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CONFIDENCE AND OVERCONFIDENCE IN BANKING

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Confidence and Overconfidence in Banking[1]

by

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Abstract

The paper investigates the causes of confidence and overconfidence and their effects on banking behavior and performance for a large sample of American banks in the period 2000-2013. We construct a new indicator of confidence based on banks' loss provisions and show that before 2007 risk-taking, lending and leverage increased relatively more for banks with an intermediate degree of confidence (mid-confidents) than for the overconfident. The former also suffered the greatest losses in the financial crash of 2007-2008. Hence, unlike the previous literature on overconfidence, we find that the financial crisis was determined mainly by the increased confidence of the mid-confident bank CEOs and not the behavioral biases of overconfident CEOs. The latter, in fact, have more persistent beliefs and react less strongly to news during cyclical upswings. Finally, we show that overconfident behavior is unlikely to maximize a bank's value.

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1. Introduction

There is evidence that banks' behavior was among the determinants of the financial crisis of 2007-2008. Brunnermeier (2009) points out that this was a classical banking crisis, with some specific features: above all the extent of securitization, which led single institutions to over-leverage, run excessive maturity mismatching between assets and liabilities, and be excessively interconnected. Demirgüc-Kunt and Huizinga (2010), Demyanyk and Van Hemert (2011), Altunbas et al. (2011), Delis et al. (2014), among others, have documented the excessive risk taken on by banks in the run-up to the crisis.

In addition, Ho et al. (2016), for American banks, and Sironi and Suntheim (2012), for a sample of international banks, show that CEOs' overconfidence played an important role in increasing leverage and risk and weakening lending standards. In this view, the financial crisis was due to biased behavior by banks, which relaxed lending standards, undertook excessive risk and created an overheated economy (Akerlof and Shiller, 2009, p. 65).

However, overconfidence involved only a small proportion of banks. Of the 153 bank CEOs in the Sironi and Suntheim (2012) sample between 2000 and 2008, those classed as overconfident number as few as 3 and in any case no more than 33, depending on which measure of overconfidence is used. Ho et al. (2016) estimates that between 1994 and 2009 47 percent of their sample (36 banks) were overconfident in the pre-crisis period, and that these increased their lending by 4.60 percentage points more per year than the other banks. Ma (2014) reports that banks with the most optimistic quintile of CEOs had on average 20 points more real estate loan growth from 2002 to 2005 and suffered 15-point lower stock returns during the crisis period. But whatever criterion is used to estimate overconfidence, it is hard to maintain that the worst financial crisis since 1929 could have been due to the behavioral bias of a small proportion of banks. Instead, we argue that the crisis was produced by more widespread phenomena among banks and other economic agents.

On the other hand, Geanokoplos (2010) and Danielsson and Shin (2009), among others, have observed that good news bolsters confidence among all economic agents and leads all the banks to be more prone to take risk and expand their balance sheets. In a boom, good news increases and non-performing loans decline, which boosts confidence and optimism and leads to further balance-sheet expansion. Reinhart and Rogoff (2009) and Akerlof and Shiller (2009) maintain that any realistic model of market dynamics and the business cycle has to incorporate fluctuations in confidence. And Barberis (2013) and Gennaioli et al. (2015b) provide models that factor in the psychological determinants of the 2007-2008 financial crisis.

In short, we consider that during the upswing confidence soared and all the banks contributed, in varying measure, to the increase in risk that resulted in the financial crash. Following Goel and Thakor (2008) and Campbell et al. (2011), we assume that at any time the economy is populated by overconfident and underconfident banks as well as banks with intermediate confidence (mid-confidents).[2] In addition, the three categories are likely to differ in amount of loans, leverage and risk.

The purpose of this paper is to assess the contribution of our three types of bank (overconfidents, mid-confidents and underconfidents) to creating the conditions that produced the financial crash of 2007-2008 and to measure the impact of the crisis on the performance of the three groups. We address a series of questions: What are the sources of confidence in banking? What type of bank contributed more to risk-taking in the run-up to the crisis? How did confidence and overconfidence affect performance in both the short and the long run? Is there some optimal degree of confidence that maximizes a bank's value? What is the value of optimism and pessimism in banking?

The paper also presents a new methodology and proxy to define confidence and overconfidence. Most of the previous literature classifies CEOs as overconfident if they repeatedly fail to exercise options that are strongly in the money, or if they habitually acquire their own company's stock (see among others Malmendier and Tate, 2005, Niu, 2010, Sironi and Suntheim, 2012, Ho et al., 2016). Although this proxy does capture important aspects of bank CEOs' behavior, it cannot measure overconfidence at unlisted banks. Odean (1998) and Ben-David et al. (2007) instead proxy overconfidence with the variance of the subjective probability distribution of the expected returns, defining overconfident investors as those who overestimate the precision of their private information signal (see Daniel et al., 1998). Such an indicator necessarily relies on survey data.

In defining the new proxy for confidence we follow Sandroni and Squintani (2004), Puri and Robinson (2007), and Schrand and Zechman (2012) in viewing overconfidence as a multifaceted phenomenon. Overconfident CEOs are likely to overestimate future cash flows (Malmendier and

[2] See Section 2 for the definition and measurement of the three types. Here the terms "overconfident banks", "overconfident bank CEOs" and "overconfidents" are used interchangeably; and similarly for the other two types.

Tate, 2005), underestimate risks (Cheng et al., 2014), and to overreact to good news and underreact to bad (Daniel et al. 1998). Moreover, they are likely to overestimate their ability to cope with adverse circumstances (Sandroni and Squintani, 2004). Accordingly, a change in degree of confidence is likely to affect a number of aspects of banking behavior and balance-sheet indicators. Assuming like Schrand and Zechman (2012) that CEOs are consistently optimistic or pessimistic in all decision-making contexts, we construct several proxies of confidence and overconfidence using balance-sheet variables that the literature has found to be relevant. Then, by estimating bank risk and the predictive power of each index for the bank's performance, we select the most efficient indicator of confidence. The paper is related to important issues investigated by the behavioral finance literature. There is ample evidence that identifying rational behavior is no straightforward matter. Kahneman (2003) and Selten (1990), among many, have observed that in a context of bounded rationality choices and decisions are determined in part by perceptions, intuition and reasoning. And confidence may affect any of these aspects of the decision-making process. We provide evidence on whether bank managers with different degrees of confidence differ in the way they process information and on the impact of their sentiments and perceptions on choices and decisions. We address such questions as: Do underconfident, mid-confident and overconfident banks differ in their reactions to good and bad news? What role do current news and expectations play in determining confidence of the three groups? To our knowledge, this is the first empirical study of these issues.

Our principal finding is that before 2007 risk-taking, lending and leverage all increased more sharply at mid-confident than overconfident banks. That is, the financial crash was not caused by the behavioral bias of a small proportion of banks but by excessive risk-taking on the part of the majority of financial institutions. This behavior is related to the fact that mid-confident banks are less persistent in their beliefs and react more strongly than the overconfident to news. So when good news prevails, the mid-confident banks increase their lending and leverage more than the others. And they consequently suffered greater losses in the crash. Our results are robust to different proxies for confidence and different estimation methodologies.

The paper is organized in ten sections. The second section describes our choice of the proxy for confidence and overconfidence, and Section 3 sets up the hypothesis on the determinants of confidence and overconfidence in banking. Section 4 sets out the data and methodology, and Section 5 provides evidence on the determinants of confidence and overconfidence. Section 6 establishes the hypothesis, Section 7 illustrates the results of the econometric analysis on the impact of confidence on risk-taking, lending, leverage and performance, and Section 8 reports some robustness checks. Section 9 then discusses the optimal degree of confidence in banking, prior to the concluding remarks in the last section.

2. Proxies for confidence and overconfidence

Overconfidence is a systematic bias in the way an individual processes information (Barberis and Thaler, 2003), a bias that is not expected to be eliminated by competition or natural selection (Daniel and Titman, 1999).

Malmendier and Tate (2005) present the most widely used proxy of overconfidence among banking CEOs. First, they set as benchmark the lowest in-the-money percentage at which CEOs should exercise their stock options for a given year as soon as the vesting period is up. If a CEO delays exercise beyond the benchmark period, this denotes overconfidence about the bank's future stock price and profits. But this gauge has drawbacks. First, it applies only to banks that are listed on the stock exchange. Second, it posits that the sole reason for non-exercise of options is overconfidence, when in practice other factors (restrictions on equity disposition, say, or market signaling) may affect the timing.[3] In any case, one of the main contributions of experimental psychology (see Barberis and Thaler, 2003) is that overconfidence is a multifaceted phenomenon. Those who are overconfident are more specific in their estimates (Ben-David et al. 2007) and more confident of their absolute abilities and relative skills and virtues (Sandroni and Squintani, 2004). In particular, overconfident managers overestimate the returns to their investment projects (Malmendier and Tate, 2005), undertake excessive risk (Barberis, 2013, Niu, 2014)[4] or underestimate the risks (Cheng et al., 2014). In addition, investors' overconfidence will cause over- or under-reaction to good or bad news (Odean, 1998, Daniel et al., 1998, Chuang and Lee, 2006, Daniel and Hirshleifer, 2015).

[3] As Ma (2014) observes, "CEOs sometimes may not be able to fully adjust their equity positions due to equity disposition restrictions, in which case the equity-based measures would be affected by the amount of equity compensation and the degree of disposition constraints. … If CEOs are not able to fully adjust their equity holdings, they could have higher equity holding growth and be mislabeled as 'optimistic'".

[4] Barberis (2013) considers excessive risk-taking owing to biased beliefs to have been a contributing factor to the financial crisis.

Given that overconfidence is multifaceted (on this, see among others, Sandroni and Squintani, 2004, Puri and Robinson, 2007, and Schrand and Zechman, 2012), we can see that confidence and overconfidence affect a number of balance-sheet variables. First we consider the indicators that reflect greater confidence on the part of CEOs and then seek to determine which of them is most likely to incorporate CEO confidence by testing the power of each to predict the bank's risk and performance. We then adopt as our indicator the indicator with the greatest predictive power.

The first two balance-sheet variables that are likely to incorporate CEOs' confidence or overconfidence are loan loss provisions and loan loss reserves, which reflect current and expected loan losses (Bikker and Metzemakers, 2005). Black and Gallemore (2012), among others, have documented the link between the overconfidence of bank executives and loan loss provisioning. The provisions recognized by overconfident CEOs and CFOs are smaller and less strongly connected with current and future non-performing loans. At the same time, however, there is ample evidence that provisions are also determined by causes other than confidence. Ahmed et al. (1999), Fonseca and González (2008), Beatty and Liao (2009), and Leventis et al. (2011) have shown that banks use provisions to manage reported capital and earnings, or for tax and signaling purposes. However, Kim and Santomero (1993) contend that we cannot distinguish window dressing from prudent provisioning, because a positive correlation between earnings and provisions could well be the result of accurate statistical forecasting of loan losses.

While loan loss provisions are recorded in the bank's income statement, loan loss reserves constitute a "contra-asset" account, to cover the expected loss from non-repayment of some portion of outstanding loans. Notwithstanding the possibility of exploiting loan loss reserves for objectives other than safety and soundness, prudential considerations suggest that larger reserves enable the bank to absorb greater unexpected losses. This consideration implies a more forward-looking approach to loan loss reserves than to provisions (Balla et al., 2012). Assuming that to some extent provisions and reserves reflect the bank's outlook on the future, we expect more confident CEOs to be more optimistic and, everything else being equal, to set aside smaller provisions and reserves relative to loan assets. As noted, overconfident CEOs are likely to overestimate their ability to cope with adverse conditions (see Chuang and Lee, 2006, Eisenbach and Schmalz, 2015), so we accordingly expect more confident CEOs to be more willing to finance long-term assets with short term liabilities.[5] Finally, we expect the more confident banks to take greater risks and to respond more strongly to good news than to bad. Daniel and Hirshleifer (2015), in fact, have shown that more confident banks overreact to good news and underreact to bad. Thus we expect banks with more confident CEOs to be characterized by greater increases in lending, leverage and total assets during the cyclical upswing and smaller contractions in the downturn.

Consequently, positing that CEOs are consistently optimistic or pessimistic in their decision-making,[6] we expect more confident banks to hold less loan loss provisions and reserves in proportion to gross loans, to fund more long-term assets with short-term liabilities, to expand lending, leverage and total assets more sharply during upswings and reduce activity less significantly in downswings.

We accordingly consider the following proxies for confidence and overconfidence:

- Index1=Loan loss provisions/Gross loans
- Index2=Loan loss reserves/Gross loans
- Indice3=log(Liquid assets/ (Total liabilities – Total long-term funding)
- Indice4=Sum of the standardized values of:
  - Index4.1=100*Gross loans(t)/Gross loans(t-1)
  - Index4.2=100* Leverage(t)/Leverage(t-1)
  - Index4.3=100* Total assets(t)/Total assets(t-1)

Hypothesis: the greater the CEO's confidence, the lower the first three indexes and the higher the last.

In Table 2.1 we report the correlation coefficients between the indexes.

Table 2.1 Correlations between proxies of confidence

	Index1	Index2	Δ(Index2)	Index3	Index4
Index1	1.000	0.371	0.439	0.420	0.279
Index2	0.371	1.000	0.142	-0.157	0.022
Δ(Index2)	0.439	0.142	1.000	-0.044	0.012
Index3	0.420	-0.157	-0.044	1.000	-0.026
Index4	0.279	0.022	0.012	-0.026	1.000

Spearman Rank Order Correlation; for 1% significance, |ρ| = 0.013

[5] As Demirguc-Kunt and Huizinga (2010) observe, maturity mismatching characterized most banks in the run-up to the crash of 2007-2008.

[6] Goel and Thakor (2008) show that CEOs who overestimate the precision of their information will also be over-optimistic about the project portfolio they accept when they base the acceptance decision on their information. Moreover, an extensive literature in psychology and in experimental economics has provided evidence that overconfidence spreads from one domain to others (e.g., West and Stanovich, 1997, Klayman et al., 1999, Jonsson and Allwood, 2003, Glaser et al., 2005, Glaser and Weber, 2007, Ben-David et al., 2007).

In general, the correlation between the different proxies of confidence is quite low, suggesting that they capture different aspects of confidence-related behavior. Index 4 in particular has very low correlations with the others. By contrast, loan loss provisions are more closely correlated with loan loss reserves (37%) and with the change in reserves (44%).

Since each index is likely to capture a particular aspect of confidence, we expect our proxies to differ in explanatory power concerning future risk and performance. Following the methodology of Beatty and Liao (2015),[7] we measured the efficiency of each index by evaluating its power to explain the future risk of the bank (i.e., total assets, leverage and loans) and its performance (ROAA, non-performing loans, uncollectable loans), on the assumption that greater explanatory power means that the index is a better gauge of the CEO's degree of confidence. To this end, we regressed each index on future levels and variations of Return on average assets (ROAA), Total assets (TA), Gross loans (GL), New loans/gross loans (NEWL), Non-performing loans over gross loans (NPL), Uncollectable loans/gross loans (UNC), and leverage (Y_L1).
Since the several indexes do display some degree of correlation, we also estimated their joint effects, not only the separate effect of each.

Table 2.2 below displays the results of the regressions.

[7] They compare the accuracy of analysts' forecasts of provisions with time-series forecasts of non-performing assets.

Table 2.2: **Predictive power of the confidence indexes for US banks**.
P-value of index coefficients in the regression y(t+1) = a +Σᵢ bᵢ indexᵢ(t) + cy(t). Quantile Regression (Median). Estimation successfully identifies unique optimal solution. */**/*** indicate significance at 10%/5%/1% respectively.

		Index i coefficient p-value and significance			
		Index1	Index2	Index3	Index4
RWATA	t+1	0.097829 *	0.000336 ***	0.138576	0.113411
	t+2	0.016214 **	0.003764 ***	0.617791	0.048053 **
	t+3	0.793974	0.061352 *	0.122211	7.13E-06 ***
ROAA	t+1	1.44E-13 ***	9.04E-11 ***	0.022379 **	7.51E-60 ***
	t+2	2.45E-18 ***	1.10E-17 ***	0.335992	3.86E-62 ***
	t+3	4.10E-10 ***	4.17E-14 ***	0.001213 **	6.72E-46 ***
ROAE	t+1	4.11E-05 ***	0.506294	0.000361 **	2.24E-42 ***
	t+2	1.21E-23 ***	0.00848 ***	0.682534	1.90E-232 ***
	t+3	0 ***	2.40E-05 ***	0.005179 **	8.98E-90 ***
ΔLOGTA	t+1	0.900281	0.059866 *	2.46E-50 **	1.25E-13 ***
	t+2	0.796666	0.426465	1.49E-13 **	0.087233 *
	t+3	0.35558	0.0285 **	2.43E-06 **	0.425689
ΔGL	t+1	2.03E-06 ***	0.702232	0.453182	0.832153
	t+2	0.713844	0.534978	0.053666 *	0.967826
	t+3	0.031166 **	0.420622	0.768701	0.270868
NEWL	t+1	0.915975	8.29E-10 ***	1.76E-08 **	3.85E-05 ***
	t+2	0.118451	0.053428 *	3.26E-05 **	4.49E-06 ***
	t+3	0.046832 **	0.25997	0.237612	0.030999 **
NPL	t+1	1	1	1	1
	t+2	0.936701	0.00711 ***	7.99E-13 **	0.156719
	t+3	0.844933	5.60E-06 ***	1.50E-27 **	0.000803 ***
UNC	t+1	9.93E-84 ***	6.27E-27 ***	7.53E-07 **	6.89E-12 ***
	t+2	0.00056 ***	2.63E-13 ***	0.00056 **	1.00E-12 ***
	t+3	7.19E-06 ***	1.80E-06 ***	3.60E-05 **	5.06E-07 ***
Average number of observations	t+1	*38316.6*	*38316.6*	*38316.6*	*38316.6*
	t+2	*30366.9*	*30366.9*	*30366.9*	*30366.9*
	t+3	*25170.2*	*25170.2*	*25170.2*	*25170.2*

The results reported in Table 2.2 show that Index 2 (Loan loss reserves/Gross loans) has the greatest effect on the indicators of future risk and performance, supporting the hypothesis that this is the best proxy of CEO confidence and overconfidence.[8] However, in the econometric analysis we also used the other indexes as robustness checks, finding qualitatively similar results (see Appendix).

With respect to the nature of confidence, most of the literature distinguishes between confidence and overconfidence (Malmendier and Tate, 2005, Chuang and Lee, 2006, Eisenbach and Schmalz, 2015, Ho, 2016) and characterizes the latter as a behavioral bias. Puri and Robinson (2007) study the effects of optimism on work/life choices, showing a marked difference between the behavior of moderate and extreme optimists – moderate optimists appear to have prudent financial habits, while extreme optimists do not; the authors conclude (p. 97) that "modest amounts of behavioral bias, be it overconfidence, self-attribution bias, or optimism, may indeed be associated

[8] Notice that if one uses estimation devices more appropriate to fat-tail distributions (Spearman Rank Order Correlation, and quantile regressions including the present value of the dependent variable among the regressors), the differences in predictive capacity diminish, but the foregoing conclusion still applies.

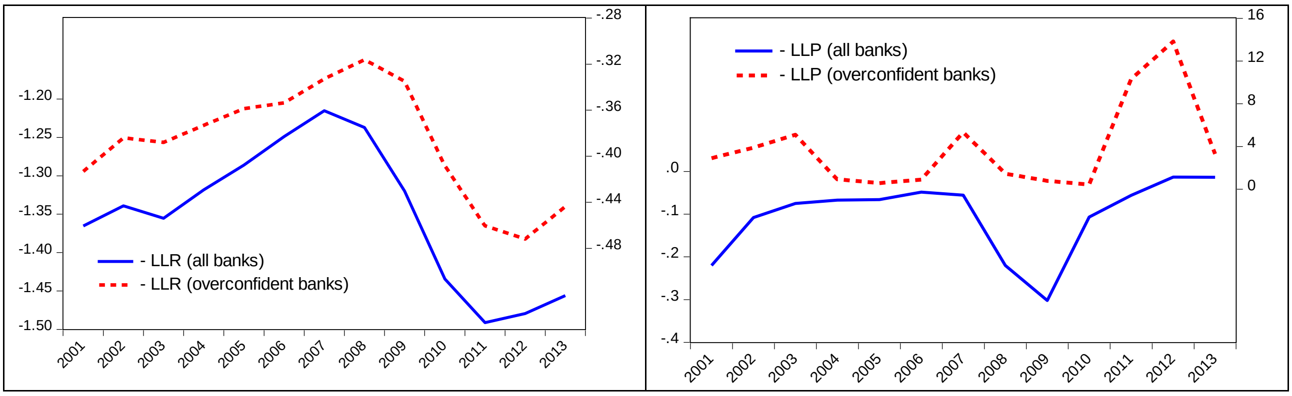
with seemingly reasonable decision-making." On the same theme, Goel and Thakor (2008) distinguish three degrees of confidence: extravagant diffidence, moderate overconfidence, and extravagant overconfidence. Extravagantly diffident CEOs reject high-profit projects, to the detriment of the company's value, while the extravagantly overconfident invest less in information and so jeopardize stakeholders. Moderately overconfident CEOs are found to benefit shareholders and increase the value of the firm.

Following Goel and Thakor, we too distinguish three levels of confidence: underconfidence, mid-confidence and overconfidence, positing qualitative behavioral differences between the three types of bank. In addition, we define as overconfident the banks in the bottom decile of the distribution of Loan loss reserves/Gross loans (or Loan loss provisions/Gross loans), and as underconfident those in the top decile. All the other banks are defined as mid-confident, i.e. having an intermediate level of confidence.[9]

In fact, Figure 2.1 shows that banks' confidence increased between 2001 and 2007 and dropped sharply in 2008-2009. It was not restored until after 2011; the trend is more distinct when the proxy is loan loss reserves (not provisions) over gross loans.

Figure 2.1. American banks' confidence and over-confidence in the period 2001-2013

Confidence on the left-hand scale, overconfidence on the right. The confidence index is a weighted average of Loan loss reserves/Gross loans and Loan loss provisions /Gross loans for all the banks and for the banks in the bottom decile of the annual distribution of the corresponding indicator.



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9 Puri and Robinson (2005) take the right-most 5% of CEOs in their proxy of optimism to be extreme optimists, while Ma (2014) defines the top 10% of his confidence indicator as overconfident. However, as a robustness check, we also considered the top and bottom 20% of the distribution of loan loss reserves/gross loans , finding similar results. See Appendix.

Next we investigate the determinants of confidence for our three categories, including the impact of current news and expectations on confidence, and responses to bad and good news.

3. The determinants of confidence and overconfidence in banking

Barberis (2013), Foote et al. (2012) and Gennaioli et al. (2015b) all emphasize that in a context of bounded rationality decision-makers extrapolate past trends. Akerlof and Shiller (2009) note the role of success stories in the formation of expectations, likening the transmission of confidence between individuals to that of epidemic disease. We therefore expect good news on past performance to fuel confidence and expectations of still better performance by all the banks. In a boom, good news increases and non-performing loans decline, both factors favoring greater confidence and optimism and further balance-sheet expansion.

Hypothesis 1. Banks' confidence increases with good news and decreases with bad news.

In addition, we hypothesize that banks differ in their responses to good and bad news.

Hypothesis 2. Overconfident (underconfident) banks respond more (less) to good news and less (more) to bad news than the other banks.

Overconfident CEOs are likely to overestimate the importance of good news and underestimate bad, reflecting their overoptimistic view of the economy (Odean, 1998, Daniel et al., 1998, Daniel and Hirshleifer, 2015); for underconfident banks, the inverse holds, given their pessimism over the economy.

Therefore, we expect current news to have differential effects on different types of bank. Good news will induce the overconfident to trim their loan loss reserves and provisions more significantly, and they will increase their provisioning less in response to bad news. Pain (2003) and Bikker and Metzemakers (2005) document that an increase in real GDP growth reduces banks' provisions. Laeven and Majnoni (2003) and Black and Gallemore (2012) report that during a business expansion banks tend to defer the accounting recognition of expected losses until adverse cyclical conditions start to set in.

Beyond their response to current news, we also assume that CEOs differ in their expectations for the future.

Hypothesis 3. Overconfident (underconfident) banks' CEOs have an optimistically (pessimistically) biased view of the future.

Gennaioli et al. (2015a) gives evidence that the actual investments of non-financial corporations are driven by expectations, which are not rational. Moreover, Barberis and Thaler (2003), among others, state that overconfident CEOs have more optimistic views of the future, while Malmendier and Tate (2005) show that they overestimate the returns to their investment projects. Ahmed et al. (1999) document that loan loss provisions are negatively correlated with changes in expected earnings and with contemporaneous stock returns. We therefore assume that excessive optimism or pessimism leads respectively to overestimation or underestimation of future returns.

Summarizing our hypothesis, we posit that the level of confidence is the result of good and bad news today and expectations of good and bad news tomorrow. Good news and a better outlook on the future increase confidence, but overconfident CEOs respond more strongly to good news and less to bad. Consequently, we expect that the more confident banks will hold smaller loan loss provisions and loan loss reserves relative to gross loans, owing to their rosier view of current news and more optimistic vision of the future. For underconfident banks, the opposite holds.

Next, we evaluate the impact of current news on confidence and then assess how expectations affect confidence for our three bank types.

To test the first two assumptions we estimated the following:

$$\Delta(LLR)*100= \beta_0 + \beta_1 LLR(-1)*100+ \beta_2 \Delta LLR(-1) + \beta_3 UNC*100+ \beta_4 \Delta GL + \beta_5 \Delta NPL + \beta_6 NPL *100+ \beta_7 LOGTA(-1)+ \beta_8 \Delta LOGTA+\beta_9 LOGTA+ \beta_{10} IMPTE + \beta_{11} TIER1+ \beta_{12} OP+\beta_{13} PBT+ \beta_{14} \Delta PBT +\beta_{15} GDP+ \beta_{16} CLIF(-1)+ \beta_{17} LOGSMK(-1) + \beta_{18} \Delta LOGSMK + \beta_{19} FEDFUND + \varepsilon \quad (1)$$

in which Δ denotes absolute variation, LOG denotes natural logarithm, (-1) indicates the previous year, and ε is the error term. Table 4.1 gives the definitions of the variables. We distinguish between internal and external determinants of confidence. Regressors from 1-14 are internal, regressors 15-19 external. The former include balance-sheet determinants (non-performing loans, uncollectable loans, profits, tier 1 regulatory capital and gross loans), while the latter comprise macroeconomic indicators (real GDP growth, the value of current leading indicators, and the stock market index).

4. Data and methodology

We tested our hypotheses on a sample of American commercial, cooperative, and savings banks.[10] The data set includes the consolidated annual balance sheets of 10,223 banks in the United States, or 84% of the American banks reported in the Bankscope database, provided by Bureau van Dijk.[11] We also used other data sources, such as Bondware, to compute loans net of securitization.

Table 4.1 shows the variables used in the econometric analysis and their sources.

Table 4.1 Variables and sources of the data

Definition	Symbol	Source
Bank-specific variables:		
Size (log of total assets)	LOGTA	BankScope
Risk-weighted assets/Total assets	RWATA	BankScope
Risk Weighted Assets including floor/cap per Basel II	RWAF	BankScope
Leverage (Total assets / Total equity)	Y_L1	BankScope
Loan loss provisions/Gross loans(-1)	LLP	BankScope
Loan loss reserves/Gross loans(-1)	LLR	BankScope
Non-performing Loans/Gross Loans	NPL	BankScope
Non-performing Loans/Total Equity	NPLTE	BankScope
Impaired loans/Gross loans	IMP	BankScope
Impaired Loans/Total Equity	IMPTE	BankScope
Uncollectable loans/Gross loans(-1).	UNC	BankScope
Liquid assets / Total assets	LIQU	BankScope
Deposits and short term funding/ Total assets	DEP	BankScope
Tier1 Regulatory capital ratio	TIER1	BankScope
Operating profits / Total assets(-1)	OP	BankScope
Profits before taxes/Total assets	PBT	BankScope
Return on assets	ROAA	BankScope

[10] We used only these categories of banks because of the substantial differences from other classes of banks reported in the Bankscope dataset (notably, bank holding & holding companies, finance companies, investment banks, real estate & mortgage banks, and specialized governmental credit institutions).

[11] However, because observations for some banks were incomplete, our econometric analysis covers only 9,845 banks in the open sample and 5,838 banks in the closed sample.

Return on equity	ROAE	BankScope
Gross Loans	GL	BankScope
ΔGross Loans/Gross_Loans(-1))	ΔGL	BankScope
Gross loans/Total assets(-1).	GLTA	BankScope
New loans/Gross loans(-1)	NEWL	BankScope
Net_interest_margin	NIM	BankScope
Total_long_term_funding /Total_liabilities	LTF	BankScope
Interbank_ratio	IBR	BankScope
(Operating profits +Loan Loss Provisions)/Total assets	OPBT	Bankscope, Bondware
Macro variables:		
Three-month unsecured interbank rate – IRS corresponding secured interest rate	RISK3	Fed
Three-month unsecured interbank rate	R3M	Fed
Treasury bond Long term rate	LTTB	Fed
Official interest rates	FED_FUND	Fed
Stock market index (log) (year 2000=100)	LOGSMK	Yahoo Finance
Composite leading indicator (end year)	CLIF	OECD
Real annual GDP growth	GDP	World Bank

Table 4.2 reports the summary statistics for the banks present in all the years considered.

Table 4.2 Summary statistics. American commercial, cooperative and savings banks. Period 2001-2013. Closed sample.

	All Obs.	All Mean	Over Mean	Inter Mean	Under Mean	All Max	All Min	All Std. Dev.	All Skew.	All Kurtosis
LLR	36884	1.33	0.376	1.221	3.155	32.2	0	0.923	7.349	135.665
100*LLP	36884	0.113	0.021	0.085	0.398	45.751	-23.077	0.719	12.214	634.955
Δ(LLR)	36884	-0.007	-0.026	-0.024	0.111	17.75	-12.36	0.392	0.968	235.141
100*UNC	36884	-0.002	0.016	-0.024	0.096	66.4	-618.5	3.943	-132.434	19233.7
ΔGL	36884	0.116	0.124	0.136	0.08	192	-0.976	1.36	96.425	12031.6
ΔGL	36884	0.116	0.124	0.135	0.081	185.815	-0.966	1.327	94.633	11668.6
Δ (NPL)	36732	0.032	0.002	-0.014	-0.015	18.89	-24.05	0.787	2.394	91.096
NPL	36782	0.454	0.273	0.362	0.765	50.53	0	1.004	11.284	327.227
LOGTA	36884	4.399	4.764	4.456	3.937	13.221	1.099	1.049	0.954	6.43
Δ LOGTA	36884	0.07	0.06	0.083	0.035	4.995	-1.93	0.138	6.201	121.381
GLTA	36623	0.599	0.642	0.603	0.448	1.060	0.002	0.170	-0.433	2.831
IMPTE	36782	0.027	0.018	0.023	0.034	4.34	0	0.071	18.749	709.147
TIER1TIER1	36876	19.154	24.965	16.873	25.167	485.7	2.58	11.801	6.386	128.864

OP	36883	1.246	1.103	1.381	1.444	39.78	-23.4	1.076	4.818	200.252
OPBT	36883	1.325	1.117	1.442	1.716	42.053	-23.4	1.124	8.183	237.163
Δ (OPBT)	36879	0	-0.05	0.038	0	144.9	-14.871	1.053	71.616	9744.15
ROAA	36625	0.99	0.711	0,881	1.045	25.09	-21.69	0.886	2.269	117.74
ROAE	36625	9.1	6.378	8,963	7.711	181.71	-124.03	7.738	0.472	33.55
NIM	36625	3.99	3.279	4,119	4.392	70.58	0	1.264	11.786	380.18
100*LTF	36884	3.402	6.947	3.463	1.646	98.734	-6.8	6.418	3.111	17.328
100*DEP	36883	95.817	92.106	95.794	97.226	142.157	0	6.65	-3.092	18.307
100*LIQU	36884	10.834	9.363	9.491	13.462	86.885	0	9.244	2.227	10.142
IBR	1563	45.548	NA	NA	NA	962.75	0	128.131	3.924	19.836
RWAF	32758	176.704	220.821	216.451	245.88	455722	1	4166.13	84.164	8015.10
RWATA	32758	0.635	0.551	0.66	0.593	3.151	0.025	0.144	0.692	14.21
Y_L1	36623	9.709	9.299	10.143	8.417	65.5	1.037	2.891	0.692	9.748
GDP	36623	0.945	-	-	-	2.9	-3.6	1.542	-1.323	4.834
CLIF	36623	99.645	-	-	-	101.396	95.647	1.608	-0.965	3.202
LOGSMK	36623	7.076	-	-	-	7.41	6.855	0.146	0.235	2.531
100*Δ LOGSMK	36623	-0.013	-	-	-	0.176	-0.248	0.148	-0.262	1.403
FED_FUND	36623	2.377	-	-	-	5.05	0.125	1.741	0.219	1.659
R3M	36623	2.626	-	-	-	5.319	0.281	1.687	0.232	1.705
RISK3	36623	0.196	-	-	-	1.414	-0.025	0.386	2.315	7.312
RTREASURY	36623	4.11	-	-	-	5.021	1.803	0.835	-1.149	3.623

The closed sample counts some 36,800 observations. Of these, 9.79% refer to overconfident banks and 9.95% to underconfident banks.

Banks at our three degrees of confidence differ in several aspects. Overconfident banks are larger and have a greater propensity to lend (their lending is equal to 64% of total assets, compared with 60% for mid-confidents and 45% for underconfidents). On average, however, during our period it was mid-confident, not overconfident, banks that registered the sharpest increases in lending and total assets. In addition, mid-confident banks are more highly leveraged, with the highest portfolio risk and the lowest profits, but they also give the highest return on capital to investors. Underconfident banks have a lower propensity to lend, with the highest non-performing loan and loan loss ratios, but also the highest operating profits and interest rate margins. This suggests that underconfident banks may be lending to riskier borrowers. For the period as a whole, the mid-confident banks increased their ratio of loan loss reserves to gross loans, while the other banks lowered it.

Finally, Table 4.3 reports the correlation matrix among the variables. We opted for rank correlations instead of the traditional Pearson r correlation, in view of the high Kurtosis value of all the balance-sheet data.

Table 4.3 Rank correlations (American commercial, cooperative and savings banks**, 2000-2013)**

	LLR	LLP	RWATA	NPL	ΔNPL	UNC	GLTA	ΔGL	Y_L1	TIER1	LIQU	DEP	OP	PBT	ROAA	ROAE	GDP	LOGSMK	ΔLOGS MK	Fed_ fund
LLR	1.00	0.38	-0.05	0.16	-0.01	-0.02	-0.17	-0.11	-0.16	0.15	0.14	-0.05	0.04	0.07	0.04	-0.03	0.01	-0.03	-0.01	0.00
LLP	0.38	1.00	0.47	0.41	0.40	0.60	0.42	0.43	0.41	0.22	0.27	0.32	0.32	0.45	0.30	0.33	0.27	0.38	0.41	0.28
RWATA	-0.05	0.47	1.00	-0.00	0.03	-0.08	0.37	0.24	0.14	-0.65	-0.25	-0.01	0.11	0.16	0.09	0.15	0.03	0.17	0.04	-0.02
NPL	0.16	0.41	-0.00	1.00	0.33	0.12	-0.14	-0.09	0.08	-0.04	0.00	0.03	-0.02	0.01	-0.03	-0.00	-0.10	-0.01	0.11	-0.07
ΔNPL	-0.01	0.40	0.03	0.33	1.00	-0.01	-0.01	0.03	0.01	-0.01	-0.01	-0.02	-0.04	-0.02	-0.04	-0.04	-0.08	0.02	0.08	-0.07
UNC	-0.02	0.60	-0.08	0.12	-0.01	1.00	-0.29	-0.21	0.01	0.04	-0.02	-0.04	0.04	0.15	0.02	0.01	-0.05	0.02	0.06	-0.01
GLTA	-0.17	0.42	0.37	-0.14	-0.01	-0.29	1.00	0.57	0.11	-0.29	-0.18	0.04	-0.07	-0.05	-0.06	0.00	0.07	0.13	0.01	0.01
ΔGL	-0.11	0.43	0.24	-0.09	0.03	-0.21	0.57	1.00	0.17	-0.27	-0.03	0.06	-0.08	-0.05	-0.06	0.01	-0.07	0.08	0.07	-0.08
Y_L1	-0.16	0.41	0.14	0.08	0.01	0.01	0.11	0.17	1.00	-0.73	-0.12	0.57	-0.01	0.02	-0.00	0.36	0.03	0.06	0.01	-0.03
TIER1	0.15	0.22	-0.65	-0.04	-0.01	0.04	-0.29	-0.27	-0.73	1.00	0.26	-0.38	-0.07	-0.12	-0.06	-0.35	0.01	-0.12	-0.03	0.07
LIQU	0.14	0.27	-0.25	0.00	-0.01	-0.02	-0.18	-0.03	-0.12	0.26	1.00	0.14	-0.14	-0.16	-0.13	-0.17	-0.05	-0.12	0.02	0.01
DEP	-0.05	0.32	-0.01	0.03	-0.02	-0.04	0.04	0.06	0.57	-0.38	0.14	1.00	-0.02	-0.02	0.01	0.23	0.07	-0.03	-0.04	0.04
OP	0.04	0.32	0.11	-0.02	-0.04	0.04	-0.07	-0.08	-0.01	-0.07	-0.14	-0.02	1.00	0.95	0.93	0.83	0.10	0.11	-0.04	0.01
PBT	0.07	0.45	0.16	0.01	-0.02	0.15	-0.05	-0.05	0.02	-0.12	-0.16	-0.02	0.95	1.00	0.88	0.79	0.07	0.12	-0.01	-0.03
ROAA	0.04	0.30	0.09	-0.03	-0.04	0.02	-0.06	-0.06	-0.00	-0.06	-0.13	0.01	0.93	0.88	1.00	0.89	0.10	0.08	-0.05	0.03
ROAE	-0.03	0.33	0.15	-0.00	-0.04	0.01	0.00	0.01	0.36	-0.35	-0.17	0.23	0.83	0.79	0.89	1.00	0.10	0.11	-0.03	0.02
GDP	0.01	0.27	0.03	-0.10	-0.08	-0.05	0.07	-0.07	0.03	0.01	-0.05	0.07	0.10	0.07	0.10	0.10	1.00	-0.11	-0.78	0.67
LOGSMK	-0.03	0.38	0.17	-0.01	0.02	0.02	0.13	0.08	0.06	-0.12	-0.12	-0.03	0.11	0.12	0.08	0.11	-0.11	1.00	0.48	-0.03
ΔLOGSMK	-0.01	0.41	0.04	0.11	0.08	0.06	0.01	0.07	0.01	-0.03	0.02	-0.04	-0.04	-0.01	-0.05	-0.03	-0.78	0.48	1.00	-0.46
Fed_fund	0.00	0.28	-0.02	-0.07	-0.07	-0.01	0.01	-0.08	-0.03	0.07	0.01	0.04	0.01	-0.03	0.03	0.02	0.67	-0.03	-0.46	1.00

Observations: 44734; 5% significance=0.009; 1% significance=0.014

The main variables reflecting the effects of confidence were identified by a group of equations that capture banking behavior and performance from 2000 to 2013. The econometric package used for the estimation is Eviews-9.5. Given the excessive fat tails of all the residual distributions (see Table 4.2), in lieu of OLS we elected quantile regression (QREG) based on medians. In a few cases, in order to check the results more carefully we also applied robust LS for comparison, obtaining similar results. In addition, we compared QREG to robust LS estimations in some cases where we were not satisfied with the significance of the QREG parameter. For the comparison of QREG, robust LS and OLS, see the appendix. Finally, to avoid endogeneity problems, where possible the explanatory variables were lagged; in some cases, when lagged regressors were unavoidable or they were not appropriate economically, we also used instrumental variables, substituting for the true regressors the corresponding fitted values obtained by "marginal" regressions for predetermined variables only. For the most part the results are quite similar to those without instrumental variables (see the appendix).

5. The evidence on the determinants of confidence and overconfidence in banking

Here we set forth the estimations for hypotheses 1-3. First, we tested the hypothesis that the bank's confidence increases with good news and decreases with bad. Examples of good news are an increase in profits and a reduction in non-performing loans, or an increase in real GDP and a rise in the stock market index.

Table 5.1 Estimation of the determinants of confidence

Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; Δ() indicate change; */**/*** indicate significance at 10/5/1% of probability respectively. *Notice that a higher value of the dependent variable corresponds to a lower level of confidence. Hence (apart from the lagged dependent variable) a negative coefficient corresponds to an increase in confidence.*

Dependent Variable:	Δ(LLR)	Δ(LLR)	LLR	LLR	Δ(LLR)	Δ(LLR)
Type of sample	Open	close	open	close	open	close
Fixed effects	No	no	yes	yes	yes	yes
Estimation Method	QREG	QREG	QREG with IV	QREG with IV	QREG with IV	QREG with IV
Regressors / Equations	(1)	(2)	(3)	(4)	(5)	(6)
C	-0.03422	-0.01783	-0.01937***	-0.01869***	-0.00973***	-0.00930***
LLR(-1)	*-0.06440****	*-0.05824****	0.47074***	0.55502***	-0.35972***	-0.21639***
Δ (LLR(-1))	-0.00135	0.00255**	-0.07631*	-0.11297**	0.14529***	0.09141***
100* UNC	-0.06270***	-0.27417**	-0.06411***	-0.09217***	-0.23681***	-0.30414***
Δ GL	-0.08140***	-0.50676***	-0.15280***	-0.25381***	-0.34077***	-0.50310***
Δ (NPL)	0.04208***	0.01561**	0.06239***	0.04438***	0.03943***	-0.00189
NPL(-1)	0.01078***	-0.00176	0.06385***	0.03816***	0.04326***	-0.00066
LOGTA (-1)	0.00080	0.00592***	0.02525**	-0.00701	0.04828***	0.04978***
Δ LOGTA	-0.01299	0.15891	-0.06225**	0.02454	0.01372	0.06134***
LOG(GLTA (-1)))	0.00469	-0.01244***	-0.11555	-0.20173***	0.12889***	0.09943***
IMP	0.10057***	0.38963***	0.02261***	0.21870*	0.13464***	0.66834***
TIER1	-0.00014***	-0.00034**	0.00642***	0.00462***	0.00460***	0.00264***
OP(-1)	-0.08332***	-0.20593**	-0.20289***	-0.20645***	-0.05026	-0.08698***
PBT	0.08670***	0.21230**	0.20099***	0.20958***	0.04365	0.08756***
Δ(PBT)	-0.06781***	-0.17999	-0.18533***	-0.18462***	-0.03089	-0.06830**
GDP	-0.00343***	-0.00098	0.01215***	0.00825***	0.00307**	0.00172
CLIF	0.00117	0.00072	0.00369**	0.00313	0.00142	0.00052
LOG(SMK(-1))	-0.00065	-0.00253	-0.04056*	-0.03337	-0.04580	-0.03312***
ΔLOG(SMK)	-0.06763***	-0.05759***	-0.18914***	-0.14143***	-0.08588***	-0.06180***
Fed_fund	-0.00644***	-0.00384***	-0.00417***	-0.00313*	-0.00435***	-0.00374***
No. observations:	50,461	36,454	28,674	22,898	28,674	22,898
Adj, Pseudo R-squared	0.04556	0.10897	0.06761	0.06797	0.09968	0.12301

In the QREG estimations with Instrumental Variables (IV), the latter are applied to the lagged variables in the case of fixed effects. Employing IV, the parameter values change when we estimate both the level and the variation of the dependent variables.

This is confirmed by the results shown in the table. An increase in non-performing loans reduces confidence, while an increase in profitability, GDP, current leading indicators and stock market performance increase the confidence of all banks. In addition, a rise in the fed funds rate has a positive impact on confidence, as banks' profits are higher (see Table 4.3), since among other things their interest rate margins widen. The results do not vary greatly between the open and the closed sample, or for the most part between estimates with and without instrumental variables estimations.

Finally, we again estimated equation (1), this time with the fixed effect model, to check whether the results may not depend on bank idiosyncratic factors.[12] In general the results (columns 5 and 6 in Table 5.1) are not very different from the quantile regression estimations without fixed effects (columns 1 and 2).

Table 5.1 shows that almost all the internal and external determinants of confidence are significant. To determine which are more relevant, we ran estimations of the relevance of the regressors. The results are given in Table 5.2, which after the value of the coefficient also shows (in brackets) the importance of the regressors, 1 indicating the most relevant.

In the short run, the most important determinant is profitability, followed by uncollectable loans/gross loans and non-performing loans/gross loans. Past profits increase confidence, non-performing loans reduce it. On the other hand, current gross profits increase reserves, suggesting that banks may use the latter, among other things, to smooth income. Interestingly, an increase in gross loans (net of securitized loans) has a positive impact on confidence, and so does larger bank size. This suggests that when banks expand loans they are strongly confident of their profitability. The lagged dependent variable is also relevant, suggesting that confidence is highly persistent. Overall, the external determinants of confidence are less relevant than the internal. The most important external factors are stock market performance and the federal funds rate. As we expected, an increase in both of these variables has a positive effect on confidence. That is, the empirical evidence supports hypothesis 1.

[12] Since the quantile regression does not compute the fixed effects, we calculated them by de-meaning the value of each regressor for each bank. And for the open sample we deleted all the banks with fewer than five observations (3% of the total).

Table 5.2 Estimation of the determinants of confidence: Relevance of the regressors

Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution. N*otice that a higher value of the dependent variable corresponds to a lower level of confidence. Hence, (apart from the lagged dependent variable) a negative coefficient corresponds to an increase in confidence.*

Dependent Variable:	Δ(LLR)	Δ(LLR)	Δ(LLR)	Δ(LLR)	LLR	LLR
Type of sample	open	closed	open	Same sample of column(3) without risk	open	closed
Fixed effects	no	no	no	no	yes	yes
Estimation Method	qreg	qreg	qreg	qreg	qreg with IV	qreg with IV
Regressors / equations	(1)	(2)	(3)	(4)	(5)	(6)
LLR(-1)	-3.671(3)	-3.320(6)	-3.528(6)	-3.528(6)	-3.156(4)	-2.653(4)
Δ (LLR(-1))	-0.047(17)	0.089(15)	0.038(18)	0.038(17)	-0.396(15)	-0.586(12)
100* UNC (-1)	-1.602(5)	-7.005(3)	-10.144(3)	-10.144(3)	-1.606(6)	-2.309(5)
Δ GL	-0.581(9)	-3.620(5)	-4.758(5)	-4.758(5)	-0.971(11)	-1.614(7)
Δ (NPL)	0.800(7)	0.297(12)	0.488(9)	0.488(8)	1.092(9)	0.777(11)
NPL(-1)	0.280(10)	-0.046(18)	0.381(11)	0.381(10)	1.657(5)	0.990(10)
LOGTA (-1)	0.047(18)	0.348(11)	0.301(12)	0.301(11)	0.211(17)	-0.059(19)
Δ LOGTA	-0.061(16)	0.742(7)	0.680(7)	0.680(7)	-0.284(16)	0.112(18)
LOG(GLTA (-1)))	0.141(12)	-0.374(10)	-0.404(10)	-0.404(9)	-1.027(10)	-1.793(6)
IMP	0.074(15)	0.287(13)	-0.120(17)	-0.120(16)	0.016(19)	0.151(17)
TIER1	-0.107(14)	-0.249(14)	0.011(19)	0.011(18)	1.456(7)	1.048(8)
OP(-1)	-4.999(2)	-12.356(2)	-13.861(2)	-13.861(2)	-5.876(2)	-5.979(2)
PBT	5.202(1)	12.738(1)	15.085(1)	15.085(1)	5.930(1)	6.184(1)
Δ(PBT)	-1.695(4)	-4.500(4)	-7.660(4)	-7.660(4)	-4.753(3)	-4.734(3)
GDP	-0.241(11)	-0.069(17)	-0.147(16)	-0.147(15)	0.860(12)	0.584(13)
CLIF	0.140(13)	0.086(16)	-0.005(20)	-0.005(19)	0.191(18)	0.162(16)
LOG(SMK(-1))	-0.009(19)	-0.035(19)	-0.202(15)	-0.202(14)	-0.530(13)	-0.436(14)
ΔLOG(SMK)	-0.644(8)	-0.549(9)	-0.292(14)	-0.292(13)	-1.338(8)	-1.001(9)
Fed_fund	-0.997(6)	-0.595(8)	-0.295(13)	-0.295(12)	-0.415(14)	-0.312(15)
RWATA(-1)	-	-	0.661(8)	-	-	-

The relevance is estimated by multiplying every absolute coefficient value by the median absolute deviation (MAD) of its corresponding regressor. QREG with IV = IV are applied to the lagged variables in the case of fixed effects. In equation (3) the variable risk_weighted_assets(-1) is also included among the regressors. Parameters are multiplied by 100.

As a robustness check, we divided the sample period into pre- and post-2007. Since up to 2007 good news predominated and bad news afterwards, banks should respond in the two sub-periods similarly to the way they respond to good and to bad news respectively. And the results confirm this prediction. Banks' confidence rose before 2007 and declined thereafter. In any case, for all the categories of bank the effect of news on confidence was greater after 2007 than before.[13]

Notice that the lagged dependent variable in the foregoing regressions may produce biased estimations if the residuals are autocorrelated. We accordingly checked for autocorrelation, which in most cases is not significant, save where the dependent variable is the level of confidence and

13 Specifically, the econometric analysis on fitted values shows that after 2007 overconfident banks reduced their confidence in response to bad news, but they also became systematically less confident, shifting the entire relationship between confidence and their determinants downward. By contrast, underconfident banks became systematically more confident after the crisis. These results hold for both the open and the closed sample. To save on space we do not report them, but they are available from the authors upon request.

fixed effects estimation is employed (see Table 5.3). However, when fixed effects were considered, we always used instruments for the lagged dependent variable, as in that case coefficients are always biased if the number of banks is large and the number of observations is small. And even then the problem of bias owing to autocorrelation of residuals should not be serious.

TABLE 5.3: Residuals autocorrelation (QREG estimation). Years: 2001-2013

Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution.

Residuals from Equation 1 in Column	1 Tab.5.1	2 Tab 5.1	3 Tab. 5.1	4 Tab. 5.1	5 Tab. 5.1	6 Tab. 5.1
Sample	open	closed	open	closed	open	closed
Fixed effects	no	no	Yes (with IV for the lagged dependent variable)	Yes (with IV for the lagged dependent variable)	Yes (with IV for the lagged dependent variable)	Yes (with IV for the lagged dependent variable)
Dependent variable	Δ(LLR)	Δ(LLR)	LLR	LLR	Δ(LLR)	Δ(LLR)
Without constant	0.01179 (0.1892)	-0.00630 (0.5824)	0.708080 (0.0000)	0.73508 (0.0000)	-0.01497 (0.4014)	-0.00700 (0.7256)
With constant	0.01147 (0.1928)	0.00655 (0.5575)	0.70808 (0.0000)	0.73452 (0.0000)	-0.01520 (0.3932)	-0.00790 (0.7077)

Numbers in brackets are the probability level.

Next, we checked for heteroscedasticity, finding that the absolute value of the residuals is positively correlated with confidence. So we tested whether the relationship between confidence and residuals is the same for our three confidence levels. The results are reported in Table 5.4: the dummies for overconfidence and underconfidence are both significant, indicating that extreme degrees of confidence have a positive effect on the absolute value of the residuals.

Since the Ramsey test on the equations of Table 5.1 suggests non-linearity, we controlled for it in the relationship between confidence and its determinants. In particular, we considered whether the determinants of confidence differ with the bank's degree of confidence,[14] by applying dummy variables to the parameters of the different categories.[15]

[14] To select overconfident (underconfident) banks, we cut the observations off at the bottom and top 10% for the ratio of loan loss reserves to gross loans. Then for each year we defined as overconfident or underconfident the banks that in that year had a value of the confidence index below or above this threshold value.

[15] In estimating the separate effect of the three types of bank we considered the problem that overconfident or underconfident banks may be so classed in part because their residuals are particularly low or high, but this creates a correlation between residuals and the dummy used to define the group, resulting in biased estimates. In order to avoid this, we applied instruments to the dummies defining the types. We estimated the dummies by considering the fitted values of loan loss reserves given in Table 5.1. Then for each type we used a probit to estimate the probability of the

Table 5.4: Analysis of residual volatility

Dependent variable: absolute value of the residuals from the equation estimated in Table 5.1. Estimation method: Quantile regression.

	Open sample	Open sample	Closed	Open sample	Closed sample
Fixed effects	No	no	no	yes	yes
eq	(1)	(2)	(3)	(4)	(5)
Residuals from	Eq.1 Table 5.1	Eq.1 Table 5.1	Eq.2 Table 5.1	Eq.3 Table 5.1	Eq.4 Table 5.1
CONST	-0.016350***	-0.01090***	0.00166	-0.03158***	-0.02197***
Abs(resid) at t-1	0.152691***	0.15733***	0.01890	-0.06178***	-0.05476***
E[LLR/GL]	0.071738***	-	0.05233***	0.12109***	0.11322***
LLR(t-1)/GL(-1)	-	0.06772***	-	-	
Overconfidence IV dummy	0.036549***	-	0.02844***	0.06481***	0.05715***
Underconfidence IV dummy	0.052143***	-	0.10253***	0.11908***	0.10848***
Overconfidence dummy at t-1	-	0.02877***	-	-	
Underconfidence dummy at t-1	-	0.02879***	-	-	
Obs	38,454	38,454	28,769	23,667	19,141
Adj Pseudo R-squared	0.09645	0.09458	0.06295	0.09926	0.09542

The overall impact of the determinants of confidence is similar to that reported in Table 5.1, but in Table 5.5 the determinants differ between bank types . First, overconfident CEOs have greater persistence of confidence than others. Second, mid-confident CEOs respond more strongly to news than overconfident CEOs, and sometimes in the opposite direction. Specifically, mid-confident CEOs react more forcefully to news of profits and losses and to changes in the stock market. Interestingly, regardless of the CEO's level of confidence, it never reacts to indicators of real economic performance (see Table 5.5).[16] Moreover, using the methodology of Engle and Hendry (1993), we estimated whether the differences between confidence classes are temporary or persistent, finding qualitatively similar results in the long run as well.[17]

bank belonging to a given group in relation to this fitted value and the dummy for confidence taken at t-1.The results are available from the authors upon request.

[16] The qualitative results hold for the closed sample as well. To save on space, we do not report these results, but they are available from the authors upon request.

[17]We performed the econometric analysis also using the fixed effect model, again obtaining results similar to those in Table 5.5. They are available from the authors upon request.

Table 5.5: Estimation of the determinants of confidence with dummy variables by category of bank

Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, IV applied to dummies for over- and under-confident banks. Estimation successfully identifies unique optimal solution; D() indicate change; */**/*** refer to the coefficient significance at 10%/5%/1% level respectively; and °/°°/°°° refer to the significance of the difference between coefficients of overconfidents and underconfidents with respect to mid-confident banks. *Notice that a higher value of the dependent variable corresponds to a lower level of confidence. Hence (apart from the lagged dependent variable) a negative coefficient of* LLR *and D(LLR) corresponds to an increase in confidence.*

Dependent Variable:		Δ(LLR)	
Type of sample		open	
Fixed effects		no	
Estimation Method		QREG	
	mid-confident	overconfident	underconfident
Constant	-0.00071	-0.26610/	-0.22178/
LLR(-1)	-0.07471***	0.02013***/°°°	-0.05617***/°
Δ (LLR(-1))	0.00887	-0.00499/	-0.00054/
100* UNC	-0.33037***	0.02238***/°°°	-0.52971***/°°°
Δ GL	-0.49889***	0.00518**/°°°	-1.99297***/°°°
Δ (NPL)	0.01294***	0.01717**/	0.03432/
NPL(-1)	-0.00354	0.00115/	0.00266/
LOGTA (-1)	0.00923***	-0.00209**/°°°	0.02259***/°
Δ LOGTA	0.14921***	0.02226/°°°	0.08731/
LOG(GLTA (-1)))	-0.00172	-0.00097/	-0.00184/
IMP	0.53156***	0.43058***/	0.12698***/°°°
TIER1	0.00023**	-0.00003**/°°	0.00219*/
OP(-1)	-0.25218***	0.00042/°°°	-0.42398***/°°
PBT	0.25585***	-0.00194/°°°	0.45988***/°°
Δ(PBT)	-0.22015***	-0.00218/°°°	-0.43521***/°°
GDP	-0.00150	-0.00305/	-0.00335/
CLIF	0.00078	0.00263/	-0.00298/
LOG(SMK(-1))	-0.00521	0.00304/	0.06746/
ΔLOG(SMK)	-0.06594***	-0.03202**/°	0.05317/
Fed_fund	-0.00323***	-0.00438***/	-0.00553/
Obs.		45,999	
Adj Pseudo R-squared		0.15674	

This evidence supports the finding of previous work that overconfident CEOs are more strongly affected by conservative bias, which leads investors to underweight new information relative to priors (see Daniel et al., 1998).

Having established that overconfident CEOs react less than others to news, we investigated whether CEOs differ in the reaction to good and bad news. Following the literature, our Hypothesis 2 is that overconfident CEOs react more strongly than other CEOs to good news and less strongly to bad, while the reverse holds for underconfident CEOs.

Table 5.6. CEOs' reactions to good and bad news

Dependent variable: Δ (LLR); Estimation Method: Quantile Regression (Median) with IV applied to the bank dummy classification (over, mid- and under-confidence). Estimation successfully identifies unique optimal solution. */**/*** indicate significance at 10/5/1% level. After slash °/°°/°°° indicate significance at 10/5/1% of probability of different coefficients between good and bad news.

			Mid-confident	Overconfident	Underconfident
Δ (NPL)	>0	Bad news	0.01559**	0.02361**	0.02798
	≤0	Good news	0.00472	-0.01004	0.04447**
			/	/°°	/
PBT	<1%	Bad news	0.22914***	0.00538	0.40483***
	≥1%	Good news	0.24115***	0.00894	0.46347***
			/°°°	/	/°°°
Δ(PBT)	<0	Bad news	-0.23726***	-0.02094	-0.41496***
	≥0	Good news	-0.16939***	0.00440	-0.44168***
			/°°°	/°°°	/
GDP	<1%	Bad news	-0.00062	0.00049	-0.00868
	≥1%	Good news	-0.00192	-0.00456**	-0.00766
			/	/°°	/
CLIF	<100	Bad news	0.00190	0.00413**	-0.00793
	≥100	Good news	0.00184	0.00412**	-0.00816
			/	/	/
ΔLOG(SMK)	<0	Bad news	-0.05447*	-0.04585	0.30788
	≥0	Good news	-0.05601***	-0.02116	-0.02293
			/	/	/
Obs				45,999	
Adj Pseudo R2				0.16046	
IV					

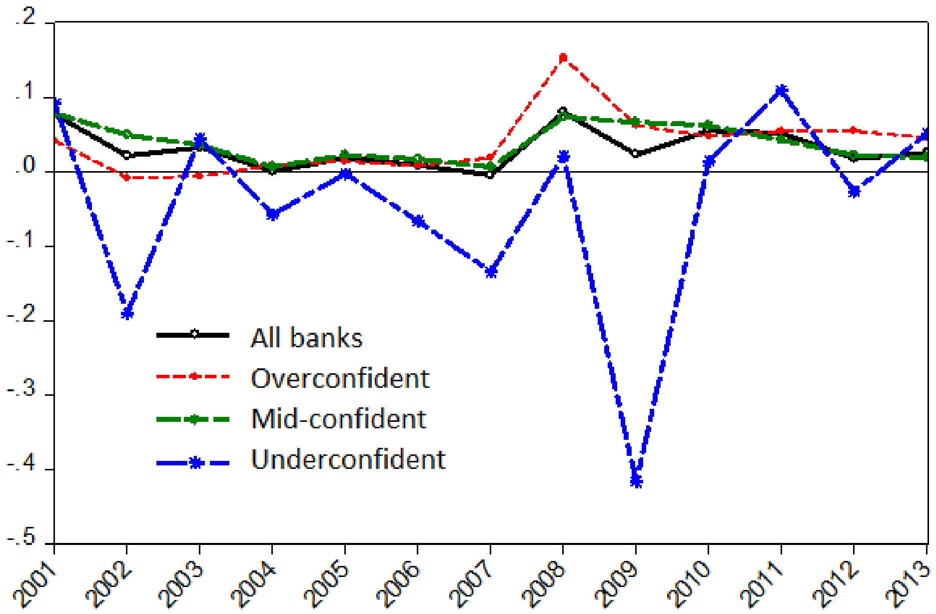
Examples of good news are increases in profitability, real GDP, the stock market index and CLIF, as well as a decline in Non-performing loans/total loans. Bad news consists in declines in the above variables.

In Table 5.6 we report the estimates for banks' reaction to good and bad news, which yield some surprising results. Overconfident CEOs react more sharply to bad than to good news concerning Δ (NPL), while the reverse holds for an increase in GDP. By contrast, mid-confident CEOs react more strongly to good news on profitability and to better stock market performance. Thus the results given in Table 5.6 provide only weak support for the thesis that overconfident banks, by comparison with other banks, react more to good news and less to bad news. But the result does constitute evidence that overconfident CEOs react less strongly to news, due to the greater persistency of their beliefs. Indeed, our results bolster the thesis that this feature of overconfident behavior is more important than the overreaction to good news and underreaction to bad that the literature describes (Daniel et al., 1998).[18]

[18] Additional support comes from the evidence that overconfident CEOs react less to internal than to external news. Internal news relates more closely to their own behavior, external news to that of others.

Table 5.4 shows that both overconfident and underconfident banks have a higher absolute value of the residuals than the other banks. However, the residuals in the estimation of equation (1) may reflect idiosyncratic factors, such as the quality of the management, irrational behavior, or other determinants of confidence not included among our regressors, such as expectations about the future. Accordingly we posit that the higher the absolute value of the residuals are, the more relevant are expectations to the CEOs' degree of confidence. To test this hypothesis, we performed the following exercise. Using the fitted values of the dependent variable from the equation estimated in Table 5.1, we computed the value of the residuals for the three confidence levels. It is worth noting, as a preliminary, that if all three types attribute the same relevance to the future, the absolute values of the residuals will not differ. The results, plotted in Figure 5.1, are surprising indeed: other things being equal, the underconfident banks have a lower absolute value of the residuals than the other banks practically throughout the period. Assuming that the residuals reflect expectations about the future, this indicates that these banks have a systematically more optimistic view of the future than the other banks.

Figure 5.1. Residuals of LLR/GL by category of bank (2001-2013)
We used instrumental variables to correct for simultaneity bias between residuals and fitted values.



By contrast, the expectations of overconfident banks are more similar to those of the mid-confident, albeit slightly more optimistic than the latter before the crisis and more pessimistic afterwards. These results do not corroborate our hypothesis that more confident CEOs are more optimistic about the future, but they do indicate that overconfident CEOs change their expectations more than mid-confident CEOs (see Figure 5.1).[19]

Summing up the foregoing findings, confidence is the product of current news and expectations about the future. Overconfident CEOs are more persistent in their beliefs and react less to current news, while the contrary applies to mid-confident and underconfident CEOs. Finally, the overconfident CEOs do not have an optimistically biased view of the future, but they change their expectations more significantly than do mid-confident CEOs.

6. The effects of confidence on banking behavior and performance: the hypothesis

Above, we studied the determinants of confidence for our three types of bank. Now we address the effects of confidence on banking behavior and performance, in both the short and the long run.

Delis et al. (2014), for US banks, and Demirguc-Kunt and Huizinga (2010), for a large sample of international banks, find that risk was fairly stable up to 2001 and rose sharply between then and 2007. IMF (2014) also offers evidence that excessive risk-taking contributed to the global financial crisis.

One strand of the literature has established that bank CEOs' overconfidence played an important role in increasing bank lending and leverage and weakening lending standards (Ho et al., 2016; Ma, 2014; Sironi and Suntheim, 2012; Niu, 2010). Implicit in this literature is the assumption that the financial crisis stemmed from the irrational conduct of bank managers and other economic agents.

By contrast, for Geanokoplos (2010) and Danielsson and Shin (2009) rational behavior implies that good news will build up confidence among all economic agents and lead banks to be more prone to take risk and to expand their balance sheet. In this view, an increase in risk-taking is not the product of behavioral bias but of greater confidence fueled by good economic performance. On the other hand, Minsky (1992) and Shleifer and Vishny (2010) have shown that financial intermediaries operating in markets influenced by investor sentiment have a cyclical behavior of credit and investment and are unstable.

[19] The values of the residuals in Figure 5.1 are obtained assuming that the values of the coefficients are equal for the three categories of banks; the results in Table 5.3 show that the coefficients are lower for overconfident banks, which may explain the corresponding residuals in Figure 5.1.

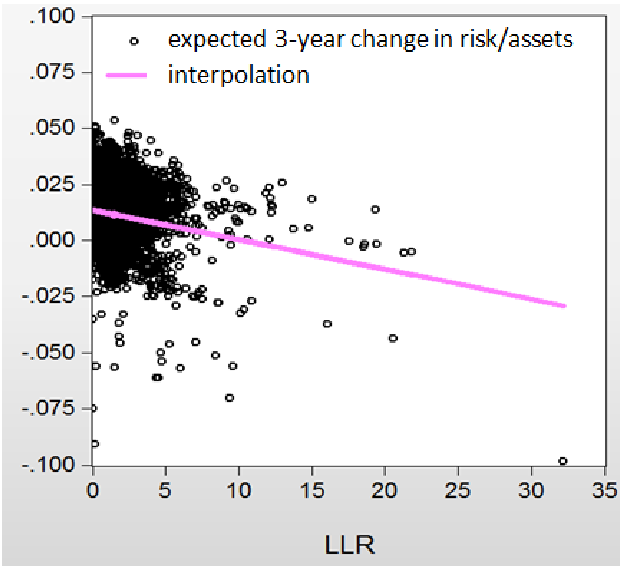
financial intermediaries operating in markets influenced by investor sentiment. Surprisingly, the literature offers scanty evidence on the determinants of banks' risk-taking before 2007.

Following this last approach, we assume that increases in confidence among all economic agents spurred risk-taking, lending growth, and an increase in leverage.

Hypothesis 4: *More confident bank managers take more risk.*

This hypothesis rests on the assumption that more confident CEOs will tend to have better expectations for future macroeconomic conditions and the opportunity for profit, and will expand their banks' business more forcefully. In addition, more confident CEOs take on more risk because they feel better equipped to manage it. Takor (2014) examines a model in which thanks to sustained banking profitability, all agents—banks, their fund suppliers and regulators—end up in an "availability cascade" in which they overestimate the ability of bankers to manage risks and become more tolerant of banks' risk-taking, and banks invest in riskier and riskier assets. Goel and Thakor (2008) and Eisenbach and Schmalz (2015) argue that overconfident managers underestimate risk and so undertake actions entailing excessive risk. Figure 6.1 provides evidence for this hypothesis, plotting the relationship between confidence and change in risk for the banks of our sample.

Figure 6.1 Loan loss reserves/Gross loans (LLR) and expected change in portfolio risk three years ahead



The horizontal axis shows the ratio of loan loss reserves to gross loans (LLR); the vertical axis, the expected change in Risk-weighted/Total assets three years ahead. The data show an inverse correlation between the two variables, suggesting that more confident banks (those with lower LLR) increase their portfolio risk more substantially in the subsequent period.

Hypothesis 5. *More confident banks lend more.*

More confident banks are more optimistic that borrowers will be able to repay and are therefore more willing to lend (see, e.g., Malmendier and Tate, 2005; Goel and Thakor, 2008; Campbell et al., 2011; Ben-David et al., 2013). What is more, overconfident banks underestimate risk and so are more likely to lend more and to grant credit to high-risk borrowers (Hirshleifer and Luo, 2001). Both these effects lead the more confident banks to lend more and to loosen lending standards (Ma, 2014, Eisenbach and Schmalz, 2015).

Figure 6.2 Annual percentage growth in loans and leverage for confident and overconfident American banks

(a) Percentage variation in Gross loans **(b) Percentage variation in Leverage**

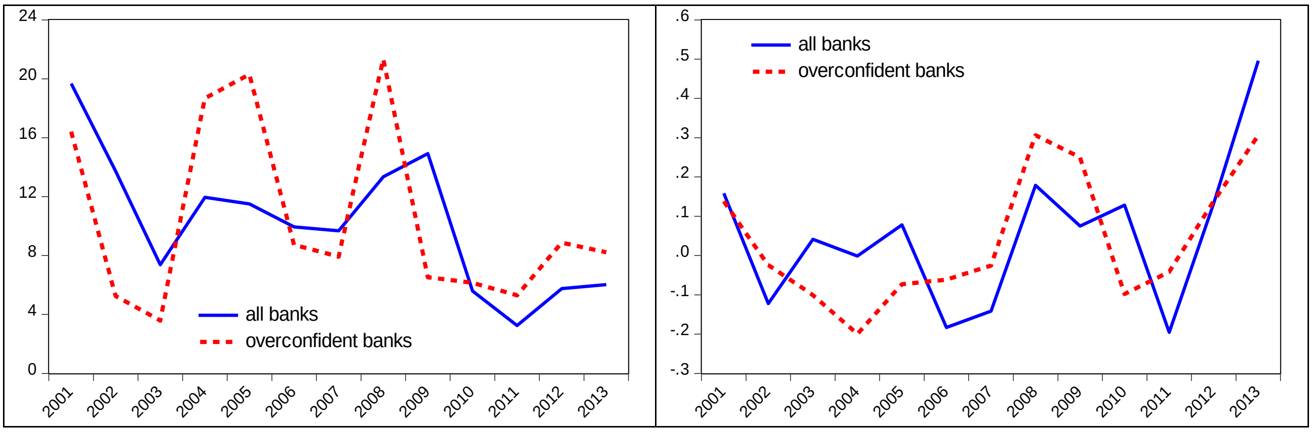


Figure 6.2 shows that both lending and leverage rose until 2009 and declined thereafter. But in both cases the downturn was sharper at the overconfident banks. Moreover, the trends in lending and leverage show some connection with the trend in confidence before and after the 2007 financial crash (see Figure 2.1).

Hypothesis 6: *More confident banks are more indebted.*

Other things being equal, more confident banks expand their balance sheets more and are consequently more likely to face capital constraints and resort to external funding.

Geanakoplos (2010) sets out a theoretical model to explain endogenous increases in optimism and pessimism and how they affect leverage; Adrian and Shin (2010), and Malmendier *et al.* (2011) find that banks prefer debt to equity when there are good opportunities for growth during a credit boom. Beltratti and Stulz (2012) and Fahlenbrach et al. (2012) show that the preceding rise in leverage played an important role in the ensuing financial crisis.[20]

Hypothesis 7: *More confident banks fund their activities with a higher proportion of short-term debt.*

More confident banks overvalue their ability to cope with adverse conditions, with high self-attributions of the capacity to handle liquidity and market crises. So they are less worried about the risk of funding long-term assets with short-term liabilities. Demirguc-Kunt and Huizinga (2010) document that before 2007-2008 a sizable proportion of banks relied largely on short-term non-deposit funding and on non-interest income.[21]

Hypothesis 8. *More confident and riskier banks perform better in cyclical upswings and make larger losses in downturns.*

In favorable market conditions, banking confidence grows, spurring risk-taking and business expansion. Consequently, in upswings the more confident banks are likely to make greater profits. It follows that when the cycle turns downward, the banks whose assets were higher-risk are likely to suffer more severe losses. This is the case for at least two reasons. First, in a crisis the riskier and more highly indebted banks face worse conditions for refunding. And second, they are likely to suffer larger losses as their borrowers presumably default more frequently.

Some researchers have investigated the effects of managerial overconfidence on the performance of firms, showing that overconfident CEOs reduce firm value by overinvesting (see, e.g., Goel and Thakor, 2008; Malmendier and Tate, 2008; Campbell et al., 2011). Fahlenbrach et al. (2012) find that some bank characteristics connoting risk-taking are significantly correlated with poor performance

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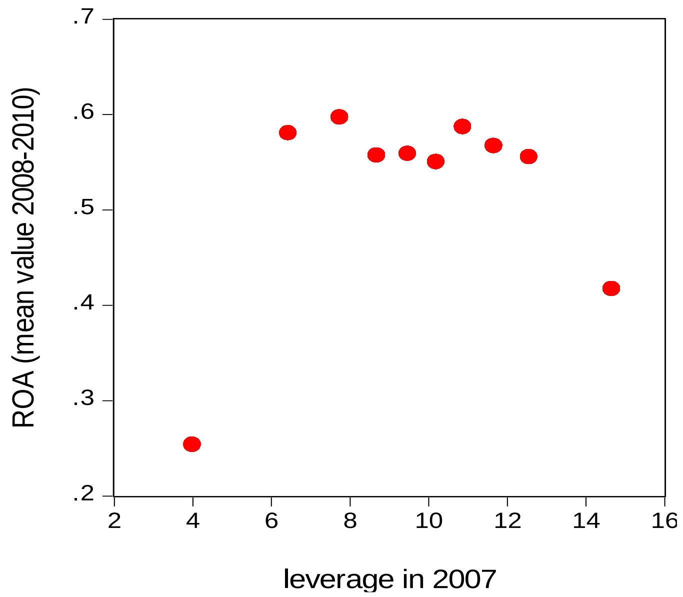
[20] However, Geanakoplos (2010) points out that while the leverage cycle is not new, some new elements made the leverage cycle crisis of 2007-09 worse than its predecessors. First, leverage reached unprecedented levels. Second, this leverage cycle was actually double – both in securities on the repo market and on homes in the mortgage market – and the two cycles fed off one another. Third, CDSs, which were absent in previous cycles, enabled pessimists to leverage and thus made the crash much more precipitous than it would otherwise have been.

[21] Palumbo and Parker (2009) and Fahlenbrach et al. (2012) show that the banks that expanded their activities more significantly before the 1998 crisis relied more heavily on short-term funding.

in both the 1998 and the 2007-08 crises. Laeven (2011) shows that after the global financial crisis started in the summer of 2007 many US banks suffered deposit runs, fire sales, declining asset values, and greater risk of being unable to meet their obligations. Finally, Beltratti and Stultz (2012) and Ho et. al. (2016) provide evidence that during and after 2007-2008 the better-performing banks were less highly leveraged, and that in the immediate run-up to the crisis they realized lower returns. Thus there is evidence that the performance of banks during the crisis may be explained by pre-crisis risk-taking.

Figure 6.3 provides evidence that the most heavily indebted American banks in 2007 also had also the worst performance in 2008-2010.

Figure 6.3 American banks' leverage in 2007 and ROA in 2008-2010 (Average values by decile).



In the sections that follow we check the foregoing hypothesis empirically. Specifically, we examine the contributions of underconfident, mid-confident and overconfident banks to the increase in risk, lending and leveraging in the run-up to the crisis and their effects on performance before and after the 2007-2008 financial crash.

7. The effects of confidence on banks' behavior and performance

7.1 Portfolio risk

Our measure of portfolio risk is the ratio of risk-weighted assets to total assets, weighting the risk of each single asset with its importance in the total portfolio. Table 7.1 reports level of portfolio risk and changes in it for the three types of bank before, during and after the 2008-2009 financial crash.

Table 7.1 Level and average yearly change in portfolio risk by type of bank.

Years	Mid-confident		Overconfident		Underconfident		All banks	
2002-2007	Level	Change	Level	Change	Level	Change	Level	Change
Mean	0.696066	0.005921	0.612748	0.009319	0.627328	0.000947	0.682488	0.008638
Median	0.703364	0.007692	0.609358	0.006933	0.617450	0.000000	0.692308	0.007557
Observations	40379	40355	3226	3212	3114	3111	49082	48812

2008-2009	Mid-confident		Overconfident		Underconfident		All banks	
All banks	Level	Change	Level	Change	Level	Change	Level	Change
Mean	0.711739	-0.014377	0.626371	-0.002438	0.670883	-0.022999	0.697704	-0.011229
Median	0.724138	-0.010155	0.629518	-0.001110	0.684658	-0.014022	0.715148	-0.008888
Observations	12730	12363	1541	1205	982	953	16766	15218

20010-2013	Mid-confident		Overconfident		Underconfident		All banks	
	Level	Change	Level	Change	Level	Change	Level	Change
Mean	0.649970	-0.013543	0.567893	-0.003028	0.648673	-0.019234	0.642918	-0.012277
Median	0.658251	-0.009468	0.562731	-0.004517	0.659440	-0.015145	0.655556	-0.009403
Observations	26992	26989	2310	2310	5928	5928	39413	39336

Surprisingly, it was mid-confident banks that had the greatest portfolio risk before, during and after the crisis; and before 2008 they increased their risk more than the other banks. The underconfident banks reduced portfolio risk most sharply during and after the crisis.[22]

To analyze the effects of confidence on banking behavior and performance, we consider separately the impact of the explained level and/or variation of loan loss reserves (E[LRR] (or E[ΔLRR]), i.e. of confidence, and its unexplained value (u[LRR]), derived from eq. 1, Table 5.1. Explained confidence captures the effects of the bank's characteristics and current news on risk (see Table 5.3). Unexplained confidence values are obtained from the value of the residuals of the estimated equation (1), and also reflect the bank's expectations for future performance. However, splitting a variable (LLR in our case) into its expected values and residuals by means of an estimated regression results in an econometric problem of "error in variables", generating biased coefficient estimates. To attenuate this bias, we followed Shanken (1992) and used a rolling five-year estimated equation ending in year t-1, applying its parameters to establish the values of E[LRR] and u[LRR] in year t.[23] In

[22] We also performed the test of equality of medians and means for level of risk, and the differences are all significant. They are also significant for the change in risk, but only relative to the mean values.

[23] The estimations are not reported here, but the corresponding Eviews code for the generation of these variables is available upon request.

any event, inserting two constant dummies for overconfident and underconfident banks or using a shorter rolling estimate of just two years rather than five does not alter the results.

We have shown (see Figure 5.1) that overconfident and underconfident CEOs have biased expectations. Our separate measurement of the impact of explained and unexplained confidence enables us to assess the contribution of current and expected news on behavior and performance.

The impact of explained and unexplained confidence on portfolio risk is determined by estimating the following equation:

$$\Delta RWATA_{t+1} = \beta_0 + \beta_1 RWATA_t + \beta_2 E[\Delta LLR_t] + \beta_3 LRR_{t-1} + \beta_4 u[LRR_t] + \beta_5 Mid_t + \beta_6 Over_t + \beta_7 Under_t + \xi_t \qquad (2)$$

where RWATA is the bank's portfolio risk (Risk-weighted assets/Total assets), E[LLR] is explained confidence and u[LRR] unexplained confidence. Mid, Under and Over are the dummies for mid-confidence, underconfidence and overconfidence. Table 7.2 reports the results.

Apart from the period as a whole, we also estimated the impact of confidence on risk-taking for our three sub–periods: before, during and after the financial crisis.

First, as the coefficient of the lagged dependent variable shows, there is considerable persistency in risk-taking. In addition, both explained and unexplained confidence have a positive impact on risk-taking throughout the period, though the coefficients indicate that current news is more important than expectations. And other things being equal, confidence has a smaller effect on risk-taking at overconfident than at mid-confident banks.

Table 7.2. The impact of confidence on change in risk-taking by type of bank before, during and after the 2007-2008 financial crash.

Method: Quantile Regression (Median). *Notice that negative coefficients of* E[ΔLLR] and u[LLR] *correspond to a positive impact of confidence on the dependent variable.*

Dependent variable	ΔRWATA(t+1)	ΔRWATA(t+1)	ΔRWATA(t+1)	ΔRWATA(t+1)
Estimation method	QREG	QREG	QREG	QREG
sample	All years	Before 2008	2008-2009	After 2009
Const	0.017915***	0.035862***	0.025402***	0.01787***
RWATA	-0.022912***	-0.035055***	-0.038939***	-0.04289***
E[ΔLLR]	-0.017620***	-0.001839***	-0.016090***	
LLR(t-1)	-0.002009**		-0.003272**	0.00014
u[LLR]	-0.003078**	0.001265	-0.002538	
Dummy OVER	-0.003446**	-0.006012**	-0.005477	-0.00018
Dummy UNDER	0.000361	-0.001405	-0.001367	0.00170
Obs	16,421	6,774	4,094	5,553
Adj R2	0.003167	0.009016	0.007485	0.00975

Finally, during the financial crisis there were no significant differences between bank types in the reaction of risk-taking.[24] However, the coefficients of the dummies for underconfidence and overconfidence indicate that the relationship between confidence and risk-taking is not linear when we switch between types of bank. Surprisingly, the intercept of the relationship between confidence and change in risk is lowest at overconfident banks.[25] While by definition the level of loss reserves is lower (confidence is greater) at overconfident banks, these banks also show the lowest intercept in the estimated relation between confidence and risk. In other words, banks with lower reserves (greater confidence) tend to show an increase in risk the next year – ΔRWATA(t+1) – since the coefficient of reserves is negative. But at the same time overconfident banks have an idiosyncratic tendency not to increase risk (their dummy is negative). It follows that the overall impact on risk-taking by overconfident CEOs depends on the relative weights of these two countervailing effects; and analogously for underconfident banks.

Hence, to estimate the overall impact of confidence on risk-taking for the three types of bank, we performed another exercise as well, estimating the level of risk-taking by overconfident and underconfident banks using alternatively the coefficients estimated with the mid-confident sample only, and samples including the mid-confident as well as the overconfident or underconfident respectively. The difference between the estimated values of the dependent variable for these alternative samples reflects the contribution of overconfident or underconfident banks to risk-taking. The results are reported in Figure 7.1.

Consistently with the foregoing, these results show that overconfident banks do not take on more risk than the mid-confident. This suggests that overconfident banks may not have been crucial to bringing about the conditions that led to the financial crash, or at any rate no more than the mid-confident. Next, we investigate whether this conclusion extends to lending and leverage behavior.

[24] The results (not reported here) show that most of the above conclusions apply also to the level of risk-taking, not only the variation.

[25] These results hold when we use Robust Least Squares instead of Quantile regression.

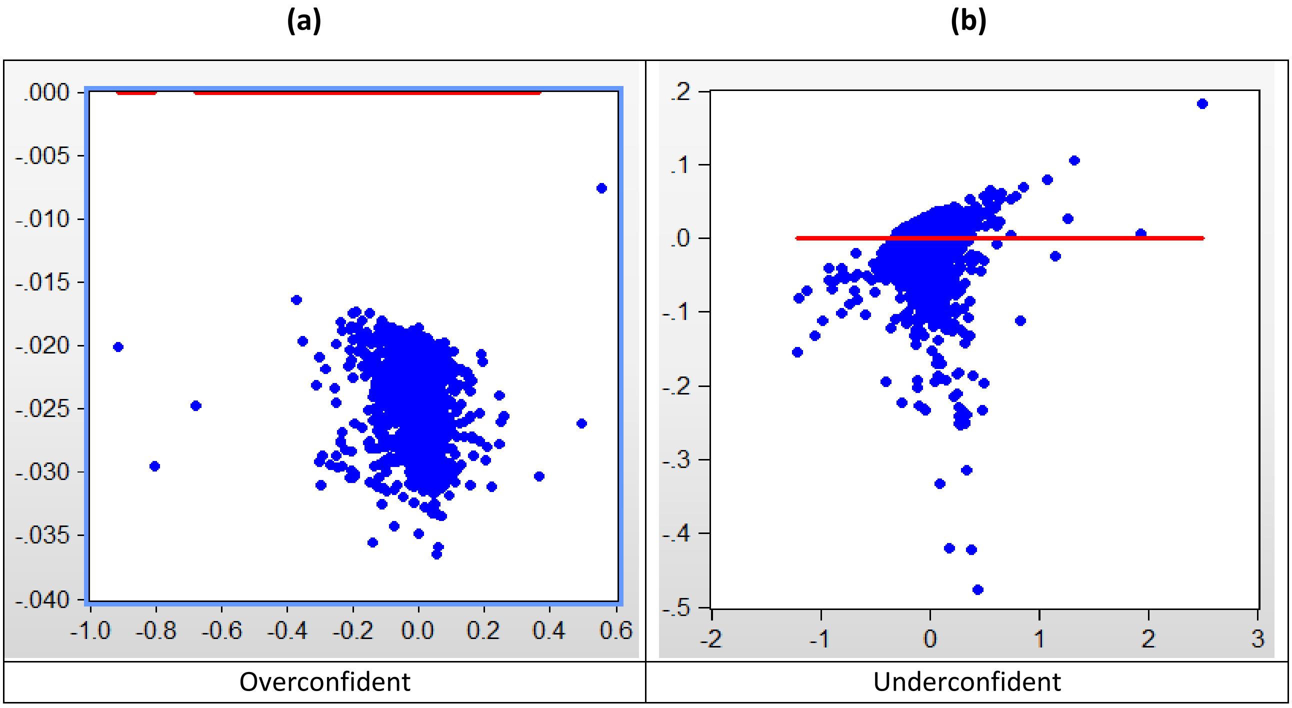
Figure 7.1 Contribution to risk-taking by type of bank

Estimated equation:

$RWATA_t = \beta_0 + (1+\beta_1) RWATA_{t-1} + \beta_2 E[LLR_{t-1}] + \beta_3 ULLR_{t-1} + \xi_t$

The estimates are obtained by quantile regression. Observations: 87540. Huber Sandwich Standard Errors & Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall-Sheather, bw=0.021881

In (a) the blue (red) dots indicate the estimated values of the level of risk-taking for overconfident (mid-confident) banks using the coefficients estimated with the mid-confident banks. The corresponding lines in (b) refer to comparison between underconfident and mid-confident banks.



7.2 The effects on lending and leverage

Hypothesis 5 posits that more confident banks are more willing to lend, because they are more optimistic about the success of projects. In addition, banks that expand lending more sharply are more likely to face capital constraints, so they are also more heavily indebted.

Table 7.3 shows that confidence does have significant effects on banks' lending, leverage, and proportion of short-term funding. An increase in confidence leads them to expand lending, increase leverage, and augment the proportion of deposits and short-term funding.[26] However, there are some interesting differences. While lending and the deposit and short-term funding ratios are affected by both current news and expectations, leverage is affected only by current news. The

[26] We also ran this regression with the ratio between short-term and long-term debt as dependent variable, and the results are similar.

correlation between confidence and the dependent variables in Table 7.3 is lower for overconfident than mid-confident banks. So we ran exercises similar to those reported in Figure 7.1, with results qualitatively similar to those for portfolio risk (see Appendix). The overall impact of confidence on lending and leverage is smaller for overconfident than mid-confident bank CEOs. Thus the previous conclusions on risk-taking also extend to the other behavioral variables. It follows that, in contrast with most of the literature on overconfidence, the largest contribution to the increase in risk, lending and leverage came from mid-confident rather than overconfident bank CEOs.

Table 7.3 The impact of confidence on changes in lending, leverage and short-term funding by type of bank.

Method: Quantile Regression (Median). *NOTICE THAT negative coefficients of* E[ΔLLR] and u[LLR] *correspond to a positive impact of confidence on the dependent variable.*

Dependent variable	Δ GL(t+1)	ΔLog(Y_L1(t+1))	Δ (DEP ST_FUND/TA)(t+1)
Estimation method	QREG	QREG	QREG
sample	All years	All years	All years
Const	0.013624***	0.171099***	0.06309***
GL	0.013391***	-	-
Log(Y_L1)	-	-0.068610***	-
Δ (DEP ST_FUND/TA)	-	-	-0.06996***
E[ΔLLR]	-0.154771***	-0.035695**	
LLR(t-1)	-0.011361***	-0.006323**	-0.00078***
u[LLR]	-0.032081***	-0.002811	
Dummy OVER	-0.029690***	-0.015686***	-0.00433***
Dummy UNDER	-0.009445**	-0.007915	0
Obs	19340	19325	38552
Adj R2	0.027211	0.019102	0.01570

To summarize our results on banking behavior, we have shown that risk, lending and leverage all increase with confidence, but that the relationships are not linear. Overconfident CEOs did not have a greater impact than others on the increases in risk, lending and leverage. On the contrary, the sharpest rise in these variables can be attributed to mid-confident CEOs. And these results hold also when we define the overconfident as the bottom 20% of the distribution of the ratio of loan loss reserves to gross loans.

7.3 The effects on performance

Finally, we investigated the impact of confidence on banks' performance, gauged by two indicators: return on average assets (ROAA) and the ratio of non-performing loans to total loans (NPL); other indicators of performance (e.g. ROE or operating profits) produce similar conclusions.

Table 7.4. The impact of confidence on change in ROAA by type of bank before, during and after the 2007-2008 financial crash.

Method: Quantile Regression (Median). *Notice that negative coefficients of* E[ΔLLR] and u[LLR] *correspond to a positive impact of confidence on the dependent variable.*

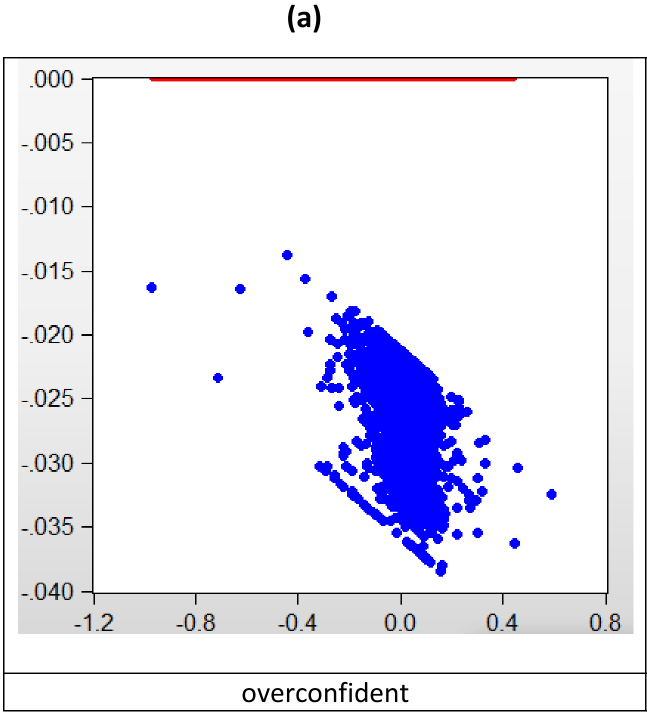
Dependent variable	ΔROAA(t+1)	ΔROAA(t+1)	ΔROAA(t+1)	ΔROAA(t+1)
Estimation method	QREG	QREG	QREG	QREG
sample	All years	Before 2008	2008-2009	After 2009
Const	0.17108***	0.10633***	0.31374***	0.15137***
ROAA	-0.20601***	-0.14909***	-0.50402***	-0.18112***
E[ΔLLR]	-0.17637***	0.02174***	-0.54665**	0.10503
LLR(t-1)	0.00287		-0.02554	0.00736
u[LLR]	0.05150***	0.12423***	-0.13732	0.01554
Dummy OVER	-0.1201***	-0.12750***	-0.11229***	-0.03962**
Dummy UNDER	-0.03805***	-0.01286	-0.10148	-0.04626***
Obs	15,601	8,282	3,059	4,260
Adj R2	0.05523	0.04732	0.12747	0.05338

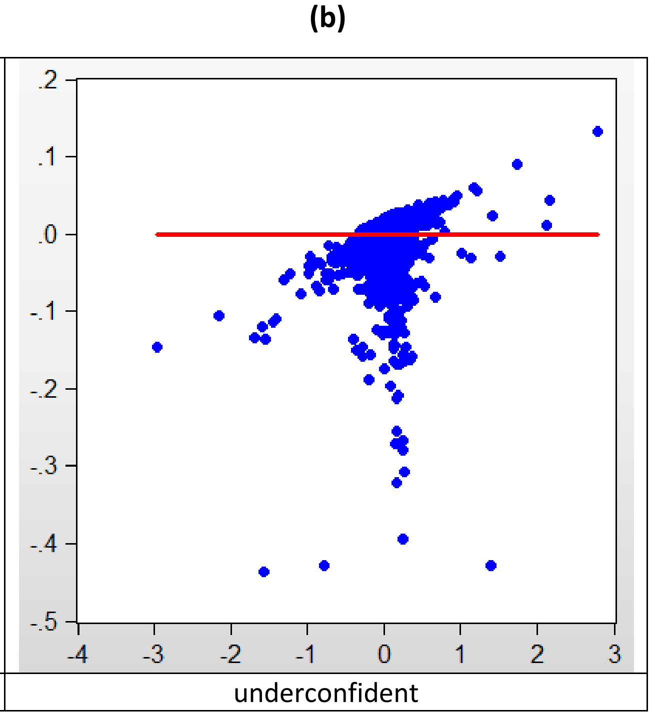
We established above (Tables 7.2 and 7.3) that an increase in confidence increases portfolio risk. So we would expect to find a similar relationship between confidence and profitability, and in fact there is a negative correlation between estimated reserves E[ΔLLR] and ΔROAA (see Table 7.4). At the same time, however, banks with higher u[LLR]>0 (i.e. those that were more pessimistic about the future) got better results. And Table 7.4 shows that before the crisis the less confident banks got the best results, whereas reserves were correlated negatively with ROAA during the crisis and positively after it. In any case, the correlation between confidence and profitability is lower at overconfident than at mid-confident banks, indicating that here too non-linearity prevails, and that in general overconfidence does not pay. This result is confirmed by the analysis of the overall impact of confidence on profitability reported in Figure 7.2.

Figure 7.2 Contribution to change in profitability by type of bank

Estimated equation:
$\Delta ROAA_t = \beta_0 + (1+\beta_1)\,\Delta ROAA_{t-1} + \beta_2 E[LLR_{t-1}] + \beta_3 ULLR_{t-1} + \xi_t$

The estimates are obtained by using quantile regression methods. No. observations: 87540. Huber Sandwich Standard Errors & Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall-Sheather, bw=0.021881
In (a) the blue (red) dots indicate the estimated values of the level of risk-taking for overconfident (mid-confident) banks using the coefficients estimated with the mid-confident banks. The correspondent lines in (b) refer to comparison between underconfident and mid-confident banks.





As with the impact of confidence on risk-taking, overconfident banks (not taking on more risk) did not increase profitability more than the mid-confident. And again, the underconfident banks resembled the mid-confident more in performance.

However, the econometric results indicate that the relationship of confidence to profitability is less clear-cut than to risk-taking. In fact, as we will see later in Figure 9.1, profitability did not always increase along with risk, and in some years they moved in opposite directions.

Finally, we estimated the impact of confidence on non-performing loans, but unfortunately we could not use either QREG or robust LS owing to convergence problems, so the results are produced only by the OLS method. First, there is a positive relationship, historically, between portfolio risk and non-performing and uncollectable loans (Figure 7.3). And this relationship strengthened during the financial crisis (see Figure 7.3), contributing to the decline in banks' profitability.

Figure 7.3 Portfolio risk, non-performing loans and uncollectable loans. Values corresponding to the decile distribution of risk/assets

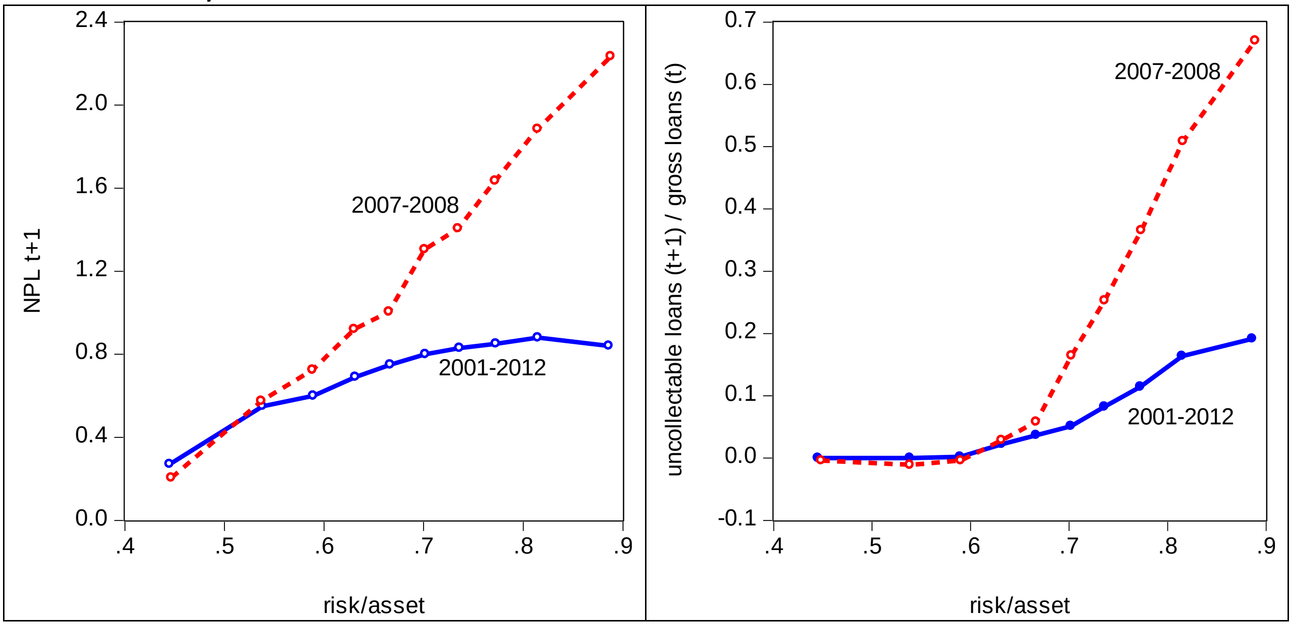


Table 7.5 reports the results of the estimations of the impact of confidence on non-performing loans during and after the financial crash.

Table 7.5 The impact of confidence on non-performing loans

Method: OLS. *Notice that negative coefficients of* E[ΔLLR] and u[LLR] *correspond to a positive impact of confidence on the dependent variable.*

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Dependent variable	Δ NPL(t+1)	Δ NPL(t+1)	Δ NPL(t+1)	Δ NPL(t+1)
Estimation method	OLS	OLS	OLS	OLS
sample	All years	Before 2007	2007-2008	After 2008
Const	0.24243***	0.12844***	0.43803***	0.19120**
NPL	-0.02635**	-0.21240***	0.44068***	-0.50632***
E[ΔLLR]	0.37590***	0.11120*	0.59488***	-0.35065
LLR(t-1)	-0.05634***	-0.01951	-0.04476	-0.00199
u[LLR]	0.39930***	0.15931***	0.41411***	0.01663
Dummy OVER	0.20012***	0.10453***	0.23576**	-0.00937
Dummy UNDER	0.02458	0.05390	-0.32982**	0.25865***
Obs	16,643	8,270	3,393	3,380
Adj R2	0.01501	0.02901	0.13718	0.11479

Interestingly, an increase in confidence (E[ΔLLR] and u[ΔLLR]) leads to a reduction in non-performing loans in the subsequent period. And other things equal, overconfident and underconfident banks now usually show a sharper rise in non-performing loans (which helps explain the negative impact on performance).

We also evaluated the overall effect of confidence on the increase in non-performing loans. The results (not reported here) indicate that non-performing loans increase with confidence, but the relationship is not significant either before or during the 2008-2009 financial crisis, bolstering our earlier conclusion of a weak relationship between confidence and performance. The fact is that performance is not a decision variable for banks but is determined ex post and depends not only on CEOs' decisions but also on macroeconomic conditions and other determinants not directly related to confidence. By contrast, a bank's portfolio risk, lending and leverage depend more closely on the CEO's confidence. In Section 9 we provide additional evidence on the relationship between confidence and performance.

8. ROBUSTNESS CHECKS

First, we checked whether the results on the determinants of confidence are robust to other estimation methods. Specifically, we ran the econometric analysis by both the OLS and the robust LS methods. Quantile regression and robust least squares assign less weight than OLS to the fat tails. These checks showed that the results do not depend on the specific econometric method adopted (see Appendix A1).

The foregoing analysis proxied confidence by loan loss reserves. As a first robustness check, we take as proxies the ratio of loan loss provisions to gross loans and the composite Index 4. The results of these estimations are qualitatively similar (see Appendix A2). However, these results suggest that loan loss reserves is a better indicator of confidence than the alternative proxies.

Since listed banks are assumed to be more subject to market discipline and are also likely to differ in other respects, we tested the determinants of confidence for listed and unlisted banks separately. The results (Appendix A3) show that unlisted banks react more to balance sheet determinants of confidence, and listed banks react more to macroeconomics and stock market conditions.

We also tested whether the determinants of confidence are robust to different definitions of overconfidence and underconfidence: specifically, defining overconfident and underconfident banks as respectively the bottom and top 20% of the distribution of loan loss reserves. The results are qualitatively similar to those produced by the narrower definition of overconfidence and underconfidence (see Appendix A5), and also using this alternative measures of over and underconfidence the impact on portfolio risk and performance are similar (Appendix 6).

It is remarkable to notice that the main relationships between confidence, risk and performance of the banks hold also when we perform a more complex estimation of the link between economic results (ROAA), confidence and assets' risk, which takes account of the feedback effects among these variables (see Appendix A7).

Finally, we addressed how "confidence" differs from risk aversion. We used two indicators of risk aversion: Risk-weighted assets/Liquid assets and Risk-weighted assets/LLRxGross loans, assuming that the higher they are, the lower is the bank's degree of risk aversion. The results of the correlations between loan loss provisions and the two indicators (reported in the Appendix A8) show no strong correlation between confidence and risk aversion, although more confident banks are also less risk-averse. And the estimations of the residuals of LLR confirm that risk aversion and confidence, although correlated, capture different phenomena.

9. The optimal degree of confidence in banking

Puri and Robinson (2007) examine the effects of moderate and extreme optimism in several contexts involving individual choice, concluding that "a moderate amount of optimism can be positive; it is associated with good financial habits and prudent choices". Campbell et al. (2011), studying non-financial firms, provide empirical evidence that there is an interior optimum level of managerial optimism that maximizes firm value.

Here we address an analogous question: Does there exist some degree of confidence that maximizes a bank's value? And, as a follow-up, is this degree of confidence socially desirable?

Addressing these issues is no easy task. The optimal degree of confidence may change according to the economic conditions and the nature of the bank.

Figure 9.1 Portfolio risk and return to American banks by decile

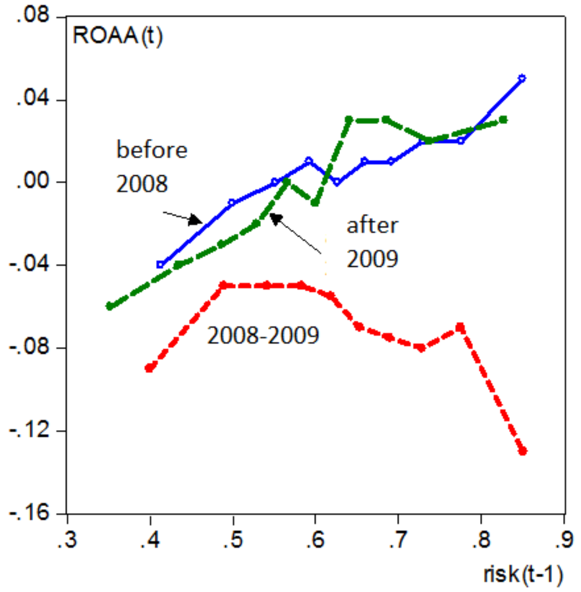
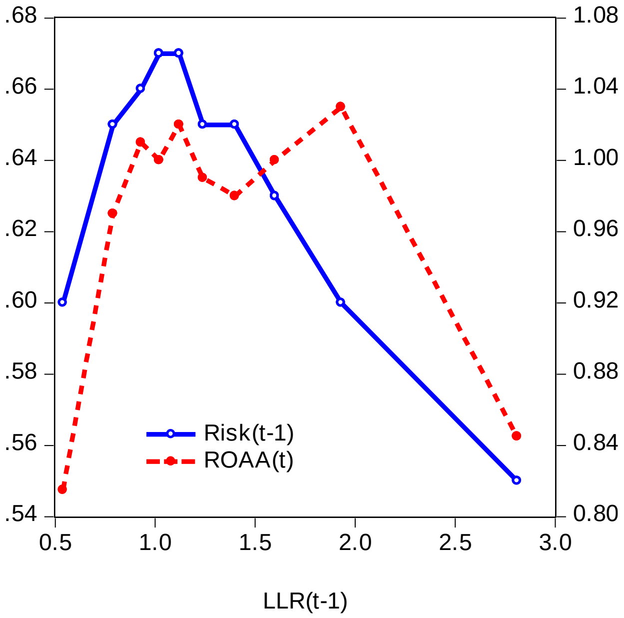


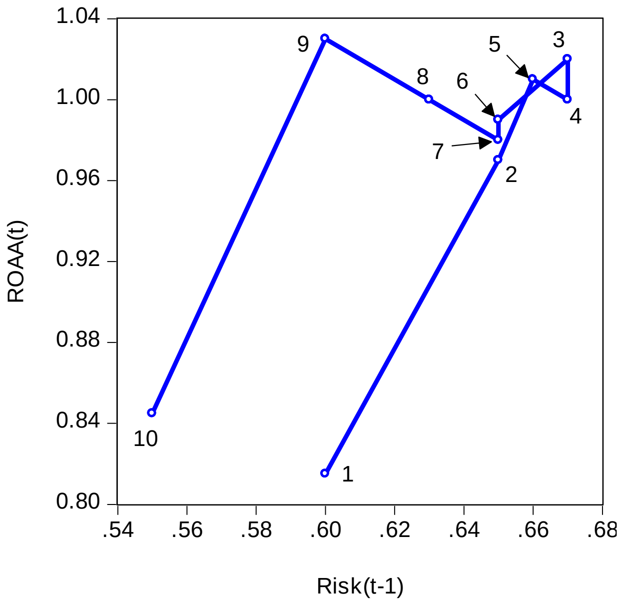
Figure 9.1 shows that the risk/return combination is positive both before and after the crisis, but that precisely in 2008-2009 the relationship between risk and return is mainly negative. It follows that the degree of confidence that maximizes the value of the bank is very different in the two cases. Yet the data reported in Figure 9.2 show that the relationships between confidence and both risk and return are non-linear.

Figure 9.2 Confidence, estimated risk and return for American banks by decile. Period 2000-2013. (LLR= Loan loss reserves/Gross loans, ROAA=Return on average assets. Risk= Risk weighted assets/Total assets)



For greater insight into this issue, Figure 9.3 shows our computation of the average risk and return for each decile of the confidence index.

Figure 9.3. Combination risk-return by decile of confidence: 1 = bottom decile (overconfident banks) and 10 = the top decile (underconfident banks). 2000-2013.



Assuming that the most efficient banks are those with the highest return/risk ratios, Figure 9.3 shows that overconfident are on average less efficient than mid-confident banks. On the other hand, Figure 9.1 shows that the group of banks that is more efficient may change with economic circumstances.

To inquire more deeply into what type of bank is more likely to be efficient, we computed the median values of portfolio risk and return on assets, assigning banks to classes according to these threshold values. Thus we move from the most efficient banks, with higher-than-median ROA and lower-than-median risk, to the least efficient, risk above and return below the median. The results are reported in Table 9.1.

Table 9.1 Risk and ROA by type of bank. Periods 2000-2013 and 2007-2008.

All period No. obs	All banks	ROA(t+1)					
		< median			>median		
		over	mid	under	over	mid	under
Risk(t+1)	< median	3104	16228	3088	1524	16335	1805
	(%)	47.44	22.36	36.43	23.29	22.51	21.30
	> median	922	18431	2310	993	21584	1273
	(%)	14.09	25.39	27.25	15.18	29.74	15.02

2007-2008	All banks	ROA(t+1)					
		< median			>median		
		over	mid	under	over	mid	under
Risk(t+1)	< median	723	2513	267	237	1854	137
	(%)	48.07	20.51	31.34	15.76	15.13	16.08
	> median	374	5550	354	170	2334	94
	(%)	24.87	45.30	41.55	11.30	19.05	11.03

As expected, a third of the mid-confident banks are in the high risk-high return group but only 15% of the overconfidents. By contrast, 47% of the latter and only 22% of the former are in the low risk-low return group. The proportion achieving greatest efficiency (ROA>median and Risk<median) is practically the same for all three types. Finally, 25% of the mid-confident but only 14% of the overconfident belong to the inefficient combination (ROA<median and Risk>median), suggesting that the former may have suffered greater losses during the financial crisis. The results reported in Table 9.1 support this conclusion. The crisis of 2007-2008 pushed a larger proportion of the mid-confident from the high risk-high return to the high risk-low return. A similar result holds if we consider the variation rather than the level of risk and return (see Table 9.2).

Table 9.2 Variation in risk and ROA by type of bank. Periods before 2007 and 2007-2008.

2007-2008	All banks	ΔROA(t+1)					
		< median			>median		
		over	mid	under	Over	mid	under
ΔRisk(t+1)	< median	378	5068	284	226	1890	162
	(%)	33.19	43.31	35.68	19.84	16.15	20.35
	> median	322	3123	222	213	1621	128
	(%)	28.27	26.69	27.89	18.70	13.85	16.08

Before 2007	All banks	ΔROA(t+1)					
		< median			>median		
		over	mid	under	over	mid	under
ΔRisk(t+1)	< median	529	6360	526	486	6566	645
	(%)	21.69	20.15	21.26	19.93	20.80	26.07
	> median	732	8540	589	692	10098	714
	(%)	30.01	27.06	23.81	28.37	31.99	28.86

Our evidence, then, does not support earlier works (e.g., Ho et al., 2016) that found overconfident banks had a higher risk profile before the crisis and were hit harder by it. Instead, on our evidence, the mid-confident banks took on more risk before the crisis and suffered more serious losses during it.

10. Concluding remarks

We inquired into the role of confidence and overconfidence in shaping the behavior and performance of US banks before, during and after the financial crash of 2007-2008. Developing new indicators of confidence and overconfidence, based on loan loss provisions, we have shown that more confident banks are more willing to take risk and are more heavily indebted. But in our study the relationship between confidence and risk-taking is not linear: as the bank's level of confidence rises, risk, lending and leverage all increase less sharply, rising less among overconfident than among mid-confident banks. Moreover, our evidence indicates that banks with an intermediate degree of confidence played a greater role in the increase in banking risk in the run-up to the 2007-2008 financial crisis, and that these banks also suffered the most severe losses in its wake. This reflects the fact that prior to the crisis mid-confident CEOs reacted more strongly to good news, while the overconfident were more persistent in their beliefs and did not overreact to good news during the cyclical upswing. In other terms, our findings do not support the thesis that overconfidents overreact to good news and underreact to bad (Daniel and Hirshleifer, 2015). Rather, we find that overconfident CEOs underweight both good and bad news. In addition, we have assessed the impact of current news and expectations on banks' risk-taking, lending, leverage and performance, finding that current news affects both behavior and performance more strongly than expected developments. In addition, our evidence indicates that in a period of crisis expectations lose their explanatory power and only current news shapes banking behavior. In any case, however, mid-confident and overconfident bank CEOs do not differ too greatly in expectations for the future.

Finally, we asked whether there exists some level of confidence that maximizes the value of the bank. Our conclusion is that there may actually exist more than one level of confidence that maximizes expected return relative to risk, and that this level depends on the characteristics of the bank and on general economic conditions. This is because the relationship between risk and return differs drastically between good and bad times. In any case, our results suggest that overconfidence never leads to an efficient combination of risk and return, while both underconfidence and mid-confidence may be optimal, depending on the economic circumstances.

The essential conclusion of this study is that the primary factor in creating the conditions of the financial crash of 2007-2008 and determining its effects was the evolution of the confidence and behavior of average banks, the bulk of the banking system. This implies that in order to attenuate the impact of a financial crisis, it is more important to prevent overconfidence and excessive risk-taking by the mass of ordinary economic agents than to curb the "irrational exuberance" of a few.

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Appendix

A1. Robustness of the estimation method (appendix to section 5 of the text)

The tails of the regression residuals of any equation based on balance-sheet items are particularly fat (Kurtosis on the order of 1000, as against 3 in normal distributions). This phenomenon renders the OLS method ineffective. Possible solutions are quantile regression estimators (QREG) and robust least squares (robust LS). Since in this paper we employed QREG, it will be useful to compare the estimations obtained by QREG, robust LS, and OLS. The equations selected for the comparison are those reported in columns (1) and (2) of Table 5.1 of the text, and the results are shown in Table A1.1. The signs of the significant parameters are usually the same for any estimator, but the QREG estimated parameters generally lie between those obtained by OLS and robust LS. These results support our choice of QREG. The residual distribution Kurtosis of eq. (1) is 1034.826, and the residuals from alternative methods have quite similar Kurtosis.

Table A1.1 Estimation of the determinants of loan loss reserves/gross loans; comparison of regression methods

Years: 2001-2013; */**/*** indicate significance at 10/5/1% respectively. *Notice that a higher value for the dependent variable corresponds to a lower level of confidence. Hence (apart from the lagged dependent variable) a negative coefficient corresponds to an increase in confidence.*

Original equations		Eq (1) Table 5.1			Eq (2) Table 5.1	
Equation	(1)	(2)	(3)	(4)	(5)	(6)
Estimation Method for comparison	QREG	OLS	RobustLS	QREG	OLS	RobustLS
Type of sample	open	open	open	closed	closed	closed
Regressors / Equations	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.03423	0.68986*	0.17512**	-0.01783	-0.11218	0.16964**
LLR(t-1)	-0.06440***	-0.12109***	-0.05890***	-0.05824***	-0.11043***	-0.04625***
LLP(t-1)	-0.00135	-0.00828***	-0.00059	0.00255**	-0.00397	0.00004
100* UNC	-0.06270***	-0.00526***	-0.73700***	-0.27417**	-0.01615***	-0.86783***
Δ GL	-0.08140***	-0.02176***	-0.96151***	-0.50676***	-0.05899***	-1.07536***
Δ (NPL)	0.04208***	0.08961***	0.00913***	0.01561**	0.07901***	0.00697***
NPL(t-1)	0.01078***	0.02634***	0.00107	-0.00176	0.04134***	0.00432***
LOG(TA(t-1))	0.00080	0.00001	0.01116***	0.00592***	-0.00445**	0.00372***
ΔLOG(TA)	-0.01299	-0.14369***	0.13318***	0.15891	-0.14463***	0.05813***
LOG(GLTA (t-1))	0.00469	0.00623	-0.01394***	-0.01244***	-0.01505**	-0.01324***
IMP	0.10058***	0.01501	0.20397***	0.38963***	-0.10979*	-0.02085
TIER1	-0.00014***	0.00194***	-0.00016***	-0.00034***	0.00028	-0.00019***
OP(t-1)	-0.08332***	-0.07753***	-0.70809***	-0.20593**	-0.07116***	-1.10061***
PBT	0.08671***	0.07634***	0.70870***	0.21230**	0.08828***	1.09953***
Δ(PBT)	-0.06781***	-0.06934***	-0.70031***	-0.17999**	-0.05905***	-1.09787***
GDP	-0.00344***	0.00010	-0.00121**	-0.00098	0.00320	-0.00054
CLIF	0.00117	-0.00476*	-0.00102	0.00072	0.00083	-0.00102*
LOG(SMK(t-1))	-0.00065	-0.01081	-0.00710	-0.00253	0.02362	-0.00359
ΔLOG(SMK)	-0.06763***	-0.09058***	-0.02045***	-0.05759***	-0.13856***	0.00247
Fed_fund	-0.00644***	-0.00693***	-0.00048	-0.00384***	-0.01048***	-0.00016
No. observations:	50,461	50,461	50,461	*36,454*	36,454	36,454
R-squared/Pseudo R-squared	0.04690	0.11869	0.23156	*0.10897*	0.10538	0.43243

Qreg= Years: 2001-2013. Qreg = Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; OLS = ordinary least square; RobustLS = Method: Robust Least Squares; M-estimation; M settings: weight=Bisquare, tuning=4.685, scale=MAD (median centered); Huber Type II Standard Errors & Covariance

Our regressions to explain the values of LLR, the ratio of loan loss reserves to gross loans, contain some variables at *t* that we considered exogenous. In order to verify this hypothesis we employed the procedure suggested by Engle and Hendry (1993), namely estimating an equation (marginal equation) for every variable under examination where all regressors are "predetermined" (instruments) and taking their residuals as additional variables to include in the regressions of LLR. If their coefficients are not significant, the corresponding variables cannot be rejected as exogenous. The marginal equations we used contained only lagged variables, apart from the macroeconomic variables taken at *t*. The results of the test are reported in column 2 of Table A.1.2: none of these variables proved to be significant, even at the 10% level: "weak exogeneity" cannot be rejected, and the parameters can be regarded as unbiased.

In equation 5 of the same table, the variable RWTA at *t-1* was introduced as a further explanatory variable for LLR. Its coefficient turned out to be positive and significant, meaning that an increase in asset riskiness reduces confidence, but, at the same time, other coefficients remain almost the same. Unfortunately the number of observations diminishes, since RWTA(-1) is not always available, so in the rest of the paper we continued to prefer the equations without this variable. Interestingly, the inclusion of RWTA at time *t* gives a coefficient with the "wrong" sign (negative instead of positive), while other coefficients remain almost the same.

Table A1.2 Estimation of the determinants of loan loss reserves/gross loans with and without portfolio risk as regressor Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; Δ() indicate change; */**/*** indicate significance at 10/5/1% of probability respectively. *Notice that a higher value for the dependent variable corresponds to a lower level of confidence. Hence (apart from the lagged dependent variable) a negative coefficient corresponds to an increase in confidence.*

Dependent Variable:	Δ(LLR)	Δ(LLR)	Δ(LLR)	Δ(LLR)	Δ(LLR)	Δ(LLR)
Equation	(1)	(2)	(3)	(4)	(5)	
Type of sample	open	open	open with RWATA among regressors	Open, but same sample as eq(3)	open with risk(6)_asset at t-1 among regressors	Open, but same smple as eq(5)
Fixed effects	no	no	no	no	no	no
Estimation Method	QREG	QREG	QREG	QREG		
	-	(Coefficients of BIAS TEST for weak exogeneity variables at t)	-	-	-	-
Regressors / Equations	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.03423	-0.03821	0.15712	0.10194	0.20623*	0.28714***
LLR(t-1)	-0.06440***	-0.06425***	-0.07301***	-0.07456***	-0.06300***	-0.06099***
LLP(-t-1)	-0.00135	-0.00188	-0.00130	-0.00128	0.00105	-0.00001
100* UNC	-0.06270***	-0.06141***	-0.09228***	-0.09171***	-0.44927***	-0.45119***
Δ GL	-0.08140***	-0.05432	-0.11084***	-0.11242***	-0.68824***	-0.69044***
Δ (NPL)	0.04208***	0.02959	0.04513***	0.04551***	0.03255***	0.03090***
NPL(t-1)	0.01078***	0.00766	0.02004***	0.02005***	0.01814***	0.01588***
LOG(TA(t-1))	0.00080	0.00128	0.00398***	0.00397***	0.00551**	0.00559***
ΔLOG(TA)	-0.01299	-0.09334	-0.01343	-0.01526	0.15251***	0.15924***
LOG(GLTA (t-1))	0.00469	0.00945	0.02307***	0.01136**	-0.01312***	0.00414
IMP	0.10058***	0.06654	0.03034***	0.02999***	-0.23536***	-0.20953***
TIER1	-0.00014***	-0.00010	-4.72E-0	0.00011	0	-0.00010*
OP(t-1)	-0.08332***	-0.08273***	-0.09792***	-0.09604***	-0.27722***	-0.27940***
PBT	0.08671***	0.08578***	0.10196***	0.09985***	0.27791***	0.28098***
Δ(PBT)	-0.06781***	-0.06637***	-0.07885***	-0.07787***	-0.25533***	-0.25686***
GDP	-0.00344***	-0.00360	-0.00233**	-0.00234**	-0.00183**	-0.00233***
CLIF	0.00117	0.00123	0.00027	0.00040	-9.66E-0	-0.00027
LOG(SMK(t-1))	-0.00065	-0.00043	-0.01066	-0.00948	-0.02623***	-0.02859***
ΔLOG(SMK)	-0.06763***	-0.07230**	-0.06936***	-0.07104***	-0.03700***	-0.03183***
Fed_fund	-0.00644***	-0.00649***	-0.00516***	-0.00536***	-0.00241***	-0.00210***

RWATA	-	-	-0.04628***	-	-	-
RWATA(t-1)	-	-	-	-	0.06267***	-
U1 (= resid of estimation of D(GROSS_LOANS)/GROSS_LOANS(-1))	-	-0.03204	-	-	-	-
U2(= resid of estimation of D(NPL)	-	0.01187	-	-	-	-
U3 (resid of estimation of DLOG(T_ASSET)	-	0.08039	-	-	-	-
U4 (= resid of estimation of IMPAIRED_LOANX/TOTAL_EQUITY)	-	0.03513	-	-	-	-
U5 (= resid of estimation of TIER_1_REG_CAP_RAT)	-	-0.00034	-	-	-	-
No. observations:	50,461	50,386	44,655	44,655	35732	35732
Pseudo R-squared	0.04690	0.04680	0.05249	0.05223	0.15712	0.15648

A2. Other main indicators for confidence (appendix to section 5 of the text)

Since we also considered LLP, the ratio of loan loss provisions to gross loans, as a possible measure of confidence, we estimated some equations relating to the determinants of this variable. Since in over 80% of the cases LLP turns out to be zero, the QREG estimator provides weak results and the robust LS method did not converge. The regressors employed for LLP are the same as for LLR, with LLP(t-1) instead of Δ(LLR(t-1)). LLP is introduced in level and not in Δ, since it is a flow and not a stock variable. The sign of the coefficients of non-performing loans is wrongly negative instead of positive (Table A2.1), while the other main variables have same sign as in the LLR equations. That negative sign of NPL remains even when the LLP regression is limited to the cases in which the dependent variable is different from zero. The same result emerges if the estimation is performed with a QREG with tau=0.8 instead of the usual 0.5.If OLS is used, the NPL parameters turn positive, but the absolute values of the coefficients are in general very high and the kurtosis of the residuals is 1076.6.

Table A2.1 Estimation of the determinants of LLP (loan loss provision/gross loans). Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; Δ() indicate change; */**/*** indicate significance at 10/5/1% respectively. _Notice that a higher value of the dependent variable corresponds to a lower level of confidence. Hence (apart from the lagged dependent variable) a negative coefficient corresponds to an increase in confidence._

Dependent Variable:	LLP	LLP	LLP	LLP	LLP

Type of sample	Open	Open	Open (Only LLP/GL>0)	Open, but same smple of eq(3)	close
Fixed effects	No	no	no	no	no
Estimation Method	QREG	OLS	QREG	QREG	QREG (tau=0.8)
Regressors / Equations	(1)	(2)	(3)	(5)	(6)
const	-0.01081	4.23068***	4.03079***	-0.01656*	0.08007
LLR(t-1)	-0.00043***	0.04757***	0.07033*	-0.00069***	0.00265***
LLP(t-1)	-0.11563***	-0.01542**	0.05451	-0.14135***	0.32943***
100* UNC	0.03121***	0.07335***	0.65139***	0.02975***	0.11448***
Δ GL	0.03362***	0.13322***	-0.13867***	0.03225***	0.14016***
Δ (NPL)	-0.00429	0.15423***	0.09605***	-0.00498	-0.01754***
NPL(t-1)	-0.00556	0.06852***	0.05459**	-0.00595	-0.02034***
LOG(TA(t-1))	0.00136***	0.06517***	-0.07370***	0.00127***	0.00525***
ΔLOG(TA)	0.00267	-0.24614***	0.27353**	0.00266	0.00029
LOG(GLTA (t-1))	-0.00068	0.09106***	-0.15788***	-0.00056	-0.00608***
IMP	0.17128**	0.26661***	0.09641***	0.17773*	1.12665***
TIER1	4.77E-0**	0.00065***	0.00309	0.00006**	0.00032***
OP(t-1)	-0.82236***	-0.58674***	-0.07747	-0.82502***	-0.71490***
PBT	0.82287***	0.62221***	0.09892	0.82552***	0.71754***
Δ(PBT)	-0.82036***	-0.56366***	-0.0590	-0.82287***	-0.70568***
GDP	-0.00032***	-0.03192***	-0.02591***	-0.00023***	-0.00347***
CLIF	0.00000	-0.03392***	-0.02668***	0.00008	-0.00032
LOG(SMK(t-1))	0.00000	-0.16090***	-0.12390	0.00022	-0.00985***
ΔLOG(SMK)	-0.00253***	0.15570***	0.32795***	-0.00330***	-0.01308***
Fed_fund	-0.00022***	0.00992***	0.00073	-0.00021***	-0.00076***
No. observations:	50,553	50,553	6,370	44,737	36,460
Adj Pseudo R-squared	0.09195	0.30295	0.41732	0.08562	0.2722

Table A2.2 reports the equations explaining the three variables, LRR, LLP, INDEX4 for a comparison, of which INDEX4 can be considered an additional alternative to LLR and LLP as a confidence indicator. The variable INDEX4 too is a flow and so did not have to be expressed in Δ; unlike LLR and LLP, it is positively related to confidence, so the parameters of its explanatory equation should normally be of the opposite sign. Unfortunately, while NPL coefficients present the right sign (negative for INDEX4), the variables relating to profits were mostly negative, whereas they should be positively correlated with confidence; the same applikes for all the macroeconomic variables except the fed funds rate. In general, then, all these results favour our choice of LLR as a (negative) indicator of confidence, at least on the base of LLP and INDEX4 explanatory equations.

Table A2.2 Estimation of the determinants of INDEX4, and comparison of equations of loss reserves/gross loans and of LLP/gross loans. Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method:

Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; Δ() indicate change; */**/*** indicate significance at 10/5/1% of probability respectively. *Notice that higher values LLR and LLP of the dependent variable correspond to a lower level of confidence, while a higher value of INDEX4 corresponds to a higher level of confidenc*

Dependent Variable:	LLR	LLP	INDEX4
Type of sample	open	open	open
Fixed effects	no	no	no
Estimation Method	QREG	QREG	QREG
Regressors / Equations	(1)	(2)	(3)
const	-0.03423	-0.01081	148.1118***
LLR(t-1)	-0.06440***	-0.00043***	-
LLP(t-1)	-	-0.11563***	-
INDEX4(t-1)	-	-	-0.54570***
ΔLLR(t-1)	-0.00135	-	-
100* UNC	-0.06270***	0.03121***	0.02511
Δ GL	-0.08140***	0.03362***	0.33870***
Δ (NPL)	0.04208***	-0.00429	-0.03371***
NPL(t-1)	0.01078***	-0.00556	-0.01491**
LOG(TA(t-1))	0.00080	0.00136***	0.00621*
ΔLOG(TA)	-0.01299	0.00267	1.97296***
LOG(GLTA (t-1))	0.00469	-0.00068	-0.04761***
IMP	0.10058***	0.17128**	0.58502***
TIER1	-0.00014***	4.77E-0**	-0.00195***
OP(t-1)	-0.08332***	-0.82236***	-0.02888
PBT	0.08671***	0.82287***	0.01878
Δ(PBT)	-0.06781***	-0.82036***	-0.07108***
GDP	-0.00344***	-0.00032***	-0.69318***
CLIF	0.00117	0	-0.46095***
LOG(SMK(t-1))	-0.00065	0	- 14.93065***
ΔLOG(SMK)	-0.06763***	-0.00253***	-2.31330***
Fed_fund	-0.00644***	-0.00022***	0.72881***
RWATA	-	-	-
No. observations:	50,461	50,553	50.369
Adj Pseudo R-squared	0.04690	0.09195	0.25830

A3. The difference in the determinants of confidence between listed and unlisted banks (appendix to section 5 of the text)

The regressions for LLR, estimated separately for listed and unlisted banks, are reported in Table A.3.1. The signs of the coefficients are the same for all the significant parameter values, with the adjustment coefficient for listed companies being higher (by about three times). The estimate for the entire sample of banks is almost the same as that for unlisted banks only. In general, the coefficients of balance-sheet items are higher for unlisted banks and those of macroeconomic variables are higher for listed banks. Closed samples cannot be estimated, since the number of listed banks is too small.

Table A3.1 Estimation of the determinants of loss reserves/gross loans and of LLP/gross loans: Listed and unlisted banks. Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; Δ() indicate change; */**/*** and °/°°/** indicate significance at 10/5/1% respectively, where * refers to coefficient significance, ° refers to the significance of the difference with respect to the previous column.

Dependent variable	Δ (LLR)		
Method	QREG		
Sample	Open		
Listed/unlisted banks	All banks	Unlisted bank coefficients	Listed bank coefficients
Constant	-0.03422	-0.04814	2.99517/
LLR(t-1)	-0.06440***	-0.06362***	-0.18448***/°
Δ (LLR(t-1))	-0.00135	-0.00135	0.01287/
100* UNC	-0.06270***	-0.06634***	-0.00265**/°°°
Δ GL	-0.08140***	-0.08689***	0.00096/°°°
Δ (NPL)	0.04208***	0.04209***	0.03084***/
NPL(t-1)	0.01078***	0.01099***	-0.02235/°
LOG(TA(t-1))	0.00080	0.00127	-0.00446/
ΔLOG(TA)	-0.01299	-0.01168	0.07989**/°°
LOG(GLTA (t-1))	0.00469	0.00465*	-0.01087/
IMP	0.10057***	0.10074***	0.31491***/°°°
TIER1	-0.00014***	-0.00014***	0.00334**/°°°
OP(t-1)	-0.08332***	-0.08412***	-0.01180/°°°
PBT	0.08670***	0.08732***	0.01619/°°°
Δ(PBT)	-0.06781***	-0.06784***	-0.02185/°
GDP	-0.00343***	-0.00320***	-0.02933***/°°
CLIF	0.00117	0.00105	-0.00734/
LOG(SMK(t-1))	-0.00065	0.00268	-0.29328*/°
ΔLOG(SMK)	-0.06763***	-0.06619***	0.03802/
Fed_fund	-0.00644***	-0.00646***	0.00279/
Obs	0.04556	0.04833	

A4. The Ramsey test for the equations of table 5.1 (appendix to section 5 of the text)

The Ramsey test applied to the equations of Table 5.1 always gives zero-probability for all regressions, whether reserves are expressed in level or in change. This means that some non-linearities exist in our equations, suggesting the need for further analysis of the coefficients, dividing banks into three groups according to confidence. Actually, the results obtained when the test is applied to the level of the fitted values suggests that the phenomenon might be due to different behaviour on the part of overconfident, underconfident, and mid-confident CEOS. Table A4.1 reports the Ramsey RESET test for equations (1) and (2) of TABLE 5.1, with the depend variable LLR taken in changes as well as in levels

Table A4.1 Ramsey RESET test applied to equations (1) and (2) of table 5.1

Equations of Table 5.1	(1)		(2)	
Dependent Variable expressed as:	Δ(LLR)	LLR	Δ(LLR)	LLR
Type of sample	Open	close	close	close
Fixed effects	No	no	no	yes
Estimation Method	QREG	QREG	QREG	QREG with IV
QLR L-statistic	1963.735	261.2707	5434.661	3942.457
(probability)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
QLR Lambda-statistic	1948.707	260.9968	5302.612	3870.149
(probability)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Number of fitted terms =2, Omitted Variables: Powers of fitted values from 2 to 3

A5. Estimation of the determinants of confidence with dummy variables by category of bank when the overconfident are defined as below the 20th percentile and the underconfident as above the 80th percentile (appendix to Table 5.5 of section 5 of the text)

Table A5.1 replicates Table 5.5 of the text, identifying overconfident and underconfident banks as the 20th and 80th percentiles of LLR respectively, instead of 10th and 90th. The results are qualitatively similar to those of the original table, meaning that the definition of under- and over-confident need not to be limited to very restricted cases.

Table A5.1: Estimation of the determinants of confidence with dummy variables by category of bank

Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, IV applied to dummies for over- and under-confident banks. Estimation successfully identifies unique optimal solution; D() indicate change; */**/*** refer to the coefficient significance at 10%/5%/1% respectively; and °/°°/°°° refer to the significance of the difference between the coefficients of overconfidents and underconfidents with respect to mid-confident banks. *Notice that a higher value of the dependent variable corresponds to a lower level of confidence. Hence (apart from the lagged dependent variable) a negative coefficient of* LLR *and D(LLR) corresponds to an increase in confidence.*

Dependent Variable:		Δ(LLR)	
Type of sample		open	
Fixed effects		no	
Estimation Method		QREG	
	mid-confident	overconfident	underconfident
Constant	-0.70507***	-0.53449**/	0.46233/
LLR(-1)	-0.10057***	0.00792/°°°	-0.06849***/°°°
Δ (LLR(-1))	0.00772	0.01435/	0.01304/
100* UNC	-0.24394***	-0.01120/°°°	-0.41748***/°°°
Δ GL	-0.34804***	0.00743/°°°	-1.58127***/°°°
Δ (NPL)	0.02123**	0.01571*/	0.03703***/
NPL(-1)	-0.00130	0.00529/	0.00425/
LOGTA (-1)	0.00840***	-0.00211**/°°°	0.01445**/
Δ LOGTA	0.12698***	0.01019/°°°	0.18733**/
LOG(GLTA (-1)))	0.00677	-0.00072/	0.00492/
IMP	0.46828**	0.42647***/	0.09702***/°
TIER1	0.00052***	-0.00004**/°°°	0.00182***/°
OP(-1)	-0.18384***	-0.02955/°°°	-0.32765***/
PBT	0.18748***	0.02876/°°°	0.35499***/°
Δ(PBT)	-0.14704***	-0.03119/°°	-0.31759***/°
GDP	-0.00224	0.00144/	-0.01603***/
CLIF	0.00552***	0.00334**/	-0.00148/
LOG(SMK(-1))	0.03360**	0.03093**/	-0.03777/
ΔLOG(SMK)	-0.13124***	-0.08072***/°°	0.03982/°
Fed_fund	-0.00744***	-0.00531***/	-0.00632/
Obs.		42,628	
Adj Pseudo R-squared		0.15036	

A6. Effect on performance and risk-weighted assets when the overconfident are below the 20th percentile and the underconfident above the 80th percentile of the confidence distribution (appendix to sections 7.1 and 7.3 of the text)

In this appendix we compare the relation between ROAA and risk when the dummies for overconfident and underconfident banks are identified as the 20th and 80th percentile instead of the 10th and 90th, as in the text (Table A6.1)

Table A6.1. The impact of confidence on change in ROAA and risk weighted assets

Method: Quantile Regression (Median). *Notice that negative coefficients of* E[ΔLLR] and u[LLR] *correspond to a positive impact of confidence on the dependent variable.*

Dependent variable	ΔROAA(t+1)	ΔROAA(t+1)	ΔRWATA(t+1)	ΔRWATA(t+1)
Estimation method	QREG	QREG	QREG	QREG
Identification of over and underconfident banks	10% and 90% quantiles of LLR	20% and 80% quantiles of LLR	10% and 90% quantiles of LLR	20% and 80% quantiles of LLR
sample	All years	All years	All years	All years
Const	0.17108***	0.17593***	0.02086***	0.02249***
ROAA	-0.20601***	-0.19405***	-0.02494***	-0.02785***
E[ΔLLR]	-0.17637***	-0.17303***	-0.01723***	-0.01559***
LLR(t-1)	0.00287	-0.00356	-0.00237***	-0.00083
u[LLR]	0.05150***	0.04879**	-0.00293*	-0.00211
Dummy OVER	-0.1201***	-0.0939***	-0.00467**	-0.00488***
Dummy UNDER	-0.03805***	-0.02571*	0.00071	-0.00487***
Obs	15,601	15.981	13,048	13,048
Adj R2	0.05523	0.05692	0.004752	0.004752

Again in this case the values of the parameters are similar, confirming that our results do not depend on some particular measure of over- and under-confidence.

Table A6.2. The impact of confidence on change in ROAA by type of bank before, during and after the 2007-2008 financial crash.

Method: Quantile Regression (Median). *Notice that negative coefficients of* E[ΔLLR] and u[LLR] *correspond to a positive impact of confidence on the dependent variable.*

Dependent variable	ΔROAA(t+1)	ΔROAA(t+1)	ΔROAA(t+1)	ΔROAA(t+1)
Estimation method	QREG	QREG	QREG	QREG
sample	All years	Before 2008	2008-2009	After 2009
Const	0.17108***	0.10633***	0.31374***	0.15137***
ROAA	-0.20601***	-0.14909***	-0.50402***	-0.18112***
E[ΔLLR]	-0.17637***	0.02174***	-0.54665**	0.10503
LLR(t-1)	0.00287		-0.02554	0.00736
u[LLR]	0.05150***	0.12423***	-0.13732	0.01554
Dummy OVER	-0.1201***	-0.12750***	-0.11229***	-0.03962**
Dummy UNDER	-0.03805***	-0.01286	-0.10148	-0.04626***
Obs	15,601	8,282	3,059	4,260
Adj R2	0.05523	0.04732	0.12747	0.05338

A7. A more complex estimation of the relationship between confidence, risk-weighted assets (RWATA) and bank's performance (ROAA) (appendix to section 7 of the text)

A more complete equation for the relationship between RWATA, ROAA and LLR (taken as an inverse measure of confidence) must take into account that:

1) Δ(RWATA) and Δ(ROAA) are related to their previous level, since after a particularly high (low) level of this variable, they should move in the opposite direction.
2) There might be positive / negative economies of scale, so the coefficient of LOGTA has to be considered as an important signal.
3) A favourable GDP scenario increases RWATA and ROAA, owing to a reduction in both economic risk and in the negative components of banks' profit-and-loss accounts.
4) The higher the interest rate, the greater the interest margin and the higher the banks' profits.
5) Measuring capitalization as the Tier1 Regulatory capital ratio TIER1 or total equity /total assets (EQTA) might influence ROAA positively.
6) The liquidity of assets/liabilities (LIQU and DEP) may influence risk or profits.
7) Under normal conditions, a higher RWATA should correspond to higher ROAA since greater risk has to be rewarded by a higher return.

The first results from the estimation of RWATA and ROAA are reported in Table A7.1

Table A7.1 Estimation of change in RWATA and ROAA. Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; Δ() indicate change; */**/*** indicate significance at 10/5/1% respectively.

Dependent variable	Δ (RWATA)	Δ (ROAA)
equation	(1)	(2)
const	-0.01807***	-0.07709***
ROAA(t-1)	-0.00198***	-0.15352***
RWATA(t-1)	-0.04902***	0.24169***
RWATA(t-1)*crisis	-	-0.08617***
Δ (RWATA(t-1))	-0.09631***	0.12979***
LOGTA(t-1)	0.00530***	0.01330***
EQTA(-1)	-	0.00148**
LIQU	0.02832***	-
E(Δ LLR(t-1)]	-0.00183	-0.00981
LLR(t-2)	0.00160	-0.14363
u[LLR(t-1)]	-0.00499***	0.06831**
NPL(t-1)	-0.00099	-
GL(t-1)/TA(t-1)	0.01996***	-
Δ (GDP)*GL(t-1)/TA(t-1)	-	0.02325***
GDP(t-1)	0.00326***	
Δ (Fed-fund)	-	0.01392***
Fed_fund	0.00380***	-
Dummy OVER(t-1)	-0.00354*	-0.03461***
Dummy UNDER(t-1)	0.00287	0.00461
No. observations	12,526	12,530
Adjusted Pseudo R2	0.03693	0.04485

In both equations, the coefficients are as one would expect. Risk and ROAA variations are negatively correlated with their lagged values, the coefficient of LOGTA suggests the presence of scale economies, and the percentage of equity over assets has a positive impact on ROAA. GDP growth exerts a positive effect on RWATA as well as ROAA; the same is true for the interest rate (Fed_fund). The effect of the unexplained component of LLR, i.e. u[LLR(t-1)], on risked assets is negative and highly significant: this means that the more optimistic and confident banks are willing to assume more risk. The increase in risk depends also on the percentage of asset liquidity and of loans. ROAA is positively influenced by RWATA (riskier assets are usually more profitable), but, of course, crisis has a negative impact on this relation. On the other side, u[LLR], which increases ROAA via RWATA, also exerts a direct negative effect on ROAA itself: this might suggest that excessive confidence may be dangerous.
The dummy for overconfidence is negative and particularly significant for ROAA, confirming that being overconfident is generally negative for ROAA. The underconfidence dummy is instead never significant.

A8. Risk aversion and confidence (appendix to section 8 of the text)

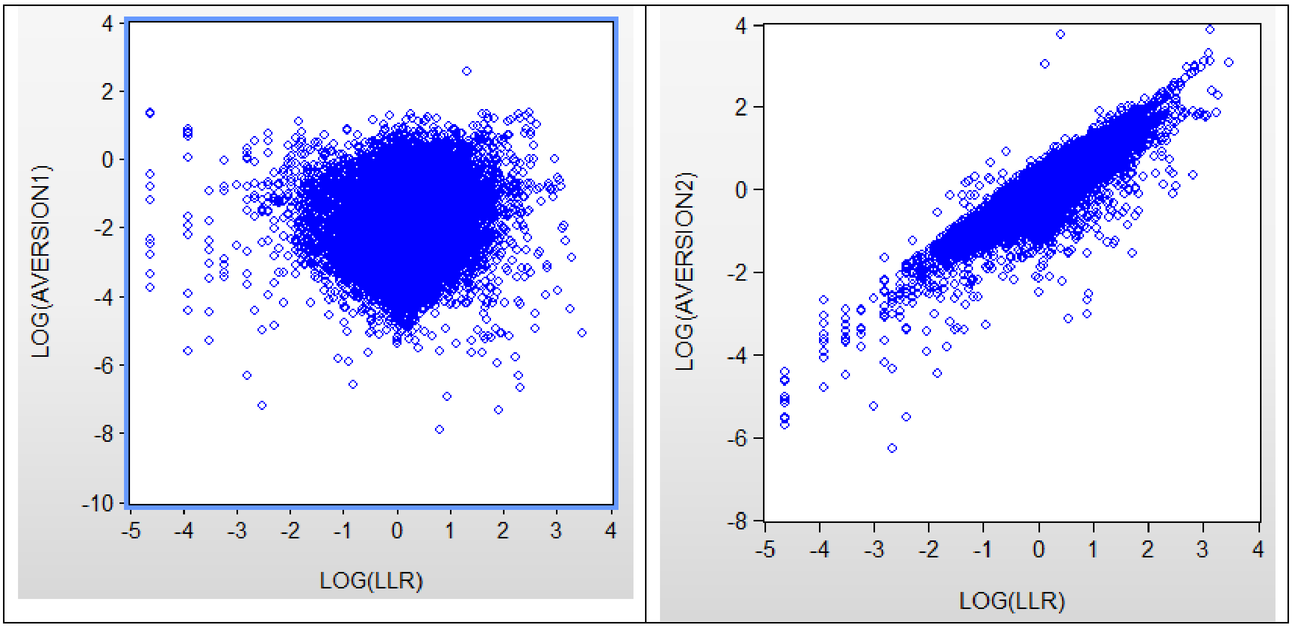
We used two indicators of risk aversion. Aversion1 is defined as Liquid assets/Risk-weighted assets; Aversion2 is Total loan loss reserves LLR / Risk-weighted assets, i.e. LLR*GL/RWATA). The higher those indicators, the greater the CEO's risk aversion. The results of the regression between the two proxies of risk aversion and LLR are reported in Table A8.1

Table A8.1 Estimation of change in ROAA and in RWATA. Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors & Covariance, Sparsity method: Kernel (Epanechnikov) using residuals, Bandwidth method: Hall-Sheather, bw=0.020706, Estimation successfully identifies unique optimal solution; Δ() indicate change; */**/*** indicate significance at 10/5/1% of probability respectively.

Dependent variable	Log(LLR)
equation	(1)
const	-0.17559***
log(aversion1)	-0.23834***
log(aversion2)	0.02655***
No. observations	41,847
Adjusted Pseudo R2	0.58439

The first figure below shows no strong correlation between confidence and risk aversion, while the second shows a strong positive correlation between risk taking and LLR: the less confident banks are also more highly risk averse. However, the coefficients of both risk-aversion measures in a regression of LLR on the two indicators are highly significant, so we infer that risk aversion and confidence are highly correlated even if the variables capture different phenomena.

Fig. A8.1 Loan loss reserves and risk-aversion



LOG(AVERSION1)
LOG(LLR)
LOG(AVERSION2)
LOG(LLR)