume that $b_g = \bar{b}_1$ in this contract.

Finally, we can get r_g^k for this type of contract using the binding participation constraint (32)

$$r_g^k = \left(Ak_g^\alpha - \frac{1-p_g}{p_g}b_g - \frac{\gamma\pi_g^*}{p_g}\right)\frac{1}{k_g}$$

Now the type two contract is the case in which $\tilde{b}$ is lower than $\bar{b}_1$ and as a consequence (33) binds implying that $\theta_1 > 0$ and $b_g = \tilde{b}$. From (37) we know that $\eta_1 > 0$ and the incentive compatibility constraint (31) binds. Hence, using the two binding constraints (31) and (32) we get the the interest rate and the amount lent in this contract,

$$k_g = \left(\frac{\left(\frac{p_g - p_b}{p_g}\right)\tilde{b} - \frac{p_b\gamma\pi_g^*}{p_g}}{p_b\left(A_b - A_g\right)}\right)^{\frac{1}{\alpha}}$$
$$r_g^k = \left(A_g k_g^\alpha - \frac{1-p_g}{p_g}b_g - \frac{\gamma\pi_g^*}{p_g}\right)\frac{1}{k_g}$$

The third type of contract happens when the banker decides to lend to both types of entrepreneurs. Hence, the problem is now,

$$\max_{k_g, r_g^k, b_g, k_b, r_b^k, b_b} \quad \chi\left(p_g r_g^k k_g + (1-p_g)b_g - r^* k_g - \psi(A_t, r_t^*)\right)$$
$$+ (1-\chi)\left(p_b r_b^k k_b + (1-p_b)b_b - r^* k_b - \psi(A_t, r_t^*)\right)$$

s.t.

$$p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)b_b \geq p_b\left(A_b k_g^\alpha - r_g^k k_g\right) - (1-p_b)b_g \tag{38}$$

$$p_g\left(A_g k_g^\alpha - r_g^k k_g\right) - (1-p_g)b_g \geq \gamma\pi_g^* \tag{39}$$

$$p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)b_b \geq 0 \tag{40}$$

$$b_g \leq \tilde{b} \tag{41}$$

$$b_g \geq 0 \tag{42}$$

$$b_b \leq \tilde{b} \tag{43}$$

$$b_b \geq 0 \tag{44}$$

It is straightforward to check that any contract satisfying the first order conditions of the previous problem that sets a binding participation constraint for bad entrepreneurs (40) does not maximize banker's profits. The reason is that the contracts would look the same to type one or two contracts (depending on whether (38) binds or not) with the difference that bankers also lend to bad projects with negative net present value. Hence, these contracts will naturally generate lower profits compared to types one and two contracts. For that reason we focus on contracts with a slack participation constraint (40).

Now, getting the FOC with respect to r_b^k,

$$1 - \chi = \eta_1 \tag{45}$$

where is the multiplier of constraint (38). Equation (45) implies that $\eta_1 > 0$ and already tells us that bankers want to relax credit standards only when the constraint (38) is binding. In other words, incentives to start lending to bad entrepreneurs start when collateral is scarce with respect to the desired optimal loan to good entrepreneurs.

Taking derivatives with respect to k_b and using (45) we get

$$k_b = \left(\frac{\alpha p_b A_b}{r^*} \right)^{\frac{1}{1-\alpha}}$$

Not surprisingly bankers choose the level of capital for bad projects that minimizes the loss of this investment. Also, taking the first order condition with respect to b_b we get,

$$-\theta_3 + \theta_4 = 0$$

Hence, $\theta_3 = \theta_4 = 0$ and any level of collateral $b_b \in (0, \tilde{b})$ is optimal of the banker. However, if we incorporated an infinitesimal cost of liquidating collateral after default in the problem the banker would choose $b_b = 0$. As a consequence, we assume that $b_b = 0$ is the banker's choice. Getting the FOC with respect to r_g^k and using (45),

$$\frac{\chi p_g + p_b(1-\chi)}{p_g} = \eta_2$$

where η_2 is the multiplier of constraint (39). Hence, the last expression implies that $\eta_2 > 0$ and (39) is binding. Now getting the FOC with respect to k_g,

$$k_g = \left[\frac{\alpha \left(\bar{p} A_g - (1-\chi) p_b A_b \right)}{r^* \chi} \right]^{\frac{1}{1-\alpha}}$$

where $\bar{p} \equiv \chi p_g + (1-\chi) p_b$. Now going to the FOC with respect to b_g,

$$\frac{(p_g - p_b)}{p_g}(1-\chi) - \theta_1 + \theta_2 = 0$$

which implies that $\theta_1 > 0, \theta_2 = 0$ and $b_g = \tilde{b}$.

Finally to get r_b^k and r_g^k just use the binding constraints (38) and (39) to get,

$$r_b^k = \left[p_b A_b k_b^\alpha - p_b (A_b - A_g) k_g^\alpha + \frac{p_g - p_b}{p_g} \tilde{b} - \frac{p_b \gamma \pi_g^*}{p_g} \right] \frac{1}{p_b k_b}$$
$$r_g^k = \left(A_g k_g^\alpha - \frac{1 - p_g}{p_g} b_g - \frac{\gamma \pi_g^*}{p_g} \right) \frac{1}{k_g}$$

The last two equations complete the description of type 3 credit contracts.

Note that in all contract derivations we assumed that the incentive compatibility constraint for good entrepreneurs is slack. In other words, we assumed that good entrepreneurs do not want to mimic bad ones. It can be trivially shown that this is actually the case for type 1 and 2 contracts. Nevertheless, for type 3 contracts, collateral has to be higher than a lower bound so that good entrepreneurs do not want to mimic bad ones. In particular, this condition has to be met,

$$\tilde{b} \geq \frac{p_b p_g}{p_g - p_b} \left(A_b - A_g \right) \left(k_g^\alpha - k_b^\alpha \right)$$

where k_g and k_b are the capital allocation under type 3 contract. We check that the last inequality holds in equilibrium in our numerical solution.

B Data sources

Table A4: Descriptions of Selected Variables Across BEEPS Waves

Variable	2002 Description	2005 Description	2009 Description
`collat`	`q65a`: Was collateral required for the most recent loan?	`q46a`: Was collateral required for the most recent loan?	`k13`: Was collateral required for the most recent loan?
`size_cat`	`s4a2`: Full-time employees (categorical)	`s4b`: Full-time employees (categorical)	`a6b`: Full-time employees (categorical)
`s2a`	`s2a`: Legal status detail	`s2a`: Legal status detail	`b1`: Legal status detail
`city`	`city`: Size of city	`city`: Size of city	`a3`: City population category
`a1`	`a1`: Country code	`a1`: Country code	`a1`: Country code
`s3`	`s3`: Main sales activity	`s3`: Main sales activity	`a4a/a4b`: Industry sector
`assets`	`q82b`: Replacement value of physical assets	`q57b`: Replacement value of physical assets	`n7a + n7b`: Replacement value of physical assets
`sales`	`q82a`: Total 2001 sales	`q57a`: Estimated 2004 sales	`d2`: Total annual sales (LCU)
`audit`	`q74`: Does your establishment have its annual financial statement reviewed by an external auditor?	`q49`: Does your firm have its annual financial statement checked and certified by an external auditor?	`k21`: Does your firm have its annual financial statement checked and certified by an external auditor?
`employment`	`s4a`: How many full-time employees work for this company?	`s4`: How many full-time employees work for this company today?	`L1`: Permanent, full-time employees end of last fiscal year

Table A5: BEEPS - Descriptive Statistics

Variable	Mean	Median	Std. Dev.	25th Percentile	75th Percentile	Count
Panel A: Low productivity firm						
collat	.80		.40	1	1	4537
audit	.53		.50	0	1	4537
employment	160		471	12	140	4537
sales/employee	2.55e+08		2.98e+09	8571	314857	4537
Panel B: High productivity firm						
collat	.82		.38	1	1	4975
audit	.58		.49	0	1	4975
employment	152		459	12	120	4975
sales/employee	1.80e+09		1.90e+10	29071	3038782	4975

Notes: The table reports descriptive statistics for the entire sample of BEEPS data. Audit and collat are 0/1 variables. *Low Productivity* is a binary indicator equal to 1 if a firm's sales/employee is below the median value within its sector. See Table A4 for variable descriptions and Table A7 for the list of countries in our sample. We use the 2002, 2005, and 2009 survey waves in our analysis. Data is available for download at https://www.beeps-ebrd.com/data/.

Table A6: ORBIS - Descriptive Statistics

Variable	Mean	Median	Std. Dev.	25th Percentile	75th Percentile	Count
Panel A: Low productivity firm						
Tangible Fixed Assets	11.63	1.58	10.68	11.70	12.62	28014
Bank Credit	11.37	1.63	10.40	11.38	12.29	28388
Collateral Required	0.26	1.40	-0.36	0.32	0.95	28014
Value Added	12.34	1.12	11.62	12.28	13.01	28106
Employees	28.82	259.95	6.00	10.00	20.00	28388
Labor Productivity	9.92	0.36	9.76	9.96	10.15	28106
Panel B: High productivity firm						
Tangible Fixed Assets	12.61	1.86	11.49	12.61	13.73	29361
Bank Credit	12.36	2.03	11.10	12.24	13.59	29836
Collateral Required	0.25	1.66	-0.48	0.31	1.02	29361
Value Added	13.32	1.37	12.37	13.16	14.10	28475
Employees	46.55	431.38	5.00	11.00	28.00	29801
Labor Productivity	10.77	0.56	10.42	10.64	10.94	28443

Notes: The table reports descriptive statistics based on ORBIS firm-level data for the year 2002. *Low Productivity* is a binary indicator equal to 1 if a firm's labor productivity in 2002 is below the median value within its sector. *Tangible Fixed Assets*, *Bank Credit*, *Collateral Required*, *Value Added*, and *Labor Productivity* are expressed in natural logarithms. *Bank Credit* denotes the sum of long- and short-term financial debt. *Collateral Required* is calculated as the ratio of tangible fixed assets to bank credit. *Employees* refers to the number of persons employed. *Labor Productivity* is measured as value added per employee.

Table A7: GFC Credit Boom Outcomes by Country

Country	Classification	Rationale
Albania	Bad Boom	Rapid credit growth; NPLs jumped from $<5\%$ in 2007 to $\sim$25% by 2014.
Armenia	Bad Boom	Aggressive construction-driven credit boom; severe GDP contraction ($\sim$14%); NPLs low due to restructuring but significant IMF support needed.
Belarus	Bad Boom	Directed lending caused large external imbalances; major currency devaluations (2009, 2011); modest official NPLs masked by state interventions and inflation.
Bosnia and Herzegovina	Bad Boom	Credit/GDP tripled; harsh GFC adjustment; NPLs from 3% to $\sim$14%; prolonged stagnation.
Bulgaria	Bad Boom	Rapid credit expansion; external deficit; hard landing; NPLs in mid-teens; subsequent banking fragility.
Croatia	Bad Boom	Euro-linked loans fed bubble; prolonged recession; NPLs rose sharply ($\sim$15%+); substantial bank cleanup required.
Georgia	Bad Boom	Foreign-funded credit surge ended with 2008 war/crisis; GDP contracted 6.8%; sharp NPL rise; IMF program required.
Hungary	Bad Boom	FX loans triggered crisis; IMF/EU rescue; NPLs climbed to $\sim$15%; severe banking distress.
Kazakhstan	Bad Boom	Extreme foreign-funded credit boom; bank defaults; massive NPL surge ($\sim$26%); major government intervention required.
Kyrgyz Republic	Bad Boom	Institutional weaknesses; political upheaval and banking crisis; NPL rise to $\sim$15–16%.
Latvia	Bad Boom	Extreme credit boom and deep crisis (GDP –25%); IMF/EU bailout; NPLs $\sim$20%; major bank failure (Parex).
Lithuania	Bad Boom	Large credit expansion; deep recession; NPL spike ($\sim$20%); banking system required external support.
Moldova	Bad Boom	Remittance-driven boom; significant NPL increase ($\sim$17%); weak governance exacerbated issues.
Mongolia	Bad Boom	Commodity-fueled boom; IMF bailout needed; NPL rise ($\sim$10%); banking stress and balance-of-payments crisis.
Romania	Bad Boom	Rapid FX credit growth; severe bust; IMF/EU bailout; NPLs surged from single digits to $>20\%$.
Russian Federation	Bad Boom	Oil-fueled credit surge; GDP fell 7.8%; bank profits wiped out; severe NPL spike.
Serbia	Bad Boom	Foreign-bank fueled boom; GFC caused prolonged NPL surge ($>20\%$); bank restructuring needed.
Slovenia	Bad Boom	Excessive corporate lending; delayed bust (2012–13 banking crisis); NPLs $>17\%$; state recapitalization required.
Tajikistan	Bad Boom	Credit boom and cotton debt crisis; NPLs $\sim$22%; currency crisis with $\sim$30% devaluation; bank restructuring necessary.
Ukraine	Bad Boom	FX-driven boom; systemic crisis, GDP -15%; quadrupled NPLs ($\sim$16%); IMF rescue necessary.
Azerbaijan	Good Boom	Oil-backed boom; avoided banking crisis; NPLs remained low ($\sim$5%); large buffers protected economy.
Czech Republic	Good Boom	Moderate credit growth; banks stable; mild recession impact; modest NPL rise (mid-single digits).
Estonia	Good Boom	Rapid credit expansion cushioned by strong fiscal buffers; limited NPL peak ($\sim$7%); no banking collapse.
North Macedonia	Good Boom	Moderate credit boom; mild crisis impacts; limited NPL rise (7.5% to $\sim$10%); no major bank failures.
Poland	Good Boom	Rapid but prudent credit growth; avoided recession and crisis; moderate NPL rise ($\sim$9%).
Slovak Republic	Good Boom	Contained boom; no banking crisis; mild NPL rise (single digits); euro adoption amid downturn.
Turkey	Good Boom	Post-2001 banking reforms; modest NPL peak ($\sim$5.7%); strong fundamentals and no banking crisis during GFC.
Uzbekistan	Good Boom	Moderate, state-controlled credit growth; no crisis; stable growth (8.1% in 2009); low NPLs.

Sources: Central bank and IMF reports; World Bank, BIS, and EBRD analyses. Key indicators include peak NPL ratios and macroeconomic outcomes.

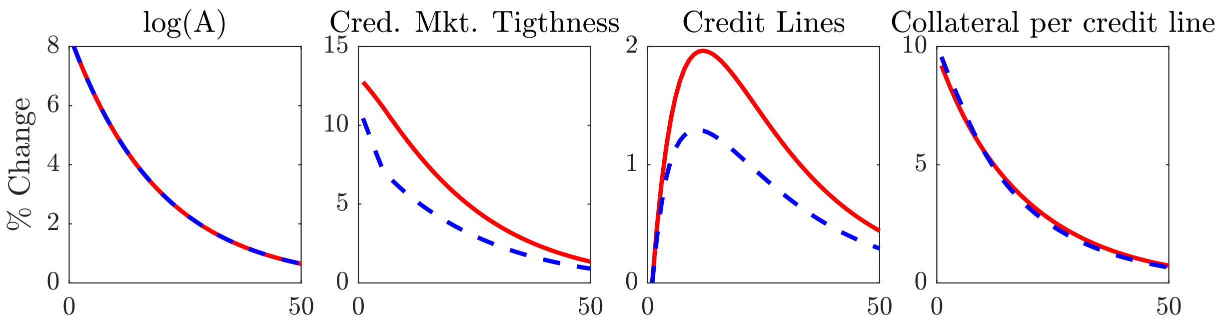
C Appendix tables and figures

Table A8: Parameter Values

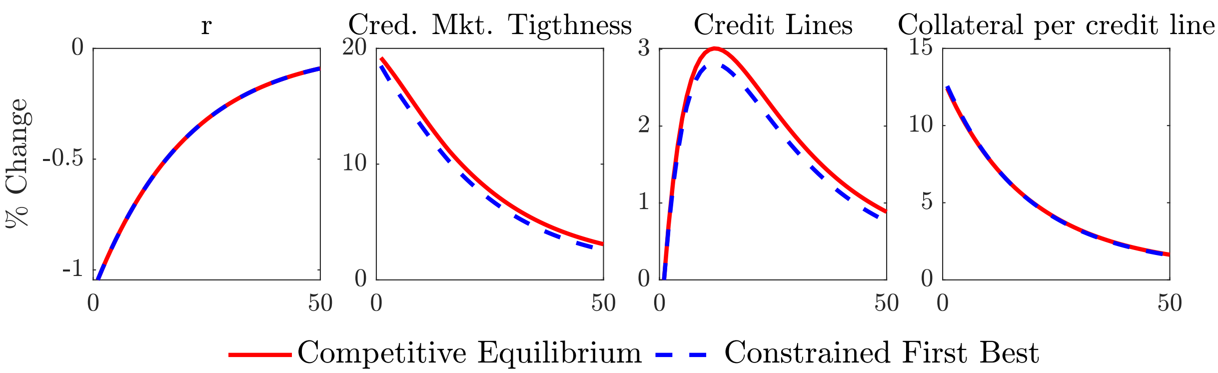
Parameter	**Description**	**Value**
β	Discount factor	0.9
α	Capital elasticity	1/3
σ	Risk aversion ("bad boom" parameterization)	0.8
$\bar{r^*}$	Steady state r^*	0.08
ν	Matching elasticity	0.3
κ	Cost of posting credit offer	0.5
p_g	Good success probability	0.9
p_b	Bad success probability	0.5
χ	Good entrepreneur measure	0.95
γ	Entrepreneur outside option	0.73
$\bar{\psi}$	Intermediation cost	0.65
ϕ	Land utility	0.1
σ	Risk aversion ("good boom" parameterization)	0.85

Notes: This table shows the parameters used to produce the simulated credit booms, impulse responses, and welfare calculations. The "good boom" parameterization of σ is used to produce the dashed green lines in Figure 1.

Figure A6: Impulse Responses to Productivity and Interest Rate Shocks



(a) Impulse Response to Productivity Shock



(b) Impulse Response to Interest Rate Shock

Impulse responses to a one-time positive productivity shock (panel a) and a one-time fall in the international interest rate (panel b) for the parameterized model (see Table A8). Each panel traces percentage deviations from steady state over 50 periods for the lending rate r, credit market tightness, the number of active credit lines, and collateral per credit line. Solid red lines plot the competitive-equilibrium response; dashed blue lines plot the constrained first-best response.

Table A9: Impact of Credit Booms on Collateral Requirements by Firm Productivity

Dependent variable:	*Collateral required (log)*	
	(1)	(2)
		Exc Construction
Low-Prod × $D_{Year=2000}$	0.00409	0.00650
	(0.00959)	(0.0108)
Low-Prod × $D_{Year=2001}$	0.0102	0.00887
	(0.00942)	(0.00823)
Low-Prod × $D_{Year=2003}$	0.000238	-0.00476
	(0.00929)	(0.00915)
Low-Prod × $D_{Year=2004}$	-0.0228**	-0.0261**
	(0.0107)	(0.0129)
Low-Prod × $D_{Year=2005}$	-0.0339***	-0.0420***
	(0.0127)	(0.0137)
Low-Prod × $D_{Year=2006}$	-0.0316**	-0.0410***
	(0.0121)	(0.0141)
Low-Prod × $D_{Year=2007}$	-0.0338**	-0.0453***
	(0.0136)	(0.0149)
Firm FE	Yes	Yes
Industry-Time FE	Yes	Yes
Observations	458601	373456
R-squared	0.708	0.694

Notes: This table reports OLS estimates of the following model:

$$\ln \frac{\text{Collateral}_{ist}}{\text{Bank Credit}_{ist}} = \sum_{2000}^{2007} \beta_t \text{Low-Prod}_i \times D_{\text{Year}=t} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{46}$$

where i stands for firm i working sector s at time t. The dependent variable in this analysis is the Collateral Requirement at the firm level, defined as the ratio of Collateral to Bank Credit. Collateral refers to the Tangible Fixed Assets as recorded in the Orbis database, while Bank Credit is the total of both Long- and Short-Term Financial Debt, as recorded in Orbis. The variable `Low-Prod` is a dummy variable that takes a value of 1 if the firm's productivity in 2002 is below the median productivity of its respective sector in 2002. Labor productivity is calculated as Value Added divided by the Number of Employees. Additionally, $D_{\text{Year}=t}$ is a set of time-specific dummy variables that take the value of 1 for years $t = \{2000, \ldots, 2007\}$, with 2002 being the reference year. Standard errors are presented in parentheses below the coefficient estimates. Robust standard errors are clustered at the industry level.
****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*

Table A10: Impact of Credit Boom on Collateral Requirements - full sample robustness

Dependent variable:	*Collateral required (0/1)*				
	(1)	(2)	(3)	(4)	(5) Exc. Construction
$D_{\text{Year}>2002}$		0.0237		0.0565**	
		(0.0159)		(0.0257)	
Low-Prod	0.0362*	0.0357*	0.0724**	0.0727**	0.0628*
	(0.0197)	(0.0194)	(0.0307)	(0.0296)	(0.0336)
Low-Prod × $D_{\text{Year}>2002}$	-0.0586***	-0.0592***	-0.110***	-0.114***	-0.108***
	(0.0222)	(0.0208)	(0.0317)	(0.0301)	(0.0337)
Low-Prod × High-Info × $D_{\text{Year}>2002}$			0.0956**	0.0980**	0.115***
			(0.0402)	(0.0384)	(0.0432)
Firm Controls	No	Yes	No	Yes	Yes
Country-Industry-Time FE	Yes	No	Yes	No	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	9037	9076	9037	9076	8080
R2	0.130	0.0981	0.132	0.0988	0.138

Notes: This table reports OLS estimates from difference-in-differences regressions evaluating the change in collateral requirements during credit booms. The dependent variable is an indicator of whether collateral was required for the firm's most recent loan. $D_{Year>2002}$ indicates the period after 2002. *Low-Prod* is an indicator equal to one if the firm's labor productivity (sales per employee) is below the median. *High-Info* is an indicator equal to one if the firm's accounts are externally audited. Columns (3) and (4) split the sample into countries experiencing bad and good credit booms, respectively. Firm controls (employment indicator, industry, size of city where firm is based, firm's legal status) are included but not reported. Robust standard errors are clustered at the country-industry level.
****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*

C.1 Robustness Check: Leave-one-out and add-one-in checks on bad boom classification

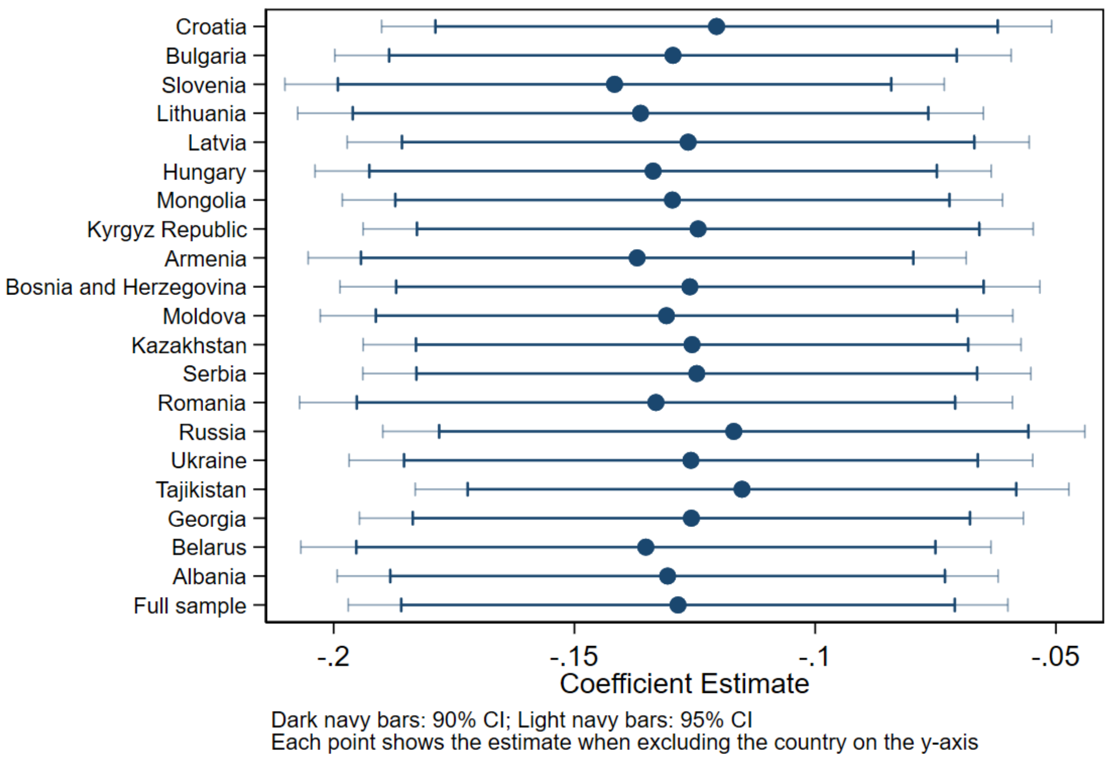


Figure A7: Leave-one-out sensitivity analysis for collateralization treatment effect in bad boom countries. Each point shows the estimated coefficient on the Low-Prod $\times D_{\text{Year}>2002}$ interaction from equation 22, after excluding the specified country from the sample. The regression uses collateral requirements as the dependent variable with country-industry-year fixed effects and clustering at the country-industry level. The baseline specification (top row) includes all bad boom countries. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals.

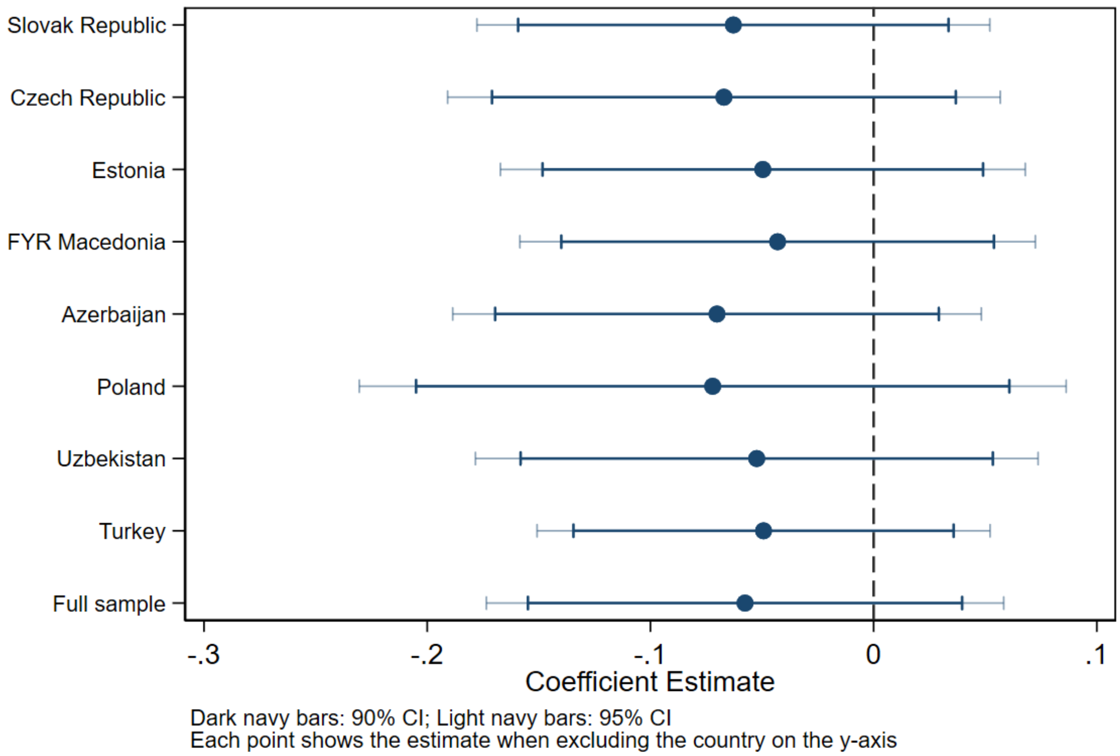


Figure A8: Leave-one-out sensitivity analysis for collateralization treatment effect in good boom countries. Each point shows the estimated coefficient on the Low-Prod $\times$ $D_{\text{Year}>2002}$ interaction from equation 22, after excluding the specified country from the sample. The regression uses collateral requirements as the dependent variable with country-industry-year fixed effects and clustering at the country-industry level. The baseline specification (top row) includes all good boom countries. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals.

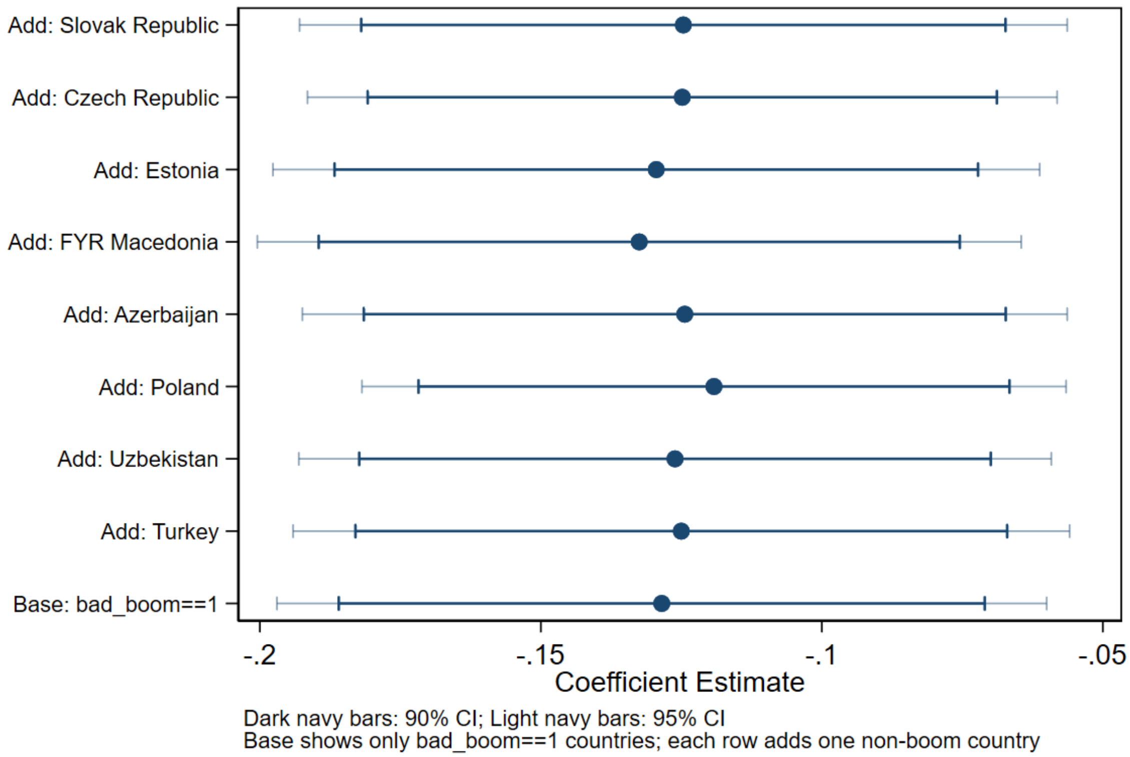


Figure A9: Add-one-in sensitivity analysis for collateralization treatment effect starting with bad boom countries. Each point shows the estimated coefficient on the Low-Prod $\times$ $D_{\text{Year}>2002}$ interaction from equation 22, where the baseline (top row) uses only bad boom countries and each subsequent row adds one non-boom country to the sample. The regression uses collateral requirements as the dependent variable with country-industry-year fixed effects and clustering at the country-industry level. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals. This illustrates how the differential treatment effect on collateralization changes as individual non-boom countries are incorporated.

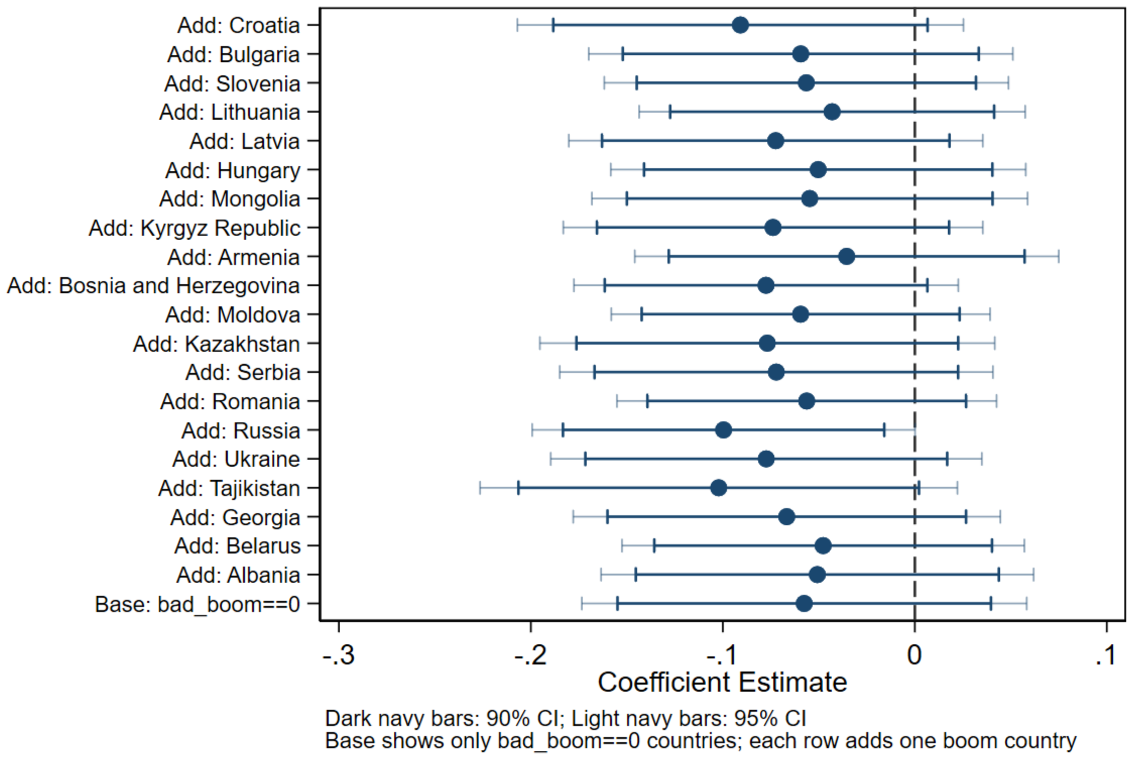


Figure A10: Add-one-in sensitivity analysis for collateralization treatment effect starting with good boom countries. Each point shows the estimated coefficient on the Low-Prod $\times$ $D_{\text{Year}>2002}$ interaction from equation 22, where the baseline (top row) uses only good boom countries and each subsequent row adds one boom country to the sample. The regression uses collateral requirements as the dependent variable with country-industry-year fixed effects and clustering at the country-industry level. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals. This illustrates how the differential treatment effect on collateralization changes as individual boom countries are incorporated.

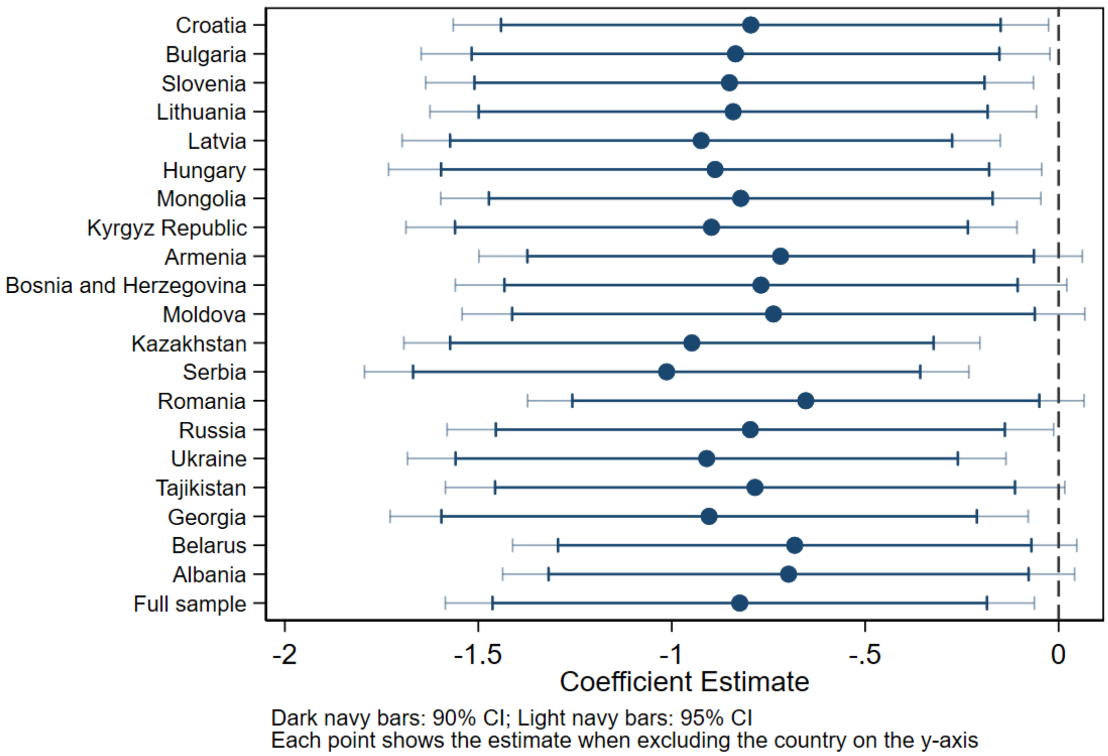


Figure A11: Leave-one-out sensitivity analysis for collateral scarcity treatment effect in bad boom countries. Each point shows the estimated coefficient on the High-Prod $\times$ $D_{\text{Year}>2002}$ interaction from equation 24, after excluding the specified country from the sample. The regression uses ln(Assets/Sales) as the dependent variable with country fixed effects and clustering at the country level. The baseline specification (top row) includes all bad boom countries. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals.

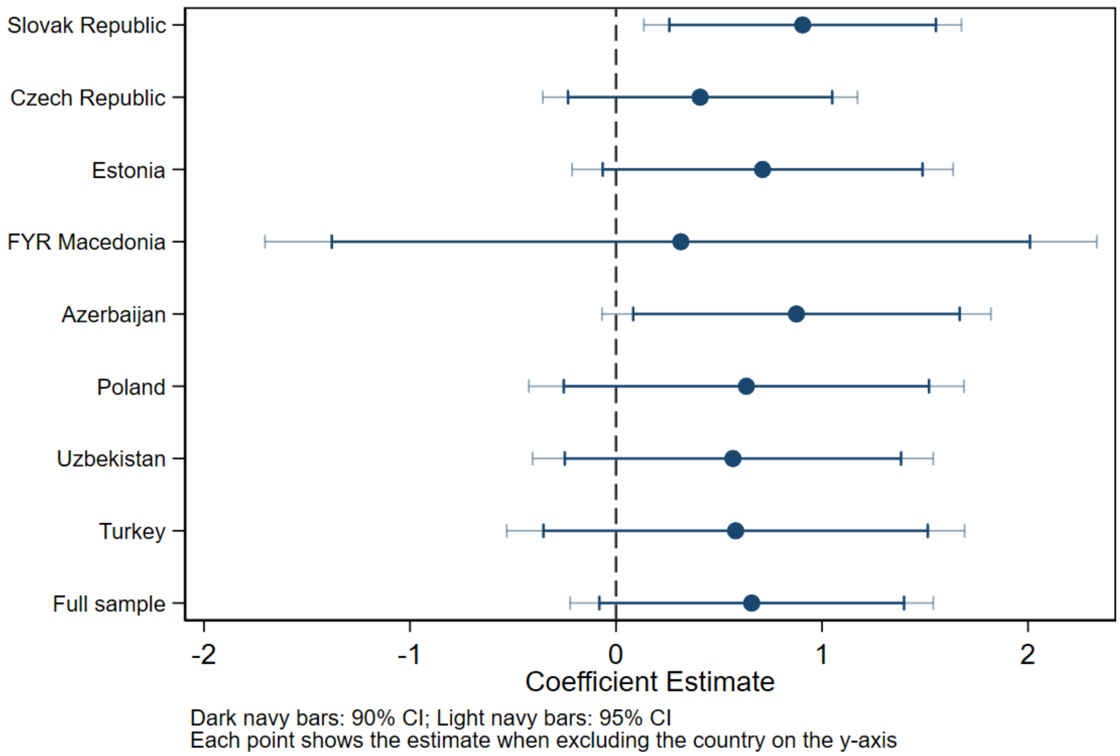


Figure A12: Leave-one-out sensitivity analysis for collateral scarcity treatment effect in good boom countries. Each point shows the estimated coefficient on the High-Prod $\times$ $D_{\text{Year}>2002}$ interaction from equation 24, after excluding the specified country from the sample. The regression uses ln(Assets/Sales) as the dependent variable with country fixed effects and clustering at the country level. The baseline specification (top row) includes all good boom countries. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals.

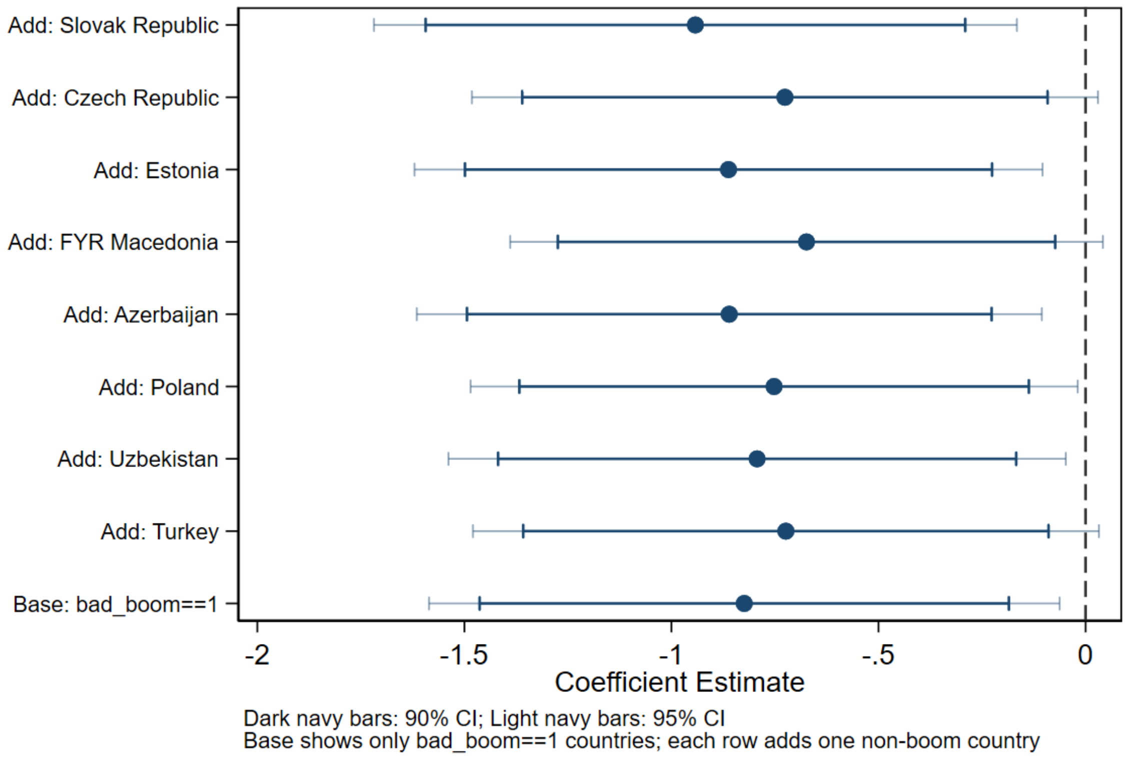


Figure A13: Add-one-in sensitivity analysis for collateral scarcity treatment effect starting with bad boom countries. Each point shows the estimated coefficient on the High-Prod × $D_{\text{Year}>2002}$ interaction from equation 24, where the baseline (top row) uses only bad boom countries and each subsequent row adds one non-boom country to the sample. The regression uses ln(Assets/Sales) as the dependent variable with country fixed effects and clustering at the country level. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals. This illustrates how the differential treatment effect on collateral scarcity changes as individual good-boom countries are incorporated.

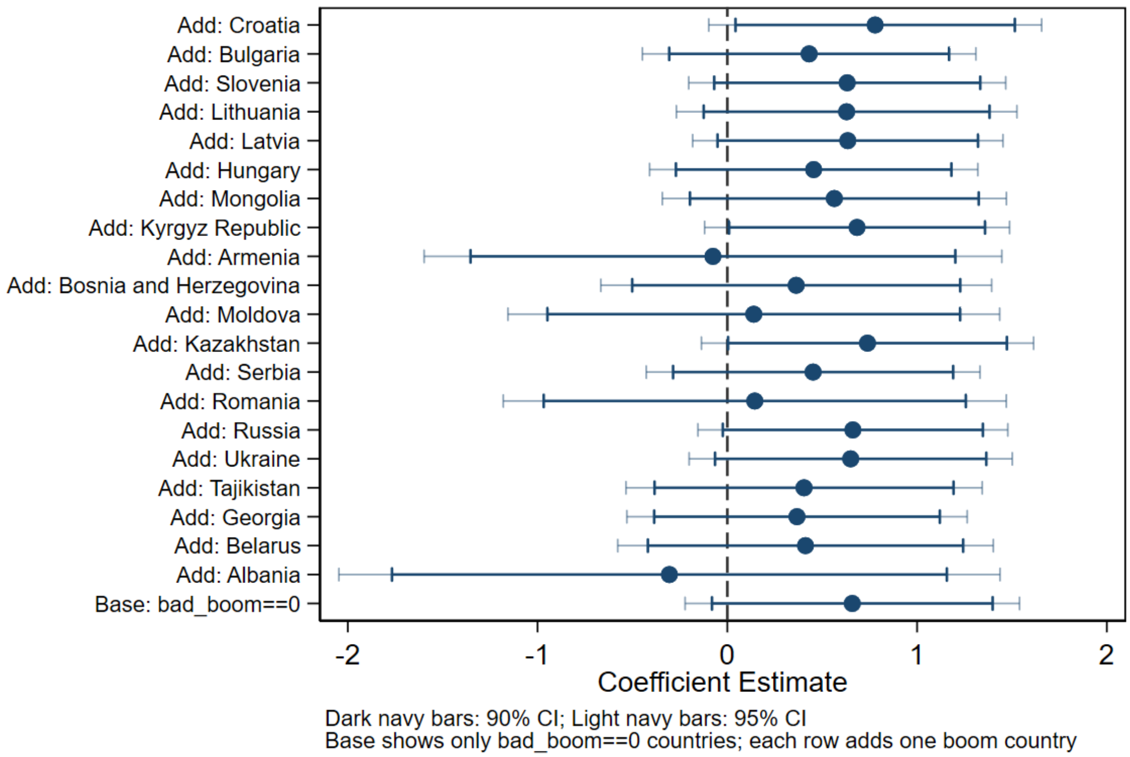


Figure A14: Add-one-in sensitivity analysis for collateral scarcity treatment effect starting with good boom countries. Each point shows the estimated coefficient on the High-Prod $\times$ $D_{\text{Year}>2002}$ interaction from equation 24, where the baseline (top row) uses only good boom countries and each subsequent row adds one non-boom country to the sample. The regression uses ln(Assets/Sales) as the dependent variable with country fixed effects and clustering at the country level. Dark navy bars represent 90% confidence intervals, while light navy bars show 95% confidence intervals. This illustrates how the differential treatment effect on collateral scarcity changes as individual bad-boom countries are incorporated.

C.2 Robustness Check: Extended Pre-Treatment Period in BEEPS survey

In this section, we present a robustness check that incorporates an additional pretreatment and post-treatment year using the 1999 and 2012 BEEPS waves. This extension allows us to check the robustness of the effect on low-productivity firms that we present in the main empirical results.

The 1999 BEEPS data presents measurement challenges: unlike later survey waves, it reports employment and sales only in categorical form. We construct a proxy measure of labor productivity by dividing categorical sales by categorical employment values, acknowledging the inherent noise in this approximation. Following consistent methodology across survey years, we classify firms as low-productivity if they fall below the country-industry-year median.

On the left-hand side, we construct a measure of ease of access to finance based on a survey question in BEEPS that has been asked consistently across waves. Specifically, we employ a binary indicator derived from responses to questions about obstacles to obtaining finance. We code responses of "no obstacle" and "minor obstacle" as 0, while "moderate obstacle" and above are coded as 1, providing a consistent measure of perceived financing constraints across survey waves. We estimate the following linear probability model using OLS:

$$\text{Financial Access}_{isct} = \beta \text{Low-Prod}_{isct} \times D_{\text{Year}>2002} + \delta_{sc} + \gamma' X_{isc} + \varepsilon_{isct}. \tag{47}$$

where i indexes firm, s indexes sector, c indexes country, and t indexes time. The treatment period is defined as years after 2002, X_{isc} includes controls for firm size, location, and audit status (the same controls as in the BEEPS firm-level regression in the text), and δ_{sc} represents industry-country fixed effects. We estimate this model separately for countries experiencing "bad booms" versus "good booms" to examine heterogeneous effects across these distinct credit expansion environments.

Table A11 shows the results of estimating Equation 47. In both bad and good boom countries, we observe a significant overall decrease in the financial access variable after 2002, indicating a relaxation of credit standards for high-productivity borrowers which is larger in good boom countries. However, the interaction term shows a clear divergence in outcomes for low-productivity firms. In bad boom countries (Column 1), low-productivity firms experienced no differential change in their access to finance relative to high-productivity firms, as evidenced by the near-zero and statistically insignificant coefficient (0.0006). By contrast, in good boom countries (Column 2), low-productivity firms saw a relative increase in the difficulty of accessing finance, with a positive coefficient of 0.0842 that is significant at the 1% level. Consistent with the findings in the main text, credit standards are relaxed relatively more for low-productivity borrowers in the bad boom countries.

Table A11: Impact of Credit Boom on Financial Access

Dependent variable:	*Financial Access (0/1)*	
	(1) Bad Boom	(2) Good Boom
$D_{\text{Year}>2002}$	-0.203***	-0.286***
	(0.0187)	(0.0244)
Low-Prod $\times$ $D_{\text{Year}>2002}$	0.000565	0.0842***
	(0.0162)	(0.0297)
Controls	Yes	Yes
Country-Industry FE	Yes	Yes
Observations	22154	8620
R2	0.0560	0.129

Notes: This table reports OLS estimates from difference-in-differences regressions evaluating the change in financial access during credit booms. $D_{Year>2002}$ is a dummy equal to 1 for years after 2002. *Low-Prod* is an indicator equal to 1 if the firm has below-median labor productivity (sales per employee) within its country-industry-year group. The interaction *Low-Prod* $\times$ $D_{Year>2002}$ captures the differential change in reported financial access obstacles for low-productivity firms after 2002. Column (1) reports results for countries classified as experiencing bad credit booms, while Column (2) shows results for good boom countries. All regressions include country-industry fixed effects and controls for firm size, location, and audit status. Standard errors are clustered at the country-industry level.
****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*