Larger Crises, Slower Recoveries: The Asymmetric Effects of Financial Frictions

Guillermo L. Ordoñez*

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Abstract

Lending rates are more likely to experience big jumps rather than big drops. I compare this asymmetry across countries. First, I document that lending rates are more asymmetric in economies with poor financial systems. Second, I explain this finding by introducing agency costs into a model with endogenous flow of information about the aggregate state of the economy. High monitoring costs magnify the size of crises and restrict the generation of information that fuels recoveries. Finally, by calibrating the model, I show that cross-country differences in the asymmetry of lending rate fluctuations are well explained by differences in these financial frictions.

1 Introduction

Asymmetry is a well-known feature of asset markets. Lending rates, for example, exhibit sudden jumps but slow and gradual drops. The 1994 Mexican peso crisis was a typical case. It took just 4 months for Mexican lending rates to rise 70 percentage points, but more than 30 months to return to pre-crisis levels.[1]

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[1]Recent crises are also good examples. In October 1997, Brazilian real lending rates rose from 71% to 98% and it took 10 months to return to pre-crisis levels. In Indonesia, the 8 months following the Asian crisis experienced a rise in real lending rates from 18% to 35%, and it took 24 months to return to pre-crisis levels. During the first half of 1998, Russian real lending rates rose from 24% to 48%, and it took 25 months to return to pre-crisis levels.

Although the explanation for this asymmetry has attracted a lot of attention in economics,[2] differences across countries have been surprisingly absent from this literature. However, the study of these differences is of the utmost importance. First, high asymmetry in lending rate fluctuations may cause financial distresses, banking crises, and inefficient reallocations of resources (Bergoeing, Loayza, and Repetto (2004)). Second, since there are gains from reducing business cycle fluctuations and improving the forecasting of macroeconomic aggregates, the benefits from understanding the source of asymmetry in asset prices are non trivial (Van Nieuwerburgh and Veldkamp (2006); Chen and Chan (1989)). Finally, a preference for (positive) skewness in rates of return is a general characteristic of investors having utility functions displaying the desirable behavioristic attributes (Kraus and Litzenberger (1976)).

In this paper I make three contributions. The first one is empirical. By focusing on real lending rates, I document a negative relationship between financial development and asymmetry. Lending rates in countries with high levels of monitoring and bankruptcy costs tend to be more asymmetric. This result is robust to cross-country comparisons for a given period or over time comparisons for a given country.

The second contribution is theoretical. I explain this empirical fact by introducing financial frictions - specifically, agency and monitoring costs - into the Veldkamp (2005) model of endogenous flow of information. In her complete information setting, agents choose to invest or not in a risky asset based on an inference about an unobserved state of the economy that drives failure probabilities. This inference is constructed using signals from previous ventures' results, all of which are perfectly observed. When agents think the state is good, there are many ventures that generate a large sample of observations. When the state changes to bad, all these signals allow investors to easily deduce that conditions have changed, and interest rates jump. Contrarily, when the state is bad and changes to good, the limited number of existing ventures offer few signals about the switch, agents slowly learn about it, and lending rates drop gradually.

We introduce asymmetric information between borrowers and lenders into this setup such that the observation of the signals to infer the state of the economy is not costless anymore. To motivate truth telling by borrowers, lenders have to spend on monitoring costs sometimes, but more frequently during periods of high failure rates. Hence, high agency costs (such as monitoring and bankruptcy costs) have two effects. First, they lower the number of signals

[2] Banerjee (1992), Banerjee and Newman (1993), and Welch (1992) explained crashes from herd behavior and information cascades. Jacklin, Kleidon, and Pfleiderer (1992), based on Glosten and Milgrom (1985), used a portfolio insurance model of stock market crashes. Allen, Morris, and Shin (2006) used an information-based model of bubbles. Zeira (1994, 1999) proposed models of informational overshooting to explain booms and crashes in stock prices. Veldkamp (2005) used a model with endogenous flow of information to explain unconditional asymmetry. For a review of asymmetries in real economic variables, see Van Nieuwerburgh and Veldkamp (2006) and Jovanovic (2006).

available in the economy. However, the reduction of economic activity is not symmetric across states. In times where the likelihood that a venture fails is large, high agency costs impose big restrictions on loans, slowing down the creation of new economic activity. Contrarily, in times where the likelihood that a venture fails is low, high agency costs are irrelevant in determining the number of ventures. Hence, high agency costs slow down the learning that fuels booms but not the information that sustains big crashes. Second, they push large jumps in lending rates when failure rates increase, magnifying the size of a crash. These two effects generate larger jumps and slower drops of lending rates, hence more asymmetry.

The third contribution is quantitative. Calibrations of the model closely match the data on cross-country differences of asymmetry in lending rate fluctuations. I estimate agency costs per country by calibrating the model to match the cross-country differences in asymmetry observed in the data. These estimations are consistent with the limited evidence (mainly anecdotal and survey based) from the literature. Roughly speaking, data on the asymmetry of lending rates are consistent with monitoring costs of around 5% over initial investment for developed countries and 30% for underdeveloped ones. The calibration of the model also allows for an estimation of the share of monitoring costs in lending rate spreads, being only 2% for developed countries but 25% for underdeveloped countries.

In Section 2, I report stylized facts about the negative relation between the development of financial systems and the asymmetry of lending rates and the positive relation between agency costs and asymmetry. In Section 3, I explain these findings by introducing agency costs into a model with endogenous flow of information about the aggregate state of the economy. In Section 4, I calibrate the model and obtain estimations of agency costs for different countries by matching the model with asymmetry data. In Section 5, I make some final remarks.

2 Stylized Facts

In this section, I show that cross-country differences in the asymmetry of real lending rates are closely related to differences in the development of financial systems and in agency cost levels. In general, countries with under-developed financial systems are more asymmetric. In particular, countries with high monitoring and bankruptcy costs, low contract enforcement, and difficulties in the flow of information about previous venture results are more asymmetric.

Asymmetry on real lending rates is measured by the unbiased skewness of the distribution of log changes.

$$Skewness = \frac{T\sqrt{T-1}}{T-2}\frac{\left[\sum_{t=1}^{T}(x_t-\overline{x})^3\right]}{\left[\sum_{t=1}^{T}(x_t-\overline{x})^2\right]^{\frac{3}{2}}}, \quad (1)$$

where T is the number of observations (periods per country), $x_t = \ln(\rho_t) - \ln(\rho_{t-1})$, ρ_t is the real lending rate at period t and $\overline{x}$ is the sample mean of the time series.

I compute skewness using International Monetary Fund (IMF) monthly data on real lending rates from 1960 to 2008.[3] I use information on 96 countries that fulfill certain minimum requirements.[4] A list of all countries in the sample, their individual skewness, and their classifications are detailed in Appendix A.1. Since skewness is a tail property that keeps track of booms and crashes, a higher positive skewness means a higher probability of showing a large crash when compared with the probability of having a boom of the same magnitude.

2.1 Negative relation between asymmetry on lending rates and financial development

First, I run a series of regressions between measures of financial development and real lending rate skewness. Financial development is measured for each country by the credit to private sector as a percentage of GDP from the World Development Indicators (WDI) database. As shown in Table 1, just regressing these two variables for different period samples (1960 - 1985 and 1985 - 2008) and different country samples (all countries and non-african countries) makes it possible to find a statistically significant negative relation in all cases. The same results are obtained when controlling by the volatility of GDP per capita, the volatility of lending rates, and average inflation.

Second, I classify countries in groups correlated with financial development and compute the average asymmetry on lending rates. This classification will also be handy in performing the simulation exercises in Section 4. The following classifications are used:

- **Income groups** as defined by the World Bank.
- **OECD and non-OECD countries**.

[3] I use information from the International Financial Statistics (IFS) to obtain real lending rates by subtracting the Hodrick-Prescott trend of inflation (IFS figure $64P..ZF...$) from nominal lending rates (IFS figure $60P..ZF...$). Two caveats are relevant. First, deflating nominal rates by using other measures of expected inflation does not modify the results. Second, even when countries do not measure lending rates in the same way, it is unlikely that these differences bias the measure of skewness, which is based on changes over time for a given country.

[4] They have more than 48 observations (4 years) and have a defined cyclical pattern.

Table 1: Asymmetry of lending rates and financial development

Dependent Variable	All Countries		Non-African Countries	
Lending rate skewness	1960 - 1985	1985 - 2008	1960 - 1985	1985 - 2008
Credit to Private Sector / GDP	-0.037	-0.024	-0.044	-0.019
	(0.014)**	(0.005)***	(0.018)**	(0.005)***
Constant	4.88	2.71	5.38	2.21
	(0.72)***	(0.41)***	(1.07)***	(0.48)***
Observations	47	94	31	70

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. The dependent variable is the skewness measured over the distribution of log changes in monthly lending rates, obtained from the IMF's IFS database. Yearly data on the credit to private sector as a percentage of GDP from the World Bank's WDI database. The simple average per country over the period sample is considered.

- **Countries with high and low contract enforcement**. I use the ”contract enforcement” indicator from Levine, Loayza, and Beck (2000), which is an average between the ”rule of law” (an assessment of the law and order tradition of the country) and ”government risk” (an assessment of the risk that the government will modify a contract after it has been signed) from La Porta et al. (1998). In both cases, the indices go from 1 (the worst possible situation) to 10 (the best possible situation). I use 5 as the cutoff between low and high contract enforcement to have the same number of countries in both groups.

- **Countries with and without Private Bureau**. In Djankov, McLiesh, and Shleifer (2007), a ”private bureau” is defined as a private commercial firm or nonprofit organization that maintains a database on the standing of borrowers in the financial system and facilitates the exchange of information among banks and financial institutions.

While the use of the first two classifications is justified by the well-known positive relation between economic and financial development (Levine (1997)), the last two classifications reflect the situation in terms of contract enforcement and availability of information to lenders, more in line with specific channels through which financial development affects asymmetry.

In Table 2, I show simple averages of skewness across countries belonging to each group for the whole sample and also for two subperiods. Richer countries, OECD countries, and countries with good contract enforcement and information flows always show less asymmetry than poorer countries, non-OECD countries, or countries with bad contract enforcement and information flows, respectively. This evidence reinforces the conclusions of a negative relation between asymmetry on lending rates and financial development.

This table is informative about asymmetry differences across country classifications. Since skewness numbers are difficult to interpret in real terms, we translate them in the number of

Table 2: Asymmetry of lending rates by country classification

Country Classification	1960 - 1985	1985 - 2008	1960 - 2008
Income group 1 (richest)	2.69	0.21	**1.52**
Income group 2	3.17	1.55	**1.72**
Income group 3	4.22	1.77	**2.08**
Income group 4 (poorest)	4.87	2.91	**3.33**
OECD	2.46	0.80	**1.73**
Non-OECD	4.40	1.89	**2.35**
High contract enforcement	2.09	0.39	**1.34**
Low contract enforcement	4.17	2.44	**2.92**
Private bureau	2.02	0.83	**1.39**
No private bureau	5.16	2.25	**2.66**

Notes: Income classifications from the World Bank (WDI). Contract enforcement indicator from Levine, Loayza, and Beck (2000). Existence of a private bureau from Djankov, McLiesh, and Shleifer (2007). Skewness by group is the simple average of the skewness of "member" countries for the referred period.

months required to recover after a one-month 10% increase in lending rates. The skewness levels in the first two income groups represent recoveries that last 2 or 3 months, recoveries in the third income group last 6 months, and recoveries in the poorest group last 15 months. This is a way to interpret the differences in asymmetries across countries, the potential effects on efficiency, and how painful crises can be in poor countries.

In Appendix A.2, we repeat this exercise but with two different approaches. In the first approach, I obtain skewness in log deviations from trend rather than in log changes. In the second approach, I obtain skewness in log changes of lending rate spreads with respect to 3-month T-bills (a standard measure of risk-free interest rate) rather than levels. Results for both cases are consistent with conclusions from Table 2.

2.2 Positive relation between asymmetry on lending rates and agency costs

Since I propose that asymmetry is specifically linked to differences in monitoring and bankruptcy costs and the degree of information asymmetry, we should also find a positive relation between asymmetry on lending rates and the level of agency costs. The problem is the lack of information about monitoring costs for many countries. In fact, even estimations of bankruptcy costs for the United States are subjects of a great controversy (Carlstrom and Fuerst (1997)). To cope with the unavailability of direct information, I use the following alternative indicators.

2.2.1 Evolution of technology and monitoring costs

Monitoring and bankruptcy costs are closely related to technology improvements, since they are based on the efficiency of auditing accounts and on the ease of sharing and transmitting information. The better the available technology (such as computers and telecommunications), the less the monitoring costs within the financial sectors.[5] Information technologies have improved significantly and continuously from 1960 on. Table 2 also shows that, for each classification group, asymmetry in lending rates decreases over time. Hence, both asymmetry and monitoring costs decreased over time for all countries.

2.2.2 Proxies for monitoring costs

Another alternative is to use proxies for monitoring costs, which are available for many countries. We use two sets of proxies. The first set is based on Djankov et al. (2005), who specifically analyze the time and cost of closing businesses. The second set is based on the *Global Competitiveness Report* (World Economic Forum, 1999) and refers to the performance of financial and banking systems in improving information access and availability.

1) Bankruptcy costs and duration (Djankov et al. (2005)).

- **Cost of bankruptcy**: Bankruptcy proceedings (in percentage of the estate value) that include court costs, fees of insolvency practitioners, independent assessors, lawyers, accountants, and so on.
- **Time for bankruptcy**: Years to complete a bankruptcy procedure.
- **Recovery rate**: A measure of foreclosure efficiency. It shows how many cents on the dollar claimants (creditors, tax authorities, and employees) recover from an insolvent firm. The calculation takes into account whether the business is kept as a going concern during the proceedings, the discounted value due to the time spent closing down and court costs, attorneys, and so on.

Although it seems that these variables are exactly the measures of monitoring and agency costs we require, they also have some drawbacks we should mention. First, the estimation of bankruptcy costs is based on multiple-choice questions to insolvency lawyers, where the answer options are biased toward zero.[6] Second, the variable has a low variability, with 30%

[5] Merton (1987) earlier analyzed the impact of the evolution in informational technologies on finance monitoring.

[6] The options in the survey are 0 - 2 %, 3 - 5 %, 6 - 10 %, 11 - 15 %, 16 - 20 %, 21 - 25 %, 26 - 50 %, and more than 50 % of the estate value of the bankrupt business.

Table 3: Asymmetry of lending rates and proxies for bankruptcy costs and duration

Dependent Variable Lending Rate Skewness	1960 - 2008			1985 - 2008		
Cost of bankruptcy	0.042			0.050		
	(0.012)***			(0.012)***		
Time for bankruptcy		0.233			0.221	
		(0.079)**			(0.091)**	
Recovery rate			-0.019			-0.024
			(0.007)***			(0.007)***
Constant	1.178	1.138	2.507	0.561	0.688	2.292
	(0.320)***	(0.348)***	(0.408)***	(0.290)*	(0.374)*	(0.412)***
Observations	83	83	83	83	83	83

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. All independent variables were obtained from Djankov et al. (2005).

of the countries reporting that 8% of the estate value corresponds to bankruptcy costs and 30% reporting 18%. In this sense, the recovery rate seems a better variable to capture our ideal measure of monitoring costs, given it is constructed using more bankruptcy elements.

Table 3 shows simple ordinary least squares (OLS) regressions between skewness on lending rates and these proxies. The positive relation between monitoring costs and asymmetry (positive coefficients for cost and time of bankruptcy and negative for recovery rate of claimants) is statistically significant in all cases. Since proxies are measured for 2004, we also report results for the more recent period corresponding to 1985 - 2008.

2) Financial sector quality and health (Global Competitiveness Report, 1999).

- **Legal protection to financial assets**
- **Sophistication of financial markets**
- **Availability of Internet banking**
- **Health of banking systems**

These variables are measured by an index that goes from 1 to 7 (from the worst possible situation to the best possible situation). Table 4 shows simple OLS regressions of skewness on these proxies, obtaining statistically significant negative coefficients in all cases. The general conclusion is, again, that a difficult flow of information in financial and banking sectors increases the asymmetry on lending rates. Even when I report the regressions only for the more

Table 4: Asymmetry of lending rates and proxies for financial quality and health

Dependent Variable Lending Rate Skewness	1985 - 2008			
Legal protection to financial assets	-0.75 (0.24)***			
Sophistication of financial markets		-0.66 (0.19)***		
Availability of Internet banking			-0.59 (0.25)**	
Health of banking systems				-0.58 (0.16)***
Constant	4.71 (1.41)***	3.76 (0.97)***	3.49 (1.21)***	3.90 (0.99)***
Observations	56	56	56	56

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. All independent variables were obtained from surveys conducted by the *Global Competitiveness Report* (World Economic Forum, 1999).

recent period 1985 - 2008 (since proxies are more relevant for the latest years), results using 1960 - 2008 are almost identical.

2.2.3 Financial liberalization

An alternative test of the negative relation between skewness and monitoring costs, not subject to the correlation of different proxies across countries, is to compare skewness in a given country before and after a financial liberalization process. This is a shock that abruptly reduces monitoring costs by opening financial systems to competition and by inducing the adoption of modern and more efficient monitoring practices, a better enforcement of contracts, and an easier flow of information.

Data on financial liberalization are obtained from Kaminsky and Schmukler (2001) for the period 1973 - 1998, including information on liberalization of capital accounts, domestic financial sectors, and stock market capitalization. Capital accounts liberalization considers whether corporations are allowed to borrow abroad and whether multiple exchange rate mechanisms or other sorts of capital controls are in place. Domestic financial liberalization considers interest rate controls (lending and deposits) and other restrictions such as directed credit policies or limitations on foreign currency deposits. Stock market liberalization considers the degree to which foreigners are allowed to own domestic equity and restrictions on repatriation of capital, dividends, and interests.

Table 5: Asymmetry of lending rates before and after a main financial liberalization event

Country	Main Financial Liberalization Event		Type of Liberalization	Skewness	
	Month	Year		Pre-event	Post-event
Canada	March	1975	KA	0.88	0.41
Finland	January	1990	SM and DFS	0.43	0.13
France	January	1985	DFS and KA	3.94	0.05
Ireland	January	1992	SM and DFS	0.57	0.95
Italy	January	1992	KA	0.63	0.60
Japan	January	1985	SM	1.95	-0.30
Korea	January	1999	SM	-0.10	-0.27
Philippines	January	1994	KA and SM	0.37	0.17
Portugal	January	1986	SM	4.05	-0.33
Spain	December	1992	KA	2.09	0.48
Sweden	January	1984	KA	3.48	0.02
UK	October	1973	KA	3.91	1.49
Venezuela	April	1996	SM	3.75	0.32

Notes: KA stands for Capital Account, SM stands for Stock Market, and DFS stands for Domestic Financial System. Data on liberalization dates from Kaminsky and Schmukler (2001).

We use data on 16 countries that have enough data to reliably obtain skewness before and after important liberalization events (more than 47 observations on each side). Table 5 shows a comparison of skewness in lending rates before and after the main financial liberalization event in 13 countries (I do not report Chile, Indonesia, and Thailand, since they have experienced both financial liberalization and restriction processes over the relevant period).[7] In our sample, 12 out of 13 countries experienced a reduction on the lending rates asymmetry right after the main liberalization event.

As a robustness check, I also compare asymmetry before and after the whole liberalization process, not just the main event. Since Chile, Indonesia, and Thailand experienced both liberalization and restriction processes, this exercise allows us to analyze these cases as well. In Table 6, I show skewness before and after the whole financial liberalization process for each country, and in Table 7 I show skewness before and after a financial restriction process. Out of the 16 countries in the sample that liberalized, only Korea did not experience a reduction in skewness. Contrarily, the three countries that restricted the financial system experienced an increase in skewness.

[7]The main financial liberalization process is defined as the month at which the maximum number of liberal changes have been introduced into the financial system.

Table 6: Asymmetry of lending rates before and after a financial liberalization process

Country	Start of Financial Liberalization Process		End of Financial Liberalization Process		Skewness	
	Month	Year	Month	Year	Pre-process	Post-process
Canada	March	1975	March	1975	0.88	0.41
Chile	January	1984	September	1998	1.17	-0.15
Finland	January	1986	January	1990	1.83	0.13
France	January	1985	January	1990	3.94	0.08
Indonesia	January	1983	August	1989	1.38	0.95
Ireland	May	1985	January	1992	1.82	0.95
Italy	May	1987	January	1992	1.42	0.60
Japan	January	1979	December	1991	1.64	-1.39
Korea	January	1988	January	1999	-0.58	-0.27
Philippines	January	1976	January	1994	8.04	0.17
Portugal	January	1976	August	1992	4.60	-0.09
Spain	January	1981	December	1992	2.22	0.48
Sweden	January	1978	January	1989	3.76	0.68
Thailand	January	1979	June	1992	1.81	0.13
UK	October	1973	January	1981	3.91	2.00
Venezuela	April	1996	April	1996	3.75	0.32

Note: Data on liberalization dates from Kaminsky and Schmukler (2001).

Table 7: Asymmetry of lending rates before and after a financial restriction process

Country	Start of Financial Restriction Process		End of Financial Restriction Process		Skewness	
	Month	Year	Month	Year	Pre-process	Post-process
Chile	June	1979	January	1983	0.66	1.17
Indonesia	March	1991	March	1991	0.95	5.32
Thailand	August	1995	May	1997	0.13	0.81

Note: Data on liberalization dates from Kaminsky and Schmukler (2001).

Table 8: Correlation coefficients between skewness on lending rates and skewness on real variables

Real Variables	Correlation		
	1960 - 2008	1975 - 2008	1990 - 2008
Real GDP (deflated by CPI)	0.12	0.16	0.14
Real GDP (in volumes)	0.01	0.13	0.09
Real HH consumption	0.10	0.09	0.07

Notes: Real variables are obtained yearly from the IMF's IFS. Skewness of log changes in lending rates has been obtained annually considering the information from December of each year.

To conclude, regardless of considering the historical evolution of technology for all countries, bankruptcy costs and duration, enforcement of contracts, health or sophistication of financial markets or financial liberalization processes as proxies of monitoring costs and financial frictions in countries, it seems robust to the existence of a positive relation between the asymmetry of lending rates and monitoring costs.

2.3 Is the asymmetry on lending rates just a reflection of the asymmetry on real variables?

An obvious question at this point is whether the results are just reflecting movements on the real side of the economy. If this is the case, the question should change from explaining why lending rates are more asymmetric in less developed countries to explaining why booms and crashes in output depend on the development of financial systems. Table 8, however, shows that skewness on lending rates is not correlated with skewness on real variables such as real household (HH) consumption or real GDP.[8] This means that a country with high asymmetry on real GDP, for example, does not necessarily show a high asymmetry on interest rates.

3 The Model

3.1 Description

This model captures the positive relation between asymmetry and agency costs by introducing these financial frictions into a model with endogenous flow of information about the

[8] I compute real GDP both by deflating yearly nominal GDP and by directly considering yearly GDP in volumes from the IFS database.

aggregate state of the economy. As in Veldkamp (2005), assume a credit market with a finite number N of risk-neutral entrepreneurs and M perfectly competitive and risk-neutral investors, where $N < M$.

At each period t, each entrepreneur i observes a business opportunity that pays v_{it} (drawn from a support $(\underline{v}; \overline{v})$) in case of success[9] and zero otherwise. All ventures require the same initial investment (normalized to 1). If entrepreneurs decide to undertake the project, they should borrow the money. If not, they can always work for a exogenously fixed wage w. Investors can either lend the indivisible unit of capital to entrepreneurs or invest it in a riskless bond that pays an exogenous and constant rate $(1 + r)$.

The probability of success is the same for all ventures at period t, θ_g in good times and θ_b in bad times, where $\theta_g > \theta_b$ and good (G) and bad (B) times are the two possible states of an aggregate variable that follows a Markov process with persistence $1 - \lambda$. I assume that neither borrowers nor lenders can observe the state of the economy when negotiating a loan, but can infer it based on observations about venture realizations in the previous period.

More explicitly, the expected probability of success in period $t + 1$ is determined in the following way. From the n_t funded ventures in period t, agents observe a number of successes (s_t) and form posterior beliefs μ_t^P, using Bayes' rule[10] and a prior $\mu_t = Pr(G)_t$:

$$\mu_t^P = \Pr(G|s_t)_t = \frac{\theta_g^{s_t}(1-\theta_g)^{n_t-s_t}\mu_t}{\theta_g^{s_t}(1-\theta_g)^{n_t-s_t}\mu_t + \theta_b^{s_t}(1-\theta_b)^{n_t-s_t}(1-\mu_t)}. \tag{2}$$

Adjusting these posteriors by the probability of a change in state, the probability of being in a good state at $t + 1$ is

$$\mu_{t+1} = \Pr(G)_{t+1} = (1-\lambda)\mu_t^P + \lambda(1-\mu_t^P). \tag{3}$$

And finally, the expected probability of success of a given venture at $t + 1$ is

$$\theta_{t+1} = \Pr(s)_{t+1} = \mu_{t+1}\theta_g + (1-\mu_{t+1})\theta_b. \tag{4}$$

When the loan is negotiated between an entrepreneur i and an investor j, v_{it} is observable ex ante, but ex post the lender can observe whether the borrower was successful or not, but only at a positive cost c. At the end of the period, borrowers may pay the stipulated lending rate to lender j, $(1 + \rho_{jt})$, or default. Depending on this action, the lender monitors the result or not, following the specifications of the contract. Hence, I assume full commitment.

[9]This support does not include trivial agents who always invest or who never invest.
[10]Recall $C_s^n = C_{n-s}^n = n!/((n-s)!s!)$ and then drop from the equation.

Summarizing, the timing of the model in each period is as follows:

- Entrepreneurs and investors share beliefs on the probability of having a good state (μ_t).
- Investors offer a loan contract, taking into account the costly state verification. Entrepreneurs decide whether or not to take a loan and start a venture. Entrepreneurs not taking a loan work in a job that pays w. Investors not making a loan invest in a riskless bond that pays $(1 + r)$.
- Production takes place. Borrowers receive cash flows in case of success.
- Borrowers report the result of their ventures to lenders and contracts are fulfilled. All reports and monitoring results are publicly observed.
- Beliefs about the probability of being in a good state in the next period (μ_{t+1}) are updated. State changes with a probability λ.

3.2 Equilibrium

Definition 1 *A subgame perfect Nash equilibrium (SPNE), for an initial belief μ_0, is given by time sequences of borrowing (b_{it}) and payment decisions in case of success (z_{it}) by each entrepreneur i, lending rates (ρ_{jt}) and monitoring decisions (γ_{jt})[11] by each lender j, and Bayesian beliefs about the probability of being in a good state μ_t, such that the following problems are solved at each period t:*

- *Each entrepreneur i maximizes expected utility.*

$$\max_{b_{it}\in\{0,1\};z_{it}\in\{0,1\};j\in\{1,\ldots,M\}} b_{it}\theta_t\{z_{it}(v_{it} - (1 + \rho_{jt})) + (1 - z_{it})(1 - \gamma_{jt})v_{it}\} + (1 - b_{it})w$$

being $\theta_t = \mu_t\theta_g + (1 - \mu_t)\theta_b$ the expected probability of a successful venture, which depends on the expected state of the economy.

- *Each investor j maximizes expected profits.*

$$\max_{\rho_{jt}\in\mathbb{R},\gamma_{jt}\in\{0,1\}} l_{jt}\theta_t\{z_{it}(1 + \rho_{jt}) + (1 - z_{it})\gamma_{jt}(v_{it} - c)\} - l_{jt}\gamma_{jt}(1 - \theta_t)c + (1 - l_{jt})(1 + r)$$

being $l_{jt} = 1$ if some borrower decides to take a loan from this investor at period t.

[11]Recall I'm not allowing mixing strategies in monitoring decisions (i.e., $\gamma_{jt} \in \{0, 1\}$). In the case of assuming stochastic monitoring (i.e., $\gamma_{jt} \in [0, 1]$), the model has multiple equilibria and the standard debt contract is not optimal anymore. Here I focus on non stochastic monitoring for expositional reasons, since it is cleaner to highlight the effects of monitoring costs on asymmetry. In Appendix A.4, I describe the optimal equilibrium with stochastic monitoring and discuss why the results are the same.

- *Beliefs are updated using Bayes' rule, following equations (2), (3), and (4), where the total number of ventures funded is* $n_t = \sum_{i=1}^{N} b_{it}$.

The next proposition characterizes the unique SPNE with non stochastic monitoring, which takes the form of an optimal standard debt contract.

Proposition 2 *At each period t, in equilibrium, all lenders* j *set a lending rate* $1+\rho_t = \frac{1+r}{\theta_t} + \frac{(1-\theta_t)}{\theta_t}c$ *and monitor every default* ($\gamma_{jt} = 1$)*. All entrepreneurs* i *borrow* ($b_{it} = 1$) *from any lender* j *whenever* $v_{it} \geq \widetilde{\nu}_t = \frac{1}{\theta_t}[1+r+w+(1-\theta_t)c]$*. All borrowers report the truth* ($z_{it} = 1$)*.*

Proof. First we obtain the optimal debt contract that lenders chose. Second, we discuss entrepreneurs' actions under this optimal contract.

Step 1: Optimal decisions by lenders

As in Townsend (1979) and Gale and Hellwig (1985), the standard debt contract is optimal under costly state verification with non stochastic monitoring. In our setting, this result is even more trivial, since there is a known cash flow in case of success and only the event is unknown. If lenders do not monitor a default, borrowers always default, in which case lenders would not lend. Hence, $\gamma_{jt} = 1$. Since lenders act in a competitive market, expected profits from lending should equalize expected profits from the riskless bond $(1+r)$,

$$(1-\theta_t)(-c) + \theta_t(1+\rho_{jt}) = 1+r.$$

Since the expected probability of success is the same for all ventures, lending rates are too (i.e., $\rho_{jt} = \rho_t$ for all j). Furthermore, lending rates are independent of the cash flow.

$$(1+\rho_t) = \frac{1+r}{\theta_t} + \frac{(1-\theta_t)}{\theta_t}c \tag{5}$$

Step 2: Optimal decisions by entrepreneurs

Since lending rates are the same across lenders, borrowers are indifferent to taking a loan from any lender j. Given the optimal contract, successful borrowers always prefer to repay the loan, obtaining $\nu_{it} - (1+\rho_t) > 0$ rather than 0 if defaulting. The only choice left to obtain in equilibrium is whether entrepreneurs borrow or not (i.e., $b_{it} \in \{0,1\}$). This choice is given by a cutoff value over v_{it} such that an entrepreneur i borrows ($b_{it} = 1$) at period t whenever $\theta_t(v_{it} - (1+\rho_t)) \geq w$. From equation (5), the borrowing rule is

$$v_{it} \geq \widetilde{\nu}_t = \frac{1}{\theta_t}[1+r+w+(1-\theta_t)c]. \tag{6}$$

$\blacksquare$

An important variable is the number of ventures n_t funded in the economy. This is the sum of entrepreneurs who borrow at period t, and it is the number of signals agents use to update beliefs and modify interest rates. In equilibrium,

$$n_t = \sum_{i\in\{1,\ldots,N\}} \mathbf{1}_{\{v_{it}\geq\widetilde{\nu}_t=\frac{1}{\theta_t}[1+r+w+(1-\theta_t)c]\}}. \tag{7}$$

The number of ventures depends positively on the probability of success θ_t in two ways. First, a higher θ_t increases expected profits. Second, a higher θ_t decreases market interest rate ρ, directly by decreasing the probability of default and indirectly by reducing expected monitoring costs. Formally, $\frac{\partial\widetilde{\nu}_t}{\partial\theta_t} = -\frac{1+r+w+c}{\theta_t^2} < 0$.[12] More interestingly, since θ_t increases with the probability of being in a good state μ_t, $\frac{\partial\widetilde{\nu}_t}{\partial\mu_t} = -(\theta_g - \theta_b)\frac{[1+r+w+c]}{(\mu_t\theta_g+(1-\mu_t)\theta_b)^2} < 0$ (since $\theta_g - \theta_b > 0$ by assumption). This is important for the determination of signals in the economy. The greater the value for μ_t, the greater is θ_t, the smaller the cutoff value $\widetilde{\nu}_t$ and the more the number of funded ventures.

At this point, it is important to analyze more specifically the effects of costly state verification in the generation of signals. First, when the state verification is costless to the lenders ($c = 0$), this solution coincides with Veldkamp's original model solution. Second, monitoring costs c increase lending rate levels and cutoffs $\widetilde{\nu}_t$, reducing the number of funded ventures and generating underinvestment in all states. Formally,

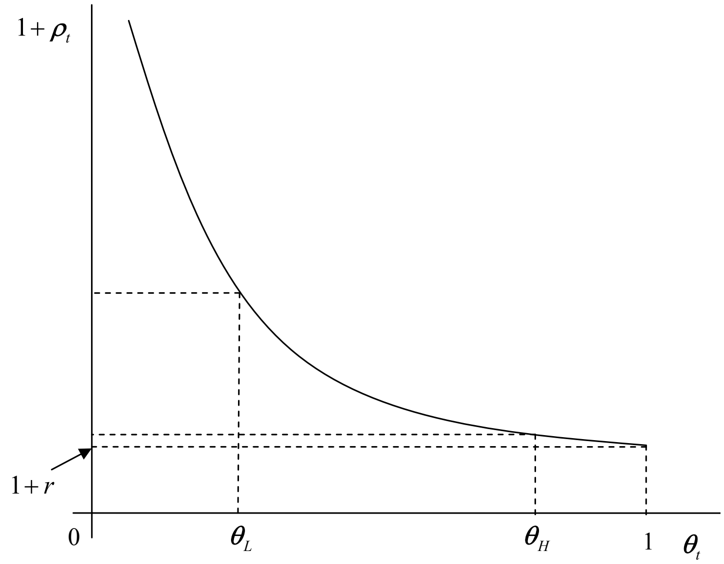
$$\frac{\partial\widetilde{\nu}_t}{\partial c} = \frac{\partial(1+\rho_t)}{\partial c} = \frac{1-\theta_t}{\theta_t} > 0. \tag{8}$$

Third, this reduction in ventures is not constant across states, since θ_t affects lending rates non linearly. As θ_t varies, c is scaled by a double effect in the numerator $(1 - \theta_t)$ and in the denominator (θ_t). Figure 1 shows the relation between lending rates ($1 + \rho_t$) and the expected probability of success (θ_t) for a given level of monitoring costs c. When the market believes the probability of success is very high, lenders assign a low probability to spend on bankruptcy at the end of the period and monitoring costs do not impose serious restrictions on lending rates and signals. Contrarily, when the market believes the probability of success is low, lenders assign a high probability to spend on bankruptcy at the end of the period and monitoring costs matter a lot for the determination of lending rates and signals.

Since the number of signals is changing continuously in this model, writing an explicit analytical solution is intractable. Results from the model are discussed using Monte Carlo simu-

[12] A smaller $\widetilde{\nu}_t$ strictly implies higher n_t whenever the density function has mass at all points $v_i \in (\underline{v};\overline{v})$.

Figure 1: Lending Rates and Expected Probability of Success



lations in Section 4. However, asymmetry implications can be discussed analytically.

3.3 Asymmetry implications

The model generates time-irreversible lending rates. Changes on lending rates have an asymmetric unconditional distribution where the probability of an increase in rates is higher than the probability of a decrease of the same magnitude. This result contrasts with a constant information economy, where the number of signals is given exogenously and changes on interest rates are time reversible and symmetric. The following proposition shows agency costs increase the skewness on the distribution of lending rate changes. In the proof, we sketch out why endogenous information generates asymmetry in the first place. Veldkamp (2005) provides a full formal proof of lending rate time irreversibility in a similar framework.

Proposition 3 *In an endogenous information economy, agency costs increase the asymmetry on changes in lending rates by magnifying crashes and delaying recoveries.*

Proof. This proof proceeds in three steps. First, the concept of time reversibility is introduced, showing why lending rates are symmetric in a constant information economy. The second step shows time irreversibility and asymmetry in an endogenous information economy. The third step shows that agency costs increase asymmetry.

Step 1: Time reversibility in a constant information economy

Time reversibility is defined as the property of a stochastic process in which beliefs in a good state are the time-reverse of beliefs in a bad state. In symbols, $\Pr[\mu_{G,t+1} = x|\mu_{G,t} = y] = \Pr[\mu_{B,t+1} = x|\mu_{B,t} = y]$. In plain words, the increase in beliefs of being in good times if, for example, all signals are successful has the same magnitude as the decrease of beliefs if all signals are unsuccessful. Assume the prior of a good state probability is $\mu_t = x$. If all n_t signals fail ($s_t = 0$), $\mu_{t+1} = y < x$. If in the following period all n_{t+1} signals are successful ($s_{t+1} = n_{t+1}$) and the process is time reversible, we obtain $\mu_{t+2} = z = x$. These extreme situations represent maximum possible booms and crashes, respectively.

In a constant information economy, the number of signals is given exogenously, say n. Without loss of generality, assume equally informative signals ($\theta = \theta_g = 1 - \theta_b > \frac{1}{2}$) and no state change ($\lambda = 0$).[13] If initial beliefs at period t are $\mu_t = x$ and all n signals fail ($s = 0$), using equations (2) and (3),

$$\mu_{t+1} = y = \frac{(1-\theta)^n x}{(1-\theta)^n x + \theta^n (1-x)}. \tag{9}$$

If in the following period $t+1$ all n signals are successful ($s = n$), then

$$\mu_{t+2} = z = \frac{\theta^n y}{\theta^n y + (1-\theta)^n (1-y)}. \tag{10}$$

Replacing (9) with (10), $\mu_{t+2} = z = x$. Hence, in a constant information economy, beliefs follow a time reversible stochastic process.

Step 2: Time irreversibility in an endogenous information economy

In an endogenous information economy, the number of signals depend on the beliefs of being in a good state. A higher probability of being in good times μ_t represents a lower cutoff $\widetilde{\nu}_t$ and more signals n_t. In this framework, beliefs are not time reversible anymore. Assume at period t, $\mu_t = x$ and all n_t^x signals fail ($s_t = 0$). The subscript t is now necessary because n varies with time and the superscript x because n depends on beliefs $\mu_t = x$.

$$\mu_{t+1} = y = \frac{(1-\theta)^{n_t^x} x}{(1-\theta)^{n_t^x} x + \theta^{n_t^x} (1-x)} \tag{11}$$

Now, given $y < x$, borrowers are less confident about being in good times, reducing the number of ventures, $n_{t+1}^y < n_t^x$. Assume in the following period all n_{t+1}^y signals are successful[14]

[13] This proof is based on the case in which there is no state change ($\lambda = 0$). The purpose is just to sketch out the main points about why the endogenous information model delivers asymmetry on interest rates. This is not a critical assumption to show the impact of agency costs. A more general proof (with $\lambda > 0$) can be found in Veldkamp (2005).

[14] The same conclusion is obtained when reverting the order of successes and failures.

$(s_{t+1} = n^y_{t+1})$, then

$$\mu_{t+2} = z = \frac{\theta^{n^y_{t+1}} y}{\theta^{n^y_{t+1}} y + (1-\theta)^{n^y_{t+1}}(1-y)}. \tag{12}$$

Now replacing (11) with (12),

$$\mu_{t+2} = z = \frac{\left[\theta^{n^y_{t+1}}(1-\theta)^{n^x_t}\right] x}{\left[\theta^{n^y_{t+1}}(1-\theta)^{n^x_t}\right] x + \left[(1-\theta)^{n^y_{t+1}}\theta^{n^x_t}\right](1-x)},$$

we can compute

$$z - x = \frac{\left[\theta^{n^y_{t+1}}(1-\theta)^{n^x_t} - (1-\theta)^{n^y_{t+1}}\theta^{n^x_t}\right] x(1-x)}{\left[\theta^{n^y_{t+1}}(1-\theta)^{n^x_t}\right] x + \left[(1-\theta)^{n^y_{t+1}}\theta^{n^x_t}\right](1-x)}. \tag{13}$$

It is straightforward to check that $z < x$ as long as $\theta > \frac{1}{2}$ and $n^y_{t+1} < n^x_t$. It means that the highest possible decreases in beliefs (from x to y) are more likely than increases in beliefs (from y to z) of the same magnitude. Hence, considering equation (5), the highest possible increase in lending rates is more likely than a decrease of the same magnitude, a necessary and sufficient condition for the existence of positive asymmetry on lending rates. Hence, in an endogenous information economy, beliefs follow a time-irreversible stochastic process and changes in lending rates have a positive asymmetry.

Step 3: The effect of monitoring costs on lending rate asymmetry

Monitoring costs increase asymmetry via two channels: by magnifying crises and by delaying recoveries. We will tackle these two channels separately.

a) Magnification of crises

Even without time irreversibility, consider two countries with same lending rate levels and initial beliefs μ_t that experience the same reduction of beliefs. Lending rates will increase more in the country with the highest monitoring costs, from a direct interpretation of equation (5).

b) Delaying of recoveries

This effect comes from the irreversibility of beliefs. The magnitude of the asymmetry is summarized by the gap $z - x$ (equation 13), since it shows the degree of irreversibility in the stochastic process and the difference between the probability of an increase in lending rates and the probability of a decrease of the same magnitude.

For an initial belief x and a given θ, the gap $z - x$ depends on the difference (not on the levels) between n^y_{t+1} and n^x_t, which is a negative function of the difference between cutoffs,

$$\widetilde{\nu}^y_{t+1} - \widetilde{\nu}^x_t = \frac{(x-y)}{xy}[1 + r + w + c]. \tag{14}$$

When $x > y$, $\widetilde{\nu}^y_{t+1} > \widetilde{\nu}^x_t$ (since the confidence on good states decreases), and the number of funded ventures decreases ($n^y_{t+1} < n^x_t$). The opposite happens when $x < y$. Hence, the impact of monitoring costs c on the gap $n^y_{t+1} - n^x_t$ can be obtained from its impact over ($\widetilde{\nu}^y_{t+1} - \widetilde{\nu}^x_t$). Taking derivatives we have that.

$$\frac{\partial(\widetilde{\nu}^y_{t+1} - \widetilde{\nu}^x_t)}{\partial c} = \frac{(x-y)}{xy}. \tag{15}$$

Two conclusions can be drawn from this equation. First, the higher the differences in beliefs $(x - y)$, the greater the impact of c on the number of funded ventures. Second, monitoring cost effects depend on whether initial beliefs μ_t are closer to 1 or to 0. When agents are confident to be in bad times (x close enough to 0), for a given difference in beliefs $(x - y)$, the impact of c on the gap between signals is large, since monitoring costs are very restrictive.

Assume the initial belief is $\mu_t = x$ and all ventures fail such that $x > y$. By equation (14), large agency costs c imply large gaps $(n^y_{t+1} - n^x_t)$. Hence, from equation (13), large monitoring costs widen time irreversibility (given by $z - x$). Hence, in an endogenous information economy with financial frictions, the greater the agency costs c, the more important the asymmetry on lending rates. ■

This proposition shows that countries with larger monitoring costs experience larger crashes (increases of lending rates) and slower booms (decreases of lending rates). This translates into a greater asymmetry of changes in lending rates. This result is empirically confirmed in subsection 3.4 and is consistent with the literature highlighting that underdeveloped countries have large crises and slow recoveries.[15]

The intuition for this result is captured by Figures 2 and 3. Figure 2 shows the crises magnification force of monitoring costs. A given decrease in the expected probability of venture success generates a larger jump of lending rates in countries with higher monitoring costs. Figure 3 shows the recovery delaying force of monitoring costs. The gap between lending rates in countries with different monitoring costs widens as the expected probability of venture success decreases. This implies that the speed of recoveries after bad times differs between the two countries more than the speed of crises after good times.

[15] See, for example, Bergoeing, Loayza, and Repetto (2004).

Figure 2: Magnification of Crises

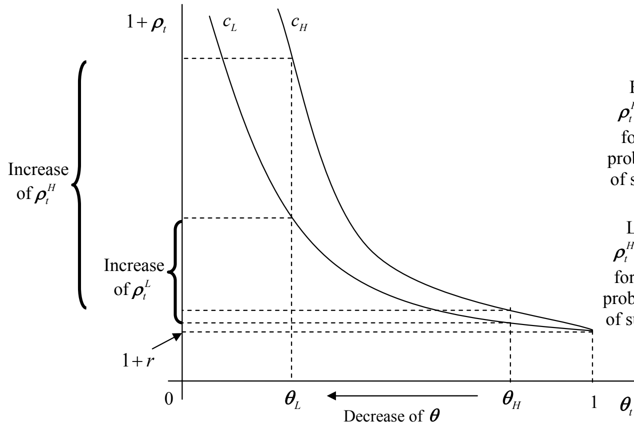
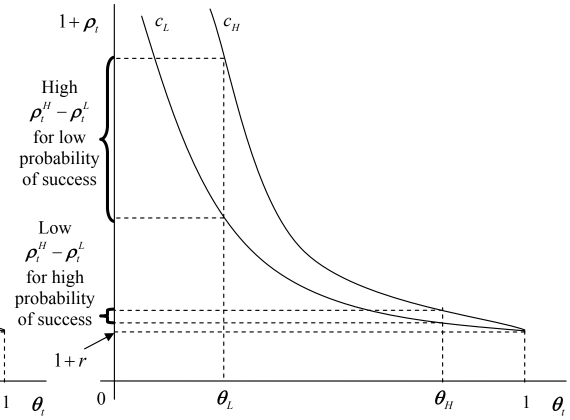


Figure 3: Delaying of Recoveries



3.4 Testable predictions in terms of levels

A testable prediction of the model is that countries with less developed financial systems show, on average, higher levels of lending rates than countries with highly developed financial systems and less financial frictions. Formally, from equation (5),

$$\frac{\partial(1+\rho_t)}{\partial c} = \frac{1-\theta_t}{\theta_t} > 0.$$

Table 9 shows regressions between average levels of lending rates and financial development. Coefficients are negative and statistically significant in all cases. An increase of 1% in credit to private sectors as a percentage of GDP implies a reduction of around 0.15 percentage points in lending rates. Table 10 repeats Tables 3 and 4 but uses as a dependent variable average levels of lending rates.[16] An important drawback is that, unlike regressions to explain skewness, comparisons of levels across countries may be capturing important differences in methodologies and definitions from the dataset. Even when we have to be more careful in interpreting these regressions, results seem consistent with the prediction that agency costs increase lending rates.

4 Simulations

In this section, I calibrate an endogenous information economy with agency costs to check whether the model is able to replicate the empirical magnitude of cross-country differences in skewness for reasonable levels of monitoring costs. When possible, I use the same calibration

[16]Brazil and Uruguay are not included, since lending rates are reported with a persistent upward bias.

Table 9: Lending rate average and financial development

Dependent Variable Lending Rate Average	1960 - 2008 All Countries	 Non-African	 OECD Countries
Credit to private sector / GDP	-0.139	-0.161	-0.129
	(0.025)***	(0.033)***	(0.059)**
Constant	22.49	24.31	20.39
	(1.56)***	(2.35)***	(5.08)***
Observations	92	68	23

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses.

Table 10: Lending rates average and proxies for bankruptcy costs and flow of information

Dependent Variable Lending Rate Skewness	1985 - 2008		
Cost of bankruptcy	0.131		
	(0.055)**		
Time for bankruptcy		0.748	
		(0.596)	
Recovery rate			-0.163
			(0.039)***
Constant	15.43	15.30	23.94
	(1.50)***	(2.08)***	(2.03)***
Observations	81	81	81

Dependent Variable Lending Rate Skewness	1985 - 2008			
Legal protection to financial assets	-3.16			
	(0.89)***			
Sophistication of financial markets		-4.47		
		(0.98)***		
Availability of Internet banking			-3.11	
			(0.79)***	
Health of banking systems				-2.13
				(0.81)***
Constant	29.46	38.34	29.02	26.46
	(4.57)***	(5.26)***	(3.84)***	(4.51)***
Observations	54	54	54	54

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses.

Table 11: Parameters used in the simulation

$\boldsymbol{\theta}_g$	$\boldsymbol{\theta}_b$	$\boldsymbol{\lambda}$	**r**	**w**	**N**
0.97	0.95	0.027	0.0042	1	25

parameters as Veldkamp (2005) for comparison purposes. Table 11 summarizes the list of parameters.

The probabilities of success θ_g and θ_b are calibrated using bond default rates listed by Moody's from 1970 - 2000. Main results use the probabilities of success of US speculative-grade bonds, which are riskier than typical US corporate bonds, because information on default rates of emerging markets bonds is unavailable.[17] The probability of a state transition λ was obtained using world GDP from the Penn World Tables. I follow Veldkamp (2005) in the use of the largest potential number of independent observable signals N, which she cleverly obtained by measuring the speed of price adjustments in the United States.[18] Parameters r and w only affect the scale of the lending rate, and skewness is invariant in scale.[19] Even when I use the same parameters to represent a whole array of countries, I will argue later that this is in fact a conservative exercise that underestimates the monitoring costs in poor countries.

Figure 4 shows estimated skewness and two standard deviations bounds for each level of monitoring costs, obtained from 10,000 repeated simulations, each with 10,000 periods. Since we assumed the initiation cost for each venture is 1, a monitoring or bankruptcy cost given, for example, by $c = 0.3$ represents a cost of 30% of initial investment. As formally shown, monitoring costs increase skewness of changes in lending rates. Furthermore, Monte Carlo standard errors show that differences in asymmetry caused by different monitoring costs are statistically significant at standard confidence levels.[20]

The result without monitoring costs (skewness around 1.60) is the same as in Veldkamp (2005) when using uniformly distributed investment payoffs. She is able to successfully match the asymmetry of lending rates for 13 emerging markets, with an average skewness of 2.9, by decreasing the probability of state switching (reducing λ), generating clearer signals (increasing

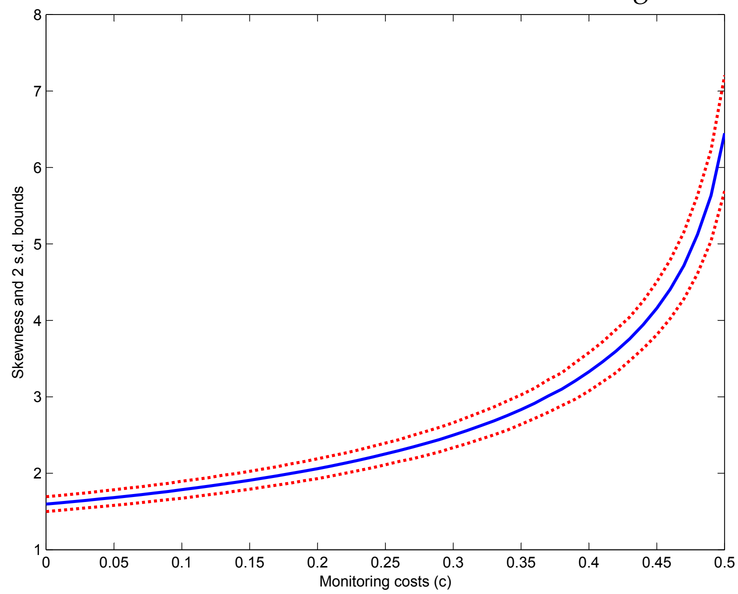
[17]For developed countries, I also perform the exercise using information on "all corporate" bonds ($\theta_b = 0.97$ and $\theta_g = 0.98$), but results are very similar.

[18]This parameter is very important, since it determines the speed at which the economy learns about the aggregate state. When N goes to infinity, the economy learns immediately about the true state, and hence, asymmetry is nonexistent. Since our main goal is to calibrate differences across countries, an alternative way to calibrate N is to match the skewness of developed countries (1.51) and use it for the rest of the countries. This alternative N is just a little higher (31), and results are almost identical. For comparison purposes, results in the text are based on the calibration in Veldkamp (2005).

[19]Skewness is independent from r and w because the support for the distribution of v_i is $[\underline{v}, \overline{v}]$, where $\underline{v} = \frac{1+w+r}{\overline{\theta}}$ and $\overline{v} = \frac{1+w+r}{\underline{\theta}}$, where $\overline{\theta}$ is the most optimistic probability of success and $\underline{\theta}$ the most pessimistic one.

[20]Even when the simulation results displayed in the main text are based on pure monitoring strategies (consistent with the theoretical section), very similar results are obtained using the equilibrium based on random monitoring.

Figure 4: Simulated skewness for different monitoring cost levels



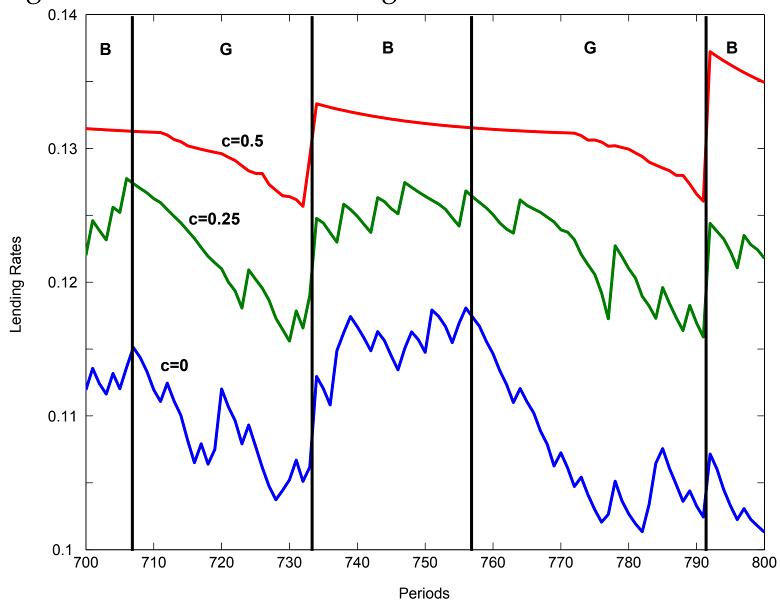
$\theta_g - \theta_b$), or changing the assumed distribution of potential profits ν_i. However, these changes imply that countries with stable states and clearer signals, standard characteristics in developed countries, are those with higher asymmetry, which seems at odd with the data. In this paper, when using the calibrated parameters, a skewness of 2.9 is consistent with bankruptcy costs of around 35% of initial investment. Monitoring costs introduce a compensating force to more volatile states or noisy signals in developing countries, which tend to reduce asymmetry levels in the first place.

Figure 5 shows an example of lending rate dynamics under the same shock realizations but with different levels of monitoring costs. More precisely, Figure 5 displays 100 simulated periods (out of 10,000 periods) of 1 simulation (out of 10,000 simulations) for three different economies, with monitoring costs $c = 0$, $c = 0.25$, and $c = 0.5$.

First, note that the levels of interest rates are higher in economies with higher monitoring costs. Second, when the economy moves from good times (**G**) to bad times (**B**), the increase in the lending rate is bigger in the country with $c = 0.5$ than in the country without monitoring costs. Finally, when the economy moves from bad times (**B**) to good times (**G**), the reduction in lending rates that follows is slower in the country with $c = 0.5$ than in the country without monitoring costs. High monitoring costs generate high levels of lending rates, magnify crises, and delay the generation of signals that allow fast recoveries.

An interesting question we can answer from these exercises is: What is the magnitude of monitoring costs that is consistent with the empirical skewness reported in Section 2? Table

Figure 5: Evolution of Lending Rates in Different Economies



12 shows the range of monitoring costs that is consistent with skewness in each classification group, using two Monte Carlo standard deviations. In this Table I also compare the bankruptcy costs implied by the model with the subjective measure of bankruptcy costs offered by Djankov et al. (2005).

In the latter case, monitoring costs are more concentrated, being higher than simulation results for developed countries and lower for underdeveloped countries. However, certain differences can partially explain the disparity. First, monitoring costs from the model replicate skewness measured for the period 1960 - 2008 while bankruptcy costs from Djankov et al. (2005) are measured for the year 2004. As discussed in Section 2, technological improvements and an easier flow of information imply that modern measures of bankruptcy costs are lower than older ones. Matching skewness for the period 1985 - 2008 closes the gap for poorer countries but delivers zero monitoring costs for richer ones. Second, bankruptcy costs as measured by Djankov et al. (2005) exclude bribes, which can raise monitoring costs considerably. Furthermore, this will be true fundamentally for poorer countries with low contract enforcement. This may be the reason why the gap between monitoring costs implied by the model and obtained by Djankov et al. (2005) is not only positive but also increasing as countries become less financially developed.

In general, the literature on monitoring technology and bankruptcy costs is the subject of a great debate about the right measurement of agency costs. One of the first attempts to estimate bankruptcy costs was Warner (1977) who, considering only direct costs for the railroad

Table 12: Implied monitoring costs to match data on lending rate asymmetry

Country Classification	**Data Skewness**	**Bankruptcy Costs**	**Consistent *c* Range (in %)**
Income group 1	1.52	7.0	$0-4$
Income group 2	1.72	17.6	$5-15$
Income group 3	2.08	18.6	$18-24$
Income group 4	3.33	24.6	$38-42$
OECD	1.73	8.5	$5-15$
Non-OECD	2.35	18.6	$24-29$
High contract enforcement	1.34	10.7	0
Low contract enforcement	2.92	23.0	$33-37$
Private bureau	1.39	11.4	$0-1$
No private bureau	2.66	20.9	$29-35$

Notes: Country classification and data skewness columns are taken from columns 1 and 4 of Table 2. Bankruptcy costs are taken from Djankov et al. (2005). Consistent c refers to monitoring costs that, given the parameters, allows us to match the skewness observed in data. The range is determined by using two Monte Carlo standard deviations at each side of the point estimation.

industry, estimated a cost of around 4% of the firm's total assets. Altman (1984) also included indirect costs (such as lost sales and lost profits), raising the estimation to 20%. Finally Alderson and Betker (1995) compared the value of the firm as a going concern with the liquidation value of the firm, raising the estimation even further to approximately 36%. Since Warner (1977) considers only the direct costs of bankruptcy, it is the closest interpretation to our model.

4.1 What about levels?

A natural question at this point is whether monitoring costs are able to explain the large differences we observe in levels of lending rates across countries (the first column of Table 13 shows that rates in poor countries almost double those in rich countries). In the model, the levels of lending rates can be expressed as the sum of three terms: a risk-free rate, a risk premium (which depends on the risk-free rate adjusted by default probabilities), and financial frictions costs. From equation (5), we have that

$$\rho_t = r + \frac{(1-\theta_t)}{\theta_t}(1+r) + \frac{(1-\theta_t)}{\theta_t}c. \tag{16}$$

I show that most of the differences in levels comes from differences in risk-free rates, which affect levels but not skewness. Since our model is silent about the determination of risk-free

Table 13: Real vs. Estimated lending rates

Country Classification	Real Lending Rates	Estimated Lending Rates			
		Total	Components		
			r	$\frac{(1-\theta)(1+r)}{\theta}$	$\frac{(1-\theta)}{\theta}c$
Income group 1	**12.5**	**10.8**	6.3	4.4	0.1
Income group 2	**19.2**	**19.3**	14.1	4.8	0.4
Income group 3	**17.7**	**15.7**	10.2	4.6	0.9
Income group 4	**22.5**	**23.4**	16.9	4.9	1.7
OECD	**11.9**	**13.8**	8.8	4.5	0.4
Non-OECD	**20.2**	**18.3**	12.5	4.7	1.1
High contract enforcement	**14.9**	**12.9**	8.4	4.5	0.0
Low contract enforcement	**18.4**	**19.2**	13.0	4.7	1.5
Private bureau	**16.4**	**13.6**	9.1	4.5	0.0
No private bureau	**19.7**	**20.3**	14.2	4.8	1.3

interest rates, to simulate levels we need to calibrate them to every country.[21] As shown in column 3 of Table 13, there are important disparities across countries (government bonds in developing countries include default risks, country risks, exchange volatility risks, etc.). Finally, to simulate the levels, we use the simulated monitoring costs from the previous section. The three components of lending rates from equation (16) are displayed in Table 13.

Even when monitoring costs are not very important in explaining differences in lending rate levels, they are important to explain spread differences. Monitoring costs account for more than 25% of spreads in developing countries ($1.7/6.6$ for income group 4) and less than 2% in developed ones ($0.1/4.5$ for income group 1). I have not found evidence of large cross-country differences in the volatility of lending rate log change differences. This is also consistent with the model, as shown in Appendix A.3.

Cross-country differences in first and second moments of changes in real lending rates depend importantly on first and second moments of risk-free interest rates. However, the third moment of risk-free rates runs in an inverse direction to the third moment of lending rates. Hence, monitoring costs have an important role in the understanding of the asymmetry of lending rates.

5 Conclusions

A well-documented feature of financial markets is their asymmetry of changes over cycles. While crashes are sudden and sharp, booms are slow and gradual. This is a non trivial fact,

[21] This information was obtained from the Global Financial Dataset (GFD), taking averages of 3-month Treasury bill yields for each country in the sample between 1990 and 2008 when available.

since it may generate financial distresses and banking crises, and may eventually also have real consequences, such as a costly reallocation of resources. In this paper, I show that less developed financial systems, with high monitoring and bankruptcy costs, have, on average, higher levels of asymmetry in lending rates.

I consider a model where the state of the economy, which affects the probability of venture default, is unknown. Agents make inferences about that state using information from the results of previous ventures. If agents believe they are in good times (low default probability), the level of economic activity is high, which provides many signals to learn from in case the economy switches to bad times. This generates a sudden jump in lending rates, the magnitude of which grows with levels of monitoring and bankruptcy costs. Contrarily, if agents believe they are in bad times (high default probability), the level of economic activity is low, which provides few signals to learn from in case the economy switches to good times. This generates gradual drops in lending rates as agents gradually learn. Since higher monitoring costs generate higher levels of lending rates in bad times, and hence, a fewer number of signals, the learning process regarding the switch is even slower. Hence, high monitoring costs in an environment with endogenous generation of information generate crises of larger magnitude and recoveries of slower speed.

A model calibration allows for the estimation of cross-country differences in monitoring costs that match observed skewness differences. Direct monitoring costs of around 5% match the data for developed countries, while monitoring costs of around 30% match the data for developing countries. These figures are consistent with some new ”survey-based” evidence of differences in bankruptcy costs across economies. The results also show the relevance of monitoring costs in lending rate spreads, representing only 2% for developed countries but 25% for underdeveloped ones.

The first-order effect of financial frictions in raising the cost of capital and decreasing the level of investment is well known. In this paper I show that financial frictions are also pervasive at magnifying crises and slowing recoveries, generating potentially large inefficiencies in reallocating resources over the business cycle. This is an additional reason to reduce monitoring and bankruptcy costs in financial systems and an additional source of gains from financial liberalization processes.

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A Appendix

A.1 Sample of Countries

All countries in the sample, based on income classification, are shown in table 14. Reported skewness correspond to the period 1960 - 2008.

Table 14: Countries included in classification by income

LR Skewness (1960-2008) by Income Classification					
Income Group 1 (Richest)					
Singapore	-0.64	Italy	0.59	Norway	1.79
Hong Kong	-0.22	Japan	0.60	Portugal	2.11
Macao	-0.21	Slovenia	0.60	Sweden	2.99
Israel	-0.07	Ireland	0.76	Korea	3.47
Switzerland	-0.04	Spain	0.77	France	4.30
Belgium	0.12	Netherlands	0.78	Greece	4.51
United States	0.31	Iceland	1.20	Kuwait	5.50
Canada	0.43	Germany	1.41	Cyprus	6.82
Finland	0.58	United Kingdom	1.58		
Income Group 2					
Chile	-0.50	Hungary	0.85	Brazil	2.92
Estonia	-0.36	Romania	1.03	Czech Republic	3.65
Uruguay	-0.30	Argentina	1.46	Poland	5.70
Slovak Republic	0.19	Croatia	1.48	Gabon	6.38
Barbados	0.69	Venezuela, Rep. Bol.	1.73		
South Africa	0.80	Mexico	1.80		
Income Group 3					
Latvia	-0.42	Philippines	0.22	Equatorial Guinea	3.61
Namibia	-0.34	Sri Lanka	0.44	Guatemala	3.86
Thailand	-0.26	Swaziland	0.45	Botswana	4.54
Russia	-0.23	Paraguay	0.75	Indonesia	4.62
Lithuania	-0.14	Bolivia	1.14	Cape Verde	6.22
Dominican Republic	-0.08	Jordan	1.83	Morocco	8.14
Colombia	-0.05	Jamaica	2.01	Guyana	10.25
Grenada	0.10	El Salvador	2.35		
Peru	0.20	Egypt	2.82		
Income Group 4 (Poorest)					
Angola	-0.61	Haiti	1.09	Chad	4.43
Mozambique	-0.52	Vietnam	1.95	Lao People's Dem.Rep	4.73
Moldova	-0.47	Rwanda	2.17	Congo, Republic of	4.99
Nigeria	-0.46	Honduras	2.64	Senegal	5.13
Nicaragua	-0.39	India	2.91	Central African Rep.	5.73
Kenya	-0.08	Uganda	2.95	Madagascar	8.01
Armenia	0.14	Zambia	3.22	Albania	8.01
Burundi	0.49	Tanzania	3.30	Ethiopia	8.44
Lesotho	0.70	Tunisia	3.49	Bangladesh	8.80
Solomon Islands	1.00	Malawi	3.91	Gambia, The	9.01
Sierra Leone	1.01	Cameroon	4.31	Mauritania	10.16

The rest of country classifications are reported in table 15.

Table 15: Countries included in other classifications

OECD (24 countries)	Non-OECD Countries (72 countries)
Belgium, Canada, Czech Republic, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Mexico, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.	Albania, Angola, Argentina, Armenia, Bangladesh, Barbados, Bolivia, Botswana, Brazil, Burundi, Cameroon, Cape Verde, Central African Rep., Chad, Chile, Hong Kong, Macao, Colombia, Congo, Croatia, Cyprus, Dominican Republic, Egypt, El Salvador, Equatorial Guinea, Estonia, Ethiopia, Gabon, Gambia, Grenada, Guatemala, Guyana, Haiti, Honduras, India, Indonesia, Israel, Jamaica, Jordan, Kenya, Kuwait, Lao People's Dem. Rep., Latvia, Lesotho, Lithuania, Madagascar, Malawi, Moldova, Morocco, Mozambique, Namibia, Nicaragua, Nigeria, Paraguay, Peru, Philippines, Russia, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, Sri Lanka, Swaziland, Tanzania, Thailand, Uganda, Uruguay, Venezuela, Vietnam, Zambia.
High Contract Enforcement (28 countries)	**Low Contract Enforcement (28 countries)**
Argentina, Belgium, Brazil, Canada, Chile, Finland, France, Germany, Greece, India, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Thailand, United Kingdom, United States, Uruguay, Venezuela.	Botswana, Burundi, Cameroon, Cape Verde, Central African Rep., Chad, Colombia, Congo, Equatorial Guinea, Ethiopia, Gabon, Gambia, Kenya, Lesotho, Madagascar, Malawi, Mozambique, Namibia, Nigeria, Peru, Philippines, Sierra Leone, South Africa, Sri Lanka, Swaziland, Tanzania, Uganda, Zambia.
Private Bureau (41 countries)	**Non-Private Bureau (41 countries)**
Argentina, Bolivia, Botswana, Brazil, Canada, Chile, Hong Kong, Colombia, Czech Republic, El Salvador, Finland, Germany, Greece, Guatemala, Hungary, Ireland, Israel, Italy, Japan, Kenya, Korea, Kuwait, Mexico, Namibia, Netherlands, Norway, Paraguay, Peru, Philippines, Poland, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, United Kingdom, United States, Uruguay.	Albania, Angola, Armenia, Bangladesh, Belgium, Burundi, Cameroon, Central African Rep., Chad, Congo, Croatia, Egypt, Ethiopia, France, Haiti, Honduras, India, Indonesia, Jamaica, Jordan, Lao People's Dem. Rep., Latvia, Lesotho, Lithuania, Madagascar, Malawi, Moldova, Morocco, Mozambique, Nicaragua, Nigeria, Russia, Sierra Leone, Slovak Republic, Slovenia, Tanzania, Uganda, Venezuela, Vietnam, Zambia.

A.2 Robustness on Skewness Classification

In the main text, I analyze differences of skewness in log changes of real lending rates across countries, using several classifications related to financial development. Here, I extend the analysis following two alternative approaches.

First, I compute skewness in the distribution of log deviations from a real lending rate trend (at each month, I obtain the difference between the log of lending rates and the log of the HP trend). Table 16 shows that the results are very similar to those in the main text, since they do not depend on specific properties of the trend across countries.

Table 16: Asymmetry on lending rates and financial development (using differences in the log deviation from trend)

Country Classification	1960 - 1985	1985 - 2008	1960 - 2008
Income group 1 (richest)	2.56	-0.15	**0.84**
Income group 2	2.59	1.80	**1.90**
Income group 3	4.12	1.93	**1.92**
Income group 4 (poorest)	4.46	2.34	**2.63**
OECD	2.21	1.27	**2.06**
Non-OECD	4.08	1.49	**1.71**
High contract enforcement	1.94	0.62	**1.52**
Low contract enforcement	3.65	2.11	**2.34**
Private bureau	1.82	0.83	**1.06**
No private bureau	4.82	1.86	**2.20**

Dependent Variable	All Countries		Non-African Countries	
Lending Rate Skewness	1960 - 1985	1985 - 2008	1960 - 1985	1985 - 2008
Credit to private sector / GDP	-0.033	-0.020	-0.044	-0.016
	(0.014)**	(0.005)***	(0.015)***	(0.005)***
Constant	4.44	2.34	5.22	2.00
	(0.68)***	(0.40)***	(0.90)***	(0.49)***
Observations	47	94	31	70

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. The dependent variable is the skewness measured over the distribution of log changes in monthly lending rates in deviations from HP trend, obtained from the IMF's IFS database. Yearly data on credit to private sector as a percentage of GDP from the World Bank's WDI database. The simple average per country over the period sample is considered.

Table 17: Asymmetry on spreads and risk-free interest rates by country classification

Country Classification	Spread Skewness	T-Bill Skewness
Income group 1 (richest)	-0.02	0.59
Income group 2	-0.02	0.58
Income group 3	0.38	0.69
Income group 4 (poorest)	0.51	-0.36
OECD	-0.37	0.68
Non-OECD	0.43	0.21
High contract enforcement	-0.18	0.58
Low contract enforcement	0.50	-0.31
Private bureau	0.01	0.56
No private bureau	0.27	-0.01

Second, the model in this paper is in fact a model of skewness in lending rate spreads rather than a model of skewness in lending rate levels, since we do not discuss the determination of risk-free interest rates. Table 17 shows cross-country differences in skewness of log changes in spreads and log changes in risk-free rates. Risk-free rates are measured by the average of 3-month Treasury bill yields for each country from the Global Financial Dataset (GFD) during the period 1960 - 2005. Spreads are obtained by subtracting real risk-free interest rates from real lending rates each month. Skewness is obtained from the log changes in these two variables. Spread results are consistent with the ones obtained in the main text. Asymmetry seems to be higher among poor, non-OECD countries with low enforcement of contracts. Furthermore, unlike levels and volatilities, skewness in lending rates is not driven by skewness in risk-free interest rates, which are more skewed in developed countries than in underdeveloped ones.

An important drawback is that the measure of Treasury bill yields in underdeveloped countries is not available on a high-quality basis. Hence, the use of spreads to compare developed and underdeveloped countries is seriously hindered. This is the main reason we focus directly on analyzing levels of lending rates in the main text.

A.3 Volatility of Lending Rates

Table 18 shows that it is not possible to distinguish a clear difference among countries in terms of volatility of changes in lending rates, T-bills, or spreads. The model is consistent with the data, since differences in monitoring costs and financial systems do not deliver any pattern of cross-country differences in lending rate volatility. However, the model fails in matching the level of volatility.

Table 18: Data vs. Estimated Volatility in changes of lending rates

Country Classification	**Volatility (in % - St. Dev.)**			
	Data			Model
	Lending Rates	T-Bill Rates	Spread	Spread
Income group 1	4.3	12.6	25.8	**1.1**
Income group 2	9.8	13.8	40.8	**1.0**
Income group 3	5.4	11.5	32.6	**0.9**
Income group 4	6.1	13.0	27.4	**0.9**
OECD	5.0	9.8	32.9	**0.9**
Non-OECD	6.6	13.9	29.2	**0.9**
High contract enforcement	5.7	11.2	31.8	**0.9**
Low contract enforcement	4.7	11.8	26.8	**0.8**
Private bureau	6.2	12.4	30.7	**0.7**
No private bureau	6.7	13.5	31.4	**0.7**

A.4 Optimal Equilibrium with Stochastic Monitoring

Proposition 4 *In the optimal equilibrium with stochastic monitoring ($\gamma_t \in [0,1]$) at each period t, all lenders j optimal monitoring and lending rates are:*

$$\gamma_t = \begin{cases} 1 & if \quad v_{it} < \frac{1+r+(1-\theta_t)c}{\theta_t} \\ \frac{1+r}{\theta_t v_{it} - (1-\theta_t)c} & otherwise \end{cases} \tag{17}$$

$$(1+\rho_t) = \begin{cases} \frac{1+r+(1-\theta_t)c}{\theta_t} & if \quad v_{it} < \frac{1+r+(1-\theta_t)c}{\theta_t} \\ \frac{(1+r)v_{it}}{\theta_t v_{it} - (1-\theta_t)c} & otherwise \end{cases} \tag{18}$$

Entrepreneurs i borrow ($b_{it} = 1$) from any lender j whenever

$$v_{it} \geq \widetilde{\nu}_t = \frac{1+r+w+(1-\theta_t)c}{2\theta_t} + \frac{\sqrt{(1+r+w)^2 + (1-\theta_t)c[2(1+r-w)+(1-\theta_t)c]}}{2\theta_t} \tag{19}$$

All borrowers always report the truth ($z_{it} = 1$).

Proof. First, note the standard debt contract where $\gamma_t = 1$ regardless of v_{it} is also an equilibrium. However, when v_{it} is high enough, it is not necessary γ_t be 1 to achieve truth telling. Reducing the probability of monitoring reduces lending rates, which is naturally preferred by borrowers. Hence, the optimal equilibrium that maximizes entrepreneurs profits is the one that reduces monitoring probabilities subject to incentive compatibility constraints. Borrowers tell the truth if $v_{it} - (1+\rho_t) > (1-\gamma_t)v_{it}$, subject to $\gamma_t \leq 1$. The solution is $\gamma_t = max\{\frac{(1+\rho_t)}{v_{it}}, 1\}$.

From perfect competition, considering the previous γ_t, $\theta_t(1+\rho_t) - (1-\theta_t)c\frac{(1+\rho_t)}{v_{it}} = 1+r$. Solving first for $1+\rho_t$ and then for γ_t, we obtain equations (17) and (18). Given this contract conditional on v_{it}, entrepreneurs borrow if $\theta_t v_{it}\left[1-\frac{1+r}{\theta_t v_{it}-(1-\theta_t)c}\right] \geq w$. From this equation, we obtain the cutoff in equation (19. $\blacksquare$).

Four features of this equilibrium are worth noting. First, $\widetilde{\nu}_t > \frac{1+r+(1-\theta_t)c}{\theta_t}$ for all monitoring costs $c \geq 0$. This means that, effectively, borrowers have a level of v_{it} such that monitoring costs are given by $\gamma_t(v_{it}) = \frac{1+r}{\theta_t v_{it}-(1-\theta_t)c}$ from equation (17) and lending rates are given by $(1+\rho_t)(v_{it}) = \frac{(1+r)v_{it}}{\theta_t v_{it}-(1-\theta_t)c}$ from equation (18). Second, if $c=0$ or $\theta_t=1$, this equilibrium collapses to the standard debt contract, which is also an equilibrium with stochastic monitoring. Third, cutoffs in the optimal equilibrium are smaller than those under a standard debt contract, which is obvious from smaller lending rates. Finally, the optimal equilibrium generates the same asymmetry implications as the standard debt contract. Monitoring costs still magnify crushes (c increases levels of lending rates), and beliefs still follow a time-irreversible process that delays recoveries. This proof follows the same logic as the one in Proposition 3.