Essays in Macroeconomics and Finance

Author: Marco Macchiavelli

Boston College Electronic Thesis or Dissertation, 2015

Boston College

The Graduate School of Arts and Sciences

Department of Economics

ESSAYS IN MACROECONOMICS AND FINANCE

a dissertation

by

MARCO MACCHIAVELLI

submitted in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

May 2015

Essays in Macroeconomics and Finance

Marco Macchiavelli

Advised by Professor Susanto Basu

Abstract

The goal of this dissertation is to shed some light on three separate aspects of the financial system that can lead to greater instability in the banking sector and greater macroeconomic volatility. The starting point of the Great Recession was the collapse of the banking sector in late 2007; in the subsequent months, liquidity evaporated in many markets for short term funding. The process of creating liquidity carried out by the banking system involves the transformation of long term illiquid assets into short term liquid liabilities. This engine functions properly as long as cash lenders continue to roll over short term funding to banks; whenever these lenders fear that banks will not be able to pay back these obligations, they immediately stop funding banks' short term liabilities. This makes banks unable to repay maturing short term debt, which leads to large spikes in default risk. This is often referred to as a modern bank run. Virtually all the theories of bank runs suggest that the severity of a run depends on how well lenders can coordinate their beliefs: whenever a lender expects many others to run, he becomes more likely to run as well.

In a joint work with Emanuele Brancati, the first chapter of my dissertation, we empirically document the role of coordination in explaining bank runs and default risk. We establish two new results. First, when information is more precise and agents can better coordinate their actions, a change in market expectations has a larger impact on default risk; this implies that more precise information increases the vulnerability or instability of the banking system. This result has a clear policy implication: if policymakers want to stabilize the banking system they should promote opacity instead of transparency, especially during periods of financial turmoil. Second, we show that when a bank is expected to perform poorly, lower dispersion of beliefs actually increases default risk; this result is in contrast with standard theories in finance and can be rationalized by thinking about the impact that more precise information has on the ability of creditors to coordinate on a bank run.

Another aspect of the banking system that is creating a lot of instability in Europe is the so called "disastrous banks-sovereign nexus": many banks in troubled countries owned a disproportionately large amount of domestic sovereign bonds; therefore, in case of a default of the sovereign country, the whole domestic banking sector would incur insurmountable losses. This behavior is puzzling because these banks in troubled countries would greatly benefit from having a more diversified asset portfolio, but instead decide to load up with domestic sovereign debt only. In a joint work with Filippo De Marco, the second chapter of my dissertation, we show that banks receive political pressures from their respective governments to load up on domestic sovereigns. First, we show that banks with a larger fraction of politicians as shareholders display greater home bias. More importantly, we exploit the fact that low-performing banks received liquidity injections by their domestic governments to show that, among those banks, only the "political banks" drastically increased their home bias upon receiving government help. Furthermore, it appears that the extent of political pressure on banks is much stronger on those "political banks" belonging to troubled countries. These findings suggest that troubled countries that would need to pay a high premium to issue new debt force their "political banks" to purchase part of the debt issuance. This greater risk-synchronization can create a dangerous loop of higher sovereign default risk leading to insolvency of the domestic banking system, which in turn would require a bail-out from the local government, further exacerbating the sovereign default risk.

Finally, the third chapter of my dissertation, a joint work with Susanto Basu, investigates the sources of excess consumption volatility in emerging markets. It is a well documented fact that, in emerging markets, consumption is more volatile than output whereas the opposite is true in developed economies. We propose an explanation for this phenomenon that relies on a specific form of financial markets incompleteness: we assume that households would always want to front-load consumption and they can borrow from abroad up to a fraction of the value of posted collateral. With the value of collateral being procyclical, households are able to increase borrowing during an expansion and ultimately consume more than they produce; this mechanism is then able to generate a ratio of consumption volatility to output volatility grater than one. Most importantly, the model delivers the implication that a better ability to borrow vis-a-vis the same value of collateral generates greater relative consumption volatility. We then bring this model's implication to the data and find empirical support for it. We proxy the ability to borrow with various measures of effectiveness of lending regulation and more standard indicators of financial development. Consistent with the model's implication, more lending friendly regulation leads to greater relative consumption volatility in emerging markets; moreover, this link breaks down among developed countries. In addition, among emerging countries, it appears that deeper domestic capital markets have a destabilizing effect in terms of greater relative consumption volatility while a more developed domestic banking system does not exerts any such detrimental effect.

To Carolyn and Luca

Acknowledgments

This work would not be possible without the inspiration and guidance of many Professors at Boston College. I am indebted to Susanto Basu and Fabio Ghironi for making me curious about studying and doing research in Economics. I am also grateful to Ryan Chahrour, Eyal Dvir and Fabio Schiantarelli for constant guidance and to Emanuele Brancati and Filippo De Marco for being great research partners. I would also like to thank my colleagues in the Department of Economics for useful discussions and comments. I am grateful for financial and fellowship support from the Department of Economics and the Graduate School of Arts and Sciences at Boston College and from the Becker-Friedman Institute and the Macroeconomic Modeling and Systemic Risk Research Initiative.

A special thanks goes to my wife Carolyn, my son Luca and my parents Simonetta and Vincenzo for sharing happiness, love and balance.

Contents

List of Tables

List of Figures

1. The Role of Dispersed Information in Pricing Default: Evidence from the Great Recession

1.1. Introduction

During financial turmoil, coordination motives among creditors are often thought to be crucial in determining whether a financial institution will be granted access to credit or default on its maturing debt. Which outcome will prevail is often regarded as being unpredictable; for this reason many have thought about banks' defaults as being triggered by sunspots. Diamond and Dybvig (1983) formalize this idea of *sunspots-driven* financial crises in a model of bank runs.[1] The limitation of this approach is that, by relying on multiple equilibria, it does not explain what triggers a crisis, making the theory virtually untestable; this fact,

[1]Prominent advocates of this view of bank runs as random events are Friedman and Schwartz (1963) and Kindleberger (1978). For models of banking panics with multiple equilibria, see also Chen (1999) and Peck and Shell (2003) even though the focus of the former is on the possibility of contagious bank runs.

together with the availability of new evidence that banking panics are not random events, leads theorists to focus on the predictability of bank runs.[2] Morris and Shin (2001) provide a theory that explicitly models coordination among market participants; the usefulness of this theory rests on its ability to predict how the probability of a crisis depends on market expectations and dispersion of beliefs.

We extend Morris and Shin (2004)' s model so that it directly maps into the empirical data and then test the implications of this theory. We find evidence that more concentrated beliefs act as a coordination device that, under certain conditions, reduces creditors' willingness to roll over debt to a bank, thus increasing both its probability of default and its vulnerability to changes in market expectations. We use Credit Default Swap (CDS) spreads as a proxy for banks' default risk and a survey of professional forecasters to measure both market expectations and dispersion of beliefs. Our empirical analysis delivers two main results.

First, when forecasts about a bank's future profitability are unfavorable, lower dispersion of beliefs greatly increases the bank's default risk: a one standard deviation *decrease* in dispersion of beliefs leads to an *increase* in the CDS spread that ranges from 104 to 201 basis points, which is between 43% and 83% of a standard deviations of CDS spread in times of crisis (Sep 2007 - Dec 2012). This result is consistent with incomplete information

[2] See Gorton (1988) and Calomiris and Gorton (1991) for early evidence against the sunspot view of bank runs; see Calomiris and Mason (2003) for more recent evidence on runs during the Great Depression and Covitz, Liang and Suarez (2013) for what concerns the predictability of runs on short term debt in the 2007 crisis. See Postlewaite and Vives (1987), Chari and Jagannathan (1988) and Jacklin and Bhattacharya (1988) for early papers of bank runs featuring equilibrium uniqueness; for more recent studies, see Morris and Shin (2004), Rochet and Vives (2004), Goldstein and Pauzner (2005) and He and Xiong (2012).

models that incorporate coordination motives, such as Morris and Shin (2004) and Rochet and Vives (2004), while it is in contrast with a wide range of incomplete information models that neglect coordination risk and focus solely on the Jensen inequality effect, whereby less dispersion decreases credit spreads. Moreover, prior to the crisis (Jan 2005 - Aug 2007) the direct effect of dispersion of beliefs on default risk is not statistically significant in most specifications and it becomes slightly positive and significant at the 10% level only when we consider favorable forecasts.[3] This suggests that when a bank is expected to perform well, debt is largely informationally insensitive and greater dispersion slightly increases default risk, i.e. the Jensen inequality effect prevails; however, when a bank is expected to perform poorly, debt becomes much more sensitive to information, coordination motives among creditors become very important and less dispersion increases default risk. The evidence that the information sensitivity of debt largely depends on how poorly a bank is expected to perform is consistent with Dang, Gorton and Holmström (2012); they theorize that bad news can make debt informationally sensitive, potentially leading to endogenous adverse selection and credit freezes.[4]

Second, precise information has an indirect effect on default risk as well; this operates through amplifying the impact of market expectations on the CDS spread. Compared to the amplification due to high leverage or greater reliance on unstable sources of funding, the largest multiplier is obtained by more precise information. In particular, the marginal

[3]However, the reliability of pre-crisis estimates is undermined by weak instruments problems.

[4]Similarly, Gorton and Ordoñez (2012) show that during periods of financial tranquillity debt is informationally insensitive, but when a crisis occurs agents have incentives to produce information on counterparty risk.

effect of forecasts on default risk is 2.5 times larger when information is precise rather than imprecise, an "unconditional" multiplier of 2.5; moreover, if we consider only fragile banks the "conditional" multiplier due to precise information ranges from 3.5 to 5.5.[5] This last set of findings suggests that more concentrated information greatly increases banks' vulnerability to changes in market expectations. Additional research is needed to better understand the determinants of dispersed information at both theoretical and empirical levels. Moreover, as the degree of information precision is the primary factor affecting banks' vulnerability, our results suggest that the stability of the banking system can be improved in possibly two ways: first, by monitoring the evolution of bank-specific measures of dispersion of beliefs and targeting liquidity support especially to banks about which forecasters hold more homogeneous beliefs; second, in times of crisis, *ex-ante* stability of the banking system can be improved by reducing the degree of information precision. The last point resembles what the first U.S. clearinghouses used to do during financial turmoil, as described in Gorton (1985). Moreover, this empirical finding that precise information increases the vulnerability of banks is not only consistent with our model but also with a subset of the literature that studies the effect of transparency on bank runs: in Siritto (2013) an increase in transparency leads to greater banks' vulnerability to runs and, in a model of bank runs and adverse selection, de Faria e Castro, Martinez and Philippon (2014) show that more precise information greatly benefits good banks while exposing worse banks to

[5] On the other hand, unconditional multipliers due to the different measures of fragility range from 1.3 to 2.8, but are not statistically different from 1; in addition, conditional on information being precise, the different measures of fragility carry conditional multipliers ranging from 2 to 2.5.

a higher chance of runs. In addition, the evidence provided in this paper is also consistent with Holmström (2014)'s view of opacity, liquidity and panics.[6]

Overall, our results are generally consistent with our extension of Morris and Shin (2004), as shown in Section 1.5.4 which evaluates the likelihood of the calibrated model to qualitatively reproduce our findings. We can interpret our results in light of their theory with a simple example. First of all, in games with strategic complementarities, such as those involving rollover risk or bank runs,[7] each agent would like to mimic what other people do because everyone benefits from coordinated actions. If information is relatively precise agents receiving a bad signal believe that many others observe similar bad signals too (see Figure 1.1). In such a situation, each individual believes that many agents are likely to stop funding the bank, which makes him more likely to do the same. Therefore, when forecasts are unfavorable, more precise information acts as a coordination device that amplifies the size of a credit freeze.[8]

Importantly, from the point of view of identifying the causal effect of expectations and dispersed beliefs on default risk, we introduce a novel set of instruments to tackle possible endogeneity issues whereby shocks to default risk affect both current expectations and dispersion of beliefs. For instance, an unexpected increase in the default risk of a bank could induce the manager to undertake risky projects in an attempt to "gamble for resurrection";

[6] Dang et al. (2014) offer a similar rationale for why banks should be opaque.

[7] Brunnermeier (2009) argues that bank runs and rollover risk are incarnations of the same risk, which he calls *funding liquidity risk*; financial institutions face this risk when assets can be readily sold only at a large discount and there is a maturity mismatch between short term or demandable funds and long term assets, so that a lack of confidence can lead to the default of the entity.

[8] Note that, when the situation is reversed and agents expect a bank to perform well, more precise information can dampen the size of the attack (see Figure 1.2).

if forecasters internalize this possibility they will then revise upward both expected returns on the bank's assets and expected variance of returns. This would generate an upward bias in the OLS estimates of the effects of both dispersion and market expectations on default risk, which is indeed what we find; the difference between the IV and the OLS estimates is also consistent with attenuation bias due to i.i.d. measurement error in both regressors. Our instrumenting strategy goes beyond standard approaches in the Dynamic Panel Data literature and exploits both internal and external instruments: the former are lagged endogenous variables while the latter are lagged forecast errors. In a context where market participants learn about the law of motion of banks' fundamentals, previous forecast errors are used to update parameters of the perceived law of motion (see Appendix A.2); indeed, from first stage regressions we observe that past underestimations of banks' profitability lead to an upward adjustment of current forecasts. Finally, the exclusion restriction requires that today's CDS spreads are affected by today's market expectations and that past expectations affect CDS spreads only indirectly throughout the learning process. This is a reasonable assumption to make, especially nowadays where market participants continuously process new information to update their trading decisions.

The remainder of the paper is organized as follows. Section 1.2 briefly reviews the related literature, Section 1.3 presents our extension of Morris and Shin (2004)' s model and derives some new testable implications. Section 1.4 presents the data and discusses the empirical strategy while Section 1.5 shows the empirical results and assesses the performance of the model. Finally, Section 1.6 concludes.

1.2. Related Literature

Our paper is mainly related to the Global Games literature that studies the impact of incomplete information on financial crises. After Morris and Shin (2001)'s original contribution, a lot of theoretical work has been done to understand if equilibrium uniqueness is robust to alternative features of the model.[9] However, before us, only Prati and Sbracia (2010) tried to bring these models to the data by studying the role of dispersed information on speculative pressures against currencies in the 1997-98 Asian crises.

Our work is also related to the finance literature studying the effect of noisy information and disagreement on excess returns and credit spreads. Duffie and Lando (2001), Albagli, Hellwig and Tsyvinski (2014) and Buraschi, Trojani and Vedolin (2013) focus on the term structure of credit spreads under noisy information. Even though the models are different, they all predict that greater noise or disagreement increases credit spreads and default risk,[10] which is in contrast with what we find in the data. Importantly, they do not consider coordination motives among creditors, which instead is the focus of Morris and Shin (2004). Empirically, Güntay and Hackbarth (2010) focus on non-financial firms in US from 1987 to 1998 and document a positive association between credit spreads and firm-specific measures of disagreement in earnings forecasts. Differently from our paper, they do not account for either any direct effect of expectations, or the endogeneity of forecast measures.

[9] Just to cite a few, Angeletos and Werning (2004) show that if public signals are endogenously provided by financial markets precise private signals do not deliver uniqueness anymore; Angeletos, Hellwig and Pavan (2006) show that signals conveyed by policy interventions lead to multiplicity; Angeletos, Hellwig and Pavan (2007) consider the effect of learning in a dynamic version of the standard model.

[10] This is mainly due to a Jensen inequality effect: a mean preserving spread in the distribution of posterior beliefs decreases bond prices and hence increases credit spreads due to the concavity of bond's payoffs.

Our paper is also linked to the literature studying the effect of fundamentals on default risk and bank runs. Gorton (1988) examines the determinants of deposits withdrawals and dismisses the sunspot view of panics. More recently, Calomiris and Mason (2003) show that bank's characteristics and regional level data explain a lot of default risk during the Great Depression while panic indicators are largely insignificant. Closer to our work, Gorton and Metrick (2012) study the anatomy of the 2007-2008 runs on repos and Covitz, Liang and Suarez (2013) study the determinants of runs on Asset-Backed Commercial Paper (ABCP) programs in 2007; both repos and ABCP are major sources of very short term funding for financial institutions.

1.3. Model and Testable Implications

This section presents our extension of Morris and Shin (2004)'s model which is required to bring the model to the data. Specifically, in the original paper the probability of a bank defaulting is either zero or one once the signals are privately observed; this does not allow to map the model to CDS spreads which measure the perceived probability of default in a continuous fashion. In order to accommodate for this possibility we introduce a "late realization" shock (τ) to perturb the default decision. We should think about bank's fundamentals as the sum of a predictable component, θ, and an unpredictable component, τ. A large number of individually small risk-neutral creditors finances a project through a collateralized debt contract. To capture the essence of rollover risk, it is assumed that in stage one creditors decide whether to seize the loan and get the collateral, valued at $\lambda < 1$, or to roll-over the debt and go to stage two. In the second stage, they get the face value of the debt contract, normalized to one, if the bank does not default or zero if the bank defaults. The bank defaults if its fundamentals $(\theta + \tau)$ are not large enough to cope with the liquidity shortage (zl) induced by those creditors not rolling over short term debt; l is the share of creditors not rolling over debt, which is endogenously determined, while the parameter z measures the degree of disruption caused by the lack of coordination in rolling over debt. We can think of z as being a function of the entity's leverage. More precisely, we assume that at stage two the bank defaults if $\theta + \tau \leq zl$ and succeeds otherwise. The payoffs to a creditor are given by the following matrix:

	Success $zl < \theta + \tau$	Failure $zl \geq \theta + \tau$
Roll over	1	0
Foreclose	λ	λ

Complete Information. In the perfect information case, namely when θ is common knowledge, and with $\tau = 0$ the game is simple: if $\theta > z$ it is optimal to roll over the loan, since default will not occur even when everybody else forecloses the loan; if, on the other hand, $\theta < 0$ it is always optimal to foreclose the loan as the bank will default even when everyone else tries to keep the bank afloat. Finally, when θ belongs to the interval $(0, z)$, creditors face a coordination problem which leads to multiple equilibria: if each creditor expects everyone else to roll over debt it is individually optimal to keep funding the bank; however, if each creditor expects everyone else to foreclose the loan, then the optimal strategy is to foreclose the loan as well, thus liquidating a bank that would have been otherwise solvent. This is analogous to the bank run scenario outlined in Diamond and Dybvig (1983).

Incomplete Information. As Morris and Shin (2004) show, multiplicity disappears once we depart from the assumption of common knowledge of the fundamental state θ; suppose now that θ is normally distributed with mean y and variance $1/\alpha$ (precision α). At the beginning of stage 1, each creditor receives a private noisy signal x_j of the predictable component of fundamentals: $x_j = \theta + \varepsilon_j$, where ε_j is normally distributed with mean 0 and variance $1/\beta$ (precision β). Once observing the private signal, a creditor believes that the posterior distribution of θ has mean $\xi_j = \frac{\alpha y + \beta x_j}{\alpha + \beta}$ and precision $\alpha + \beta$. In addition, the "late realization" shock τ is known to be independent from both y and θ and normally distributed with mean zero and precision γ and it is realized in stage two, after each creditor decides whether or not to roll over debt.

Equilibrium. The equilibrium is a couple (x^*, ψ) such that a creditor forecloses the loan if $x_j < x^*$, where x^* is the cutoff signal, and rolls over the loan if $x_j \geq x^*$; in addition, the bank decides to default in stage two if $\theta + \tau \leq \psi$ and survives otherwise, where $\psi = zl^*$ is the equilibrium liquidity shortage and l^* is the equilibrium share of foreclosers. Morris and Shin (2004) prove that the equilibrium strategy is a switching strategy indeed. Given the cutoff signal x^*, the share of creditors foreclosing the loan is then given by the mass of signals below x^*, namely

$$l = \Phi(\sqrt{\beta}(x^* - \theta)) \tag{1.1}$$

where Φ is the cdf of the standard normal distribution. The decision of whether or not to roll over debt is taken at stage one, before τ is realized; thus the equilibrium liquidity shortage ψ does not depend on τ. There exists a critical level of θ which in expectation makes the bank indifferent between defaulting or not, given the information available at stage one. The critical level of θ is such that

$$0 = \mathbb{E}[\theta + \tau - z\Phi(\sqrt{\beta}(x^* - \theta)) \mid \theta] = \theta - z\Phi(\sqrt{\beta}(x^* - \theta)) \tag{1.2}$$

This critical level of θ is the fixed point ψ, which is then implicitly defined by

$$\psi = z\Phi(\sqrt{\beta}(x^* - \psi)) \tag{1.3}$$

Equation 1.3 specifies the equilibrium liquidity shortage ψ as a function of the cutoff signal x^*. Note that the right-hand-side of equation 1.3 is continuous and monotonically decreasing in ψ and takes values in the open interval $(0, z)$. Thus, there exists a unique ψ that solves equation 1.3 for a given x^*.

Moreover, a creditor who receives the cutoff signal x^* will be, by definition, indifferent between foreclosing and rolling over debt; the payoff from foreclosing is λ while that from rolling over is $Pr(\theta + \tau > \psi \mid x_j = x^*)$. Conditional on receiving the signal x^*, $\theta + \tau$

is normally distributed with mean ξ^* and variance $\frac{1}{\alpha+\beta} + \frac{1}{\gamma} = \frac{\alpha+\beta+\gamma}{\gamma(\alpha+\beta)}$. Therefore, this indifference condition leads to

$$\lambda = Pr(\theta + \tau > \psi \mid x_j = x^*) = 1 - \Phi\left(\frac{\sqrt{\gamma(\alpha+\beta)}}{\sqrt{\alpha+\beta+\gamma}}(\psi - \xi^*)\right) \tag{1.4}$$

where $\xi^* \equiv \frac{\alpha y + \beta x^*}{\alpha+\beta}$ is the posterior expectation of θ formed by the agent who received x^* as private signal. Thus, the definition of ξ^*, together with equation 1.4, leads to

$$x^* = \frac{\alpha+\beta}{\beta}\left(\psi + \Phi^{-1}(\lambda)\frac{\sqrt{\alpha+\beta+\gamma}}{\sqrt{\gamma(\alpha+\beta)}}\right) - \frac{\alpha}{\beta}y \tag{1.5}$$

Finally, from equations 1.3 and 1.5 we have that

$$\psi = z\Phi\left(\frac{\alpha}{\sqrt{\beta}}(\psi - y) + \frac{\sqrt{\alpha+\beta}\sqrt{\alpha+\beta+\gamma}}{\sqrt{\beta\gamma}}\Phi^{-1}(\lambda)\right) \tag{1.6}$$

which implicitly defines ψ as a function of the model's parameters. Following Morris and Shin (2004), equation 1.6 has a unique fixed point if its right-hand side has a slope of less than one everywhere. This requires $z\phi(\alpha/\sqrt{\beta}) < 1$, where ϕ is the pdf of the standard normal evaluated at the appropriate point. The previous condition is the same condition that guarantees a unique solution in Morris and Shin (2004). Thus, their uniqueness Theorem[11] applies to our model as well. A sufficient condition for uniqueness is $\frac{\alpha}{\sqrt{\beta}} < \frac{\sqrt{2\pi}}{z}$ (Assumption 1); this condition requires private signals to be precise enough relative to the

[11]See Theorem 1 in Morris and Shin (2004).

underlying uncertainty. We assume that this condition is satisfied.

Without the introduction of the "late realization" shock τ we would go back to Morris and Shin (2004)'s model and have the following implication: the probability of default conditional on private signals is either one if $\theta \leq \psi$ or zero if $\theta > \psi$. In order to have a continuum of possible default probabilities, we introduced the shock τ; now we have that the probability of default conditional on observing the median signal is

$$Pr(\theta + \tau < \psi \mid \xi) = \Phi\left(\frac{\sqrt{\gamma(\alpha+\beta)}}{\sqrt{\alpha+\beta+\gamma}}(\psi - \xi)\right) \tag{1.7}$$

which we proxy by the CDS spread as described in Section 1.4.

We define $P(def) \equiv Pr(\theta + \tau < \psi \mid \xi)$. ξ is the median[12] posterior expectation of θ, or alternatively the median forecast which is observable. Moreover, we also observe the standard deviation of individual forecasts, δ. Since the individual forecast of a creditor observing x_j is $\xi_j = \frac{\alpha y + \beta x_j}{\alpha+\beta}$, we obtain that the variance of individual forecasts is

$$\delta^2 = \int (\xi_j - \xi)^2 \, dj = \frac{\beta^2}{(\alpha+\beta)^2} \int (x_j - \theta)^2 \, dj = \frac{\beta}{(\alpha+\beta)^2} \tag{1.8}$$

Notice that an increase in the precision of public signals decreases dispersion of beliefs: $\frac{\partial \delta^2}{\partial \alpha} = -\frac{2\beta}{(\alpha+\beta)^3} < 0$; in addition, under the assumption that $\beta > \alpha$, we have that more precise private information decreases dispersion of beliefs as well. Indeed, $\frac{\partial \delta^2}{\partial \alpha} = \frac{(\alpha-\beta)}{(\alpha+\beta)^3}$ which is negative if and only if $\beta > \alpha$. Therefore, under the working assumption, both

[12] Since a property of normal distributions is that the mean value is also the median value, ξ is both the mean and the median expectation.

more precise public and private signals decrease dispersion of beliefs. See Appendix A.3 for a discussion on the impossibility to back out α and β from the data.

1.3.1. Comparative Statics

We are interested in understanding how the probability of default is affected by changes in both median beliefs, ξ, and dispersion of beliefs, $\delta = \frac{\sqrt{\beta}}{\alpha+\beta}$. First of all, we study the effect of ξ, β, α and z on $P(def)$. By differentiating equation 1.7 we have that

$$\begin{aligned} \frac{dP(def)}{d\xi} &= -\eta\phi_1 \\ \frac{dP(def)}{d\beta} &= \eta\phi_1\left(\frac{\gamma(\psi-\xi)}{2(\alpha+\beta)(\alpha+\beta+\gamma)} + \frac{\partial\psi}{\partial\beta}\right) \\ \frac{dP(def)}{d\alpha} &= \eta\phi_1\left(\frac{\gamma(\psi-\xi)}{2(\alpha+\beta)(\alpha+\beta+\gamma)} + \frac{\partial\psi}{\partial\alpha}\right) \\ \frac{dP(def)}{dz} &= \eta\phi_1\frac{\partial\psi}{\partial z} \end{aligned} \tag{1.9}$$

where $\eta \equiv \frac{\sqrt{\gamma(\alpha+\beta)}}{\sqrt{\alpha+\beta+\gamma}}$ and ϕ_1 is the pdf of the standard normal evaluated at $\eta(\psi-\xi)$. The partial derivatives of ψ with respect to β, α and z are found by applying the Implicit Function Theorem to equation 1.6:

$$\begin{aligned} \frac{\partial\psi}{\partial\beta} &= -\frac{z\phi_2\left[\psi-y+\left(\frac{\beta^2-\alpha^2-\alpha\gamma}{\sqrt{\gamma(\alpha+\beta)(\alpha+\beta+\gamma)}}\right)\Phi^{-1}(\lambda)\right]}{2\sqrt[3]{\beta}\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)} \\ \frac{\partial\psi}{\partial\alpha} &= \frac{z\phi_2\left[\psi-y+\frac{2\alpha+2\beta+\gamma}{2\sqrt{\gamma(\alpha+\beta)(\alpha+\beta+\gamma)}}\Phi^{-1}(\lambda)\right]}{\sqrt{\beta}\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)} \\ \frac{\partial\psi}{\partial z} &= \frac{\psi}{z\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)} \end{aligned} \tag{1.10}$$

where ϕ_2 is the pdf of the standard normal evaluated at $\frac{\alpha}{\sqrt{\beta}}(\psi-y) + \frac{\sqrt{\alpha+\beta}\sqrt{\alpha+\beta+\gamma}}{\sqrt{\beta\gamma}}\Phi^{-1}(\lambda)$.

Next, we want to investigate how the effect of forecasts on default risk is affected by both private and public signals' precision and bank's characteristics. To this regard, we differentiate $\frac{dP(def)}{d\xi}$ with respect to β, α and z respectively:

$$\begin{aligned}
\frac{d^2P(def)}{d\xi d\beta} &= \eta\phi_1\left[\eta^2\left(\frac{\gamma(\psi-\xi)^2}{2(\alpha+\beta)(\alpha+\beta+\gamma)}+(\psi-\xi)\frac{\partial\psi}{\partial\beta}\right)-\frac{\gamma}{2(\alpha+\beta)(\alpha+\beta+\gamma)}\right]\\
\frac{d^2P(def)}{d\xi d\alpha} &= \eta\phi_1\left[\eta^2\left(\frac{\gamma(\psi-\xi)^2}{2(\alpha+\beta)(\alpha+\beta+\gamma)}+(\psi-\xi)\frac{\partial\psi}{\partial\alpha}\right)-\frac{\gamma}{2(\alpha+\beta)(\alpha+\beta+\gamma)}\right]\\
\frac{d^2P(def)}{d\xi dz} &= \eta^3\phi_1\frac{\psi(\psi-\xi)}{z\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)}
\end{aligned} \tag{1.11}$$

Proposition 1 *More precise signals, either private or public, increase default risk when expectations are not favorable and reduce it when forecasts are good enough.*

$$\begin{aligned}
\frac{dP(def)}{d\beta} &> 0 \qquad \text{iff } \xi<\xi_\beta\\
\frac{dP(def)}{d\alpha} &> 0 \qquad \text{iff } \xi<\xi_\alpha
\end{aligned} \tag{1.12}$$

All the proofs and thresholds' definitions can be found in Appendix A.1.

Proposition 2 *More favorable forecasts reduce default risk. Moreover, the impact of expectations on default risk is amplified by more precise signals, whether private or public, for intermediate forecasts while it is dampened for either bad or great ones. More precisely,*

$$\begin{aligned}
\frac{dP(def)}{d\xi} &< 0\\
\frac{d^2P(def)}{d\xi d\beta} &< 0 \qquad \text{iff } \xi\in[\xi_{L\beta}\ ,\ \xi_{H\beta}]\\
\frac{d^2P(def)}{d\xi d\alpha} &< 0 \qquad \text{iff } \xi\in[\xi_{L\alpha}\ ,\ \xi_{H\alpha}]
\end{aligned} \tag{1.13}$$

Proposition 3 *Worse bank's characteristics increase default risk. Moreover, the impact of expectations on default risk is amplified by worse bank's characteristics for good enough forecasts only. More precisely,*

$$\begin{aligned} \frac{dP(def)}{dz} &> 0 \\ \frac{d^2P(def)}{d\xi dz} &< 0 \qquad \textit{iff } \xi > \psi \end{aligned} \tag{1.14}$$

1.4. Data and Empirical Strategy

1.4.1. Data

The dataset used for the estimations combines banks' CDS spreads (Markit), analysts' earning forecast (Institutional Brokers' Estimate System – IBES database), and balance-sheet data (Bankscope Bureau van Dijk).

We use the CDS spreads as a measure of banks' default risk.[13] CDS spreads actually embed both perceived probability of default and expected recovery rate. We factor out the latter by controlling for net charge-offs, the share of non-performing loans over gross loans, and the share of liquid assets over total assets, on top of bank and time fixed effects (capturing persistent heterogeneities and homogeneous shocks in times of crisis).[14]

Analysts' median forecasts on banks' future performances are adopted to measure the me-

[13]We average across the 5-year daily CDS spreads on senior debt to obtain monthly series. The choice of the maturity is entirely driven by data availability, and by the higher liquidity of this market. Moreover, in order to be consistent with the timing of the surveys (see footnote 16), administered within the first half of the month, we construct monthly CDS data disregarding the second half of the month.

[14]Upon default, the recovery rate will be larger the more liquid assets the bank has and the smaller the ratio of non-performing loans over total loans.

dian market expectation of banks' fundamentals; for the sake of matching observables to their theoretical counterparts, both mean and median expectations are appropriate counterparts of ξ and we choose the latter to minimize the impact of outliers. Additionally, we use the standard deviation of forecasters' expectations (for each bank and each period) because it is the empirical counterpart of the standard deviation of posterior beliefs, δ. The last two pieces of data are obtained from IBES, which is a widely used survey of professional forecasters.[15] As a proxy for expected bank's fundamentals we use one-year-ahead forecasts on returns on assets (ROA).[16] Finally, we control for bank-specific characteristics with a rich set of balance-sheet ratios from Bankscope. Our final dataset covers about 190 banks worldwide from 2005 to 2012 at monthly frequency (see Table 1.25 for a detailed list of the banks in the sample).

Table 1.1 shows some correlations before and during the crisis; in the top and bottom panels we use variables in levels while the middle panel displays correlations of first differenced variables. While during the crisis CDS spreads are negatively associated with both realized and expected returns on assets, it appears from the top panel that dispersion of beliefs is positively associated with CDS spreads; however, by looking at the middle panel we see that reductions in dispersion of beliefs are associated with increases in the CDS

[15] IBES is a widely used dataset in Finance; for instance, it has been used in Ajinkya and Gift (1985), Bartov and Bodnar (1994) and more recently in Diether, Malloy and Scherbina (2002) and Balduzzi and Lan (2012).

[16] IBES surveys several professional forecasters within the first 15 days of every month asking for their forecasts at different horizons on several key indicators, ROA, ROE and EPS included. The dataset contains forecast horizons of one, two and three years ahead and long run forecasts; we end up using one-year-ahead forecasts on ROA to limit the drop of observations and to ensure the highest explanatory power.

spread. Therefore, from this first look at the data we do not get a clear idea of the relationship between default risk and dispersed information in times of crisis. The bottom panel shows that the various measures of fragility we use later on are positively correlated: higher leverage is associated with more unstable sources of funding, namely lower customer deposits over total funding and lower net interbank positions.

Table 1.2 summarizes means and standard deviations of the main variables in the two subperiods, namely pre-crisis (January 2005 to August 2007) and crisis (September 2007 to December 2012) and shows significant changes in the aftermath of the crisis, with both level and volatility of banks' CDS spreads that are about eight times larger than in normal times, as portrayed in Figure 1.3. At first, explaining this eight-fold increase in CDS spreads through dispersion of beliefs seems hard to accomplish. While from Figure 3.2 we can see that expectations on future profitability follow the market perception of risk, Figure 3.3 does not display any clear cyclicality in the evolution of dispersed beliefs. However, we will show that the interplay between expectations and dispersion of beliefs can explain quite a lot of variation in banks' CDS spreads. Notice also that the regression analysis uses bank level data while Figures 1.3 to 3.3 use bank-level data aggregated across regions, namely USA, PIIGS and Asia; this aggregation, while necessary for visualization purposes, hides interesting variation.

1.4.2. Empirical Strategy

The evolution of banks' CDS spreads in our baseline specification is modeled as follows:

$$
\begin{aligned}
CDS_{i,t} = \quad & \rho CDS_{i,t-1} + \gamma_1[\mathbb{E}_t(\mathrm{ROA}_{i,t+1})(Precise_{i,t})] + \gamma_2[\mathbb{E}_t(\mathrm{ROA}_{i,t+1})(1 - Precise_{i,t})] \\
& + \gamma_3 \delta_{\mathbb{E}_{i,t}} + \beta^\top x_{i,t-1} + \eta_i + \lambda_t + \varepsilon_{i,t}
\end{aligned}
\tag{1.15}
$$

where $CDS_{i,t}$ is the monthly average of daily Credit Default Swap spreads of bank i at time t. $\mathbb{E}_t(\mathrm{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $Precise_{i,t}$ is an indicator function identifying precise information. At each point in time, the information received by market participants is defined as "precise" if the standard deviation of the forecasts on bank i is below the median (or the first tercile) of its time-specific cross-sectional distribution.[17] $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed at time t on the ROA of bank i in $t+1$.

Finally, $x_{i,t-1}$ is a rich vector of controls for banks' fundamentals, η_i are bank-specific (CDS-specific) fixed effects controlling for unobserved heterogeneity that is constant over time, and λ_t are time fixed effects capturing common shocks and cyclical factors.

Our crisis regressions displayed in Tables 1.3 to 1.6 use data from September 2007 to December 2012; we use September 2007 as the starting period of the financial crisis.[18] When

[17] The threshold value of the indicator for precise information is computed on a monthly basis instead of over the full time period in order to have enough flexibility to recognize precision also in times of generalized and increased uncertainty. Results are practically identical if the threshold that identifies precise information is the median (or 33^{rd} percentile) of either the full 2005-2012 sample or the crisis period only.

[18] From Figure 4 in Gorton and Metrick (2012) it appears that the haircut rate on repos jumps up for the first time in September 2007; large haircuts can be thought of as debt runs. Gorton and Metrick (2012) also show that the first signals of danger in the interbank market (LIBOR-OIS spread) arrive in August 2007. A very similar chronology of events is described in Brunnermeier (2009). Also, looking at the ABCP market, see Panel A in Covitz, Liang and Suarez (2013), we notice a large collapse in the outstanding value of ABCP around August-September 2007.

we compare pre-crisis and crisis estimates as in Tables 1.7 and 1.8, we just allow all coefficients to have a structural break in September 2007.

If more precise information amplifies the reaction of CDS spreads to expected future profitability we expect $|\gamma_1| > |\gamma_2|$; since the effect of expected profitability on default risk is negative, this translates into $\gamma_1 < \gamma_2$. In addition, if more precise information has a negative impact on default risk we expect $\gamma_3 < 0$.

There are two main issues we have to address in order to identify the role of market expectations and dispersed information on default risk: simultaneity and omitted variables biases.

Reverse Causality. Since we are interested in the causal effect of current expectations on banks' CDS spreads, we have to deal with problems of reverse causality: shocks to CDS spreads could be observed by forecasters and thus internalized in their current expectations. For instance, an unexpectedly large increase in the default probability of a bank could push the institution to undertake very risky projects so as to get a chance to stay in business in case the risk pays off.[19] In this circumstance, the variance of future returns on assets is now larger, and the associated risk premium could push the expected future ROA up as well. Therefore, we could obtain an upward bias in the OLS estimate of the effect of expectations on default risk, as it turns out to be the case (see Table 1.3). Moreover, if the additional risk undertaken by the bank is internalized by forecasters the variance of posterior beliefs would rise as well; thus, we also need to treat the dispersion of beliefs as an endogenous

[19] This is the "gamble for resurrection" story of Cheng and Milbradt (2011).

regressor. Notice that not doing so would, according to this example, bias the OLS estimate of the effect of dispersion on default risk upwards, as it turns out to be the case (see Table 1.3). The OLS biases are also consistent with the presence of i.i.d. measurement error in forecast measures that yields attenuation bias. We can interpret i.i.d. measurement error as random deviations of sample moments from the population moments of forecast measures due to having a finite number of forecasters.

Instrumenting the lagged dependent variable ($CDS_{i,t-1}$) with lags of its first difference, while necessary in a small-T panel setting, is not needed here because we have a quite large time dimension (T=64).[20]

Potentially endogenous variables are current expectations on banks' future ROA and the dispersion of forecasts. Our instrumenting set includes both internal and external instruments; the use of internal instruments, i.e. lagged values of endogenous covariates is a standard approach in the Dynamic Panel Data literature.[21] In addition, we introduce a novel set of instruments, whose validity stems from the theory of learning.

We believe that each market participant is uncertain about the data generating process of banks' fundamentals and thus engages in a learning process. Under bayesian learning, we show (see Appendix A.2) that agents use previous forecast errors to correct and update their estimates. Therefore, past forecast errors are in theory correlated with current expectations; finally, the exclusion restriction requires that past forecast errors do not directly influence

[20] The so called Nickell bias, Nickell (1981), induced by the demeaning process through bank fixed effects tends to vanish as the time dimension increases. Indeed, whether or not we instrument the lagged dependent variable, the coefficients of interest are essentially unchanged.

[21] See for instance, Arellano and Bover, 1995; Blundell and Bond, 1998.

today's default risk. Since the forecast error is the difference between the realized measure and its expectation formed one period in advance, we need to assume that the median market participant engages in a process of learning and updates her beliefs at least once a month, which is very reasonable in the current financial context.

Regarding the instrumentation of dispersion of beliefs, we show in Appendix A.2.1 that, whenever the variance of fundamental innovations is unknown and priors are diffuse, the expected value of this variance depends on its previous period expectation; since dispersion of beliefs is a combination of the expected variance of both fundamental innovations and private signals, this result proves that lags of dispersed beliefs are in theory correlated with current values. This in turns rationalizes the choice of lags of $\delta_{\mathbb{E}_{i,t}}$ in the instrumenting set. Moreover, in a world in which agents choose the precision of the signals they acquire, we could imagine that past expectations and past forecast errors about the profitability of a bank may impact the agents' choice of signals' accuracy. This would then motivate the use of past expectations and forecast errors as instruments for current dispersion of beliefs.

We then test for the correlation of excluded instruments with the error term (Hansen J-test of overidentifying restrictions), and we assess the power of our instruments (under-identification test and F test of the excluded instruments in the first stage regressions). Finally, the implement a test proposed in Godfrey (1994) to access whether or not the error term is serially correlated; this is of particular relevance for our identification because the use of lagged endogenous covariates as instruments is valid only in the presence of serially uncorrelated residuals.[22] In all the regressions we reject the null of serial correlation of the error term. Therefore, under the assumption that the instruments are correctly excluded from the second stage regression our instrumenting strategy is internally consistent.

Omitted Variables. Regarding the set of controls, we cover a large spectrum of financial ratios. x_i is a vector of covariates accounting for realized profitability (return on average assets, ROAA), leverage (total assets to common equity ratio), composition of funding (deposits to total funding ratio), capitalization (tier1 capital ratio), liquidity (liquid to total assets ratio), losses (net charge-offs to gross loans ratio), and impaired loans (non-performing loans to gross loans ratio). In some specifications we also control for other measures of capitalization, composition of funding, cost of funding, composition of loans, roll-over risk, returns of equity, liquidity and bank size.[23] All covariates are lagged once to avoid simultaneity bias.

Notice that controlling for both leverage, namely total assets over equity, and Tier1 ratio, namely equity over risk weighted assets, implicitly controls for the amount of risk undertaken by the bank. Moreover, controlling for the previous realization of banks' CDS spreads virtually eliminates residual problems of omitted variables.

Finally, the econometric estimation is performed via two-stage GMM models with bank

[22] Godfrey proposes the test for time series data and we adapt it to a panel data setting by assuming that the autoregressive coefficient of the error term is common across banks.

[23] More specifically, we introduce the following set of additional controls: total-capital ratio, deposits from banks to total funding ratio, interest expenses to total funding ratio, short-term funding to total funding ratio, short-term funding to long-term funding ratio, return on average equity (ROAE), cash from banks to total funding ratio, deposits from customers to total funding ratio, loans to banks to total assets ratio, total loans to total deposits ratio, liquid assets to total assets ratio, liquid assets to short-term funding ratio (quick ratio), log of total assets, income to total assets ratio.

and time fixed effects and White, heteroskedasticity-consistent, standard errors.

1.5. Results

1.5.1. Amplification: the indirect effect of dispersed beliefs

Table 1.3 shows the heterogeneous effect of market expectations on banks' CDS spreads in times of crisis. In every specification, expected profitability significantly affects the perceived default probability of a financial institution, and its impact is greatly amplified when beliefs are less dispersed. In other words, more concentrated beliefs increase the vulnerability of a bank to changes in market expectations. These findings are consistent with $\frac{dP(def)}{d\xi} < 0$ and $\frac{d^2P(def)}{d\xi d\beta} < 0$ or $\frac{d^2P(def)}{d\xi d\alpha} < 0$ from Proposition 2. Details about each regression are reported in the notes underneath the table. Regardless of the specific threshold used to identify precise information, the results are consistent: during the crisis, more agreement among forecasters amplifies the effect of expected profitability on the default risk of a financial institution. Everything else equal, a one percent increase in expected ROA reduces the CDS spread by 11 basis points if beliefs are dispersed and by 26 basis points in case they are more concentrated; the two coefficients are statistically and economically significant, and different from each other (with a p-value for the test $\gamma_1 = \gamma_2$ equal to 0.001 in column 2). Thus, precise information carries an unconditional multiplier of around 2.5. We call it unconditional to differentiate it from the conditional multiplier which relates to the degree of amplification attained once we restrict to a certain subset of banks, such as highly leveraged ones.

Next, we study whether certain bank's characteristics amplify the reaction of default risk to market expectations. To this regard, banks' leverage, the share of customer deposits to total funding, and the net interbank position may expose financial institutions to significantly different degrees of fragility in times of crisis.[24] While the first two measures of fragility are well known in the literature, the net interbank position is, to our knowledge, never been used before. We define the latter as loans to banks minus deposits from banks divided by total assets. A negative value indicates that the bank is a net borrower of funds from other banks. Prior to us, Calomiris and Mason (2003) showed that interbank deposits were a powerful predictor of bank's future distress during the Great Depression. Instead of using interbank deposits which measures the total amount of funds borrowed from other banks, we consider the net flow of funds vis a vis other banks. To us, this is a better measure of liquidity risk because it captures the reliance on interbank liquidity in net terms: a bank with some interbank deposits and an equally large amount of loans to other banks can, in case of market illiquidity, withdraw its funds from other banks to cope with its liquidity shortage; therefore, it is important to track its net position more than just the amount of deposits from other banks.

Table 1.4 explores whether fragile banks are more sensitive to market expectations than sound ones. Details about each regression are reported in the notes underneath the table. As expected, a general pattern emerges whereby fragile institutions are more sensitive to

[24]By fragility and vulnerability we mean larger sensitivity to shocks.

market expectations than sound banks in times of crisis. This is especially true in column 1 where market expectations on future profitability have a large impact on highly leveraged institutions and no sizable effect on more capitalized banks.[25] Finally, it is worth emphasizing that the degree of amplification originated by greater fragility is lower than that coming from more precise information, which is shown in Table 1.3. In other words, the largest unconditional multiplier is achieved by more precise information, not by higher leverage or by more unstable sources of funding. All together, the fact that fragility increases the sensitivity of CDS spreads to expectations is consistent with $\frac{d^2P(def)}{d\xi dz} < 0$ in Proposition 3.

Next, Table 1.5 blends in the two sources of amplification highlighted so far by simultaneously accounting for different degrees of fragility and dispersion of beliefs. It is evident that market expectations affect CDS spreads the most when the bank is fragile and forecasts are less dispersed. This finding is robust to the different definitions of fragility we consider, whether it is high leverage, low deposits over total funding or low net interbank positions. Across all dimensions of fragility, the sensitivity of default risk to market expectations is 3.5 to 5.5 times larger when information about fragile banks is precise rather than imprecise; on the other hand, conditional on information being precise, the effect of market expectations on CDS spreads for fragile banks about twice as big as the one for sound institutions. In other words, the conditional multiplier of precise information ranges from 3.5 to 5.5 whereas the conditional multipliers of various fragility measures lie between 2 and 2.5. The two sets of multipliers are both economically and statistically significant as the tests at the bottom

[25] This is in a way reminiscent of Calomiris and Gorton (1991)'s finding that bad news together with high leverage are necessary for banking panics.

of Table 1.5 show.[26] Moreover, these findings are robust to different specifications of the time fixed effects and different thresholds for fragility and information precision, as shown in the robustness checks (see Section 1.5.6).

Once again, less dispersion of beliefs plays a key role in amplifying the effect of market expectations on default risk. In addition, the findings that more precise information carries the largest multipliers suggest that the degree of information precision should be closely monitored by Central Banks and its determinants better understood at both theoretical and empirical levels.

1.5.2. The direct effect of dispersed beliefs

We still have to assess whether dispersion of beliefs has a strong first order effect on CDS spreads in addition to the amplifying role documented so far. This is what we accomplish in this section: Table 1.6 shows that, during the crisis, less dispersion of beliefs (lower $\delta_{\mathbb{E}_{i,t}}$) drastically increases CDS spreads especially when forecasts are unfavorable; this is consistent with Proposition 1 regardless of whether changes in dispersion come from variation in the precision of public or private signals. Indeed, Proposition 1 states that lower dispersion of beliefs, either coming from a higher α or β, increases default risk if and only if the median forecast is low enough.

[26] The coefficients for precise information and fragile banks are statistically different from both those entailing imprecise information about fragile banks, and those concerning precise information about sound institutions. We also tried alternative definition of fragility based upon capitalization (tier-1 capital ratio), liquidity (liquid assets to total assets ratio), losses (net-charge-offs to total assets ratio), composition of funding (deposits from banks to total funding), and rollover risk (short-term funding to long-term funding ratio). Results are mostly coherent even though the degrees of amplification induced by fragility are less pronounced than those presented in the paper.

Column 1 considers forecasts to be bad if expected future profitability belongs to the lowest quartile while in column 2 they are regarded as bad if expected future ROAA is in the bottom 10% of its time-specific empirical distribution.

The second column of Table 1.6 shows that, when expectations about future profitability are bad, more precise information (less dispersion in beliefs) greatly increases default risk: a one standard deviation decrease in dispersion of beliefs leads to an increase of the CDS spread by 201 basis points, which is 84% of a standard deviation of CDS spreads during the crisis period. The negative impact of precise information on default risk is robust to the inclusion of a richer set of time-region or time-country fixed effects,[27] as shown in Section 1.5.6.

Once again, we can interpret the negative effect of dispersion as evidence that precise information acts as a coordination device that aligns creditors' actions towards not rolling over debt to the bank under consideration, thus increasing its probability of default.

Finally, it is important to stress that the negative impact of more concentrated beliefs on default risk is consistent with incomplete information models that focus on coordination motives among creditors, such as Morris and Shin (2004), while in contrast with models that only capture the Jensen inequality effect of dispersed information; this last effect refers to how a mean preserving spread in posterior beliefs increases the probability of default and, due to the concavity of bond's payoffs, produces larger credit spreads.

[27] The effect of dispersion of beliefs when forecasts are unfavorable is even larger when we use quarter-region fixed effects while smaller when country-month fixed effects are introduced.

1.5.3. Before and During the Crisis

Next, we discuss similarities and differences in the effect of dispersed information before and during the financial crisis. Tables 1.7 shows that the amplifying role of more precise information is also at work in the pre-crisis period; indeed, the hypothesis that the effect of expectations is the same whether or not information is precise is rejected at the 5% level. However, it appears that the marginal effect of forecasts on default risk is smaller in magnitude in the pre-crisis period than during the crisis. Table 1.8 shows that in the pre-crisis period the amplification due to fragility is larger than that due to precise information, whereas we have shown the opposite to be true during the crisis. Notice also that, prior to the crisis, the direct effect of dispersion is never significant, even at the 10% level.

Next, Table 1.9 investigates whether this last result could mask some heterogeneity in the direct effect of dispersion on default risk; we therefore allow for this effect to depend on whether median forecasts are favorable or not. The last column shows that, when the bank is expected to perform poorly, the direct effect of dispersion is negative as it is the case during the crisis; however, the effect is much smaller than the one estimated during the crisis. Most importantly, when forecasts are favorable enough, the direct effect turns out to be positive contrarily to what is the case during the crisis. This suggests that when a bank is expected to perform well, debt is largely informationally insensitive and greater dispersion slightly increases default risk, i.e. the Jensen inequality effect prevails; however, when a bank is expected to enter into a danger zone, debt becomes much more sensitive to information, coordination motives among creditors become very important and less dispersion increases default risk.[28]

It is important to notice however that the pre-crisis regressions in Table 1.9 suffer from weak instruments, thus undermining the overall reliability of these pre-crisis estimates.

1.5.4. Assessment of the model's performance

In this section we assess the likelihood that our extension of Morris and Shin (2004)'s model would deliver results that are consistent with our empirical findings. Specifically, we compute the probability that $\frac{dP(def)}{d\beta} > 0$, $\frac{dP(def)}{d\alpha} > 0$, $\frac{d^2P(def)}{d\xi d\beta} < 0$, $\frac{d^2P(def)}{d\xi d\alpha} < 0$ and $\frac{d^2P(def)}{d\xi dz} < 0$ for different calibrations of the model. We set the priors on the fundamental state to be normally distributed with mean $y = 0.8$ and precision $\alpha = 10$ and we set the precision of private signals to be large enough so as to satisfy Assumption 1 for all the calibrations; specifically $\beta = \kappa\frac{(\alpha\bar{z})^2}{2\pi}$ with $\kappa = 1.2$ and $\bar{z}$ being the largest value of z in the simulations. Moreover, the precision of the late realization shock is set to $\gamma = 2\alpha$. Next, we allow z and λ to take different values so as to encompass many scenarios: $z \in \{0.5, 0.7, 0.9, 0.95\}$ and $\lambda \in \{0.5, 0.7, 0.9, 0.95\}$. While we can interpret λ as the recovery rate upon default, z has no direct counterpart, but it can be transformed to yield a measure of leverage. Indeed, leverage, being the ratio of total assets to equity, is equal to $1/(1-z)$, so that the sequence of z implies the following sequence of leverage: $2, 3.\bar{3}, 10, 20$. For each of the sixteen combinations we numerically find the corresponding value of ψ and then obtain from Propositions 1, 2, 3 the intervals in which the derivatives of interest have the signs

[28] The positive effect of dispersion on default risk is in line with what Güntay and Hackbarth (2010) find and indeed they look at a time period, 1987-1998, which was not characterized by major financial unrest.

reported above. Then, for each calibration we compute the probability that the posterior mean (ξ) falls within the wanted intervals, as reported in Tables 1.11 to 1.15. Finally, Table 1.16 reports the conditional probability of default generated by each calibration to have a sense of the scenario that each calibration entails. It appears that high probabilities of default are generated when both leverage and recovery rates are high.

The Direct Effect. Table 1.11 shows that the model is capable of generating the negative impact of concentrated beliefs on default risk when the recovery rate is larger than 0.5. Indeed, if this is the case, the probability that market forecasts fall within the interval that generates $\frac{dP(def)}{d\beta} > 0$ is 99% in all cases but one. Interestingly, the cases in which more precision increases default risk are those in which the conditional probability of default is non-negligible, which seems to be the case in the data as well.

The Indirect Effect. Table 1.13 shows that the range of values of ξ that deliver the amplifying role of dispersed information is so large that the conditions for amplification are very likely across various calibrations: the probability that $\frac{d^2P(def)}{d\xi d\beta} < 0$ is very high for all cases but those involving a low recovery rate ($\lambda = 0.5$). Also note from Table 1.15 that fragility has the amplifying effect that we find in the data.

The Anomaly of the Recovery Rate. The only noticeable anomaly generated by the model is that high probabilities of default are due to very high recovery rates upon default which is in contrast with common sense; indeed, we believe that failures tend to happen exactly when recovery rates are low. However, it is also clear why the model yields such a result: from the payoff matrix we can see that an increase in λ makes the foreclose action more profitable, thus increasing the share of creditors not rolling over debt (l increases) which leads to a higher probability of default. This is also corroborated by the fact that $\frac{dP(def)}{d\lambda} = \frac{z\eta\phi_1\phi_2\sqrt{(\alpha+\beta)(\alpha+\beta+\gamma)}}{\phi(\Phi^{-1}(\lambda))(1-z\phi_2\alpha/\sqrt{\beta})\sqrt{\beta\gamma}} > 0$.

This could be potentially amended by making the payoff from foreclosing the loan a negative function of the share of creditors attacking the bank, l; indeed, Eisenbach (2013) allows for the liquidation value to be endogenously determined in a global game model of rollover risk and obtains that banks' defaults are more likely in the bad state in which the assets' liquidation value is lower.

1.5.5. Learning from forecast errors

In what follows we assess the power of our novel instruments by documenting the impact of past forecast errors on current expectations. Forecast errors are defined as the difference between the current (realized) value of ROA and last period expectation of it: $\text{FE}_t \equiv \text{ROA}_t$ - $\mathbb{E}_{t-1}(\text{ROA}_t)$. The theory of learning establishes a tight link between current expectations and past forecast errors as we show in Appendix A.2: as agents learn about the structural parameters governing the evolution of banks' fundamentals, past forecast errors help agents to adjust their expectations. However, there is very little theoretical work to guide us in understanding how dispersion of beliefs evolves over time. Appendix A.2.1 shows that, if we allow agents to learn about the variance of fundamental innovations and priors are diffuse, past expectations of the variance affect the current expectation. This is the simplest framework that allows for dispersion of beliefs to have some dynamics, but the story could be more involved once agents can costly choose the precision of private information. Hellwig and Veldkamp (2009), Myatt and Wallace (2012) and Chahrour (2012) study the endogenous choice of information acquisition in static Global Games; however, to the best of our knowledge there is no work on the interplay of signal acquisition and learning in a dynamic context. We can still reasonably expect agents to react to past mistakes by adjusting the precision with which they currently acquire information. We then allow for both past forecast errors and past squared forecast errors to affect the choice of information acquisition in the current period.

Table 1.10 shows a baseline specification which is similar to the first stage regression of the models estimated in Table 1.3; in the actual first stage regressions we do not include lagged squared forecast errors, we usually have more lags of excluded instruments and the dependent variable itself is not just the current forecast but its interaction with the precision indicator or the fragility indicator. The results show a significant autoregressive component for both expectations and dispersion of beliefs, together with a strong effect of past forecast errors. Notice that positive errors correspond by definition to past underestimations of current profitability. If a bank turns out to be more profitable than expected, current expectations tend to be adjusted upward. On the other hand, past underestimations predict less dispersion of beliefs in the subsequent period or, more intuitively, agents tend to agree more once they have been positively surprised. Finally, notice that lagged squared forecast errors do not significantly affect current dispersion of beliefs during the crisis.

1.5.6. Robustness Checks

In this section we reproduce the main results of the paper by allowing for more heterogeneity in time fixed effects (Tables 1.17 to 1.23) and by changing the thresholds that identify fragile banks (Table 1.23) and precise information (Table 1.24). The purpose of adopting different thresholds for fragility and precision of information is to show that, consistently across all specifications, the conditional multiplier of precise information is larger than each of the conditional multipliers due to the various measures of bank's fragility.

Alternative specification for time fixed effects. While the main regressions so far adopt time fixed effects that are common to all banks worldwide, Tables 1.17 to 1.19 allow for the time fixed effect to vary depending on the geographical region in which each bank is headquartered. To this purpose we identify four main regions: North America, Eurozone, Asia and the rest of the world.[29] Due to problems in inverting the variance-covariance matrix with month-region or month-country fixed effects, we decide to use quarter-region fixed effects.

Lastly, in order to control for country-month fixed effects without incurring in the non-invertibility of the variance-covariance matrix, we demean each variable in use by subtracting its time and country-specific mean from it; practically, instead of using $X_{i,j,t}$ which

[29] North America includes Canada and USA. The Eurozone includes the EU countries that have adopted the common currency: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.

denotes variable X for bank i in country j at time t, we use $x_{i,t} = X_{i,j,t} - \bar{X}_{j,t}$, where $\bar{X}_{j,t} = \sum_{i \in j} X_{i,j,t}$. Results obtained with country-month demeaned variables are shown in Tables 1.20 to 1.23.

Alternative threshold for fragility. In Table 1.23 we identify a bank as fragile if it belongs to the top 25% of the time specific distribution of leverage or to the bottom 25% of the time specific distribution of both the customer deposits to total funding ratio and the net interbank position.

Alternative threshold for precision. In Table 1.24 we identify information about a bank to be precise if the dispersion of forecasts about that bank's future profitability is below the 25^{th} percentile of the time specific distribution.

1.6. Conclusion

In the aftermath of the recent crisis, both level and volatility of banks' CDS spreads experienced an eightfold increase. This work shows that market expectations and dispersion of beliefs play a crucial role in explaining banks' default risk. Specifically, the reaction of CDS spreads to market expectations is amplified when beliefs are less dispersed; importantly, the multiplier of precise information turns out to be larger than any multiplier carried by various measures of bank's fragility, suggesting that the primary factor that enhances vulnerability among financial institutions is the degree of information precision.

In addition, dispersion of beliefs has a large direct effect on default risk as well. When forecasts are unfavorable, a one-standard-deviation drop in the dispersion of beliefs leads to an increase in the CDS spread that ranges from 104 to 201 basis points, which is between 43% and 83% of a standard deviations of CDS spreads during the crisis. However, this effect is at large not statistically significant before the unfolding of the crisis and, in a few cases, mildly positive and significant only at the 10% level; this suggests that debt is largely informationally insensitive in normal times but it becomes sensitive to information once creditors fear about a financial collapse; in this scenario, coordination motives among creditors become very important and less dispersion greatly increases default risk.

The finding that more precise information increases default risk is in line with dispersed information models that focus on coordination motives among creditors, such as Morris and Shin (2004), Rochet and Vives (2004) and Goldstein and Pauzner (2005), while in contrast with other models that rely solely on the Jensen inequality effect of dispersion. Overall, our empirical results suggest that, under certain conditions, precise information act as a coordination device that reduces creditors' willingness to roll over debt to a financial institution, hence increasing both its default risk and its vulnerability to changes in market expectations. Future research should aim at better understanding the determinants of dispersion of beliefs at both theoretical and empirical levels. Moreover, our results suggest that the stability of the banking system can be improved in possibly two ways. First, by monitoring the evolution of bank-specific measures of dispersion of beliefs, central banks can target liquidity support especially to banks about which forecasters hold more homogeneous beliefs. Second, in times of crisis, stability of the banking system can be improved by reducing the degree of information precision, similarly to what the first U.S. clearinghouses used to do during panics, as described in Gorton (1985).

Table 1.1.: Correlations

	Precrisis ($t < 2007Q4$)				Crisis ($t \geq 2007Q4$)			
	CDS_t	$\delta_{\mathbb{E}_t}$	$\mathbb{E}_t(\text{ROA})$	ROA_t	CDS_t	$\delta_{\mathbb{E}_t}$	$\mathbb{E}_t(\text{ROA})$	ROA_t
CDS_t	1				1			
$\delta_{\mathbb{E}_t}$	0.06***	1			0.21***	1		
$\mathbb{E}_t(\text{ROA})$	0.06***	0.48***	1		-0.17***	0.16***	1	
ROA_t	-0.13***	0.35***	0.36***	1	-0.33***	-0.05***	0.26***	1
	ΔCDS_t	$\Delta\delta_{\mathbb{E}_t}$	$\Delta\mathbb{E}_t(\text{ROA})$	$\Delta\ \text{ROA}_t$	ΔCDS_t	$\Delta\delta_{\mathbb{E}_t}$	$\Delta\mathbb{E}_t(\text{ROA})$	ΔROA_t
ΔCDS_t	1				1			
$\Delta\delta_{\mathbb{E}_t}$	-0.00	1			-0.12***	1		
$\Delta\mathbb{E}_t(\text{ROA})$	-0.00	-0.14***	1		-0.08***	-0.03***	1	
ΔROA_t	0.06***	-0.02	0.05***	1	-0.05***	0.00	0.01	1
	$\delta_{\mathbb{E}_t}$	Lev_t	$(\text{CD/TF})_t$	IntB_t	$\delta_{\mathbb{E}_t}$	Lev_t	$(\text{CD/TF})_t$	IntB_t
$\delta_{\mathbb{E}_t}$	1				1			
Lev_t	-0.11***	1			-0.02*	1		
$(\text{CD/TF})_t$	-0.03	-0.35***	1		-0.03***	-0.09***	1	
IntB_t	0.02	-0.07***	0.48***	1	-0.10***	-0.01	0.41***	1

Notes: correlations for the banks in the sample. CDS is average of daily CDS spreads across the month. $\mathbb{E}_t(\text{ROA})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. ROA is the realized return on average assets of bank i at time t. Lev is leverage (total assets to common equity), CD/TF is customer deposits over total funding ratio and IntB is the net interbank position (loans to bank − deposits from banks). The Δ symbol in front of each variable is the first difference operator. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.2.: Summary Statistics

	Precrisis ($t < 2007Q4$)			Crisis ($t \geq 2007Q4$)		
Variable	**Mean**	**Std. Dev.**	**# obs.**	**Mean**	**Std. Dev.**	**# obs.**
CDS_t	48.891	28.855	8682	381.613	240.394	10702
$\delta_{\mathbb{E}_t}$	0.269	0.938	6383	0.279	1.000	8954
$\mathbb{E}_t(\text{ROA}_{t+1})$	1.473	0.944	9441	1.011	0.887	10797
ROA_t	1.346	0.666	6152	0.285	2.434	17143
Lev_t	23.26	27.82	5881	20.43	66.04	13187
$(\text{CD/TF})_t$	0.604	0.242	4933	0.604	0.243	11469
IntB_t	-0.016	0.104	4356	-0.024	0.111	10026

Notes: summary statistics for the banks in the sample. CDS is average of daily CDS spreads across the month. $\mathbb{E}_t(\text{ROA}_{t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. ROA is the realized return on average assets of bank i at time t. Lev is leverage (total assets to common equity), CD/TF is customer deposits over total funding ratio and IntB is the net interbank position (loans to bank − deposits from banks).

Table 1.3.: The effect of expectations and precision

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Precise if $\delta < p(50)$		Precise if $\delta < p(33)$	
	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-9.498**	-26.37***	-11.49**	-25.09***
	[4.772]	[7.515]	[5.336]	[8.516]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-7.492**	-11.53*	-7.455**	-10.33*
	[3.497]	[5.894]	[3.496]	[5.737]
$\delta_{\mathbb{E}_{i,t}}$	-1.282	-11.66**	-1.304	-10.71*
	[2.085]	[5.874]	[2.081]	[5.668]
$\text{CDS}_{i,t-1}$	0.938***	0.929***	0.938***	0.933***
	[0.031]	[0.029]	[0.031]	[0.030]
Bank + Time FE	yes	yes	yes	yes
IV	no	yes	no	yes
# obs.	3343	3052	3343	3052
R^2	0.881	0.880	0.881	0.880
p-val of Hansen stat		0.832		0.502
p-val of Underid. test		0.000		0.000
Kleibergen-Paap F stat		24.76		35.48
p-val of Godfrey test		0.278		0.241
	Tests (p-values)			
$\mathbb{1}(\text{Pre}_t) = \mathbb{1}(\text{Impr}_t)$	0.518	0.001	0.328	0.010

Notes: within estimator (columns 1 and 3) and two-step GMM estimator (columns 2, and 4) with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median (in columns 1 and 2), or the 25^{th} percentile (in columns 3 and 4), of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. Instrumented regressors in columns 2 and 4: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments in columns 2 and 4: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.4.: The effect of expectations and fragility

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Fragility		
	Leverage (1)	Customer dep. (2)	Interbank (3)
$\mathbb{1}(\text{Fragile}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-17.62***	-13.91**	-13.75**
	[6.742]	[6.417]	[5.721]
$\mathbb{1}(\text{Sound}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-6.065	-10.09*	-8.284
	[6.085]	[5.190]	[6.095]
$\delta_{\mathbb{E}_{i,t}}$	-12.25**	-7.517	-9.546*
	[5.261]	[5.213]	[5.383]
$\text{CDS}_{i,t-1}$	0.939***	0.942***	0.943***
	[0.029]	[0.029]	[0.029]
# obs	3017	3017	3017
R^2	0.880	0.879	0.880
p-val of Hansen stat	0.646	0.532	0.612
p-val of Underid. test	0.000	0.000	0.000
Kleibergen-Paap F statistic	20.77	46.53	88.67
p-val of Godfrey test	0.282	0.344	0.342
	Tests (p-values)		
$\mathbb{1}(\text{Sound}_t) = \mathbb{1}(\text{Fragile}_t)$	0.077	0.266	0.190

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Fragile}_t)$ is an indicator function identifying fragile banks. $\mathbb{1}(\text{Fragile}_t)$ takes unitary value if banks' measure of structural solidity is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Sound}_t)$ identifies sound banks and is defined as $\mathbb{1}(\text{Sound}_t) = 1 - \mathbb{1}(\text{Fragile}_t)$. Fragility measures vary across columns: leverage (total assets to common equity) in column 1, customer deposits to total funding ratio in column 2, and net exposure towards other banks (loans to banks – deposits from banks) to total assets ratio in column 3. Instrumented regressors: $\mathbb{1}(\text{Fragile}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Sound}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Fragile}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Sound}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$ and the lag of the variable used in the definition of fragility. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.5.: The effect of expectations, precision and fragility

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Fragility		
	Leverage	Customer dep.	Interbank
	(1)	(2)	(3)
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-36.63***	-36.86***	-30.88***
	[10.02]	[10.88]	[10.48]
$\mathbb{1}(\text{Fragile}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-10.47	-6.750	-7.813
	[7.781]	[7.620]	[6.826]
$\mathbb{1}(\text{Sound}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-15.75**	-14.26*	-14.10*
	[6.961]	[7.972]	[8.188]
$\mathbb{1}(\text{Sound}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-8.396	-5.084	-4.000
	[6.516]	[6.116]	[6.950]
$\delta_{\mathbb{E}_{i,t}}$	-12.47**	-10.77*	-11.41*
	[6.252]	[6.065]	[6.058]
$\text{CDS}_{i,t-1}$	0.937***	0.933***	0.931***
	[0.028]	[0.030]	[0.030]
Bank + Time FE	yes	yes	yes
IV	yes	yes	yes
# obs.	3017	3052	3052
R^2	0.880	0.880	0.881
p-val of Hansen stat	0.520	0.736	0.740
p-val of Underid. test	0.000	0.000	0.000
Kleibergen-Paap F stat	12.36	20.53	24.32
p-val of Godfrey test	0.365	0.357	0.352
	Tests (p-values)		
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Fragile}_t, \text{Impr}_t)$	0.013	0.001	0.006
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Sound}_t, \text{Pre}_t)$	0.012	0.015	0.052

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Fragile}_t)$ is an indicator function identifying fragile banks. $\mathbb{1}(\text{Fragile}_t)$ takes unitary value if banks' measure of structural solidity is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Sound}_t)$ identifies sound banks and is defined as $\mathbb{1}(\text{Sound}_t) = 1 - \mathbb{1}(\text{Fragile}_t)$. Fragility measures vary across columns: leverage (total assets to common equity) in column 1, customer deposits to total funding ratio in column 2, and net exposure towards other banks (loans to banks − deposits from banks) to total assets ratio in column 3. Instrumented regressors: $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$ and the lag of the variable used in the definition of fragility. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.6.: The direct effect of dispersion of beliefs

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Bad_t: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(25)$	Bad_t: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(10)$
	(1)	(2)
$\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$	-104.89***	-201.04**
	[40.00]	[84.46]
$\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$	-7.952	-12.00**
	[4.965]	[5.597]
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-36.07***	-33.78***
	[10.47]	[11.30]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$	-20.49**	-18.91*
	[9.058]	[10.05]
$\text{CDS}_{i,t-1}$	0.941***	0.963***
	[0.028]	[0.029]
Bank + Time FE	yes	yes
IV	yes	yes
# obs	2967	2998
R^2	0.881	0.883
p-val of Hansen stat	0.992	0.988
p-val of Underid. test	0.000	0.000
Kleibergen-Paap F stat	17.55	22.58
p-val of Godfrey test	0.883	0.323

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Bad}_t)$ is an indicator function identifying bad forecasts. $\mathbb{1}(\text{Bad}_t)$ takes unitary value if the forecasted ROA of bank i at time t is below the 25^{th} (column 1) or the 10^{th} (column 2) of its cross-sectional distribution in time t. $\mathbb{1}(\text{Good}_t)$ identifies good forecasts and is defined as $\mathbb{1}(\text{Good}_t) = 1 - \mathbb{1}(\text{Bad}_t)$. Instrumented regressors: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.7.: The effect of expectations and precision before and during the crisis

Dependent variable: CDS spread. Sample: Jan 2005 - Dec 2012.

	Precise if $\delta < p(50)$ (1)	Precise if $\delta < p(33)$ (2)
Crisis		
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-23.54***	-22.35***
	[6.655]	[7.581]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-10.78**	-10.14**
	[5.256]	[5.120]
$\delta_{\mathbb{E}_{i,t}}$	-10.37*	-9.734*
	[5.708]	[5.548]
Pre-crisis		
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-13.09**	-15.76**
	[6.667]	[7.053]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-4.243	-5.213
	[5.466]	[5.685]
$\delta_{\mathbb{E}_{i,t}}$	-6.617	-12.69
	[17.64]	[17.12]
Bank + Time FE	yes	yes
IV	yes	yes
# obs.	3552	3552
R^2	0.903	0.903
p-val of Hansen stat	0.711	0.554
p-val of Underid. test	0.000	0.000
Kleibergen-Paap F stat	17.23	19.01
p-val of Godfrey test	0.279	0.300
	Tests (p-values)	
Pre-crisis: $\mathbb{1}(\text{Pre}_t) = \mathbb{1}(\text{Impr}_t)$	0.043	0.020
$\mathbb{1}(\text{Before,Pre}_t) = \mathbb{1}(\text{After,Pre}_t)$	0.148	0.414

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median (in column 1), or the 25^{th} percentile (in column 2), of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. Instrumented regressors: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.8.: The effect of expectations, precision and fragility before and during the crisis

Dependent variable: CDS spread. Sample: Jan 2005 - Dec 2012.

	Fragility		
	Leverage	Customer dep.	Interbank
	(1)	(2)	(3)
Crisis			
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-39.50***	-36.82***	-28.71***
	[10.36]	[10.27]	[9.169]
$\mathbb{1}(\text{Fragile}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-9.903	-10.59	-10.96*
	[8.073]	[6.516]	[6.028]
$\mathbb{1}(\text{Sound}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-15.60**	-13.95**	-15.79**
	[6.718]	[6.852]	[7.273]
$\mathbb{1}(\text{Sound}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-7.900	-7.352	-7.416
	[6.074]	[5.163]	[5.866]
$\delta_{\mathbb{E}_{i,t}}$	-11.61*	-9.795*	-10.82*
	[6.187]	[5.905]	[5.915]
Pre-crisis			
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-50.06***	-32.88**	-21.25**
	[16.12]	[13.39]	[9.771]
$\mathbb{1}(\text{Fragile}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-17.01*	-23.47**	-5.637
	[9.003]	[11.50]	[6.125]
$\mathbb{1}(\text{Sound}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-5.827	1.901	-6.591
	[6.467]	[8.047]	[8.121]
$\mathbb{1}(\text{Sound}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	0.497	4.657	-2.566
	[5.481]	[5.600]	[6.974]
$\delta_{\mathbb{E}_{i,t}}$	-45.89	18.09	-4.761
	[28.75]	[23.46]	[20.31]
Bank + Time FE	yes	yes	yes
IV	yes	yes	yes
# obs.	3552	3552	3552
R^2	0.903	0.903	0.903
p-val of Hansen stat	0.427	0.350	0.335
p-val of Underid. test	0.000	0.000	0.000
Kleibergen-Paap F stat	12.21	11.45	12.75
p-val of Godfrey test	0.243	0.269	0.275
		Tests (p-values)	
Pre-crisis: $\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Fragile}_t, \text{Impr}_t)$	0.003	0.378	0.079
Pre-crisis: $\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Sound}_t, \text{Pre}_t)$	0.001	0.014	0.148
$\mathbb{1}(\text{After,Frag}_t, \text{Pre}_t) = \mathbb{1}(\text{Before,Frag}_t, \text{Pre}_t)$	0.525	0.784	0.505

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ is defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Fragile}_t)$ is an indicator function identifying fragile banks. $\mathbb{1}(\text{Fragile}_t)$ takes unitary value if banks' measure of structural solidity is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Sound}_t)$ is defined as $\mathbb{1}(\text{Sound}_t) = 1 - \mathbb{1}(\text{Fragile}_t)$. Fragility measures vary across columns: leverage (total assets to common equity) in column 1, customer deposits to total funding ratio in column 2, and net exposure towards other banks (loans to banks – deposits from banks) to total assets ratio in column 3. Instrumented regressors: $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$ and the lag of the variable used in the definition of fragility. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.9.: The effect of expectations and precision before the crisis

Dependent variable: CDS spread. Sample: Jan 2005 - Aug 2007.

	Bad$_t$: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(25)$		Bad$_t$: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(10)$	
	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$	1.708	2.173	-3.038	-25.92**
	[4.171]	[9.672]	[3.943]	[12.81]
$\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$	-3.259	-8.737	1.091	23.2*
	[6.824]	[9.998]	[5.935]	[13.80]
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	2.576	2.276	1.599	-3.762
	[1.642]	[4.166]	[1.716]	[4.080]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	2.904*	2.387	1.734	-5.388
	[1.533]	[3.402]	[1.708]	[3.363]
$\text{CDS}_{i,t-1}$	0.642***	0.624***	0.646***	0.653***
	[0.056]	[0.053]	[0.056]	[0.050]
Bank + Time FE	yes	yes	yes	yes
IV	no	yes	no	yes
# obs	581	444	581	444
R^2	0.832	0.838	0.832	0.829
p-val of Hansen stat		0.757		0.877
p-val of Underid. test		0.324		0.011
Kleibergen-Paap F stat		1.138		2.874
p-val of Godfrey test		0.668		0.148

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Bad}_t)$ is an indicator function identifying bad forecasts. $\mathbb{1}(\text{Bad}_t)$ takes unitary value if the forecasted ROA of bank i at time t is below the 25^{th} (columns 1 and 2) or the 10^{th} (columns 3 and 4) of its cross-sectional distribution in time t. $\mathbb{1}(\text{Good}_t)$ identifies good forecasts and is defined as $\mathbb{1}(\text{Good}_t) = 1 - \mathbb{1}(\text{Bad}_t)$. Instrumented regressors in columns 2 and 4: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$. Set of instruments in columns 2 and 4: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.10.: Learning and Forecast Errors

	$\mathbb{E}_t(\text{ROA}_{i,t+1})$ (1)	$\delta_{\mathbb{E}_{i,t}}$ (2)
Crisis		
$\mathbb{E}_{t-1}(\text{ROA}_{i,t})$	0.801*** [0.021]	
FE_{t-1}	0.0648** [0.028]	-0.0849*** [0.027]
$\delta_{\mathbb{E}_{i,t-1}}$		0.649*** [0.117]
FE^2_{t-1}		0.00344 [0.005]
Pre-crisis		
$\mathbb{E}_{t-1}(\text{ROA}_{i,t})$	0.909*** [0.087]	
FE_{t-1}	0.275* [0.152]	-0.102*** [0.029]
$\delta_{\mathbb{E}_{i,t-1}}$		0.715*** [0.099]
FE^2_{t-1}		0.00823*** [0.003]
Bank + Time FE	yes	yes
# obs.	4551	3688
R^2	0.83	0.72

Notes: within estimator with time and bank-specific fixed effects. The dependent variable is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$ ($\mathbb{E}_t(\text{ROA}_{t+1})$ in column 1) or the standard deviation of analysts' forecasts formed at time t on the ROA of bank i in $t+1$ ($\delta_{\mathbb{E}_t}$ in column 2). FE is the forecast error in previous forecasts defined as $\text{FE}_t = \text{ROA}_t - \mathbb{E}_{t-1}\text{ROA}_t$. Coefficients are allowed to vary in times of crisis (post September 2007). Additional controls: $\text{CDS}_{i,t-1}$, actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.11.: $P\left(\frac{dP(def)}{d\beta} > 0\right)$

		λ			
		0.5	0.7	0.9	0.95
	0.5	0	0.22	0.99	0.99
z	0.7	0	0.99	0.99	0.99
	0.9	0	0.99	0.99	0.99
	0.95	0	0.99	0.99	0.99

Table 1.12.: $P\left(\frac{dP(def)}{d\alpha} > 0\right)$

		λ			
		0.5	0.7	0.9	0.95
	0.5	0	0	0.05	0.06
z	0.7	0	0	0.29	0.31
	0.9	0	0.31	0.69	0.69
	0.95	0	0.55	0.77	0.77

Table 1.13.: $P\left(\frac{d^2P(def)}{d\xi d\beta} < 0\right)$

		λ			
		0.5	0.7	0.9	0.95
	0.5	0.01	0.12	0.56	0.56
z	0.7	0.01	0.75	0.86	0.86
	0.9	0.02	0.92	0.86	0.86
	0.95	0.02	0.89	0.81	0.81

Table 1.14.: $P\left(\frac{d^2P(def)}{d\xi d\alpha} < 0\right)$

		λ			
		0.5	0.7	0.9	0.95
	0.5	0	0	0.47	0.58
z	0.7	0	0	0.91	0.87
	0.9	0	0.91	0.82	0.86
	0.95	0	0.59	0.76	0.80

Table 1.15.: $P\left(\frac{d^2P(def)}{d\xi dz} < 0\right)$

		λ			
		0.5	0.7	0.9	0.95
	0.5	0.99	0.99	0.95	0.94
z	0.7	0.99	0.99	0.71	0.70
	0.9	0.99	0.70	0.31	0.31
	0.95	0.99	0.49	0.23	0.22

Table 1.16.: P(Default)

		λ			
		0.5	0.7	0.9	0.95
	0.5	0.01	0.02	0.16	0.18
z	0.7	0.01	0.04	0.37	0.38
	0.9	0.01	0.38	0.62	0.62
	0.95	0.01	0.51	0.67	0.68

Table 1.17.: Robustness: the effect of expectations and precision

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Precise if $\delta < p(50)$ (1)	Precise if $\delta < p(33)$ (2)
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-20.34*	-28.49**
	[11.64]	[14.21]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	0.772	0.621
	[9.197]	[9.150]
$\delta_{\mathbb{E}_{i,t}}$	5.360	4.778
	[8.436]	[8.429]
$\text{CDS}_{i,t-1}$	0.877***	0.877***
	[0.0461]	[0.0461]
Bank FE	yes	yes
Quarter-region FE	yes	yes
IV	yes	yes
# obs.	1807	1807
R^2	0.881	0.880
p-val of Hansen stat	0.385	0.346
p-val of Underid. test	0.000	0.000
Kleibergen-Paap F stat	24.46	15.49
p-val of Godfrey test	0.445	0.369
	Tests (p-values)	
$\mathbb{1}(\text{Pre}_t) = \mathbb{1}(\text{Impr}_t)$	0.009	0.012

Notes: two-step GMM estimator with time and bank-specific fixed effects. We allow the time fixed effect to be specific to the geographical region (North America, Eurozone, Asia, and rest of the world) of localization of bank's headquarter. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median (in column 1), or the 25^{th} percentile (in column 2), of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. Instrumented regressors: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.18.: Robustness: the direct effect of dispersion of beliefs

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Bad_t: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(25)$ (1)	Bad_t: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(10)$ (2)
$\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$	-91.30**	-283.8**
	[45.08]	[144.7]
$\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$	4.117	-19.97
	[9.784]	[30.15]
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$	-22.73**	-15.07
	[11.57]	[16.91]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$	-4.984	3.652
	[9.171]	[14.39]
$\text{CDS}_{i,t-1}$	0.922***	0.906***
	[0.0451]	[0.0452]
Bank FE	yes	yes
Quarter-region FE	yes	yes
IV	yes	yes
# obs	1742	1734
R^2	0.882	0.881
p-val of Hansen stat	0.707	0.748
p-val of Underid. test	0.000	0.033
Kleibergen-Paap F stat	12.58	13.97
p-val of Godfrey test	0.924	0.245

Notes: two-step GMM estimator with time and bank-specific fixed effects. We allow the time fixed effect to be specific to the geographical region (North America, Eurozone, Asia, and rest of the world) of localization of bank's headquarter. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Bad}_t)$ is an indicator function identifying bad forecasts. $\mathbb{1}(\text{Bad}_t)$ takes unitary value if the forecasted ROA of bank i at time t is below the 25^{th} (column 1) or the 10^{th} (column 2) of its cross-sectional distribution in time t. $\mathbb{1}(\text{Good}_t)$ identifies good forecasts and is defined as $\mathbb{1}(\text{Good}_t) = 1 - \mathbb{1}(\text{Bad}_t)$. Instrumented regressors: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.19.: Robustness: the effect of expectations, precision and fragility

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Fragility		
	Leverage (1)	Customer dep. (2)	Interbank (3)
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-34.06***	-41.55***	-28.33***
	[10.46]	[11.56]	[9.454]
$\mathbb{1}(\text{Fragile}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-6.171	-7.600	-11.32*
	[8.135]	[7.938]	[6.003]
$\mathbb{1}(\text{Sound}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-12.51*	-13.32	-15.98**
	[7.121]	[8.166]	[7.338]
$\mathbb{1}(\text{Sound}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-4.421	-0.980	-8.022
	[6.572]	[6.209]	[6.274]
$\delta_{\mathbb{E}_{i,t}}$	-6.364	-7.937	-9.339
	[6.629]	[6.759]	[6.043]
$\text{CDS}_{i,t-1}$	0.926***	0.922***	0.934***
	[0.0279]	[0.0305]	[0.0299]
Bank FE	yes	yes	yes
Quarter-region FE	yes	yes	yes
IV	yes	yes	yes
# obs.	3016	3051	3012
R^2	0.884	0.889	0.885
p-val of Hansen stat	0.343	0.906	0.813
p-val of Underid. test	0.000	0.000	0.000
Kleibergen-Paap F stat	12.55	20.86	15.21
p-val of Godfrey test	0.406	0.634	0.302
		Tests (p-values)	
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Fragile}_t, \text{Impr}_t)$	0.009	0.000	0.045
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Sound}_t, \text{Pre}_t)$	0.022	0.007	0.194

Notes: two-step GMM estimator with time and bank-specific fixed effects. We allow the time fixed effect to be specific to the fragility of the bank. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Fragile}_t)$ is an indicator function identifying fragile banks. $\mathbb{1}(\text{Fragile}_t)$ takes unitary value if banks' measure of structural solidity is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Sound}_t)$ identifies sound banks and is defined as $\mathbb{1}(\text{Sound}_t) = 1 - \mathbb{1}(\text{Fragile}_t)$. Fragility measures vary across columns: leverage (total assets to common equity) in column 1, customer deposits to total funding ratio in column 2, and net exposure towards other banks (loans to banks – deposits from banks) to total assets ratio in column 3. Instrumented regressors: $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$ and the lag of the variable used in the definition of fragility. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.20.: Robustness: the effect of expectations and precision

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Precise if $\delta < p(50)$ (1)	Precise if $\delta < p(33)$ (2)
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-19.30**	-38.45**
	[9.153]	[15.60]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-5.304	-4.899
	[6.274]	[6.186]
$\delta_{\mathbb{E}_{i,t}}$	-1.126	-3.228
	[10.81]	[10.89]
$\text{CDS}_{i,t-1}$	0.933***	0.915***
	[0.0357]	[0.0343]
Bank FE	yes	yes
Country-Month FE	yes	yes
IV	yes	yes
# obs.	2857	2857
R^2	0.634	0.635
p-value of Hansen statistic	0.475	0.534
p-value of Underidentification test	0.000	0.000
Kleibergen-Paap F statistic	22.86	9.36
p-val of Godfrey test	0.251	0.295
	Tests (p-values)	
$\mathbb{1}(\text{Pre}_t) = \mathbb{1}(\text{Impr}_t)$	0.033	0.016

Notes: two-step GMM estimator with time and bank-specific fixed effects. We allow the time fixed effect to be specific to the geographical region (North America, Eurozone, Asia, and rest of the world) of localization of bank's headquarter. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median (in column 1), or the 25^{th} percentile (in column 2), of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. Instrumented regressors: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.21.: Robustness: the direct effect of dispersion of beliefs

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Bad_t: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(25)$	Bad_t: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(10)$
	(1)	(2)
$\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$	-44.49**	-83.66*
	[21.86]	[43.43]
$\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$	-8.869	-12.19
	[7.448]	[7.796]
$\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-12.19*	-12.84*
	[7.098]	[7.182]
$\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$	0.877	0.309
	[4.125]	[4.369]
$\text{CDS}_{i,t-1}$	0.905***	0.905***
	[0.0300]	[0.0304]
Bank FE	yes	yes
Country-Month FE	yes	yes
IV	yes	yes
# obs	2781	2772
R^2	0.657	0.649
p-val of Hansen stat	0.520	0.467
p-val of Underid. test	0.000	0.000
Kleibergen-Paap F stat	15.57	15.23
p-val of Godfrey test	0.221	0.207

Notes: two-step GMM estimator with time and bank-specific fixed effects. We allow the time fixed effect to be specific to the geographical region (North America, Eurozone, Asia, and rest of the world) of localization of bank's headquarter. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{i,t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_{i,t}}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Bad}_t)$ is an indicator function identifying bad forecasts. $\mathbb{1}(\text{Bad}_t)$ takes unitary value if the forecasted ROA of bank i at time t is below the 25^{th} (column 1) or the 10^{th} (column 2) of its cross-sectional distribution in time t. $\mathbb{1}(\text{Good}_t)$ identifies good forecasts and is defined as $\mathbb{1}(\text{Good}_t) = 1 - \mathbb{1}(\text{Bad}_t)$. Instrumented regressors: $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Pre}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Impr}_t)\mathbb{E}_t(\text{ROA}_{t+1})$, $\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$ and $\mathbb{1}(\text{Good}_t)\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.22.: Robustness: the effect of expectations, precision and fragility

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Fragility		
	Leverage (1)	Customer dep. (2)	Interbank (3)
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-26.08**	-26.74**	-16.07*
	[11.29]	[10.89]	[9.323]
$\mathbb{1}(\text{Fragile}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-2.675	-5.645	-2.738
	[9.128]	[6.704]	[6.341]
$\mathbb{1}(\text{Sound}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-19.42**	-12.59	-5.029
	[9.262]	[9.368]	[8.899]
$\mathbb{1}(\text{Sound}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-8.228	-1.289	0.127
	[6.380]	[5.993]	[5.882]
$\delta_{\mathbb{E}_{i,t}}$	1.069	-2.007	-5.864
	[9.341]	[9.084]	[8.910]
$\text{CDS}_{i,t-1}$	0.905***	0.917***	0.897***
	[0.0361]	[0.0357]	[0.0336]
Bank FE	yes	yes	yes
Country-Month FE	yes	yes	yes
IV	yes	yes	yes
# obs.	2942	2942	2886
R^2	0.676	0.670	0.679
p-val of Hansen stat	0.308	0.302	0.230
p-val of Underid. test	0.000	0.000	0.000
Kleibergen-Paap F stat	22.49	24.26	15.98
p-val of Godfrey test	0.229	0.230	0.234
	Tests (p-values)		
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Fragile}_t, \text{Impr}_t)$	0.019	0.021	0.039
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Sound}_t, \text{Pre}_t)$	0.528	0.171	0.231

Notes: two-step GMM estimator with time and bank-specific fixed effects. We allow the time fixed effect to be specific to the fragility of the bank. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Fragile}_t)$ is an indicator function identifying fragile banks. $\mathbb{1}(\text{Fragile}_t)$ takes unitary value if banks' measure of structural solidity is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Sound}_t)$ identifies sound banks and is defined as $\mathbb{1}(\text{Sound}_t) = 1 - \mathbb{1}(\text{Fragile}_t)$. Fragility measures vary across columns: leverage (total assets to common equity) in column 1, customer deposits to total funding ratio in column 2, and net exposure towards other banks (loans to banks – deposits from banks) to total assets ratio in column 3. Instrumented regressors: $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$ and the lag of the variable used in the definition of fragility. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.23.: Robustness: the effect of expectations, precision and fragility

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Fragility		
	Leverage (top 25%) (1)	Customer dep. (bottom 25%) (2)	Interbank (bottom 25%) (3)
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-33.33*	-33.64*	-27.45**
	[18.88]	[17.89]	[12.07]
$\mathbb{1}(\text{Fragile}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-1.980	-5.971	-8.616
	[9.705]	[17.23]	[6.868]
$\mathbb{1}(\text{Sound}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-24.54***	-36.72***	-19.27**
	[8.129]	[12.70]	[8.203]
$\mathbb{1}(\text{Sound}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-11.20*	-19.60**	-5.268
	[6.564]	[8.185]	[7.026]
$\delta_{\mathbb{E}_{i,t}}$	-10.25	-11.74**	-11.26*
	[6.736]	[5.718]	[5.984]
$\text{CDS}_{i,t-1}$	0.931***	0.842***	0.932***
	[0.0305]	[0.0782]	[0.0303]
Bank + Time FE	yes	yes	yes
IV	yes	yes	yes
# obs.	3052	3017	3052
R^2	0.880	0.875	0.880
p-val of Hansen stat	0.696	0.306	0.740
p-val of Underid. test	0.002	0.000	0.000
Kleibergen-Paap F stat	10.74	2.159	27.81
p-val of Godfrey test	0.313	0.212	0.350
	Tests (p-values)		
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Fragile}_t, \text{Impr}_t)$	0.115	0.036	0.058
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Sound}_t, \text{Pre}_t)$	0.612	0.831	0.396

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ is defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Fragile}_t)$ is an indicator function identifying fragile banks. Fragility measures vary across columns: leverage (total assets to common equity) in column 1, customer deposits to total funding ratio in column 2, and net exposure towards other banks (loans to banks – deposits from banks) to total assets ratio in column 3. Instrumented regressors: $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments: lags of $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$ and the lag of the variable used in the definition of fragility. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.24.: Robustness: the effect of expectations, precision and fragility

Dependent variable: CDS spread. Sample: Sep 2007 - Dec 2012.

	Fragility		
	Leverage (1)	Customer dep. (2)	Interbank (3)
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-42.93***	-50.61***	-43.91***
	[12.64]	[15.53]	[15.51]
$\mathbb{1}(\text{Fragile}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-6.666	-20.45**	-7.219
	[8.693]	[9.326]	[6.747]
$\mathbb{1}(\text{Sound}_t, \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-13.11	-31.01**	-13.38
	[9.143]	[14.44]	[9.104]
$\mathbb{1}(\text{Sound}_t, \text{Impr}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-6.184	-14.67**	-3.775
	[6.269]	[7.477]	[6.839]
$\delta_{\mathbb{E}_{i,t}}$	-11.13*	-9.350*	-10.80*
	[6.021]	[5.602]	[5.981]
$\text{CDS}_{i,t-1}$	0.930***	0.843***	0.930***
	[0.030]	[0.075]	[0.030]
Bank + Time FE	yes	yes	yes
IV	yes	yes	yes
# obs.	3052	3017	3052
R^2	0.881	0.875	0.881
p-val of Hansen stat	0.801	0.597	0.786
p-val of Underid. test	0.000	0.001	0.000
Kleibergen-Paap F stat	17.65	2.396	9.828
p-val of Godfrey test	0.347	0.152	0.353
	Tests (p-values)		
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Fragile}_t, \text{Impr}_t)$	0.002	0.012	0.011
$\mathbb{1}(\text{Fragile}_t, \text{Pre}_t) = \mathbb{1}(\text{Sound}_t, \text{Pre}_t)$	0.012	0.148	0.041

Notes: two-step GMM estimator with time and bank-specific fixed effects. The dependent variable is bank CDS spread at time t, defined as the monthly average of daily CDS spreads. $\mathbb{E}_t(\text{ROA}_{t+1})$ is the median of the analysts' forecasts formed at time t on the ROA of bank i in $t+1$. $\delta_{\mathbb{E}_t}$ is the standard deviation of analysts' forecasts formed on at time t on the ROA of bank i in $t+1$. $\mathbb{1}(\text{Pre}_t)$ is an indicator function identifying precise signals. $\mathbb{1}(\text{Pre}_t)$ takes unitary value if the standard deviation of the forecasts on bank i is below the 25^{th} percentile of its cross-sectional distribution in time t. $\mathbb{1}(\text{Impr}_t)$ identifies imprecise signals defined as $\mathbb{1}(\text{Impr}_t) = 1 - \mathbb{1}(\text{Pre}_t)$. $\mathbb{1}(\text{Fragile}_t)$ is an indicator function identifying fragile banks. $\mathbb{1}(\text{Fragile}_t)$ takes unitary value if banks' measure of structural solidity is below the median of its cross-sectional distribution in time t. $\mathbb{1}(\text{Sound}_t)$ identifies sound banks and is defined as $\mathbb{1}(\text{Sound}_t) = 1 - \mathbb{1}(\text{Fragile}_t)$. Fragility measures vary across columns: leverage (total assets to common equity) in column 1, customer deposits to total funding ratio in column 2, and net exposure towards other banks (loans to banks – deposits from banks) to total assets ratio in column 3. Instrumented regressors: $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$. Set of instruments in columns: lags of $\mathbb{1}(\text{Fragile}_t)\otimes\mathbb{1}(\text{Precise}_t)\mathbb{E}_t(\text{ROA}_{t+1})$ and $\delta_{\mathbb{E}_{i,t}}$ and forecast errors lagged once or more. Additional controls: , actual $\text{ROA}_{i,t-1}$, $\text{leverage}_{i,t-1}$, deposit to total funding $\text{ratio}_{i,t-1}$, tier-1 capital $\text{ratio}_{i,t-1}$, net charge-offs to gross loans $\text{ratio}_{i,t-1}$, non-performing loans to gross loans $\text{ratio}_{i,t-1}$ and the lag of the variable used in the definition of fragility. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 1.25.: Banks in the Sample

Arab Emirates	Wing Hang Bank	Qatar National Bank
Abu Dhabi Comm Bank	**Hungary**	**Russia**
Dubai Islamic Bank	OTP Bank	Joint-Stock Investment Comm. Bank
Austria	**India**	MDM Bank
Erste Group Bank	AXIS Bank	Sberbank of Russia
Raiffeisen Bank	Bank of India	**Saudi Arabia**
Australia	Canara Bank	Riyad Bank
Adelaide Bank	ICICI Bank	Samba Financial Group
Australia and NZL Bank	Indian Overseas Bank	Saudi British Bank
Bank of Queensland	**Ireland**	**Singapore**
Bendigo and Adelaide Bank	Allied Irish Banks	Oversea-Chinese Banking Corporation
Commonwealth Bank of Austr.	Bank of Ireland	United Overseas Bank
Macquarie Bank	**Israel**	**Spain**
Macquarie Group	Bank Hapoalim	Banco Bilbao Vizcaya Argentaria
St. George Bank	**Italy**	Banco Espanol de Crédito
Suncorp-Metway	Banca Generali	Banco Pastor
Westpac Banking Corporation	Banca Nazionale del Lavoro	Banco Popular Espanol
Brazil	Banca Popolare di Milano	Banco de Sabadell
Banco Bradesco	Banca Popolare di Verona	Bankia
Banco Itau	Capitalia	Bankinter
Uniao de Bancos Brasileiros	Intesa Sanpaolo	Caja de Ahorros y Pensiones de Barc.
Canada	Mediobanca	**Sweden**
Bank of Montreal	UniCredit	Nordea Bank
Bank of Nova Scotia	Unione di Banche Italiane	Svenska Handelsbanken
Brookfield Office Prop. Canada	**Japan**	Swedbank
Can. Imperial Bank of Comm.	Acom	**Switzerland**
National Bank of Canada	Aeon Financial Service	UBS
Royal Bank of Canada	Aiful Corporation	**Thailand**
Toronto Dominion Bank	Aozora Bank	Bangkok Bank
Chile	Bank of Fukuoka	Kasikornbank
Banco Santander	Bank of Kyoto	Siam Commercial Bank
Banco de Chile	Bank of Yokohama	TMB Bank
China	Chiba Bank	**Turkey**
Bank of China	Citigroup Global Markets JP	Akbank
Cathay Financial Holdings	Credit Saison	Turkiye Garanti Bankasi
Cathay United Bank	Daiwa Securities Group	Turkiye is Bankasi
Chinatrust Commercial Bank	Hiroshima Bank	**Ukraine**
Chinatrust Financial Holding	Joyo Bank	Joint Stock Commercial Bank
E. Sun Financial Holding	NIS Group	**USA**
Fubon Financial Holding	Nishi-Nippon City Bank	AmSouth Bancorporation
Mega Financial Holding	Nomura Holdings	BB&T Corporation
Shin Kong Financial Holding	Orix Corporation	BNY Mellon, National Association
Sinopac Financial Holdings	Sanyo Shinpan Finance	Bank of America
Taishin Financial Holding	Shinsei Bank	Bank of New York Mellon
Denmark	Shizuoka Bank	Capital One Bank
Danske Bank	Sumitomo Mitsui Fin. & Lease	Capital One Financial Corporation
Jyske Bank	Sumitomo Mitsui Fin. Gr.	Charles Schwab
France	Sumitomo Mitsui Trust Bank	Citigroup
BNP Paribas	Takefuji Corporation	Discover Financial Services
Credit Agricole Corp. and Invest.	Tokio Marine Financial Sol.	Doral Financial Corporation
Credit Agricole	**Kazakhstan**	Fifth Third Bancorp
Natixis	Bank CenterCredit	Franklin Resources
Société Générale	Kazkommertsbank	Goldman Sachs Group
Germany	OJSC Halyk Bank of Kaz.	JP Morgan Chase & Co.
Commerzbank	**Malaysia**	KeyCorp
DePfa Deutsche Pfandbriefbank	CIMB Bank Berhad	Legg Mason
Deutsche Bank	CIMB Inv. Bank Berhad	Lehman Brothers Holdings
Deutsche Postbank	EON Bank Berhad	MBNA
UniCredit Bank	Malayan Banking Berhad	Marshall & Ilsley
Great Britain	**Netherlands**	Mellon Financial
Alliance & Leicester	AEGON Bank	Merrill Lynch & Co.
Barclays	Ageas Finance	Metlife
Bradford & Bingley	Ageas	Morgan Stanley
HBOS	Royal Bank of Scotland NV	PNC Financial Services Group
HSBC Holdings	**Norway**	Principal Financial Group
Invesco Holding	Storebrand Bank ASA	Prudential Financial
Lloyds Banking Group	**Philippines**	Regions Financial Corporation
Man Strategic Holdings	Equitable PCI Bank	SLM Corporation-Sallie Mae
Royal Bank of Scotland Group	Rizal Commercial Banking	State Street Corporation
Greece	**Portugal**	SunTrust Banks
Alpha Bank	Banco BPI	United Western Bancorp
Piraeus Bank	Banco Espirito Santo	Wachovia Corporation
Hong Kong	**Qatar**	Wells Fargo & Company
Bank of East Asia	Commercial Bank of Qatar	iStar Financial
Hang Seng Bank	Doha Bank	

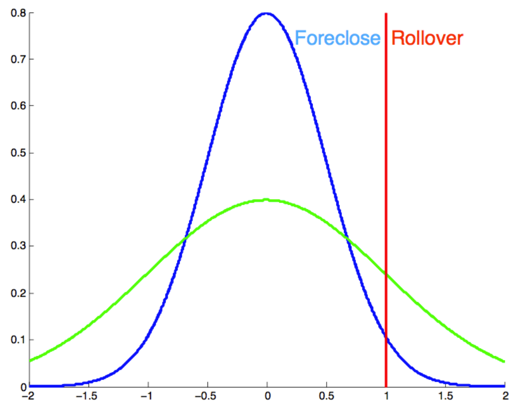


Figure 1.1.: Bad Expectations

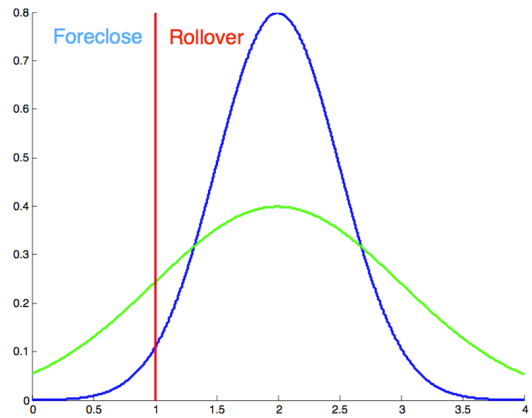


Figure 1.2.: Good Expectations

The blue line displays an agent's expectation about the distribution of others' beliefs about the profitability of a bank when information is precise, whereas the green line shows that distribution when information is imprecise. Note that the distributions are centers around the agent's own expectation about the bank's profitability. Agents believing that a bank's profitability level lies to the right of the red line roll over debt to the bank whereas the opposite is true if profitability is expected to lie to the left of the red line.

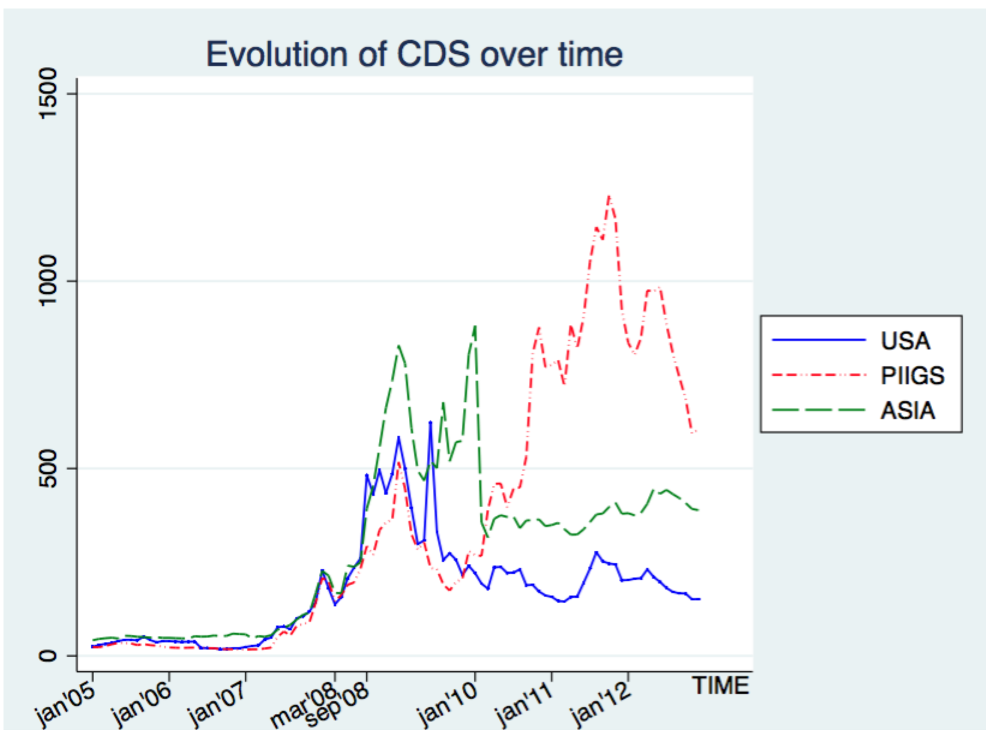


Figure 1.3.: Monthly CDS spreads over time for banks operating in USA, Asia, and PIIGS.

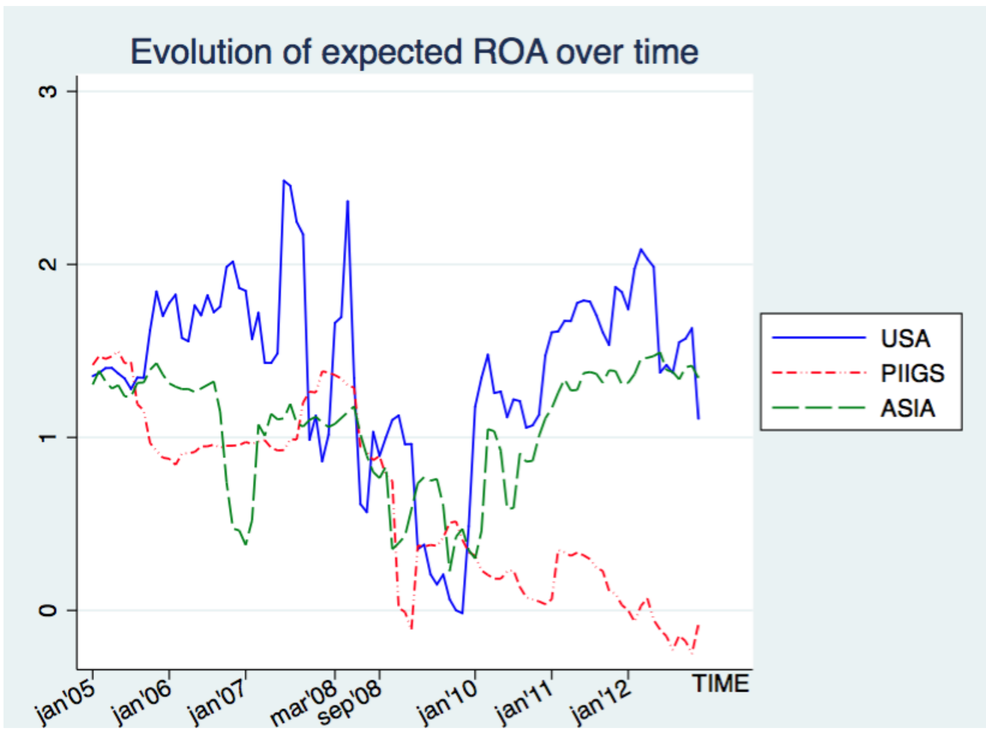


Figure 1.4.: Expected ROA over time for banks operating in USA, Asia, and PIIGS.

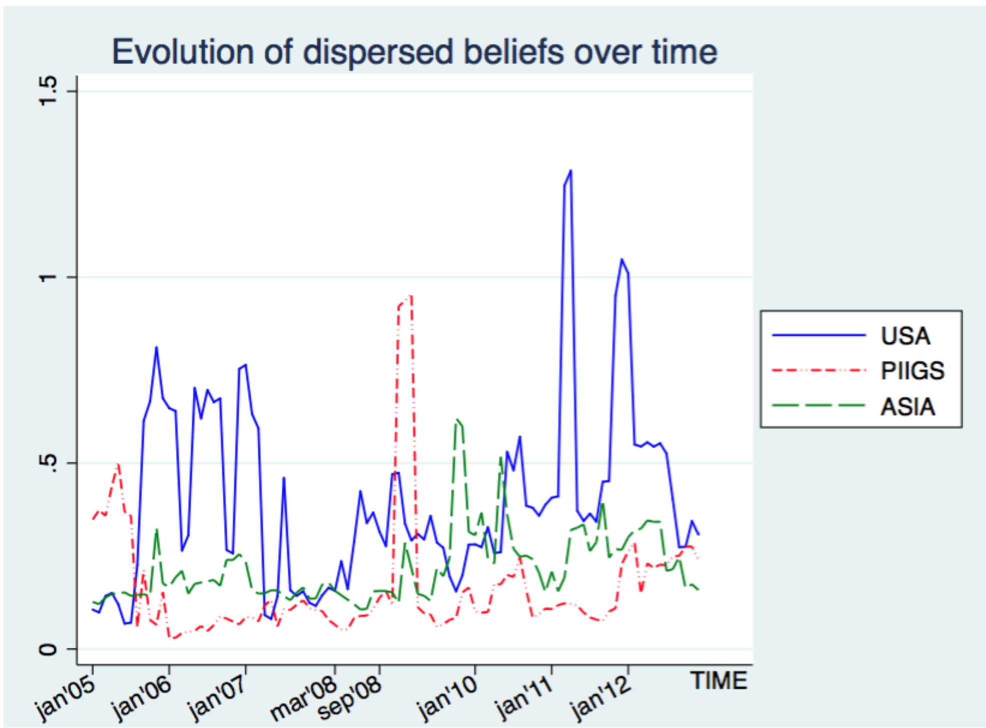


Figure 1.5.: Dispersion of beliefs over time for banks operating in USA, Asia, and PIIGS.

2. The Political Origin of Home Bias: the Case of Europe

2.1. Introduction

The European sovereign debt crisis has emphasized the importance of banks' exposure to sovereign debt. Banks' sovereign portfolios in Europe consist almost entirely of *domestic* government debt. The average (median) own exposure, defined as the proportion of domestic debt over the total sovereign portfolio, was 74% (86%) at the end of 2010. Figure 2.1 reveals that there is a significant degree of heterogeneity in banks' holdings of domestic debt within Europe: the median own exposure is in general higher in the periphery (PIIGS) than in Northern Europe, with Germany (DE) being a notable exception. The level of domestic exposures is well in excess of what standard finance theory would predict: there is significant *home bias* (Figure 2.2) [1]. In general, the home bias in sovereign bonds among

[1] The Capital Asset Pricing Model (CAPM) predicts that, in frictionless financial markets, homogenous investors would hold a share of financial asset equal to the share of the financial assets of that country in the world portfolio (see Cochrane (2005), page 155, and Coeurdacier and Rey (2012)). In the context

European banks is quite persistent over time (Figure 2.3) and it tends to be higher in the periphery than in Northern Europe [2]. The sovereign exposures have important implications for the real economy. During the sovereign debt crisis, banks incurred losses owing to the decline in market value of the sovereign debt in their balance sheets and some recent papers have shown that these potential losses are responsible for a sizable portion of the decline in lending.[3] Given that the riskiest bonds during the sovereign debt crisis were those issued by the PIIGS, the large degree of home bias is especially troubling among PIIGS banks and it may have exacerbated the recent recession.

In this paper, we investigate why European banks display a significant home bias in sovereign bond holdings. We believe that certain banks hold a disproportionate amount of their own country's sovereign debt because they are controlled by domestic politicians. In fact, many European banks have an explicit political participation through a block of shares owned by either the regional state in which the bank is headquartered (Germany) or the national government (Spain, Sweden, Portugal) or an indirect control exerted through private foundations whose directors are appointed by local or national politicians (Italy). These politicians may be interested in financing discretionary public spending to maximize

---

of sovereign bonds, we use the home bias measure as defined in Coeurdacier and Rey (2012):

$$HomeBias = 1 - \frac{\text{Share of Foreign Sovereigns in Bank } i \text{ Sovereign Holding}}{\text{Share of Foreign Sovereign Bonds in the Global Portfolio}}$$

When the home bias measure is equal to zero there is perfect diversification; when it is equal to one there is perfect home bias. Anything in excess of zero indicates some level of home bias.

[2] Ireland is a noticeable exception, with an extremely volatile home bias. We believe this may be due to the fact that these are raw data that do not take into account changing composition at the bank level (mergers & acquisitions and bank failures).

[3] See Bofondi, Carpinelli and Sette (2013), Popov and Van Horen (2013) and De Marco (2013).

their own objectives. These objectives may be increasing the chances of re–election or diverting public funds to friends, relatives or controlled firms. They would then persuade the politically controlled banks to finance national or local state borrowing by purchasing government bonds [4].

We define our "political influence" variable as the total percentage of shares held by central or local governments or by political foundations in the *pre–crisis* period (2006 or 2009). The reason for using pre–crisis data is twofold: first we want to avoid biases given by bank nationalizations that occurred in 2010–2011. In fact, during the crisis, many governments, especially in Germany, Spain and the UK, were forced to intervene to recapitalize or bail–out insolvent banks. Thus, if we were to measure "political influence" in 2011, we would largely overestimate the state's presence in the banking sector. Second, we claim that, although clearly endogenous, public ownership of these banks is a historical, predetermined presence, thus unlikely to be correlated with the error term in our main regression. The hypothesis we take to the data is that a bank that has a historically strong political presence among its shareholders will purchase more domestic sovereign bonds relative to a bank that does not receive any political pressure. We find evidence for this hypothesis both before and during the European sovereign debt crisis: a bank above the median political control has, ceteris paribus, a home bias of 10 to 19 percentage points higher than a bank below the median.

Moreover, we exploit the fact that there have been plenty of equity injections by each member State in the domestic banking system in both 2010 and 2011 to document the

[4] The European Banking Authority (EBA) data we use unfortunately do not distinguish between central and local government debt. The sovereign exposure we refer to in this paper are the sum of the two.

extent of *political pressure/moral suasion* on the controlled banks. We show that, during the sovereign debt crisis and upon receiving government support, banks significantly increased their exposure to domestic sovereign bonds *only if* they have strong political affiliations. The effect is twice as large for "political" banks located in the periphery (+8.9%) than for other "political" banks located elsewhere in Europe (+4.2%). These results are not explained by other country–time factors such as higher sovereign yields in the periphery, that would encourage purchase of sovereign bonds bonds from peripheral banks.

But government equity injections may be specifically targeted to political banks. If this were the case, it would not be surprising that only political banks buy domestic bonds after receiving government help. However, this does not appear to be the case: in 2010 and 2011, equity injections were not directly targeted to banks that have larger political affiliations, but rather to banks that performed worse in the previous year in terms of lower profitability and a larger pool of non performing loans. In other words, although governments seem to "twist arms" of politically controlled institutions into buying domestic debt, they also provide financial aid to those that actually need it.

The *political channel/moral suasion* hypothesis is not the only explanation for the home bias in sovereign bonds, both before and during the sovereign debt crisis. Standard information asymmetries arguments, where the local investors are better informed about the domestic sovereign than foreign investors, or other hedging motives may still be present. More recently, several papers explain the increase in home bias in the PIIGS countries during the sovereign debt crisis with creditor discrimination theories (Broner et al. (2014) and

Brutti and Sauré (2013)) or as arbitrage opportunities fueled by the ECB LTROs (Acharya and Steffen (2013)). We do not challenge these hypotheses, we only show that politics also plays a role.

There is yet another reason for banks to hold sovereign bonds, which is sometimes refer to as *capital arbitrage*. Under Basel II, government bonds are considered almost risk free [5] so that banks would load their balance sheets with sovereigns to reduce risk–weighted assets and increase capital ratios. We argue that while the regulatory framework has certainly been a key factor in the excessive sovereign exposure among European banks, it cannot explain home bias. In fact, the zero risk weight applies not only to domestic sovereign debt, but to all countries in the European Union.

The paper proceeds as follows. Section II reviews the related literature. In Section III, we highlight some country-specific institutional details that are relevant to our analysis; Section IV describes the data and the methodology used in the paper. Section V presents the results and Section VI concludes.

[5] According to Basel II regulation, in order to compute Risk Weight Assets (RWA), banks can use two approaches: the Standardized Approach and the Internal–Ratings Based (IRB) approach. According to the first, government bonds receive a 0% risk weight as in Basel I. Under the IRB instead, the weight should be strictly positive, because, even though the model may assign a very low probability of default (PD) to a sovereign issuer, the loss given default (LGD) is positive. In practice, PD on sovereign debt are equal 0.1% for 201 major international banks (BIS Quarterly Review, December 2013). Moreover, in the European Union, there is a loophole that allows banks using the IRB to switch back to the Standardized Approach when evaluating sovereign bonds "IRB permanent partial use".

2.2. Related Literature

The relationship between home bias in sovereign holdings and political influence at the bank level, is, to the best of our knowledge, not been established in the literature.

First, we contribute to the enormous international finance literature pioneered by French and Poterba (1991) that studies home bias in portfolio holdings. Most papers in this area have documented home bias in equity rather than bond holdings. A few exceptions are Bertaut, Tabova and Wong (2013), who show the decline in financial bonds' home bias among U.S. investors and Lane (2006), who shows that member countries of the European Economic and Monetary Union disproportionately invest in one another and especially towards their trade partners. Several recent papers analyze the increase in sovereign home bias among banks during the recent sovereign debt crisis. Battistini, Pagano and Simonelli (2014) document that only PIIGS banks respond to increases in country risk by increasing their exposure to domestic sovereign bonds, while banks from core countries do not, suggesting that *redenomination/repatriation* risk, *i.e.* the risk that the liabilities of banks would be renominated in the local currency, is the driving force behind the increase in home bias. Becker and Ivashina (2014) document a positive correlation at the country level between domestic government holdings by national banks and aggregate measures of state ownership in the banking system. Brutti and Sauré (2013) analyze cross–country evidence in favor of the secondary market theory suggested by Broner et al. (2014). According to this hypothesis, in a crisis period, domestic banks would buy domestic debt in the expectation that the government will not default on domestic creditors. All these papers analyze country level data, which ignores the cross–sectional heterogeneity at the bank level. Using a bank-level panel, and constructing a measure of direct government ownership at the bank level, we are able to dig deeper and provide an explanation for why some banking institutions hold a disproportionately large amount of domestic sovereign bonds over total sovereigns.

Some theoretical papers also explore the home bias issue. Diamond and Rajan (2011) advance the hypothesis that banks are keen to load up with illiquid assets because the states of nature in which these assets default is the same in which the bank itself goes bankrupt; in other words, banks rationally put all their risk in a state of the world that would be catastrophic for them anyways (*risk synchronization*). Their argument has a natural application if one considers sovereign bonds an illiquid asset. Acharya and Rajan (2013) and Crosignani (2014) show that myopic governments have incentives to increase risk synchronization. The evidence we find suggests that, upon receiving liquidity injections, only the "political banks" boost their exposure to domestic government bonds relative to foreign ones, thus synchronizing even more their default risk with that of their respective domestic country.

Our findings also contribute to the literature on the perfomance of state-owned banks and to the literature on related lending. Barth, Caprio Jr and Levine (2001) provide a broad overview on the effects of regulation and ownership structure on the performance of the banking system. In general, they find that greater state ownership of banks tends to be associated with less developed banks and financial markets. Sapienza (2004) finds that firms located in areas where the party of affiliation of the bank's chairman is stronger receive more favorable loan conditions; Cuñat and Garicano (2010) show that banks whose chairman held a political position in the past perform worse than other banks. La Porta, Lopez-de Silanes and Zamarripa (2003) find evidence that loans extended to related parties, either family members or controlled firms, have on average lower rates, lower collateral requirements and are more likely to default than unrelated ones.

2.3. Institutional Details

There are three European countries that stand out for the pervasive and systematic role of politicians and local governments in the management of banks: Italy, Germany and Spain. In what follows we provide some key features that distinguish each of these countries in terms of political presence in the banking system. We also discuss the case of France as an example of a banking sector without any direct political influence, at least in the last decade.

Italy

Following the wave of liberalizations and privatizations that started at the European level in the 1980s, the Bank of Italy and the government made an attempt to privatize the numerous state-owned banks. In 1990, the Amato–Carli law transformed the state-owned banks into private entities; these were controlled by Foundations (non–profit organizations), that would have had to place their shares on the market at a later date to complete the privatization. In 1998, however, the Amato–Ciampi law superseded the 1992 law, reiterating that Foundations are non-profit organizations, but adding that these should operate under private law and not under public law as in the previous regime. As they became private entities, they could no longer be forced to progressively sell off their shares on the market. Thus, Foundations were able to maintain their controlling stakes in most Italian banks to the present day.[6] Importantly for our purposes, even though they became private, non-profit entities, they are still under the influence of political groups. The members of the board of directors in the Foundations are often appointed by local or national politicians.

Apart from one specific bank, MPS, the other four Italian banks in our dataset present more than one Foundation among their shareholders. Moreover, most of the times, within each Foundation there are members coming from both left and right wing parties. This degree of heterogeneity should convey the idea that, in the majority of the cases, banks with a large concentration of Foundations are influenced by a wide range of political parties.

Germany

The German banking system is organized in three different "pillars": private banks, such as Deutsche Bank and Commerzbank; cooperative banks, based on a member-structure where each member has one vote and, finally, *public banks*.

The latter are financial institutions, typically owned by the regional states (*Lander*) or by administrative districts or cities in which they are headquartered. Among these there

[6] Boeri (2012)http://www.lavoce.info/i-politici-ai-vertici-delle-fondazioni-bancarie/ (in Italian)

are savings banks (*Sparkassen*) whose shareholders are usually local municipalities and the regional banks (*Landesbanken*), that are mostly owned by their respective *Lander* through a regional savings bank association.

Thus, in the case of Germany the definition of "political banks" is clear: those that have a direct state participation among their shareholders. In the EBA dataset, the political banks will mostly be the *Landesbanken*.

Spain

Savings banks represent a fundamental pillar of the Spanish banking system: founded in the 18*th* century with the objective of channeling private savings towards socially beneficially investments, savings banks accounted for 40 percent of Spanish banks' total assets in 2010. They became financial institutions that do not distribute profits, that have no formal owner, but several governing bodies representing two different classes of stakeholders: *insiders* and *outsiders*.

Insiders are employees, depositors and private founders; outsiders are the regional governments and other public entities. The relative voting power of the two groups in each bank depends on the specific regional law. Around a decade ago, in 2002, a national reform capped the representation of public entities, including regional governments, at *50 percent of the voting rights* in each bank [7].

Since outsiders, *i.e.* the public entities, are focused on achieving socially oriented goals,

[7] In July 2010, the ceiling on voting rights of public entities was reduced to 40 percent and professional expertise was required to sit in a governing bodies.

improving profitability has not always been the main objective of savings banks. In this regard, Illueca, Norden and Udell (2008) document that Savings banks were more likely to open new branches and extend new loans in provinces that were politically close; additionally, Cuñat and Garicano (2010) provide some evidence that savings banks whose chairman has political affiliations performed worse than other banks.

France

A different path has been followed by France.[8] After World War II and up to the late 1980s, almost all banks, both investment and commercial, were either state-owned or co-operatives. The Chirac government changed the situation when, in 1987, he privatized several major banks, including *Societe Generale* and *Paribas*. Another wave followed few years later in 1993, with the privatization of BNP among others. The complete privatization of the banking system was accomplished in 2001.

2.3.1. Theory of Inter-Party Support

Whereas the political influence in the case of direct state ownership (Germany, Spain) is clear, the case of foundations' ownership (Italy) requires a more careful analysis: certain banks are affiliated with only one political party that is not necessarily in power at any given point in time. Monte Dei Paschi (MPS) in Italy is an example of such a bank: it is affiliated with the centre–left municipal government and it has a strong home bias (96%) even in 2010, when the national government is from centre–right. For these institutions, it

[8] Alain Plessis (2003), The history of banks in France, *Federation Bancaire Francaise*.

is not clear why a political party that is not ruling the country would be interested in buying sovereign bonds and finance public spending of their opponents. It may be interested in doing quite the opposite in order to destabilize the incumbent government.

We claim that there are two main reasons that may explain that behavior. First of all, local politicians can sustain a central government of the opposite political affiliation in exchange for monetary transfers to the respective region or local municipality. There is suggestive evidence, for the case of Italy, that regional transfers are not primarily dictated by shared political affiliation; a more crucial determinant is the political strength of the party in the specific region, regardless of political affiliation.[9]

Second, a theory that supports inter-party funding is borrowed from the political science literature. Katz and Mair (1995) and Katz and Mair (2009) are the first to document that political parties in a wide range of developed countries have started to behave like a cartel. Instead of competing against each other on relevant issues, they transfer more and more competences upward to technocratic and non-partisan commissions. Perhaps more importantly, they decided to alter the structure of payoffs: they agreed on the introduction of public financial subventions to political parties that are guaranteed regardless of whether a party wins or loses. This last piece of regulation severely limits the incentives to compete in order to win the elections, as the monetary payoffs are not linked to the election's outcome. Hence, the concern that a bank affiliated with a leftist party would have the incentive to destabilize the governing right wing party is clearly downsized in light of the findings of

[9] Greco (2009) (mimeo).

Katz and Mair.

2.4. Data and Methodology

Data

The dataset is the result of the merger of three different sources: detailed bank level data on the exposure to sovereign bonds and liquidity injections from the EU–wide Stress Test and Recapitalization Exercises; information on the *pre–crisis* degree of political presence for each bank is collected from Annual Reports whenever available; other balance sheet data comes from Bankscope.

The key dataset contains the information on political influence. Specifically, we want to create a variable that captures the degree of government or politicians' control within each bank. We also want this measure to be dated *prior* to the sovereign debt crisis so as not to bias the degree of political control with any bail out or nationalization policy that occurred in 2010–2011. Hence we collect 2006 Annual Reports for all banks, except Spanish ones. It is in fact difficult to find Annual Reports at earlier dates for some small Spanish Savings banks, because many were recently acquired or merged with other banks. For this reason, we resort to IMF data, which list for each savings bank the percentage of voting rights held by local governments prior to 2009.[10] We construct the variable *Political* as the sum of any participation held by the local or central governments and by political foundations in each bank; we then normalize it by its standard deviation. We sometimes find useful

[10] IMF (June 2012)

to use a dummy variable, $\mathbb{1}$*(Political)*, which takes value of one if the degree of political control in a specific bank is above the median of the domestic country and zero otherwise. We also create a dummy variable, $\mathbb{1}$*(Cooperative)*, which takes value of one if the bank is a cooperative and zero otherwise. It is important to distinguish between a non–cooperative and cooperative bank, since the latter display certain features that are similar to those of highly politicized banks even though they are not owned by the state (diffuse ownership among cooperative members). Notably, cooperative banks display a high degree of home bias in sovereign bonds, similar to political banks, probably due to the very "local" nature of their business model.

Sovereign exposure data have been collected by the EBA in the context of the EU–wide Stress Test and Recapitalization Exercises. Specifically in an effort to enhance transparency and restore confidence in the financial system, the EBA decided to disclose bank-by-bank result for both the 2010 and 2011 Stress Test Results and the so-called 2011 and 2012 Recapitalization Exercises. These exercises contain information on the capital composition, including government aid in the form of equity support measures, credit risk exposure and sovereign debt exposure to each of the 30 members of the European Economic Area (EEA 30) for all the participating banks. The sample consists of 90 European banks in March 2010, which we will refer to as end–of–year 2009, and December 2010; 61 banks in December 2011 and June 2012, covering at least 60% of banking assets in Europe and at least 50% in each Member State. For December 2010 only, a breakdown of the credit portfolio by categories of borrowers is available. For instance, we know the amount of credit granted to private corporations, public institutions, small and medium enterprises, the exposure to residential mortgages and the amount of defaulted loans.

Finally, we match the EBA dataset with banks' balance sheet data obtained from Bankscope.

Empirical Methodology

To measure the effect of political presence in a bank on its degree of home bias in sovereign bonds, we run a set of *cross-sectional* regressions for 2009, 2010, 2011.[11] For each year we employ the following specification:

$$HomeBias_i = \beta_1 Political_i + \gamma' X_i + \mathbb{1}(Cooperative_i) + D_i + \varepsilon_i \tag{2.1}$$

where $HomeBias_i$ is one of two measures: i) the ratio of domestic bonds held by bank i over the total European debt ($\frac{Own}{TS}$) [12] or ii) the home bias measure in Coeurdacier and Rey (2012). The first measure is the most intuitive, but it ignores the nominal size of each country's stock of debt. For example, it is reasonable for Italian and German banks to have a larger exposure to their home country's debt than Belgian and Dutch banks because Italian and German public debt are much larger. However, this does not pose a problem in estimation because we control for country fixed effects that also absorb the size of a country's stock of debt. The second measure, on the other hand, explicitly takes this into

[11] The main variable of interest $Political_{i,j}$ does not vary over time, so we cannot use panel regressions with bank fixed effects.

[12] The EBA sovereign exposure data contains only countries belonging to the European Economic Area (EEA30), a group of 30 countries which broadly coincides with the European Union. Only in December 2010 exposure to US and Japan was disclosed, but we drop these countries from our analysis as they are only available for one year.

account. It is defined as follows in Coeurdacier and Rey (2012):

$$HomeBias = 1 - \frac{\text{Share of Foreign Sovereigns in Bank } b \text{ Sovereign Holding}}{\text{Share of Foreign Sovereigns in the Global Portfolio}}$$

where *Global* is represented by the EEA30 countries in our data. This measure is bounded between zero (perfect diversification) and one (perfect home bias), while anything in excess of zero indicates some level of home bias.[13] Comparing Fig. 2.1 and Fig. 2.2 reveals however that the difference between the two measures is negligible: neither the country ranking nor the level of home bias is very much affected. For example, Italian and German banks have high positive values in both cases.

$Political_i$ is also one of two measures. It is either the percentage of shares owned by the domestic government or other domestic political entities (Foundations in Italy, for example) divided by its standard deviation; or it is a dummy, $\mathbb{1}(Political_i)$, equal to one if the bank is above the median of the distribution of government ownership in each country.

Other explanatory variables we use are: X_i, a set of *lagged* bank balance sheet characteristics (log of total assets, Tier1 ratio, Leverage, Deposits over Total Funding, ROAA, Non Performing Loans over Gross Loans) and $\mathbb{1}(Cooperative_i)$ a dummy equal to one if bank i is a cooperative bank. We allow for a different intercept in home bias for cooperative banks because these banks are characterized by dispersed ownership among members

[13] Note that the first measure of home sovereign bonds over total sovereigns does not exactly replicate this: it is also equal to one in case of perfect home bias, but it is equal to zero if the bank does not own any domestic debt, not if the bank is perfectly diversified. This difference turns out not to matter in the regression analysis.

(one–head–one–vote) and no share directly owned by the domestic government: nonetheless, they usually exhibit a large home bias given by the very "local" nature of their business model. It is also possible that others, more indirect forms of political influence are at play in cooperative banks: it is often the case, in Italy for example, that cooperative firms have strong ties with political parties. Finally, D_i a country dummy identifying where the bank is headquartered. Country dummies are important because they control for country specific factors; more specifically, they take into account i) institutional characteristics and ii) optimal portfolio considerations.

The first motivation pertains to countries' institutional heterogeneity; for example, we need to control for the fact that in Spain the government participation in each bank, by law, cannot exceed 50%, whereas in Germany the local government can hold any number of shares. German *Landers* very often holds around 85% of shares in the *Landesbanken*. Since we are interested in evaluating whether a certain political ownership is large or small in a given country, a set of country–specific intercepts in the above regression is appropriate.

The second consideration has to do with asset pricing theory. The CAPM implies the following pricing equation: $1 = E_t\left[M_{j,t+1}R_{i,t+1}\right] = Cov_t\left[M_{j,t+1}, R_{i,t+1}\right] + E_t\left[M_{j,t+1}\right]E_t\left[R_{i,t+1}\right]$. $M_{j,t+1}$ is the stochastic discount factor or pricing kernel of country j at time $t+1$ and $R_{i,t+1}$ is the real rate of return on asset i at time $t+1$. The above equilibrium condition implies that the optimal holding of any asset, sovereign bonds included, depends on the covariance between a country specific factor and an asset specific component. Therefore, each bank in country j should have the same exposure to the set of sovereign bonds. For this reason, the set of country dummies also reflects country specific portfolio aspects. We use country dummies with both dependent variables, the home exposure over the total and the Coeurdacier and Rey (2012) home bias measure.

In our second specification, we exploit the time dimension of the panel to investigate how home bias varied *during* the crisis. We want to test the hypothesis that, upon receiving an equity injection from the domestic government, only political banks increase their home bias relative to other banks, especially if they are located in the periphery. This would be consistent with a *political pressure/moral suasion* hypothesis, where the domestic government calls on banks to buy sovereign debt at a time of low demand. Therefore, we run the following *panel* regression:

$$\begin{aligned}\Delta HomeBias_{i,t} = \beta_1 GovHelp_{i,t-1} + \beta_2\big(\mathbb{1}(PIIGS) \times \mathbb{1}(Political_i)\big)GovHelp_{i,t-1} + \\ + \beta_3\big(\mathbb{1}(NOPIIGS) \times \mathbb{1}(Political_i)\big)GovHelp_{i,t-1} + \gamma' X_{i,t-1} + \eta_i + \lambda_t + \varepsilon_{i,t}\end{aligned} \tag{2.2}$$

where $\Delta HomeBias_{i,t}$ represents the change in home bias of bank i at time t, $GovHelp_{i,t-1}$ is the amount of equity injection given by the domestic government to bank i at the beginning of the year as a fraction of Risk Weighted Assets (RWA). $\mathbb{1}(Political_i)$ is a non–time varying dummy if bank i is above the median political control in each country and $\mathbb{1}(PIIGS)$ $\mathbb{1}(NOPIIGS)$ are dummies for whether bank i belongs to PIIGS or not. In this regression we allow for the effect of equity injections to differ depending on whether a bank is politically influenced and *at the same time* whether or not it belongs to the PIIGS. Finally we control for bank fixed–effects, η_i, and for either year– or country–year fixed–effects λ_t.

Table 2.1 reports some summary statistics of the dataset. On average, the pre–crisis (2006) ownership by domestic government or political entities in Europe is at 20% among the 90 banks participating in the European Stress Test in 2010. However, only 48 banks (53% of the sample) have at least some level of political ownership and the dummy $\mathbb{1}(Political_i)$ shows that only 34% of the sample can be classified with an above the median political control in each country. Home bias is high on average according to both measures, however there is also a large heterogeneity, as it is evident from Figures 2.1 and 2.2. Also, 38% of the banks in our sample received some form government help at the end of 2010, with an average, conditional on the help being positive, of 3.6% of RWA. These are big numbers considering that, on average, the Tier1 over RWA ratio is at 11% for all banks.

2.5. Results

Table 2.2 reports the results for the main set of cross-sectional regressions. In the first three columns we regress the exposure to domestic sovereigns over total sovereigns in 2009, 2010 and 2011 on our continuous variable for political influence, *Political*, and a set of controls. In the last three columns we repeat the exercise but now we use a dummy variable, $\mathbb{1}$(Political), to capture political influence within each bank.

From the first two rows we notice that the coefficients of interest are always positive and significant at 5%.[14] This implies that banks that are more politically influenced display greater home bias in sovereign bond holdings. If we take a look at the first column, which we can think of as a pre-sovereign debt crisis regression, we have that a one standard deviation increase in the level of political influence (30 pct.points) is associated with an increase in the domestic composition of the sovereign bond holdings by 8%, which is about one third of a standard deviation of $\frac{Own}{TS}$.

On the other hand, by looking at the fourth column, the coefficient on the political dummy implies that a bank that moves from the bottom 50% to the top 50% of the distribution of political influence displays on average 12% more weight to domestic sovereigns relative to the total, which is about half of a standard deviation of $\frac{Own}{TS}$.

A covariate that is always highly significant is bank size, as measured by the log of total assets. The coefficient is a semi–elasticity and it implies that for a 1% increase in total assets, the own exposure is expected to decline by 0.1 percentage points on average across all the years. The punchline is that larger banks have a smaller home bias in sovereign bonds: the sovereign portfolios of larger institutions are more diversified. Also cooperative banks, on average and all else equal, have a own exposure 13 to 17 percentage points higher than other banks, at least before 2011. Note that cooperative banks have no direct political or state ownership, but the significant degree of home bias may be explained by the very "local" nature of their business model. Or, possibly, it indicates that cooperative banks may be subject to other forms of indirect political influence, that our measure of political

[14] Only in one out of six cases, the coefficient on $\mathbb{1}(Political_i)$ is significant at 10%. Notice how it is significant at 1% using the $Political_i/std.dev$ measure in 2009 too.

control cannot capture. It is often the case, at least in Italy, that cooperative savings bank have strong political ties to political parties.

Next, in Table 2.3, we run the same regression but changing the dependent variable to the Coeurdacier and Rey (2012) measure. The main results are basically unchanged, if anything both the magnitude and the significance of the coefficients is larger in this specification.

2.5.1. Panel Regression: Political Pressures during the Sovereign Debt Crisis

Now we ask whether politicians exerted pressures on controlled banks during the sovereign debt crisis; more specifically, we want to test whether, upon receiving equity injections, political banks increased their exposure to domestic sovereign bonds. We expect the effect to be stronger for banks in the PIIGS, where the respective governments had an incentive to encourage the purchase of government bonds so as to lower the yields.

Table 2.4 summarizes this heterogeneous impact of liquidity injections of banks' portfolio decisions. It displays the panel regression of changes in exposure to domestic relative to total sovereigns. Government help here is defined as any form of equity injection, measured as a fraction of Risk Weighted Assets (RWA), given by the respective governments. The data come from the EBA Stress Tests and Recapitalization exercises, where either purchase of ordinary bank shares by the government or government support measures count as government help in the calculation of common equity of the bank. Column (1) suggests that receiving government help by itself does not affect the bank's choice between buying domestic or foreign sovereigns. However, a political bank that receives liquidity injections by the local government would increase its exposure to domestic sovereigns. The effect is larger if the bank is located in particularly distressed countries, namely the PIIGS. Column (2) indicates that an additional equity injection of 1% of risk weighted assets is associated with an increase in domestic relative to total sovereign exposure by almost 9%, compared to 4% for non PIIGS banks. The two coefficients are sufficiently precisely estimated so that a simple hypothesis test rejects the null that the two effects are the same at the 5% level. The results would look very similar if we used the alternative definition of home bias in Coeurdacier and Rey (2012).

These results suggest that sovereign countries, especially the PIIGS, use domestic political banks to purchase the bonds they issue when there is a lack of demand. Indeed, upon receiving freshly injected equity, only the politically controlled banks increase their degree of home bias.

The panel regressions in Table 2.4 are not controlling for the fact that, during the crisis, we may observe an increase in home bias because of country and time specific factors. In particular, it is conceivable that PIIGS banks may have decided to increase their home bias because of the very high yields in PIIGS sovereign bonds. Investing in these bonds was risky, but for PIIGS banks it may be perfectly rational to put all risk in a state of the world, a sovereign default, that corresponds to banks' defaulting themselves (*risk synchronization*). Also, these risky behaviors may have been funded by the ECB 3 year Long Term Refinancing Operations (LTRO) in December 2011 and February 2012 that injected large amounts of liquidity, borrowed at 100 and 75 bps. respectively, into participating banks (part of the *carry trade* hypothesis advanced by Acharya and Steffen (2013)). We test these hypotheses and the robustness of our results in Table 2.5.

Columns (1)–(3) and (4)–(6) have the same set of controls, but the latter three split the effect of the interaction between government help and political banks among PIIGS and non–PIIGS banks. In particular, column (1) and (4) control for the *change* in the sovereign yield and CDS in each period.[15] We would expect the increase in the yield to increase home bias, but the increase in CDS, a proxy for risk of default, should offset it. The estimated coefficients are in fact positive and negative, respectively, but they turn out to be non–significant. Column (2)–(3) and (5)–(6) use a set of country–time FE that absorb all unobserved heterogeneity that is country and time specific, including yields and CDS. Finally, column (3) and (6) include bank specific usage of LTRO funds divided by total assets. Bank by bank figures on LTRO usage have not been released by the ECB, however we have collected data from banks' annual reports and industry reports for 47 major EBA banks. These banks borrowed €514 bn. in both LTROs, around half of total gross funds.[16] Figure 2.4 reveals that the LTRO have been dominated by Italian and Spanish banks (50% of the LTRO 1+2 funds), although, admittedly, the disclosure for French and German banks has been poor. In some cases we had to rely on industry estimates by Morgan Stanley

[15] The periods are: 2010Q4–2010Q1, 2011Q4–2010Q4, 2012Q2–2011Q4. The number of observations is differentin column (1) and (3) because Bloomberg does not provide data for the sovereign yields and CDS in all countries. We do not have information on Cyprus, Denmark, Finland, Hungary, Luxembourg, Malta, Poland and Slovenia.

[16] According to industry reports by Morgan Stanley Research (2012), only around half of gross funds were actually new *net funding*, as banks rolled over existing ECB facilities into the LTRO. The data we have collected are *mostly* on gross funds usage.

Research (2012), because although it is known that a bank has participated, the actual amount was not disclosed on annual reports. Since both 3 year LTRO operations took place in December 2011 and February 2012, the LTRO variable takes a value of zero before 2012Q2 for *all* banks and then it is equal to the amount borrowed only for the 47 banks for which information is available (it is missing in 2012Q2 for the other banks).

The results in all columns show that our hypothesis is robust even controlling for country–time specific trends and the LTRO interventions: the coefficient on the interaction term between government help and political banks is significant in all specifications. Moreover, it appears that, after we take into account country–time characteristics, the political banks in the PIIGS are the only ones that increase home bias after receiving government help. It makes sense that the significance of the coefficient survives only for PIIGS banks, because these are the countries whose governments have a higher incentive to pressure banks into buying domestic government bonds during the crisis.

2.5.2. Determinants of Government Help: Not just for Political Banks

One could think that our previous set of results, the fact that political banks buy more domestic government bonds during the crisis, could be explained by the fact that only political banks received government help during the crisis. In that case it would not be surprising that only political banks increase their respective own exposure to domestic governments. In Table 2.6 we show that this is not the case. We estimate the relationship between the amount of equity provided by local governments to each bank and a set of regressors, including past performance and political influence. The punchline is that equity injections are targeting banks with low prior profitability and larger pools of non-performing loans, not political banks directly. However, upon receiving these injections, only politically controlled banks increase their holdings of domestic sovereigns.

The first two columns report OLS regressions while the last two use the Tobit estimator (we report the slope coefficients in both cases). The last approach is more appropriate for this scenario because we should think of government help as a censored variable. It is equal to zero if the bank is in good shape and the government decides not to extend support or any positive value otherwise. The right specification that takes in to account both the discrete choice of whether or not to support a bank and the magnitude of the liquidity injection is the Tobit model.

The qualitative outcome of the OLS and the Tobit regressions are the same: political influence has not played any additional role in attracting more support from the government. The two main factors associated with greater government help are lower profitability (Return on Average Assets, ROAA) and more non-performing loans over gross loans (NPL/GL). By looking at the marginal effects (not reported in the table) for 2010, we see that a decrease in lagged return on assets by 1% is associated with an increase in the probability of receiving positive government support by 41% while an increase in non-performing loans over gross loans by 1% is associated with an increase in the probability of receiving support by 7.4%; all these effects are significant at 1%. The marginal effects are around two to three times smaller for the 2011 case but still significant at 1%. These effects may seem large at first, especially that on profitability. However, it has to be kept in mind that a change in ROAA of 1% is quite big, almost one standard deviation, while a change in non-performing loans over gross loans by 1% is relatively small if compared to its standard deviation which is 4%. For 2010, conditional on receiving support, a decrease in ROAA by 1% is associated with an increase in liquidity injection over risk weighted assets by 1.5%, around one third of its standard deviation; the effect of an increase of non-performing loans over gross loans by 1% is an increase in liquidity injections over risk weighted assets by about one tenth of its standard deviation.

2.5.3. Cross Validation: Allocation of Credit and Political Influence

Next, we ask whether politically influenced banks tend to facilitate their respective governments in more general terms, not only through purchasing more domestic sovereigns, but also by extending more loans to domestic government institutions. To this purpose we take advantage of the fact that, in 2010 only, the European Banking Authority released data on each bank' s allocation of credit broken down by country of destination and by type of loan; for instance, we know the amount of credit that each bank issued to small and medium enterprises (SME) and to government institutions broken down by the country in which the borrower is located. We then call $DomSME$ the share of domestic SME credit over total SME credit and $DomINST$ the share of loans to public institutions given to the domestic government.

Table 2.7 indeed shows that the effect of political influence of banks' behaviors is not specific to the purchase of domestic sovereign, but it is valid in more general terms: politically controlled banks extend more credit to domestic public entities than other banks do.

Contrary to our expectations, there is not strong evidence that political banks systematically extend more credit to small and medium enterprises; what seems to count to this regard is bank size. This suggests that small banks may proxy for regional banks which tend to lend more locally to small and medium enterprises.

2.6. Conclusions

We investigate why European banks suffer from a significant home bias in sovereign bond holdings. We believe that certain banks hold a disproportionate amount of their own country's sovereign debt because they are coerced by domestic politicians. In order to test this, we analyze recently collected data from Stress Tests on European banks and we find evidence supportive of this hypothesis: political banks hold more domestic sovereign bonds and they increase their home bias in sovereign holdings conditional on receiving liquidity injections by the respective local governments; this effect is more than twice as big for political banks belonging to the PIIGS than for other European banks. Interestingly, these equity injections seem to be directed towards banks that need it rather than to political banks in particular.

Moreover, we find that politically influenced banks tend to facilitate their respective governments in more general terms, not only through purchasing more domestic sovereigns, but also by extending more loans to domestic government institutions.

Table 2.1.: Summary Statistics at December 2010

	N	Mean	St.Dev.	Min	Max
Political ownership in 2006, (%)	90	21.3	31.3	0	100
$\mathbb{1}(Political_i)$ in 2006	90	0.34	0.47	0	1
Home Bias (Own/TotSov), (%)	90	74	26.4	9.8	100
Home Bias (CR(2012)), (%)	87	71.7	29	.05	100
Gov Help/RWA, (%)	90	1.4	3	0	21.85
$\mathbb{1}(GovHelp > 0)$	90	.38	.46	0	1
Gov Help/RWA if > 0, (%)	35	3.6	4	.32	21.84
Tier1/RWA, (%)	90	11	3.7	4.3	34.7

Table 2.2.: Home Bias (Own/TotalSovereign) and Political Presence.

	HB_{2009} (1)	HB_{2010} (2)	HB_{2011} (3)	HB_{2009} (4)	HB_{2010} (5)	HB_{2011} (6)
Political$_i$/std.dev.	7.747***	5.867***	5.717***			
	(3.34)	(2.71)	(3.28)			
$\mathbb{1}$(Political)$_i$				11.86*	10.19**	15.89***
				(1.95)	(2.41)	(4.11)
$\mathbb{1}$(Cooperative)	18.11***	16.38**	10.16	18.51**	16.74**	12.42**
	(2.92)	(2.67)	(1.68)	(2.54)	(2.62)	(2.20)
log(Asset)$_{t-1}$	-7.241**	-10.13***	-14.47***	-7.779***	-10.24***	-14.99***
	(-2.47)	(-3.94)	(-4.38)	(-3.95)	(-4.25)	(-5.40)
Tier1$_{t-1}$	1.426	-2.520**	-0.902	1.014	-2.256*	-0.973*
	(0.88)	(-2.12)	(-1.63)	(0.64)	(-1.85)	(-1.89)
Leverage$_{t-1}$	-0.350***	0.0892	-0.248	-0.398***	0.0495	-0.224
	(-3.26)	(0.69)	(-1.61)	(-3.51)	(0.39)	(-1.55)
(Dep/TF)$_{t-1}$	-0.513**	0.134	0.0195	-0.556**	0.141	0.0213
	(-2.14)	(0.62)	(0.05)	(-2.06)	(0.60)	(0.05)
ROAA$_{t-1}$	-0.113	5.995	-0.0235	-0.0733	4.018	-1.633
	(-0.03)	(1.18)	(-0.01)	(-0.02)	(0.84)	(-0.52)
(NPL/GL)$_{t-1}$	3.540**	-0.816	-1.139	4.091**	-0.613	-1.054
	(2.35)	(-0.68)	(-1.64)	(2.34)	(-0.54)	(-1.66)
N	71	77	57	71	77	57
Country Dummies	yes	yes	yes	yes	yes	yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: set of cross–sectional regressions of banks in 2009, 2010, 2011. The dependent variable is the ratio of domestic sovereign over total sovereign. $Political_i/std.dev$ is the ratio of political ownership over its standard deviation; $\mathbb{1}(Political)_i$ is a dummy equal to one if the bank is above the median of the distribution of political ownership in each country; $\mathbb{1}(Cooperative_i)$ is a dummy equal to one if bank i is a cooperative; $\log(Assets_{t-1})$, $Tier1_{t-1}$, $Leverage_{t-1}$, $(Dep/TF)_{t-1}$, $ROAA_{t-1}$, $(NPL/GL)_{t-1}$ are, respectively, the log of total assets, the Tier1 ratio over RWA, the ratio of total assets and common equity, the deposits to total funding ratio, the average return on assets and the ratio of non–performing loans over total loans, all lagged by one year. Std.err. are White HAC robust.

Table 2.3.: Home Bias (Coeurdacier and Rey (2012)) and Political Presence

	HB_{2009} (1)	HB_{2010} (2)	HB_{2011} (3)	HB_{2009} (4)	HB_{2010} (5)	HB_{2011} (6)
$Political_i$	10.09^{***}	7.527^{***}	7.220^{***}			
	(3.81)	(3.01)	(4.05)			
$\mathbb{1}(Political)_i$				15.71^{**}	12.45^{**}	18.81^{***}
				(2.27)	(2.67)	(4.59)
N	69	75	58	69	75	58
Country Dummies	yes	yes	yes	yes	yes	yes
Other: Log(TA)(-)***, Coop(+)***, Tier1(-), Lev(-), NPL(-), Dep(-) and ROAA(+)						

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: set of cross–sectional regressions of banks in 2009, 2010, 2011. The dependent variable is the Coeurdacier and Rey (2012) measure:

$$HomeBias = 1 - \frac{\text{Share of Foreign Sovereigns in Bank } b \text{ Sovereign Holding}}{\text{Share of Foreign Sovereign Bonds in the Global Portfolio}}$$

Other bank controls defined as before.

Table 2.4.: Political Pressure on the Banks. Panel regression.

	(1) $\Delta HomeBias_{i,t}$	(2) $\Delta HomeBias_{i,t}$
Gov Help$_{t-1}$	-.746	-0.739
	(-1.13)	(-1.12)
$\mathbb{1}(Political) \times GovHelp_{i,t-1}$	7.877***	
	(5.51)	
$\mathbb{1}(Political, Piigs) \times GovHelp_{i,t-1}$		8.981***
		(8.15)
$\mathbb{1}(Political, NoPiigs) \times GovHelp_{i,t-1}$		4.192**
		(2.08)
$N \times T$	187	187
N of banks	77	77
Bank + Year FE	yes	yes
Other Bank Controls: Tier1(-)***,Log(TA)(-)*,Lev(-),NPL(-),Dep(-)		
P-Value of the Test		
$\mathbb{1}$(Pol,Piigs)Gov = $\mathbb{1}$(Pol,NoPiigs)Gov		0.0337

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel regressions. The dependent variable is $\Delta HomeBias_{i,t}$ defined as the change in the ratio of domestic sovereign bonds over total sovereigns between 2010Q4–2010Q1, 2011Q4–2010Q4, 2012Q2–2011Q4. $GovHelp_{i,t-1}$ is the government equity injection as a percentage of RWA given to bank i at the beginning of the period. Other variables are defined as before. Std.err. are clustered at the bank–year level.

Table 2.5.: Political Pressure on the Banks: Robustness

	Yields and CDS (1)	Country–time FE (2)	LTRO (3)	Yields and CDS (4)	Country–time FE (5)	LTRO (6)
$\Delta Yield$	220.3			295.8		
	(0.77)			(0.98)		
$\Delta CDS5Y$	-254.9			-408.9		
	(-1.15)			(-1.49)		
LTRO/TotalAssets			-2.877			-3.360
			(-0.81)			(-0.93)
Gov $\text{Help}_{i,t-1}$	-1.149	0.369	0.489	-0.719	0.685	0.179
	(-1.62)	(0.48)	(0.66)	(-0.89)	(0.87)	(0.30)
$\mathbb{1}$(Political)×	5.050^{*}	10.94^{**}	12.17^{**}			
Gov $\text{Help}_{i,t-1}$	(1.85)	(2.05)	(2.47)			
$\mathbb{1}$(Political, Piigs)×				7.343^{***}	16.53^{**}	16.53^{**}
Gov Help_{t-1}				(2.26)	(2.42)	(2.08)
$\mathbb{1}$(Political, NoPiigs)×				4.096	4.814	11.15^{*}
Gov $\text{Help}_{i,t-1}$				(0.72)	(1.36)	(1.67)
N	155	187	176	155	187	176
N bank	66	77	76	66	77	76
Bank + Year FE	yes	yes	yes	yes	yes	yes
Country–time FE	no	yes	yes	no	yes	yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel regressions. The dependent variable is $\Delta HomeBias_{i,t}$ defined as the change in the ratio of domestic sovereign bonds over total sovereigns between 2010Q4–2010Q1, 2011Q4–2010Q4, 2012Q2–2011Q4. $GovHelp_{i,t-1}$ is the government equity injection as a percentage of RWA given to bank i at the beginning of the period. $\Delta Yield$, $\Delta CDS5Y$ are the growth rates of sovereign yields for 10 year bonds and 5 years CDS rates over the relevant periods. $LTRO/TotalAssets$ is the borrowing from the 3–year LTRO operation in December 2011 and February 2012 at the bank level (47 banks) over total assets. It is equal to zero for *all* banks before 2012Q2 and equal to the LTRO amount for the 47 banks for which information on the borrowed amount was found and missing otherwise. Other variables are defined as before. Std.err. are clustered at the bank–year level.

Table 2.6.: Determinants of Government Help

	(1) OLS Gov Help$_{2010}$	(2) OLS Gov Help$_{2011}$	(3) Tobit Gov Help$_{2010}$	(4) Tobit Gov Help$_{2011}$
$\mathbb{1}$(Political)$_i$	-0.572	-0.560	-0.462	-0.000265
	(-0.86)	(-0.62)	(-0.37)	(-0.00)
ROAA$_{t-1}$	-1.880***	-1.361***	-5.222***	-1.928***
	(-3.16)	(-6.81)	(-4.96)	(-3.95)
(NPL/GL)$_{t-1}$	0.300**	0.146**	0.935***	0.525***
	(2.60)	(2.01)	(2.90)	(2.84)
$\mathbb{1}$(Cooperative)	-2.360***	-1.100	-6.226**	-2.210
	(-2.71)	(-1.58)	(-2.46)	(-0.88)
$\mathbb{1}$(PIIGS)	0.172	1.488	-0.0145	0.653
	(0.37)	(1.56)	(-0.01)	(0.30)
log(Asset)$_{t-1}$	0.114	-0.160	0.753*	-0.316
	(0.56)	(-0.63)	(1.73)	(-0.47)
Tier1$_{t-1}$	0.164	0.463***	0.202	0.683***
	(1.11)	(5.27)	(0.57)	(4.77)
(Dep/TF)$_{t-1}$	-0.0401	-0.0248	-0.0288	-0.0130
	(-0.82)	(-0.74)	(-0.42)	(-0.16)
N	77	57	77	57

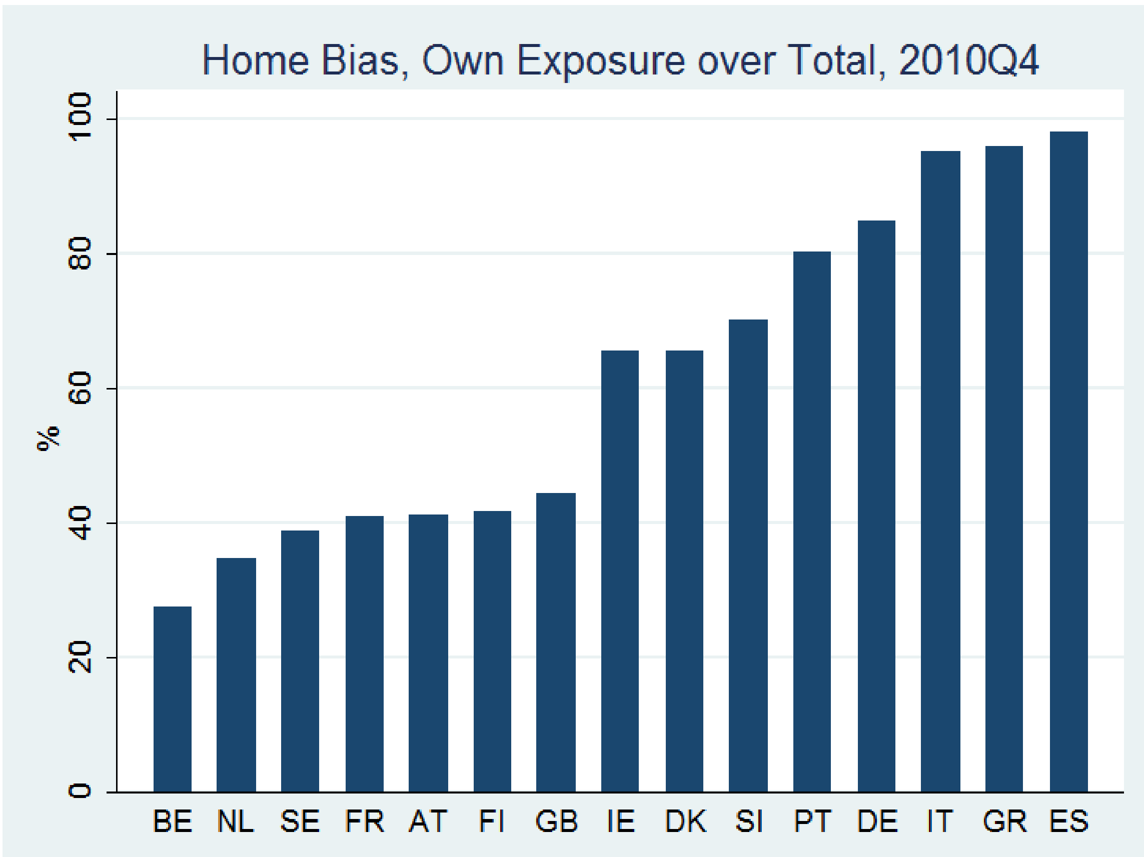
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7.: Allocation of Credit and Political Influence

	(1) DomSME_{2010}	(2) DomINST_{2010}	(3) DomSME_{2010}	(4) DomINST_{2010}
Political_i/std.dev.	4.874*	5.751**		
	(1.87)	(2.06)		
$\mathbb{1}(\text{Political})_i$			8.687	17.17**
			(1.60)	(2.15)
$\mathbb{1}$(Cooperative)	0.483	3.552	0.361	5.232
	(0.04)	(0.37)	(0.03)	(0.54)
$\log(\text{Asset})_{t-1}$	-5.646***	-7.592***	-5.813***	-7.346***
	(-2.90)	(-3.49)	(-2.95)	(-3.46)
$(\text{Dep/TF})_{t-1}$	-0.425**	-0.363*	-0.392*	-0.332*
	(-2.10)	(-1.86)	(-1.86)	(-1.72)
Tier1_{t-1}	0.432	-0.297	0.294	-0.482
	(0.39)	(-0.18)	(0.27)	(-0.29)
N	70	79	70	79

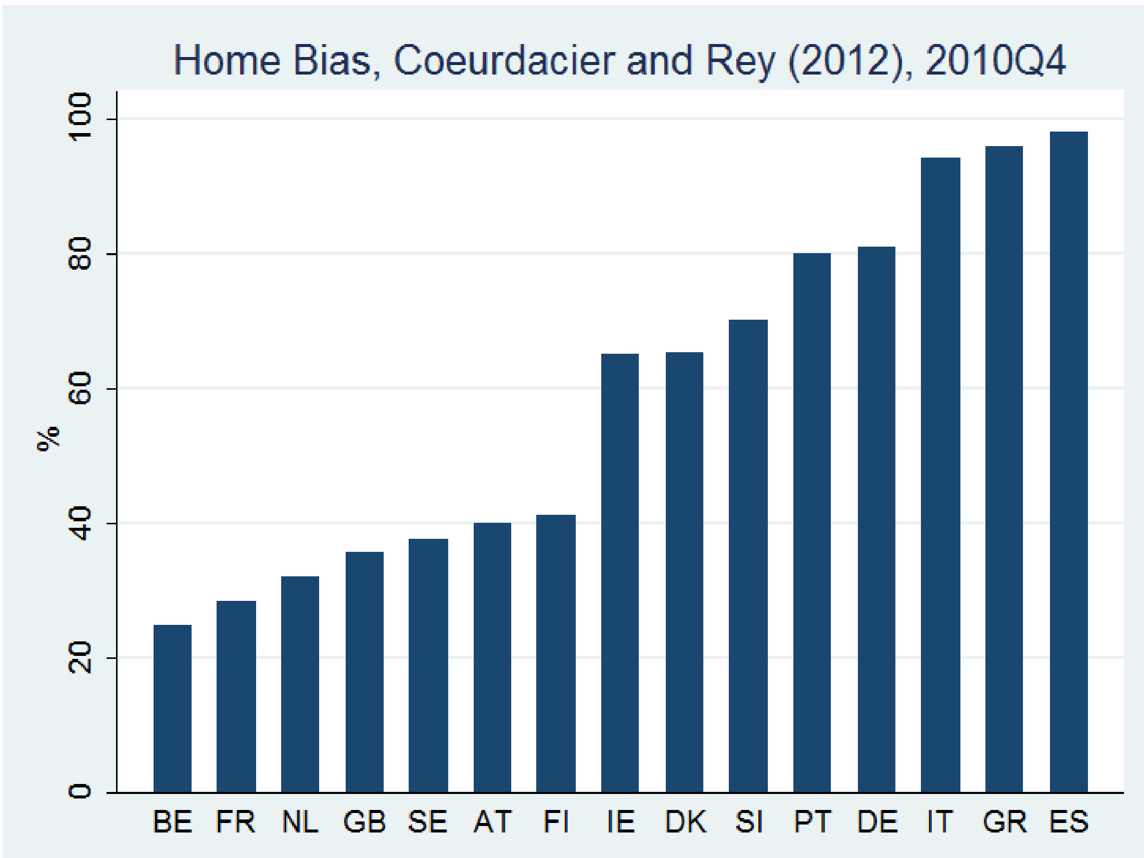
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2.1.: Median Sovereign Home Bias by country, December 2010



Source: EBA Stress Test 2011. Home Bias defined as the ratio of domestic sovereign by bank b over the total: $HomeBias = Own_b/TotalSovereign_b$. Country codes are the following: Belgium (BE), France (FR), Netherlands (NL), Great Britain (GB), Sweden (SE), Austria (AT), Finland (FI), Ireland (IE), Denmark (DK), Slovenia (SI), Portugal (PT), Germany (DE), Italy (IT), Greece (GR), Spain (ES).

Figure 2.2.: Median Sovereign Home Bias by country, December 2010

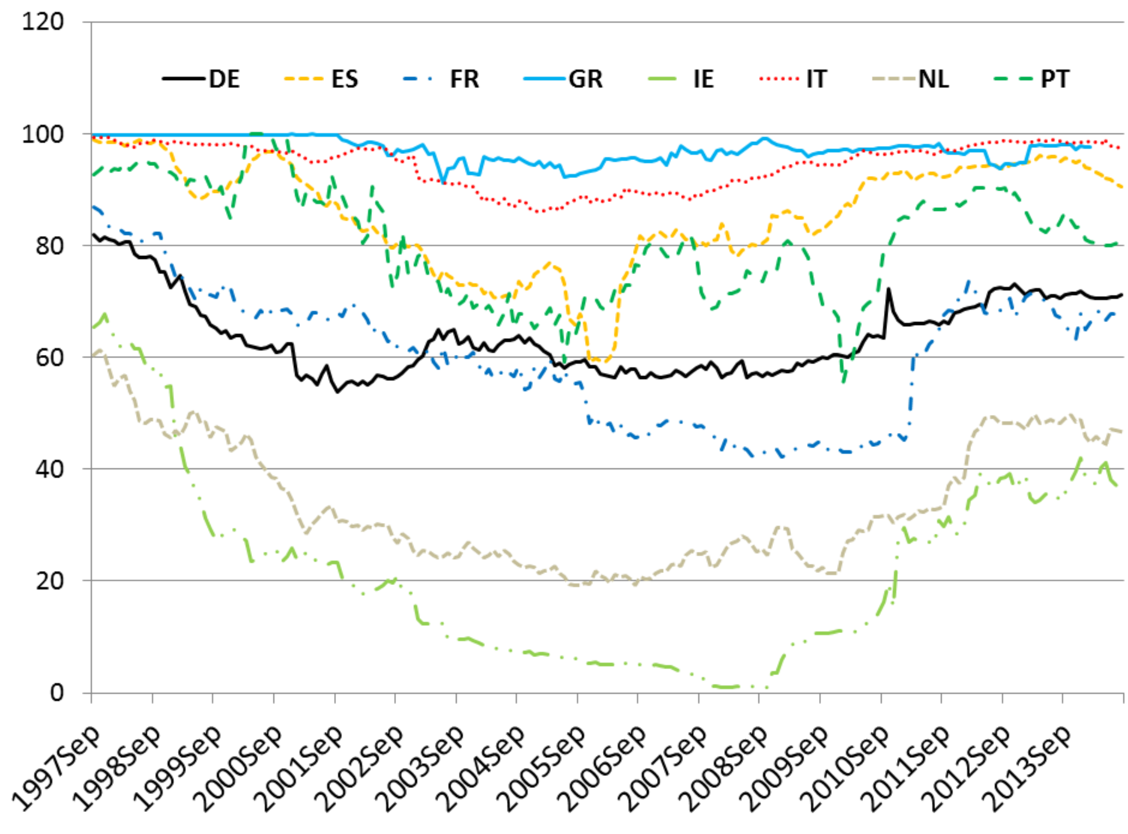


Source: EBA Stress Test 2011. Home bias measure as defined in Coeurdacier and Rey (2012):

$$HomeBias = 1 - \frac{\text{Share of Foreign Sovereigns in Bank } b \text{ Sovereign Holding}}{\text{Share of Foreign Sovereign Bonds in the Global Portfolio}}$$

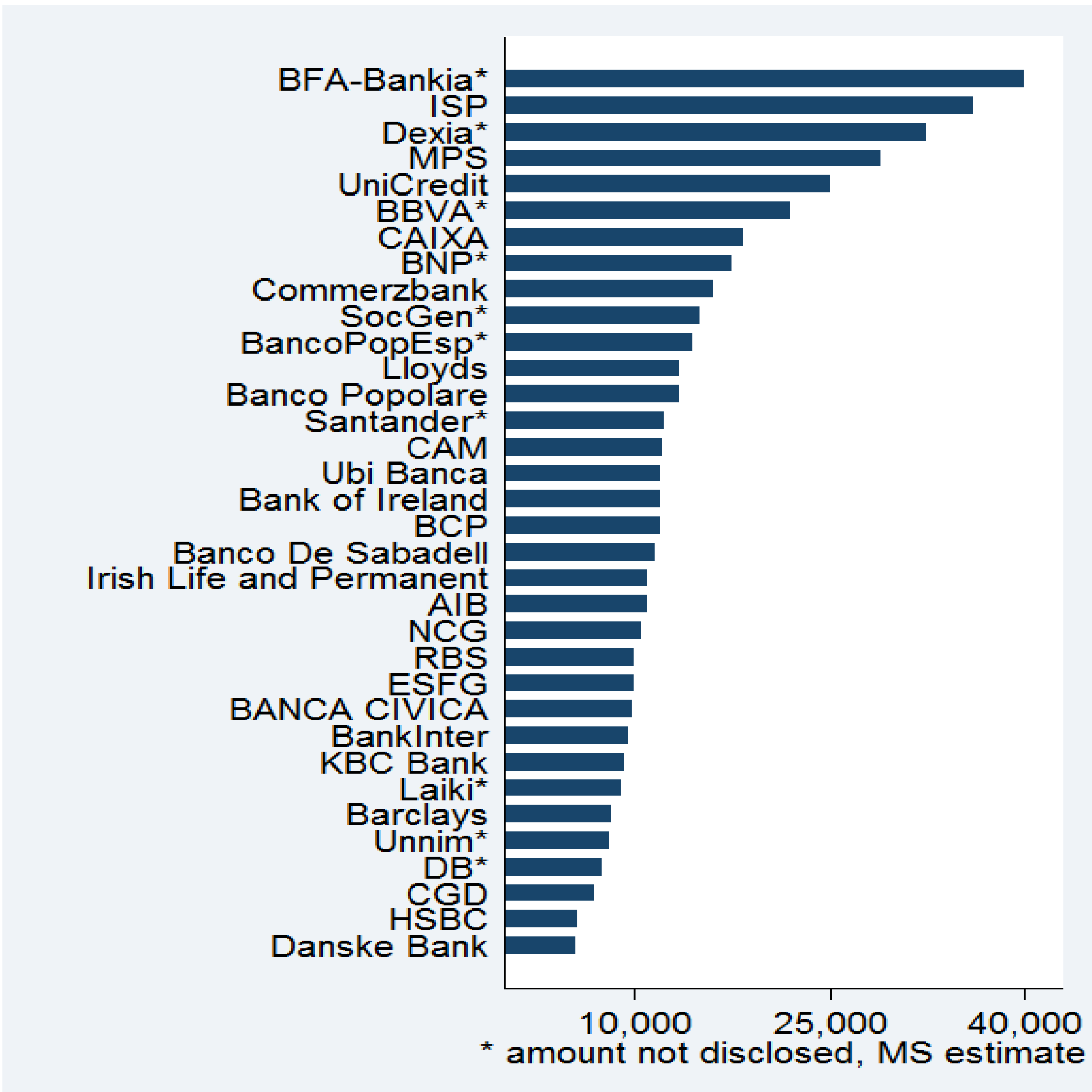
The *Global* portfolio in our case is the EEA30 portfolio, as we have sovereign exposure data for these countries only. When the home bias measure is equal to zero there is perfect diversification; when it is equal to one there is perfect home bias. Anything in excess of zero indicates some level of home bias.

Figure 2.3.: Aggregate Sovereign Home Bias by country, Sept 1997 – Sept 2014



Source: ECB Monetary Financial Institutions (MFI) aggregate statistics: ratio between Home and Total of "Securities other than shares" on the Government portfolio (MFI assets). These statistics are given at the country level for all financial institutions (excl. European Central Banks) with a changing composition (*i.e.* this is the raw data that does not take into account mergers&acquisitions and bank failures).

Figure 2.4.: LTRO(1+2) 3 year



3. Consumption Volatility and Borrowing Constraints in Small Open Economies

3.1. Introduction

The business cycle of emerging markets is quite different from that of developed economies, the most striking difference being that consumption is more volatile than output in emerging economies whereas the opposite is true in developed countries. We rationalize this phenomenon by introducing borrowing constraints in an otherwise standard small open economy model; the purpose is to characterize an economy that is borrowing from abroad but does not have access to a full set of state contingent contracts. Domestic agents are only able to borrow up to a certain fraction of the expected next-period value of their collateral as in Kiyotaki and Moore (1997). With the value of collateral being procyclical, agents are able to consume more than what they produce after a positive TFP shock, making consumption more volatile than output. The main model's implication is that a better ability to borrow, namely a larger loan-to-value (LTV) ratio, leads to a greater consumption volatility relative to output.

When we bring this model's implication to the data, we use indices of financial development and lending regulation to proxy for the loan-to-value ratio; we do so because the theory of corporate finance establishes a link between the two:[1] in the simplest model of credit allocation under limited enforcement, an agent can choose between running a project that has a high probability of success and another one that yields some private benefits and has a smaller probability of success. One outcome of this agency problem is that a greater ability to extract private benefits is associated with a reduced capability to pledge income which translates into a lower LTV ratio.

We then proceed to empirically test the relationship between various indices of financial development and relative consumption volatility, finding that the model's implication is supported by the data: in emerging countries, deeper capital markets and more lending-friendly regulation lead to greater volatility of consumption relative to output; on the contrary, in developed economies, these indicators of financial and regulatory development are either exerting no effect or actually stabilizing consumption relative to output. This empirical dichotomy between emerging and developed countries is in line with our modeling choice of characterizing an emerging country that is subject to borrowing constraints.

Another dichotomy emerges between the two indices of financial development we use: on the one side, deeper capital markets increase the relative consumption volatility in emerging countries but not in developed ones; on the other hand, more credit channeled by banks

[1] See Tirole (2010).

reduces the relative consumption volatility in developed countries while it has no effect in emerging economies.

In a standard open economy model with stationary TFP processes, the complete market allocation involves consumption being less volatile than output.[2] Usually financial globalization and financial development are believed to bring countries closer to the complete market benchmark which allows to achieve high levels of consumption risk sharing and low levels of relative consumption volatility. However, this paper shows both theoretically and empirically that financial development may actually lead to the opposite and unwanted result. From the model's point of view, more financial development translates into a greater ability to borrow against collateral which leads to more procyclical net debt (more countercyclical net exports) and thus more volatility in consumption relative to output.

Moreover, our findings suggest that the destabilizing effect of financial development is only at work among emerging economies whereas developed countries are not harmed by it. In addition, it also appears that, among emerging countries, it is more desirable to develop the domestic banking sector instead of the domestic equity market because the development of the latter significantly increases relative consumption volatility while the former does not.

A vast body of theoretical models have been proposed to rationalize this consumption volatility pattern of emerging markets: Aguiar and Gopinath (2007) rely on trend growth shocks which ultimately make permanent income more volatile than transitory income;

[2] In practice, consumption risk sharing is achieved through procyclical net exports: when the domestic economy is hit by a negative TFP shock it borrows from abroad in order to smooth consumption; this requires the domestic economy to import more goods from abroad by accumulating liabilities.

Neumeyer and Perri (2005) and Arellano (2008), although with different modeling strategies, deliver the above result through countercyclical interest rates. More similar to our analysis is Mendoza (2010): motivated by explaining some key facts about sudden stops, he generates high consumption volatility by interacting disturbances in interest rate, price of imported intermediate goods and TFP which get amplified by a collateral constraint.[3] Even though our model shares some features that characterize sudden stops, our model is geared towards capturing standard business cycles frequency events instead of sudden stops and surges, which are considered tail events.[4]

A lot of attention has been devoted to the links between financial development and growth,[5] but relatively less emphasis has been directed towards the link between financial development and consumption volatility. On the theoretical side, Aghion, Bacchetta and Banerjee (2004) show that the relationship between financial development and stability is not monotonic. Levchenko (2005) stresses that financial liberalization greatly benefit agents with direct access to international financial markets while it can generate higher consumption volatility for agents without access while Leblebicioğlu (2009) points out that financial integration may induce consumption to react more to TFP shocks than under autarky. Other papers, such as Baxter and Crucini (1995) and Heathcote and Perri (2002), also study how different degrees of financial integration affect international risk sharing and the transmission of business cycles.

[3] See also Akinci and Chahrour (2014) for a model that displays sudden stops and leverage cycles with borrowing constraints and news shocks.

[4] See Forbes and Warnock (2012) for a detailed empirical analysis of sudden stops and surges.

[5] See for instance Aghion, Howitt and Mayer-Foulkes (2005), King and Levine (1993), Levine, Loayza and Beck (2000) and Rajan and Zingales (1998).

On the empirical side, there is a number of papers that analyze the link between financial development and macroeconomic volatility. Loayza and Ranciere (2005) and Ranciere, Tornell and Westermann (2006) provide evidence on the contrasting effects of financial development which can bring both higher short-run volatility and greater long-run growth. Closer in spirit to our research question, Fulford (2011), Kose, Prasad and Terrones (2003), Kose, Prasad and Terrones (2007) and Bekaert, Harvey and Lundblad (2006) study the impact of financial development and financial liberalization on consumption volatility. Fulford (2011) shows how access to credit creates consumption booms in the short run, followed by lower consumption in the long run. Kose, Prasad and Terrones (2003) document that, especially among emerging markets, financial openness is associated with an increase in relative consumption volatility, which is in contrast with the notion that financial integration improves consumption risk sharing. Similarly, Kose, Prasad and Terrones (2007) highlight that financial globalization has opposite effects on industrial and emerging economies: it improves risk sharing among industrial countries whereas it reduces risk sharing among emerging markets. Bekaert, Harvey and Lundblad (2006) restrict the effect of financial liberalization to be homogeneous across industrial and emerging economies and obtain that financial liberalization is associated with lower relative consumption volatility.

Finally, our work shares similar results with Aizenman and Jinjarak (2009) and Cesa-Bianchi, Cespedes and Rebucci (2015) which study the link between international capital flows, house prices appreciation and financial conditions: Aizenman and Jinjarak (2009) find that in non-OECD countries there is a strong positive association between current account deficits and real estate appreciation, the more so the greater financial depth is in the specific country; Cesa-Bianchi, Cespedes and Rebucci (2015) document that exogenous changes in global liquidity have a much stronger impact on house prices and consumption in emerging markets than in advanced economies.

The paper proceeds as follows. Section II introduces the model; Section III presents the model's impulse responses and testable implications while Section IV describes the empirical methodology and the data. Section V shows the empirical results and Section VI concludes.

3.2. Model

Households. The representative household has GHH utility, $u(C_t, h_t) = \frac{[C_t - \Psi_t h_t^{\nu}]^{1-\sigma}}{1-\sigma}$, where C is consumption, h is hours worked.[6] Each household has K_t units of capital, which he can sell at price q_t or rent out to firms which will correspond d_t units of final good as dividends for each unit of borrowed capital. Moreover, each household can borrow internationally at the world interest rate, $1 + r$; however, the amount of borrowing cannot exceed a fraction χ of the expected next-period value of capital owned; χ is usually refereed to as the loan-to-value ratio. Capital here plays a dual role: it is both a factor of production and collateral against which to borrow; moreover, it depreciates at rate δ and each household can decide to invest the amount I_t in new capital, where $I_t = K_{t+1} - (1-\delta)K_t$; this process of capital creation however depletes some real resources, the more so the faster the rate of

[6]In Greenwood, Hercowitz and Huffman (1988), Ψ_t is a constant term while here $\Psi_t = \Psi X_t$, where X_t is the deterministic trend component the economy; this modification has to be introduced to make hours worked stationary.

capital creation is. In the spirit of Abel and Blanchard (1983), the cost of adjusting capital is convex in investment: $\Phi(K_{t+1}, K_t) \equiv \frac{\phi}{2}\left(\frac{K_{t+1}}{\gamma K_t} - 1\right)^2 K_t$.

The flow budget constraint, the law of motion of capital and the borrowing constraint for the representative household take the form

$$(1+r)B_t + C_t + +I_t + \Phi(K_{t+1}, K_t) \leq W_t h_t + d_t K_t + B_{t+1} \ ; \ \lambda_t$$

$$K_{t+1} \leq I_t + (1-\delta)K_t \ ; \ q_t\lambda_t$$

$$B_{t+1} \leq \chi E_t[q_{t+1}K_{t+1}] \ ; \ \mu_t$$

Firms. The representative firm produces final good Y_t by employing labor and capital according to the labor-augmenting production function $Y_t = z_t(X_t h_t)^{\alpha}(K_t)^{1-\alpha}$, where z_t is a stationary productivity shock and X_t is a deterministic trend component that evolves according to the process $X_{t+1} = \gamma X_t$, where $\gamma > 1$.

Transformed Model. It is useful to transform upper case variables into stationary variables expressed in units of effective labor. Thus, lower case variables, such as c_t, b_t, w_t, q_t, d_t, y_t, k_t, i_t, are expressed in units of effective labor; for instance, $c_t = C_t/X_t$.

As a result, the period utility of the representative household becomes $u(C_t, h_t) = \frac{X_t^{1-\sigma}[c_t - \Psi h_t^{\nu}]^{1-\sigma}}{1-\sigma}$

while budget constraint, law of motion of capital and borrowing constraint are rewritten as

$$(1+r)b_t + c_t + i_t + \frac{\phi}{2}\left(\frac{k_{t+1}}{k_t} - 1\right)^2 k_t \leq w_t h_t + d_t k_t + \gamma b_{t+1} \;;\; \lambda_t$$

$$\gamma k_{t+1} \leq i_t + (1-\delta)k_t \;;\; \lambda_t q_t$$

$$b_{t+1} \leq \chi E_t[q_{t+1}k_{t+1}] \;;\; \mu_t$$

and finally the production function becomes $y_t = z_t h_t^{\alpha} k_t^{1-\alpha}$.

The representative household chooses sequences of consumption, labor, capital, investment and debt to maximize expected lifetime utility subject to the above set of constraints. The lagrangean associated to this problem is

$$\begin{aligned}\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t X_t^{1-\sigma} \Big\{ \frac{\left(c_t - \Psi h_t^{\nu}\right)^{1-\sigma}}{1-\sigma} &+ \lambda_t[w_t h_t + d_t k_t + \gamma b_{t+1} - (1+r)b_t - c_t - i_t + \\ &- \frac{\phi}{2}\left(\frac{i_t - (\delta+\gamma-1)k_t}{\gamma k_t}\right)^2 k_t + \\ &+ q_t(i_t + (1-\delta)k_t - \gamma k_{t+1})] + \\ &+ \mu_t[\chi q_{t+1} k_{t+1} - \gamma b_{t+1}] \Big\}\end{aligned}$$

and the first order conditions with respect to c_t, h_t, i_t, k_{t+1} and b_{t+1} are

$$[c_t - \Psi h_t^{\nu}]^{-\sigma} = \lambda_t$$

$$[c_t - \Psi h_t^{\nu}]^{-\sigma}\, \Psi \nu h_t^{\nu-1} = w_t \lambda_t$$

$$q_t = 1 + \frac{\phi}{\gamma}\left(\frac{i_t - (\delta + \gamma - 1)k_t}{\gamma k_t}\right)$$

$$\gamma \lambda_t q_t = E_t \left\{ \tilde{\beta}\lambda_{t+1}\left[d_{t+1} + (1-\delta)q_{t+1} + \frac{\phi}{2\gamma^2}\left(\left(\frac{i_{t+1}}{k_{t+1}}\right)^2 - (\delta + \gamma - 1)^2\right)\right] + \chi \mu_t q_{t+1} \right\}$$

$$\gamma \lambda_t = \mu_t(1+r) + \tilde{\beta}(1+r)E_t \lambda_{t+1}$$

where we define $\tilde{\beta} \equiv \beta\gamma^{1-\sigma}$ and we do not specify the extra Kuhn-Tucker conditions as we assume that the credit constraint is binding in the steady state and in a small neighborhood of it. The second to last equation is the Capital Euler Equation, which states that the marginal cost (in terms of lower consumption today) of postponing consumption in the future is equal to the marginal benefit of investment: by investing one unit of capital, in the next period agents gain the real interest rate, they face a lower adjustment cost of capital and they relax the borrowing constraint as the value of collateral increases. The representative firm maximizes profits taking prices as given and so it ends up paying factors their marginal products: $w_t = \alpha y_t / h_t$ and $d_t = (1-\alpha) y_t / k_t$.

The steady state equations and the log-linear approximation of the model's dynamics are displayed in Appendix B.1 and B.2 respectively. Few facts about the steady state ought to be underlined. First, since the pioneering work of Obstfeld and Rogoff (1995) it was clear that simple open economy models could not pin down a steady state level of net foreign assets; thus, in order to study dynamic responses, one has to assume an initial value for net foreign assets. However, any temporary shock would lead to a new steady state. Our model does not suffer from this problem as the borrowing constraint pins down a unique steady state level of net foreign assets and any stationary shock will induce stationary dynamic responses. The use of always binding borrowing constraints thus adds to the list of stationarity-inducing devices studied in Schmitt-Grohé and Uribe (2003).

Second, given $\lambda > 0$, the credit constraint multiplier $\mu = \lambda(\frac{\gamma}{1+r} - \tilde{\beta})$ is positive if and only if $\gamma^{\sigma} > \beta(1+r)$, which does not necessarily require the country to grow faster than the world interest rate; the more impatient or risk averse agents are, the lower is the lower bound on the growth rate.

Finally, as shown in Appendix B.1, the steady state level of capital is decreasing in χ : a better ability to borrow (larger χ) increases the collateral value of capital, captured by $\chi\frac{\mu}{\lambda}$, as agents can borrow more against the same level of capital. Therefore agents need to accumulate less collateral in order to frontload consumption.

3.2.1. Calibration

We calibrate the model at quarterly frequency; we set the world interest rate to 3%, the capital depreciation rate to 8%, and $\Psi = 1$. Each of the remaining seven parameters is allowed to vary on a grid:

$\gamma \in [1, 1.05]$, $\alpha \in [0.4, 0.6]$, $\beta \in [0.85, 0.995]$, $\varepsilon_{hw} \in [0.2, 4]$, $\sigma \in [1, 5]$, $\chi \in [0.01, 0.99]$ and $\phi \in [0.02, 4]$, where ε_{hw} is the Frisch elasticity of labor supply which equals to $\frac{1}{\nu - 1}$.

We discard the calibrations that do not satisfy the steady state restrictions on both multipliers; more specifically, in order for the economy to be constrained in the transitional dynamics, we need it to be constrained at the steady state as well, since we are solving the model linearly around the steady state. Thus, we require the borrowing constraint multiplier to be positive in steady state, $\mu = \left(\frac{\gamma}{1+r} - \tilde{\beta}\right)\lambda > 0$, and we also make sure that the marginal utility of consumption is positive, $\lambda > 0$.

For each calibration that satisfies these restrictions, we simulate the model and we collect the second moments that we want to match; these are the same moments targeted by Aguiar and Gopinath (2007). Table 3.1 shows both the moments estimated by Aguiar and Gopinath (2007) and our estimates based on a sample of 100 countries instead of 13, using annual data.[7] Finally, we pick the calibration that minimizes the Loss Function $L = \sum_i \omega_i \left(\frac{\tilde{m}_i - m_i^*}{m_i^*}\right)^2$, where m_i^* is our estimate of the $i-th$ moment, $\tilde{m}_i$ is the simulated one and ω_i is a weight; the choice to minimize a sum of squared *percentage* deviations instead of squared deviations is motivated by the following fact: the moments that we target are both correlations that lie in the $[-1, 1]$ interval and ratios of standard deviations that range from zero to $+\infty$, so that a reasonable measure of distance that does not favor reaching one target instead of another has to scale the moments to make them comparable. For instance, if we were to minimize the sum of squared deviations, we would end up picking a calibration that targets more closely ratios of standard deviations instead of correlations; indeed, the largest squared deviation admissible for a correlation is $(-1-1)^2 = 4$ while the

[7] The countries we consider here are the bottom 75% by trend component of the log of real gdp averaged from the beginning of the sample to 1990.

largest squared deviation admissible for a ratio of standard deviations is infinite. On the contrary, minimizing a sum of squared percentage deviations attenuates this problem.

If we weigh each squared percentage deviation equally, we obtain the following calibration, which we will refer to as the baseline calibration: $\alpha = 0.4$, $\beta = 0.985$, $\gamma = 1.008$, $\varepsilon_{hw} = 0.45$, $\phi = 1.9$, $\sigma = 2$, $\chi = 0.99$ and $\rho_z = 0.68$.

The model matches the moments well, but cannot perfectly match the large values of both $\sigma(C)/\sigma(Y)$ and $\sigma(I)/\sigma(Y)$ at the same time. This tradeoff can be understood by thinking about the role played by the capital adjustment cost: if we want to increase consumption volatility we need the collateral value of capital to be more procyclical and this can be attained more easily with larger spikes in the price of capital; this last result arises from a larger capital adjustment cost (higher ϕ) which however tends to reduce investment volatility by penalizing spikes in investment.

Indeed, if we were to exactly match the relative standard deviation of consumption by allowing ϕ to vary from the baseline calibration, we would need $\phi = 2.4$ instead of 1.9. This result supports our intuition on the role played by the capital adjustment cost.

3.3. Impulse Responses and Model's Implications

The impulse responses to a 1% increase in TFP under the baseline calibration,[8] which involves the highest possible loan to value ratio ($\chi = 0.99$), are shown in Figure 3.1 with the solid blue lines. Additionally, the dashed green lines depict the responses to the same

[8]We set $\rho = 0.95$ in order to deliver a cleaner visualization of the dynamics.

shock when the model is calibrated with a lower ability to borrow, $\chi = 0.7$, while keeping the other parameters unchanged.

Notice that every series but consumption and net debt behave in very similar ways. As a result, the two calibrations imply a very similar collateral appreciation after a positive TFP shock. However, the high χ economy is able to increase borrowing by more and therefore displays a greater jump in consumption relative to the economy with a lower loan-to-value ratio (lower χ).

This result provides the intuition for the positive relationship between ability to borrow and relative consumption volatility that we show in Figure 3.2.

Another interesting implication has to do with the relationship between the persistence of the TFP process and the relative consumption volatility. Figure 3.3 shows how this relationship is not monotonic: on the one side, a very transitory process gives households little incentives for an investment boom after a one time increase in TFP; the moderate increase in investment translates into a small collateral appreciation and thus a small jump in consumption. At the other extreme, when TFP is close to a unit root, households still have little incentives to generate an investment boom as they can spread investment over time and still take advantage of higher TFP while not having to incur large adjustment costs; it is only at an intermediate level of persistence that households have the greatest incentive to produce an investment boom since they know that soon enough TFP will revert to trend. In this intermediate situation collateral is very procyclical which translates into high relative consumption volatility.

Figures 3.2 and 3.3 are obtained by changing the parameter values of χ and ρ respectively, away from the baseline calibration and simulating the relative standard deviation of consumption to output.

3.4. Empirical Methodology and Data

3.4.1. Empirical Methodology

In order to assess the causal effect of financial development on consumption volatility relative to output we have to consider issues of reverse causality by which countries with very volatile consumption paths may decide to change financial or business regulation in order to stabilize the economy. Our identification strategy relies on an instrumental variable approach: we use the country's legal origin as an instrument for the country specific index of financial development or lending regulation. We argue that the country's legal origin is exogenous to consumption volatility while it affects relative consumption volatility only indirectly by shaping the specific financial and lending regulation of the country. Each Table displays tests for the correlation of the excluded instruments with the error term (Hansen J-test of overidentifying restrictions) and for the power of our instruments (under-identification test and Kleibergen-Paap F test of the excluded instruments in the first stage regressions).

La Porta et al. (1999) show cross-country evidence that a country's legal origin is a key determinant in shaping property rights, business regulation and development of both equity and bond markets. French civil law countries are characterized by weaker investor protection and less developed capital markets compared to common law countries. Previously, Levine, Loayza and Beck (2000) and Levine (2002) have used the legal origin of a country as an instrument for the country's financial development in order to study the causal effect of finance on growth in a cross section of countries.

Consider the following equations describing this two-way interaction between country i's relative consumption volatility, $relstd_i$, and lending regulation, REG_i:

$$\begin{aligned} relstd_i =& \alpha_1 + \beta REG_i + \epsilon_i \\ REG_i =& \alpha_2 + \gamma relstd_i + \delta LEGOR_i + u_i \end{aligned}$$

where the coefficient of interest is β and the second equation illustrates the endogeneity of regulation: it can be affected by both the legal system, $LEGOR_i$, and consumption volatility. By manipulating the above equation we can express $relstd_i$ and REG_i as a function of the two disturbance terms ϵ_i and u_i and the legal origin index $LEGOR_i$:

$$\begin{aligned} relstd_i &= \frac{1}{1-\gamma\beta}(\alpha_1 + \beta\alpha_2) + \frac{1}{1-\gamma\beta}\epsilon_i + \frac{\beta}{1-\gamma\beta}u_i + \frac{\gamma\beta}{1-\gamma\beta}LEGOR_i \\ REG_i &= \frac{1}{1-\gamma\beta}(\gamma\alpha_1 + \alpha_2) + \frac{\gamma}{1-\gamma\beta}\epsilon_i + \frac{1}{1-\gamma\beta}u_i + \frac{\delta}{1-\gamma\beta}LEGOR_i \end{aligned}$$

where we assume that $E(\epsilon_i u_i) = 0$, $E(LEGOR_i \epsilon_i) = 0$, $E(LEGOR_i u_i) = 0$ and $E(relstd_i u_i) = 0$.

We are interested in comparing the coefficients of the OLS regression with that of the IV regression, whose probability limits are

$$plim\ \hat{\beta}_{OLS} = \frac{Cov(REG, relstd)}{Var(REG)}$$
$$plim\ \hat{\beta}_{IV} = \frac{Cov(LEGOR, relstd)}{Cov(LEGOR, REG)}$$

which, after some algebra, yield

$$plim\ \hat{\beta}_{OLS} = \beta + \frac{\gamma(1-\beta\gamma)\sigma_{\epsilon}^2}{Var(REG)}$$
$$plim\ \hat{\beta}_{IV} = \beta$$

where $Var(REG) = \gamma^2\sigma_{\epsilon}^2 + \sigma_u^2 + \delta^2 Var(LEGOR)$. For stability $\beta\gamma < 1$, so that the sign of the bias will depend on whether countries with unexpectedly high consumption volatility tend to improve ($\gamma > 0$) or worsen ($\gamma < 0$) lending regulation. In the former scenario, the OLS coefficient would overestimate the true effect while in the latter it would underestimate it. After each IV regression, we test for the correlation of excluded instruments with the error term (Hansen J-test of overidentifying restrictions), and we assess the power of our instruments (under-identification test and Kleibergen-Paap F Statistic of the excluded instruments in the first stage regressions).

3.4.2. Data

Annual data from 1960 to 2012 on real consumption and real GDP are obtained from the World Bank database.[9] Since we are interested in analyzing the volatility of cyclical components, we filter these time series with the HP filter. Ravn and Uhlig (2001) proved that the filter parameter for annual data is 6.25 given a value of 1600 for quarterly data. We drop from the sample countries that do not have at least 18 consecutive observation for either consumption or output. We choose this cutoff value as it appears to be a natural threshold in the data. Results are robust if we only consider countries with at least 30 consecutive observations.

The dependent variable is the relative standard deviation of consumption to output, *relstd*. It is obtained by filtering the log of both series, computing their standard deviations and finally taking the ratio of the two. In this paper, for the sake of computing the relative standard deviation of consumption to output, we start our sample in 1990. We do so because prior to 1990 most of the countries in our sample were not financially liberalized; both de jure and de facto dates in which countries lift capital controls are available in Ranciere, Tornell and Westermann (2006). As the main results in our model come from movements in the current account, it is crucial to focus on times in which countries were allowing for

[9] Consumption includes the market value of all goods and services, including durable products (such as cars, washing machines, and home computers), purchased by households. It excludes purchases of dwellings but includes imputed rent for owner-occupied dwellings. It also includes payments and fees to governments to obtain permits and licenses. Here, household consumption expenditure includes the expenditures of nonprofit institutions serving households, even when reported separately by the country. Investment is gross fixed capital formation which includes land improvements (fences, ditches, drains, and so on), plant, machinery, equipment purchases and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings.

financial claims to move in and out of the borders.

We then merge this dataset with financial development indicators and data on the legal origin of each country. The former are obtained from the World Bank Database, while the latter come from La Porta et al. (1999). The final sample contains 130 countries. They are evenly split among low, low-middle, middle and high income countries, as defined by the World Bank.

Next, we describe the financial development indicators in use: Business Regulation, Investor Protection, Credit Information, Capitalization and Bank Credit. The first index is taken from La Porta et al. (1999) while the others are taken from the World Bank Database, whose definitions we closely follow.[10] The business regulation index is dated 1997, Capitalization and Bank Credit are time averages over the period 1960-2011 whereas the other regulatory indices, namely Investor Protection and Credit Information, are available starting in 2004 on a yearly basis and they very rarely change over time.

In the regressions, each of the financial development indices is normalized by its standard deviation to simplify the interpretation of the results.

Business Regulation. This is a rating of regulation policies related to opening and keeping open a business. The index ranges from 1 to 5, with higher numbers indicating that "regulations are straight-forward and applied uniformly to all businesses and that regulations are less of a burden to businesses".

[10] http://www.doingbusiness.org/methodology/methodology-note

Strength of Investor Protection. This index is the average of the Extent of Disclosure index, the Extent of Director Liability Index and the Ease of Shareholder Suit Index: the Extent of Disclosure index ranges from 0 to 10 with higher values indicating greater disclosure regarding conflicts of interest among controlling shareholders; the Extent of Director Liability Index ranges from 0 to 10, with higher values indicating greater liability of directors and members of the supervisory board of a company; finally, the Shareholders Suits Index ranges from 0 to 10, with higher values indicating greater powers of shareholders to challenge transactions undertaken by the company managers.

Credit Information. The index ranges from 0 to 6, with higher values indicating the availability of more credit information, from either a public credit registry or a private credit bureau, to facilitate lending decisions. Whether public or private, a credit registry is defined as a database that collects information on the creditworthiness of borrowers, both individuals and firms.

Capitalization. This variable represents the market value of domestic companies listed on the own country's stock exchanges as a percentage of GDP.

Bank Credit. This variable equals the domestic credit provided by the banking sector as a percentage of GDP.

The first three indices, namely Business Regulation, Strength of Investor Protection and Credit Information, are chosen because they capture the nature of the limited enforcement friction behind the credit constraint we use: standard models of credit allocation under limited enforcement[11] hinge on the fact that a better regulatory system that defends creditors' rights and limits expropriation threats enables creditors to obtain larger loans for a given value of the collateral they post; in other words, a regulatory environment that protects creditors' rights should give rise to a greater loan-to-value ratio.

On the other hand, the last two indices, namely Capitalization and Bank Credit, are chosen because they are the most commonly used indices of financial development in the finance and growth literature.[12]

Table 3.2 shows summary statistics for some key variables we use; note that the regulatory variables shown here are not yet normalized by their respective standard deviations. Importantly, we classify countries as Emerging if they belong to the bottom 75% of the pre-1990 income distribution. Since we want to classify countries according to the distribution of a predetermined variable, the initial output distribution considers the average from 1960 to 1990 of the trend component of the log of real GDP. Countries are then classified as Developed if they fall in the top 25% of the initial output distribution.

A crucial assumption of the model is that agents in the economy have always the desire to borrow, both in steady state and along the transition path. Therefore, we need to check whether this assumption has some bearing in the data. We do so by showing some summary statistics taken from the dataset compiled by Lane and Milesi-Ferretti (2007). It appears that all the non-OECD countries but oil exporting ones and few asian countries, namely

[11] See Tirole (2010).
[12] See Levine (2002).

China, Taiwan, Singapore and Hong Kong, are on average net borrowers, which is in line with our assumption. Table 3.3 shows the relative standard deviation of consumption to output and the time average of net foreign assets over GDP for Emerging and Developed countries.

3.5. Results

In each regression, the respective financial or regulatory index is instrumented for by the set of dummies indicating the country' s legal origin. Additionally, we control for the initial level of GDP;[13] this choice is motivated by two reasons: first, richer countries can afford to implement larger stabilizing programs that reduce consumption volatility; second, once a country is rich enough, households may decide to accumulate buffer-stock savings in order to partially insulate consumption streams from exogenous disturbances.

Table 3.4 shows the causal effects of different indices of financial development on relative consumption volatility when coefficients are not allowed to vary depending on whether a country is Emerging or Developed. The regressions point to the fact that facilitating borrowing and lending causes the standard deviation of consumption relative to output to increase. The channel identified by the theoretical model suggests that better lending regulation allows agents to borrow more after a positive TFP shock, thus generating greater consumption volatility.

For the case of Investor Protection, a one standard deviation increase in this index generates

[13]More precisely, the time average of the trend component of log real GDP per capita from 1960 to 1990.

on average an increase in the standard deviation of consumption relative to output by 69 percentage points. Notice however that the Kleibergen-Paap F Statistic points to a weak instruments problem; next, we show that this problem can be overcome by allowing for the effect of financial development on consumption volatility to depend on whether the country is Emerging or Developed.[14]

Table 3.5 below shows the heterogeneous impact of lending regulation and financial development on relative consumption volatility depending on whether a country is Emerging or Developed: the detrimental effect of better lending regulation on relative consumption volatility applies only to emerging countries, not to developed ones. For emerging markets, the only coefficient that is not negative and significant is that of Bank Credit, suggesting that the role of banks in lending to households and businesses is not destabilizing, while funding channeled through the capital market is. Regarding developed countries, most of the financial development indicators do not significantly affect the relative consumption volatility, and better credit information and a more developed banking system tend to stabilize fluctuations of consumption relative to output.[15]

These finding are in line with the assumptions behind our model: the ability to borrow amplifies consumption fluctuation only to the extent that financial markets are not complete, the representative household is borrowing constrained and the country is a net borrower in steady state. These assumptions are more relevant for emerging economies than for devel-

[14] Tables 3.8, 3.9 and 3.10 show the first stage regressions.

[15] The reliability of the regressions for developed countries is however undermined by weak instruments problems.

oped ones and our findings support this perspective.

Moreover, notice that the regressions for emerging markets that use Capitalization and Credit Information successfully pass all the diagnostic tests, while the other three regressions suffer from weak instruments.[16]

Next, Table 3.6 shows that the previous results are robust to the inclusion of a larger set of controls that affect both consumption and output volatility. Here we mainly follow Kose, Prasad and Terrones (2007) in the choice of additional controls: government expenditure over GDP aims at capturing the potential reduction in consumption volatility due to the implementation of stabilization programs; volatility in terms of trade and net exports over GDP can affect both consumption and output volatility by altering the international competitiveness of the country. All the controls are computed on the pre-1990 period in order to avoid as much as possible the inclusion of additional simultaneity bias.[17]

In emerging economies, stock market capitalization and credit information are still the only two variables that significantly increase relative consumption volatility and that successfully pass the diagnostic tests. Notice also that adding further controls reinforces the main results: the coefficients of interest are indeed larger in Table 3.6 than in Table 3.5.

Finally, Table 3.7 provides some evidence on the direction of the OLS bias. By comparing the IV and OLS coefficients we notice that OLS largely underestimates the effect of financial development on the dependent variable when we use Investor Protection, Business

[16] Following Stock, Wright and Yogo (2002) we consider a value of the Kleibergen-Paap F Statistic below 10 as suggestive of weak instruments.

[17] Variables are obtained from the World Bank Database.

Regulation and Capitalization whereas it slightly overestimates the effects of Bank Credit and Credit Information.

3.6. Conclusion

We build a small open economy model with borrowing constrained agents in order to identify a channel through which stationary technology shocks can make consumption more volatile than output. The main implication of the model is that a better ability to borrow against collateral, namely a higher loan-to-value ratio, translates into greater consumption volatility relative to output. The theory of corporate finance establishes a negative relationship between the loan-to-value ratio and the borrower's ability to extract private benefits from running a project. We thus proxy the LTV ratio with indices pertaining to the quality of lending regulation. Then, we perform an empirical analysis to check whether the model's prediction is supported by the data. In order to avoid issues of reverse causality, we instrument each index of regulatory standards or financial development by the country's legal origin. We find that improvements in lending regulation and deeper domestic capital markets lead to an increase in the relative volatility of consumption to output; moreover, this effect is only present in low and middle income economies. Financial globalization and financial development are often believed to benefit emerging economies in particular; while it is well documented that financial development has positive effects on output growth, its impact on volatility has received less attention in the literature. To this regard, our findings suggest that deeper capital markets and more lending friendly regulation do not improve consumption risk sharing in emerging markets; instead they increase the ratio of consumption volatility to output volatility, in accordance with the prediction of our model.

Table 3.1.: Empirical Moments and Simulated Moments for Emerging Economies

	Empirical Moments (AG)	Empirical Moments (our sample)	Simulated Moments
$\sigma(C)/\sigma(Y)$	1.45	1.49	1.33
$\sigma(I)/\sigma(Y)$	3.91	4.2	3.13
$\sigma(NX/Y)$	3.22	3.46	4.02
$\rho(C,Y)$	0.72	0.56	0.65
$\rho(I,Y)$	0.77	0.49	0.63
$\rho(NX/Y,Y)$	-0.51	-0.1	-0.74

Table 3.2.: Summary Statistics by Income Level

	Full Sample		**Emerging**		**Developed**	
Variable	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Relative St.Dev. of Consumption	1.38	0.72	1.49	0.78	0.98	0.29
Business Regulation	2.85	0.86	2.62	0.81	3.63	0.63
Investors Protection	4.92	1.60	4.61	1.41	6.03	1.79
Credit Information	2.60	2.15	2.22	2.02	4.00	2.05
Capitalization	42.62	46.32	31.59	34.81	81.64	60.00
Bank Credit	46.89	35.33	38.41	26.16	93.85	42.54
log(Initial GDP)	7.52	1.48	6.87	1.07	9.51	0.35
N	130		102		28	

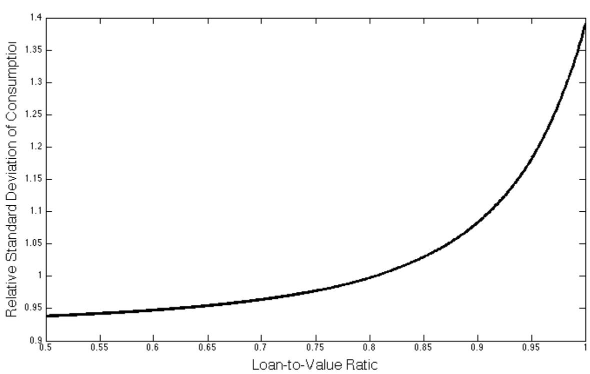


Figure 3.2.: LTV ratio and $\sigma(C)/\sigma(Y)$

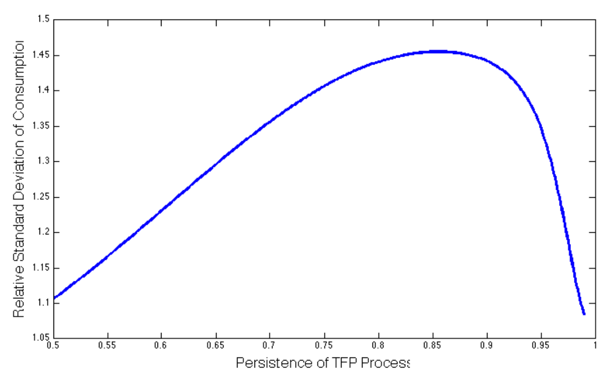


Figure 3.3.: TFP persistence and $\sigma(C)/\sigma(Y)$

Table 3.3.: Summary Statistics by Income Level

	Emerging		**Developed**	
Variable	Mean	St.Dev.	Mean	St.Dev.
Relative St.Dev. of Consumption	1.49	0.78	0.98	0.29
Average NFA/GDP	-0.44	0.52	0.19	1.07
N	102		28	

Table 3.4.: The Effect of Regulation on Consumption Volatility

	All Countries				
	relstd	relstd	relstd	relstd	relstd
Investor Protection	0.689**				
	(0.307)				
Business Regulation		0.690**			
		(0.304)			
Capitalization			0.769**		
			(0.307)		
Bank Credit				-0.338**	
				(0.166)	
Credit Info					-0.305
					(0.253)
Initial GDP	-0.393***	-0.563***	-0.497***	-0.054	-0.107
	(0.092)	(0.137)	(0.146)	(0.092)	(0.117)
N	115	109	86	115	115
p-val of Hansen	0.292	0.347	0.826	0.032	0.017
p-val of Underid	0.008	0.008	0.006	0.282	0.046
K-P F stat	4.152	5.121	4.079	2.159	7.534

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5.: The Heterogeneous Effect of Regulation on Consumption Volatility

	Emerging					Developed				
	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd
Investor Protection	1.206**					0.369				
	(0.486)					(0.296)				
Business Regulation		1.667*					0.052			
		(0.999)					(0.177)			
Bank Credit			8.113					-0.343*		
			(13.98)					(0.190)		
Capitalization				0.628***					0.106	
				(0.238)					(0.118)	
Credit Info					0.398**					-0.879***
					(0.176)					(0.273)
Initial GDP	-0.540***	-1.119*	-2.400	-0.305*	-0.408***	-0.219	-0.548***	-0.067	-0.636***	0.241
	(0.184)	(0.572)	(3.821)	(0.160)	(0.120)	(0.474)	(0.194)	(0.352)	(0.214)	(0.308)
N	100	93	100	71	100	28	27	28	26	28
p-val Hansen	0.176	0.892	0.990	0.157	0.143	0.364	0.0879	0.441	0.114	0.683
p-val Underid	0.065	0.143	0.961	0.004	0.032	0.101	0.021	0.123	0.179	0.274
K-P F stat	2.819	1.818	0.094	34.08	20.02	2.865	4.127	3.542	1.719	6.673

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6.: The Heterogeneous Effect of Regulation on Consumption Volatility - Robustness

	Emerging					Developed				
	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd
Investor Protection	0.278					0.155^{**}				
	(0.347)					(0.074)				
Business Regulation		-0.037					-0.032			
		(0.654)					(0.207)			
Bank Credit			0.280					-0.347		
			(0.500)					(0.974)		
Capitalization				0.731^{**}					0.0780	
				(0.335)					(0.147)	
Credit Info					0.878^{**}					0.417
					(0.419)					(0.458)
Initial GDP	-0.091	-0.066	-0.124	-0.143	-0.525^{*}	-0.393^{*}	-0.535^{***}	-0.333	-0.448	-0.467
	(0.103)	(0.310)	(0.154)	(0.127)	(0.317)	(0.219)	(0.195)	(0.394)	(0.274)	(0.456)
G/Y	-0.026	-0.031	-0.035	-0.066	0.018	-0.041^{**}	-0.007	-0.026	-0.011	-0.023
	(0.025)	(0.038)	(0.033)	(0.047)	(0.042)	(0.019)	(0.031)	(0.049)	(0.020)	(0.019)
σ(G/Y)	0.145^{***}	0.118	0.133^{**}	0.441^{**}	0.082	0.093	-0.029	-0.116	0.058	0.108
	(0.055)	(0.076)	(0.054)	(0.189)	(0.065)	(0.107)	(0.103)	(0.556)	(0.097)	(0.129)
σ(TOT)	-0.000^{***}	-0.000^{*}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000	0.000	-0.000	-0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
σ(NX/Y)	0.247^{**}	0.299^{***}	0.290^{*}	0.265^{**}	0.313^{**}	0.270^{**}	0.313^{***}	0.196	0.318^{***}	0.470
	(0.125)	(0.087)	(0.150)	(0.127)	(0.154)	(0.111)	(0.094)	(0.212)	(0.111)	(0.330)
N	68	65	68	45	68	23	23	23	23	23
p-val of Hansen	0.580	0.870	0.555	0.396	0.960	0.148	0.056	0.525	0.082	0.141
p-val of Underid	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.005	0.002
K-P F stat	220.9	162.3	54.13	13.46	39.46	70.91	18.19	68.70	13.68	100.4

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
G/Y stands for government expenditure over GDP, TOT stands for terms of trade, NX/Y stands for net export over GDP; σ(X) indicates the standard deviation of variable X.

Table 3.7.: The Effect of Regulation on Consumption Volatility - All Countries

	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS
	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd	relstd
Investor Protection	0.689^{**}	-0.0689								
	(0.307)	(0.0860)								
Business Regulation			0.690^{**}	-0.0725						
			(0.304)	(0.110)						
Capitalization					0.769^{**}	-0.0145				
					(0.307)	(0.0504)				
Bank Credit							-0.338^{**}	-0.297^{**}		
							(0.166)	(0.119)		
Credit Info									-0.305	-0.246^{**}
									(0.253)	(0.101)
Initial GDP	-0.393^{***}	-0.190^{***}	-0.563^{***}	-0.222^{***}	-0.497^{***}	-0.206^{***}	-0.0546	-0.0749	-0.107	-0.126^{*}
	(0.0922)	(0.0672)	(0.137)	(0.0712)	(0.146)	(0.0735)	(0.0917)	(0.0852)	(0.117)	(0.0725)
N	115	115	109	109	86	86	115	115	115	115
p-val of Hansen	0.292		0.347		0.826		0.032		0.017	
p-val of Underid	0.008		0.008		0.006		0.282		0.046	
K-P F stat	4.152		5.121		4.079		2.159		7.534	

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8.: First Stage Regressions - All Countries

	Investor Protection	Business Regulation	Stock Market Capitalization	Bank Credit	Credit Information
Initial GDP	0.292***	0.496***	0.381***	0.427***	0.322***
	(0.0634)	(0.0490)	(0.0918)	(0.0645)	(0.0649)
United Kingdom	0.817**	0.858***	0.871**	0.421	-0.166
	(0.360)	(0.295)	(0.427)	(0.302)	(0.267)
France	-0.0558	0.478*	0.0253	0.293	0.125
	(0.315)	(0.279)	(0.291)	(0.246)	(0.232)
Soviet Union	-0.0188	0.163	-0.0798	0.494*	-0.364
	(0.364)	(0.326)	(0.335)	(0.285)	(0.276)
Germany	-0.251		0.312	1.566**	0.745***
	(0.481)		(0.543)	(0.624)	(0.160)
Scandinavia		-0.145			
		(0.322)			
N	115	109	86	115	115

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9.: First Stage Regressions - Emerging Markets

	Investor Protection	Business Regulation	Stock Market Capitalization	Bank Credit	Credit Information
Initial GDP	0.349***	0.596***	0.392***	0.279***	0.365***
	(0.0945)	(0.0759)	(0.107)	(0.0671)	(0.0813)
United Kingdom	0.474			0.0684	-0.943***
	(0.308)			(0.224)	(0.242)
France	-0.188	-0.177	-0.819***	-0.0100	-0.656***
	(0.163)	(0.176)	(0.296)	(0.140)	(0.183)
Soviet Union	-0.138	-0.515**	-1.143***	-0.0384	-1.243***
	(0.135)	(0.243)	(0.314)	(0.117)	(0.167)
Germany		-0.465**	-0.475		
		(0.199)	(0.341)		
Scandinavia					
N	100	93	71	100	100

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10.: First Stage Regressions - Developed Countries

	Investor Protection	Business Regulation	Stock Market Capitalization	Bank Credit	Credit Information
Initial GDP	-0.0158	0.169	1.118*	-0.194	-0.246
	(0.631)	(0.290)	(0.548)	(0.700)	(0.641)
United Kingdom	1.331*	1.101***	1.231**	-1.694	-1.229**
	(0.709)	(0.346)	(0.566)	(1.013)	(0.551)
France	-0.0177	0.326	0.561	-1.374	-1.017*
	(0.644)	(0.349)	(0.473)	(0.901)	(0.562)
Soviet Union					
Germany		0.0281	0.107		
		(0.370)	(0.732)		
Scandinavia	0.371			-1.985**	-0.763***
	(0.567)			(0.777)	(0.178)
N	28	27	26	28	28

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

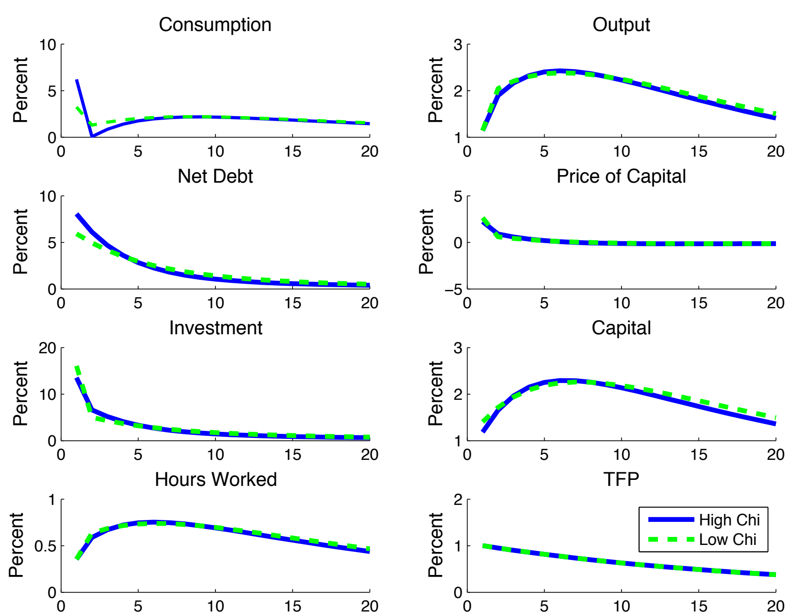


Figure 3.1.: Impulse responses to a 1% increase in TFP.

A. The Role of Dispersed Information in Pricing Default: Evidence from the Great Recession

A.1. Proofs

Proof of Proposition 1 The proof simply follows from inspecting the system of equations 1.9: $\frac{dP(def)}{d\beta} > 0$ if and only if $\xi < \psi + \frac{2}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\frac{\partial\psi}{\partial\beta} \equiv \xi_\beta$, and $\frac{dP(def)}{d\alpha} > 0$ if and only if $\xi < \psi + \frac{2}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\frac{\partial\psi}{\partial\alpha} \equiv \xi_\alpha$. ■

Proof of Proposition 2 From the first equation in 1.9, $\frac{dP(def)}{d\xi} < 0$ follows from the fact that $\phi_1 \in (0, \frac{1}{\sqrt{2\pi}}]$. Next, we prove the second derivative result for the case of the precision of private signals; the proof is similar for the case of the precision of public signals. From the first equation in 1.11, the second derivative is negative if and only if

$$(\psi-\xi)^2+\frac{2}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\frac{\partial\psi}{\partial\beta}(\psi-\xi)-\frac{1}{\eta^2}<0 \tag{A.1}$$

which is a convex parabola in $(\psi-\xi)$ with critical point $(\psi-\xi)^*=-\frac{1}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\frac{\partial\psi}{\partial\beta}$. The quadratic equation obtained by replacing the inequality in A.1 with an equality has two solutions,

$$x_1=(\psi-\xi)^*-\sqrt{\Delta_\beta} \quad \text{and} \quad x_2=(\psi-\xi)^*+\sqrt{\Delta_\beta} \tag{A.2}$$

where

$$\Delta_\beta \equiv [(\psi-\xi)^*]^2+\frac{1}{\eta^2} \tag{A.3}$$

and A.1 is satisfied for $(\psi-\xi)\in(x_1,x_2)$ or $\xi\in(\xi_{L\beta},\xi_{H\beta})$, where

$$\begin{aligned} \xi_{L\beta} &\equiv \psi-(\psi-\xi)^*-\sqrt{\Delta_\beta} \\ &\text{and} \\ \xi_{H\beta} &\equiv \psi-(\psi-\xi)^*+\sqrt{\Delta_\beta} \end{aligned} \tag{A.4}$$

Repeating the same logic for $\frac{d^2P(def)}{d\xi d\alpha}$ we get

$$\begin{aligned} \xi_{L\alpha} &\equiv \psi+\tfrac{1}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\tfrac{\partial\psi}{\partial\alpha}-\sqrt{\Delta_\alpha} \\ &\text{and} \\ \xi_{H\alpha} &\equiv \psi+\tfrac{1}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\tfrac{\partial\psi}{\partial\alpha}+\sqrt{\Delta_\alpha} \end{aligned} \tag{A.5}$$

where

$$\Delta_\alpha \equiv \left[\frac{1}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\frac{\partial\psi}{\partial\alpha}\right]^2 + \frac{1}{\eta^2} \tag{A.6}$$

■

Proof of Proposition 3 The first result follows from the last equation in 1.9, recalling that that the sufficient condition for uniqueness, i.e. $\frac{\alpha}{\sqrt{\beta}} < \frac{\sqrt{2\pi}}{z}$, implies that $1 - z\phi_2\frac{\alpha}{\sqrt{\beta}} \geq 1 - z\frac{1}{\sqrt{2\pi}}\frac{\alpha}{\sqrt{\beta}} > 0$ and that $\psi \in [0, z]$. The last statement follows from equation 1.6; indeed, as $y \to -\infty$ we get that $\psi \to 0$ and when $y \to +\infty$ we get that $\psi \to z$. Regarding the second result, by looking at the last equation in 1.11 we see that the sign of the second derivative is the same as the sign of $(\psi - \xi)\psi$. As $\psi > 0$, we conclude that $\frac{d^2P(def)}{d\xi dz} < 0$ if and only if $\xi > \psi$.

■

A.2. Bayesian Learning and Forecast Errors

Here we show that under Bayesian Learning, current expectations are affected by past forecast errors; this, together with the assumption that exclusion restriction holds, establishes the validity of past forecast errors as instruments for current forecasts. We closely follow Bullard and Suda (2008). Suppose that the true fundamental, θ, follows an AR(1) process:

$$\theta_t = a + b\theta_{t-1} + u_t \tag{A.7}$$

where a and b are unknown parameters, and $u_t \sim N(0, \nu^2)$. A Bayesian Learner has priors on the parameters of equation A.7: $\phi_0' = (a_0\ b_0) \sim N(\mu_0, \Omega_0)$. In her mind, the conditional distribution of θ_t given all the information known in the period before is

$\theta_t \mid \Theta_{t-1}, \phi_{t-1} \sim N(a_{t-1} + b_{t-1}\theta_{t-1}, \nu^2)$, where Θ_t is the history of θ_s up to period t.

By Bayes' rule, $f(\phi \mid \Theta_t) \propto f(\Theta_t \mid \phi) f(\phi) \propto f(\theta_t \mid \phi, \Theta_{t-1}) f(\theta_{t-1} \mid \phi, \Theta_{t-2}) \ldots f(\theta_1 \mid \phi) f(\phi)$.

Define $z_t = (1\ \theta_{t-1})'$ and Z_t being the history of z_s up to period t. Then, $f(\phi \mid \Theta_t) = N(\mu_t, \Omega_t)$, where $\mu_t = \Omega_t \left(\Omega_0^{-1}\phi_0 + \nu^{-2}(Z_t'\Theta_t)\right)$ and $\Omega_t = \left(\Omega_0^{-1} + \nu^{-2}(Z_t'Z_t)\right)^{-1}$.

In recursive form, $\Omega_t^{-1} = \Omega_{t-1}^{-1} + \nu^{-2} z_t z_t'$ and $\mu_t = \mu_{t-1} + \Omega_t \nu^{-2} z_t(\theta_t - z_t'\mu_{t-1})$.

Finally, $E_t\theta_{t+1} = z_{t+1}'\mu_t = z_{t+1}'\mu_{t-1} + z_{t+1}'\Omega_t\nu^{-2}z_t(\theta_t - z_t'\mu_{t-1})$, where $\theta_t - z_t'\mu_{t-1}$ is last period's forecast error. We can also write it as a weighted sum of all the past forecast errors:

$$E_t\theta_{t+1} = z_{t+1}' \sum_{j=0}^{\infty} \Omega_{t-j}\nu^{-2} z_{t-j}(\theta_{t-j} - z_{t-j}'\mu_{t-j-1}) \tag{A.8}$$

Therefore, today's forecast $E_t\theta_{t+1}$ is a weighted sum of past forecast errors. We would obtain essentially the same expression for the case of Recursive Learning[1].

Finally, we take a linear approximation of equation A.8 around the unbiased stochastic

[1] See Evans and Honkapohja (2001) for a reference.

steady state[2] to obtain

$$dE_t\theta_{t+1} \approx \sum_{j=0}^{\infty} \bar{c}_{-j} dfe_{t-j} + \sum_{j=0}^{\infty} dc_{t-j} \bar{fe} \tag{A.9}$$

where $fe_{t-j} \equiv (\theta_{t-j} - z'_{t-j}\mu_{t-j-1})$, $c_{t-j} \equiv z'_{t+1}\Omega_{t-j}\nu^{-2}z_{t-j}$ and the upper bar denotes a variable at the non-stochastic steady state. Since on average forecast errors are zero, i.e. $\bar{fe} = 0$, equation A.9 simplifies to

$$dE_t\theta_{t+1} \approx \sum_{j=0}^{\infty} \bar{c}_{-j} dfe_{t-j} \tag{A.10}$$

which is linear in the forecast errors. '

A.2.1. Unknown Variance of the Error Term

In what follows we show that, when the variance of the error term is also unknown, the expected variance can be written recursively; this means that past expectations over the variance are correlated with current expectations. Once we assume that past expectations of the error term variance do not directly affect CDS spreads, we have that the previous period expectation of the error term variance is a valid instrument for its current expectation.

Going back to the previous setup, instead of assuming that $u_t \sim N(0, \nu^2)$, where ν is known, we now suppose that the prior of ν^{-2} follows a Gamma distribution, $\nu^{-2} \sim \Gamma(N, \tau)$;

[2] By unbiased we mean that forecast errors are on average zero and the notion of a stochastic steady state is required for the sequence of variance-covariance matrices $\{\Omega_{t-j}\}$ not to be degenerate at the steady state, which would have been the case at a non-stochastic steady state.

according to the priors, the expected value and the variance of ν^{-2} are N and $2N/\tau^2$ respectively.

Proposition 12.3 at page 356 in Hamilton (1994) provides two useful results: first, the bayesian estimate of the coefficient vector is identical to the estimate obtained for the case of known variance of the error term; second, the time t expected variance of the error term is

$$\begin{aligned} E(\nu^2 \mid Z_t) &= \tau_t^*/N_t^* \\ &\text{where} \\ N_t^* &= N + t \\ \tau_t^* &= \tau + U_t'U_t + (\beta_t - \mu_0)'\Omega_0^{-1}(Z_t'Z_t + \Omega_0^{-1})^{-1}Z_t'Z_t(\beta_t - \mu_0) \end{aligned} \tag{A.11}$$

for $U_t = [u_1, u_2, ..., u_t]'$ and $\beta_t = (Z_t'Z_t)^{-1}Z_t\theta_t$, the OLS estimator of the AR(1) coefficients a and b.

Following Hamilton (1994) at page 357, if we further assume diffuse prior information which is represented by $N = \tau = 0$ and $\Omega_0 = \mathbf{0}$, we obtain that the expected variance of the error term can be written recursively in an additive fashion:

$$\begin{aligned} E(\nu^2 \mid Z_t) &= \tfrac{1}{t}U_t'U_t = \tfrac{1}{t}\textstyle\sum_{i=1}^{t} u_i^2 \\ &= \tfrac{t-1}{t}E(\nu^2 \mid Z_{t-1}) + \tfrac{1}{t}u_t^2 \end{aligned} \tag{A.12}$$

A.3. On the Identification of α and β

In this subsection we explicitly index each variable by time (t) and bank's identity (i). For instance, δ_{it} refers to the dispersion of beliefs regarding bank i at time t. We have previously shown in equation 1.8 that $\delta_{it}^2 = \frac{\beta_{it}}{(\alpha_{it}+\beta_{it})^2}$. One could think that by exploiting some other source of variation we would be able to obtain another equation that relates an observable to both α_{it} and β_{it}; if that was the case we would have two equations in two unknowns, potentially backing out both variables of interest, α_{it} and β_{it}. We are going to show that in order to do so we have to impose restrictions that we believe to be too restrictive.[3] The other source of variation we could exploit is the variance of forecast errors. Consistently with the model previously presented, we think that the performance of the bank is the sum of a predictable component, θ_{it}, and an unpredictable component, τ_{it}. For simplicity, we define $r_{it} \equiv \theta_{it} + \tau_{it}$ to be such a variable. Then, the model suggests that the mean (or median) forecast error is $fe_{it} \equiv r_{it} - \xi_{it} = \tau_{it} + \frac{\alpha_{it}(\theta_{it}-y_{it})}{\alpha_{it}+\beta_{it}}$. Under the same assumptions about τ presented in the model, the variance of forecast errors is $V(fe_{it}) = \frac{1}{\gamma_{it}} + \frac{\alpha_{it}}{(\alpha_{it}+\beta_{it})^2}$. There are two reasons for not being able to obtain the two variables of interest: first, a third term appears, γ_{it}, which is not observable; secondly, even if we were to set $\gamma_{it} = \infty$, we would still be unable to compute $V(fe_{it})$. Indeed, we only observe one forecast error for each bank at each point in time. In order to circumvent this problem we would have to impose some restrictions, such as assuming that $V(fe_{it})$ is the same across banks within each period or that it is constant across time within each bank. We believe that any of

[3]We thank Nikola Tarashev for helpful suggestions.

those assumptions is too restrictive. On the other hand, we prefer to assume that $\beta > \alpha$ so that (as previously shown) both of them have the same impact on dispersion of beliefs, which we observe.

B. Consumption Volatility and Borrowing Constraints in Small Open Economies

B.1. Steady State

The steady state is characterized by the following system of equations:

$$q = 1$$

$$b = \frac{\chi k}{1+r}$$

$$y = h^{\alpha} k^{1-\alpha}$$

$$\frac{i}{k} = \gamma + \delta - 1$$

$$\frac{\mu}{\lambda} = \frac{\gamma}{1+r} - \tilde{\beta}$$

$$\lambda = (c - \Psi h^{\nu})^{-\sigma}$$

$$h = \left(\frac{\alpha}{\nu\Psi} k^{1-\alpha}\right)^{\frac{1}{\nu-\alpha}}$$

$$c = y - k\left(\frac{\chi(1+r-\gamma)}{1+r} + (\gamma + \delta - 1)\right)$$

$$k = \left(\frac{\gamma - \tilde{\beta}(1-\delta) - \chi(\gamma/(1+r) - \tilde{\beta})}{\tilde{\beta}(1-\alpha)} \left(\frac{\nu\Psi}{\alpha}\right)^{\frac{\alpha}{\nu-\alpha}}\right)^{\frac{\nu-\alpha}{\nu(1-\alpha)}}$$

B.2. Log Linear Approximation

Output:

$$\hat{y}_t = \hat{z}_t + \alpha \hat{h}_t + (1-\alpha)\hat{k}_t \tag{B.1}$$

Labor Demand:

$$\hat{w}_t = \hat{y}_t - \hat{h}_t \tag{B.2}$$

Labor Supply:

$$\hat{h}_t = \varepsilon_{hw} \hat{w}_t \tag{B.3}$$

where $\varepsilon_{hw} = \frac{1}{\nu - 1}$ is the Frisch elasticity of labor supply.

Marginal Utility of Consumption:

$$\hat{\lambda}_t = -\sigma\big(\theta_1 \hat{c}_t + \nu(1-\theta_1)\hat{h}_t\big) \tag{B.4}$$

where $\theta_1 \equiv \frac{c}{c - \Psi h^{\nu}}$.

Law of Motion of Capital:

$$\hat{i}_t = \frac{1}{\gamma + \delta - 1}(\gamma \hat{k}_{t+1} - (1-\delta)\hat{k}_t) \tag{B.5}$$

Price of Capital:

$$\hat{q}_t = \frac{\phi}{\gamma^2}(\gamma + \delta - 1)(\hat{i}_t - \hat{k}_t) \tag{B.6}$$

Capital Euler Equation:

$$\gamma\left(1-\frac{\chi}{1+r}\right)\hat{\lambda}_t+\gamma\hat{q}_t=\left[\gamma-\chi\Big(\tilde{\beta}+\frac{\mu}{\lambda}\Big)\right]E_t\hat{\lambda}_{t+1}+\left[\chi\frac{\mu}{\lambda}+\tilde{\beta}(1-\delta)\right]E_t\hat{q}_{t+1}+$$
$$+\left[\tilde{\beta}(1-\alpha)\frac{y}{k}\right]E_t\hat{d}_{t+1}+\tilde{\beta}\phi\left(\frac{\gamma+\delta-1}{\gamma}\right)^2E_t(\hat{i}_{t+1}-\hat{k}_{t+1})$$

Capital Demand:

$$\hat{d}_t=\hat{y}_t-\hat{k}_t \tag{B.7}$$

Bond Euler Equation:

$$\frac{\mu}{\lambda}\hat{\mu}_t=\frac{\gamma}{1+r}\hat{\lambda}_t-\tilde{\beta}(1+r)E_t\hat{\lambda}_{t+1} \tag{B.8}$$

Credit Constraint:

$$\hat{b}_{t+1}=\hat{k}_{t+1}+\frac{1}{k}E_t\hat{q}_{t+1} \tag{B.9}$$

Budget Constraint:

$$\hat{y}_t=s_c\hat{c}_t+s_b\left((1+r)\hat{b}_t-\gamma\hat{b}_{t+1}\right)+s_i\hat{i}_t \tag{B.10}$$

Bibliography

Abel, Andrew B., and Olivier J. Blanchard. 1983. "An Intertemporal Model of Saving and Investment." *Econometrica*, 51(3): pp. 675–692.

Acharya, Viral, and Sascha Steffen. 2013. "The Greatest Carry Trade Ever? Understanding Eurozone Bank Risks." *R&R Journal of Financial Economics.*

Acharya, Viral V, and Raghuram G Rajan. 2013. "Sovereign debt, government myopia, and the financial sector." *Review of Financial Studies*, 26(6): 1526–1560.

Aghion, Philippe, Peter Howitt, and David Mayer-Foulkes. 2005. "The Effect of Financial Development on Convergence: Theory and Evidence." *The Quarterly Journal of Economics*, 173–222.

Aghion, Philippe, Philippe Bacchetta, and Abhijit Banerjee. 2004. "Financial development and the instability of open economies." *Journal of Monetary Economics*, 51(6): 1077–1106.

Bibliography

Aguiar, Mark, and Gita Gopinath. 2007. "Emerging Market Business Cycles: The Cycle is the Trend." *Journal of Political Economy*, 115(1): 69–102.

Aizenman, Joshua, and Yothin Jinjarak. 2009. "Current account patterns and national real estate markets." *Journal of Urban Economics*, 66(2): 75–89.

Ajinkya, Bipin B, and Michael J Gift. 1985. "Dispersion of financial analysts' earnings forecasts and the (option model) implied standard deviations of stock returns." *The Journal of Finance*, 40(5): 1353–1365.

Akinci, Ozge, and Ryan Chahrour. 2014. "Good News is Bad News: Leverage Cycles and Sudden Stops." *Boston College Department of Economics Working Paper*, 866.

Albagli, Elias, Christian Hellwig, and Aleh Tsyvinski. 2014. "Dynamic Dispersed Information and the Credit Spread Puzzle." National Bureau of Economic Research.

Angeletos, George-Marios, and Iván Werning. 2004. "Crises and prices: Information aggregation, multiplicity and volatility." National Bureau of Economic Research.

Angeletos, George-Marios, Christian Hellwig, and Alessandro Pavan. 2006. "Signaling in a global game: Coordination and policy traps." *Journal of Political Economy*, 114: 452–484.

Angeletos, George-Marios, Christian Hellwig, and Alessandro Pavan. 2007. "Dynamic global games of regime change: Learning, multiplicity, and the timing of attacks." *Econometrica*, 75(3): 711–756.

Arellano, Cristina. 2008. "Default risk and income fluctuations in emerging economies." *The American Economic Review*, 690–712.

Arellano, Manuel, and Olympia Bover. 1995. "Another Look at the Instrumental Variable Estimation of Error-Components Models." *Journal of Econometrics*, 68: 29–51.

Balduzzi, Pierluigi, and Chunhua Lan. 2012. "Survey Forecasts and the Time-varying Second Moments of Stock and Bond Returns." *Available at SSRN 2022274*.

Barth, James R, Gerard Caprio Jr, and Ross Levine. 2001. "Banking systems around the globe: Do regulation and ownership affect performance and stability?" In *Prudential supervision: What works and what doesn't.* 31–96. University of Chicago Press.

Bartov, Eli, and Gordon M Bodnar. 1994. "Firm valuation, earnings expectations, and the exchange-rate exposure effect." *The Journal of Finance*, 49(5): 1755–1785.

Battistini, Niccolò, Marco Pagano, and Saverio Simonelli. 2014. "Systemic risk, sovereign yields and bank exposures in the euro crisis." *Economic Policy*, 29(78): 203–251.

Baxter, Marianne, and Mario J Crucini. 1995. "Business Cycles and the Asset Structure of Foreign Trade." *International Economic Review*, 821–854.

Becker, Bo, and Victoria Ivashina. 2014. "Financial Repression in the European Sovereign Debt Crisis." *Available at SSRN 2429767*.

Bekaert, Geert, Campbell R Harvey, and Christian Lundblad. 2006. "Growth volatility and financial liberalization." *Journal of international money and finance*, 25(3): 370–403.

Bertaut, Carol, Alexandra Tabova, and Vivian Wong. 2013. "The replacement of safe assets in the U.S. financial bond portfolio and implications for the U.S. financial bond home bias." *mimeo.*

Blundell, Richard, and Stephen Bond. 1998. "Initial conditions and moment restrictions in dynamic panel data models." *Journal of econometrics*, 87(1): 115–143.

Bofondi, Marcello, Luisa Carpinelli, and Enrico Sette. 2013. "Credit supply during a sovereign debt crisis." *Bank of Italy Temi di Discussione (Working Paper) No*, 909.

Broner, Fernando, Aitor Erce, Alberto Martin, and Jaume Ventura. 2014. "Sovereign Debt Markets in Turbulent Times: Creditor Discrimination and Crowding–out Effects." *Journal of Monetary Economics*, 61: 114–142.

Brunnermeier, Markus K. 2009. "Deciphering the Liquidity and Credit Crunch 2007-2008." *Journal of Economic Perspectives*, 23(1): 77–100.

Brutti, Filippo, and Philip U Sauré. 2013. "Repatriation of debt in the euro crisis: evidence for the secondary market theory." *Available at SSRN 2253404*.

Bullard, James, and Jacek Suda. 2008. "The Stability of Macroeconomic Systems with Bayesian Learners." *Federal Reserve Bank of St. Louis Working Paper Series*, , (2008-043).

Buraschi, Andrea, Fabio Trojani, and Andrea Vedolin. 2013. "Economic uncertainty, disagreement, and credit markets." *Management Science*.

Calomiris, Charles W, and Gary Gorton. 1991. "The origins of banking panics: models, facts, and bank regulation." In *Financial markets and financial crises*. 109–174. University of Chicago Press.

Calomiris, Charles W, and Joseph R Mason. 2003. "Consequences of bank distress during the Great Depression." *The American Economic Review*, 93(3): 937–947.

Cesa-Bianchi, Ambrogio, Luis F Cespedes, and Alessandro Rebucci. 2015. "Global liquidity, house prices and the macroeconomy: evidence from advanced and emerging economies." *IMF Working Paper No. 15/23*.

Chahrour, Ryan. 2012. "Public Communication and Information Acquisition." Boston College Department of Economics.

Chari, Varadarajan V, and Ravi Jagannathan. 1988. "Banking panics, information, and rational expectations equilibrium." *The Journal of Finance*, 43(3): 749–761.

Cheng, Haw, and Konstantin Milbradt. 2011. "The hazards of debt: Rollover freezes, incentives, and bailouts." *Review of Financial Studies*, hhr142.

Chen, Yehning. 1999. "Banking panics: The role of the first-come, first-served rule and information externalities." *Journal of Political Economy*, 107(5): 946–968.

Cochrane, John Howland. 2005. *Asset pricing.* Vol. 1, Princeton university press.

Coeurdacier, Nicolas, and Helene Rey. 2012. "Home Bias in Open Economy Financial Macroeconomics." *Journal of Economic Literature.*

Covitz, Daniel, Nellie Liang, and Gustavo A Suarez. 2013. "The Evolution of a Financial Crisis: Collapse of the Asset-Backed Commercial Paper Market." *The Journal of Finance*, 68(3): 815–848.

Crosignani, Matteo. 2014. "Why Are Banks Not Recapitalized During Crises? A Political Economy Explanation." *mimeo (May 4, 2014).*

Cuñat, Vicente, and Luis Garicano. 2010. "Did Good Cajas Extend Bad Loans? Governance, Human Capital and Loan Portfolios." *Fedea Working Paper.*

Dang, Tri Vi, Gary Gorton, and Bengt Holmström. 2012. "Ignorance, debt and financial crises." *Yale University and Massachusetts Institute of Technology, working paper.*

Dang, Tri Vi, Gary Gorton, Bengt Holmström, and Guillermo Ordonez. 2014. "Banks as secret keepers." National Bureau of Economic Research.

de Faria e Castro, Miguel, Joseba Martinez, and Thomas Philippon. 2014. "Runs versus Lemons: Information Disclosure, Fiscal Capacity and Financial Stability." *mimeo.*

De Marco, Filippo. 2013. "Bank Lending and the Sovereign Debt Crisis." Boston College working paper.

Diamond, Douglas W, and Philip H Dybvig. 1983. "Bank runs, deposit insurance, and liquidity." *The journal of political economy*, 401–419.

Diamond, Douglas W, and Raghuram G Rajan. 2011. "Fear of fire sales, illiquidity seeking, and credit freezes." *The Quarterly Journal of Economics*, 126(2): 557–591.

Diether, Karl B, Christopher J Malloy, and Anna Scherbina. 2002. "Differences of opinion and the cross section of stock returns." *The Journal of Finance*, 57(5): 2113–2141.

Duffie, Darrell, and David Lando. 2001. "Term structures of credit spreads with incomplete accounting information." *Econometrica*, 69(3): 633–664.

Eisenbach, Thomas M. 2013. "Rollover risk as market discipline: A two-sided inefficiency." Staff Report, Federal Reserve Bank of New York.

Evans, George W, and Seppo Honkapohja. 2001. *Learning and expectations in macroeconomics.* Princeton University Press.

Forbes, Kristin J, and Francis E Warnock. 2012. "Capital flow waves: Surges, stops, flight, and retrenchment." *Journal of International Economics*, 88(2): 235–251.

French, Kenneth R, and James M Poterba. 1991. "Investor Diversification and International Equity Markets." *The American Economic Review.*

Friedman, Milton, and Anna Jacobson Schwartz. 1963. *A monetary history of the United States, 1867-1960.* Princeton University Press.

Fulford, Scott. 2011. "The effects of financial development in the short and long run." *Boston College Department of Economics Working Paper*, 741.

Godfrey, Leslie G. 1994. "Testing for serial correlation by variable addition in dynamic models estimated by instrumental variables." *The Review of Economics and Statistics*, 550–559.

Goldstein, Itay, and Ady Pauzner. 2005. "Demand–deposit contracts and the probability of bank runs." *the Journal of Finance*, 60(3): 1293–1327.

Gorton, Gary. 1985. "Clearinghouses and the origin of central banking in the United States." *The Journal of Economic History*, 45(02): 277–283.

Gorton, Gary. 1988. "Banking panics and business cycles." *Oxford economic papers*, 751–781.

Gorton, Gary, and Andrew Metrick. 2012. "Securitized banking and the run on repo." *Journal of Financial Economics*, 104(3): 425–451.

Gorton, Gary B, and Guillermo Ordoñez. 2012. "Collateral crises." National Bureau of Economic Research.

Greenwood, Jeremy, Zvi Hercowitz, and Gregory W Huffman. 1988. "Investment, capacity utilization, and the real business cycle." *The American Economic Review*, 402–417.

Güntay, Levent, and Dirk Hackbarth. 2010. "Corporate bond credit spreads and forecast dispersion." *Journal of Banking and Finance*, 34(10): 2328–2345.

Hamilton, James Douglas. 1994. *Time series analysis.* Vol. 2, Princeton university press Princeton.

Heathcote, Jonathan, and Fabrizio Perri. 2002. "Financial autarky and international business cycles." *Journal of Monetary Economics*, 49(3): 601–627.

Hellwig, Christian, and Laura Veldkamp. 2009. "Knowing what others know: Coordination motives in information acquisition." *The Review of Economic Studies*, 76(1): 223–251.

He, Zhiguo, and Wei Xiong. 2012. "Dynamic debt runs." *Review of Financial Studies*, 25(6): 1799–1843.

Holmström, Bengt. 2014. "Understanding the Role of Debt in the Financial System."

Illueca, Manuel, Lars Norden, and Gregory F Udell. 2008. "Liberalization, corporate governance, and savings banks."

IMF. June 2012. "Spain: The Reform of Spanish Savings Banks Technical Notes." *IMF Country Report No. 12/141.*

Jacklin, Charles J, and Sudipto Bhattacharya. 1988. "Distinguishing panics and information-based bank runs: Welfare and policy implications." *The Journal of Political Economy*, 568–592.

Katz, Richard S, and Peter Mair. 1995. "Changing Models of Party Organization and Party Democracy The Emergence of the Cartel Party." *Party politics*, 1(1): 5–28.

Katz, Richard S, and Peter Mair. 2009. "The cartel party thesis: A restatement." *Perspectives on Politics*, 7(04): 753–766.

Kindleberger, Charles. 1978. *Manias, panics and crashes: a history of financial crises.* Basic Books, New York, N.Y.

King, Robert G, and Ross Levine. 1993. "Finance and growth: Schumpeter might be right." *The Quarterly Journal of Economics*, 717–737.

Kiyotaki, N, and J Moore. 1997. "Credit Cycle." *Journal of Political Economy*, 105(2).

Kose, M Ayhan, Eswar S Prasad, and Marco E Terrones. 2003. "Financial integration and macroeconomic volatility." *IMF Staff papers*, 119–142.

Kose, M Ayhan, Eswar S Prasad, and Marco E Terrones. 2007. "How Does Financial Globalization Affect Risk Sharing? Patterns and Channels." *IMF Working Papers*, 1–41.

Lane, Philip R. 2006. "Global Bond Portfolios and EMU." *International Journal of Central Banking.*

Lane, Philip R, and Gian Maria Milesi-Ferretti. 2007. "The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970–2004." *Journal of international Economics*, 73(2): 223–250.

La Porta, Rafael, Florencio Lopez-de Silanes, and Guillermo Zamarripa. 2003. "Related lending." *The Quarterly Journal of Economics*, 118(1): 231–268.

La Porta, Rafael, Florencio Lopez-de Silanes, Andrei Shleifer, and Robert Vishny. 1999. "The quality of government." *Journal of Law, Economics, and organization*, 15(1): 222–279.

Leblebicioğlu, Aslı. 2009. "Financial integration, credit market imperfections and consumption smoothing." *Journal of Economic Dynamics and Control*, 33(2): 377–393.

Levchenko, Andrei A. 2005. "Financial liberalization and consumption volatility in developing countries." *IMF Staff Papers*, 237–259.

Levine, Ross. 2002. "Bank-based or market-based financial systems: which is better?" *Journal of financial intermediation*, 11(4): 398–428.

Levine, Ross, Norman Loayza, and Thorsten Beck. 2000. "Financial intermediation and growth: Causality and causes." *Journal of Monetary Economics*, 46(1): 31–77.

Loayza, Norman, and Romain Ranciere. 2005. "Financial development, financial fragility, and growth." *Financial Fragility, and Growth (September 2004)*.

Mendoza, Enrique G. 2010. "Sudden stops, financial crises, and leverage." *The American Economic Review*, 100(5): 1941–1966.

Morris, Stephen, and Hyun Song Shin. 2001. "Rethinking multiple equilibria in macroeconomic modeling." In *NBER Macroeconomics Annual 2000, Volume 15.* 139–182. MIT PRess.

Morris, Stephen, and Hyun Song Shin. 2004. "Coordination risk and the price of debt." *European Economic Review*, 48(1): 133–153.

Myatt, David P, and Chris Wallace. 2012. "Endogenous Information Acquisition in Coordination Games." *The Review of Economic Studies*, 79(1): 340–374.

Neumeyer, Pablo A, and Fabrizio Perri. 2005. "Business cycles in emerging economies: the role of interest rates." *Journal of monetary Economics*, 52(2): 345–380.

Nickell, Stephen. 1981. "Biases in dynamic models with fixed effects." *Econometrica: Journal of the Econometric Society*, 1417–1426.

Obstfeld, Maurice, and Kenneth Rogoff. 1995. "Exchange Rate Dynamics Redux." *Journal of Political Economy*, 103(3): pp. 624–660.

Peck, James, and Karl Shell. 2003. "Equilibrium bank runs." *Journal of Political Economy*, 111(1): 103–123.

Popov, Alexander, and Neeltje Van Horen. 2013. "The impact of sovereign debt exposure on bank lending: Evidence from the European debt crisis." Netherlands Central Bank, Research Department.

Postlewaite, Andrew, and Xavier Vives. 1987. "Bank runs as an equilibrium phenomenon." *The Journal of Political Economy*, 485–491.

Prati, Alessandro, and Massimo Sbracia. 2010. "Uncertainty and currency crises: evidence from survey data." *Journal of Monetary Economics*, 57(6): 668–681.

Rajan, Raghuram G, and Luigi Zingales. 1998. "Financial Dependence and Growth." *The American Economic Review*, 88(3): 559–586.

Ranciere, Romain, Aaron Tornell, and Frank Westermann. 2006. "Decomposing the effects of financial liberalization: Crises vs. growth." *Journal of Banking and Finance*, 30(12): 3331–3348.

Ravn, Morten O, and Harald Uhlig. 2001. *On adjusting the HP-filter for the frequency of obsevations.* CESifo.

Rochet, Jean-Charles, and Xavier Vives. 2004. "Coordination failures and the lender of last resort: was Bagehot right after all?" *Journal of the European Economic Association*, 2(6): 1116–1147.

Sapienza, Paola. 2004. "The effects of government ownership on bank lending." *Journal of Financial Economics*, 72(2): 357–384.

Schmitt-Grohé, Stephanie, and Martın Uribe. 2003. “Closing small open economy models.” *Journal of international Economics*, 61(1): 163–185.

Siritto, Cecilia Parlatore. 2013. “Transparency and bank runs.” *Department of Economics, New York University*, 548: 549.

Stock, James H, Jonathan H Wright, and Motohiro Yogo. 2002. “A survey of weak instruments and weak identification in generalized method of moments.” *Journal of Business & Economic Statistics*, 20(4).

Tirole, Jean. 2010. *The theory of corporate finance.* Princeton University Press.