Collateral Scarcity and Bad Credit Booms*

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Abstract

What distinguishes good credit booms from bad ones? We propose a new mechanism: collateral scarcity. When shocks raise investment demand but collateral values fail to keep pace, banks can no longer screen borrowers effectively using collateral. Banks optimally respond by relaxing lending standards, funding negative-NPV projects to sustain lending to positive-NPV ones. This is a bad credit boom. We show that bad booms are constrained inefficient because banks do not internalize the equilibrium effects on collateral supply of forming new credit relationships. Optimal policy dampens credit growth during booms and captures one-fifth of the welfare gains from eliminating asymmetric information. We find support for the theoretical prediction that collateral requirements fall disproportionately for low-productivity borrowers during bad booms in firm-level data. Exploiting regional variation in house prices, we find that this effect is stronger where collateral supply is less responsive, distinguishing our mechanism from theories based on collateral supply.

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1 Introduction

Credit booms are a recurrent feature of economic history. While many credit expansions coincide with periods of robust growth and rising productivity, others culminate in severe financial distress and deep recessions. Ex post, the distinction between "good" and "bad" credit booms is stark: the average cumulative output loss associated with a systemic banking crisis is close to 20% over roughly two years (Laeven and Valencia, 2020). Ex ante, however, this distinction is elusive, and policymakers learn whether a boom was harmful only once the costs have materialized.

This paper proposes a new explanation for why some credit booms turn bad. We argue that credit booms become inefficient when collateral becomes scarce relative to the investment demand of productive firms, weakening banks' ability to screen borrowers using collateral.

Our theory combines asymmetric information about borrower quality with a frictional credit market in which banks use collateral to screen borrowers. The key insight is that favorable aggregate shocks increase the desired investment scale of productive firms and therefore their demand for collateral. If aggregate collateral value does not rise proportionally, separating contracts that exclude bad borrowers become too costly for banks to sustain. Banks respond by offering low-collateral contracts that attract low-quality borrowers, relaxing incentive-compatibility constraints and thereby expanding lending to good borrowers. This cross-subsidization of low-quality borrowers is sustained in equilibrium because banks maximize the present value of a credit relationship with an unknown-quality borrower.

We characterize efficiency by comparing the decentralized equilibrium with that of a constrained planner who faces the same informational and contractual frictions as private agents. The equilibrium is constrained-inefficient because banks do not internalize that expanding credit dilutes the collateral available per relationship and affects collateral prices. A planner who internalizes these externalities optimally dampens credit expansion during booms. In a calibrated model, correcting this inefficiency delivers roughly one-fifth of the gains from eliminating asymmetric information altogether, suggesting substantial scope for policy.

Our mechanism is distinct from existing theories. Models emphasizing collateral value as an amplifier of shocks (Kiyotaki and Moore, 1997; Bernanke et al., 1999) take credit standards as given; models linking collateral to information production (Gorton and Ordoñez, 2014; Asriyan et al., 2021) emphasize that collateral abundance depletes incentives to produce information. In our theory, bad booms arise not because collateral is abundant, but because it is insufficiently responsive to increases in productive capacity.

The model delivers two testable predictions. First, during bad booms, collateral requirements fall disproportionately for low-quality borrowers. Second, bad booms are characterized by collateral scarcity, a decline in the aggregate value of collateral relative to economic activity.

We test these predictions using firm-level data from two complementary settings around the global credit expansion preceding the Global Financial Crisis. First, using Spanish ORBIS firm-level data, we show that collateral ratios declined disproportionately for low-productivity firms in the boom years preceding the crisis. A further empirical challenge is distinguishing our mechanism from theories in which collateral abundance reduces information production and leads to lower lending standards for low-quality borrowers. Regional variation in Spanish house prices provides a test. We find that the relaxation of standards for low-productivity firms was more pronounced in regions with below-average house price growth, consistent with collateral scarcity, rather than abundance, driving the pattern.

Second, we exploit three features of cross-country firm-level survey data from Central and Eastern Europe and Central Asia to broaden the empirical analysis. The survey includes a proxy for information transparency, and we find that collateral requirements fell disproportionately for low-productivity, low-information firms. The countries in our sample all experienced credit booms, but with divergent outcomes; we find that collateral requirements fell for low-quality borrowers during bad booms but not during good ones. Finally, the survey reports estimated market values of collateral assets rather than book values, information we can use to more directly examine the scarcity channel. Collateral values relative to economic activity declined during bad booms, particularly for high-productivity firms.

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), Greenwood and Hanson (2013), 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 such as Jimenez et al. (2006), Berger et al. (2011), and Ioannidou et al. (2022) that study how the role of collateral in alleviating asymmetric information in credit markets changes in response to aggregate fluctuations and shocks.

Second, we contribute to theoretical work on endogenous credit standards under asymmetric information, including Dell'Ariccia and Marquez (2006), Martin (2008), Gorton and Ordoñez (2014), Hu (2022), Figueroa and Leukhina (2018), Gorton and Ordoñez (2019), Ordoñez et al. (2019), Ozdenoren et al. (2023), Farboodi and Kondor (2023), and Fishman et al. (2024).

Our closest antecedent is Asriyan et al. (2021), who show that collateral *abundance* can cause bad booms by depleting incentives to produce information. We show that collateral *scarcity* can cause bad booms by eroding screening. The two mechanisms are complementary and may operate jointly in practice. Asymmetric information persists even in settings with efficient information technology and public credit registries (Albertazzi et al., 2025), and may be particularly severe during booms, due to the counter-cyclicality of information production (Weitzner and Howes, 2025).

More broadly, our model is related to studies 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 at a given level of credit standards, as summarized by the collateral constraint parameter related to moral hazard friction in credit markets. In our model, credit contracts depend on the aggregate state of the economy, and the total value of collateral determines lending 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 represents a small open economy populated by entrepreneurs and bankers that interact in a frictional credit market. We introduce two aggregate shocks into the model: productivity shocks and shocks to the international interest rate. This focus is motivated by the empirical literature, which identifies these as key precursors of credit booms (Mendoza and Terrones, 2008; Gorton and Ordoñez, 2019), and by theoretical work examining their role in driving credit cycles (Bernanke et al., 1999; Mendoza, 2010).

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, which is the numeraire. Each entrepreneur i can produce the quantity y_{it} in time t using the following technology:

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

Entrepreneurs have access to a decreasing-returns-to-scale technology in capital k_{it}, with a capital-output elasticity $0 < \alpha < 1$. The technology produces a positive amount only when the project is successful, which happens with probability p_{it} at 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 in any given year t. A good entrepreneur has a productivity level A_{gt} and a constant success probability p_g, and a bad one has productivity and 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 following AR(1) process in logs,

$$\log(A_t) = \rho \log(A_{t-1}) + \sigma_a \varepsilon_{at}, \quad \varepsilon_{at} \sim N(0,1), \tag{2}$$

with $\rho \in (0,1)$. 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 require an active credit line to finance production each 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 ($1 - N_t$).

In the numerical simulations, we assume a constant returns to scale credit market matching function given by

$$M(F_t, 1 - N_t) = \bar{m} F_t^{\nu} (1 - N_t)^{1-\nu}, \tag{3}$$

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 $\lambda^f(\theta_t) = \bar{m}\theta_t^{\nu-1}$.

Search frictions serve two purposes in our analysis. First, the gradual formation and dis-

solution of credit relationships provides a natural propagation mechanism for aggregate shocks. Second, the search framework embeds a bargaining problem between bankers and entrepreneurs that permits cross-subsidization across contract types in equilibrium.

Once an entrepreneur and a banker meet, they must agree on a credit contract for their 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 that specifies the loan amount, interest rate, and collateral required. We assume there is a non-perishable good, called land, ℓ_t, that trades at a price q_t and serves as a savings vehicle and collateral asset.

We assume perfect consumption insurance within the family of entrepreneurs. A representative family makes the consumption-saving decision, and every entrepreneur consumes the same amount. The family saves in land ℓ_t, which is distributed within the 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 selected contract requires pledging collateral, the entrepreneur requests the necessary land from the household. The household distributes the total collateral value $q_t\ell_t$ among the entrepreneurs who request it.[1] The family's utility maximization problem is given by:

$$\begin{aligned}
\max_{\{C_t,\ell_{t+1}\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{C_t^{1-\sigma}}{1-\sigma} + \phi l_t \right\} \quad \text{s.t.} \\
C_t + q_t\ell_{t+1} = \left[\chi\pi_{gt} + (1-\chi)\pi_{bt}\right] N_t + q_t\ell_t + T_t \\
N_{t+1} = \left[\chi p_g + (1-\chi)p_b\right] N_t + \lambda^e(\theta_t)(1-N_t)
\end{aligned}$$

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 ($q_t\ell_{t+1}$) to the sum of profits from production ($[\chi\pi_{gt} + (1-\chi)\pi_{bt}]\, N_t$), land holdings from the previous period ($q_t\ell_t$) 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 upon project failure. The house-

[1] We assume frictionless reallocation of collateral among entrepreneurs. Introducing reallocation frictions would likely strengthen our results, as collateral misallocation would compound credit misallocation by leaving good entrepreneurs with a smaller share of collateral in equilibrium.

hold first-order conditions give the following Euler equation for the price of land:

$$q_t = \phi C_t^{\sigma} + \mathbb{E}_t \left\{ \Lambda_{t,t+1} q_{t+1} \right\}, \tag{4}$$

where $\Lambda_{t,t+1} \equiv \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\sigma}$ is the household discount factor.

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,

$$V_t = \max \left\{ -\kappa + \lambda^f(\theta_t) \mathbb{E}_t \left\{ \Lambda_{t,t+1} \left[\chi J_{t+1}^g + (1-\chi) J_{t+1}^b \right] \right\}, 0 \right\} \tag{5}$$

A banker can remain idle and receive zero value, as represented by the second term in the max, or 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_{t+1}^g (J_{t+1}^b). 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_t^g or J_t^b depending on the quality of the time-t match. The value function is

$$J_t^i = \Pi_{it} + \mathbb{E}_t \left\{ \Lambda_{t,t+1} \left[p_i \left(\chi J_{t+1}^g + (1-\chi) J_{t+1}^b \right) + (1-p_i) V_{t+1} \right] \right\}, \tag{6}$$

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] Using this free entry condition and the value functions defined in Equations 5 and 6 gives the following expression for market tightness in equilibrium:

$$\frac{\kappa}{\lambda^f(\theta_t)} = \mathbb{E}_t \left\{ \Lambda_{t,t+1} \left[\chi \Pi_{gt+1} + (1-\chi) \Pi_{bt+1} + \frac{\bar{p} \kappa}{\lambda^f(\theta_{t+1})} \right] \right\}, \tag{7}$$

where $\bar{p} \equiv \chi p_g + (1-\chi) p_b$.

[2] Free entry abstracts from bank capital structure and its interaction with risk-taking (Dell'Ariccia et al., 2014). Incorporating bank capital constraints is a natural extension that could generate additional amplification during credit booms.

2.3 Credit Contract

In each period, entrepreneurs and bankers in a credit relationship engage in a one-period credit contract specifying the loan size (k_t), interest rate (r_t^k), and collateral requirement (x_t). Collateral is denominated in units of the numeraire, so that upon acceptance, the entrepreneur pledges land valued at x_t.

Bankers may make take-it-or-leave-it offers to entrepreneurs in the form of a menu of contracts without directly observing borrower type. For analytical convenience, we allow bankers to offer type-contingent contracts indexed by $i \in \{g, b\}$, where g and b denote good and bad entrepreneurs, respectively. This is a notational simplification rather than an equilibrium assumption; bankers are ex ante uninformed about borrower type, and expressing the problem in type-specific terms simplifies the exposition. In equilibrium, the allocation may feature separation or pooling depending on collateral availability. Our focus, however, is on the analysis of separating equilibria, which is the paper's central contribution.

A contract $(k_{i,t}, r_{i,t}^k, x_{i,t})$ yields bankers an expected profit of

$$\Pi_{it} = p_i r_{i,t}^k k_{i,t} + (1 - p_i) x_{i,t} - r_t^* k_{i,t} - \psi(A_t, r_t^*) \mathbb{1}_{\{k_{i,t}>0\}}, \quad i \in \{g, b\}, \tag{8}$$

where the first term represents expected repayment, the second term captures expected collateral recovery in default, and the third term denotes the cost of funds. Bankers obtain external financing at an interest rate r_t^*, which follows the exogenous stochastic process

$$\log(r_t^*) = (1 - \rho) \log(\bar{r}^*) + \rho \log(r_{t-1}^*) + \sigma_r \varepsilon_{rt}, \quad \varepsilon_{rt} \sim N(0, 1), \tag{9}$$

with $\rho \in (0, 1)$ and $\bar{r}^* > 0$. The final term, $\psi(A_t, r_t^*) \mathbb{1}_{\{ki,t>0\}}$, captures a fixed intermediation cost incurred only when lending occurs. This cost depends on aggregate conditions (A_t, r_t^*) and reflects variations in monitoring intensity or the opportunity cost of intermediation.

Entrepreneurs' expected profits under contract $(k_{i,t}, r_{i,t}^k, x_{i,t})$ are given by

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

With probability p_i, the project succeeds, yielding production $A_{it} k_{it}^{\alpha}$ net of interest payments; and, with probability $1 - p_i$, the project fails, and the entrepreneur forfeits the pledged collateral.

Let $\tilde{x}$ denote the entrepreneur's available collateral in equilibrium. The banker chooses the menu of contracts $\{(k_g, r_g^k, x_g), (k_b, r_b^k, x_b)\}$ to maximize expected profit (we omit time

subscripts to save notation):

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

$$\left[p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)x_b\right]\mathbb{1}_{\{k_b>0\}} \geq \left[p_b\left(A_b k_g^\alpha - r_g^k k_g\right) - (1-p_b)x_g\right]\mathbb{1}_{\{k_g>0\}} \tag{10}$$

$$\left[p_g\left(A_g k_g^\alpha - r_g^k k_g\right) - (1-p_g)x_g\right]\mathbb{1}_{\{k_g>0\}} \geq \left[p_g\left(A_g k_b^\alpha - r_b^k k_b\right) - (1-p_g)x_b\right]\mathbb{1}_{\{k_b>0\}} \tag{11}$$

$$\left[p_g\left(A_g k_g^\alpha - r_g^k k_g\right) - (1-p_g)x_g - \gamma\pi_g^*\right]\mathbb{1}_{\{k_g>0\}} \geq 0 \tag{12}$$

$$\left[p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)x_b - \gamma\pi_b^*\right]\mathbb{1}_{\{k_b>0\}} \geq 0 \tag{13}$$

$$\mathbb{1}_{\{k_g>0\}} x_g \geq 0 \qquad \mathbb{1}_{\{k_g>0\}}(x_g - \tilde{x}) \leq 0 \tag{14}$$

$$\mathbb{1}_{\{k_b>0\}} x_b \geq 0 \qquad \mathbb{1}_{\{k_b>0\}}(x_b - \tilde{x}) \leq 0 \tag{15}$$

The incentive-compatibility constraints 10–11 ensure that entrepreneurs of each type prefer the contract intended for them. The participation constraints 12–13 guarantee that accepting the contract yields expected profits at least as high as the outside option. The outside options are given by $\gamma\pi_i^*$, where $\gamma \in (0,1)$ parametrizes entrepreneurs' bargaining power and

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

is the first-best surplus of the entrepreneur under symmetric information. This formulation of the outside option allows us to calibrate γ to eliminate any search-related inefficiency in the non-stochastic steady state, since congestion externalities are not the focus of our analysis.[3] Finally, note that when collateral is below a given threshold, the banker may optimally offer a pooling contract. However, the primary focus of this paper is on the separating equilibria that emerge when collateral requirements are sufficiently high to induce type separation. These equilibria capture the model's central mechanism.

Further, we make the following assumption about the profitability of bad projects:

Assumption 1 (Unprofitable Bad Projects)**.** *Bad projects have a negative expected net present value at the optimal scale, net of the fixed cost of intermediation. Hence, under symmetric information, it is never optimal to fund bad projects:*

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

[3] A possible microfoundation for γ is a two-stage bargaining process in which entrepreneurs can make a counteroffer with probability γ, after which types are revealed with some probability.

which implies that the first-best expected profit for a bad entrepreneur, π_b^*, is zero in every period. To implement this restriction, we assume

$$\psi(A, r^*) = \bar{\psi} \cdot r^* \cdot \left(\frac{A}{r^*}\right)^{\frac{1}{1-\alpha}}$$

and we parameterize $\bar{\psi}$ so the interior positive-scale optimum NPV of a bad project is strictly negative for all relevant (A, r^*), so that $\pi_b^* = 0$ in equilibrium.

We assume bad projects are loss-making for two reasons. First, it guarantees a clear benchmark against which the effects of asymmetric information can be evaluated: in the first-best, only good projects are funded. Second, it provides a precise definition of a *bad credit boom* as an episode in which, despite bad projects having negative NPV, credit standards are relaxed, and such projects receive funding in equilibrium.

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 $\left\{k_{gt}, r_{gt}^k, x_{gt}, k_{bt}, r_{bt}^k, x_{bt}\right\}_{t=0}^{\infty}$ and allocations $\{Y_t, C_t, N_{t+1}, \theta_t, \ell_t\}_{t=0}^{\infty}$, such that:

1. C_t, ℓ_{t+1}, N_{t+1} solve the household's problem every period,
2. $k_{gt}, r_{gt}^k, x_{gt}, k_{bt}, r_{bt}^k, x_{bt}$ is a solution to the contracting problem,
3. market tightness, θ_t, is consistent with the bankers' problem and the free entry condition,
4. markets clear

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

where $\bar{\ell}$ is the fixed land supply.[4]

[4]Note that market clearing in collateral is given by $q_t \bar{\ell} \geq [\chi x_{gt} + (1-\chi) x_{bt}] N_t$, where $q_t \ell$ is the aggregate collateral supply. Collateral may be in "excess supply" in equilibrium in regime 1 when $\tilde{x} > \bar{x}_1$. Collateral market clearing holds with equality whenever $\tilde{x} \leq \bar{x}_1$.

3 The Collateral Scarcity Channel

This section analyzes the core theoretical mechanism of the paper. We first characterize the credit contracts that emerge in equilibrium when bankers use collateral as a screening device. We then show how collateral scarcity can trigger a relaxation of lending standards during credit expansions.

3.1 Equilibrium Credit Contracts

Equilibrium credit contracts depend on the availability of collateral relative to screening needs. When collateral is abundant, banks screen effectively and lend only to good borrowers. As collateral becomes scarce, banks face a choice: ration credit to good borrowers, or relax standards and lend to bad borrowers as well. The following proposition formalizes this trade-off.

Proposition 1 (Equilibrium Credit Contracts)**.** *There exist thresholds $\bar{x}_1$, $\bar{x}_2$, and $\bar{x}_3$, which are functions of parameters and the state vector (A_t, r_t^*, N_t), such that the contract bankers offer satisfies the following (where we are omitting time subscripts),*

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

$$(k_g, r_g^k, x_g) = \left(k_g^*, \left(Ak_g^\alpha - \frac{1-p_g}{p_g}\bar{x}_1 - \frac{\gamma\pi_g^*}{p_g}\right)\frac{1}{k_g}, \bar{x}_1\right),$$

   where $k_g^* \equiv \left(\frac{\alpha p_g A}{r^*}\right)^{\frac{1}{1-\alpha}}$ is the optimal project scale for good entrepreneurs.

2. ***Constrained separation.*** *If $\bar{x}_2 \leq \tilde{x} < \bar{x}_1$, where $\bar{x}_2 = \bar{x}_2(A, r^*, N)$ is the value of collateral that makes bankers indifferent between lending only to good entrepreneurs and lending to both good and bad, only good entrepreneurs get credit but less than the optimal allocation, with*

$$(k_g, r_g^k, x_g) = \left(\left(\frac{\left(\frac{p_g - p_b}{p_g}\right)\tilde{x} - \frac{p_b\gamma\pi_g^*}{p_g}}{p_b\left(\mu-1\right)A}\right)^{\frac{1}{\alpha}}, \left(Ak_g^\alpha - \frac{1-p_g}{p_g}\tilde{x} - \frac{\gamma\pi_g^*}{p_g}\right)\frac{1}{k_g}, \tilde{x}\right).$$

3. ***Relaxed standards (bad boom).*** *If $\bar{x}_3 \leq \tilde{x} < \bar{x}_2$ then bankers relax credit standards*

and good and bad entrepreneurs get credit. The two contracts are,

$$(k_g, r_g^k, x_g) = \left(\left(\frac{[\chi p_g - (1-\chi)(\mu-1)p_b]\,\alpha A}{r^*\chi} \right)^{\frac{1}{1-\alpha}}, \left(A k_g^\alpha - \frac{1-p_g}{p_g}\tilde{x} - \frac{\gamma \pi_g^*}{p_g} \right) \frac{1}{k_g}, \tilde{x} \right)$$

and

$$(k_b, r_b^k, x_b) = \left(\left(\frac{\alpha p_b \mu A}{r^*} \right)^{\frac{1}{1-\alpha}}, \left[p_b \mu A k_b^\alpha - p_b(\mu-1) A k_g^\alpha + \frac{p_g - p_b}{p_g}\tilde{x} - \frac{p_b \gamma \pi_g^*}{p_g} \right] \frac{1}{p_b k_b}, 0 \right),$$

with $\bar{x}_3 = \frac{p_b p_g}{p_g - p_b} \left(A_b - A_g \right) \left(k_g^\alpha - k_b^\alpha \right)$.

If $\tilde{x} < \bar{x}_3$*, there may exist a pooling contract.*

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, $\tilde{x}$, and the thresholds $\bar{x}_1 > \bar{x}_2 > \bar{x}_3$, which in turn are functions of parameters and the state vector (A, r^*, N). In the separating equilibria characterized by Proposition 1, only good entrepreneurs are (optimally) required to post collateral. It follows that collateral available to each good entrepreneur is always $\tilde{x} = \frac{q\bar{\ell}}{\chi N}$, which is the total value of collateral over the number of good entrepreneurs with a credit line.

The first contract achieves the first-best, because collateral is sufficiently abundant that banks can screen out bad borrowers while lending at the efficient scale. The second contract arises when collateral is scarce but not critically so. Banks still exclude bad borrowers, but must distort lending to good borrowers downward. The intuition is that the first-best loan size is too attractive to bad borrowers, and, given limited collateral, the only way to deter mimicking is to shrink the loan. Formally, banks reduce k_g until the bad borrower's incentive constraint binds.

The third contract features lending to bad borrowers despite their negative NPV. Why do profit-maximizing banks do this? Funding bad borrowers relaxes their incentive-compatibility constraint, allowing banks to expand lending to good borrowers for a given collateral stock. Banks cross-subsidize bad projects to extract more surplus from good ones. This is the defining feature of a bad credit boom in our model: credit standards endogenously relax to sustain lending to productive firms when collateral is scarce.

Cross-subsidization arises endogenously in our model because bankers maximize the expected

value of a credit relationship, and free entry pins down the value of an idle banker at zero. This contrasts with models of asymmetric information in loan markets, such as Besanko and Thakor (1987) and Martin (2008), in which zero-profit conditions are imposed contract-by-contract, thereby precluding cross-subsidization. Recent empirical evidence in Faria-e-Castro et al. (2024) and Artavanis et al. (2024) documents cross-subsidization by banks even under symmetric information, suggesting that similar mechanisms are likely to operate in asymmetric-information environments.

3.2 Collateral Scarcity and Bad Credit Booms

Proposition 1 characterizes contracts taking the aggregate state vector as given. We now ask: when do rising productivity or falling interest rates move the economy towards the bad boom regime?

Our focus on productivity and international interest rate shocks is motivated by empirical evidence that they are key precursors of credit booms. Gorton and Ordoñez (2019) document that credit booms are systematically preceded by increases in productivity growth, while Mendoza and Terrones (2008) finds that booms in advanced economies are often triggered by productivity gains or financial liberalization. On the financial side, Bruno and Shin (2014) and Miranda-Agrippino and Rey (2022) show that periods of low interest rates are associated with rapid credit growth and increased risk-taking. Our analysis characterizes the conditions under which favorable realizations of these shocks induce bad credit booms through collateral scarcity.

Proposition 2 (Collateral Scarcity and Bad Booms)**.** *Suppose the economy begins in a state where collateral is sufficient for screening, $\tilde{x}_t \geq \bar{x}_{2,t}$, where $\tilde{x}_t$ is available collateral value per active good entrepreneur, and $\bar{x}_{2,t}$ is the equilibrium collateral threshold derived in Proposition 1. Define the* ***screening gap*** *as $\ln \tilde{x}_t - \ln \bar{x}_{2,t} \geq 0$. The screening gap falls in response to a positive productivity shock ($A_t \uparrow$) or an interest rate cut ($r_t^* \downarrow$) if and only if the elasticity of collateral supply to an increase in the economy's scale is strictly less than that of collateral demand:*

$$\underbrace{\sigma\left[1-\zeta_t\left(\frac{\Omega}{1-\nu}-1\right)\right]}_{\textit{Collateral Supply Elasticity}} < \underbrace{1}_{\textit{Collateral Demand Elasticity}} \tag{16}$$

where σ is the household's coefficient of relative risk aversion, $\zeta_t \equiv \kappa F_t / C_t$ is the equilibrium ratio of aggregate search costs to consumption, $\nu \in (0,1)$ is the elasticity of the matching function, and $\Omega \equiv \frac{\rho(1-\beta\bar{p})}{1-\beta\bar{p}\,\rho}$ is the elasticity of the value of a credit line to the shock.

Proof. See Appendix A. □

The proposition provides a sharp condition under which the economy moves closer to relaxed credit standards in response to shocks. To understand this condition, note that, as we show in the proof of Proposition 2, both collateral demand and the economy's productive capacity scale with a common index $Z_t \equiv A_t^{1/(1-\alpha)}(r_t^*)^{-\alpha/(1-\alpha)}$. On the demand side, higher productivity or lower interest rates raise the optimal investment scale for good entrepreneurs, increasing the collateral threshold $\bar{x}_{2,t}$ with unit elasticity. On the supply side, net output also scales with Z_t, but whether this translates into proportional increases in collateral values depends on how consumption responds to higher output, and how asset prices respond to higher consumption.

The left-hand side of Equation (16) decomposes the elasticity of collateral supply into these two channels. Risk aversion σ governs the response of asset prices to consumption, whereas the term in square brackets governs the response of consumption to productive capacity.

Risk aversion (σ). Collateral is priced through the household's Euler equation (equation (4)), where the land price loads on C_t^{σ}. Higher risk aversion makes marginal utility more sensitive to changes in consumption, so households bid up asset prices more aggressively to smooth consumption when favorable shocks raise output.

The term in square brackets reflects three factors that determine the extent to which an increase in productive capacity translates into higher consumption.

Search intensity (ζ_t). When favorable shocks arrive, bankers increase search effort, diverting resources from consumption. This dampens the consumption response and hence the asset price response. The larger the share $\zeta_t \equiv \kappa F_t / C_t$ of resources devoted to search, the stronger this dampening.

Matching elasticity (ν). A higher ν means search effort is more responsive to the value of credit relationships, amplifying the dampening effect described above.

Shock persistence (Ω). More persistent shocks imply a larger increase in the expected future value of a match, strengthening search incentives and therefore the crowding-out of consumption. At the extremes, purely transitory shocks ($\rho = 0$) have no effect on vacancy posting (as expected future profits are unchanged), whereas permanent shocks ($\rho = 1$) maximize the valuation effect ($\Omega = 1$), generating the strongest displacement of collateral.

Three remarks on the scope of Proposition 2 are in order. First, the condition is necessary but not sufficient for a bad boom to arise in response to shocks that increase productive capacity.

If the economy begins in a state where collateral is sufficiently abundant ($\tilde{x}_t >> \bar{x}_{2,t}$), favorable shocks may shrink the screening gap without pushing the economy into the relaxed-standards regime. The proposition characterizes when the gap narrows, not when it closes entirely.

Second, we focus on the link between favorable shocks, a relaxation of lending standards, and bad booms because this appears as the empirically relevant case. In addition to evidence on positive shocks as precursors of bad booms, a wealth of evidence suggests that standards relax pro-cyclically during expansions (Asea and Blomberg, 1998; Jimenez et al., 2006; Dell'Ariccia et al., 2012). When the inequality in (16) is reversed, the model can generate relaxation of credit standards in response to adverse shocks. This is a theoretically interesting case, but one we do not focus on given the weight of evidence for pro-cyclicality.

Third, when search frictions are negligible ($\zeta_t \approx 0$), the condition simplifies to $\sigma < 1$. This knife-edge dependence on risk aversion is an artifact of the baseline specification; introducing fixed costs of intermediation that do not scale one-for-one with economic scale or more flexible preferences over land would break the link without altering the core mechanism. We do not pursue these extensions as they complicate the exposition without adding insight.

3.3 Credit Boom Simulations

Proposition 2 establishes a local sufficient condition for a bad boom, capturing the first-order response to shocks while holding the number of credit lines fixed. To study global dynamics and shock propagation, we turn to numerical simulations.

We parameterize the model (see Appendix B for details) to generate credit booms with and without endogenous changes in lending standards. In the baseline ("bad boom") calibration, $\sigma = 0.4$ implies an insufficient asset price response, per Proposition 2. The alternative ("good boom") calibration ($\sigma = 1.01$) generates a sufficiently large collateral supply response to prevent the economy from entering the bad-boom region in response to positive shocks.[5]. We simulate the model for 10,000 periods, feeding in the same sequences of uncorrelated productivity and interest rate shocks into the good and bad boom simulations. We identify credit booms following Mendoza and Terrones (2008) as episodes where HP-detrended log credit exceeds 1.65 standard deviations above trend. We then construct event windows showing average dynamics seven years before and after boom peaks.

Figure 1 displays average dynamics around simulated credit booms. The top row shows that

[5]The collateral supply and demand responses to shocks are approximately equal when $\sigma = 1.01$, which also rules out the seemingly counterfactual case in which negative shocks lead to relaxed lending standards.

booms coincide with rapid increases in GDP, consumption, and credit, driven by favorable productivity and interest rate shocks, consistent with empirical evidence.

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; 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 and D) 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 examine in the empirical analysis of Section 5.

The dashed green lines show the alternative "good boom" parameterization. With higher risk aversion, collateral prices rise sufficiently to sustain screening, and the economy remains in the first-best separation regime throughout. The comparison is revealing: consumption is higher in the "good boom" parametrization (panel B), but GDP and credit expand less in good booms (panels A, C), and there is no lending to bad borrowers (panel D). The additional output in bad booms reflects lending to negative-NPV projects, an activity that, in aggregate, destroys value.

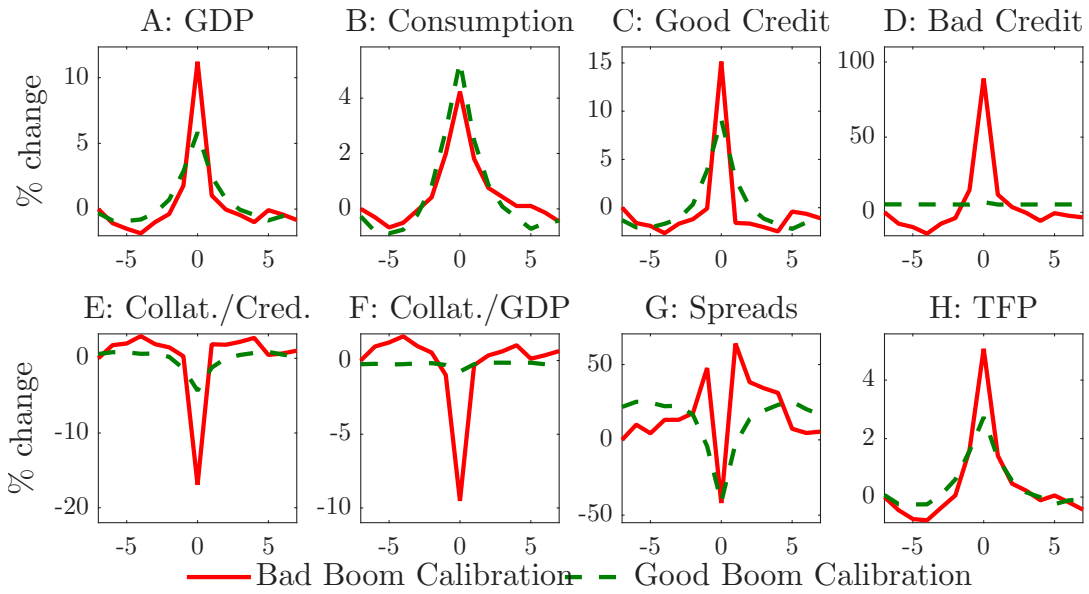
Credit spreads (panel G) decline in good and bad booms, consistent with the evidence of Krishnamurthy and Muir (2025), who find that spreads alone do not predict crisis outcomes; what matters is the combination of spread compression and rapid credit growth. Finally, TFP dynamics (panel H) in our simulations share features with those documented by Gorton and Ordoñez (2019): productivity rises and declines sharply in bad booms, and this pattern is less evident in good booms.

4 Constrained Efficiency and Optimal Policy

Proposition 2 characterized the conditions under which favorable shocks push the economy into the bad boom regime, and the numerical simulation shows that the model can generate dynamics consistent with the stylized facts highlighted by the literature on credit booms and with the empirical evidence presented in Section 5. We now ask: are these dynamics efficient, or is there scope for welfare-improving policy?

The answer hinges on a key observation. The economy enters the bad boom regime when collateral per good entrepreneur, $\tilde{x}_t = q_t\bar{\ell}/(\chi N_t)$, falls below the threshold $\bar{x}_{2,t}$. This can happen for two reasons: collateral prices q_t fail to rise sufficiently (the supply channel in Proposition 2), or the number of credit lines N_t rises too much. In equilibrium, both channels

Figure 1: Model Credit Booms - Bad and Good Booms



This figure shows the dynamics around model-simulated credit booms (see text for details). Solid red lines show the baseline parameterization that produces "bad" booms; dashed green lines show the alternative parametrization that produces "good" booms (see Table A5).

operate. Banks respond to favorable shocks by expending resources to create new credit lines, which lowers consumption and asset prices, and dilutes collateral per relationship. Individual banks do not internalize these effects. This is the source of inefficiency we now formalize.

To characterize these externalities, we compare the decentralized equilibrium with a constrained planner who maximizes household utility, taking as given how credit contracts and prices are determined. Formally, the planner's problem is:

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

$$C_t^* = \Psi_t N_t^* - \kappa F_t^* \tag{17}$$

$$N_{t+1}^* = \left[\chi p_g + (1-\chi) p_b\right] N_t^* + \bar{m} \left(F_t^*\right)^{\nu} \left(1 - N_t^*\right)^{1-\nu} \tag{18}$$

$$q_t = \phi \left(C_t^*\right)^{\sigma} + \mathbb{E}_t \left\{ \beta \left(\frac{C_{t+1}^*}{C_t^*} \right)^{-\sigma} q_{t+1} \right\} \tag{19}$$

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

which depends on both exogenous states and on collateral per good entrepreneur, $\tilde{x}_t = q_t \bar{\ell} / (\chi N_t^*)$.

A key property is that $\Psi_t' \equiv \partial \Psi_t / \partial \tilde{x}_t \geq 0$, with strict inequality when the economy is away from the first-best allocation. When collateral is abundant and banks offer first-best contracts (case 1 of Proposition 1), additional collateral has no marginal value, so $\Psi_t' = 0$. But when collateral scarcity binds and banks distort lending or relax standards (cases 2 and 3), more collateral improves screening and raises surplus, so $\Psi_t' > 0$. This property is central to understanding when optimal policy is active.

The planner chooses search intensity F_t^* and thereby the evolution of credit relationships N_{t+1}^*, subject to constraints (17)–(19). The first-order conditions yield:

$$\frac{\kappa}{\lambda^f(\theta_t^*)} = \mathbb{E}_t \left\{ \Lambda_{t,t+1} \underbrace{\frac{1 - \Psi_t' q_t' \bar{\ell}/\chi}{1 - \Psi_{t+1}' q_{t+1}' \bar{\ell}/\chi}}_{\substack{\text{Pecuniary} \\ \text{externality}}} \left[\underbrace{\nu \Psi_{t+1} - (1-\nu)\kappa \theta_{t+1}^*}_{\text{Search externality}} - \underbrace{\nu \Psi_{t+1}' \frac{q_{t+1} \bar{\ell}}{\chi N_{t+1}}}_{\substack{\text{Collateral} \\ \text{dilution}}} + \frac{\bar{p}\kappa}{\lambda^f(\theta_{t+1}^*)} \right] \right\}, \tag{20}$$

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

Equation (20) differs from the Equation (7) in three ways, each reflecting a distinct source of inefficiency.

Search externality. In equilibrium, bankers value a match at their own expected profit, $\chi \Pi_{gt+1} + (1-\chi)\Pi_{bt+1}$. The planner values it at the social return, $\nu \Psi_{t+1} - (1-\nu)\kappa\theta_{t+1}^*$, which accounts for both the total surplus generated and the congestion that search imposes on other searchers.[6]

Pecuniary externality. The planner's stochastic discount factor differs from the household's because search decisions affect collateral prices, which in turn affect surplus when the economy is away from first-best. The current-period effect works as follows. Increasing search intensity today diverts resources from consumption, thereby lowering C_t and, hence, the collateral price q_t. When $\Psi_t' > 0$, this price decline reduces the surplus generated in credit relationships. The planner internalizes this cost; individual banks do not. The future effect operates in the opposite direction. More credit relationships today mean higher future consumption, raising future collateral prices. When $\Psi_{t+1}' > 0$, this benefits future surplus. In principle, these effects have opposing signs. However, the current effect tends to dominate quantitatively. The reason is mean reversion: because shocks are stationary, there exist fu-

[6] Since credit market search frictions are not our main focus, in the numerical simulations we parametrize the outside option parameter γ such that the search externality vanishes in the steady state.

ture states where the economy returns to first-best and $\Psi'_{t+1} = 0$. This reduces the expected value of the future benefit. The net effect is that the pecuniary externality leads the planner to dampen credit expansion during booms.

Collateral dilution. The term $-\nu\Psi'_{t+1}q_{t+1}\bar{\ell}/(\chi N_{t+1})$ appears in the planner's condition but not in decentralized equilibrium. It captures the fact that creating a new credit line dilutes collateral across all relationships. Collateral per good entrepreneur is $q_t\bar{\ell}/(\chi N_t)$. When a bank creates a new credit line, it increases N_{t+1}, reducing collateral per relationship for everyone. If the economy is away from first-best ($\Psi'_{t+1} > 0$), this dilution reduces aggregate surplus. Individual banks, taking aggregate N_t as given, ignore this effect. The planner internalizes it and therefore creates fewer credit lines during booms than the decentralized equilibrium. Online Appendix Figure OA.1 shows numerically the response of credit lines to interest rate and productivity shocks in the decentralized and planning solutions; in response to both shocks, the planner dampens the response of new credit lines.

The three externalities all point in the same direction during booms: the planner optimally dampens credit expansion relative to laissez-faire. Importantly, this intervention is state-contingent. When collateral is abundant, and the economy is at first-best ($\Psi'_t = 0$), the planner's solution coincides with the competitive equilibrium. Policy is active only when collateral scarcity binds, and screening is impaired.

4.1 Welfare and Implementation

We quantify the welfare gains from optimal policy by simulating the calibrated model (see Appendix B) for 10,000 periods and computing consumption-equivalent welfare. Moving from the competitive equilibrium to the constrained optimum yields a welfare gain of 0.4% of consumption. To benchmark this gain, we compute the welfare gain from eliminating asymmetric information entirely while retaining search frictions, which amounts to 2.3% of consumption. The optimal policy, therefore, captures roughly one-fifth of the gains available from resolving the underlying informational friction.

Appendix OA.4 shows that the optimal policy can be approximately decentralized through a simple macro-prudential instrument, a state-contingent tax on credit line issuance. We consider a tax $\tau_t = \tau_0 \max\{\theta_t - \theta_{ss}, 0\}$ that activates only when market tightness exceeds its steady-state level. With $\tau_0 \approx 0.5$, this policy captures nearly 90% of the welfare gains from the fully optimal policy. The simplicity of this implementation suggests that substantial welfare improvements are achievable without requiring the planner to observe or respond to collateral scarcity directly.

5 Empirical Evidence

The model delivers two testable predictions that distinguish bad credit booms from good ones. First, collateral requirements should fall disproportionately for low-productivity borrowers during bad booms. In the model, banks relax standards for bad borrowers to sustain lending to good borrowers when collateral is scarce; in the data, we identify "bad" firms as those below the median productivity within their sector. Second, bad booms should feature collateral scarcity, a decline in the aggregate value of collateral relative to economic activity.

We test these predictions using the global credit shock that preceded the 2008 financial crisis as our source of variation in two different settings: Spain and a sample of Central and Eastern European and Central Asian countries. Following the evidence in Miranda-Agrippino and Rey (2022), we date the boom's onset to 2002, the trough in the global financial cycle after which cross-border capital flows accelerated. Our identification strategy uses difference-in-differences, comparing outcomes for low- versus high-productivity firms before and after 2002.

The two settings offer complementary strengths. ORBIS Spain provides panel data with consistent coverage from 2000 to 2007, allowing us to control for firm fixed effects and verify pre-trends, and Spain provides a canonical example of a bad credit boom (Ortega and Peñalosa, 2012). However, the collateralization measure relies on book values of tangible assets, and the data do not allow us to assess the severity of asymmetric information.

Our second setting, the Business Environment and Enterprise Performance Survey (BEEPS), which covers 28 countries in Central and Eastern Europe and Central Asia, addresses some of these limitations. The survey includes a direct measure of whether collateral was required for a loan, a proxy for information transparency (external auditing), and estimated market values of collateral assets rather than book values. The cross-country sample also allows us to compare outcomes across booms that ended differently. The cost is a shorter time dimension that complicates pre-trend analysis and the absence of a firm panel. Together, the two datasets allow us to rule out pre-trend differences and better control for firm heterogeneity in Spain while testing broader predictions about information, collateral values, and boom outcomes in the cross-country data.

5.1 Setting 1: Spain (ORBIS)

5.1.1 Data

ORBIS provides harmonized firm-level balance sheet and income statement data for Spain with consistent coverage from 2000 to 2007. The data includes both listed and unlisted firms across all sectors, with good coverage of small and medium-sized enterprises that rely heavily on bank credit. This broad coverage makes ORBIS well-suited for studying how collateral requirements vary with firm productivity during credit booms. Table OA.1 reports summary statistics.

5.1.2 Empirical specifications

Collateral requirements. Our main specification estimates whether collateral requirements fell disproportionately for low-productivity firms after the onset of the credit boom:

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

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_i 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-year fixed effects.

The inclusion of sector-by-year fixed effects is important. Müller and Verner (2023) show that credit reallocation toward non-tradable sectors is a hallmark of harmful credit expansions. Our specification absorbs such reallocation, isolating within-sector variation in collateral requirements for high- versus low-productivity borrowers.[7]

A key identifying condition for our difference-in-differences approach is the parallel trends 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

[7] As a robustness check, we verify that results hold when excluding the construction sector, the primary driver of Spanish credit growth in the Müller and Verner (2023) data.

the following event-study specification:

$$\log \frac{\text{TFA}_{ist}}{\text{Bank Credit}_{ist}} = \sum_{2000}^{2007} \beta_t \text{Low-Prod}_i \times D_{\text{Year}=t} + \alpha_i + \delta_{st} + \epsilon_{ist}, \tag{22}$$

with 2002 as the (omitted) reference year. Equation (22) 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.

Separating collateral demand from supply. A challenge to connecting our baseline specification to the theory is that falling collateral requirements could reflect either demand or supply channels. In our theory, on the demand side, banks relax collateral requirements for low-productivity firms because screening becomes costly when collateral is scarce relative to lending opportunities. On the supply side, banks may relax requirements differentially because the increased value of collateral reduces incentives to produce information, as emphasized by Asriyan et al. (2021).

To distinguish these channels, we exploit regional variation in house price growth across Spain's 17 autonomous communities. During 2000–2002, house price growth ranged from 7.5% (Castilla y León) to 22% (Madrid), with a national average of 12.5% (see Figure OA.2 for details). Housing may directly serve as collateral for some entrepreneurs; moreover, evidence points to a significant positive correlation between residential and commercial real estate values at the regional level (Gyourko, 2009). If banks relaxed collateral requirements because of rising collateral values (the supply channel), we should observe greater relaxation in high-growth regions. If banks relaxed requirements because of collateral scarcity relative to lending demand (our mechanism), we should observe larger relaxation in low-growth regions, where the supply response was muted.

We estimate two complementary specifications, leveraging the fact that firms' postal codes (where the first two digits correspond to Spain's 52 provinces) are matched to the 17 autonomous communities, allowing us to capture regional heterogeneity in collateral supply conditions. In the first specification, we introduce region–time fixed effects to control for region-specific variation in collateral values. The second strategy extends the main specification by incorporating a dummy variable within a triple interaction. This dummy, denoted by High-HP$_r$, takes the value of 1 when regional house price growth exceeds the national

average, and 0 otherwise.

$$\ln \frac{\text{Collateral}_{isrt}}{\text{Bank Credit}_{isrt}} = \beta \text{Low-Prod}_i \times D_{\text{Year}>2002} \times \text{High-HP}_r + \alpha_i + \delta_{srt} + \epsilon_{isrt} \tag{23}$$

We assume that banks form expectations based on the house price growth observed between 2000 and 2002, treating it as a reasonable proxy for expected developments over the 2003–2007 period. This helps to mitigate endogeneity concerns, as the credit boom began after 2002.

5.1.3 Results

Collateral requirements. Consistent with the model's prediction, collateral requirements fell disproportionately for low-productivity firms during Spain's credit boom. Figure 2 shows the pattern graphically. Before 2002, low-productivity firms faced higher collateral requirements than high-productivity firms, as one would expect given their greater risk. After 2002, this pattern reverses: collateral requirements for low-productivity firms fell below those of their high-productivity counterparts.

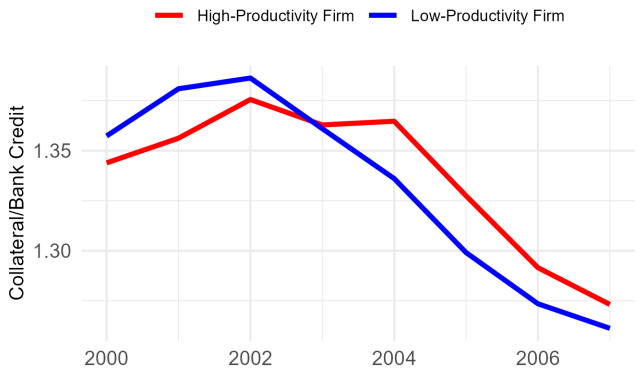


Figure 2: Collateral requirements by productivity

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 reports the estimation results of Equation (21), which provides formal empirical evidence consistent with the patterns illustrated in Figure 2. In all columns, the estimated coefficient on the interaction term, β, is negative and highly significant. This suggests that collateral requirements declined 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 decreased 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 ensures 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.

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

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 $\times$ $D_{Year>2002}$	-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:

$$\ln \frac{\text{Collateral}_{ist}}{\text{Bank Credit}_{ist}} = \beta \text{Low-Prod}_i \times D_{\text{Year}>2002} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{24}$$

where i stands for firm i operating in 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 3 plots the estimated time-varying regression coefficients of the model in Equation (22) relative to the year 2002, with 95% confidence intervals (the corresponding regression results can be found in Appendix Table OA.5). For the period 2000-2001, the coefficients are not statistically different from zero, but they become negative and significant at the 5% level during the credit boom years from 2004 to 2007. This provides further support for the causal interpretation of our results.

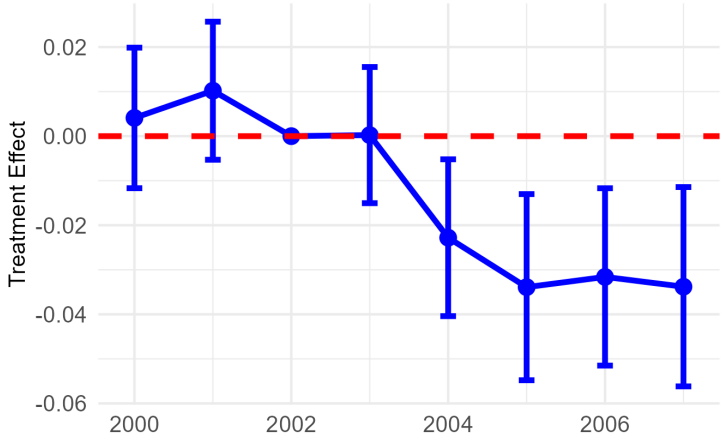


Figure 3: Impact of credit boom on collateral requirements by productivity

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.

Collateral demand versus supply. Starting with the specification that includes region–industry–time fixed effects in Column 1 of Table 2, the coefficient of interest decreases to -3.1% from -2.9%, compared with the specification containing only industry–time fixed effects in Column 3 in Table 1, which exclude regional house price dynamics and other region-specific developments. Nevertheless, some of the observed effects may still reflect broader regional factors beyond variation in collateral values, as the fixed effects structure relies on industry–region–time interactions. To further address this concern, we divide our sample into

two groups: firms operating in regions where house prices rose above the national average, and firms located in regions where price increases remained below the national average.

Table 2 presents results with the regional house price interaction. Column 2 shows that the relaxation of collateral standards for low-productivity firms was concentrated in regions where house prices grew relatively slowly. In these regions, collateral requirements fell by 4.8 percentage points more for low-productivity firms relative to high-productivity firms. In regions with above-average house price growth, this effect was largely offset, with a triple interaction coefficient of 3.6 percentage points.

This pattern is suggestive of the collateral scarcity channel, because the relaxation of lending standards for low-quality borrowers was more pronounced where collateral supply was relatively unresponsive. This does not rule out that collateral abundance may simultaneously weaken information production incentives as in Asriyan et al. (2021). The two mechanisms may operate jointly, and further work distinguishing their relative importance across different contexts is a promising direction for future research.

The Spanish evidence shows that collateral requirements fell disproportionately for low-productivity firms during a credit boom that ended badly. To test whether this pattern distinguishes bad booms from good ones, we turn to cross-country evidence from Central and Eastern Europe, where multiple countries experienced credit expansions with heterogeneous outcomes.

5.2 Setting 2: Cross-country evidence (BEEPS)

5.2.1 Data

The Business Environment and Enterprise Performance Survey (BEEPS), administered by the EBRD and World Bank, provides firm-level survey data from transition economies in Central and Eastern Europe, Central Asia, and Turkey, including a direct measure of whether collateral was required for a firm's most recent loan. We use three waves (2002, 2005, 2009) with consistent variable definitions.[8]

Crucially, the countries in our sample experienced credit booms with divergent outcomes. Some, like Latvia and Ukraine, suffered severe banking crises; others, like Poland and the Czech Republic, navigated the 2008 crisis without major financial distress. We classify countries as "bad boom" or "good boom" based on post-crisis outcomes, allowing us to test whether our predictions hold specifically in booms that ended badly. Our classification of

[8]Earlier and later waves differ substantially in questionnaire design; see Appendix Table OA.3.

Table 2: Controlling for House Price Developments: The Impact of Credit Booms on Collateral Requirements by Firm Productivity in Spain

Dependent variable:	*Collateral required (log)*		
	(1)	(2)	(3)
			Exc Construction
Low-Prod $\times$ $D_{Year>2002}$	-0.0312**	-0.0475***	-0.05518***
	(0.0106)	(0.0121)	(0.0137)
Low-Prod $\times$ $D_{Year>2002}$ $\times$ High-HP$_r$		0.0359**	0.0334*
		(0.0157)	(0.0190)
Firm FE	Yes	Yes	Yes
Sector-Region-Year FE	Yes	Yes	Yes
Observations	457829	457608	372495
R^2	0.711	0.711	0.698

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

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

where i stands for firm i working sector s in region r 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. The dummy variable $D_{\text{Year}>2002}$ takes the value of 1 for years after 2002, while High-HP$_r$ takes the value of 1 for regions where house price growth exceed the national average. 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.*

credit boom episodes into good or bad is presented in Appendix Table OA.4. We probe the sensitivity of our main empirical findings to our classification by reestimating all the main effects using a leave-one-out and an add-one-in approach. These results are presented in Appendix OA.3.3, and our results are robust to these two checks.

5.2.2 Empirical specifications

Collateral requirements. We estimate the following specification using BEEPS data:

$$\text{Collateral}_{isct} = \beta \text{Low-Prod}_{isct} \times D_{\text{Year}>2002} + \delta_{sct} + \gamma' X_{isc} + \varepsilon_{isct}. \tag{26}$$

Equation (26) defines a linear probability model in which 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. 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 rather than firm fixed effects, since BEEPS is not a panel data set. Because we are specifically 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 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.

Collateral scarcity. To examine the prediction that collateral value relative to economic activity falls (becomes scarce) during bad booms but not good booms, we estimate the following regression using BEEPS data:

$$\log\left(\text{Assets/Sales}\right)_{jct} = \beta \text{High-Prod}_{jct} \times D_{\text{Year}>2002} + \gamma' X_{jct} + \delta_{c,t} + \varepsilon_{jct}, \tag{27}$$

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: the aggregate $\log\left(\text{Assets/Sales}\right)$ summing over the above- and below-median productivity firms.

Importantly, the measure of assets reported in BEEPS is not book value, but rather 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. 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. The regression includes country-year 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).

5.2.3 Results

Collateral requirements. Table 3 presents results on collateral requirements. The key finding is in the comparison of Columns 3 and 4: the relaxation of collateral standards for low-productivity firms occurred in bad booms but not in good booms.

In the full sample (Column 1), collateral requirements fell 5.6 percentage points more for low-productivity firms after 2002. Column 2 adds an interaction with external auditing, our proxy for information transparency. The relaxation was concentrated among low-productivity, low-information firms, for whom requirements fell by 11.1 percentage points. Firms with external audits—where asymmetric information is less severe—saw significantly smaller declines.

Columns 3 and 4 split the sample by boom outcome. In bad boom countries, low-productivity, low-information firms experienced a 12.8 percentage point decline in collateral requirements. In good boom countries, the point estimate is close to zero and statistically insignificant. This contrast is in line with what the model predicts: banks relax standards for risky, opaque borrowers only when collateral scarcity forces them to do so, and this occurs in booms that subsequently turn bad.

Figures OA.4-OA.7 in the Appendix present leave-one-out and add-one-in robustness checks of our bad boom classification for column 1. 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 OA.3.4, for which we are able to add one additional pre- and post-treatment year from the BEEPS survey. Finally, Table OA.7 confirms that our main

Table 3: 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	0.034*	0.071**	0.094***	-0.0004
	(0.0198)	(0.0304)	(0.0359)	(0.0516)
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. Firm controls (employment indicator, industry, size of city where firm is based, firm's legal status) and the full set of effect interactions are included but not reported. Robust standard errors are clustered at the country-industry level.
****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*

findings are robust to alternative specifications of fixed effects and control variables, and remain quantitatively similar when excluding the construction sector.

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

Table 4: Impact of Credit Boom on Collateral Scarcity

Dependent variable:	*Assets/Sales (log)*	
	(1) Bad Boom	(2) Good Boom
High-Prod $\times$ $D_{\text{Year}>2002}$	-0.720**	-0.226
	(0.252)	(0.194)
Controls	Yes	Yes
Country-Year FE	Yes	Yes
Observations	110	44
R2	0.982	0.989

Notes: This table reports OLS estimates from difference-in-differences regressions evaluating the change in (log) Assets/Sales during credit booms. Firm-level data are winsorized at the 5th and 95th percentiles before aggregation to the country-year-productivity level. *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 relative to low-productivity firms after 2002. Columns (1) and (2) report results for bad and good booms, respectively. All regressions include country-by-year 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.*

Collateral scarcity Table 4 tests the model's prediction that bad booms should feature collateral scarcity, particularly for high-productivity firms. We use a specification with country-by-year fixed effects, which absorbs all time-varying country-level shocks and isolates the within-country-year variation between high- and low-productivity firm groups. This is our preferred specification because it controls for any macroeconomic factors that might differentially affect countries over time and confound the relationship between credit booms and collateral scarcity. The identifying variation comes from comparing how the assets-to-sales ratio evolved differently for high- versus low-productivity firms within the same country and year.

In bad boom countries (Column 1), high-productivity firms experienced a significantly larger decline in their assets-to-sales ratio compared to low-productivity firms after 2002. The

coefficient of -0.720 implies that high-productivity firms saw their collateral intensity fall by an additional 51% relative to low-productivity firms.

In good boom countries (Column 2), we find no evidence of differential collateral scarcity for high-productivity firms. The interaction coefficient is negative but small and statistically insignificant, suggesting that high-productivity firms did not experience disproportionate collateral constraints during good booms. This contrast between bad and good boom countries supports the model's central prediction that collateral scarcity is a distinguishing feature of bad booms.

5.3 Summary

The empirical evidence supports two predictions of the model. In Spain, collateral requirements fell disproportionately for low-productivity firms during the credit boom, and this pattern was strongest in regions where collateral supply (proxied by house prices) was relatively unresponsive. Across Central and Eastern Europe and Central Asia, the relaxation of collateral standards for low-productivity, low-information borrowers occurred specifically in booms that ended badly, not in those with benign outcomes, and we also find evidence of collateral scarcity during bad booms.

6 Conclusion

We proposed a theory of bad credit booms based on collateral scarcity. When favorable shocks raise the investment demand of productive firms but collateral values fail to keep pace, banks face a choice: ration credit to good borrowers, or relax screening standards and lend to bad borrowers as well. In our model, banks optimally choose the latter, cross-subsidizing negative-NPV projects to sustain lending to positive-NPV ones. This endogenous relaxation of credit standards is the hallmark of a bad boom.

We showed that such booms are constrained inefficient. Banks do not internalize that expanding credit dilutes collateral across relationships and reduces asset prices, pushing the economy into the bad boom regime. A planner who internalizes this externality optimally dampens credit expansion during booms. In a calibrated model, correcting this inefficiency captures roughly one-fifth of the welfare gains from eliminating asymmetric information entirely. A simple state-contingent tax on credit creation achieves most of these gains.

Firm-level evidence from Spain and Central and Eastern Europe supports the model's predictions. Collateral requirements fell disproportionately for low-productivity, low-information

borrowers during bad booms, but not during good ones. Collateral values relative to economic activity declined during bad booms, particularly for high-productivity firms. These patterns are consistent with our mechanism and suggest a potential diagnostic for policymakers: when rising credit is accompanied by declining collateral-to-output ratios, a boom may be at risk of turning bad.

Our analysis complements existing work on collateral and credit cycles. Models emphasizing collateral abundance (Asriyan et al., 2021) show that high collateral values can deplete information production, whereas we show that collateral scarcity can undermine screening. Both mechanisms likely operate in practice, and further distinguishing between them empirically is an important direction for future work. More broadly, integrating our framework with richer models of asset price determination would illuminate how institutional factors shape the collateral cycle and its interaction with credit.

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Appendices

A Proofs

A.1 Proof of Proposition 1

Proof. Given Assumption 1, only good entrepreneurs get credit in the first and second types of contract. Hence, for these types of contract the problem is the following,

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

$$0 \geq p_b\left[A_b(k_g)^\alpha - r_g^k k_g\right] - (1-p_b)x_g \tag{28}$$

$$p_g\left[A_g(k_g)^\alpha - r_g^k k_g\right] - (1-p_g)x_g \geq \gamma\pi_g^* \tag{29}$$

$$x_g \leq \tilde{x} \tag{30}$$

$$x_g \geq 0, \tag{31}$$

where we omit the incentive compatibility constraint of the good entrepreneurs because if $k_b = 0$ and $x_b = 0$, the IC is always slack as long as the participation constraint of the good is satisfied. The first order condition with respect to r_g^k yields,

$$\chi + \eta_1 \frac{p_b}{p_g} = \eta_2 \tag{32}$$

where η_1 and η_2 are weakly positive Lagrange multipliers related to constraints (28) and (29), respectively. This equation already reveals that $\eta_2 > 0$ and, therefore, the participation constraint (29) is binding. Now using the FOC with respect to k_g and (32),

$$\eta_1 = \frac{\alpha p_g A_g k_g^{\alpha-1} - r^*}{\alpha p_b (A_b - A_g) k_g^{\alpha-1}}\chi \tag{33}$$

Taking derivatives with respect to x_g and using (32) yields,

$$\frac{p_g - p_b}{p_g}\eta_1 + \theta_2 - \theta_1 = 0 \tag{34}$$

Where θ_1 and θ_2 are the Lagrange multipliers of constraints (30) and (31) respectively. Note that Equation (34) alone allows for a corner solution where $\theta_2 > 0$ and $x_g = 0$. However, in a separating equilibrium where bad entrepreneurs are excluded ($k_b = 0$), the bad entrepreneur's incentive compatibility constraint (10) must hold. If the contract required

zero collateral ($x_g = 0$), the bad entrepreneur would strictly prefer to mimic the good type. Thus, separation is impossible at $x_g = 0$. To satisfy the IC constraint and screen out bad types, the banker must strictly require collateral, implying $x_g > 0$ and consequently $\theta_2 = 0$.

Now the first order conditions define two different contracts. The first one is when collateral level $\tilde{x}$ is high and constraint (30) is slack. In that case $\eta_1 = \theta_1 = 0$ and the amount lent is the first best; from (33):

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

Also, using the binding constraint (29) and (28) we know that the collateral asked is,

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

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 x_g possible and the previous equation would hold with equality. As a consequence, we assume that $x_g = \bar{x}_1$ in this contract.

Finally, we can get r_g^k for this type of contract using the binding PC (29).

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

Now the type two contract is the case in which $\tilde{x}$ is lower than $\bar{x}_1$ and as a consequence (30) binds implying that $\theta_1 > 0$ and $x_g = \tilde{x}$. From (34) we know that $\eta_1 > 0$ and the incentive compatibility constraint (28) binds. Hence, using the two binding constraints (28) and (29) we get the the interest rate and the amount lent in this contract,

$$k_g = \left(\frac{\left(\frac{p_g - p_b}{p_g}\right)x_g - \frac{p_b\gamma\pi_g^*}{p_g}}{p_b\left(A_b - A_g\right)}\right)^{\frac{1}{\alpha}} \tag{35}$$

$$r_g^k = \left(A_g k_g^\alpha - \frac{1-p_g}{p_g}x_g - \frac{\gamma\pi_g^*}{p_g}\right)\frac{1}{k_g} \tag{36}$$

The third type of contract happens when the banker decides to lend to both types of en-

trepreneurs. Hence, the problem is now,

$$\max_{k_g, r_g^k, x_g, k_b, r_b^k, x_b} \quad \chi\left(p_g r_g^k k_g + (1-p_g)x_g - r^* k_g - \psi(A_t, r_t^*)\right)$$
$$+ (1-\chi)\left(p_b r_b^k k_b + (1-p_b)x_b - r^* k_b - \psi(A_t, r_t^*)\right) \quad \text{s.t.}$$
$$p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)x_b \geq p_b\left(A_b k_g^\alpha - r_g^k k_g\right) - (1-p_b)x_g \tag{37}$$
$$p_g\left(A_g k_g^\alpha - r_g^k k_g\right) - (1-p_g)x_g \geq \gamma\pi_g^* \tag{38}$$
$$p_b\left(A_b k_b^\alpha - r_b^k k_b\right) - (1-p_b)x_b \geq 0 \tag{39}$$
$$x_g \leq \tilde{x}, \quad x_g \geq 0, \quad x_b \leq \tilde{x}, \quad x_b \geq 0 \tag{40}$$

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 (39) 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 (37) 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 (39).

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

$$1 - \chi = \eta_1 \tag{41}$$

where η_1 is the multiplier of constraint (37). Equation (41) implies that $\eta_1 > 0$ and already tells us that bankers want to relax credit standards only when the constraint (37) 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 (41) 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 x_b we get,

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

Hence, $\theta_3 = \theta_4 = 0$ and any level of collateral $x_b \in (0, \tilde{x})$ is optimal of the banker. However,

if we incorporated an infinitesimal cost of liquidating collateral after default in the problem the banker would choose $x_b = 0$. As a consequence, we assume that $x_b = 0$ is the banker's choice. Getting the FOC with respect to r_g^k and using (41),

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

where η_2 is the multiplier of constraint (38). Hence, the last expression implies that $\eta_2 > 0$ and (38) 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 x_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 $x_g = \tilde{x}$.

Finally to get r_b^k and r_g^k just use the binding constraints (37) and (38) to get,

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

The last two equations complete the description of type 3 credit contracts. The threshold collateral level below which the equilibrium switches from type to type 3 contract is defined implicitly by equating the banker's expected profit from lending to only good entrepreneurs under the type 2 contract, or lending to both types under the type 3 contract:

$$\chi\left(\left(p_g\hat{r}_g - r^*\right)\hat{k}_g + (1-p_g)\,\bar{x}_2\right) = \chi\left(\left(p_g r_g - r^*\right)k_g + (1-p_g)\,\bar{x}_2\right) + (1-\chi)\left(\left(p_b r_b - r^*\right)k_b - \psi\right),$$

where $\hat{k}_g$ and $\hat{r}_g$ denote parameters of the type 2 contract (the expression does not have a closed form solution due to the dependence of $\hat{k}_g$ on $\tilde{x}$, see Equation (35)).

We have assumed that the incentive compatibility constraint for good entrepreneurs is slack. It can be trivially shown that this is actually the case for type 1 and 2 contracts. 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,

$$\tilde{x} > \bar{x}_3 \equiv \frac{p_b p_g}{p_g - p_b} \left(A_b - A_g\right) \left(k_g^\alpha - k_b^\alpha\right)$$

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. □

A.2 Proof of Proposition 2

Proof. Define the fundamental profit index

$$Z_t \equiv A_t^{\frac{1}{1-\alpha}} (r_t^*)^{-\frac{\alpha}{1-\alpha}},$$

which summarizes the scale of profitable investment opportunities in the economy. Its elasticity with respect to shocks is $\partial \ln Z_t / \partial \ln A_t = 1/(1-\alpha)$ and $\partial \ln Z_t / \partial \ln r_t^* = -\alpha/(1-\alpha)$.

Step 1: Elasticity of collateral demand. We show that both collateral thresholds $\bar{x}_{1,t}$ and $\bar{x}_{2,t}$ scale one-for-one with the fundamental profit index Z_t. Throughout the analysis we treat the matching state N_t as predetermined on impact, so that $\tilde{x}_t \equiv q_t \bar{\ell}/(\chi N_t)$ varies only through the asset price q_t.

1.1. Scaling of first-best project profits. The first-best capital choice of a good entrepreneur is

$$k_{g,t}^* = \left(\frac{\alpha p_g A_t}{r_t^*}\right)^{\frac{1}{1-\alpha}} \quad \Rightarrow \quad k_{g,t}^* \propto \left(\frac{A_t}{r_t^*}\right)^{\frac{1}{1-\alpha}}.$$

Hence both the revenue and funding-cost terms evaluated at $k_{g,t}^*$ scale with Z_t.

By Assumption 1, fixed intermediation costs scale proportionally with the same index, so the good-type first-best surplus satisfies

$$\pi_{g,t}^* \equiv \max_k \{p_g A_t k^\alpha - r_t^* k - \psi(A_t, r_t^*)\} = \bar{\pi}_g^* Z_t,$$

for a constant $\bar{\pi}_g^*$ depending only on primitives.

1.2. Scaling of Type–3 (relaxed screening) bank profits. In Type–3 (Proposition 1, case 3), bankers lend to both types. The optimal loan sizes satisfy

$$k_{b,t} = \left(\frac{\alpha p_b \mu A_t}{r_t^*}\right)^{\frac{1}{1-\alpha}}, \qquad k_{g,t} = \left(\frac{\alpha[\chi p_g - (1-\chi)(\mu-1)p_b]A_t}{\chi r_t^*}\right)^{\frac{1}{1-\alpha}},$$

so that $A_t k_{i,t}^{\alpha}$ and $r_t^* k_{i,t}$ scale with Z_t for $i \in \{g, b\}$. Using,

$$\Pi_{i,t} = p_i r_{i,t}^k k_{i,t} + (1 - p_i) x_{i,t} - r_t^* k_{i,t} - \psi(A_t, r_t^*) \mathbb{1}_{\{k_{i,t} > 0\}},$$

and the closed-form Type–3 contracts, the good-type bank profit $\Pi_{g,t}^{(3)}$ is proportional to Z_t and independent of $\tilde{x}_t$ (the collateral term cancels out after substitution). The bad-type profit is affine in collateral:

$$\Pi_{b,t}^{(3)}(\tilde{x}_t) = \underbrace{\Pi_{b,0}^{(3)}(A_t, r_t^*)}_{\propto Z_t} + \frac{p_g - p_b}{p_g} \tilde{x}_t.$$

Therefore expected bank profit per match in Type–3 can be written as

$$\Phi_{3,t}(\tilde{x}_t) \equiv \chi \Pi_{g,t}^{(3)} + (1 - \chi) \Pi_{b,t}^{(3)}(\tilde{x}_t) = a_3 Z_t + b_3 \tilde{x}_t, \qquad b_3 \equiv (1 - \chi) \frac{p_g - p_b}{p_g} > 0, \tag{42}$$

for a constant a_3 depending only on primitives.

1.3. Scaling of Type–2 (constrained separation) bank profits. In Type–2 (Proposition 1, case 2), only good entrepreneurs are funded and $x_{g,t} = \tilde{x}_t$. Using that the good-type participation constraint binds, bank profit from a good match is

$$\Pi_{g,t}^{(2)}(\tilde{x}_t) = p_g A_t k_{g,t}(\tilde{x}_t)^{\alpha} - r_t^* k_{g,t}(\tilde{x}_t) - \psi(A_t, r_t^*) - \gamma \pi_{g,t}^*,$$

where $k_{g,t}(\tilde{x}_t)$ is pinned down by the binding bad-type IC:

$$k_{g,t}(\tilde{x}_t) = \left(\frac{\left(\frac{p_g - p_b}{p_g} \right) \tilde{x}_t - \frac{p_b \gamma \pi_{g,t}^*}{p_g}}{p_b (\mu - 1) A_t} \right)^{1/\alpha}.$$

Using $\pi_{g,t}^* = \bar{\pi}_g^* Z_t$ and writing $Z_t = r_t^* B_t$ with $B_t \equiv (A_t / r_t^*)^{1/(1-\alpha)}$, the numerator of the expression inside the brackets equals

$$Z_t \left[\left(\frac{p_g - p_b}{p_g} \right) \frac{\tilde{x}_t}{Z_t} - \frac{p_b \gamma \bar{\pi}_g^*}{p_g} \right],$$

while the denominator equals $p_b(\mu - 1) r_t^* B_t^{1-\alpha}$. Hence

$$k_{g,t}(\tilde{x}_t) = B_t \cdot \kappa_k \left(\frac{\tilde{x}_t}{Z_t} \right),$$

for a function $\kappa_k(\cdot)$ depending only on primitives. Substituting into the profit expression yields

$$\Phi_{2,t}(\tilde{x}_t) \equiv \chi \Pi^{(2)}_{g,t}(\tilde{x}_t) = Z_t \cdot \varphi_2\left(\frac{\tilde{x}_t}{Z_t}\right), \tag{43}$$

for a function $\varphi_2(\cdot)$ independent of (A_t, r^*_t).

1.4. Scaling of the indifference thresholds. The Type–2 threshold $\bar{x}_{2,t}$ is defined by the indifference condition

$$\Phi_{3,t}(\bar{x}_{2,t}) = \Phi_{2,t}(\bar{x}_{2,t}).$$

Using (42) and (43), write $\bar{x}_{2,t} = u_t Z_t$ and divide both sides by Z_t:

$$a_3 + b_3 u_t = \varphi_2(u_t).$$

This equation determines u_t as a constant depending only on primitives (and the predetermined N_t). Hence

$$\bar{x}_{2,t} = \Lambda Z_t \quad \Rightarrow \quad \varepsilon_{\bar{x}_2,Z} = 1.$$

An identical argument applies to the perfect-screening threshold $\bar{x}_{1,t}$, which is pinned down by a binding bad-type incentive constraint and therefore also scales linearly with Z_t.

Step 2: The Supply Side (Asset Prices). Available collateral is $\tilde{x}_t = q_t \bar{\ell}/(\chi N_t)$. Since the measure of credit lines N_t is fixed on impact, the contemporaneous supply elasticity depends solely on the asset price response. Solving for the asset price from the household Euler equation gives $q_t \propto C_t^{\sigma}$, so

$$\varepsilon_{\tilde{x},Z} = \varepsilon_{q,Z} = \sigma\, \varepsilon_{C,Z}.$$

To find $\varepsilon_{C,Z}$, differentiate the aggregate resource constraint $C_t = Y^{net}_t - S_t$, where $S_t \equiv \kappa F_t$ denotes aggregate search costs, and Y^{net}_t is time t output net of interest and fixed costs:

$$\varepsilon_{C,Z} = \frac{Y^{net}_t}{C_t}\, \varepsilon_{Y,Z} \; - \; \frac{S_t}{C_t}\, \varepsilon_{S,Z}. \tag{44}$$

Since net output is linear in Z_t, $\varepsilon_{Y,Z} = 1$. Using $Y^{net}_t/C_t = 1 + S_t/C_t$,

$$\varepsilon_{C,Z} = \left(1 + \frac{S_t}{C_t}\right) - \frac{S_t}{C_t}\, \varepsilon_{S,Z} = 1 - \frac{S_t}{C_t}\, (\varepsilon_{S,Z} - 1). \tag{45}$$

We determine $\varepsilon_{S,Z}$ from the free-entry condition. Free entry implies $\frac{\kappa}{\lambda^f(\theta_t)} = \beta\,\mathbb{E}_t[J_{t+1}]$. Now consider the elasticity of the value of an active credit line to Z_t, $\varepsilon_{J,Z} = \frac{\partial \log J_t}{\partial \log Z_t}$. A first-order log-linearization of the banker value recursion together with $\log Z_t$ following an AR(1), $\log Z_t = (1-\rho)\log(\bar{Z}) + \rho \log Z_{t-1} + \sigma_z \varepsilon_{z,t}$[9], yields the elasticity[10]

$$\varepsilon_{J,Z} = \frac{1-\beta\bar{p}}{1-\beta\bar{p}\,\rho}, \tag{46}$$

Using free entry and that the matching function implies $\lambda^f(\theta) \propto \theta^{\nu-1}$, we have $\theta_t^{1-\nu} \propto \mathbb{E}_t[J_{t+1}]$, so (to first order) $\theta_t \propto Z_t^{\rho\varepsilon_{J,Z}/(1-\nu)}$. Since aggregate search costs are proportional to vacancy posting, $S_t \propto \theta_t$, it follows that

$$\varepsilon_{S,Z} = \frac{\Omega}{1-\nu}, \tag{47}$$

with $\Omega \equiv \frac{\rho(1-\beta\bar{p})}{1-\beta\bar{p}\,\rho}$. Substituting into consumption elasticity,

$$\varepsilon_{C,Z} = 1 - \frac{S_t}{C_t}\left(\frac{\Omega}{1-\nu} - 1\right) = 1 - \zeta_t\left(\frac{\Omega}{1-\nu} - 1\right), \qquad \zeta_t \equiv \frac{S_t}{C_t}. \tag{48}$$

Therefore the collateral supply elasticity with respect to Z_t is

$$\varepsilon_{\tilde{x},Z} = \sigma\,\varepsilon_{C,Z} = \sigma\left[1 - \zeta_t\left(\frac{\Omega}{1-\nu} - 1\right)\right]. \tag{49}$$

Finally, using $\varepsilon_{Z,A} = 1/(1-\alpha)$ and $\varepsilon_{Z,r^*} = -\alpha/(1-\alpha)$, the implied supply elasticities with respect to the primitive shocks are

$$\varepsilon_{\tilde{x},A} = \varepsilon_{\tilde{x},Z} \cdot \frac{1}{1-\alpha}, \qquad \varepsilon_{\tilde{x},r^*} = \varepsilon_{\tilde{x},Z} \cdot \left(-\frac{\alpha}{1-\alpha}\right). \tag{50}$$

Step 3: The Gap Dynamics The screening gap narrows if the supply response is smaller than the demand response. For a productivity shock (A_t):

$$\sigma\left[1 - \frac{S_t}{C_t}\left(\frac{\Omega}{1-\nu} - 1\right)\right]\left(\frac{1}{1-\alpha}\right) < \frac{1}{1-\alpha}. \tag{51}$$

[9]The AR(1) process for Z_t follows from the assumed autoregressive processes for A_t and r_t^* assumed in the text.

[10]To obtain the elasticity, we analyze the partial equilibrium response of firm value holding the real interest rate constant ($\Lambda_{t,t+1} \approx \beta$). We log-linearize the value recursion $J_t = \Pi_t + \beta\bar{p}\mathbb{E}_t[J_{t+1}]$ around the conditional expectation. Approximating the profit-to-value ratio by its long-run mean $1-\beta\bar{p}$ yields $\hat{j}_t \approx (1-\beta\bar{p})\hat{z}_t + \beta\bar{p}\mathbb{E}_t[\hat{j}_{t+1}]$. Substituting the conjecture $\hat{j}_t = \varepsilon_{J,Z}\hat{z}_t$ and $\mathbb{E}_t[\hat{z}_{t+1}] = \rho\hat{z}_t$ yields $\varepsilon_{J,Z} = (1-\beta\bar{p})/(1-\beta\bar{p}\rho)$.

For an interest rate shock (r_t^*):

$$\sigma\left[1-\frac{S_t}{C_t}\left(\frac{\Omega}{1-\nu}-1\right)\right]\left|-\frac{\alpha}{1-\alpha}\right|<\left|-\frac{\alpha}{1-\alpha}\right|. \tag{52}$$

In both cases, canceling the technology term yields the condition stated in the proposition. □

B Parameter values

Table A5: Parameter Values

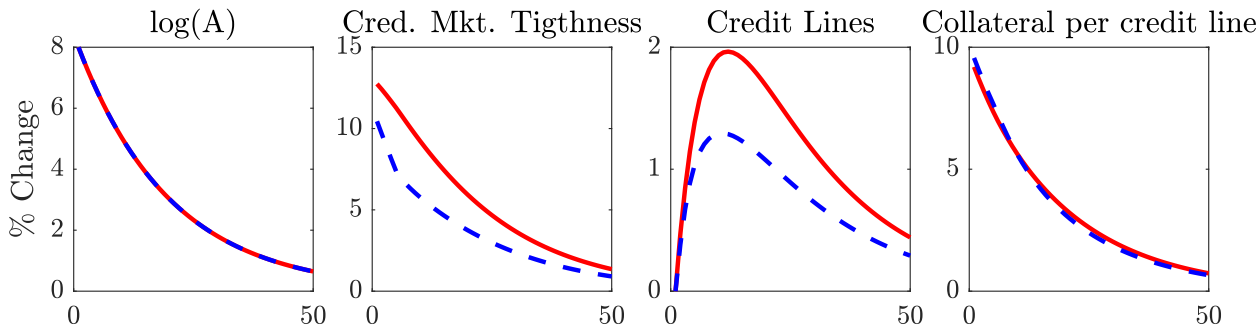
Parameter	Description	Value
β	Discount factor	0.9
α	Capital elasticity	0.33
σ	Risk aversion	0.4
$\bar{r^*}$	Steady state r^*	0.08
ν	Matching elasticity	0.3
κ	Cost of posting credit offer	0.5
p_g	Good success probability	0.9
p_b	Bad success probability	0.5
χ	Good entrepreneur measure	0.95
γ	Entrepreneur outside option	0.73
$\bar{\psi}$	Intermediation cost	0.21
ϕ	Land utility	0.1
$\bar{\ell}$	Land supply	0.3174
ρ	Shock persistence	0.95
σ_A	A shock std. dev.	0.95
σ_r	r^* shock std. dev.	0.95

Notes: This table shows the parameters used to produce the simulated credit booms, impulse responses, and welfare calculations. In the "good boom" calibration, $\sigma = 1.01$ and ϕ is adjusted to ensure that asset prices are the same in the steady state. 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). The parameter $\bar{\ell}$ is set so that in the stationary steady state, $\tilde{x} = \bar{x}_1$.

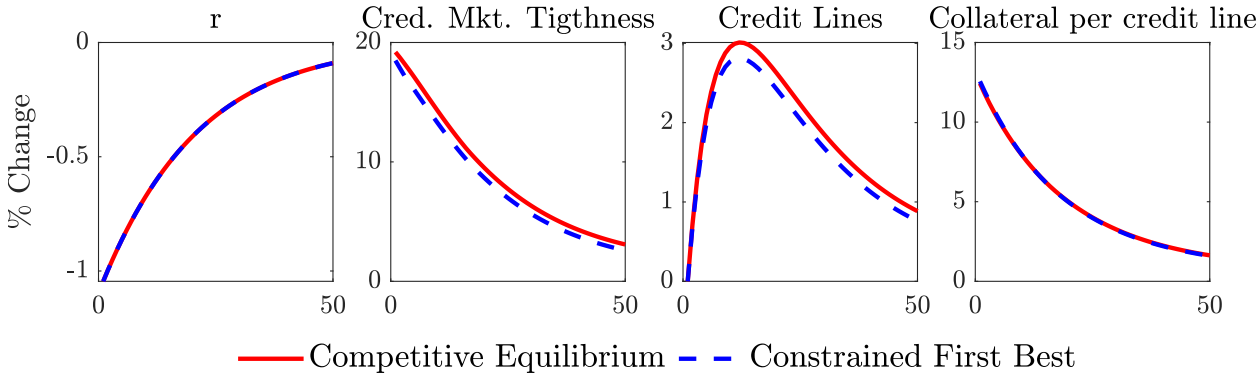
Online Appendix

OA.1 Model Appendix

Figure OA.1: 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 A5). 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.

OA.2 Data Appendix

OA.2.1 Summary Statistics

Table OA.1: ORBIS - Descriptive Statistics

Variable	Mean	Median	Std. Dev.	25th Percentile	75th Percentile	Count
Panel A: Low productivity firms						
Tangible Fixed Assets	11.63	11.70	1.58	10.68	12.62	28014
Bank Credit	11.37	11.38	1.63	10.40	12.29	28388
Collateral Required	0.26	0.32	1.40	-0.36	0.95	28014
Value Added	12.34	12.28	1.12	11.62	13.01	28106
Employees	28.82	10.00	259.95	6.00	20.00	28388
Labor Productivity	9.92	9.96	0.36	9.76	10.15	28106
Panel B: High productivity firms						
Tangible Fixed Assets	12.61	12.61	1.86	11.49	13.73	29361
Bank Credit	12.36	12.24	2.03	11.10	13.59	29836
Collateral Required	0.25	0.31	1.66	-0.48	1.02	29361
Value Added	13.32	13.16	1.37	12.37	14.10	28475
Employees	46.55	11.00	431.38	5.00	28.00	29801
Labor Productivity	10.77	10.64	0.56	10.42	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 OA.2: BEEPS - Descriptive Statistics

Variable	Mean	Std. Dev.	25th Percentile	75th Percentile	Count
Panel A: Low productivity firms					
collat	.80	.40	1	1	4537
audit	.53	.50	0	1	4537
employment	16	471	12	140	4537
sales/employee	2.55e+08	2.98e+09	8571	314857	4537
Panel B: High productivity firms					
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 OA.3 for variable descriptions and Table OA.4 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/.

OA.2.2 Regional House Prices in Spain

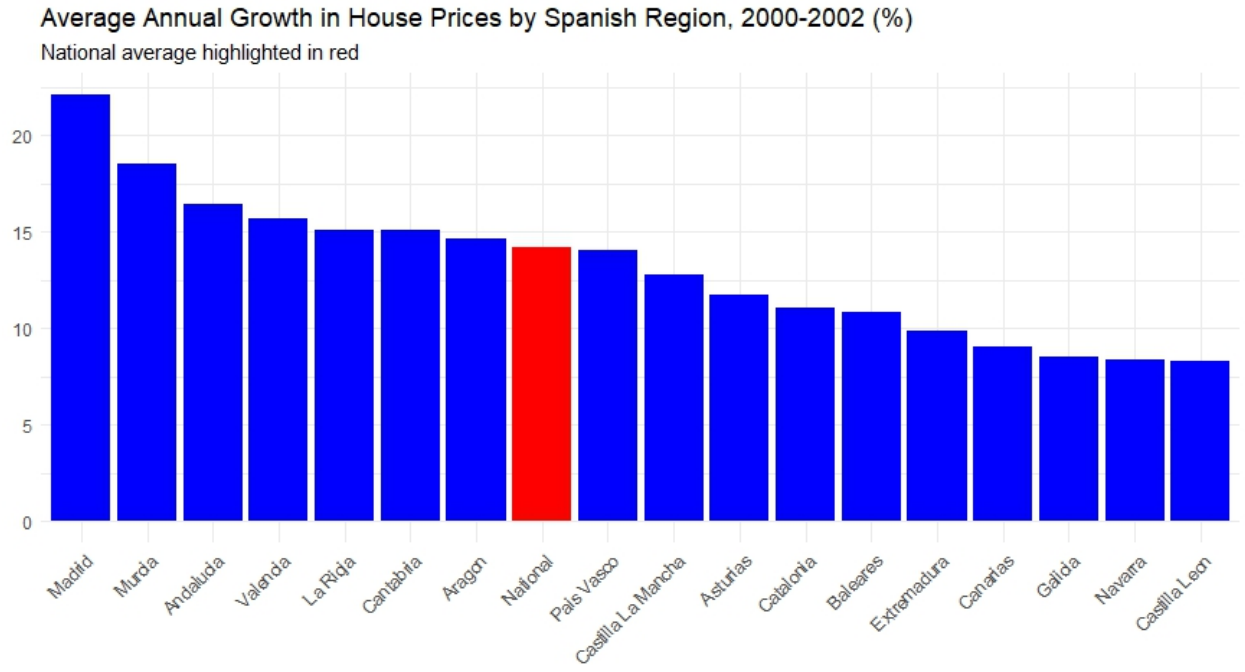


Figure OA.2: Average annual percentage growth in house prices per square meter across 17 Spanish regions between 2000 and 2002. The national average is highlighted in red for reference.

OA.2.3 Variable Definitions

Table OA.3: 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 OA.4: GFC Credit Boom Outcomes by Country

Country	Classification	Rationale
Albania	Bad Boom	Rapid credit growth; NPLs jumped from <5% in 2007 to ∼25% by 2014.
Armenia	Bad Boom	Aggressive construction-driven credit boom; severe GDP contraction (∼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 ∼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 (∼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 ∼15%; severe banking distress.
Kazakhstan	Bad Boom	Extreme foreign-funded credit boom; bank defaults; massive NPL surge (∼26%); major government intervention required.
Kyrgyz Republic	Bad Boom	Institutional weaknesses; political upheaval and banking crisis; NPL rise to ∼15–16%.
Latvia	Bad Boom	Extreme credit boom and deep crisis (GDP –25%); IMF/EU bailout; NPLs ∼20%; major bank failure (Parex).
Lithuania	Bad Boom	Large credit expansion; deep recession; NPL spike (∼20%); banking system required external support.
Moldova	Bad Boom	Remittance-driven boom; significant NPL increase (∼17%); weak governance exacerbated issues.
Mongolia	Bad Boom	Commodity-fueled boom; IMF bailout needed; NPL rise (∼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 ∼22%; currency crisis with ∼30% devaluation; bank restructuring necessary.
Ukraine	Bad Boom	FX-driven boom; systemic crisis, GDP -15%; quadrupled NPLs (∼16%); IMF rescue necessary.
Azerbaijan	Good Boom	Oil-backed boom; avoided banking crisis; NPLs remained low (∼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 (∼7%); no banking collapse.
North Macedonia	Good Boom	Moderate credit boom; mild crisis impacts; limited NPL rise (7.5% to ∼10%); no major bank failures.
Poland	Good Boom	Rapid but prudent credit growth; avoided recession and crisis; moderate NPL rise (∼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 (∼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.

OA.3 Empirical Robustness

OA.3.1 Parallel Trends: ORBIS

This subsection presents evidence supporting the parallel trends assumption underlying our difference-in-differences analysis using Spanish ORBIS data.

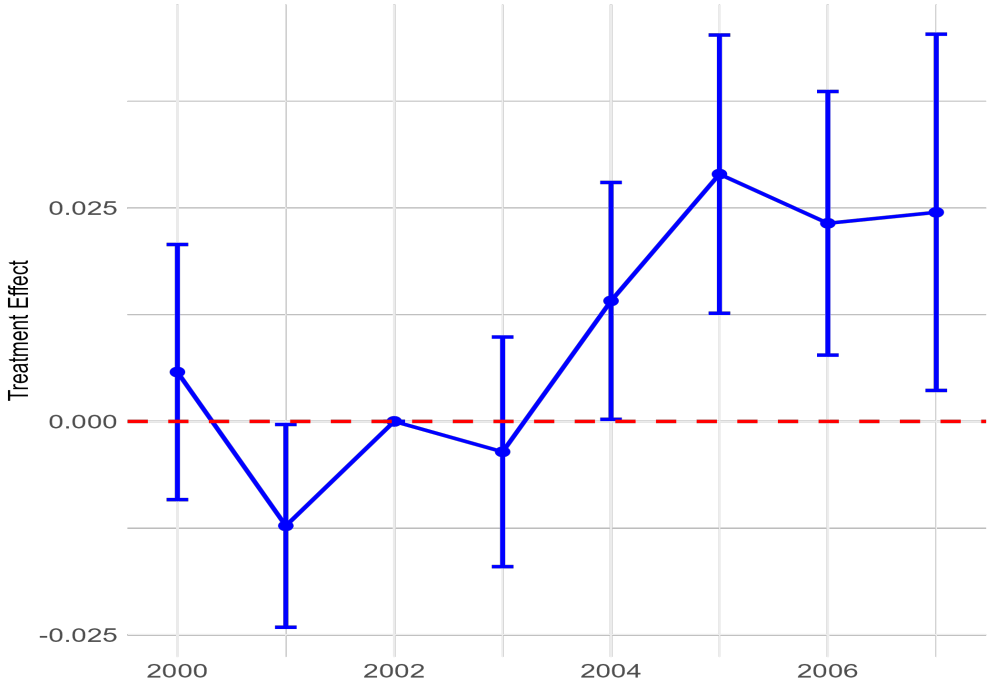


Figure OA.3: Impact of credit boom on bank credit by productivity

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

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

$\hat{\beta}_t$ is time-varying treatment effect of credit boom on bank credit. 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 bank credit, defined as the ratio of bank credit to total assets. Bank Credit refers to the sum of Long- and Short-Term Financial Debt from the Orbis database, and Total Assets is Assets. 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.

Table OA.5: 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:

$$\ln \frac{\text{Collateral}_{ist}}{\text{Bank Credit}_{ist}} = \sum_{2000}^{2007} \beta_t \text{Low-Prod}_i \times D_{\text{Year}=t} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{OA.3.1}$$

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 OA.6: Impact of Credit Booms on Bank Credit by Firm Productivity

Dependent variable:	*Bank credit (log)*	
	(1)	(2)
		Exc Construction
Low-Prod × $D_{Year=2000}$	0.00578	0.00156
	(0.00908)	(0.01019)
Low-Prod × $D_{Year=2001}$	-0.01223*	-0.01384*
	(0.00722)	(0.00809)
Low-Prod × $D_{Year=2003}$	-0.00356	0.00234
	(0.00817)	(0.00746)
Low-Prod × $D_{Year=2004}$	0.01411*	0.01858**
	(0.00843)	(0.00997)
Low-Prod × $D_{Year=2005}$	0.02896***	0.03587***
	(0.00990)	(0.01096)
Low-Prod × $D_{Year=2006}$	0.02320***	0.03003***
	(0.00938)	(0.01047)
Low-Prod × $D_{Year=2007}$	0.02449*	0.03442***
	(0.01268)	(0.01340)
Firm FE	Yes	Yes
Industry-Time FE	Yes	Yes
Observations	465792	378416
R-squared	0.659	0.663

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

$$\ln \frac{\text{Bank Credit}_{ist}}{\text{Total Assets}_{ist}} = \sum_{2000}^{2007} \beta_t \text{Low-Prod}_i \times D_{\text{Year}=t} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{OA.3.2}$$

where i stands for firm i working sector s at time t. The dependent variable in this analysis is the Bank Credit at the firm level, defined as the ratio of Bank Credit to Total Assets. Bank Credit is the total of both Long- and Short-Term Financial Debt, as recorded in Orbis database, while Total Assets is the total of Asset, 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.*

OA.3.2 Full Sample Robustness: BEEPS

Table OA.7: 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 on the full sample of firms to assess robustness to fixed effect specifications and sector composition. 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 is below the median. *High-Info* is an indicator equal to one if the firm's accounts are externally audited. Columns (1) and (2) replicate the baseline difference-in-difference specification across different combinations of fixed effects and firm controls. Columns (3) and (4) introduce the triple interaction with *High-Info*. Column (5) replicates the triple interaction specification but excludes the construction sector. Firm controls include employment, industry, city size, and legal status. Robust standard errors are clustered at the country-industry level. ****, **, and * indicate significance at 1%, 5%, and 10%, respectively.*

OA.3.3 Leave-One-Out and Add-One-In Sensitivity Analysis

This subsection presents sensitivity analyses to assess whether our main results are driven by any single country. We re-estimate our main specifications by (i) leaving one country out at a time (leave-one-out) and (ii) adding countries from the alternative classification one at a time (add-one-in).

OA.3.3.1 Collateral Requirements

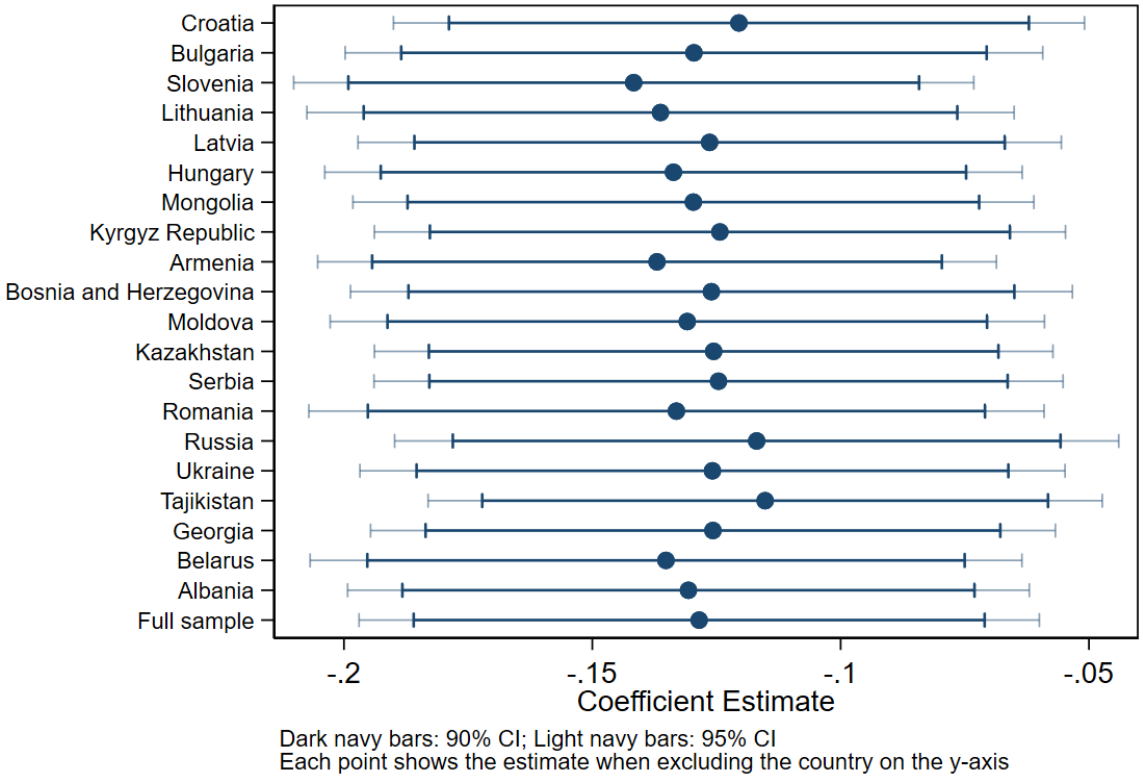


Figure OA.4: Leave-one-out sensitivity analysis for collateralization treatment effect in bad boom countries. Each point shows the estimated coefficient on the Low-Prod $\times D_{\text{Year}>2002}$ interaction from Equation (26), after excluding the specified country from the sample. The regression 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.

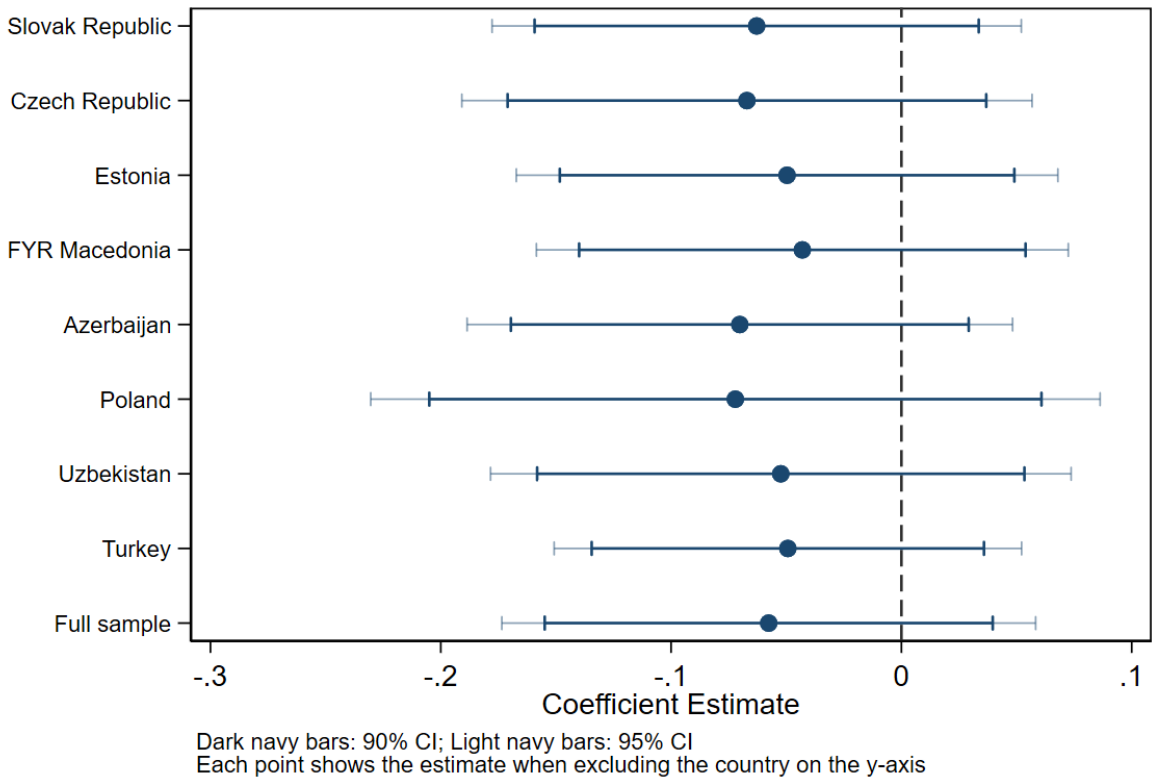


Figure OA.5: Leave-one-out sensitivity analysis for collateralization treatment effect in good boom countries. Each point shows the estimated coefficient on the Low-Prod $\times D_{\text{Year}>2002}$ interaction from Equation (26), after excluding the specified country from the sample. The regression 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.

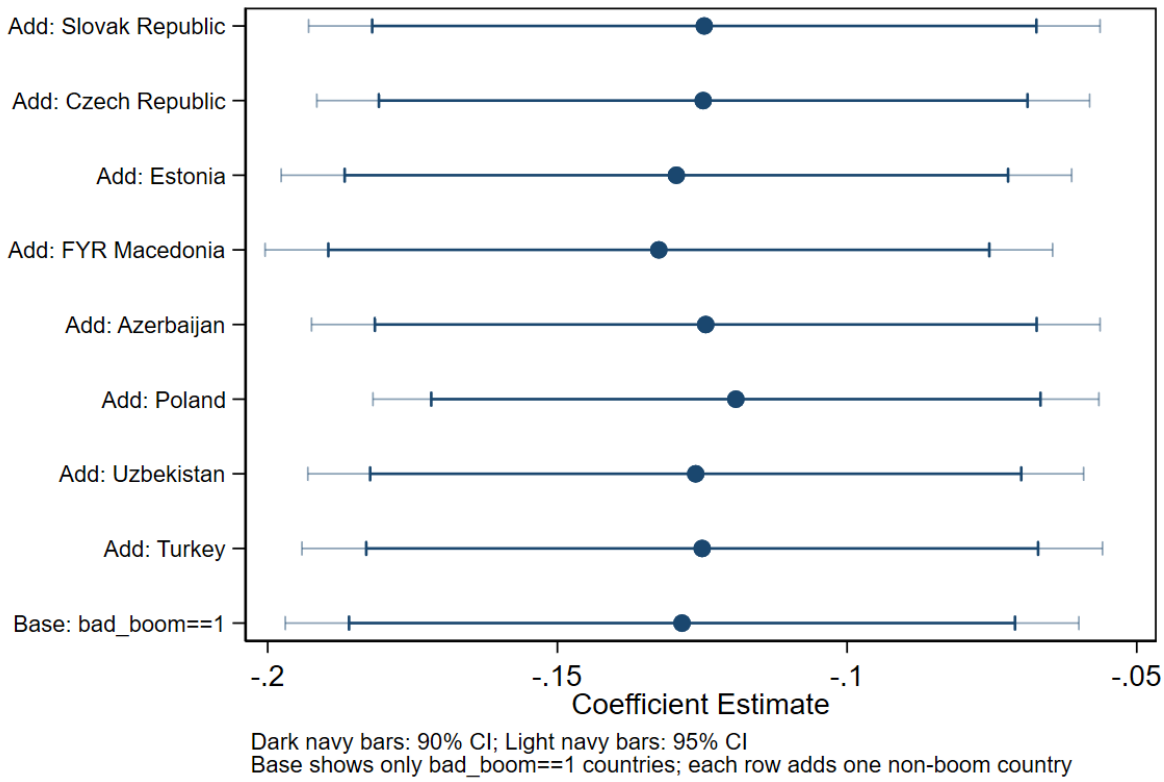


Figure OA.6: Add-one-in sensitivity analysis for collateralization treatment effect starting with bad boom countries. Each point shows the estimated coefficient on the Low-Prod $\times$ $D_{\text{Year}>2002}$ interaction from Equation (26), where the baseline (top row) uses only bad boom countries and each subsequent row adds one good 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 good boom countries are incorporated.

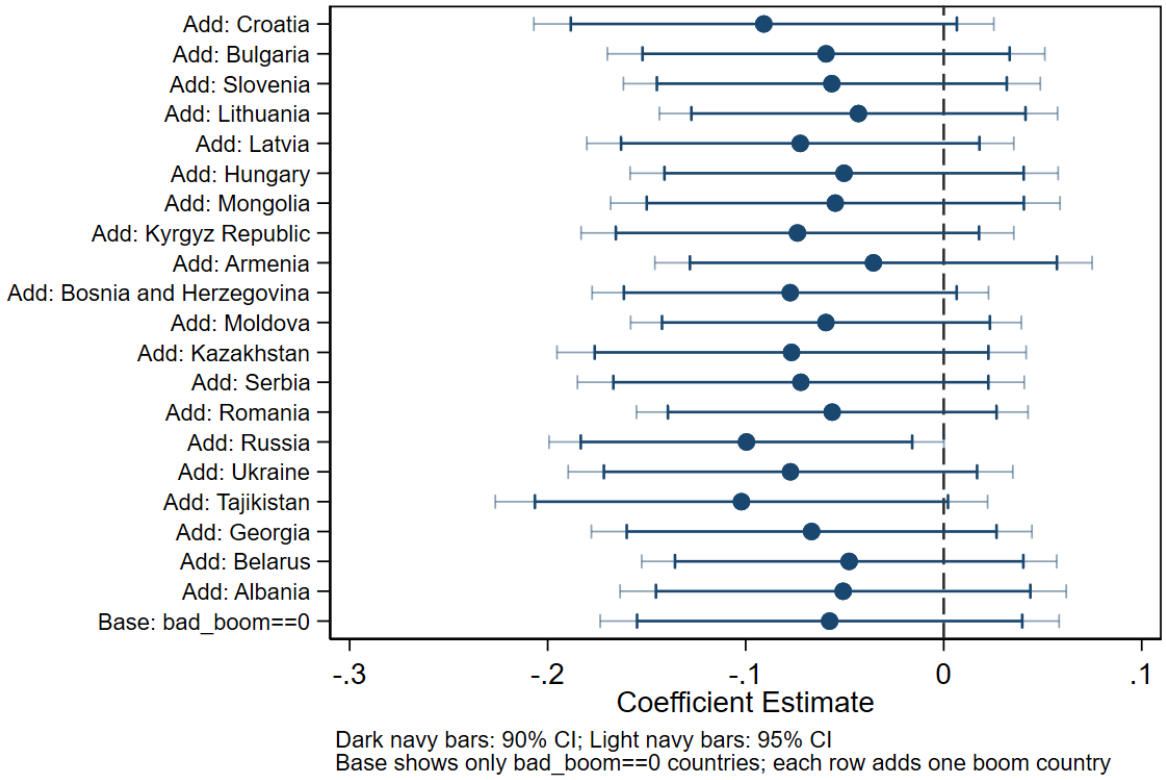


Figure OA.7: Add-one-in sensitivity analysis for collateralization treatment effect starting with good boom countries. Each point shows the estimated coefficient on the Low-Prod $\times$ $D_{\text{Year}>2002}$ interaction from Equation (26), where the baseline (top row) uses only good boom countries and each subsequent row adds one bad 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 bad boom countries are incorporated.

OA.3.3.2 Collateral Scarcity

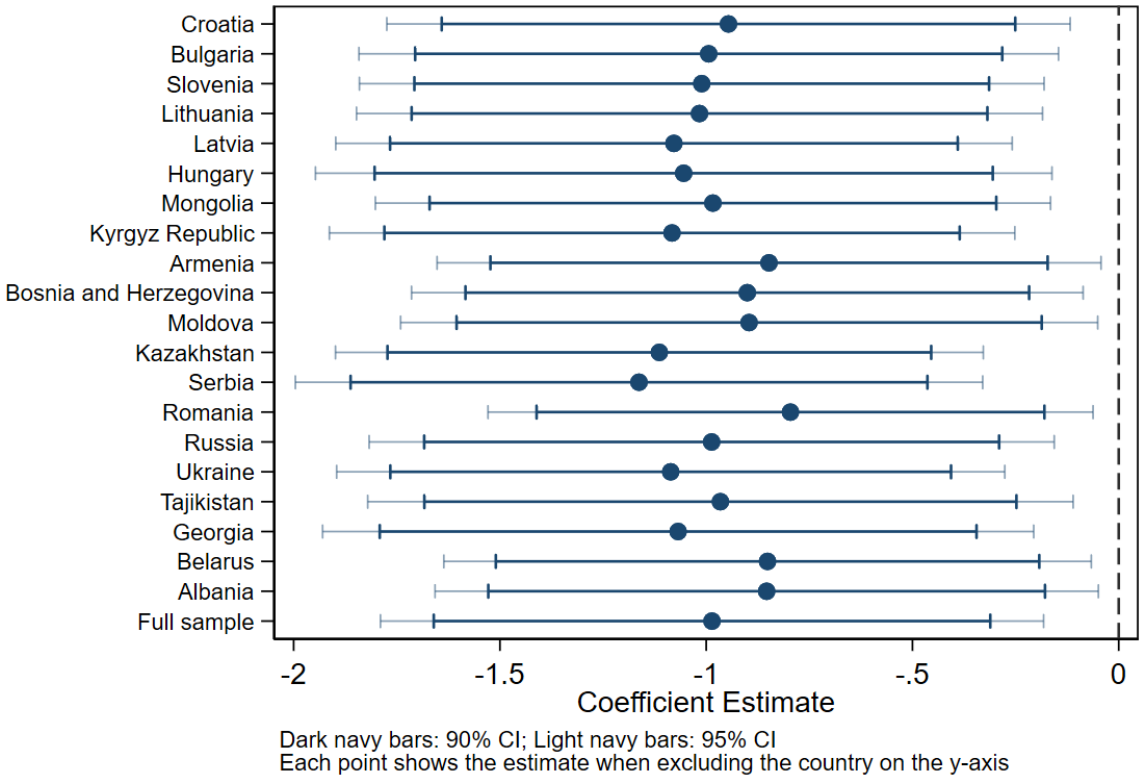


Figure OA.8: Leave-one-out sensitivity analysis for collateral scarcity treatment effect in bad boom countries. Each point shows the estimated coefficient on the High-Prod $\times$ $D_{\text{Year}>2002}$ interaction from Equation (27), after excluding the specified country from the sample. The regression 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.

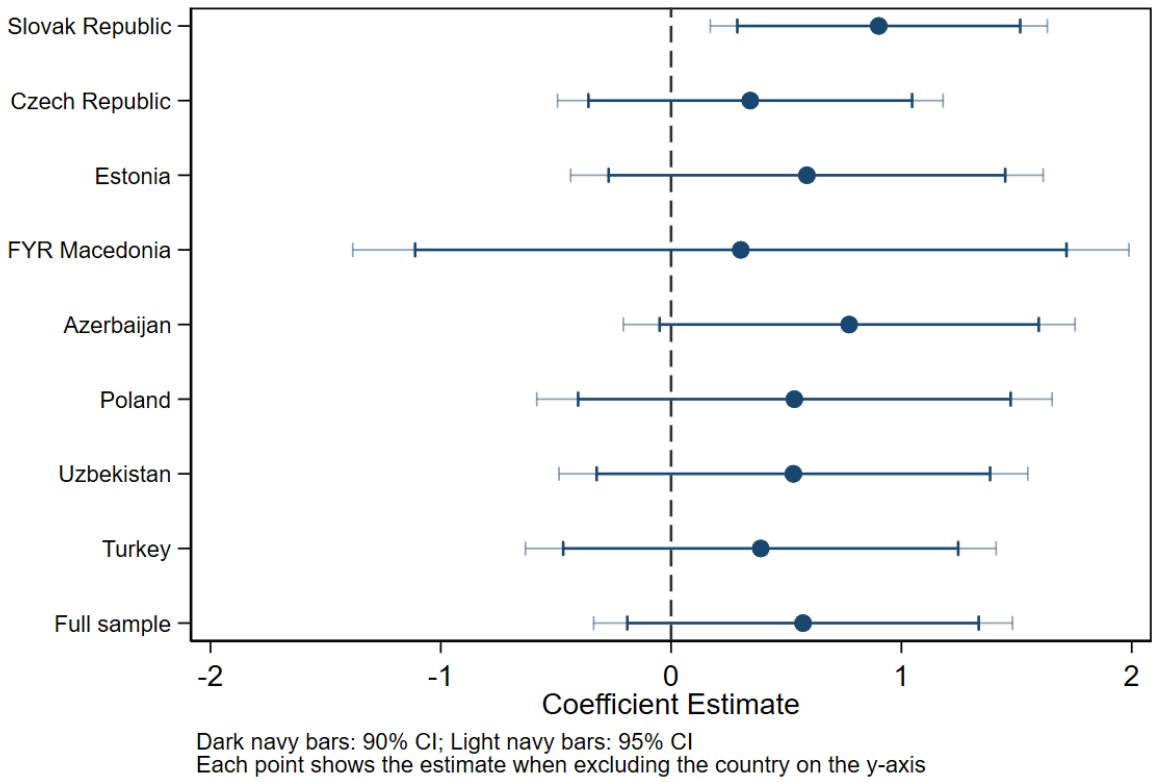


Figure OA.9: Leave-one-out sensitivity analysis for collateral scarcity treatment effect in good boom countries. Each point shows the estimated coefficient on the High-Prod $\times$ $D_{\text{Year}>2002}$ interaction from Equation (27), after excluding the specified country from the sample. The regression 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.

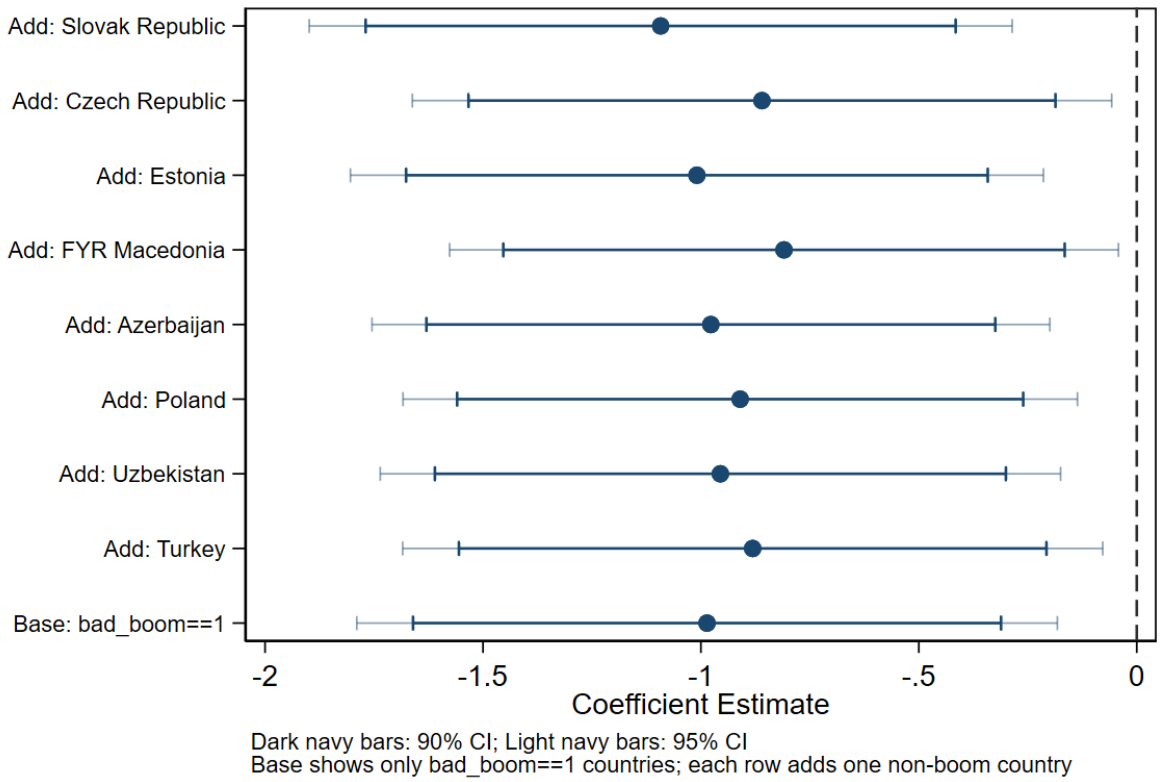


Figure OA.10: Add-one-in sensitivity analysis for collateral scarcity treatment effect starting with bad boom countries. Each point shows the estimated coefficient on the High-Prod $\times$ $D_{\text{Year}>2002}$ interaction from Equation (27), where the baseline (top row) uses only bad boom countries 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.

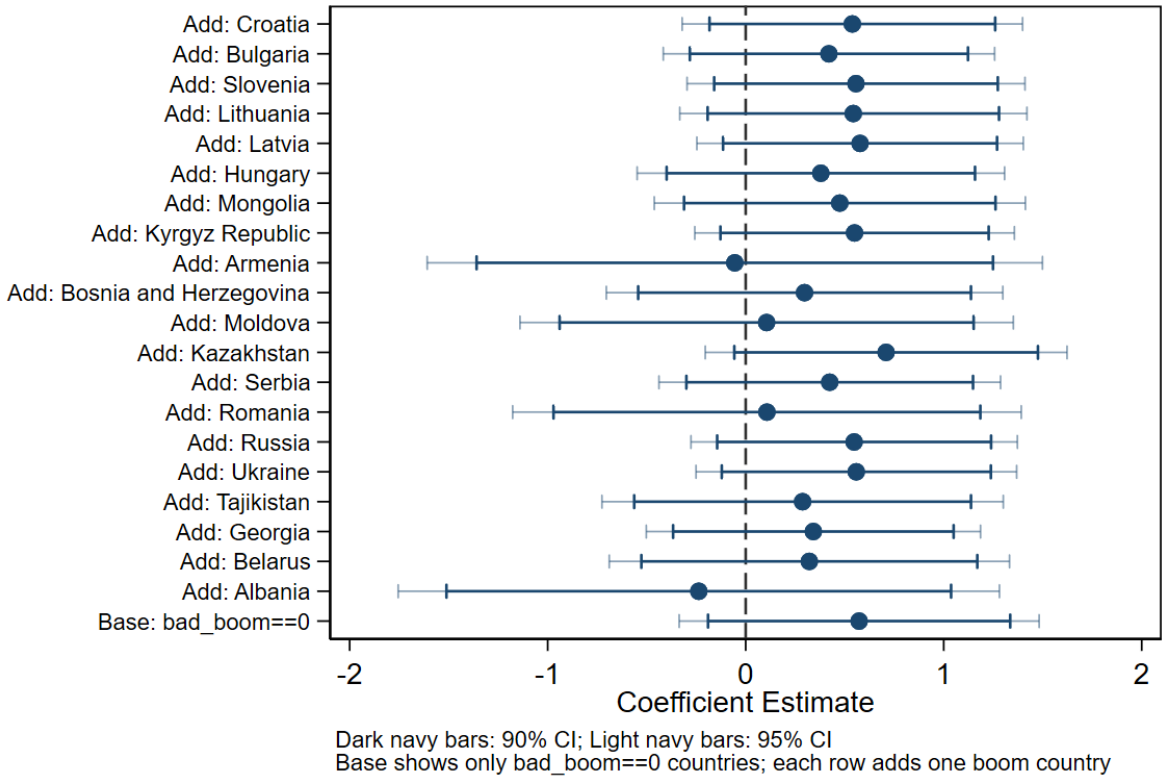


Figure OA.11: Add-one-in sensitivity analysis for collateral scarcity treatment effect starting with good boom countries. Each point shows the estimated coefficient on the High-Prod $\times D_{\text{Year}>2002}$ interaction from Equation (27), where the baseline (top row) uses only good boom countries 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.

OA.3.4 Extended Pre-Treatment Period

In this subsection, 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:

$$\text{Financial Access}_{isct} = \beta \text{Low-Prod}_{isct} \times D_{\text{Year}>2002} + \delta_{sc} + \gamma' X_{isc} + \varepsilon_{isct}. \tag{OA.3.3}$$

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 OA.8 shows the results of estimating Equation (OA.3.3). 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

Table OA.8: 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.*

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.

OA.4 Welfare Analysis and Decentralization

Section 4 shows that the model equilibrium is constrained inefficient. In this section, we compute the welfare gains from optimal policy, and show how it can be decentralized as a simple macro-prudential-style policy.

OA.4.1 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 0.4%: an entrepreneur in a world with the optimal policy in place is willing to give up 0.4% of her consumption to maintain that optimal policy and avoid living in a world without it. Under the same parameterization, the welfare gain from eliminating information frictions is 2.3% 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.

OA.4.2 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,

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

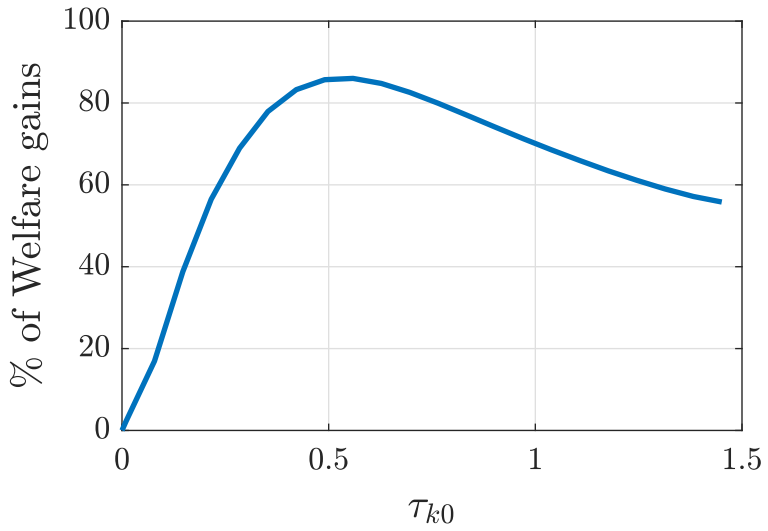
where $\tau_0 \geq 0$ and θ_{ss} is market tightness at the non-stochastic steady state. Hence, this tax is only implemented if market tightness is above steady-state levels, in which the tax increases in market tightness. With this policy in place, the equilibrium condition for θ_t

satisfies,

$$\frac{\kappa\left(1+\tau(\theta_t)\right)}{\lambda^f(\theta_t)} = \mathbb{E}_t\left\{\Lambda_{t,t+1}\left[\chi\Pi_{gt+1} + (1-\chi)\Pi_{bt+1} + \frac{\bar{p}\kappa\left(1+\tau(\theta_{t+1})\right)}{\lambda^f\left(\theta_{t+1}\right)}\right]\right\} \tag{OA.4.4}$$

Even though there is no direct mapping between equations (20) and (OA.4.4), we can compare the welfare gains from implementing the tax with those of the optimal policy. With that aim, we solve the equilibrium with the tax for different values of τ_0 and compute the welfare gain in consumption equivalent units. The results are summarized in Figure OA.12.

Figure OA.12: 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 $\tau_{\kappa 0}$.

We see that when the parameter τ_0 is around 0.5, welfare gains are almost 86% of the welfare gains achieved by the optimal policy. We conclude that, conditional on an economy facing credit booms with relaxed credit standards, there is room for simple macro-prudential policy with significant welfare gains.