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

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ABSTRACT

The recent Global Games literature makes important predictions on how financial crises unfold. We test the empirical relevance of these theories by analyzing how dispersed information affects banks' default risk. We find evidence that precise information acts as a coordination device which reduces creditors' willingness to roll over debt to a bank, thus increasing both its default risk and its vulnerability to changes in expectations. We establish two new results. First, given an unfavorable median forecast, less dispersed beliefs greatly increase default risk; this is consistent with incomplete information models that rely on coordination risk while in contrast with a wide range of models that neglect this component. Second, less dispersion of beliefs amplifies the reaction of default risk to changes in market expectations; importantly, precise information raises banks' vulnerability by more than standard measures of banks' fragility. Taken together, our results suggest that enhanced transparency, by providing agents with more precise information, increases banks' vulnerability to changes in sentiment and raises the default risk of weaker banks. Finally, we address concerns of endogeneity of market expectations by introducing a novel set of instruments.

JEL classification: D83, G01, G21.

Keywords: Financial Crisis, CDS Spreads, Global Games, Dispersed Information, Coordination Risk.

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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, 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 models that incorporate

[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.

[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 et al. (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).

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 et al. (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 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

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

[4]Similarly, Gorton and Ordoñez (2014) 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.

[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.

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 et al. (2014) show that more precise information greatly benefits good banks while exposing worse banks to 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 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). 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"; if forecasters internalize this possibility they will then revise upward both expected returns on the bank's as-

[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 2).

sets 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 7.2); 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.[9]

The remainder of the paper is organized as follows. Section 2 briefly reviews the related literature, Section 3 presents our extension of Morris and Shin (2004)' s model and derives some new testable implications. Section 4 presents the data and discusses the empirical strategy while Section 5 shows the empirical results and assesses the performance of the model. Finally, Section 6 concludes.

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.[10] 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

[9]For more details see Section 4.2.

[10] 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 et al. (2006) show that signals conveyed by policy interventions lead to multiplicity; Angeletos et al. (2007) consider the effect of learning in a dynamic version of the standard model.

currencies in the 1997-98 Asian crises. Other papers, such as Iyer and Puri (2012), Kelly and Gráda (2000) and Ziebarth (2013), even though not directly testing implications from Global Games, empirically document the role of social networks in exacerbating bank runs.

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 et al. (2014) and Buraschi et al. (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,[11] 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.

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 et al. (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.

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

[11] 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.

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

$$l = \Phi(\sqrt{\beta}(x^* - \theta)) \tag{1}$$

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

$$0 = \mathbb{E}[\theta + \tau - z\Phi(\sqrt{\beta}(x^* - \theta)) \mid \theta] = \theta - z\Phi(\sqrt{\beta}(x^* - \theta)) \tag{2}$$

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

$$\psi = z\Phi(\sqrt{\beta}(x^* - \psi)) \tag{3}$$

Equation 3 specifies the equilibrium liquidity shortage ψ as a function of the cutoff signal x^*. Note that the right-hand-side of equation 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 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

$$\lambda = Pr(\theta + \tau > \psi \mid x_j = x^*) = 1 - \Phi\left(\frac{\sqrt{\gamma(\alpha+\beta)}}{\sqrt{\alpha+\beta+\gamma}}(\psi - \xi^*)\right) \tag{4}$$

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 4, leads to

$$x^* = \frac{\alpha+\beta}{\beta}\left(\psi + \Phi^{-1}(\lambda)\frac{\sqrt{\alpha+\beta+\gamma}}{\sqrt{\gamma(\alpha+\beta)}}\right) - \frac{\alpha}{\beta}y \tag{5}$$

Finally, from equations 3 and 5 we have that

$$\psi = z\Phi\left(\frac{\alpha}{\sqrt{\beta}}(\psi - y) + \frac{\sqrt{\alpha+\beta}\sqrt{\alpha+\beta+\gamma}}{\sqrt{\beta\gamma}}\Phi^{-1}(\lambda)\right) \tag{6}$$

which implicitly defines ψ as a function of the model's parameters. Following Morris and Shin (2004), equation 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[12] 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 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

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

possible default probabilities, we introduced the shock τ; now we have that the probability of default conditional on observing the median signal is

$$Pr(\theta + \tau < \psi \mid \xi) = \Phi\left(\frac{\sqrt{\gamma(\alpha+\beta)}}{\sqrt{\alpha+\beta+\gamma}}(\psi - \xi)\right) \tag{7}$$

which we proxy by the CDS spread as described in Section 4.

We define $P(def) \equiv Pr(\theta + \tau < \psi \mid \xi)$. ξ is the median[13] 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

$$\delta^2 = \int (\xi_j - \xi)^2 \, dj = \frac{\beta^2}{(\alpha+\beta)^2} \int (x_j - \theta)^2 \, dj = \frac{\beta}{(\alpha+\beta)^2} \tag{8}$$

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 more precise public and private signals decrease dispersion of beliefs. See Appendix 7.4 for a discussion on the impossibility to back out α and β from the data.

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 7 we have that

$$\begin{aligned}
\frac{dP(def)}{d\xi} &= -\eta\phi_1 \\
\frac{dP(def)}{d\beta} &= \eta\phi_1\left(\frac{\gamma(\psi-\xi)}{2(\alpha+\beta)(\alpha+\beta+\gamma)} + \frac{\partial\psi}{\partial\beta}\right) \\
\frac{dP(def)}{d\alpha} &= \eta\phi_1\left(\frac{\gamma(\psi-\xi)}{2(\alpha+\beta)(\alpha+\beta+\gamma)} + \frac{\partial\psi}{\partial\alpha}\right) \\
\frac{dP(def)}{dz} &= \eta\phi_1\frac{\partial\psi}{\partial z}
\end{aligned} \tag{9}$$

[13] 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.

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 6:

$$\begin{aligned}
\frac{\partial\psi}{\partial\beta} &= -\frac{z\phi_2\left[\psi-y+\left(\frac{\beta^2-\alpha^2-\alpha\gamma}{\sqrt{\gamma(\alpha+\beta)(\alpha+\beta+\gamma)}}\right)\Phi^{-1}(\lambda)\right]}{2\sqrt[3]{\beta}\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)} \\
\frac{\partial\psi}{\partial\alpha} &= \frac{z\phi_2\left[\psi-y+\frac{2\alpha+2\beta+\gamma}{2\sqrt{\gamma(\alpha+\beta)(\alpha+\beta+\gamma)}}\Phi^{-1}(\lambda)\right]}{\sqrt{\beta}\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)} \\
\frac{\partial\psi}{\partial z} &= \frac{\psi}{z\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)}
\end{aligned} \tag{10}$$

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:

$$\begin{aligned}
\frac{d^2P(def)}{d\xi d\beta} &= \eta\phi_1\left[\eta^2\left(\frac{\gamma(\psi-\xi)^2}{2(\alpha+\beta)(\alpha+\beta+\gamma)}+(\psi-\xi)\frac{\partial\psi}{\partial\beta}\right)-\frac{\gamma}{2(\alpha+\beta)(\alpha+\beta+\gamma)}\right] \\
\frac{d^2P(def)}{d\xi d\alpha} &= \eta\phi_1\left[\eta^2\left(\frac{\gamma(\psi-\xi)^2}{2(\alpha+\beta)(\alpha+\beta+\gamma)}+(\psi-\xi)\frac{\partial\psi}{\partial\alpha}\right)-\frac{\gamma}{2(\alpha+\beta)(\alpha+\beta+\gamma)}\right] \\
\frac{d^2P(def)}{d\xi dz} &= \eta^3\phi_1\frac{\psi(\psi-\xi)}{z\left(1-z\phi_2\frac{\alpha}{\sqrt{\beta}}\right)}
\end{aligned} \tag{11}$$

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.*

$$\begin{aligned}
\frac{dP(def)}{d\beta} &> 0 \qquad \textit{iff}\ \xi<\xi_\beta \\
\frac{dP(def)}{d\alpha} &> 0 \qquad \textit{iff}\ \xi<\xi_\alpha
\end{aligned} \tag{12}$$

All the proofs and thresholds' definitions can be found in Appendix 7.1.

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,*

$$\begin{aligned}
\frac{dP(def)}{d\xi} &< 0 \\
\frac{d^2P(def)}{d\xi d\beta} &< 0 \qquad \textit{iff}\ \xi\in[\xi_{L\beta}\ ,\ \xi_{H\beta}] \\
\frac{d^2P(def)}{d\xi d\alpha} &< 0 \qquad \textit{iff}\ \xi\in[\xi_{L\alpha}\ ,\ \xi_{H\alpha}]
\end{aligned} \tag{13}$$

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,*

$$\begin{aligned} \frac{dP(def)}{dz} &> 0 \\ \frac{d^2P(def)}{d\xi dz} &< 0 \qquad \textit{iff } \xi > \psi \end{aligned} \tag{14}$$

4 Data and Empirical Strategy

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.[14] 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).[15]

Analysts' median forecasts on banks' future performances are adopted to measure the median 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.[16] As a proxy for expected bank's fundamentals we use one-year-ahead forecasts on returns on assets (ROA).[17]

[14] 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 17), administered within the first half of the month, we construct monthly CDS data disregarding the second half of the month.

[15] 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.

[16] 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 et al. (2002) and Balduzzi and Lan (2012).

[17] 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.

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 25 for a detailed list of the banks in the sample).

Table 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 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 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 3. At first, explaining this eight-fold increase in CDS spreads through dispersion of beliefs seems hard to accomplish. While from Figure 4 we can see that expectations on future profitability follow the market perception of risk, Figure 5 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 3 to 5 use bank-level data aggregated across regions, namely USA, PIIGS and Asia; this aggregation, while necessary for visualization purposes, hides interesting variation.

4.2 Empirical Strategy

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

$$
\begin{aligned}
CDS_{i,t} = \quad & \rho CDS_{i,t-1} + \gamma_1[\mathbb{E}_t(\mathrm{ROA}_{i,t+1})(Precise_{i,t})] + \gamma_2[\mathbb{E}_t(\mathrm{ROA}_{i,t+1})(1 - Precise_{i,t})] \\
& + \gamma_3 \delta_{\mathbb{E}_{i,t}} + \beta^\top x_{i,t-1} + \eta_i + \lambda_t + \varepsilon_{i,t}
\end{aligned}
\tag{15}
$$

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.[18] $\delta_{\mathbb{E}_{i,t}}$ 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 3 to 6 use data from September 2007 to December 2012; we use September 2007 as the starting period of the financial crisis.[19] When we compare pre-crisis and crisis estimates as in Tables 7 and 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.

[18]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.

[19]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 et al. (2013), we notice a large collapse in the outstanding value of ABCP around August-September 2007.

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.[20] 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 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 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 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).[21]

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.[22] 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 7.2) 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

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

[21]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.

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

exclusion restriction requires that past forecast errors do not directly influence 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 7.3 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. Notice that the empirical model is overidentified, namely there are more excluded instruments than endogenous regressors; this allows for one or more excluded instruments to affect both endogenous variables. For instance, it could well be the case that past forecast errors affect current expectations throught the learning channel as well as dispersion of beliefs by altering the costs and benefits of endogenous signal acquisition. Indeed, from Table 10 it appears that a past underestimation (a performance above expectations) reduces future disagreement while at the same time promoting an upward revision of next period forecasts.

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.[23] In all the regressions we reject the null of serial correlation of the error term. Therefore, under the

[23] 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.

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

5 Results

5.1 Amplification: the indirect effect of dispersed beliefs

Table 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,

[24] 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.

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.[25] 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 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 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

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

effect on more capitalized banks.[26] 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 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 $\frac{d^2P(def)}{d\xi dz} < 0$ from Proposition 3.

Next, Table 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 of Table 5 show.[27] 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 5.6).

Once again, less dispersion of beliefs plays a key role in amplifying the effect of market expectations on default risk. More research is needed at both theoretical and empirical levels to better understand the determinants of dispersed information, especially in dynamic contexts and during financial turmoil.

[26] 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.

[27] 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.

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 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.

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 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,[28] as shown in Section 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.

[28]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.

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 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 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 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.[29]

It is important to notice however that the pre-crisis regressions in Table 9 suffer from weak instruments, thus undermining the overall reliability of these pre-crisis estimates.

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

[29] 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.

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 reported above. Then, for each calibration we compute the probability that the posterior mean (ξ) falls within the wanted intervals, as reported in Tables 11 to 15. Finally, Table 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 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 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 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.

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 7.2: 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 7.3 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 10 shows a baseline specification which is similar to the first stage regression of the models estimated in Table 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.

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 17 to 23) and by changing the thresholds that identify fragile banks (Table 23) and precise information (Table 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 17 to 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.[30] 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

[30]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.

country-specific mean from it; practically, instead of using $X_{i,j,t}$ which 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 20 to 23.

Alternative threshold for fragility. In Table 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 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.

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 ways that resemble the conduct of the first U.S. clearinghouses during banking panics, as described in Gorton (1985). In particular, the clearing house would suppress the release of bank-specific balance sheet information while publishing only aggregate data; each bank could also borrow vis-a-vis collateral from the clearing house in full anonymity. Overall, these measures were meant to decrease transparency during banking panics in order to avoid the collapse of weaker banks; our results support the efficacy of the clearing house strategy.

7 Appendix

7.1 Proofs

Proof of Proposition 1 The proof simply follows from inspecting the system of equations 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 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 11, the second derivative is negative if and only if

$$(\psi-\xi)^2 + \frac{2}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\frac{\partial\psi}{\partial\beta}(\psi-\xi) - \frac{1}{\eta^2} < 0 \tag{16}$$

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 16 with an equality has two solutions,

$$x_1 = (\psi-\xi)^* - \sqrt{\Delta_\beta} \quad \text{and} \quad x_2 = (\psi-\xi)^* + \sqrt{\Delta_\beta} \tag{17}$$

where

$$\Delta_\beta \equiv [(\psi-\xi)^*]^2 + \frac{1}{\eta^2} \tag{18}$$

and 16 is satisfied for $(\psi-\xi) \in (x_1, x_2)$ or $\xi \in (\xi_{L\beta}, \xi_{H\beta})$, where

$$\begin{aligned} \xi_{L\beta} &\equiv \psi - (\psi-\xi)^* - \sqrt{\Delta_\beta} \\ &\text{and} \\ \xi_{H\beta} &\equiv \psi - (\psi-\xi)^* + \sqrt{\Delta_\beta} \end{aligned} \tag{19}$$

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

$$\begin{aligned} \xi_{L\alpha} &\equiv \psi + \tfrac{1}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\tfrac{\partial\psi}{\partial\alpha} - \sqrt{\Delta_\alpha} \\ &\text{and} \\ \xi_{H\alpha} &\equiv \psi + \tfrac{1}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\tfrac{\partial\psi}{\partial\alpha} + \sqrt{\Delta_\alpha} \end{aligned} \tag{20}$$

where

$$\Delta_\alpha \equiv \left[\frac{1}{\gamma}(\alpha+\beta)(\alpha+\beta+\gamma)\frac{\partial\psi}{\partial\alpha}\right]^2 + \frac{1}{\eta^2} \tag{21}$$

■

Proof of Proposition 3 The first result follows from the last equation in 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 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 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 $\xi > \psi$.

■

7.2 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:

$$\theta_t = a + b\theta_{t-1} + u_t \tag{22}$$

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 22: $\phi_0' = (a_0\ b_0) \sim N(\mu_0, \Omega_0)$. 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, $f(\phi \mid \Theta_t) \propto f(\Theta_t \mid \phi) f(\phi) \propto f(\theta_t \mid \phi, \Theta_{t-1}) f(\theta_{t-1} \mid \phi, \Theta_{t-2}) \ . \ . \ . \ f(\theta_1 \mid \phi) f(\phi)$.

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:

$$E_t\theta_{t+1} = z'_{t+1}\sum_{j=0}^{\infty}\Omega_{t-j}\nu^{-2}z_{t-j}(\theta_{t-j} - z'_{t-j}\mu_{t-j-1}) \tag{23}$$

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[31].

Finally, we take a linear approximation of equation 23 around the unbiased stochastic steady state[32] to obtain

$$dE_t\theta_{t+1} \approx \sum_{j=0}^{\infty}\bar{c}_{-j}dfe_{t-j} + \sum_{j=0}^{\infty}dc_{t-j}\bar{fe} \tag{24}$$

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 24 simplifies to

$$dE_t\theta_{t+1} \approx \sum_{j=0}^{\infty}\bar{c}_{-j}dfe_{t-j} \tag{25}$$

which is linear in the forecast errors. '

7.3 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, $\nu^{-2} \sim \Gamma(N, \tau)$; 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

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

[32] 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.

variance of the error term; second, the time t expected variance of the error term is

$$\begin{aligned} E(\nu^2 \mid Z_t) &= \tau_t^*/N_t^* \\ &\text{where} \\ N_t^* &= N + t \\ \tau_t^* &= \tau + U_t'U_t + (\beta_t - \mu_0)'\Omega_0^{-1}(Z_t'Z_t + \Omega_0^{-1})^{-1}Z_t'Z_t(\beta_t - \mu_0) \end{aligned} \tag{26}$$

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:

$$\begin{aligned} E(\nu^2 \mid Z_t) &= \tfrac{1}{t}U_t'U_t = \tfrac{1}{t}\textstyle\sum_{i=1}^{t} u_i^2 \\ &= \tfrac{t-1}{t}E(\nu^2 \mid Z_{t-1}) + \tfrac{1}{t}u_t^2 \end{aligned} \tag{27}$$

7.4 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 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.[33] 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

[33] We thank Nikola Tarashev for helpful suggestions.

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 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.

References

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, 1353–1365.

Albagli, Elias, Christian Hellwig, and Aleh Tsyvinski, 2014, Dynamic dispersed information and the credit spread puzzle, Technical report, 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, 711–756.

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

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* .

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

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

Brunnermeier, Markus K, 2009, Deciphering the liquidity and credit crunch 2007-2008, *Journal of Economic Perspectives* 23, 77–100.

Bullard, James, and Jacek Suda, 2008, The stability of macroeconomic systems with bayesian learners, *Federal Reserve Bank of St. Louis Working Paper Series* .

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, 937–947.

Chahrour, Ryan, 2012, Public communication and information acquisition, Technical report, Boston College Department of Economics.

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

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

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

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, 815–848.

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, Technical report, 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 .

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

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, 2113–2141.

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

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

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

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

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, 1293–1327.

Gorton, Gary, 1985, Clearinghouses and the origin of central banking in the united states, *The Journal of Economic History* 45, 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, 425–451.

Gorton, Gary B, and Guillermo Ordoñez, 2014, Collateral crises, *The American Economic Review* 104, 343–378.

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

Hamilton, James Douglas, 1994, *Time series analysis*, volume 2 (Princeton university press Princeton).

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

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

Holmström, Bengt, 2014, Understanding the role of debt in the financial system, in *paper delivered at the 13th BIS Annual Conference*.

Iyer, Rajkamal, and Manju Puri, 2012, Understanding bank runs: The importance of depositor-bank relationships and networks, *American Economic Review* 102, 1414–1445.

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.

Kelly, Morgan, and Cormac Ó Gráda, 2000, Market contagion: Evidence from the panics of 1854 and 1857, *American Economic Review* 1110–1124.

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

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, 133–153.

Myatt, David P, and Chris Wallace, 2012, Endogenous information acquisition in coordination games, *The Review of Economic Studies* 79, 340–374.

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

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

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, 668–681.

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, 1116–1147.

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

Ziebarth, Nicolas L, 2013, The radio and bank distress in the great depression, *Manuscript, University of Iowa* .

8 Figures and Tables

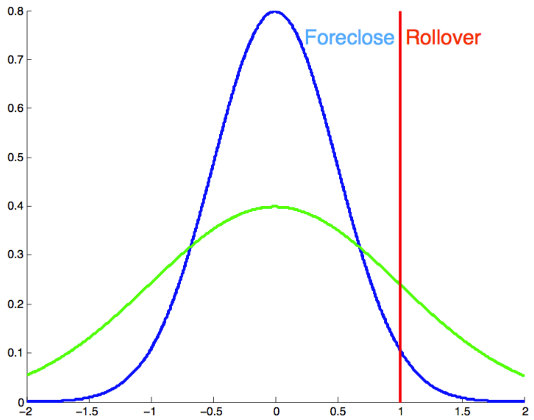

Figure 1: Bad Expectations

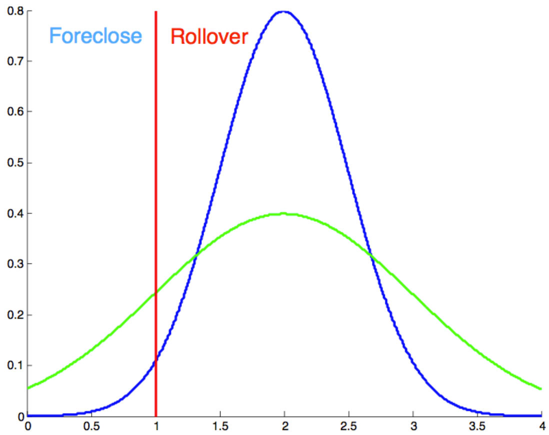

Figure 2: Good Expectations

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.

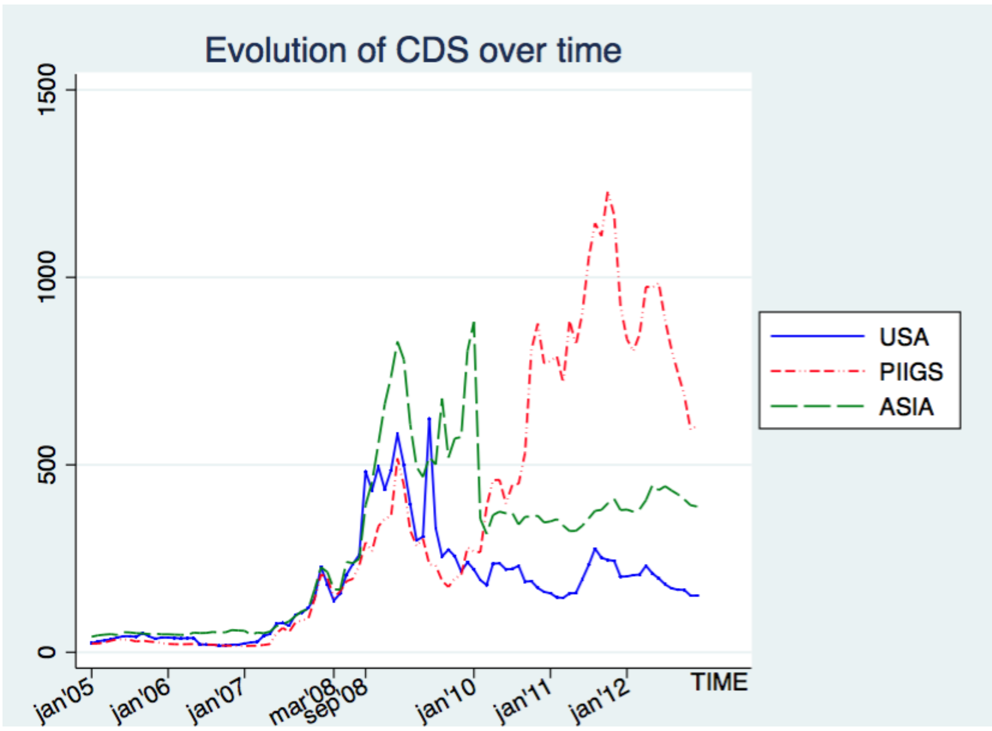

Figure 3: Monthly CDS spreads over time for banks operating in USA, Asia, and PIIGS.

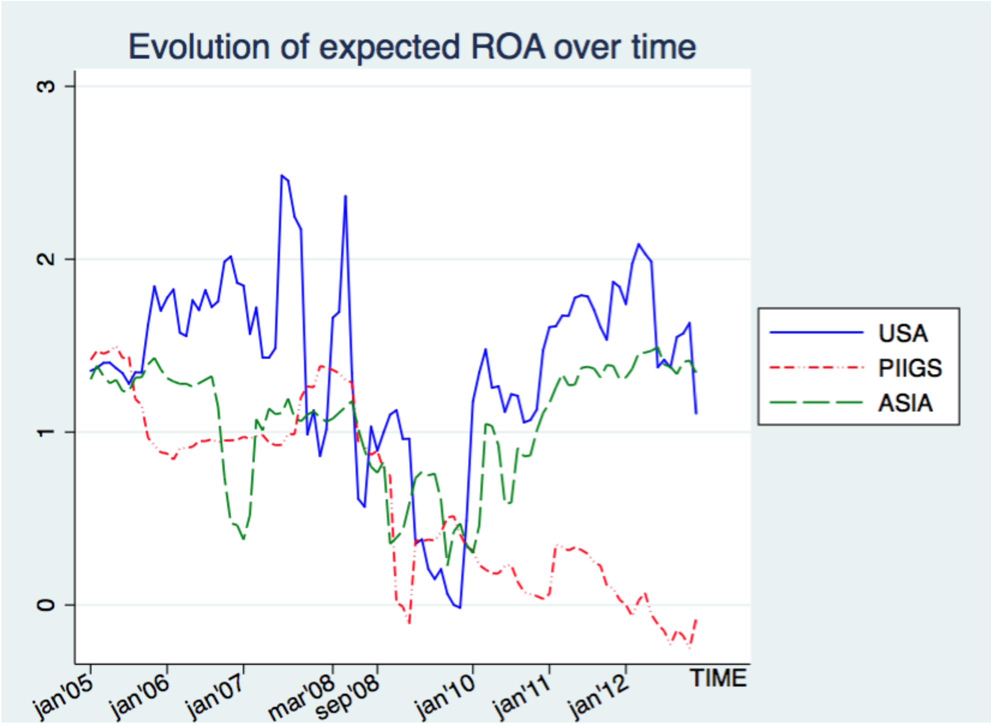

Figure 4: Expected ROA over time for banks operating in USA, Asia, and PIIGS.

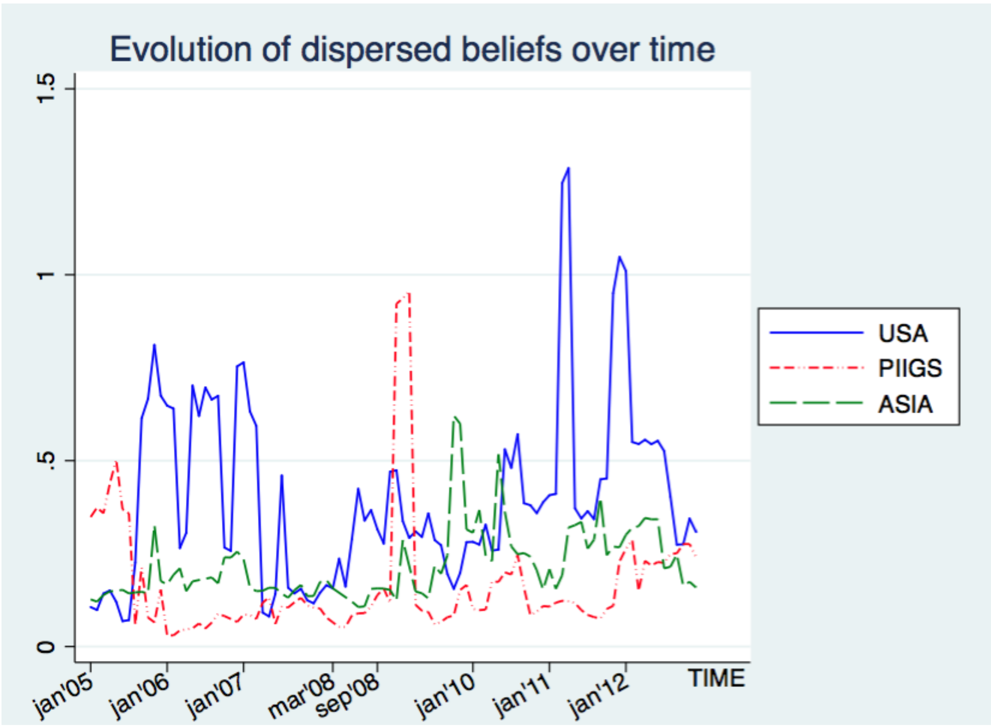

Figure 5: Dispersion of beliefs over time for banks operating in USA, Asia, and PIIGS.

Table 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	$\Delta\delta_{\mathbb{E}_t}$	$\Delta\mathbb{E}_t(\text{ROA})$	Δ 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 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
$\mathbb{E}_t(\mathrm{ROA}_{t+1})$	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
$(\mathrm{CD/TF})_t$	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. $\mathbb{E}_t(\mathrm{ROA}_{t+1})$ 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 3: The effect of expectations and information precision on default risk

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 4: The effect of expectations and bank's characteristics on default risk

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 5: The effect of expectations, information precision and bank's characteristics on default risk

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

	Fragility		
	Leverage (1)	Customer dep. (2)	Interbank (3)
$\mathbb{1}(\text{Fragile}_t,\ \text{Pre}_t)\mathbb{E}_t(\text{ROA}_{i,t+1})$	-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 6: The direct effect of dispersion of beliefs

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

	Bad$_t$: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(25)$ (1)	Bad$_t$: $\mathbb{E}_t(\text{ROA}_{i,t+1}) < p(10)$ (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 $\text{ROA}_{i,t-1}$, leverage$_{i,t-1}$, deposit to total funding ratio$_{i,t-1}$, tier-1 capital ratio$_{i,t-1}$, net charge-offs to gross loans ratio$_{i,t-1}$, non-performing loans to gross loans ratio$_{i,t-1}$. Robust standard errors in brackets. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 7: The effect of expectations and information precision on default risk 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 8: The effect of expectations, information precision and bank's characteristics on default risk before and during the crisis

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

	Fragility		
	Leverage (1)	Customer dep. (2)	Interbank (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 9: The effect of expectations and information precision on default risk 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 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 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 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 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 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 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 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 17: The effect of expectations and information precision on default risk

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 18: 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)
$\mathbb{1}(\text{Bad}_t)\delta_{\mathbb{E}_{i,t}}$	-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 19: The effect of expectations, information precision and bank's characteristics on default risk

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 20: The effect of expectations and information precision on default risk

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 21: 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 22: The effect of expectations, information precision and bank's characteristics on default risk

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 23: The effect of expectations, information precision and bank's fragility on default risk

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 24: The effect of expectations, information precision and bank's fragility on default risk

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 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	