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THE ASYMMETRIC EFFECTS OF FINANCIAL FRICTIONS

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ABSTRACT

Economic variables are known to move asymmetrically over the business cycle: quickly and sharply during crises, but slowly and gradually during recoveries. Not known is the fact that this asymmetry is stronger in countries with less-developed financial systems. This new fact is documented using cross-country data on loan interest rates, investment, and output. The fact is then explained using a learning model with endogenous flows of information about economic conditions. Asymmetry is shown to be stronger in less-developed countries because these countries have greater financial frictions, which are captured in the model by higher monitoring and bankruptcy costs. These greater frictions magnify the crisis reactions of lending rates and economic activity to shocks and then delay their recovery by restricting the generation of information after the crisis. Empirical evidence and a quantitative exploration of the model show that this explanation is consistent with the data.

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1 Introduction

Economic variables are known to move asymmetrically during the bad and good phases of a business cycle: quickly and sharply during recessions, but slowly and gradually during recoveries. Interest rates on loans, for example, tend to rise quickly during a crisis, but fall slowly and gradually during a recovery; investment and output tend to move in the opposite directions, but with the same asymmetry – falling sharply during a crisis and recovering slowly. This asymmetry has been observed worldwide in most business cycles. In Mexico's 1994-95 crisis, for example, real lending rates rose 70 percentage points in just four months and investment and output per capita dropped 35% and 17%, respectively, in three quarters. Recovery of these variables took much longer: lending rates did not reach pre-crisis levels for 30 months; investment, for two years; and output, for almost three years.[1]

Understanding the sources of this asymmetry would seem critical to minimizing lengthy processes of financial distress and the inefficient resource allocation inherent to lengthly recoveries.[2] Not surprisingly, then, many studies have offered explanations for this asymmetry.[3]

No one, however, has yet systematically examined how this business cycle asymmetry differs across countries. I do that here using standard datasets and discover a new fact: the asymmetric movements of lending rates, investment and output are stronger in less-developed countries, those with weaker financial systems. I also propose an explanation for this new fact: The stronger asymmetry in less-developed countries stems from their greater financial frictions, which restrict the flow of information in an economy, delaying recoveries.

I introduce a form of these frictions into a learning model with endogenous flows of information. Commonly in such models, the degree of precision of observed information depends on the level of economic activity, which varies in good and bad times, thus generating asymmetric lending rates (Veldkamp (2005)) and asymmetric economic activity (Van Nieuwerburgh and

[1] There are many other examples. In Brazil, just in October 1997, real lending rates rose from 71% to 98%, taking 10 months to return to pre-crisis levels. The first quarter of 1998, investment and GDP per capita declined 9% and 8% respectively, taking more than 2 years to return to pre-crisis levels. In Indonesia, the 8 months following the Asian crisis witnessed a rise in real lending rates from 18% to 35%, taking 24 months to recover. In that case, both investment and GDP per capita declined almost 50% in 1998, recovering in more than 8 years. In Russia, during April and May of 1998, real lending rates rose from 30% to 150%, taking 27 months to recover, while GDP per capita declined 12% in one quarter, recovering in more than 2 years.

[2] The negative impact of lengthy recoveries in terms of misallocations has been discussed by Bergoeing, Loayza, and Repetto (2004), while the sizable macroeconomic effects of those misallocations have been estimated by Hsieh and Klenow (2009) and calibrated by Restuccia and Rogerson (2008) and Buera, Kaboski, and Shin (2011).

[3] Veldkamp (2005) studies asymmetries of lending rates while Van Nieuwerburgh and Veldkamp (2006) and Jovanovic (2006) focus on asymmetries of real activity. The bulk of the literature, however, has focused on explanations of asymmetries in stock markets. Banerjee (1992), Welch (1992) and Banerjee and Newman (1993) explain crashes as the result of herd behavior and information cascades. Jacklin, Kleidon, and Pfleiderer (1992) use a portfolio insurance model of stock market crashes. Allen, Morris, and Shin (2006) study information-based bubbles. Finally, Zeira (1994, 1999) proposes an informational overshooting to explain booms and crashes in stock prices.

Veldkamp (2006)). These models, however, assume frictionless environments in which lenders and borrowers have symmetric information about both aggregate and idiosyncratic shocks. In my model, I assume asymmetric information about idiosyncratic shocks; they are observable to borrowers for free and observable to lenders only at a cost. I show that the financial frictions created by this costly state verification increase the asymmetry in the movements of lending rates, investment, and output.

The basic setting of my model is straightforward: entrepreneurs can start a venture only if they borrow funds. Whether they borrow or not, and how much they borrow, depend on prevailing lending rates, which are set by lenders based on their overall expectations about ventures succeeding and entrepreneurs repaying. These expectations depend on signals from previous ventures: if many have succeeded, then the economy is more likely to be in good times, or in a state in which entrepreneurs have low probability of defaulting on their loans.

In a standard setting like this, without financial frictions, whether a venture succeeds or fails is perfectly observed. When lenders think the state is good, they charge low rates, entrepreneurs borrow to start a lot of ventures, and thus, as loans are repaid, a lot of signals about the state of the economy are generated. When the state changes to bad, so that ventures have a lower probability of success, the signals of many failed ventures allow lenders to easily infer that conditions have changed, and they raise rates quickly, to account for the higher probability of default. Thus, in bad times, rates are high, and there is not much borrowing. When the state changes back to good, therefore, the limited number of existing ventures offers few signals about the switch; lenders learn about it slowly and reduce rates only gradually. This endogenous learning process is what generates asymmetric movements of lending rates, translating into asymmetric movements of investment and output.

To study the role of financial frictions on this asymmetry, I replace the standard assumption of symmetric information with an assumption of asymmetric information. I assume that borrowers know the result of a venture, but lenders can learn about it only by incurring positive costs. This asymmetric information induces borrowers to falsely renege on their loans, or to report successful ventures as failures. To motivate borrower truth-telling, lenders must spend resources to verify reports of failures and pursue defaults to bankruptcy. These monitoring and bankruptcy costs represent measures of how costly it is to overcome financial frictions.

The addition of these extra costs is reflected in the greater asymmetry in environments with frictions. The monitoring and bankruptcy costs increase lending rates, especially when the economy is moving from good times to bad. As this happens, reported failures increase, so lenders raise rates to take account of the larger probability of default. The higher expected monitoring and bankruptcy costs, that is, magnify the rate rise compared to that in a frictionless setting, depressing economic activity even further. Thus, as times turn good again, fewer signals about conditions are generated, and the learning that fuels recoveries is slower. The larger rise in lending rates combined with their slower recovery means greater asymmetry in the movements of lending rates and economic activity in economies with frictions.

I reach these conclusions by exploring the role of financial frictions on asymmetry in two version of the model. First I construct a simple partial equilibrium model with exogenous default rates, an exogenous price of capital, exogenous loan sizes, and no consumption-smoothing. My purpose here is primarily to illustrate the learning mechanism I have described. Yet I find that a calibrated version of this model is quantitatively consistent with my documented new fact: reasonable levels of monitoring and bankruptcy costs roughly predict the empirical cross-country differences in asymmetry.

In order to better assess the quantitative implications of my explanation, I extend the simple partial equilibrium version of the model into a general equilibrium version. I impose *risk shocks* to the cross-sectional variance of productivity; endogenize default rates, capital prices, and loans; and allow for consumption-smoothing. A calibrated version of this extended model does a better job than the simple model in predicting the empirical cross-country differences in asymmetry. It also better matches second moments of lending rates and economic activity.

A natural alternative view of the cross-country asymmetry I have documented is that exogenous shocks are simply more asymmetric in less-developed countries. However, the data do not support that view. Using data on default rates for different regions and countries, I document that their movements are, in fact, symmetric across crises and recoveries.

In contrast, the data do support my learning explanation. Using data on stock volatility for many countries, I show that uncertainty, a proxy for information precision in the economy, is asymmetric: uncertainty increases suddenly during crises and declines gradually thereafter. Furthermore, I document a significant positive correlation between the asymmetry of uncertainty and the asymmetry of lending rates across countries. This implies that while shocks are symmetric, information is asymmetric. Thus the asymmetry of lending rates, investment, and output is not a reflection just of asymmetric fundamentals, but of asymmetric learning.[4]

Still, my paper does not contradict recent work which suggests that the nature of shocks differs across countries. Aguiar and Gopinath (2007), for example, exploit data on consumption and net exports to disentangle permanent from transitory productivity shocks. They find that the primary sources of fluctuations in underdeveloped economies are shocks to the trend of productivity, rather than transitory fluctuations around a stable trend that characterize developed economies. My work complements these findings by providing a model with frictions that are

[4]As additional evidence, Cook and Speight (2006) find statistically significant time irreversibility for the output growth of 15 developed countries and evidence that this time irreversibility can be better accommodated by an underlying nonlinear model with symmetric shocks, rather than a linear model with asymmetric shocks.

reflected in the persistency of the Solow residuals Aguiar and Gopinath identify. Rather than imposing the feature that shocks are exogenously different in underdeveloped economies, I start from the premise that shocks are symmetric and identical across countries, but that differences in the magnitude of financial frictions generate differences in the asymmetry of endogenous variables – lending rates, investment, and output – that translate into differences in the persistency of Solow residuals.

My paper is also related to more recent work on the relevance of credit markets for economic fluctuations. Gilchrist, Yankov, and Zakrajsek (2009) study a data set of corporate bonds trading in the secondary market and find that credit market shocks have contributed significantly to US economic fluctuations during the 1990–2008 period. Gilchrist and Zakrajsek (2012) construct an index of credit spread and show that innovations to the component that is orthogonal to the current state of the economy lead to significant declines in economic activity. These finding are consistent with my results; movements in credit spreads that do not reflect the current state of the economy because of learning frictions have the quantitative potential to drive economic activity non-trivially.

Finally, my paper complements the recent work of Christiano, Motto, and Rostagno (2012). They show the quantitative relevance of risk shocks to capture crises and recoveries and match moments of financial variables, such as the counter-cyclicality of lending rates. In contrast to their work, mine focuses on a standard real business cycle model, allows for learning and asymmetries, and compares the performance of the model across countries.

Overall, therefore, my study is an empirical (Section 2), theoretical and quantitative (Sections 3 and 4) investigation of the effects of financial frictions on the asymmetric movements of lending rates, investment, and output. Section 5 provides empirical support of my explanation and Section 6 concludes.

2 Financially Underdeveloped Countries are More Asymmetric

I begin by showing empirically that movements of real lending rates, investment and output per capita are more asymmetric in less developed countries, and in particular, countries with less developed financial systems. This finding, that I will denote the *main finding* throughout the rest of the paper, is robust to many different measures of financial development. Even though in this section I just document a correlation between asymmetry and development, not a causal relation, in the next sections I propose a learning mechanism where financial development reduces asymmetry, providing evidence that supports the mechanism empirically.

As the measure of unconditional asymmetry I use the skewness of log changes over time. If, for example, lending rates in a country are more likely to experience large jumps rather than large reductions of the same magnitude, the skewness of their log changes is positive. Furthermore, a stronger asymmetry is captured by a larger positive skewness. Similarly, we expect negative skewness for investment and output per capita.

I use International Monetary Fund (IMF) monthly data on real lending rates and quarterly data on investment and real GDP per capita, from 1960 to 2008, for 100 countries. An exhaustive description of the data and the complete list of countries in the sample, their individual levels of skewness, and their classifications is in Appendix A.1.

2.1 General Measures of Financial Development

I start analyzing the relation between asymmetries and standard measures of financial development. First, for each country, I use the sample average of credit to private sector as a percentage of GDP from the World Bank's World Development Indicators (WDI) database. The first panel of Table 1 shows simple regressions between this variable and the skewness of lending rates, investment and output.[5] The second panel shows simple regressions just for lending rates, considering different sample periods (1960-1985 and 1985-2008) and different sample countries (all countries and non-African countries).[6] Since in average the skewness of lending rates is positive and the skewness of economic activity is negative, the coefficients show a statistically significant negative relationship between financial development and the magnitude of asymmetry in all cases.

To provide a better sense of the cross-country differences in asymmetry, I classify countries into groups that, according to Levine (1997), strongly correlate with financial development. The countries that belong to each group are listed in Appendix A.1. Groups are defined by:

- Level of domestic income per capita. I use the World Bank's WDI classification, where the richest countries belong to group 1 and the poorest countries belong to group 4.
- Membership or not to the OECD.

[5] In Appendix A.2, I follow three additional approaches to measure skewness of lending rates, alternative to the skewness of their log changes. First, I obtain skewness of log deviations from trend. Second, I obtain skewness in log changes of lending spreads, computed as the difference between lending rates and domestic 3-month Treasury bills, as a measure of risk-free interest rates. Finally, I obtain skewness in log changes of lending spreads, but computed with respect to U.S. 3-month Treasury bills. The relation between these alternative measures of asymmetry and financial development are consistent with those presented here.

[6] Since many African countries have high skewness levels, I restrict the sample in this particular way to confirm the relation is not just driven by African fixed effects. The analysis of these subsamples for investment and output is very noisy because data is quarterly and restricted to less countries.

Table 1: Asymmetries and financial development

Dependent Variable	Skewness Lending Rates 1960 - 2008	Skewness Investment 1960 - 2008	Skewness Output 1960 - 2008
Credit to Private Sector / GDP	-0.020	0.007	0.006
	(0.007)***	(0.003)**	(0.003)**
Constant	2.94	-0.73	-0.50
	(0.44)***	(0.19)***	(0.17)***
Observations	94	46	52

Dependent Variable	All Countries		Non-African Countries	
Skewness Lending Rates	1960 - 1985	1985 - 2008	1960 - 1985	1985 - 2008
Credit to Private Sector / GDP	-0.036	-0.023	-0.043	-0.017
	(0.014)**	(0.005)***	(0.017)**	(0.005)***
Constant	4.86	2.66	5.36	2.14
	(0.72)***	(0.42)***	(1.17)***	(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. For each country I compute the sample average of yearly credit to private sector as a percentage of GDP.

- Level of contract enforcement. I classify countries between those with low and high contract enforcement using the *contract enforcement* indicator of Levine, Loayza, and Beck (2000), which is an average between *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 lowest possible level) to 10 (the highest possible level). I use 5 as the relevant cutoff to separate countries evenly between the two groups.

- Availability of information in the financial system. I classify countries between those with and without a *private bureau*, defined by Djankov, McLiesh, and Shleifer (2007) 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.[7]

Table 2 shows simple averages of skewness for lending rates, investment and output across countries in each group for the whole sample period. Since data for lending rates is monthly I am also able to split the sample into two subperiods. The conclusion is the same in all cases. Richer countries, OECD countries, and countries with good contract enforcement and information flows show on average less asymmetry than their counterparts (poorer countries, non-

[7]Similar results hold when using the existence of either public or private bureau from Djankov et al. (2008).

OECD countries, and countries with bad contract enforcement and information flows). This evidence reinforces the initial conclusion of a negative relation between financial development and the asymmetry of lending rates, investment and output.

Table 2: Average asymmetries by country classification

Country Classification	Lending Rates			Investment	Output
	1960-1985	1985-2008	1960-2008	1960 - 2008	1960 – 2008
Income group 1 (richest)	2.71	0.28	1.54	-0.14	0.07
Income group 2	3.17	1.55	1.72	-0.48	-0.40
Income group 3	4.22	1.77	2.08	-0.68	-0.42
Income group 4 (poorest)	4.87	2.91	3.33	-1.09	-0.49
OECD	2.48	0.87	1.75	-0.28	-0.05
Non-OECD	4.36	1.98	2.46	-0.44	-0.30
High contract enforcement	2.11	0.45	1.36	-0.19	-0.01
Low contract enforcement	4.17	2.44	2.92	-0.21	-0.20
Private bureau	2.03	0.87	1.40	-0.19	-0.06
No private bureau	5.16	2.25	2.66	-0.71	-0.56

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). Asymmetry by group is the average skewness across member countries.

How to interpret these differences in skewness? Consider a variable that changes 1% in one period (lending rates rise or economic activity drops) and then it recovers to previous levels in subsequent periods. Skewness measures the speed of such a recovery. A lending rate skewness of 0.28 (for the richest countries in the period 1985-2008) implies that a 1% increase in lending rates in one month is compensated in average with a decline of 0.85% during the next month. At the other extreme, a lending rate skewness of 2.91 (for the poorest countries in the period 1985-2008) implies that a 1% increase in lending rates in one month is compensated in average with a gradual decline during the next 10 months.

Similarly, for economic activity, an investment skewness of -0.14 (for the richest countries) implies that a 1% decline in investment in one quarter is compensated in average with an increase of 0.93% during the next quarter. At the other extreme, an investment skewness of -1.09 (for the poorest countries) implies that a 1% decline in investment in one quarter is compensated in average with a gradual increase during the next 2-3 quarters.

I can use this exercise to interpret the economic significance of the coefficients in Table 1 as well. The credit to private sector as a percentage of GDP in the poorest income group is in average 13%. Using the coefficient from the first regression, a one standard deviation increase in financial development (32%) would reduce skewness by 1.15 (roughly the difference in skewness between income groups 3 and 4 during 1985-2008). This difference implies that recoveries happen in average 6 months faster, taking in average 4 months instead of 10 months.

In Appendix A.9 I repeat these regressions controlling for other, potentially relevant, variables such as GDP per capita, volatility of GDP and inflation. For lending rates, conclusions are roughly the same. For investment and output, the differences in skewness seem to be more related to the level of economic development (measured by GDP per capita) than to the level of financial development.

Still, as I show in Table 3, the quarterly asymmetry of economic activity is strongly correlated with the quarterly asymmetry of lending rates – an increase of 1 standard deviation of skewness in lending rates imply an increase of 1 standard deviation in the skewness of both investment and output. Moreover, these positive correlations remain significant even when controlling for the mentioned proxies of economic development. This is an important finding – the asymmetry in the cost of borrowing and economic activity are strongly and significantly correlated, both economically and statistically.

Table 3: The asymmetry of real activity increases with the asymmetry of lending rates

Dependent Variable	Skewness Investment		Skewness Output	
Skewness Lending Rates	-0.19	-0.14	-0.19	-0.15
	(0.09)**	(0.08) *	(0.06)***	(0.07) **
GDP per capita		-0.30		-0.33
		(0.16)*		(0.13)**
GDP Volatility		-1.08		-1.13
		(1.14)		(0.89)
Average Inflation		0.05		-0.04
		(0.11)		(0.06)
Constant	-0.22	-0.26	-0.04	-0.01
	(0.11)*	(0.29)	(0.10)	(0.22)
Observations	43	42	50	48

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. For each country I compute the sample average of quarterly GDP per capita, GDP coefficient of variation and inflation from the IMF's IFS database. Skewness of lending rates is computed from quarterly data.

2.2 Specific Measures of Financial Development: Financial Frictions

Now I study the correlation between the asymmetry of lending rates, investment and output with more specific measures of financial development that capture a particular financial friction – asymmetric information in credit markets. I perform this analysis both across countries for a given period and over time for a given country.

2.2.1 Financial Frictions Across Countries

The financial friction I consider is the asymmetric ex-post information about repayment possibilities – borrowers tend to know more about their income than lenders. A measure of the severity of this friction is the cost for lenders to verify such information, which under standard debt contracts is given by the cost of taking a defaulting borrower to bankruptcy.

Data on bankruptcy costs that are comparable across countries are taken from Djankov et al. (2008) who, based on a standardized case study of an insolvent firm called Mirage, compute estimates of how difficult it is for lenders to go through bankruptcy procedures.[8]

a) Bankruptcy costs (Djankov et al. (2008))

- **Cost of bankruptcy**: Estimated cost of debt enforcement proceedings for Mirage, reported as a percentage of the value of the estate, borne by all parties; costs include court/bankruptcy authority costs, attorney fees, bankruptcy administrator fees, accountant fees, notification and publication fees, assessor or inspector fees, asset storage and preservation costs, auctioneer fees, government levies, and other associated insolvency costs.
- **Time for bankruptcy**: Estimated duration, in years, of the time to resolve the insolvency case of Mirage; measures the duration from the moment of Mirage's default to the point at which the fate of Mirage is determined.
- **Recovery rate**: A measure of foreclosure efficiency. The recovery rate 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 proceeding, the discounted value due to the time spent closing down, court costs, attorneys, and so on (equation (3) in Djankov et al. (2008)).

Table 4 shows the results of simple regressions between these measures and skewness of lending rates, investment and output. The positive relationship between bankruptcy costs and asymmetry is captured by positive coefficients for cost and time of bankruptcy and negative for recovery rate for lending rates, and the opposite sign for investment and output. All coefficient have the expected sign and are statistically significant in almost all cases.

[8] When information was not available from Djankov et al. (2008), I completed it with data from *Doing Business*, Djankov et al. (2005). Two caveats are in order. First, these variables are measured in 2004, ends of our sample period. Second, they are constructed based on surveys to insolvency practitioners in different countries, not by direct measures. Hence, these variables should be interpreted merely as a guidance about financial frictions that involve costly state verification.

Table 4: Asymmetries and Bankruptcy Costs

Dependent Variable	Skewness of Lending Rates					
	1960 - 2008			1985 - 2008		
Cost of Bankruptcy	0.037			0.044		
	(0.012)***			(0.012)***		
Time for Bankruptcy		0.221			0.210	
		(0.100)**			(0.116)*	
Recovery Rate			-0.014			-0.019
			(0.007)**			(0.009)***
Constant	1.265	1.252	2.356	0.668	0.806	2.047
	(0.322)***	(0.347)***	(0.398)***	(0.294)**	(0.382)**	(0.407)***
Observations	85	85	85	85	85	85

Dependent Variable	Skewness of Investment			Skewness of Output		
Cost of Bankruptcy	-0.028			-0.013		
	(0.014)**			(0.013)		
Time for Bankruptcy		-0.122			-0.128	
		(0.061)**			(0.054)**	
Recovery Rate			0.005			0.007
			(0.004)			(0.003)**
Constant	-0.028	-0.058	-0.617	-0.056	0.088	-0.580
	(0.187)	(0.149)	(0.238)**	(0.167)	(0.132)**	(0.189)***
Observations	44	44	44	51	51	51

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. All independent variables are from Djankov et al. (2005, 2008).

I also use a second set of variables to proxy directly the level of asymmetric information in financial relations. These come from Porter et al. (1999), who study the performance of financial and banking systems to improve information access and quality.

b) Monitoring costs (Porter et al. (1999)) (Index that ranges from 1 (worst) to 7 (best))

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

Tables 5 and 6 show the results of running simple regressions of skewness of lending rates and economic activity on these variables. Coefficient for lending rates are negative and statistically significant, while coefficients for investment and output are positive and statistically significant in almost all cases. The general conclusion is, again, that larger financial frictions –

costly bankruptcy procedures and slow information flows in financial markets – induce larger asymmetries of movements in lending rates, investment and output.

Table 5: Asymmetries and Monitoring Costs

Dependent Variable	Skewness of Lending Rates							
	1960 - 2008				1985 - 2008			
Legal protection for financial assets	-0.40 (0.24)*				-0.71 (0.24)***			
Sophistication of financial markets		-0.40 (0.21)*				-0.62 (0.19)***		
Availability of Internet banking			-0.54 (0.25)**				-0.57 (0.24)**	
Health of banking systems				-0.33 (0.16)**				-0.56 (0.16)***
Constant	3.47 (1.40)**	3.16 (1.04)***	3.80 (1.23)***	3.14 (0.95)***	4.55 (1.40)***	3.61 (0.98)***	3.43 (1.21)***	3.82 (0.98)***
Observations	56	56	56	56	56	56	56	56

Table 6: Asymmetries and Monitoring Costs

Dependent Variable	Skewness of Investment				Skewness of Output			
Legal protection for financial assets	0.25 (0.17)				0.25 (0.14)*			
Sophistication of financial markets		0.21 (0.12) *				0.19 (0.10)*		
Availability of Internet banking			0.23 (0.13) *				0.22 (0.10)**	
Health of banking systems				0.18 (0.10) *				0.17 (0.10)*
Constant	-1.74 (0.91)**	-1.34 (0.57)**	-1.46 (0.64)**	-1.33 (0.56)**	-1.80 (0.82)**	-1.10 (0.48)**	-1.20 (0.47)**	-1.10 (0.54)**
Observations	40	40	40	40	45	45	45	45

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. All independent variables are from Porter et al. (1999).

2.2.2 Financial Frictions Over Time

Given the high correlation across countries between the development of financial systems and the development in other sectors of the economy, more asymmetries may be related to less development in those other sectors. The regressions that control for economic development in the Appendix show that general development does not reduce the significance of financial development in predicting differences in lending rates asymmetries. As expected, though, general development does reduce the predicting power of financial development on the asymmetry of investment and output, for which financial markets is only a fraction of what determines their performance.

Here I exploit time series differences in financial frictions to test the robustness of the specific relation between financial development and skewness in lending rates. Why only lending rates? Because data on lending rates is monthly, which allows to compute meaningful skewness during relatively small sub-periods. Unfortunately I cannot exploit this dimension for investment and output, based on less frequent, quarterly, information.

First, technology improvements are closely related to financial system developments, since informational frictions, and the efficiency to deal with them, are based on the ease of sharing and transmitting information and on the efficiency of auditing accounts. That is, a highly developed technology in a country, such as computers and telecommunications, translates into low monitoring and bankruptcy costs within its financial sector, as highlighted by Merton (1987). Information technologies have improved significantly and continuously since 1960. Table 2 shows that, for all classification groups, asymmetry in lending rates decreases over time, maintaining the ranking among them. A plausible interpretation is that technological improvements reduce financial frictions and asymmetry over time in all countries.

Second, we compare skewness in a given country before and after a financial liberalization process. Liberalization is a shock that abruptly opens the economy to competition and induces the adoption of modern and more efficient practices, a better enforcement of contracts, and easier flow of information, hence reducing informational frictions, as well as the monitoring and bankruptcy costs needed to deal with those frictions.

Data on financial liberalization are obtained from Kaminsky and Schmukler (2008) for 16 countries during the period 1973 – 2005. In Appendix A.3 I describe the data and show a comparison of lending rates skewness for each country before and after the main financial liberalization event. In all countries, except Ireland, lending rate skewness decline after their main liberalization event. I also show a comparison of skewness for each country before and after its whole financial liberalization process, and also before and after a financial restriction process. Of the 16 countries, only Korea did not experience a reduction in skewness after liberalization.

In contrast, the three countries that restricted the financial system during the sample period (Chile, Indonesia and Thailand) experienced an increase in skewness after that process. This test, too, supports the new finding of negative relation between asymmetry on lending rates and financial development.

To conclude, regardless of which indicator is examined as a measure of financial development – standard such as credit to the private sector as a percentage of GDP and enforcement of contracts, or more specific measures of financial frictions, both across countries or over time, such as bankruptcy costs, monitoring costs, health or sophistication of financial markets, the historical evolution of technology for all countries, or financial liberalization processes – the indicator supports the documented negative relationship between the degree of financial development and asymmetries on lending rates, investment and output.

3 A Partial Equilibrium Model

I provide now a model that captures both theoretically and quantitatively the negative relation between financial development and asymmetries. In particular I show that large financial frictions, modeled as large bankruptcy costs that turn difficult to overcome asymmetric information between borrowers and lenders, induce highly asymmetric movements of lending rates as a response to symmetric shocks to fundamentals. Furthermore, more asymmetric lending rates translates into more asymmetric investment and output.

In this section I develop a simple partial equilibrium model that introduces financial frictions into a setting with endogenous information flows, and discuss the mechanism behind the negative relation between financial development and asymmetries. In the next section I extend this simple partial equilibrium model into a general equilibrium model that endogenizes default rates, loan sizes and the price of capital, in a setting with infinitely lived households who smooth consumption and learn about aggregate fundamentals. The extension to a general equilibrium setting does not add any theoretical insight but allows to better match the data quantitatively in several dimensions.

3.1 An Overview

I embed financial frictions into the frictionless Veldkamp's (2005) partial equilibrium model, where entrepreneurs should borrow to invest in a risky venture. Without frictions, the cost of borrowing is based on lenders' expectations about an unobservable state of the economy that determines failure probabilities, where a "good state" is one with low failure probabilites, and hence low default rates. This expectation is constructed from observing previous ventures' results. When lenders think the state of the economy is good, lending rates are low and there is a large number of ventures in the economy, which generates a large number of signals about the good state. When the state changes to bad, all those signals allow lenders to easily recognize that conditions have changed, so lending rates rise quickly and sharply to account for the higher failure probability. In contrast, when the state is bad and changes to good, the limited number of existing ventures generates few signals about the change, so lenders learn about it slowly, and lending rates drop just gradually.

Into this setup, I introduce an informational friction: asymmetric information between borrowers and lenders about the ventures' results. To motivate borrowers' truth-telling, lenders should sometimes spend resources to verify the result of defaulting ventures by taking them to bankruptcy. Hence monitoring and bankruptcy costs constitute a measure of how costly it is to overcome informational frictions. For simplicity we will refer to all these costs as bankruptcy costs.

Bankruptcy costs have two effects. First, they increase lending rates and reduce economic activity, which reduce the number of signals available in the economy. However, this effect is not symmetric across economic states. In times with high failure probabilities, bankruptcy is more common, lending rates are higher, economic activity is lower and there are less signals that lenders can use to learn from. In contrast, in times with low failure probabilities, bankruptcy costs become irrelevant for the level of economic activity. This implies that bankruptcy costs slow the learning that fuels recoveries from crises but not the information that sustains crises. Second, bankruptcy costs induce large jumps in lending rates when failure rates increase, which magnifies crises relative to recoveries. Together, these two effects result in quicker, sharper rises and slower, more gradual falls in lending rates, hence more asymmetry in countries with larger frictions. Since in this simple model there is a direct mapping between lending rates and investment and output, the economic activity of countries with larger frictions is also more asymmetric.

3.2 Formal Description

The economy has a credit market with a finite number N of entrepreneurs without funds on their own and $M > N$ perfectly competitive investors, each with one unit of indivisible capital. Both entrepreneurs and investors are risk-neutral and live for a single period. Since some entrepreneurs will borrow to start a venture, some investors effectively will become lenders. Unlike Veldkamp's model, my model has ex-post asymmetric information between borrowers and lenders about the repayment possibilities of borrowers, which I refer as financial friction.

At the beginning of a period t, each entrepreneur i observes a business opportunity that pays v_{it} at the end of the period in case of success and zero otherwise. The payoffs v_{it} are drawn from a support $(\underline{v}; \overline{v})$.[9] All ventures require the same initial investment (normalized to 1). If entrepreneurs decide to undertake the venture, they must borrow the money. If they decide not to borrow, their only option is to work for an 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, $1 + r$.

In this economy, the probability of success is the same for all ventures in period t, θ_g in good times (G) and θ_b in bad times (B), where $\theta_g > \theta_b$ and G and B are the only 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 both try to infer it from observations of venture realizations in previous periods.

More explicitly, the expected probability of success of a venture 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, using Bayes' rule and a prior $\mu_t = Pr(G)_t$[10]

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

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

$$\mu_{t+1} = \Pr(G)_{t+1} = (1-\lambda)\mu'_t + \lambda(1-\mu'_t). \tag{2}$$

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

$$\theta_{t+1} = \Pr(s)_{t+1} = \mu_{t+1}\theta_g + (1-\mu_{t+1})\theta_b. \tag{3}$$

When a loan is negotiated between an entrepreneur i and an investor j at the beginning of period t, both observe the venture's potential payoff $v_{i,t}$ and agree on the expected probability of success θ_t, updated as above based on information from $t - 1$. Ex-post, however only the entrepreneur can observe for free whether the project was successful or not, while the lender can only verify it at a positive cost γ. Since initial investment for each venture was normalized to 1, a verifying cost of $\gamma = 0.3$, for example, represents a cost of 30% of the initial investment.

[9]These bounds are chosen such that an entrepreneur with a business opportunity with payoffs under $\underline{v}$ would never start the venture and an entrepreneur with a business opportunity with payoffs above $\overline{v}$ would always start the venture, for all plausible lending rates given the parameters in the economy.

[10]Recall that $C^n_s = C^n_{n-s} = n!/[(n-s)!s!]$ and then C^n_s drops from the equation.

At the end of the period, borrowers may pay the stipulated lending rate to lender j, which I refer as $(1+\rho_{jt})$, or default. In case of default the lender can take the borrower to bankruptcy at a cost γ. Bankruptcy is the procedure under which the lender verifies the failure of the project and seizes the payoff v_{it} in case of finding out the project was indeed successful.[11] Following the costly state verification literature, initiated by Townsend (1979), I assume γ is the cost of all activities involved in verification and bankruptcy, including judiciary costs and delays, accountant and attorney fees, assets storage, preservation and liquidation costs, restructuring and seniority restrictions, etc. This cost γ is intimately related to the degree of financial development in a country and it is the main parameter in the model.

Finally, I assume there is full commitment to the loan contract (lenders cannot renege from taking a borrower to bankruptcy in case of default) and pure bankruptcy strategies.[12]

In summary, the timing of the model in each period t is as follows:

1. Entrepreneurs and investors agree on their beliefs of being in a good state (μ_t).
2. Investors offer loan contracts, taking into account the potential bankruptcy costs γ. Entrepreneurs decide whether or not to borrow and start a venture given those contracts. A borrower who is indifferent between loan contracts is randomly assigned to the investors offering those contracts. Entrepreneurs who do not borrow work at an exogenous wage w. Investors who do not lend invest in a riskless bond that pays $1+r$.
3. Production occurs. A borrower receives cash flows when its venture is successful.
4. Borrowers report the result of their ventures to lenders, and contracts are fulfilled. Entrepreneurs and investors consume and die. All reports and verification results are publicly available to the next cohort of agents.
5. The new cohort of entrepreneurs and investors use the public information above to update beliefs (μ_{t+1}). The state changes with a probability λ.

3.3 Equilibrium Outcomes

Here I define and characterize the equilibrium. Even though there is an analytical solution in each period, it is not possible to write the dynamics of the model explicitly. However, the

[11] Since borrowers are short-lived and limited liable, the maximum penalty that can be imposed in case of default is seizing all current assets.

[12] I focus on non-stochastic bankruptcy just for expositional purposes. In Appendix A.4, I describe the optimal financial contract with stochastic bankruptcy and discuss why the results in terms of asymmetry are sustained. Even when I prove stochastic bankruptcy is preferred when there is full commitment, Krasa and Villamil (2000) show that the optimal contract is again one with bankruptcy in pure strategies when there is no commitment.

nature of the equilibrium sheds light on the effect of financial frictions on the asymmetry of lending rates, investment and output.

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_{ijt}) and monitoring decisions (π_{jt}) by each investor j, and Bayesian beliefs about the probability of being in a good state μ_t, such that the following problems are solved in each period t:*

- *Each entrepreneur i maximizes expected utility:*

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

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

- *Each investor j maximizes expected profits:*

$$\max_{\rho_{ijt}\in\mathbb{R},\pi_{jt}\in\{0,1\}} \mathbb{I}_{jt}\theta_t\{z_{it}(1+\rho_{ijt})+(1-z_{it})\pi_{jt}(v_{it}-\gamma)\}-\mathbb{I}_{jt}\pi_{jt}(1-\theta_t)\gamma+(1-\mathbb{I}_{jt})(1+r),$$

  where $\mathbb{I}_{jt}=1$ if some borrower decides to take a loan from this investor j in period t.

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

Since the size of every project is fixed, also is the size of the loans. Since there are more potential lenders than potential borrowers, borrowers have all the bargaining power and then there is a random assignment of borrowers to lenders conditional on borrowing. The following proposition characterizes the unique SPNE with nonstochastic monitoring, which takes the form of an optimal standard debt contract.

Proposition 1 *In each period t, all investors j set the same lending rate $1+\rho_t = \frac{1+r}{\theta_t} + \frac{(1-\theta_t)}{\theta_t}\gamma$ to all borrowers i and monitor every default ($\pi_{jt}=1$). All entrepreneurs i borrow ($b_{it}=1$) randomly from an investor j whenever $v_{it} \geq \widetilde{\nu}_t = \frac{1}{\theta_t}[1+r+w+(1-\theta_t)\gamma]$. All borrowers report the truth ($z_{it}=1$).*

Proof. I solve the equilibrium backwards.

Step 1: Entrepreneurs' ex-post decisions

If lenders take defaulting borrowers to bankruptcy, then successful borrowers prefer to repay the loan ($z_{it}=1$), obtaining $\nu_{it}-(1+\rho_t) > 0$ rather than 0 if defaulting. If lender do not take defaulting borrowers to bankruptcy, then successful borrowers always default ($z_{it} = 0$). Unsuccessful borrowers always default.

Step 2: Investors' decisions

As in Townsend (1979) and Gale and Hellwig (1985), here the standard debt contract is optimal. In my setting, this result is even more trivial because cash flows in case of success are known and only failure is not. If lenders do not monitor a default, borrowers always default and lenders never lend. Hence, lenders prefer to monitor ($\pi_{jt} = 1$), borrowers always report the truth and there are no payoffs to seize in case of default. Since investors are competitive ($M > N$), expected profits from lending equalize expected profits from the riskless bond.

$$(1 - \theta_t)(-\gamma) + \theta_t(1 + \rho_{ijt}) = 1 + r.$$

Since the expected probability of success is the same for all ventures and the above condition is independent of the cash flow of a given venture v_{it}, all investors j choose to charge the same lending rate to all entrepreneurs i (that is, $\rho_{ijt} = \rho_t$ for all i and all j).

$$(1 + \rho_t) = \frac{1 + r}{\theta_t} + \frac{(1 - \theta_t)}{\theta_t}\gamma. \tag{4}$$

Step 3: Entrepreneur's ex-ante decisions

Since all lenders offer the same lending rate, borrowers are indifferent of taking the loan from any lender, and then they are assigned randomly to investors. The only choice left to obtain in equilibrium is whether entrepreneurs borrow or not (that is, $b_{it} \in \{0, 1\}$). This choice is given by a cutoff value over v_{it} such that an entrepreneur i borrows in period t whenever $\theta_t[v_{it} - (1 + \rho_t)] \geq w$. From equation (4) it is clear that $b_{it} = 1$ if

$$v_{it} \geq \widetilde{\nu}_t = \frac{1}{\theta_t}[1 + r + w + (1 - \theta_t)\gamma]. \tag{5}$$

■

A key variable is the number of ventures n_t funded in the economy, which in this simple model is also the total investment per period, which also determines the number of signals available for agents to update beliefs. In equilibrium this number is given by the sum of entrepreneurs who borrow in period t.

$$n_t = \sum_{i \in \{1,\ldots,N\}} \mathbf{1}_{\{v_{it} \geq \widetilde{\nu}_t = \frac{1}{\theta_t}[1+r+w+(1-\theta_t)\gamma]\}}, \tag{6}$$

where **1** is an indicator function that adopts the number 1 when the condition in brackets (equation 5) is fulfilled and 0 otherwise.

The number of ventures depends positively on the probability of success θ_t in two ways: a higher θ_t increases expected profits; and a higher θ_t decreases market lending rates ρ, directly by decreasing the probability of default and indirectly by reducing expected monitoring costs. Formally, $\frac{\partial \widetilde{\nu}_t}{\partial \theta_t} = -(1 + r + w + \gamma)/\theta_t^2 < 0$.[13] More interestingly, since θ_t increases with the probability of being in a good state μ_t,

$$\frac{\partial \widetilde{\nu}_t}{\partial \mu_t} = -(\theta_g - \theta_b) \frac{[1 + r + w + \gamma]}{(\mu_t \theta_g + (1 - \mu_t)\theta_b)^2} < 0.$$

This is important for the determination of signals in the economy. When μ_t is high, θ_t is also high, the borrowing cutoff value $\widetilde{\nu}_t$ is low and the number of funded ventures is large.

What are the specific effects of bankruptcy costs γ? First, when it is costless for lenders to monitor ventures' results ($\gamma = 0$), the solution coincides with Veldkamp's model, which provides a useful benchmark. Second, when monitoring costs γ are positive, they increase lending rate levels and cutoffs $\widetilde{\nu}_t$, thus reducing the number of funded ventures in all states. Formally,

$$\frac{\partial \widetilde{\nu}_t}{\partial \gamma} = \frac{\partial (1 + \rho_t)}{\partial \gamma} = \frac{1 - \theta_t}{\theta_t} > 0. \tag{7}$$

Third, this reduction in ventures is not constant across states – the derivative above depends on beliefs θ_t. Furthermore, θ_t affects lending rates non-linearly – as θ_t varies, γ is scaled by a double effect in the numerator $(1 - \theta_t)$ and the denominator (θ_t).

For given bankruptcy costs, the relation between lending rates $(1 + \rho_t)$ and the expected probability of success (θ_t) is non-linear. When the market believes the probability of success is very high, lenders assign a low probability of having to spend on bankruptcy at the end of the period, then its 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 spending on bankruptcy at the end of the period, and its costs have a critical role on lending rates, investment and hence, the number of signals.

Finally, output in this model y_t depends both on beliefs about the probability of success (through the number of ventures) and on real probability of success (though the number of those ventures that succeed).

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

$$y_t = \sum_{i \in \{1,\dots,N\}} \mathbf{1}_{\{v_{it} \geq \widetilde{\nu}_t\}} \theta_{state} v_{it}, \tag{8}$$

where $\widetilde{\nu}_t$ depends on believed probability of success, from equation (5), and $\theta_{state} \in \{\theta_b, \theta_g\}$ is the real probability of success.

3.4 Implications for Asymmetry

Since the number of signals is changing continuously, writing an explicit analytical solution of the dynamic evolution of lending rates, investment and output is intractable. Despite this shortcoming, I can still show analytically that financial frictions tend to hinder the flow of information more after crises than before crises, inducing stronger asymmetries. Later I provide an illustration of the dynamic evolution of lending rates and economic activity by using a calibrated model and Monte Carlo simulations.

The following proposition shows the conditions for bankruptcy costs to make lending rates, investment and output more asymmetric. First, I sketch out why endogenous information generates asymmetry in the first place, by making beliefs time-irreversible.[14] Then, I introduce frictions and show their effects on asymmetries.[15]

Proposition 2 *In an endogenous information economy, the asymmetries of lending rates and economic activity increase with bankruptcy costs if bad news depresses economic activity relatively more the larger the bankruptcy costs. Specifically the sufficient condition is*

$$R > \left(\frac{\theta_b}{\theta_g}\right)^{\underline{n}}. \tag{9}$$

where $R = \min_{\nu_1 \in [\nu_2, \overline{\nu}], \nu_2 \in [\underline{\nu}, \nu_1]} \frac{f(\nu_1)}{f(\nu_2)}$ *is the minimum ratio of densities in the support* $[\underline{\nu}, \overline{\nu}]$ *and* $\underline{n}$ *is the lowest possible number of ventures (*n_t *when beliefs are* θ_b*).*

This Proposition is proved in Appendix A.5. The asymmetry of lending rates and economic activity tends to increase with bankruptcy costs, but there are limits to this result, which are characterized by condition (9) – the decline in activity after bad news is more severe in countries with higher bankruptcy costs. What is the intuition for this condition? If the initial economic activity is already very low, the effect of a large increase in lending rates is not very noticeable, and the number of signals does not drop much further. In the extreme, when bankruptcy

[14] Veldkamp (2005) contains the full-fledged formal proof of belief time-irreversibility in a frictionless economy.

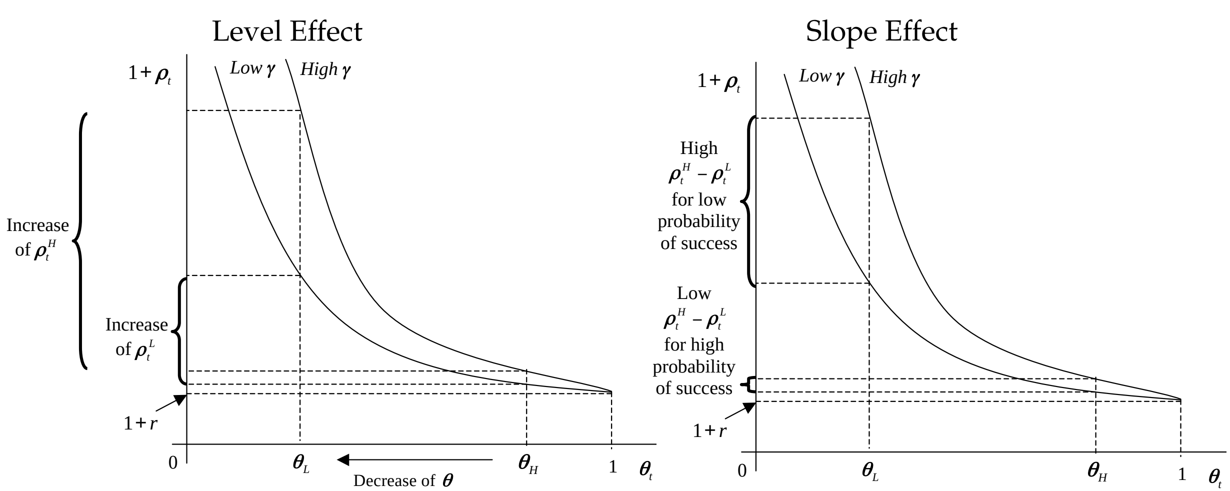
[15] The link between time irreversibility and skewness depends on distributional assumptions, so we leave for the quantitative exercise the discussion of whether the model is able to match cross-country differences in skewness.

costs are so large that they prevent economic activity almost completely. In this case more pessimistic beliefs does not have any effect on restricting activity even further, not having a large effect on fluctuations and asymmetries. The condition avoids this possibility. In the quantitative section I show that for the empirically relevant range of bankruptcy costs, the condition is fulfilled and financial frictions do increase asymmetries.

The intuition for this result is captured in Figure 1. The first panel shows the crisis magnification force of bankruptcy costs. A given decrease in the expected probability of success generates a greater jump of lending rates in countries with higher bankruptcy costs (the increase in lending rates for a country with high bankruptcy cost ρ_t^H is larger than the increase in lending rates for a country with low bankruptcy cost ρ_t^L, when both start from the same beliefs about the aggregate state). Condition (9) guarantees this larger increase in lending rates translates into a larger reduction in economic activity and number of signals.

The second panel of Figure 1 shows the recovery delaying force of bankruptcy costs. The gap between lending rates in countries with different monitoring costs widens as the expected probability of success decreases (the difference $\rho_t^H - \rho_t^L$ when the probability of success is low is larger than when the probability of success is high). This implies that the speed of recoveries after bad times differs between the two countries more than the speed of crises after good times. This is the key for having more asymmetry.

Figure 1: Monitoring Costs Magnify Crises and Delay Recoveries



In essence, bankruptcy costs increase both the level and the slope of lending rates. First, bankruptcy costs increase the level of lending rates for a given θ, reducing economic activity and the number of signals. This is what I call a "level effect". Less signals generate an environment that overall manages less information, increasing asymmetry because it takes more time to learn and recover from bad times. Second, bankruptcy costs also increase the slope for a given θ, implying that the reduction of signals is more prominent during bad times. This is what I call a"slope effect". Bankruptcy costs magnify the reduction of signals when facing a lower θ, inducing larger crises and lengthier recoveries, on top of the mechanic increase in asymmetry through less signals.

The "level effect" has been explored by Veldkamp (2005), who shows that adding exogenous signals, independent of the true state of the economy, reduces asymmetry. In this paper I am not only endogeneizing the "level effect" as a function of financial frictions, but also, as I show in the next section, the "slope effect" is quantitatively relevant in explaining the cross-country differences in asymmetry of lending rates, investment, and output.

3.5 A Quantitative Assessment

Now I perform a quantitative assessment of the simple partial equilibrium model. I calibrate and simulate the model to show that, with some limitations, it roughly matches the observed cross-country differences in skewness for reasonable levels of bankruptcy costs.

3.5.1 Parameters

I calibrate the model monthly for a country with average levels of financial development (such as Argentina, Mexico or Indonesia). Probabilities of success (θ_g and θ_b) are calibrated using corporate bond default rates listed by Moody's for 1970 - 2008. Since long time series of default rates for emerging market bonds is unavailable, I use information on U.S. speculative grade bonds, which are riskier than typical U.S. corporate bonds and investment grade bonds. Good and bad times are defined using NBER business cycle dates. Monthly default in good times is 0.35% ($\theta_g = 0.9965$) and in bad times is 0.85% ($\theta_b = 0.9915$), which is consistent with yearly default rates of 3% and 5% in good and bad times used in Veldkamp (2005).[16]

The probability of a state transition $\lambda = 0.027$ is obtained using world GDP from the Penn World Tables. As in Veldkamp (2005) booms and busts are defined for each country as years with positive and negative growth of real GDP per capita. Since there is an average of 36.5 months between state changes, there is a 2.7% probability of transition per month.

The parameter N is critical for the speed at which the economy learns about the aggregate state, but it does not have a clear empirical counterpart because it is the maximum possible number of independent pieces of information, not the number of projects. In the model these are the

[16]For developed countries, I perform the exercise using information on "all corporate" bonds, when yearly probabilities of default are 2% and 3% in good and bad times, respectively. Results are very similar.

same because I assume uncorrelated projects, but if they were highly correlated, a large number of projects would still generate a small number of independent signals. At the other extreme, if every firm in a country generates an independent signal, forecast errors for macroeconomic aggregates would be negligible, which suggests that in fact the information content of total economic activity is restricted, and correlation among projects is large.

Given this logic, I calibrate N to match the skewness of lending rates for countries of income group 3 (1.77) using their average level of bankruptcy costs from Djankov et al. (2008) (16.6%), which delivers $N = 41$. This number is also consistent with the number of independent signals $N = 25$ that Veldkamp (2005) computed by measuring the speed of price adjustments in the United States. With $N = 25$, the skewness of lending rates when $c = 16.6\%$ is 1.97, and results are quantitatively very similar.

Finally, I assume venture payoffs are distributed uniformly in $[\underline{v}, \overline{v}]$, where $\underline{v} = \frac{1+w+r}{\theta_g}$ and $\overline{v} = \frac{1+w+r}{\theta_b}$, with θ_g the most optimistic probability of success and θ_b the most pessimistic one.[17] Finally, parameters r and w only affect the scale of lending rates, and skewness is invariant in scale.[18]

Using these parameters, I simulate lending rates for 600 periods (recall we compute skewness using monthly data over 50 years) and compute the unconditional skewness of their log changes. I repeat this simulation 10,000 times, obtaining Montecarlo standard deviations. For expositional purposes I use the same parameters for all countries and compare their asymmetry purely from modifying a single parameter, bankruptcy costs, γ.

3.5.2 Implications for Asymmetry

Table 7 compares the empirical skewness of lending rates, investment and output with their model counterparts. In the model, the only difference across countries comes from different bankruptcy costs, from Djankov et al. (2008). The partial equilibrium model reproduces the positive relation between bankruptcy costs and asymmetries, but not its sensitiveness. By construction the skewness 1.77 of lending rates for income group 3 is targeted to calibrate N, but the model generates larger levels of skewness for lower levels of bankruptcy costs and smaller levels of skewness for higher levels of bankruptcy costs. Even when the model generates higher levels of skewness for investment and output, it is surprisingly successful considering the very reduced definition of investment and output and that I do not target any moment of investment or output. The fit of the model can improve considerably by introducing additional differences in default probabilities and exogenous signals. However this contaminates the exercise of identifying the contribution of bankruptcy costs in asymmetry.

[17] Results assuming a normal distribution with 95% in $[\underline{v}, \overline{v}]$ are similar, with slightly higher skewness.

[18] Skewness is independent of r and w because the support for the distribution of v_i is $[\underline{v}, \overline{v}]$.

Table 7: Skewness from the Partial Equilibrium Model

Country Classification	Bankruptcy Costs	Skewness from Data			Skewness from PE Model		
		Lending Rates	Investment	GDP per capita	Lending Rates	Investment	GDP per capita
Income group 1 (richest)	7.2	0.28	-0.14	0.07	1.54	-0.77	-0.62
Income group 2	15.8	1.55	-0.48	-0.40	1.74	-0.95	-0.77
Income group 3	16.6	1.77	-0.68	-0.42	1.77	-0.97	-0.78
Income group 4 (poorest)	24.4	2.91	-1.09	-0.49	2.02	-1.03	-0.85
OECD	8.8	0.87	-0.28	-0.05	1.56	-0.82	-0.65
Non-OECD	19.2	1.98	-0.44	-0.30	1.85	-0.99	-0.81
High contract enforcement	10.9	0.45	-0.19	-0.01	0.61	-0.87	-0.70
Low contract enforcement	23.3	2.44	-0.21	-0.20	1.98	-1.02	-0.84
Private bureau	11.5	0.87	-0.19	-0.06	1.62	-0.88	-0.70
No private bureau	21.1	2.25	-0.71	-0.56	1.90	-1.01	-0.82

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). Bankruptcy costs are from Djankov et al. (2008).

Now I assess the importance of bankruptcy costs for asymmetry in the model. First, even when the model does not match the empirical asymmetries perfectly, it requires plausible levels of bankruptcy cost to do it. For example, a skewness of 2.91 (for income group 4) is consistent with bankruptcy costs of around 38%, rather than 24.4% as provided by Djankov et al. (2008).[19] In contrast, the change of other parameters needed to match a skewness of 2.91 in a frictionless environment ($\gamma = 0$), seems implausible.[20]

- Very stable states, $\lambda = 0.002$ (states change every 42 years).
- Very persistent bad times. If $Pr(B|G) = \lambda = 0.027$, then $Pr(B|B) = 0.996$ (bad states last 20 years in average).
- Clearer and extreme signals: If annual $\theta_g = 0.97$, then $\theta_b = 0.72$ (in bad times 28% of firms default). If annual $\theta_b = 0.95$, then $\theta_g = 0.995$ (in good times the probability of default is almost 0, much less than in developed countries).

Second, we can decompose quantitatively the "level" and "slope" components of bankruptcy costs I discussed at the end of Section 3.4 above. At least 30% of the difference in skewness between the poorest countries and the benchmark countries of income group 3 can be attributed

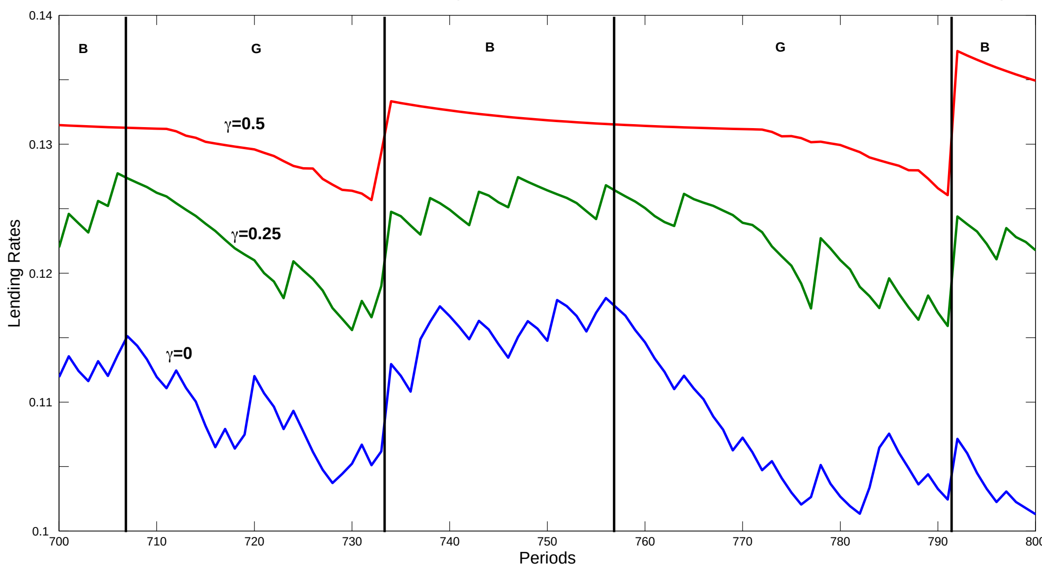
[19]There is still debate in the literature about the right measurement of monitoring and bankruptcy costs. One of the first attempts to estimate bankruptcy costs was Warner (1977) who, considering only direct costs for the railroad industry, estimated a cost of around 4% of the firm's total assets. Altman (1984) raised the estimation to 20% by including indirect costs (such as lost sales and lost profits). 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%. We use Djankov et al. (2008) since it is the only paper with a clean comparison of these costs across countries.

[20]These are conditions similar to those Veldkamp (2005) identified to match a skewness of 2.9 for the 13 emerging countries in her frictionless environment.

to the "slope effect". From the simulations, skewness is 1.77 when $\gamma = 0.16$ and 2.91 when $\gamma = 0.38$. However, since the average number of signals when $\gamma = 0.16$ is four times higher than when $\gamma = 0.38$, a natural question is the following: is just this difference in the level of economic activity what creates the difference in skewness? By holding constant monitoring costs at $\gamma = 0.16$ and imposing a four times less informative environment (i.e., $N = 10$), it is only possible to generate a skewness of 2.55, which explains 70% of the empirical difference in skewness between these two groups.

Finally, to illustrate the nature of the mechanism I show an example of the model's lending rate dynamics under the same shock realizations but different levels of bankruptcy costs. Figure 2 displays the paths of lending rates over 100 simulated periods (out of 600 periods) of 1 simulation (out of 10,000 simulations) for three economies with different levels of bankruptcy costs, $\gamma = 0$, $\gamma = 0.25$, and $\gamma = 0.5$. There are three clear patterns that stand out

Figure 2: Model's Evolution of Lending Rates with Different Levels of Monitoring Costs



- Lending rates are higher in economies with higher monitoring and bankruptcy costs.
- When the economy moves from good times (G) to bad times (B), lending rates jump everywhere, but more in countries with higher costs.
- When the economy moves from bad times (B) to good times (G), lending rates decline everywhere, but faster in countries with lower costs.

This figure illustrates the main forces behind the positive relation between asymmetries and bankruptcy costs. High bankruptcy costs induce high levels of lending rates and low levels of real activity, magnify crises, and delay the generation of signals that fuel recoveries. This simple model captures this relationship both qualitatively and quantitatively.

How about other moments for lending rates, investment and output? In Appendix A.6 I show the predictions of the model in terms of levels and volatilities of lending rates, investment and output are also consistent with the data, but with limitations I address in the next extension.

Caveats What are the limits of the model? The model fails to explain the very low levels of lending rates skewness among the richest countries. Even imposing $\gamma = 0$, the model delivers a skewness of 1.4 and the data shows skewness of 0.28 during the period 1985-2008. One interpretation is that the conditions calibrated for countries in the income group 3 in recent years are roughly the average conditions that characterized developed countries in previous years – average skewness for the richest countries in the period 1960-2008 was 1.54. An alternative way to accomodate the low skewness of the richest countries is to impose their empirical levels of default ($\theta_g - 0.98$ in good times and $\theta_b = 0.97$ in bad times) and to assume there is a large fraction of economic activity that does not require external financing.

The model also underestimates the very large levels of skewness among the poorest countries. However this can be easily accommodated with plausible levels of bankruptcy costs (as discussed above, in the order of 40% rather than the 25% reported by Djankov et al. (2008)). This caveat also begs the question of which additional channels may restrict information flows during recessions in less developed countries.

The most important caveat arise from the partial equilibrium nature of the results for economic activity. In this model, investment and output are very simplified and roughly the same object, and then are difficult to compare with data. In the next section I relax this assumption and develop a general equilibrium model with a more realistic counterpart in terms of economic activity.

4 A General Equilibrium Model

In this section I show that the positive relation between bankruptcy costs and the asymmetries of lending rates, investment and output emerges quantitatively in a full general equilibrium model as well. There are several important extensions to the simple partial equilibrium model discussed in the previous section. First, the size of investment is not assumed exogenous and normalized to one, but endogenously chosen by entrepreneurs when obtaining a loan. Second, the price of capital is endogenous, which plays a critical role in determining the level of investment and the effects of financial frictions. Third, there are still two types of agents (borrowers and lenders), but lenders are infinitely lived and smooth consumption, which has implications for the link between investment and output. Finally I do not impose an exogenous shock to the probability of default, but to the variance of entrepreneurial returns, which endogenously determines the probability of default in the economy.

Methodologically, I extend the model of Carlstrom and Fuerst (1997) by adding a sophisticated information structure that resembles the learning mechanism above. In this extension, a boom is interpreted as a period of low ”risk” (cross-sectional variance of entrepreneurial productivity), which endogenously generates low default and high output, while a recession is a period of high ”risk”, hence high default and low output. First, this is consistent with the findings of Bloom (2009), of a negative relation between uncertainty and output, but our explanation hinges on financial markets and not on investment irreversibilites. Second, I introduce a ”risk shock” instead of a ”productivity shock” mainly to tackle one of the main drawbacks of Carlstrom and Fuerst (1997), which is the procyclicality of risk premia. In contrast, my extension generates, as in the data, countercyclical risk premia. The quantitative potential of ”risk shocks” to be the most important drivers of business cycles, has been documented by Christiano, Motto, and Rostagno (2012) with a DSGE model that incorporates a financial accelerator mechanism.

To study the quantitative implications of this extension for the asymmetry of lending rates, investment and output, I calibrate the model along the lines of the previous section. Since learning is a critical addition, the simulation of the model requires a global solution and hence the use of projection methods. A local solution, as in Carlstrom and Fuerst (1997), is not suitable for our purposes because perturbing the model around a steady state impedes to match the sudden and large jumps in default rates and the large cross-country differences in skewness we observe in the data.

In summary, in a full general equilibrium model, with endogenous default, endogenous investment, endogenous price of capital, consumption smoothing and an optimal financial contract with learning, bankruptcy costs have the potential to explain quantitatively the differences in skewness across countries.

4.1 The Model

Economy Structure The economy is inhabited by a mass $1-\eta$ of infinitely lived risk-averse households, with discount rate β and utility function $U(c)$, where $U'(c) > 0$ and $U''(c) < 0$, and a mass η of short-lived risk-neutral entrepreneurs.

At the beginning of each period, both households and entrepreneurs supply work inelastically, at wages w_t^h and w_t^e respectively, and households rent their capital, at rate r_t, to a representative firm that produces aggregate output in units of consumption goods according to an aggregate production function

$$Y_t = F(K_t, H_t, H_t^e) \tag{10}$$

where K_t is the aggregate capital in the economy, which is produced by entrepreneurs, H_t is the labor supply of households and H_t^e is the labor supply of entrepreneurs.

In the middle of the period, after the production of consumption goods and payments to the inputs, households make consumption and investment choices. For each unit of investment that a household wishes to purchase, it should give q_t units of consumption goods to a risk neutral intermediary, capital mutual fund (CMF), in exchange for capital goods at the end of the period.

Entrepreneurs have access to a technology that transforms consumption goods into investment goods stochastically. The CMF uses the resources obtained from households to provide loans to entrepreneurs, who may require funds to increase their scale of production. As in the simple model, I assume symmetric information between entrepreneurs and the CMF at the time of the loan and asymmetric information ex-post, with costly state verification. I will formally show that a version of standard debt contracts is optimal in this setting.

At the end of the period, stochastic production is realized. Entrepreneurs with high enough production repay and consume the residual. Entrepreneurs with low enough production default and are monitored by the CMF. Since the CMF lends to a continuum of entrepreneurs, it diversifies their idiosyncratic risk, providing a risk-free saving opportunity to households.

The assumption of one period lived entrepreneurs make their problem static and constrain them from accumulating net worth. Net worth accumulation is an interesting possibility that has been explored by Carlstrom and Fuerst (1997). However, as I discuss later, this choice critically complicates the computation of the model, without adding much to the learning mechanism as a source of asymmetries.

Information Structure An entrepreneur who invests i gets a stochastic return equal to ωi in terms of capital goods, where ω is idiosyncratic to each entrepreneur. I assume ω is distributed log normal with fixed mean m_ω and stochastic variance $\sigma^2_{\omega,t}$.

$$\omega \sim \Upsilon(m_\omega, \sigma^2_{\omega,t}) \equiv \Upsilon_{\sigma^2_{\omega,t}} \tag{11}$$

where $\Upsilon_{\sigma^2_{\omega,t}}$ is the cdf of the log normal density $\upsilon_{\sigma^2_{\omega,t}}$.

The variance of ω is drawn each period from two possible symmetric distributions with a bounded positive support, $\sigma^2_{\omega,t} \sim \Psi(M_H, \sigma^2_{\sigma,t}) \equiv \Psi_{H,\sigma^2_{\sigma,t}}$ or $\sigma^2_{\omega,t} \sim \Psi(M_L, \sigma^2_{\sigma,t}) \equiv \Psi_{L,\sigma^2_{\sigma,t}}$, which only differ on their means, such that $M_H > M_L$.[21] These two distributions characterize two possible aggregate states of the economy, that I call a recession or bad times if Ψ_H and an expansion or good times if Ψ_L, for reasons that will become apparent later. As in the simple model, the aggregate state of the economy follows a Markov process with persistence $1-\lambda$.

At the beginning of each period, households and newborn entrepreneurs cannot observe the aggregate state, but they try to infer it using the total output and the fraction of defaulting entrepreneurs in the past: if the number of defaults was high, then agents assign a high probability the aggregate state was a recession, Ψ_H during the previous period.

The speed of updating is given by a time varying $\sigma^2_{\sigma,t}$. To capture the mechanism developed in the partial equilibrium model, where the precision of signals depends on the volume of economic activity, I assume $\sigma^2_{\sigma,t}$ vary over time as a function of investment at time t. I assume the following specification

$$\sigma^2_{\sigma,t} \equiv \frac{\sigma^2_{\sigma}}{i_t^{\phi}} \tag{12}$$

which depends on two exogenous parameters ϕ and σ^2_σ. Later, I will calibrate these two parameters in the same way I calibrated the maximum possible number of independent signals, N, in the simple model. The intuition is again that a higher volume of investment generates a larger number of signals, which makes the fraction of observed defaults more informative about the aggregate state of the economy.

To be more specific, agents at the beginning of period $t+1$ observe the fraction of entrepreneurs defaulting in the economy in the previous period (which is a perfect signal of $\sigma^2_{\omega,t}$) and the total volume of economic activity (which is a perfect signal of i_t and then $\sigma^2_{\sigma,t}$). Based on these two pieces of information, agents form beliefs about the economy having been in a good state in period t, $\mu'_t \equiv Pr\{\Psi_t = \Psi_L\}$. Using Bayesian updating

$$\mu'_t \equiv Pr\{\Psi_t = \Psi_L | \sigma^2_{\omega,t}, \sigma^2_{\sigma,t}, \mu_t\} = \frac{\psi_{L,\sigma^2_{\sigma,t}}(\sigma^2_{\omega,t} - M_L)\mu_t}{\psi_{L,\sigma^2_{\sigma,t}}(\sigma^2_{\omega,t} - M_L)\mu_t + \psi_{H,\sigma^2_{\sigma,t}}(\sigma^2_{\omega,t} - M_H)(1-\mu_t)} \tag{13}$$

where $\psi_{j,\sigma^2_{\sigma,t}}(\sigma^2_{\omega,t} - M_j)$ is the density function of $\Psi_{j,\sigma^2_{\sigma,t}}$ normalized with mean 0 when observing default rates that imply $\sigma^2_{\omega,t}$, for $j \in \{L, H\}$. Based on the updated belief about the previous variance generating distribution, Ψ_t, the belief about the current variance generating distribution Ψ_{t+1} needs to take into account the known transition probability

$$\mu_{t+1} = Pr\{\Psi_{t+1} = \Psi_L\} = Pr(1-\lambda)\mu'_t + \lambda(1-\mu'_t) \tag{14}$$

[21] It is important to assume two distributions rather than two variances. Otherwise, since agents observe total production and there is a continuum of entrepreneurs, they would learn immediate the true state of the economy.

These two equations are just a different version of equations (1) and (2).

Timing

1. Entrepreneurs and households agree on their beliefs of being in a good state (μ_t).
2. A representative firm that produces consumption goods Y_t hires labor and rent capital from households and entrepreneurs.
3. Households decide how much of their income to consume and how much to use to purchase investment goods from the CMF (claims on capital goods at the end of the period), at a price q_t per unit of investment un terms of consumption goods.
4. The CMF uses the resources from households to lend to entrepreneurs using an optimal financial contract and diversifying idiosyncratic risk.
5. Entrepreneurs borrow consumption goods from the CMF to transform i units of consumption goods into stochastic ωi units of capital goods.
6. The aggregate state and the variance of $\sigma^2_{\omega,t}$ is realized. Production happens, financial contracts are fulfilled and entrepreneurs consume.
7. Households and the new cohort of entrepreneurs use public information about i_t and $\sigma^2_{\omega,t}$ to update beliefs (μ_{t+1}). The state changes with a probability λ.

Optimal Financial Contract As in the simple model, the financial friction comes from ex-post asymmetric information between the entrepreneur and the CMF. Even when the contract still takes the form of a standard debt contract, entrepreneurs here also choose the size of the loan i. Since production is linear in i and entrepreneurs would like to borrow infinite, their net worth is critical to restrict the size of the loan. Since entrepreneurs are short lived, their net worth is simply the labor wage received at the beginning of the period,

$$n_t = w^e_t. \tag{15}$$

Costly state verification implies that, even when entrepreneurs observe their production ωi_t for free, it costs γi_t to the CMF to observe and seize the entrepreneur's production. Under the optimal contract, each entrepreneur borrows $(i_t - n_t)$ from the CMF and agrees to repay $(1+r^k_t)(i_t - n_t)$ capital goods at the end of the period. The entrepreneur defaults if production is not enough to cover the debt, i.e if $\omega < \bar{\omega}_t$, where

$$\bar{\omega}_t \equiv \frac{(1+r^k_t)(i_t - n_t)}{i_t}. \tag{16}$$

Since the price of capital in period t is q_t, the lending rate in units of consumption is

$$(1+\rho_t) = q_t(1+r_t^k) \tag{17}$$

This is an expanded version of equation (4). In the simple model we assumed $q_t = 1$, $i_t = 1$ and $n_t = 0$. Then $(1+\rho_t) = \bar{\omega}_t$, and the entrepreneur defaults if payoffs are lower than $(1+\rho_t)$.

Finally, assuming commitment, the CMF monitors the project and seizes all the production only if the entrepreneur defaults, paying the bankruptcy cost γ per unit of investment. This optimal contract is summarized in the next Proposition and proved in Appendix A.7.

Proposition 3 *The optimal financial contract is characterized by i_t and $\bar{\omega}_t$ that solve the problem*

$$\max_{i_t,\bar{\omega}_t} q_t i_t f(\bar{\omega}_t,\mu_t) \ s.t.\ q_t i_t g(\bar{\omega}_t,\mu_t) \geq (i_t - n_t) \tag{18}$$

where $n_t = w_t^e$, $f(\bar{\omega}_t,\mu_t)$ is the fraction of the expected net capital output received by the entrepreneur and $g(\bar{\omega}_t,\mu_t)$ is the fraction of the expected net capital output received by the lender. The solution is characterized by the first order conditions

$$\{i_t\}: \ q_t f(\bar{\omega}_t,\mu_t) + \lambda_t[q_t g(\bar{\omega}_t,\mu_t) - 1] = 0 \tag{19}$$

$$\{\bar{\omega}_t\}: \ \lambda_t = -\frac{f_\omega(\bar{\omega}_t,\mu_t)}{g_\omega(\bar{\omega}_t,\mu_t)} \tag{20}$$

where f_ω and g_ω are the respective derivatives $f(\bar{\omega}_t,\mu_t)$ and $g(\bar{\omega}_t,\mu_t)$ with respect to $\bar{\omega}$.

As in the simple model, the optimal level of investment, i_t, changes the speed of updating, but entrepreneurs do not internalize this positive effect when choosing the size of the loan, and each single entrepreneur takes it as given when solving his contracting problem. The speed of updating will then be determined in equilibrium by consistency with each entrepreneur's choice. This is the critical externality that introduces inefficiencies in the model. There is a non-internalized gain from having more investment in bad times and speed up recoveries.

Agents Optimization Problem In order to solve the agents' problems we first need to consider the law of motion of aggregate capital in the hand of households, which agents take as given when solving their maximization problem. On the one hand, given the linearity of the problem, the distribution of wealth does not enter as a state variable when aggregating. On the other hand, exactly as in the simple model (equation 8) capital depends both on the true variance of ω, $\sigma^2_{\omega,t}$ and on the expectation that agents have about the true variance through the financial contract, summarized by $\bar{\omega}_t$. The true law of motion of aggregate capital, as a function of $\sigma^2_{\omega,t}$ and $\bar{\omega}_t$, is

$$K^{\sigma^2_{\omega,t}}_{t+1} = (1-\delta)K_t + \eta i_t[m_\omega - \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t)\gamma] \tag{21}$$

The households' problem is dynamic, with budget constraint

$$c_t + q_t(k_{t+1} - (1-\delta)k_t) \leq w^l_t + k_t r_t \tag{22}$$

and recursively, households' problem is

$$V(K_t, \mu_t) = \max_{c_t} U(c_t) + \beta E_{t,\mu_t}[V(K_{t+1}, \mu_{t+1})] \tag{23}$$

$$s.t \ (13), (14), (21), (22)$$

The Euler Equation, which summarizes the dynamic demand for capital, is then

$$q_t U_{c,t} = \beta E_{t,\mu_t}\{U_{c,t+1}[q_{t+1}(1-\delta) + r_{t+1}]\} \tag{24}$$

Developing expectations explicitly,

$$\begin{aligned} q_t U_{c,t} \quad &= \quad \beta\{\mu_t \int [U_{c,t+1}(X^{\sigma^2_{\omega,t}}_{t+1})[q_{t+1}(X^{\sigma^2_{\omega,t}}_{t+1})((1-\delta) + r_{t+1}(K^{\sigma^2_{\omega,t}}_{t+1})]]d\Psi_{H,\sigma^2_{\sigma,t}} \\ &\quad + (1-\mu_t)\int [U_c(X^{\sigma^2_{\omega,t}}_{t+1})[q_{t+1}(X^{\sigma^2_{\omega,t}}_{t+1})((1-\delta) + r_{t+1}(K^{\sigma^2_{\omega,t}}_{t+1})]]d\Psi_{L,\sigma^2_{\sigma,t}}\} \end{aligned}$$

where $X^{\sigma^2_{\omega,t}}_{t+1} = \{K^{\sigma^2_{\omega,t}}_{t+1}, \mu^{\sigma^2_{\omega,t}}_{t+1}\}$ is the set of next period states given by equation (13), (14), (21), conditional on the realized variance $\sigma^2_{\omega,t}$. Next period consumption and price of capital depend on both states next period $X^{\sigma^2_{\omega,i}}_{t+1}$, while next period interest rate only depends on capital next period, $K^{\sigma^2_{\omega,i}}_{t+1}$.

The entrepreneurs' problem is static. They solve the contracting problem, invest in their stochastic projects, repay debt or default and consume whatever residual left. Their aggregate consumption is

$$c^e_t = q_t(\frac{w^e_t f(\bar{\omega}_t, \mu_t)}{1 - q_t g(\bar{\omega}_t, \mu_t)}) \tag{25}$$

where $f(\bar{\omega}_t, \mu_t)$ is the expected share of total capital output that goes to entrepreneurs and $g(\bar{\omega}_t, \mu_t)$ is the expected share of total capital output that goes to lenders, given the ex-ante fixed, previously to the realization of $\sigma^2_{\omega,t}$, price of capital q_t.

Market Clearing We have four markets to consider in the economy: two labor markets, the capital-goods market and the consumption-goods market (the numeraire good). Competition in the factor market implies that wage and rental rates in terms of capital are equal to their respective marginal products in the production of consumption goods:

$$r_t = F_1(t) \qquad w_t^l = F_2(t) \qquad w_t^e = F_3(t) \tag{26}$$

The expected supply of capital goods is given by the expectation of equation (21), which depends on μ_t and the financial contract $\bar{\omega}_t$. How the expected supply depends on q_t? Entrepreneurs maximize (18), which can be rewritten as the maximization of

$$i_t f(\bar{\omega}_t, \mu_t) = i_t \left[m_\omega - E_{\mu_t} \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t)\gamma - g(\bar{\omega}_t, \mu_t) \right]$$

Since an increase in q_t relaxes the constraint of the lender's return, $i_t f(\bar{\omega}_t, \mu_t)$ is increasing in q_t. Since $i_t g(\bar{\omega}_t, \mu_t)$ is also increasing in q_t, the previous equation implies that $i_t[m_\omega - E_{\mu_t} \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t)\gamma]$ increases in expectation, and from equation (21), the expected supply of capital goods is increasing in q_t. The demand of capital is given by the lenders Euler equation, which is decreasing in q_t. Market clearing happens when households decide how much money to put in the CMF, and determines q_t.

The conditions to clear the other three markets read as follows

$$H_t = 1 - \eta \tag{27}$$

$$H_t^e = \eta \tag{28}$$

$$c_t + c_t^e + \eta i_t = Y_t = F(K_t, H_t, H_t^e) \tag{29}$$

Definition 2 ***Recursive Equilibrium***

A recursive equilibrium is a set of decision rules K_{t+1}, i_t, $\bar{\omega}_t$, c_t, c_t^e, prices r_t, w_t^l, w_t^e, q_t and belief μ_{t+1}, which are expressed as functions of the two states of the economy (K_t and μ_t) such that, lenders maximize their utility subject to information and budget constraints (problem (23)), entrepreneurs maximize their utility subject to their budget constraints (25), financial contracts are optimal (Proposition 3), beliefs are updated using Bayes rule (equations (13) and (14)) and markets clear (equations (26), (27), (28) and (29)).

The challenge in solving this equilibrium is the need for a global solution. In Appendix A.8 I discuss how to compute the model using projection methods. A local solution, as the log linearization that Carlstrom and Fuerst (1997) use is not suitable for our purposes, since a steady state does not exist for one of our state variables, beliefs μ. In fact we are interested in the model dynamics when beliefs are allowed to vary widely over the whole support $[0, 1]$ in order to capture the levels of asymmetries observed in the data. When the model is perturbed around a fixed μ it is not able to match the sudden and large jumps in empirical default rates. The next Section discussed the calibration and the simulation results and implications.

4.2 A Quantitative Assessment

4.2.1 Parameters

I calibrate the model to monthly data. As in Carlstrom and Fuerst (1997), I assume a utility function $u(c) = log(c)$, a production function $F(K, H, H^e) = K^\alpha H^\psi (H^e)^{1-\alpha-\psi}$. The monthly discount rate is set to $\beta = 0.9959$, which correspond to a 5% yearly risk-free interest rate, the depreciation rate is set to 2%, the production function parameters are $\alpha = 0.3$ and $\psi = 0.6275$. Finally, the fraction of entrepreneurs η is just a normalization.

The parameters that are specific to our model are $\phi = 10.7$ $\sigma^2_\sigma = 4.1$e-014, $M_H = 0.17$ and $M_L = 0.14$. I calibrate them to match monthly default rates, both in good and bad times (0.35% and 0.85% respectively), the time-series standard deviation of defaults during bad times (0.5%) and the skewness of lending rates among emerging markets since 1985 (1.77) for their average bankruptcy costs (16.6%), as I did to compute N in the partial equilibrium model. Intuitively, M_H pins down default in bad times, M_L pins down default in good times, while ϕ and σ^2_σ pin down the skewness of lending rates and the time-series variance of defaults during bad times. It is worthwhile to note that even though I do not target the standard deviation of defaults during good times, which is 0.3%, the calibrated model generates 0.25%, showing the calibration of "risk shocks" accommodates well the process of default over time.

4.2.2 Implications for Asymmetry

The general equilibrium model improves the ability of the model to match the cross-country differences in lending rates asymmetry, in particular for developed countries. It also matches better investment skewness and its relation with output skewness – investment is more asymmetric than output, but still both investment and output are more negatively skewed when bankruptcy costs are larger.

Figure 3 is a graphical comparison of how well the general and partial equilibrium models perform in matching the empirical relation between bankruptcy costs and skewness. Each point represents the skewness of a classification group in Table 2. The general equilibrium model delivers levels of asymmetry for developed countries that are more in line with those observed in the data. Intuitively, the calibrated parameter ϕ induces a stronger reaction of the variance and precision of signals to lending rates. This makes skewness more sensitive to economic activity and then to bankruptcy costs.

Figure 3: Models' Performance on the Asymmetry of Lending Rates

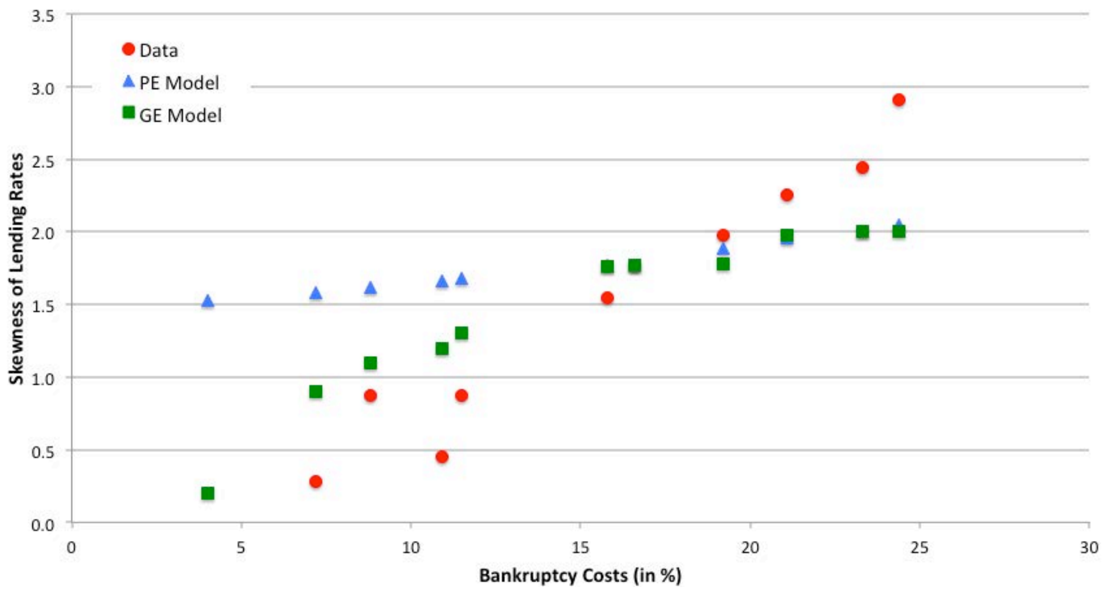
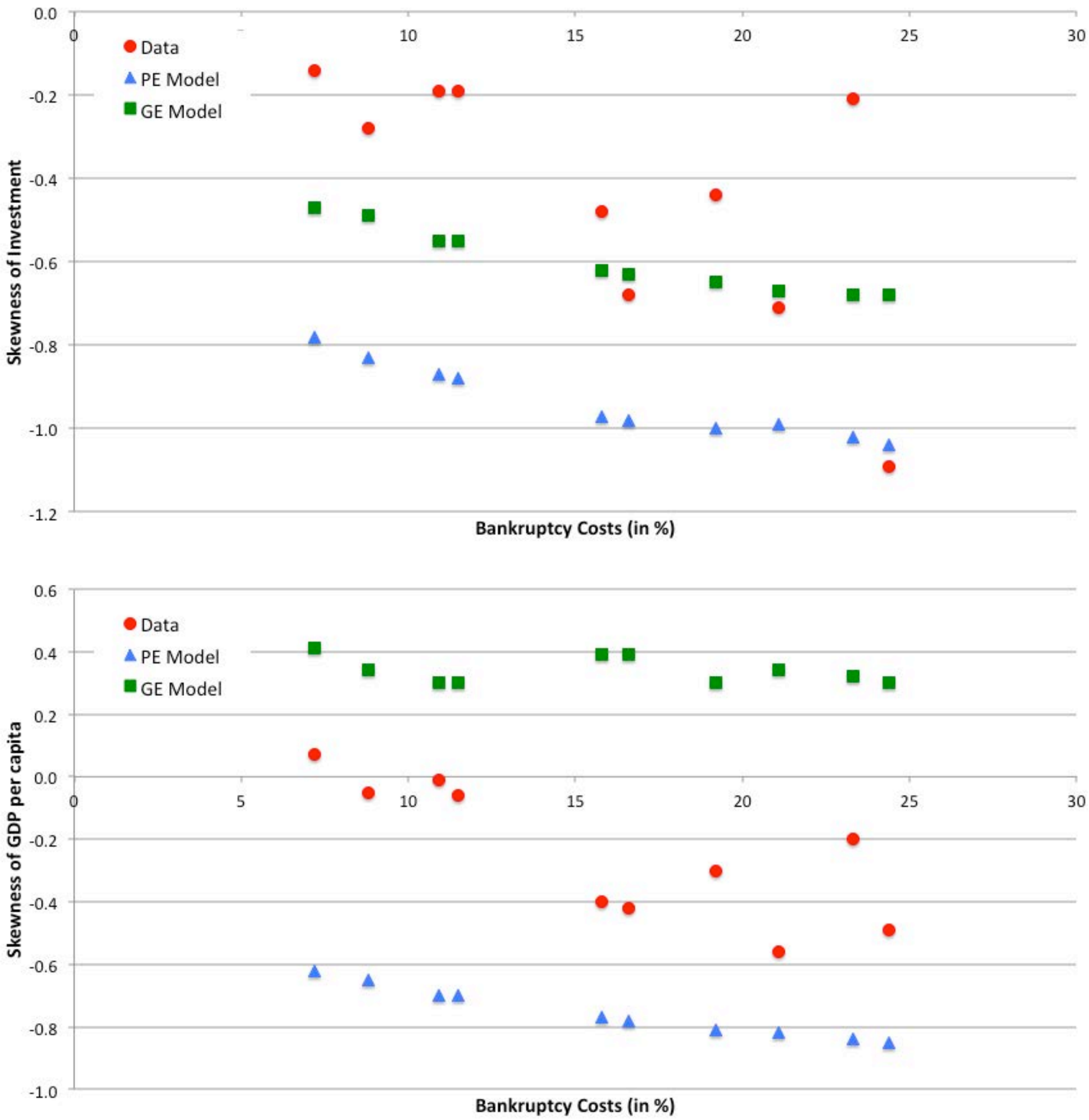


Figure 4 shows the performance of both models in matching the asymmetry of economic activity. First, both models are successful in replicating the negative relation between bankruptcy costs and the skewness of investment and output. Second, the general equilibrium model is more successful in matching the observed skewness in investment than the partial equilibrium counterpart, even when no moment of investment has been targeted. Finally, the general equilibrium model is more successful in breaking the link between investment and output in the direction suggested by the data. When the economy moves to bad times, investment and output declines. However, since households prefer to smooth consumption, the decline in output is not as large as the decline in investment, moderating its asymmetry.

Why is the skewness of output positive? In the model depreciation hardwires an artificial positive level of skewness. To gain intuition, assume investment is symmetric. When investment suddenly declines, capital declines gradually depending on depreciation, and output does not drop one for one with investment. In contrast, when investment suddenly increases, capital and output increases one for one with investment. In this example, output has positive skewness even though investment is symmetric. Conditional on this positive bias, the skewness of output declines when γ increases, with a slope similar to the empirical one.

In Appendix A.6 I show that the general equilibrium model improves in matching the volatility of lending rates, investment and output with respect to the partial equilibrium model. I also discuss in the Appendix that the general equilibrium model is particularly successful in

Figure 4: Models' Performance on the Asymmetry of Economic Activity



matching the cross-country differences in skewness and the volatility levels of lending rates and investment when default rates are slightly larger than the ones calibrated using speculative grade U.S. bonds – specifically, 0.5% in good times and 3% in bad times. First, these higher levels of default rates seem consistent with evidence from crises in emerging markets. Second, the quantitative relevance of "risk shocks" in driving large crises is consistent with the recent work of Gilchrist, Yankov, and Zakrajsek (2009), Gilchrist and Zakrajsek (2012) and Christiano, Motto, and Rostagno (2012).

Caveats An important caveat of the model is the absence of net worth accumulation that may allow entrepreneurs to rely less on external finance over time. Here I argue that net worth accumulation is unlikely to have an important effect for asymmetry, but it introduces important complications in terms of tractability, given the needs to find a global solution for the problem. In essence, net worth accumulation introduces a new state variable, namely entrepreneurs capital, increasing substantially the dimensionality of the vector of coefficients to find, both directly, through the addition of a new state variable, and indirectly, through the addition of an additional function to be approximated. I discuss in detail the modeling choices and the difficulties of adding net worth in Appendix A.8.

Still, to get a sense of the potential effects of net worth on asymmetry, I computed the global solution of a version of the model with net worth accumulation but without learning, which remains tractable. In the original setting, the maximum deviation of capital from the mean is 2%. Imposing the same capital shock in the version without learning induces a change of net worth of 2.8%, and skewness of lending rates equal to 0.14. Hence, net worth alone does not generate enough asymmetry to explain the large empirical differences across countries.

5 Plausibility of Endogenous Learning Mechanisms

Here I bring together two independent pieces of evidence to illustrate the plausibility of the mechanism and to answer the following questions. First, do lending rates just replicate asymmetric fundamentals, in this case default probabilities? The answer is no. Changes in default are in fact negatively, not positively, skewed. Then, if lenders learn fast about default, lending rates would reflect them closely and would also be negatively skewed. Second, if learning is the right story, does the precision of learning really recover slowly after a sudden decline? The answer is yes. Uncertainty, interpreted as the inverse of precision and measured by the volatility of the stock market, is positively skewed (it increases fast and recovers slowly). The first answer reveals the economic relevance of asymmetries, since they may be the reflection of inefficiencies. The second answer reveals the potential relevance of learning as the mechanism behind asymmetries.

Default Rates To compute true default probabilities I use data on Moody's monthly trailing 12-month issuer default rates for different regions and samples with available data. Table 8 shows the specific samples and types of bonds considered. In all cases, default rates is either symmetric or negatively skewed, which implies that declines in default are in fact larger than increases. If lending rates were just reflecting true default, their decline would be larger than their increase, and then they would be negatively skewed, or symmetric at most.

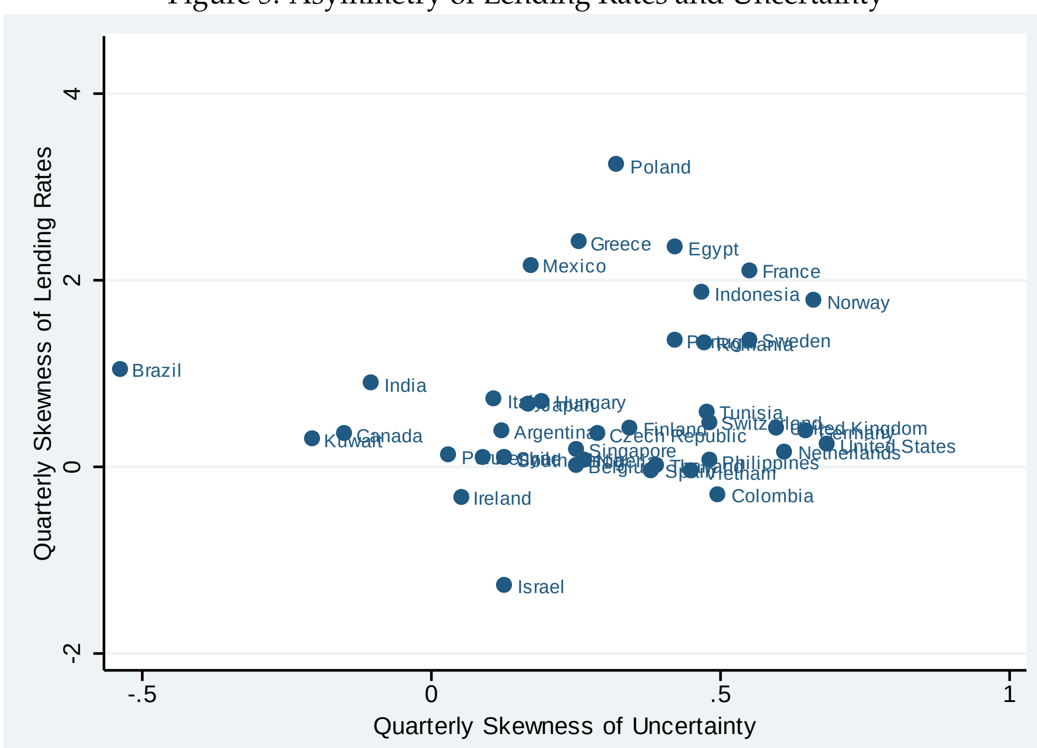
Uncertainty Following Baker and Bloom (2012), I use quarterly stock market volatility as a measure of uncertainty. From the 40 countries in our sample, only four exhibit uncertainty with

Table 8: Default Rates

Region	Moody's Rated Bonds	Sample	Skewness of log changes
United States	All Corporations	01/70 – 06/08	-1.71
United States	Speculative Grade	01/70 – 06/08	-1.39
Europe	All Corporations	01/99 – 06/08	0.06
Asia	All Corporations	01/98 – 06/08	-1.44
Latin America	Speculative Grade	01/96 – 06/08	-0.29
Argentina	Speculative Grade	01/96 – 06/08	-2.39
Brazil	Speculative Grade	01/96 – 06/08	-0.14
Mexico	Speculative Grade	01/96 – 06/08	-0.10

negative skewness, with only Brazil showing a significant degree of negative asymmetry. In Figure 5 I show the relation between the skewness of uncertainty and the skewness of quarterly real lending rates. The relation is clearly positive and, if not considering the extreme case of Brazil, the coefficient is also statistically significant, such that an increase of 1 in the skewness of uncertainty induces an increase of 0.83 in the skewness of lending rates.

Figure 5: Asymmetry of Lending Rates and Uncertainty



All these results are consistent with the model. After a sudden increase in lending rates, investment declines and takes time for it to recover (negative skewness), making the uncertainty in the economy and lending rates' decline also slow (positive skewness). Since this asymmetric pattern of movements in lending rates does not reflect the evolution of real default probabilities, which are in fact negatively skewed, it generates an inefficient reallocation of resources out of productive activities during periods of time where default probabilities are in fact low, but lenders keep learning and charging high rates in the meantime.

6 Concluding Remarks

Business cycle movements in lending rates, investment, and output are usually asymmetric: sudden and sharp during recessions, but slow and gradual during recoveries. Understanding this well-known fact matters for policymakers interested in ameliorating the financial distress and inefficient resource allocation that result from large crises and lengthy recoveries. I have documented and offered an explanation for a new, related fact: the well-known asymmetry is stronger in countries with less-developed financial systems, or those with larger financial frictions. These are countries in which financial distress and inefficient allocation of resources seem more frequent and more extreme.

I explain the new cross-country fact using a learning model with endogenous flows of information. In these models, monitoring and bankruptcy costs represent the costs of overcoming financial frictions. I show that financial frictions not only magnify crises but also restrict the generation of information after crises, which leads to slower, more gradual recoveries in less-developed countries. Calibrations of partial and general equilibrium versions of the model successfully match quantitatively the observed cross-country differences in asymmetry of lending rates, investment, and output.

My analysis has some nontrivial policy implications. It uncovers new gains from reducing financial frictions directly or improving mechanisms that are used to deal with those frictions. Policies that reduce financial frictions include inducing relationship lending and enhancing the operation of bureaus that offer public information about the credit standing of borrowers. Policies that improve mechanisms to deal with financial frictions include reductions in the complexity of bankruptcy procedures and financial liberalizations, which improve competition and the efficiency of improvements in bankruptcy courts and codes.

This analysis also has a more subtle policy implication. My work here assumes that starting a venture has a positive externality, that of providing information about economic conditions, which is not internalized when an entrepreneur decides to borrow. Therefore, my work implies that countercyclical Pigouvian subsidies to borrowing can potentially align incentives, inducing more activity and faster learning during recoveries.

At least three possible extensions to my work seem worth mentioning. One is to expand the study beyond overall country data into data on individual industries. That may prove to be a very rich source of heterogeneity with which to test the relationship between bankruptcy costs and the asymmetry of lending rates and economic activity. Another reasonable extension is to add to the model other sources of information, for example, additional public signals or private signals that induce dispersed information. Even though such an extension should not overcome my results, which depend purely on the speed of information generation, it may uncover some policy implications. A third extension is to expand the sources of shocks. Here I have explored shocks to default rates, which makes the model self-contained; defaults determine lending rates, through both credit risk and expected bankruptcy costs, which feed back into investment and information. In my general equilibrium model, I have explored risk shocks as well. Also worth studying may be other sources of shocks, such as sudden stops, shocks to aggregate demand, and productivity shocks.

A note about the timing of my data. I have focused here on the period that precedes the recent financial turmoil in developed countries, which started with the subprime crisis in the United States and was followed by the sovereign crises in the Euro area. I excluded data on these events for two main reasons. One is methodological; the data are not complete because countries have not experienced full recovery yet. My other reason is conceptual; recently-developed highly-structured financial products seem more difficult to evaluate than credit products, which have more accumulated know-how. This implies that the information environment for these newer assets may be characterized by high monitoring costs, as is true for credit products in developing countries today. Hence, including data on the recent crises in developed economies would have confused different financial products and contaminated cross-country comparisons.

Recent financial developments do, however, suggest other extensions of this paper; to accommodate learning about default rates of newly structured products and to study their implications for economic activity, crises, and recoveries. Gorton and Souleles (2006) and Ordonez (2012), for example, argue that important components of the so-called shadow banking, such as special purpose vehicles (SPVs), have been created to circumvent bankruptcy costs. If this is correct, then bankruptcy costs may discontinuously start to matter after crises, which would induce even larger asymmetries. Additional efforts to uncover the effects of the new financial landscape on the asymmetry of economic activity are likely fruitful future endeavors.

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A Appendix

A.1 Data on Skewness and Sample of Countries

To measure unconditional asymmetry, I compute the unconditional skewness of log changes. First, I construct the distribution of log changes for real lending rates, real investment and real GDP per capita in each country. Then I compute the unconditional skewness for each one of these distributions,

$$\texttt{Skewness} = \frac{T\sqrt{T-1}}{T-2} \frac{\left[\sum_{t=1}^{T}(x_t - \overline{x})^3\right]}{\left[\sum_{t=1}^{T}(x_t - \overline{x})^2\right]^{\frac{3}{2}}}, \tag{30}$$

where T is the number of observations (number of months or quarters in the sample), $x_t = \ln(X_t) - \ln(X_{t-1})$, X_t is the variable measured in period t and $\overline{x}$ is the sample mean of the time series.

I use monthly data on real lending rates and quarterly data on investment and real GDP per capita, for 100 counties and for the period 1960 - 2008, from the IMF's International Financial Statistics (IFS). I obtain real lending rates by subtracting the Hodrick-Prescott (HP) trend of inflation (IFS figure $64P..ZF...$) from nominal lending rates (IFS figure $60P..ZF...$). The IMF defines lending rate as *"the bank rate that usually meets the short- and medium-term financing needs of the private sector. This rate is normally differentiated according to creditworthiness of borrowers and objectives of financing"*. Most available data is based on mortgage and firms' loans rates applied to the private sector.

For real output I use Real GDP per capita (IFS figure $99B$ divided by population $99Z..ZF$). For investment I use gross capital formation (IFS figure $93..ZF$) deflated by GDP deflator (IFS figure $99BIIZF$). Unfortunately, comparable monthly data for these two real variables across countries is not available, which makes skewness somewhat less informative – not only there are less observations, but the lower frequency of data hides potential large changes, which are relevant in measuring asymmetries.

Three caveats are relevant. First, I choose the HP filter to deflate nominal rates in order to capture both backward and forward looking components in the formation of inflation expectations. The alternative use of ex-post real lending rates (using current inflation as a deflator) delivers similar results, but has the disadvantage of losing informative months with large shocks in expected inflation when computing log changes. Second, even when the definition of lending rates is not exactly the same across countries, it is unlikely that differences in this definition bias the measure of skewness, which is based on changes over time for a given country.

Finally I only use data up to the first half of 2008 to avoid capturing the recent global crisis. Otherwise very large crises would appear in the sample, but not their respective recoveries, biasing the estimates towards even larger skewness levels. Furthermore, the unprecedented intervention of governments and the large role of recently developed structured financial products would likely contaminate the comparison with countries in previous years and the results. I leave for research in the near future the study of the asymmetric effects of recent financial innovations during recent crises.

All countries in the sample fulfill two minimum requirements: Their data have more than 4 years of continuous observations and show a defined cyclical pattern.

All 100 countries in the sample, based on income classification, ordered by the skewness level, are shown in Tables 9 and 10.

Table 9: Countries Included in Classification by Income - Part I

Skewness of Lending Rates (LR), Investment (Inv) and GDP per capita (GDP) (1960-2008) by Income							
Country	**LR**	**Inv**	**GDP**	**Country**	**LR**	**Inv**	**GDP**
Income Group 1 (Richest)							
Singapore	-0.64		-0.25	Spain	0.77	-0.54	-0.51
Hong Kong	-0.22	-0.48	-0.50	Netherlands	0.78	1.30	1.30
Macao	-0.21	-0.42	0.04	Iceland	1.20	-1.51	-0.31
Israel	-0.07	0.54	0.50	Germany	1.41	0.76	0.73
Switzerland	-0.04	1.41	1.45	United Kingdom	1.58	-0.45	0.47
Belgium	0.12	-0.19	0.44	Norway	1.79	-0.05	-0.05
United States	0.31	-0.40	-0.27	Portugal	2.11	0.28	0.30
Canada	0.43	-0.53	0.05	Sweden	2.99	0.14	0.57
Finland	0.58	-0.85	-0.85	Korea	3.47	-0.23	-0.24
Italy	0.59	-0.18	-0.17	France	4.30	-0.37	-0.38
Japan	0.60	-0.31	-0.35	Greece	4.51	-0.60	-0.34
Slovenia	0.60	0.31	0.31	Kuwait	5.50		
Ireland	0.76	-1.06	-1.05	Cyprus	6.82	0.19	0.89
Income Group 2							
Chile	-0.50	0.21	-0.08	Argentina	1.46	-0.96	0.07
Estonia	-0.36	-0.48	0.07	Croatia	1.48	0.01	-0.39
Uruguay	-0.30		-0.41	Venezuela, Rep. Bol.	1.73		
Slovak Republic	0.19	-0.74	-0.74	Mexico	1.80	-0.76	0.12
Barbados	0.69			Brazil	2.92	0.17	-0.85
South Africa	0.80	-0.02	-0.05	Czech Republic	3.65	-0.17	-0.17
Hungary	0.85	-1.12	-0.97	Poland	5.70	-0.99	-0.82
Romania	1.03	-0.92	-0.92	Gabon	6.38		

Table 10: Countries Included in Classification by Income - Part II

Skewness of Lending Rates (LR), Investment (Inv) and GDP per capita (GDP) (1960-2008) by Income							
Country	**LR**	**Inv**	**GDP**	**Country**	**LR**	**Inv**	**GDP**
Income Group 3							
Latvia	-0.42	-0.72	-0.67	Bolivia	1.14	0.46	0.40
Namibia	-0.34			Jordan	1.83		-0.38
Thailand	-0.26	-1.12	0.29	Jamaica	2.01		-0.50
Russia	-0.23	-1.12	-0.15	El Salvador	2.35		
Lithuania	-0.14	-0.52	-0.52	Egypt	2.82	-0.62	-0.62
Dominican Republic	-0.08			Equatorial Guinea	3.61		
Colombia	-0.05	-0.06	0.05	Guatemala	3.86	-0.72	-0.51
Grenada	0.10			Botswana	4.54	0.38	-0.03
Peru	0.20	-0.75	-0.20	Indonesia	4.62	-2.77	-2.77
Philippines	0.22		-0.02	Cape Verde	6.22		
Sri Lanka	0.44			Morocco	8.14		-0.45
Swaziland	0.45			Guyana	10.25		
Paraguay	0.75		0.44				
Income Group 4 (Poorest)							
Angola	-0.61			Zambia	3.22		
Mozambique	-0.52			Tanzania	3.30		
Moldova	-0.47			Tunisia	3.49		0.12
Nigeria	-0.46			Malawi	3.91		
Nicaragua	-0.39			Cameroon	4.31		
Kenya	-0.08			Chad	4.43		
Armenia	0.14			Lao People's Dem.Rep	4.73		
Burundi	0.49			Congo, Republic of	4.99		
Lesotho	0.70			Senegal	5.13		
Solomon Islands	1.00			Central African Rep.	5.73		
Sierra Leone	1.01			Madagascar	8.01		
Haiti	1.09			Albania	8.01		
Vietnam	1.95			Ethiopia	8.44		
Rwanda	2.17			Bangladesh	8.80		
Honduras	2.64			Gambia, The	9.01		
India	2.91	-1.09	-1.10	Mauritania	10.16		
Uganda	2.95						

The rest of country classifications are reported in Table 11.

Table 11: Countries Included in Other Classifications

OECD (23 countries)	Non-OECD Countries (77 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, Mauritania, Moldova, Morocco, Mozambique, Namibia, Nicaragua, Nigeria, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Senegal, Sierra Leone, Singapore, Slovak Republic, Slovenia, Solomon Islands, South Africa, Sri Lanka, Swaziland, Tanzania, Thailand, Tunisia, Uganda, Uruguay, Venezuela, Vietnam, Zambia.
High Contract Enforcement (27 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 (40 countries)	**Non-Private Bureau (40 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 the Skewness Definition

In the main text, I analyze cross-country differences in skewness of real lending rates log changes. Here, I extend the analysis using three alternative approaches to measure skewness.

First, I compute skewness on the distribution of log deviations from a real lending rate trend. For each month, I obtain the difference between the log of real lending rates and the log of the Hodrick-Prescott trend, and compute the skewness of such distribution.

Second, the model can be interpreted as a model of skewness in lending spreads rather than a model of skewness in lending rates, since I consider exogenous risk-free interest rates. What is a good approximation of risk-free rates? I use two approaches here. First, I compute spreads between lending rates in a given country and domestic yields of 3-month Treasury Bills. There are two important drawbacks for this approach. On the one hand, information about T-Bills in developing countries is not high-quality. On the other hand, it is likely that aggregate conditions that determine default rates in a given economy also affect its sovereign risk, moving both lending rates and T-Bills. This leads us to the second approach to compute spreads, which is the difference between lending rates in a given country and the U.S. 3-month T-Bill.

Table 12 shows that using these alternative definitions leads to the same conclusion: asymmetry seems to be higher among poor, non-OECD countries with low enforcement of contracts.

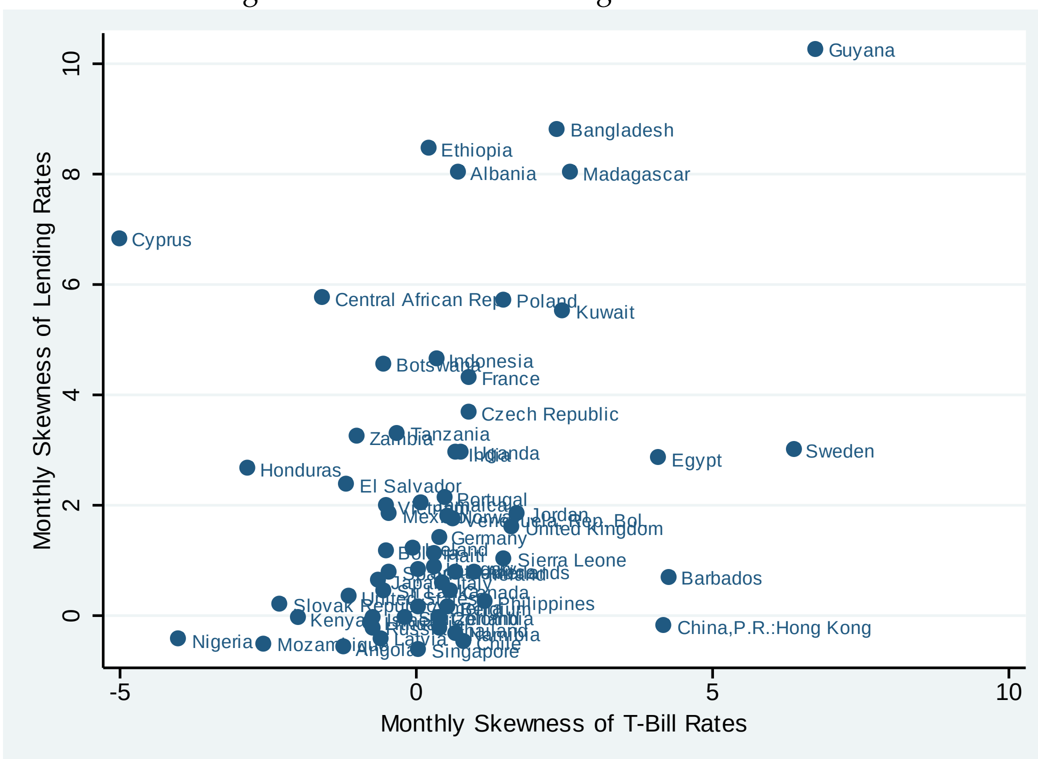
Table 12: Alternative Definitions of Asymmetric Lending Rates

Country Classification Skewness of:	Deviations of Lending Rates 1960-1985			Spreads with domestic T-Bills 1985 - 2008	Domestic T-Bills 1985-2008	Spread with US T-Bills 1985 – 2008
	1960-1985	1985-2008	1985-2008			
Income group 1 (richest)	2.55	-0.09	0.85	-0.04	0.21	-0.02
Income group 2	2.59	1.80	1.90	-0.30	0.58	1.31
Income group 3	4.12	1.93	1.92	0.37	0.64	2.10
Income group 4 (poorest)	4.46	2.34	2.63	0.52	-0.46	2.09
OECD	2.21	1.34	2.07	-0.30	0.26	0.17
Non-OECD	4.08	1.49	1.71	0.40	0.15	1.79
High contract enforcement	1.93	0.68	1.53	-0.15	0.20	-0.17
Low contract enforcement	3.65	2.11	2.34	0.67	-0.14	2.57
Private bureau	1.82	0.87	1.06	0.10	0.28	0.77
No private bureau	4.82	1.86	2.20	0.17	-0.07	1.47

Notes: Deviations of Lending Rates are obtained from the distribution of log changes in monthly lending rates in deviations from Hodrick-Prescott trend. Spreads with domestic T-Bills are measured as the difference between real lending rates and 3-month T-Bill rates for the same country, from the Global Financial Dataset. Spreads with US T-Bills are measured as the difference between real lending rates and 3-month T-Bill rates for the United States,

It is important to highlight two features of the data that are consistent with the model. First, Figure 6 shows a strong positive correlation between the skewness of real lending rates and the skewness of T-Bills. This implies that effectively sovereign debt inherits some of the risk from bad economic conditions. Furthermore, learning about these economic conditions affect sovereign and internal lending rates similarly. Still, it seems that the skewness of spreads measured vis-a-vis domestic T-Bills also increase with bankruptcy costs, which suggests learning about ventures' default probabilities is more restrictive than learning about sovereign risk.

Figure 6: Skewness in Lending Rates and T-Bills



The second important feature, is that the relation between spreads computed vis-a-vis U.S. T-Bills (which are probably a better measure of risk-free rate in light of the previous results) and different proxies for financial frictions remain highly significant, both economically and statistically. This is summarized in Table 13.

Table 13: Lending Rates Spreads and Financial Frictions

Dependent Variable	Skewness of Lending Rates Spreads with respect to the United States T-Bills (1985-2008)				
Credit to Private Sector/GDP (All countries)	-0.02 (0.01)***				
Credit to Private Sector/GDP (Non-African countries)		-0.01 (0.01) *			
Cost of Bankruptcy			0.05 (0.01)***		
Time for Bankruptcy				0.32 (0.13)**	
Recovery Rate					-0.03 (0.01)***
Constant	2.36 (0.43)***	1.53 (0.42)***	0.25 (0.40)	0.21 (0.52)	2.00 (0.39)***
Observations	90	66	81	81	81

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

Dependent Variable	Skewness of Lending Rates Spreads with respect to the United States T-Bills (1985-2008)			
Legal Protection to Financial Assets	-0.75 (0.30)**			
Sophistication for Financial Markets		-0.60 (0.26)**		
Availability of Internet Banking			-0.68 (0.26)***	
Health of Banking Systems				-0.55 (0.21)***
Constant	4.45 (1.52)***	3.21 (1.09)***	3.60 (1.14)***	3.39 (1.02)***
Observations	52	52	52	52

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

A.3 Data on Financial Liberalization and Tables for Section 2.2.2

Data on financial liberalization are obtained from Kaminsky and Schmukler (2008) for the period 1973 – 2005. Their work includes information on liberalization along three dimensions: capital accounts, domestic financial sectors, and stock market capitalization. *Capital account liberalization* refers to an increased ability of corporations to borrow abroad and fewer controls on exchange rate mechanisms and other sorts of capital. *Domestic financial liberalization* refers to a loosening of interest rate controls (lending and deposits) and other restrictions, such as directed credit policies or limitations on foreign currency deposits. *Stock market liberalization* refers to an increase in the degree to which foreigners are allowed to own domestic equity and a decrease in restrictions to repatriate capital, dividends, and interests. I focus on 16 countries for which I have enough data to reliably measure skewness before and after major liberalization events (more than 47 continuous observations before and after).

The main financial liberalization event is defined as occurring in the month in which the maximum number of liberalization changes have been introduced into the financial system. Financial liberalization and restriction processes are defined as the time frame between the first liberalization change and the last one during the sample 1973-2005.

Table 14: Asymmetry of Lending Rates Before and After Main Financial Liberalization Events

Country	Main Financial Liberalization Event		Type of Liberalization	Skewness of Lending Rates	
	Month	Year		Before	After
Canada	March	1975	KA	0.88	0.41
Finland	January	1990	DFS and SM	0.43	0.13
France	January	1985	DFS and KA	3.94	0.05
Ireland	January	1992	DFS and SM	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	SM and KA	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 Markets and DFS stands for Domestic Financial System. Data on liberalization dates are from Kaminsky and Schmukler (2008).

Table 15: Asymmetry of Lending Rates Before and After Financial Liberalization Processes

Country	Start of Financial Liberalization Event		End of Financial Liberalization Event		Skewness of Lending Rates	
	Month	Year	Month	Year	Before	After
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

Notes: Data on liberalization dates are from Kaminsky and Schmukler (2008).

Table 16: Asymmetry of Lending Rates Before and After Financial Restriction Processes

Country	Start of Financial Restriction Event		End of Financial Restriction Event		Skewness of Lending Rates	
	Month	Year	Month	Year	Before	After
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

Notes: Data on liberalization dates are from Kaminsky and Schmukler (2008).

A.4 Optimal Equilibrium with Stochastic Monitoring

Proposition 4 *In the optimal equilibrium with stochastic monitoring ($\pi_t \in [0,1]$) borrowers never lie ($z_{it} = 1$) and monitoring probabilities and lending rates are, for all lenders j at time t*

$$\pi_{it} = \begin{cases} 1 & if \quad v_{it} < \frac{1+r+(1-\theta_t)\gamma}{\theta_t} \\ \frac{1+r}{\theta_t v_{it}-(1-\theta_t)\gamma} & otherwise \end{cases} \tag{31}$$

$$(1+\rho_{it}) = \begin{cases} \frac{1+r+(1-\theta_t)\gamma}{\theta_t} & if \quad v_{it} < \frac{1+r+(1-\theta_t)\gamma}{\theta_t} \\ \frac{(1+r)v_{it}}{\theta_t v_{it}-(1-\theta_t)\gamma} & otherwise \end{cases} \tag{32}$$

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

$$v_{it} \geq \widetilde{\nu}_t = \frac{1+r+w+(1-\theta_t)\gamma}{2\theta_t} + \frac{\sqrt{(1+r+w)^2+(1-\theta_t)\gamma[2(1+r-w)+(1-\theta_t)\gamma]}}{2\theta_t} \tag{33}$$

Proof. As in the main text, we assume full commitment, which means the lender commits to follow the random strategy π_{it}. Note that the standard debt contract, where $\pi_{it} = 1$ regardless of v_{it}, is also an equilibrium. However, when v_{it} is high enough, it is not necessary $\pi_{it} = 1$ to achieve truth–telling. A lower monitoring probability reduces lending rates maintaining incentives to pay back, which is naturally preferred by borrowers. Borrowers tell the truth if $v_{it} - (1+\rho_t) > (1-\pi_t)v_{it}$, subject to $\pi_{it} \leq 1$. The solution is $\pi_{it} = min\{\frac{(1+\rho_{it})}{v_{it}}, 1\}$.

From perfect competition, the previous π_{it} implies that, $\theta_t(1+\rho_{it}) - (1-\theta_t)\gamma\frac{(1+\rho_{it})}{v_{it}} = 1+r$. Solving first for $1+\rho_{it}$ and then for π_{it}, gives equations (31) and (32). Given this contract conditional on v_{it}, entrepreneurs borrow if $\theta_{it}v_{it}\left[1 - \frac{1+r}{\theta_t v_{it}-(1-\theta_t)\gamma}\right] \geq w$. From this equation, comes the cutoff in equation (33). ∎.

Four features of this equilibrium are worth noting. First, $\widetilde{\nu}_t > \frac{1+r+(1-\theta_t)\gamma}{\theta_t}$ for all monitoring costs $\gamma \geq 0$. This means that, effectively, borrowers have a level of v_{it} such that monitoring costs are given by $\pi_{it} = \frac{1+r}{\theta_t v_{it}-(1-\theta_t)\gamma}$, from equation (31), and lending rates are given by $(1+\rho_{it}) = \frac{(1+r)v_{it}}{\theta_t v_{it}-(1-\theta_t)\gamma}$, from equation (32). Second, if $\gamma = 0$ or $\theta_t = 1$ the unique equilibrium is the standard debt contract with non-stochastic monitoring. Third, cutoffs in the optimal equilibrium are smaller than those under a standard debt contract since lending rates are lower. Finally, the optimal equilibrium generates the same asymmetry implications as the standard debt contract. Monitoring costs still magnify crashes (γ 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 for Proposition 2.

It is also worthwhile to highlight that, even when I prove stochastic bankruptcy is preferred when there is full commitment, Krasa and Villamil (2000) show that the optimal contract is again one with bankruptcy in pure strategies when there is no commitment to the conditions and previsions of the contract originally signed.

A.5 Proof of Proposition 2

The proof proceeds in three steps. First, I introduce the concept of time-reversibility and explain the symmetric nature of lending rates and investment in a constant information economy. Second, I sketch out why lending rates and investment are time-irreversible and asymmetric in an endogenous information economy. Finally, I show that bankruptcy costs make lending rates and investment more asymmetric if bad news depresses economic activity relatively more the larger the bankruptcy costs.

Step 1: Time-reversibility in a constant information economy

Time-reversibility is defined as the property of a stochastic process under which it is not possible to determine, given the states at a number of points in time after running the stochastic process, which states came first and which states arrived later. In our case beliefs of being in good times are time reversible if their increase when all signals are positive has the same magnitude as their decrease when all signals are negative. Assume that the prior of a good state is $\mu_t = x$. If all n_t ventures fail ($s_t = 0$), then $\mu_{t+1} = y < x$. If in the next period all n_{t+1} ventures succeed ($s_{t+1} = n_{t+1}$) and the process is time-reversible, then $\mu_{t+2} = z = x$ and it is not possible to tell whether successes preceded or proceeded failures.

In a constant information economy, the number of signals n is given exogenously. Without loss of generality, assume the economy has equally informative signals ($\theta = \theta_g = 1 - \theta_b > \frac{1}{2}$) and no state change ($\lambda = 0$).[22] If initial beliefs in period t are $\mu_t = x$ and all n signals fail ($s = 0$), then from equations (1) and (2) we know that

$$\mu_{t+1} = y = \frac{(1-\theta)^n x}{(1-\theta)^n x + \theta^n (1-x)}. \tag{34}$$

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

$$\mu_{t+2} = z = \frac{\theta^n y}{\theta^n y + (1-\theta)^n (1-y)}. \tag{35}$$

Replacing (34) into (35), gives $\mu_{t+2} = z = x$. 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 depends 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 no longer time-reversible. Assume that in 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_t depends on beliefs $\mu_t = x$. Then

$$\mu_{t+1} = y = \frac{(1-\theta)^{n_t^x} x}{(1-\theta)^{n_t^x} x + \theta^{n_t^x} (1-x)}. \tag{36}$$

[22] As shown by Veldkamp (2005), the proof extends to signals that are not equally informative and $\lambda > 0$.

Now, given that $y < x$, agents are less confident about being in good times, which reduces the number of ventures, $n^y_{t+1} < n^x_t$. Assume that in the following period, all n^y_{t+1} signals are successful ($s_{t+1} = n^y_{t+1}$). Then

$$\mu_{t+2} = z = \frac{\theta^{n^y_{t+1}} y}{\theta^{n^y_{t+1}} y + (1-\theta)^{n^y_{t+1}}(1-y)}. \tag{37}$$

Now replacing (36) into (37) gives

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

and we can compute

$$z - x = \frac{\left[\theta^{n^y_{t+1}}(1-\theta)^{n^x_t} - (1-\theta)^{n^y_{t+1}}\theta^{n^x_t}\right] x(1-x)}{\left[\theta^{n^y_{t+1}}(1-\theta)^{n^x_t}\right] x + \left[(1-\theta)^{n^y_{t+1}}\theta^{n^x_t}\right](1-x)}. \tag{38}$$

It is straightforward to check that $z < x$ when $\theta > \frac{1}{2}$ and $n^y_{t+1} < n^x_t$.[23] This implies that the greatest possible decrease in beliefs (from x to y) is more likely than an increase of the same magnitude (since beliefs just go from y to z).

Given equation (4), the greatest possible increase in lending rates is more likely than a decrease of the same magnitude, which is a necessary and sufficient condition for the existence of positive unconditional asymmetry in lending rates. Hence, in an endogenous information economy, beliefs follow a time-irreversible stochastic process that translates into a positive asymmetry in lending rates changes.

Given equation (5), the time-irreversibility of lending rates translates into time-irreversibility of cutoffs $\widetilde{\nu}$ linearly, and given equation (6) translates into time-irreversibility of investment and output, since $n(\widetilde{\nu}(z)) < n(\widetilde{\nu}(x))$, but in a degree that depends on the shape of the distribution of payoffs ν_{it}. In the extreme, for example, if there is no density mass between $\widetilde{\nu}(z)$ and $\widetilde{\nu}(x)$ then there is no time-irreversibility in such a range of beliefs.

Step 3: The effects of bankruptcy costs on asymmetry

Now we study the degree of irreversibility of beliefs for two countries with different levels of bankruptcy costs, $\gamma_L < \gamma_H$. We can rewrite equations (36) and (37) as,

$$y_i = \left[1 + \frac{1-x}{x}\left(\frac{\theta}{1-\theta}\right)^{n^{x_i}_t}\right]^{-1}, \tag{39}$$

[23] The same conclusion is obtained when reversing the order of successes and failures.

and

$$z_i = \left[1 + \frac{1-y_i}{y_i} \left(\frac{1-\theta}{\theta} \right)^{n_{t+1}^{y_i}} \right]^{-1}. \tag{40}$$

for $i \in \{L, H\}$. Why the subindices i? Because even when having the same belief x about the good state, from equations (5) and (6) the two countries have different cutoffs $\widetilde{\nu}_t(x|\gamma_i) = \frac{1}{x}[1 + r + w + (1-x)\gamma_i]$ and different number of active firms $n_t^{x_L} \geq n_t^{x_H}$.

It is straightforward from equation (40) that $z_L > z_H$ when

$$\frac{y_H}{1-y_H}\frac{1-y_L}{y_L} < \left(\frac{1-\theta}{\theta} \right)^{n_{t+1}^{y_H} - n_{t+1}^{y_L}}$$

Since, from equation (39),

$$\frac{1-y_i}{y_i} = \frac{1-x}{x} \left(\frac{\theta}{1-\theta} \right)^{n_t^{x_i}}$$

then, $z_L > z_H$, and hence the degree of irreversibility is larger with higher costs, when

$$n_t^{x_H} - n_{t+1}^{y_H} > n_t^{x_L} - n_{t+1}^{y_L}$$

or, which is the same

$$F(\widetilde{\nu}_{t+1}(y|\gamma_H)) - F(\widetilde{\nu}_t(x|\gamma_H)) > F(\widetilde{\nu}_{t+1}(y|\gamma_L)) - F(\widetilde{\nu}_t(x|\gamma_L)) \tag{41}$$

where $F(\nu)$ is the cumulative distribution of business opportunities' payoffs ν_{it}.

In words, the time-irreversibility of beliefs increase with bankruptcy costs when the decline in activity after bad news is more severe in countries with higher bankruptcy costs. This condition is satisfied when

$$\frac{\partial F(\widetilde{\nu}_{t+1}(y|\gamma_i)) - F(\widetilde{\nu}_t(x|\gamma_i))}{\partial \gamma_i} > 0$$

$$f(\widetilde{\nu}_{t+1}(y|\gamma_i))\frac{1-y_i}{y_i} > f(\widetilde{\nu}_t(x|\gamma_i))\frac{1-x}{x}$$

$$\frac{f(\widetilde{\nu}_{t+1}(y|\gamma_i))}{f(\widetilde{\nu}_t(x|\gamma_i))} > \left(\frac{1-\theta}{\theta} \right)^{n_t^{x_i}}. \tag{42}$$

where $f(\nu)$ is the density of the business opportunities' payoffs ν_{it}. However this is the condition for an arbitrary initial belief x. Define $R = \min_{\nu_1 \in [\nu_2, \overline{\nu}], \nu_2 \in [\underline{\nu}, \nu_1]} \frac{f(\nu_1)}{f(\nu_2)}$ and $\underline{n} = n_t^{\theta_b}$. Then, a condition for time-irreversibility of beliefs, for all possible beliefs, is

$$R > \left(\frac{1-\theta}{\theta} \right)^{\underline{n}}. \tag{43}$$

Since $\theta > 0.5$, the right hand side of this condition is less than 1, and then it is trivially fulfilled when the distribution is uniform (since the densities are constant evaluated at any ν and then $R = 1$) or when the cumulative distribution is a convex function of ν (since the densities are increasing in ν in the relevant support $\nu \in [\underline{\nu}, \overline{\nu}]$ and then $R > 1$). More importantly, this condition is more easily fulfilled when θ is large or when the number of firms financed under the most pessimistic beliefs $\underline{n}$ is also large.

Time-irreversibility of beliefs that increases with bankruptcy costs immediately translates into asymmetry of lending rates that increases with bankruptcy costs. Since lending rates are both increasing in bankruptcy costs and decreasing in beliefs, through equation (4) and assuming the same starting belief x, then $\rho_{t+2}(z|\gamma_L) - \rho_t(x|\gamma_L) < \rho_{t+2}(z|\gamma_H) - \rho_t(x|\gamma_H)$

The same reasoning can be applied for investment and output. The asymmetry of economy activity also increase with bankruptcy costs, given equations (5) and (6). This is because the differences in lending rates translate into a difference in cutoffs that is larger for γ_H than γ_L. Since we assume the distribution of payoffs ν_{it} has mass in all its points, it implies the difference in activity is larger for γ_H than for γ_L.

To grasp the intuition, assume θ is close to 1, such that $n_t^{x_H} = n_t^{x_L}$. Then, from equation (39), $y_H = y_L$, $\widetilde{\nu}_{t+1}(y|\gamma_H) > \widetilde{\nu}_{t+1}(y|\gamma_L)$ and $n_{t+1}^{y_H} < n_{t+1}^{y_L}$. This implies that lending rates increase more in a country with γ_H than in a country with γ_L, making crises more severe. Finally, from equation (40), $z_H < z_L$, beliefs are less reversible in a country with γ_H, delaying the recovery. These two effects combined make large increases in lending rates more likely and large decreases less likely in countries with high bankruptcy costs, and then lending rates, investment and output more asymmetric.

A.6 Performance of the Models for Levels and Volatilities

A.6.1 Levels of Lending Rate Spreads

I decompose lending rates in the model (equation 4) into three terms: a risk-free rate, a risk premium (the risk-free rate adjusted by default probabilities), and the expected bankruptcy costs needed to solve the frictions imposed by asymmetric information,

$$\rho_t = r + \frac{(1-\theta_t)}{\theta_t}(1+r) + \frac{(1-\theta_t)}{\theta_t}\gamma. \tag{44}$$

Lending spreads are defined as $(\rho_t - r)$. Since $\frac{\partial(\rho_t - r)}{\partial \gamma} = (1-\theta_t)/\theta_t > 0$, spreads increase with monitoring and bankruptcy costs. Here I show that this is a robust empirical prediction and that the calibrated version of the models can quantitatively explain spread differences across countries.

a. Monitoring Costs Increase Lending Spreads

I construct lending spreads by calculating the monthly difference between real lending rates and domestic three-month Treasury bill yields for each country.[24] I then calculate the average spread for each country in the sample period 1985–2005.

Table 17 shows the results of running regressions between average levels of lending spreads and my general and specific measures of financial development. All coefficients have the expected sign and are statistically significant. An important drawback is that, unlike regressions to explain skewness, level comparisons may be capturing important differences in methodologies and definitions across countries. Despite that drawback, results are robust to many sample restrictions and seem consistent with the prediction that monitoring and bankruptcy costs increase lending spreads.

b. Monitoring Costs Are Quantitatively Important

Here I show that differences in monitoring costs are also quantitatively important to explain differences of lending spreads across countries.

The first column of Table 18 shows the average real lending rates for the country classifications defined earlier, and the second column shows average lending spreads. While real lending rates among the poorest countries roughly double those among the richest countries, the spreads are more than double. The third column shows simulated spreads from the calibrated version of the model. In the fourth and fifth columns spreads are decomposed between risk premium (based on three-month Treasury bill yields for each country in the sample) and financial frictions costs (based on the estimated monitoring and bankruptcy costs from Djankov et al. (2008)) as specified in equation (44).

[24] The data on three-month Treasury bill yields was obtained from the Global Financial Database (GFD) (2008). I have monthly data for 63 countries from 1960 to 2005.

Table 17: Lending Rate Spreads and Financial Development

Dependent Variable	Average Lending Rates Spreads (1985-2008)				
Credit to Private Sector/GDP (All countries)	-0.04 (0.01)***				
Credit to Private Sector/GDP (Non-African countries)		-0.04 (0.01)***			
Cost of Bankruptcy			0.15 (0.04)***		
Time for Bankruptcy				0.56 (0.35)*	
Recovery Rate					-0.06 (0.02)***
Constant	7.16 (0.88)***	6.87 (1.14)***	2.82 (0.60)***	3.66 (0.88)***	7.68 (1.14)***
Observations	63	50	58	58	58

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

Dependent Variable	Average Lending Rates Spreads (1985-2008)			
Legal Protection to Financial Assets	-1.76 (0.55)***			
Sophistication for Financial Markets		-1.41 (0.47)***		
Availability of Internet Banking			-1.19 (0.48)**	
Health of Banking Systems				-1.16 (0.82)**
Constant	13.75 (3.20)***	10.81 (2.44)***	9.73 (2.46)***	10.59 (2.83)***
Observations	43	43	43	43

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

Two conclusions can be drawn from Table 18. First, a comparison of the data and simulated spreads (the second and third columns) shows that the partial equilibrium model matches spreads observed in developed countries and underestimates spreads in less-developed countries. However, the spread differences are significant, with spreads in the poorest countries double those in the richest countries. Second, as shown in the last column, monitoring costs account for almost 20% of spreads in developing countries (income group 4) and less than 5% in developed ones (income group 1).

Similar results are obtained from the general equilibrium model. By construction, I match the default rates observed in the data. The effects of monitoring and bankruptcy costs arise from the product of the default rates and those costs, which is the deadweight loss of financial frictions.

Table 18: Data vs. Model Spreads of Lending Rates

Country Classification	Data		PE Model			
	Lending Rates	Spreads	Spreads	$\frac{(1-\theta)(1+r)}{\theta}$	$\frac{(1-\theta)}{\theta}\gamma$	Percentage that γ explains
Income group 1 (richest)	10.4	2.9	2.9	2.8	0.1	3.4
Income group 2	19.6	4.1	3.3	3.0	0.3	9.1
Income group 3	16.9	6.0	5.4	4.7	0.7	13.0
Income group 4 (poorest)	21.5	8.0	5.7	4.7	1.0	17.5
OECD	11.9	2.9	3.0	2.8	0.2	6.7
Non-OECD	18.8	6.4	5.3	4.7	0.6	11.3
High contract enforcement	12.1	3.2	3.1	2.9	0.2	6.5
Low contract enforcement	19.2	6.0	5.4	4.7	0.7	13.0
Private bureau	14.7	3.8	3.1	2.9	0.2	6.5
No private bureau	20.0	7.0	5.4	4.7	0.7	13.0

A.6.2 Volatilities

Now I study the ability of the models to capture the level and cross-country differences in volatility of lending rates and economic activity. First, I compute the standard deviation of the logarithm of lending rates, investment, and output per capita, for 1985–2008. The standard deviation of log variables delivers a proxy of the coefficient of variation; hence, all standard deviations should be interpreted as a percentage of the mean. First, I show the empirical relation between volatility and financial development. Then, I discuss the performance of the models to accommodate such a relation.

Table 19 shows that the volatilities of lending rates and economic activity decline significantly with the level of financial development. In contrast, only investment seems to depend significantly on the level of monitoring and bankruptcy costs. The larger the level of bankruptcy costs, the larger the volatility of investment. This is also illustrated in the first three columns of Table 20. Even though the differences in volatility of lending rates and output are not large, the investment of underdeveloped countries is twice as volatile as that of developed countries (recall that income group 4 has just one observation, so it should be ignored).

Table 20 offers two main messages with respect to the performance of the models. First, it shows that both models succeed in generating a positive relation between bankruptcy costs and volatility, and in both cases, investment is the only variable showing a significant positive relation. Second, neither model matches the level of volatility in the data. However, as I show next, this result may be just the result of using data from the United States to calibrate default rates in good and bad times.

Table 19: Volatility and Financial Development

Dependent Variable: Standard Deviation - Log of	Lending Rates		Investment		GDP per capita	
Credit to Private Sector/GDP	-0.06		-0.15		-0.07	
	(0.03)*		(0.03)***		(0.02)***	
Cost of Bankruptcy		-0.18		0.30		0.04
		(0.11)		(0.18)*		(0.11)
Constant	31.1	33.1	32.3	18.2	19.3	14.5
	(3.1)***	(3.0)***	(3.6)***	(3.0)***	(2.5)***	(2.3)***
Observations	84	75	46	44	52	51

Notes: The standard deviation is computed on the logarithm of these variables. Then, these coefficients measure the change in standard deviations of the dependent variable, in terms of the mean of the dependent variable, when there is an increase of 1% in the independent variable.

Table 20: Volatilities: Data vs. Models

Country Classification	Data			PE Model			GE Model		
	LR	Inv	GDP	LR	Inv	GDP	LR	Inv	GDP
Income group 1 (richest)	5.1	6.4	4.6	2.3	72.6	67.2	5.6	0.85	0.03
Income group 2	8.7	13.4	7.0	2.0	89.8	78.1	5.6	1.35	0.08
Income group 3	4.0	14.2	5.8	2.0	90.4	78.8	5.6	1.39	0.09
Income group 4 (poorest)	5.5	3.3	2.0	1.9	100.4	84.8	5.7	1.65	0.16
OECD	4.1	8.0	4.7	2.2	74.3	68.2	5.6	1.01	0.04
Non-OECD	6.0	11.5	5.9	2.0	90.0	78.6	5.7	1.48	0.11
High contract enforcement	7.0	6.3	4.4	2.2	79.8	71.8	5.6	1.12	0.05
Low contract enforcement	4.7	9.1	5.4	2.0	106.5	8887	5.7	1.62	0.15
Private bureau	6.7	8.5	4.5	2.2	79.8	71.7	5.6	1.13	0.05
No private bureau	5.5	11.5	6.7	2.0	110.3	85.0	5.7	1.55	0.13

Notes: The standard deviation is computed on the logarithm of these variables. Then, these coefficients represent the standard deviation in terms of the percentage of the mean.

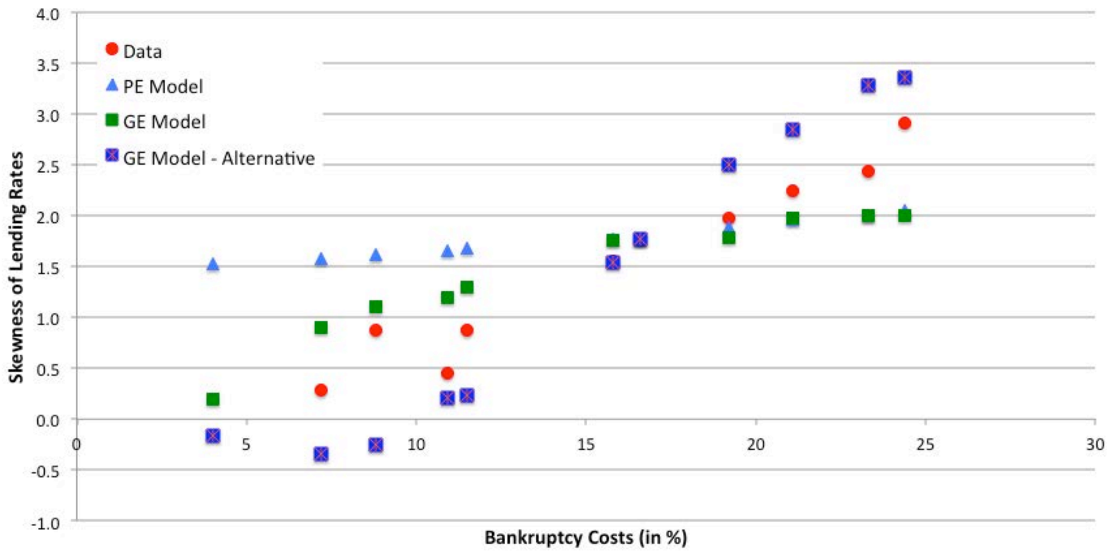
A.6.3 Alternative Calibration with Higher Default Rates

Now I recalibrate the general equilibrium model using slightly higher default rates in good times (0.5% rather than 0.35%) and in bad times (3% rather than 0.85%). Even though these default rates are chosen merely as an example, evidence of default in emerging countries during crises suggests they are not implausible.[25] As shown in Figures 7 and 8, which replicate Figures 3 and 4 in the main text, calibrating the model to these default rates critically improves its ability to accommodate the cross-country differences in skewness of lending rates and investment, without affecting much the simulated skewness of output.

Table 21 shows that this calibration also improves critically the simulated levels of volatility. Even though the relations between volatilities and bankruptcy costs maintain their sign – the volatility of lending rates is insensitive to bankruptcy costs, while the volatility of economic

[25] Default rates reached a peak of 50% in Argentina during April 2002, 18% in Brazil during November 2002, and 33% in Mexico during April 2003.

Figure 7: Models' Performance on the Asymmetry of Lending Rates



activity increases in bankruptcy costs – the levels of simulated volatilities are closer to those in the data. Why this improvement? Intuition comes from the effect on the price of capital from a larger difference in default between good and bad times. When the economy is in bad times, the decline in the price of capital, q_t, depresses investment and output. The drop in investment introduces a limit to the increase in lending rates during bad times. Recall that $(1+\rho_t) = q_t(1+r_t^k)$ (equation 17) and $(1+r_t^k) = \bar{\omega}_t \frac{i_t}{i_t - n_t}$ (equation 16). A large decline in i_t tends to increase $(1+r_t^k)$ (the interest rate in terms of capital), which is compensated for the decline in q_t (a cheaper capital price), which then moderates the volatility of lending rates.

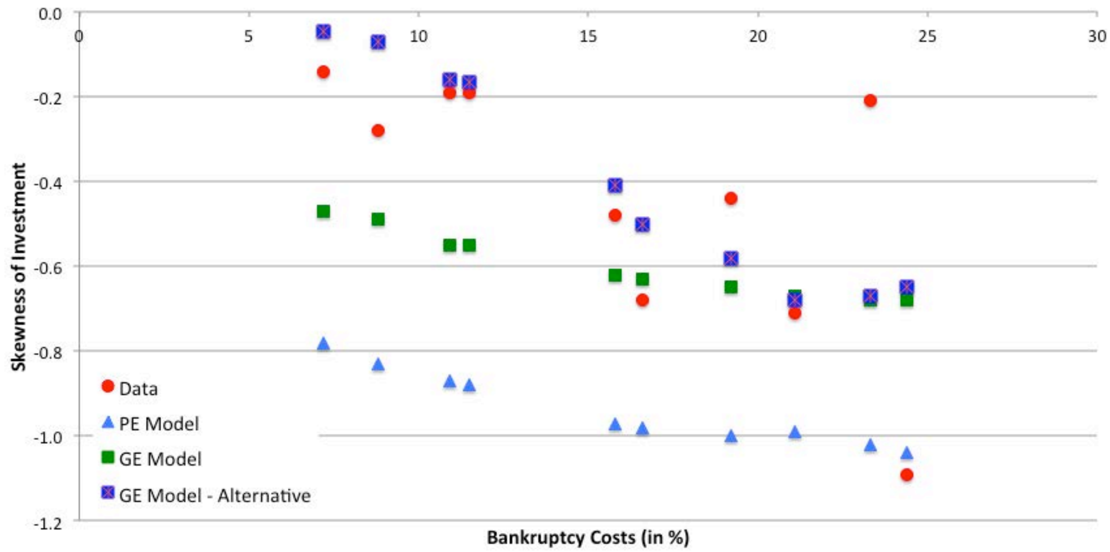
Table 21: Volatilities: Benchmark vs Alternative Calibration

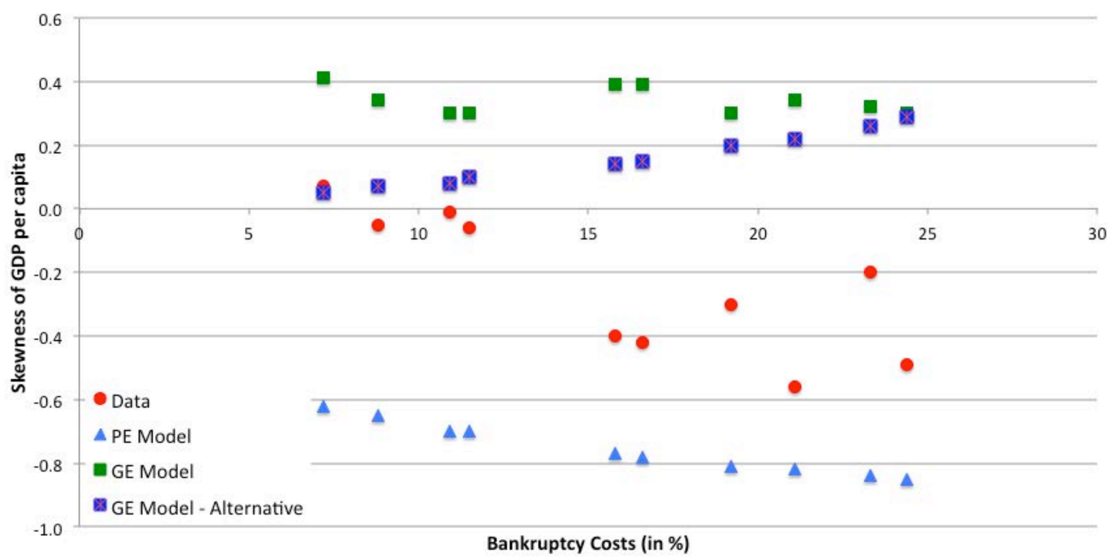
Country Classification	Data			Benchmark GE Model			GE Model – Higher Default Rates		
	LR	Inv	GDP	LR	Inv	GDP	LR	Inv	GDP
Income group 1 (richest)	5.1	6.4	4.6	5.6	0.85	0.03	7.3	4.2	0.49
Income group 2	8.7	13.4	7.0	5.6	1.35	0.08	7.5	7.9	0.95
Income group 3	4.0	14.2	5.8	5.6	1.39	0.09	7.5	8.3	0.99
Income group 4 (poorest)	5.5	3.3	2.0	5.7	1.65	0.16	7.5	11.1	1.12
OECD	4.1	8.0	4.7	5.6	1.01	0.04	7.4	5.1	0.58
Non-OECD	6.0	11.5	5.9	5.7	1.48	0.11	7.5	9.2	1.05
High contract enforcement	7.0	6.3	4.4	5.6	1.12	0.05	7.4	6.2	0.73
Low contract enforcement	4.7	9.1	5.4	5.7	1.62	0.15	7.5	10.8	1.12
Private bureau	6.7	8.5	4.5	5.6	1.13	0.05	7.4	6.3	0.77
No private bureau	5.5	11.5	6.7	5.7	1.55	0.13	7.5	9.8	1.08

Notes: The standard deviation is computed on the logarithm of these variables. Then, these coefficients represent the standard deviation in terms of the percentage of the mean.

The compensating effect of the endogenous price of capital moderates the volatility of lending

Figure 8: Models' Performance on the Asymmetry of Economic Activity





rates but not the volatility of economic activity, which reacts more to large differences of default between good and bad times.

Finally, note that, in the benchmark calibration, default rates are symmetric. However, in this alternative calibration, default rates are negatively skewed and expected default rates are positively skewed, which is consistent with the findings in Section 5.

A.7 Proof of Proposition 3

Following Townsend (1979) and Gale and Hellwig (1985), when commitment exists, the optimal contract takes the form of a standard debt contract. Since the true value of the variance $\sigma^2_{\omega,t}$ is unknown, the expected entrepreneurial income, given the beliefs about the true variance generating distribution Ψ_t, is

$$q_t\{\mu_t \int [\int_{\bar{\omega}_t}^{\infty} \omega i_t d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))(1+r^k_t)(i_t - n_t)] d\Psi_{H,\sigma^2_{\sigma,t}}$$

$$+(1-\mu_t) \int [\int_{\bar{\omega}_t}^{\infty} \omega i_t d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))(1+r^k_t)(i_t - n_t)] d\Psi_{L,\sigma^2_{\sigma,t}}\}$$

using the definition of $\bar{\omega}_t$ this expression could be simplified to $q_t i_t f(\bar{\omega}_t, \mu_t)$ where $f(\bar{\omega}_t, \mu_t)$ is the fraction of the expected net capital output received by the entrepreneur.

$$f(\bar{\omega}_t, \mu_t) \equiv \mu_t \int [\int_{\bar{\omega}}^{\infty} \omega d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))\bar{\omega}_t] d\Psi_{H,\sigma^2_{\sigma,t}} + (1-\mu_t) \int [\int_{\bar{\omega}}^{\infty} \omega d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))\bar{\omega}_t] d\Psi_{L,\sigma^2_{\sigma,t}}$$

Similarly we have that the expected payoff to the CMF is

$$q_t\{\mu_t \int [\int_{0}^{\bar{\omega}_t} \omega i_t d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t)\gamma i_t + (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))(1+r^k_t)(i_t - n_t)] d\Psi_{H,\sigma^2_{\sigma,t}} +$$

$$+(1-\mu_t) \int [\int_{0}^{\bar{\omega}_t} \omega i_t d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t)\gamma i_t + (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))(1+r^k_t)(i_t - n_t)] d\Psi_{L,\sigma^2_{\sigma,t}}\}$$

again using the definition of $\bar{\omega}_t$ this expression could be simplified to $q_t i_t g(\bar{\omega}_t, \mu_t)$ where $g(\bar{\omega}_t, \mu_t)$ is the fraction of the expected net capital output received by the CMF.

$$\begin{aligned} g(\bar{\omega}_t, \mu_t) \quad \equiv \quad & \mu_t \int [\int_{0}^{\bar{\omega}} \omega d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t)\gamma + (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))\bar{\omega}_t] d\Psi_{H,\sigma^2_{\sigma,t}} \\ & +(1-\mu_t) \int [\int_{0}^{\bar{\omega}} \omega d\Upsilon_{\sigma^2_{\omega,t}}(\omega) - \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t)\gamma + (1-\Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t))\bar{\omega}_t] d\Psi_{L,\sigma^2_{\sigma,t}} \end{aligned}$$

The total expected capital output that is produced in the economy is given by the expected return, m_ω, minus the expected monitoring cost, $\gamma[\mu_t \int \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t) d\Psi_{H,\sigma^2_{\sigma,t}} + (1-\mu_t) \int \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t) d\Psi_{L,\sigma^2_{\sigma,t}}]$. Therefore we have

$$f(\bar{\omega}_t, \mu_t) + g(\bar{\omega}_t, \mu_t) = m_\omega - [\mu_t \int \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t) d\Psi_{H,\sigma^2_{\sigma,t}} + (1-\mu_t) \int \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t) d\Psi_{L,\sigma^2_{\sigma,t}}]\gamma$$

Since the contract is determined in expectation with respect to beliefs of the agents and the true variance of ω is unique, there is a unique realized capital output, that is either smaller or larger then the expected one, which lead to learning in the next period.

The optimal contract is given by a pair $(i_t, \bar{\omega}_t)$ that maximizes the entrepreneur's expected return subject to the CMF being indifferent between lending or not (recall that loans are intraperiod, so there is no opportunity cost of funds to take into account).

$$\max_{i_t, \bar{\omega}_t} q_t i_t f(\bar{\omega}_t, \mu_t) \; s.t. \; q_t i_t g(\bar{\omega}_t, \mu_t) \geq (i_t - n_t)$$

The first order conditions for this problem are

$$\{i_t\}: \; q_t f(\bar{\omega}_t, \mu_t) + \lambda_t [q_t g(\bar{\omega}_t, \mu_t) - 1] = 0$$

$$\{\bar{\omega}_t\}: \; \lambda_t = -\frac{f_\omega(\bar{\omega}_t, \mu_t)}{g_\omega(\bar{\omega}_t, \mu_t)}$$

which combined with the constrained satisfied with equality in equilibrium give

$$q_t\{m_\omega + \gamma[\frac{f(\bar{\omega}_t, \mu_t)}{f_\omega(\bar{\omega}_t, \mu_t)} E_{\mu_t}[\upsilon_{\sigma^2_{\omega,i}}(\bar{\omega}_t)] - E_{\mu_t}[\Upsilon_{\sigma^2_{\omega,i}}(\bar{\omega}_t)]]\} = 1$$

$$i_t = \frac{n_t}{1 - q_t g(\bar{\omega}_t, \mu_t)}$$

where

$$E_{\mu_t}[\Upsilon_{\sigma^2_{\omega,i}}(\bar{\omega}_t)] \equiv \mu_t \int \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t) d\Psi_{H,\sigma^2_{\sigma,t}} + (1-\mu_t) \int \Upsilon_{\sigma^2_{\omega,t}}(\bar{\omega}_t) d\Psi_{L,\sigma^2_{\sigma,t}}$$

Equation (16) and (17) uniquely solve for $\bar{\omega}_t$ and i_t as functions of q_t, n_t and μ_t. Moreover we have an expression for the return to internal funds that is given by

$$\frac{q_t f(\bar{\omega}_t, \mu_t) i_t}{n_t} = \frac{q_t f(\bar{\omega}_t, \mu_t)}{1 - q_t g(\bar{\omega}_t, \mu_t)} \tag{45}$$

which is independent of both optimal investment i_t and entrepreneur net worth n_t.

A.8 Computation of the General Equilibrium Model

The model is solved numerically using projection method. More specifically I use Chebychev collocation and approximate the function $\bar{\omega}(K, \mu)$ with $5th$ order Chebychev basis for K and $3th$ order Chebychev basis for μ. These are chosen as the smallest orders to get a precision in the projection of $1e-5$. In order to deal with the two dimensionality of the policy $\bar{\omega}(K, \mu)$ we use the Tensor product.

To be more specific, given an approximated function $\bar{\omega}(K, \mu, \xi)$, where ξ is the vector of coefficients of the Chebychev basis, we are able to derive all the other policies, as functions of K, μ, ξ and thus we are able to compute residuals from the Euler equation (24). The vector ξ is the solution of the system of 15 equations in 15 unknowns, where the 15 unknowns are the coefficients of the Chebychev basis and the 15 equations are given by the Euler equation evaluated at the 15 collocation pairs (K_i, μ_i). In order to compute expectations we use 10 points quadratures.

To solve the model exploiting projection methods we need a functional restriction $N(h) = 0$ that is defined by the system of equilibrium equations. Using projections we find $\tilde{h}$ that approximate h such that $N(h) = 0$. Knowledge of $\tilde{h}$ allows us to get all the policy functions. There are potentially many different choices of h, we chose $\bar{\omega}(K, \mu)$ and use the dynamic Euler equation (24) as the restriction $N(\cdot)$, since within the Euler equation are nested all the other equilibrium conditions. The projection method specifically allows us to solve for an approximated function $\bar{\omega}(K, \mu)$, that satisfies the restriction. There are 5 steps necessary to approximate the solution by projection. Here I briefly outline how we dealt with each step.

Step 1 The first step is to choose a bounded state-space $X \subset R^n$ and a family of functions $\varphi_i(x) : X \to Y$, $i = 0, 1, ...$ that are the basis of the projection. We have two state variables, K and μ, thus we choose the set $X \subset R^2$ such that, during the solution of the model and the simulations, the policy for capital never hit the closure. The evolution of beliefs is bounded by definition. Hence we have $X = [0, 1] \times [K_{min}, K_{max}]$. We choose $\varphi_i(K, \mu)$ to be the terms of the Tensor product of Chebychev basis of order 3 for μ and of order 5 for K.

Step 2 The second step requires to choose a degree of approximation p, and let

$$\bar{\omega}(K, \mu, \xi) = \sum_{i=0}^{p} \xi_i \varphi_i(K, \mu) \tag{46}$$

The choice of p is is driven by the trade-off between speed of computation and precision. We choose p in order to have the Euler Equation unit free error to be smaller than $1e-5$ on the whole support X. The resulting p is 15, that is given by Tensor product of the $3rd$ order polynomium for μ and $5th$ order polynomium for K.

Step 3 The third step defines the residual function

$$R(\xi, x) \equiv R(\xi, K, \mu) \equiv N(\bar{\omega}(K, \mu, \xi))$$

using the model restrictions. The residual function is calculated from the restriction that the euler equation (24) is satisfied. Hence given a functional form $\bar{\omega}(K,\mu,\xi)$ and the equilibrium equation we need to create a functional representation of the Euler equation. In order to do so we proceed as follows

1. For a given pair (K,μ) we get $\bar{\omega} = \bar{\omega}(K,\mu,\xi)$
2. Given $\bar{\omega}$ and μ we can solve the contracting problem to get surplus shares f, g and the price of capital q. In order to calculate f and g we need to calculate the expected amount of default, that depends on the realized variance σ^2_ω. In order to calculate the expectation we use 10 points quadratures.
3. Given K we can solve for entrepreneurs wage, w^e, and net worth, n, using the production function
4. Given n, g and q we can solve for investment i by the optimality condition of the contract.
5. Using the budget constraint of the entrepreneur, that depends from q, n, f and g, we can get entrepreneur consumption c^e
6. Last by market clearing we get lenders consumption c
7. Given the equilibrium investment i we compute (K',μ'). It is important to notice that K' and μ' both depends on the true variance of entrepreneurs projects, σ^2_ω, thus we use two 10 points quadratures, one centered at M_L and one centered at M_H, in order to calculate the expectations of the lender on the pairs (K',μ').[26]
8. For each of the 20 quadratures pairs (K',μ') using steps 1-6 we calculate c', q' and r'.
9. Last we calculate the Euler equation errors using the quadrature points to take the expectation with respect to the current belief μ. For a generic x the expectation is approximated as follows
$$E(x') = \mu \sum_{i=1}^{10} x'_{i,L} s_i + (1-\mu) \sum_{i=1}^{10} x'_{i,H} s_i$$
where s_i are the quadrature weights, and $x'_{i,j}$ are the values of x' calculated for the point i of quadrature centered at M_j, with $j \in \{L,H\}$.

Step 4 The fourth step requires to choose a projection function v_i and a weighting function s to solve for the unknown vector of coefficients ξ. ξ solves $V_i = 0$, $i = 0,1,..,p$, where V_i is defined as
$$V_i \equiv \int_X s(x)R(\xi,x)v_i(x)dx$$

[26]Note that for each K' there exist a unique μ' that is obtained using the observed signal (K') and the Bayesian updating from equations (13) and (14).

We chose to use collocation method that exploits the Dirac delta function as the weighting function

$$s(x) = \begin{cases} 0 & if\, x \neq x_i \\ 1 & if\, x = x_i \end{cases}$$

and assigns $v_i = 1\, \forall i$. We last need to pick 15 collocation pairs $x_i = (K_i, \mu_i)$: we chose them to be equal to the Tensor product of the zeros of the $3rd$ and $5th$ order Chebychev polynomia. In order to solve for ξ we use a Newton-Raphson algorithm.

Step 5 The last step consist in verifying the quality of the approximation. We choose as a target that the Euler equation unit free errors, as reported in Judd and Guu (1997), are smaller than $1e-5$.

A.9 Regressions with Controls

Table 22: Asymmetry and Financial Development - With Controls

Dependent Variable	Skewness Lending Rates 1960 - 2008	Skewness Lending Rates 1985 - 2008	Skewness Investment 1960 - 2008	Skewness Output 1960 - 2008
Credit to Private Sector / GDP	-0.022	-0.020	0.007	0.003
	(0.012)*	(0.008)***	(0.004)*	(0.003)
GDP per capita	-0.153	-0.381	0.113	0.276
	(0.537)	(0.336)	(0.180)	(0.145)*
GDP Volatility	-1.000	-2.926	-1.058	-1.115
	(1.614)	(2.778)	(0.940)	(0.703)
Average Inflation	-0.600	-0.351	0.008	-0.001
	(0.247)**	(0.232)	(0.100)	(0.077)
Constant	3.960	3.533	-0.575	-0.246
	(0.807)***	(0.764)***	(0.222)**	(0.179)
Observations	94	94	46	52

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. For each country I compute the sample average of yearly credit to private sector as a percentage of GDP and quarterly GDP per capita, GDP coefficient of variation and inflation from the IMF's IFS database.

Table 23: Asymmetry of Lending Rates and Bankruptcy Costs - With Controls

Dependent Variable	Skewness of Lending Rates					
	1960 - 2008			1985 - 2008		
Cost of Bankruptcy	0.036			0.034		
	(0.015)**			(0.015)**		
Time for Bankruptcy		0.188			0.042	
		(0.136)			(0.135)	
Recovery Rate			-0.017			-0.006
			(0.013)			(0.011)
GDP per capita	-0.247	-0.332	-0.065	-0.676	-0.878	-0.764
	(0.401)	(0.424)	(0.539)	(0.298)**	(0.314)***	(0.349)**
GDP Volatility	-0.493	-0.699	-0.369	-3.688	-3.996	-3.777
	(1.937)	(1.838)	(1.964)	(2.972)	(3.008)	(2.946)
Average Inflation	-0.267	-0.277	-0.340	-0.126	-0.149	-0.170
	(0.232)	(0.238)	(0.226)	(0.221)	(0.221)	(0.220)
Constant	1.835	1.999	2.956	1.940	2.589	2.842
	(0.974)*	(1.039)*	(0.750)***	(0.875)**	(0.969)***	(0.774)***
Observations	82	82	82	82	82	82

Table 24: Asymmetry of Real Activity and Bankruptcy Costs - With Controls

Dependent Variable	Skewness of Investment			Skewness of Output		
Cost of Bankruptcy	-0.011			0.005		
	(0.012)			(0.013)		
Time for Bankruptcy		-0.058			-0.072	
		(0.068)			(0.057)	
Recovery Rate			-0.006			0.004
			(0.005)			(0.004)
GDP per capita	0.374	0.328	0.407	0.413	0.305	0.314
	(0. 154)**	(0.166)*	(0.163)**	(0.133)***	(0.144)**	(0.146)**
GDP Volatility	-0.800	-0.904	-0.819	-1.031	-1.141	-1.164
	(0.832)	(0.825)	(0.843)	(0.702)	(0.685)*	(0.705)*
Average Inflation	0.082	0.066	0.069	0.006	-0.003	0.030
	(0.110)	(0.113)	(0.115)	(0.701)	(0.067)	(0.075)
Constant	-0.359	-0.288	-0.490	-0.318	0.036	-0.348
	(0.299)	(0.342)	(0.309)	(0.289)	(0.275)	(0.197)*
Observations	43	43	43	49	49	49

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. All independent variables are from Djankov et al. (2005, 2008) and the IMF's IFS database.

Table 25: Asymmetry of Lending Rates and Monitoring Costs - With Controls

Dependent Variable	Skewness of Lending Rates							
	1960 - 2008				1985 - 2008			
Legal protection for financial assets	-0.44				-0.90			
	(0.36)				(0.39)**			
Sophistication of financial markets		-0.58				-0.86		
		(0.29)**				(0.28)***		
Availability of Internet banking			-0.65				-0.52	
			(0.31)**				(0.29)*	
Health of banking systems				-0.33				-0.57
				(0.1)*				(0.21)***
GDP per capita	0.12	0.42	0.29	0.03	0.41	0.56	0.05	0.14
	(0.35)	(0.33)	(0.34)	(0.33)	(0.29)	(0.29)*	(0.24)	(0.32)
GDP Volatility	-0.27	-0.04	-0.31	-0.93	2.37	1.26	0.86	1.20
	(1.81)	(1.64)	(1.85)	(1.66)	(3.26)	(3.16)	(3.62)	(3.08)
Average Inflation	0.07	0.17	0.11	0.08	0.43	0.57	0.47	0.49
	(0.28)	(0.30)	(0.32)	(0.30)	(0.26)*	(0.28)*	(0.28)*	(0.26)*
Constant	3.61	3.47	4.03	3.28	4.48	3.46	2.66	3.11
	(1.88)**	(1.38)**	(1.63)***	(1.16)***	(1.99)**	(0.34)**	(1.55)*	(1.24)**
Observations	56	56	56	56	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 are from Porter et al. (1999) and the IMF's IFS database.

Table 26: Asymmetry of Real Activity and Monitoring Costs - With Controls

Dependent Variable	Skewness of Investment				Skewness of Output			
Legal protection for financial assets	0.24				0.15			
	(0.24)				(0.20)			
Sophistication of financial markets		0.15				0.10		
		(0.13)*				(0.10)		
Availability of Internet banking			0.13				0.13	
			(0.12)				(0.09)	
Health of banking systems				0.10				0.08
				(0.09)				(0.09)
GDP per capita	0.12	0.17	0.25	0.24	0.24	0.25	0.27	0.29
	(0.21)	(0.19)	(0.16)	(0.15)	(0.17)	(0.13)*	(0.13)**	(0.11)**
GDP Volatility	-1.95	-1.79	-1.63	-1.57	-1.71	-1.67	-1.63	-1.52
	(1.09)*	(0.95)*	(0.83)*	(0.88)*	(0.93)*	(0.87)*	(0.80)**	(0.80)*
Average Inflation	0.04	0.02	0.05	0.04	-0.02	-0.04	-0.03	-0.03
	(0.12)	(0.12)	(0.11)	(0.12)	(0.07)	(0.08)	(0.08)	(0.08)
Constant	-1.26	-0.72	-0.77	-0.70	-0.71	-0.39	-0.53	-0.40
	(0.96)	(0.41)*	(0.58)	(0.41)*	(0.84)	(0.34)	(0.38)	(0.39)
Observations	40	40	40	40	45	45	45	45

Notes: * Significant at 10%, ** significant at 5%, and *** significant at 1%. Robust standard errors are reported in parentheses. All independent variables are from Porter et al. (1999) and the IMF's IFS database.