Banking Behavior: Managerial Confidence and Incentives

By

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Abstract

The paper studies the way in which the confidence of bank managers and the incentives for their performance affected banks' lending, leverage and risk-taking before, during and after the financial crisis of 2007-08. To this end we construct a new proxy for confidence that can measure this variable both across banks and over time. Following Rajan (2005), we posit that managerial incentives are determined by the bank's performance relative to its competitors. The paper shows that risk-taking is augmented both by an increase in confidence and by stronger managerial incentives, but that prior to the crisis confidence was a more important factor in risk-taking whereas after it incentives played a greater role. Finally, during the crash of 2007-08 confidence loses most of its explanatory power as determinant of risk-taking, supporting the thesis that banking behavior during this period may be simply explained by panic (Gorton, 2008). Our findings suggest that in order to prevent financial crises it is more important to curb overconfidence at banks and other financial institutions than to cap managers' remuneration.

Keywords: Confidence Index; Managerial Incentives; Bank Risk-Taking; 2007-08 financial crisis.

JEL Classification Number: G010, G020, G021

1. **Introduction**

There is evidence that banks' behavior was among the determinants of the financial crisis of 2007-08. Demirgüc-Kunt and Huizinga (2010), Demyanyk and Van Hemert (2011), Altunbas, Manganelli, and Marques-Ibanez (2011), Delis, Hasan, and Tsionas (2014), among others, have documented the excessive risk taken on by banks in the run-up to this crisis. Indeed, Brunnermeier (2009) contends that the last financial crisis was a classical banking crisis, albeit with some specific features: above all the extent of securitization, which led single institutions to over-leverage, engage in excessive maturity mismatching, and be excessively interconnected.

Seeking to understand why banks took excessive risk, Danielsson and Shin (2009), Geanakoplos (2009), Thakor (2015), and Gennaioli et al. (2015), among others, posit models in which good news bolsters confidence among all economic agents and leads all banks to become more risk-prone and to expand their balance sheets. In a boom, good news prevail and non-performing loans decline, boosting confidence and optimism and leading to further balance-sheet expansion. By the same token, Reinhart and Rogoff (2009) and Akerlof and Shiller (2009) argue that fluctuations in confidence are a necessary part of any realistic model of market dynamics and the business cycle. In addition, they point out that overconfidence is high at the peak of booms and underconfidence prevails in the trough of crises.

An alternative explanation for the 2007-08 financial crisis attributes the banks' excessive risk-taking to the managerial incentives arising in the drastically deregulated and competitive environment of American banking. Specifically, Rajan (2005) pointed out that the fact that bank managers' compensation is based on their performance relative to their peers, may induce superior performance by managers but can also create an incentive to take risk that is concealed from investors – risks, that is to say, that offer very generous compensation most of the time, while generating highly improbable but very severe adverse consequences (tail risks). The subprime loan crisis of 2007-08 can thus be attributed to these perverse incentives, which led managers to originate risks, move them off the banks' balance sheets and onto those of investment managers, and then originate more (Rajan, 2005).

This paper seeks to gauge the extent to which fluctuations in confidence and changes in incentives affected American banks' behavior and risk-taking before, during and after the 2007-08 financial crisis. Significantly, for the most part these two factors – confidence and incentives – are mutually independent explanations of banks' behavior. During the upswing, confidence soars and all the banks contribute, in varying measure, to the increase in risk, which may eventually result in a financial crash. In the downswing the opposite effect prevails, excessive pessimism possibly triggering a credit crunch. By contrast, the incentive to outperform peers is likely to stimulate extra risk-taking in both phases of the business cycle.

To estimate the change in confidence over the business cycle, we construct a new proxy of bank CEOs' confidence – and this constitutes the paper's second contribution.

Loan loss reserves constitute a "contra-asset" account against expected losses from default on some portion of loans. Expected loan losses (hence loan loss reserves) may be affected by various factors: bank characteristics, for instance, balance-sheet outcomes, or news on the macroeconomic conditions. In addition, banks may use the reserves to smooth earnings. Notice that if these are the sole determinants of loan loss reserves, the unexplained component of the reserves should be unrelated to any other variable. But, empirically the residuals of the explained components of loan loss reserves are related to future non-performing and uncollectable loans. Then, we assume the difference between actual reserves and their estimated value captures confidence that bank's CEOs have on their expectations about future loan losses. Bank managers who are optimistic on loan performance may keep lower reserves than would be suggested by current news and the bank's characteristics. By contrast, pessimistic managers accumulate extra reserves beyond those suggested by news and characteristics. In other words, we consider over confident (optimists) the banks that are in the lower half of the distribution of residuals of the explained components of loan loss reserves and under confident (pessimists) those that are in the higher half distribution. In practice, our proxy of confidence is closely correlated with two aggregate indicators of confidence used by the Federal Reserve.

Using this indicator, first we investigate how bank CEOs' confidence evolves over the business cycle. Next, we address whether the prime determinant of banking behavior before, during and after the 2007-08 financial crisis was confidence or the incentives determined by the relative performance of the bank. Among other things, we consider whether the crash prompted some change in the relationship between confidence, incentives and banking behavior.

We find that both an increase in confidence and incentives spur lending, leverage and risk-taking. However, prior to the crisis of 2007-08, managerial confidence was more important than incentives in determining risk-taking, but afterward incentives were the primary factor. Finally, during the crash confidence is not significant determinant of changes in portfolio size and risk-taking, buttressing the thesis that the banks' conduct during that period may be explained by other factors, such as the panic effect documented by Gorton (2008). So, increase in confidence was a more important factor affecting the incentives in building up the risk tail that eventually triggered the financial crisis of 2007-2008.

The paper contributes to the literature in several ways. First, it provides a new indicator of confidence, one that is suitable for testing the impact of confidence at all types of banks and over the business cycle. Second, the paper assesses the role of confidence and managerial incentives in the financial crash of 2007-2008 and the subsequent recovery. Since the bulk of our sample consists of unlisted American banks, the paper assesses the determinants of risk-taking at the financial institutions most relevant to small and mid-sized American firms. Our findings offer support for the position that in order to prevent a financial crisis it is more important curb the sources of overconfidence during cyclical upswings than to eliminate the perverse incentives that often characterize deregulated and competitive financial markets.

The paper is organized as follows. Section 2 reviews the relevant literature and Section 3 describes the data and methodology. Section 4 presents our new indicator of confidence, and Section 5 sets up the hypotheses and presents the main results of the estimations. Section 6 concludes.

2. The literature

There is broad consensus that excessive risk-taking by banks was a factor in the global financial crisis of 2007-08 (see Brunnermeier, 2009, IMF, 2014). Delis, Hasan and Tsionas (2014), for American banks, and Demirguc-Kunt and Huizinga (2010), for a large sample of international banks, find that risk was fairly stable up to 2001 but then rose sharply until 2007. In fact, the banks that suffered the greatest losses during the crisis relied more on short-term funding, had higher leverage, and grew more before the crisis (Fahlenbrach, Prilmeier, and Stulz, 2012, Beltratti and Stulz, 2012).

There is less consensus on what incentives led bank managers to take risk. Broadly speaking, there are two strands of the literature. One attributes risk-taking to managerial overconfidence during the boom before the crisis. The alternative blames excessive risk-taking on the perverse managerial incentives encouraged by the competitive environment of banking, in which the essential driver of each bank's behavior is the manager's need to outperform other banks.

As representatives of the first approach, let us cite Ho, Huang, Lin, and Yen (2016), Ma (2014), Sironi and Suntheim (2012), and Niu (2010). These authors have compared banks with overconfident and non-overconfident CEOs and established that overconfidence played an important role in increasing lending and leverage and weakening lending standards in the run-up to the 2007-08 financial crisis. Specifically, Ho, Huang, Lin, and Yen (2016) show that in the period 1994-2009 overconfident US (listed)_banks were more aggressive in lending and increased their leverage more than the non-overconfident. The overconfident also suffered more severe losses as a consequence of the crisis. In addition, Ma (2014) documents that banks with overconfident managers increased their real estate lending more sharply prior to the crisis. Two explanations are that overconfident managers are more optimistic that the borrowers will repay (see, e.g., Malmendier and Tate, 2005; Goel and Thakor, 2008;

Campbell et al., 2011; Ben-David et al., 2013) or they underestimate the risk (Hirshleifer and Luo, 2001, Thakor, 2015). It is worth pointing out that this approach takes overconfidence to be a character trait that persists through time (Daniel and Titman, 1999),[1] whereas other authors contend that confidence depends on the business cycle.

Among the latter, Minsky (1982) explained that in normal times success makes borrowers and lenders more assured of operational cash flows, feeding the idea that a smaller margin of safety is required. It is this increasing confidence generated by success that leads financial institutions to switch from risk hedging to a speculative or Ponzi position. Geanakoplos (2009) offers a theoretical model to explain how endogenous increases in optimism and pessimism generate a leverage cycle, and Thakor (2015) examines a model in which owing to the long period of sustained banking profitability all agents – banks, their fund suppliers and regulators – find themselves in an "availability cascade" where they overestimate the ability of bankers to manage risks and become more tolerant of risk-taking. This leads financial institutions and investors to underestimate true risk exposures and encourages banks to invest in higher-risk assets. Barberis (2013) suggests that the financial bubble before 2007 arose because investors projected past outcomes – returns, earnings growth, default rates – too far into the future; and Gennaioli et al. (2015) cited the "neglected risk" of innovative financial products as one of the causes of the crisis. Also Akerlof and Shiller (2009) have theorized the importance of success stories in forming expectations, likening the transmission of confidence between individuals to contagion of diseases. This approach offers a different perspective on the cyclical pattern of confidence, which is likely to increase and spread among all economic agents during the upswing and contract in the downswing. At the same time, risk-taking increases with confidence.

Surprisingly, although theoretical models and historical evidence (e.g. Kindleberger, 2005, Reinhart and Rogoff, 2009) pointed to the effect of changing confidence on banking behavior, the literature has little to offer on the contribution of confidence to the last financial crisis and the impact of plummeting confidence on banking behavior after the 2007-08 crash. Filling this gap is our first aim.

[1] Recent models of overconfidence (e.g.; Eisenbach and Schmalz, 2015; Merkle, 2013) explain variations in confidence levels of overconfident people as endogenously determined by preference-based rationales for overconfidence.

The alternative explanation ascribes the financial crisis to an incentive structure that prompted bank managers to take excessive risk. Deregulation and increasing competition within the banking industry induced an executive compensation system based on each bank's performance relative to its competitors. And such pressure to outperform other banks induces excessive risk-taking. Rajan (2005) was among the first to discuss the perverse effects produced by evaluating managers against others; Bannier, Feess and Packham (2012) provide a theoretical model in which the competition for talent results in executive bonuses that induce risk-taking that is excessive not only for society as a whole but even for the single banks. Empirical support for this hypothesis comes, among others, from DeYoung, Peng and Yan (2010), Bhagat and Bolton (2014), Bebchuk, Cohen and Spamann (2010), Thanassoulis (2012) for American banks; Efing, Hau, Kampkötter and Steinbrecher (2015) for banks in other countries; and Massa and Patgiri (2009) for mutual funds. By contrast, Fahlenbrach and Stulz (2011) conclude that managerial incentives did not play a significant role in the 2007-08 financial crisis, since the banks with greater option compensation and a higher fraction of CEO compensation consisting in cash bonuses did not perform worse. In this view, the poor performance of banks during the crisis was due to unforeseen risk.

Even though overconfidence and perverse incentives may both lead to excessive risk-taking, the policy implications are very different in the two cases. Setting a cap on executive remuneration may not be sufficient to curb excessive risk-taking, if it is occasioned by a widespread surge in confidence.

3. Data and methodology

We use a large sample of American commercial, cooperative, and savings banks, taking only these categories of banks because they are more homogenous than the other classes in the Bankscope dataset (notably, holding companies, bank holding companies, finance companies, investment banks, real estate and mortgage banks, and specialized governmental credit institutions).

The dataset comprises the consolidated annual balance sheets of 10,223 banks in the United States, or 84% of the American banks included in the Bankscope database, provided by Bureau van Dijk.[2] Our sample banks account for 74% of the total assets of all the Bankscope commercial, savings, cooperative and investment banks and 24% of the total assets of all the banks in this dataset. We also

[2] 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.

used other sources, such as Bondware to compute loans net of securitization, and Datastream and the World Bank for macroeconomic variables. The open sample (i.e., all the banks) counts some 103,000 observations, the closed sample (i.e., the banks with data all through the years of our investigation) 77,000. The appendix to Section 3 reports the variables used in the econometric analysis and their sources, as well as the summary statistics and the correlation matrix.

Table 1 **Percentage values of total assets: listed versus unlisted banks (2001-2013)**

Specification	All banks		Type A banks*		Of which: in this paper	
Listed/unlisted	Listed	Unlisted	Listed	Unlisted	Listed	Unlisted
Open sample	26.73	73.27	1.27	98.73	1.28	98.72
Closed sample	45.93	54.07	0.18	99.82	0.18	99.82

*Commercial banks, cooperative banks and savings banks.

Notice that our sample differs very significantly from those commonly used in the empirical literature on overconfidence (e.g., Ho, Huang, Lin, and Yen, 2016). First, the latter considers listed banks only, but of highly varied types, whereas we take a more homogeneous set of banks, mostly unlisted (see Table 1). Consequently, by comparison with earlier work our sample assigns less weight to listed and more to unlisted banks. In fact, the literature on overconfidence simply ignores unlisted banks, which make up the majority of banks. In addition, we use bank's balance-sheet data, while the literature on overconfidence relies on equity-based measures of overconfidence, which are necessarily restricted to listed banks and they may be subject to distortions.[3]

The econometric software package for our estimations is Eviews-9.5. Given the excessively fat tails of all the residual distributions (see Table 3.2), in lieu of OLS we elected quantile regression (QREG) based on medians. In the appendix to Section 4 we compare the QREQ estimations with OLS, "robust LS", 1-99% "winsorized OLS" and "LS cleared of outliers", and we show that the former is the most efficient estimator.

When QREG is used, Eviews-9.5 does not directly provide fixed effect pooling estimators, so we approximated the right econometric tool by previously diminishing every variable by its mean. However, in this case using the lagged dependent variable as a regressor produces biased estimates.

[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'".

To overcome this problem, we estimated every lagged dependent variable using a set of exogenous variables (marginal equations) and employed these estimations in lieu of the original lagged variables in our fixed effect estimators.

Another problem of bias relates to taking the unexplained component of loan loss reserves, U[LLR], as a measure of confidence, and using this variable (often along with the explained component, E[LLR]) as a regressor in some equations. Unfortunately, this automatically generates an "error in variable" problem, since our indicator of "confidence" is simply an estimated value obtained from equation 1 in Table 2. We sought to mitigate the bias following Shanken (1992): for every year t, LLR estimations were obtained by using the parameters derived from a rolling three-year regression from t-3 to t-1.[4]

4. A new proxy for confidence in banking

Banks set aside capital for contingencies, i.e. to deal with unexpected losses. Loan loss reserves, on the other hand, are built up to cover *expected* losses due to the non-repayment of some portion of outstanding loans. According to the American Institute of Certified Public Accountants, "[T]he allowance for loan losses represents an amount that, in management's judgment, approximates the current amount of loans that will not be collected" [AICPA (1983), p. 621]. Both the Financial Accounting Standards Board (FASB) and federal regulators have stated plainly that the reserve is to be based on expected losses [FASB (1989), p. 351]. However, although SFAS No. 5, SFAS No. 114 and FASB codification provide detailed rules for the recognition and measurement of loan loss provisions, some degree of management discretion is inherent in the provisioning process. The imprecise words in the FASB standards that describe the amount of loss as "probable" or "reasonably estimated" allow some discretion in accounting for loan loss provisioning (El-Sood, 2012). It is reasonable to assume that in determining their loan loss reserves, bank managers exploit this leeway.

At first glance, expectations of loan losses (hence loan loss reserves) are determined by current news on the performance of the bank and the economy and the bank's characteristics. Notice that if only current news and bank's characteristics affect loan loss reserves, the residuals of the regression should be purely random. Actually, the unexplained component of loan loss reserves systematically relates to future values of non-performing and uncollectable loans, and we assume the unexplained

[4] Using a longer rolling estimate of five years does not alter the results.

component of loan loss reserves reflects confidence about the future. Some managers may be optimists, and they believe future loan losses will lower than those suggested by current news, while some others are pessimists, and they believe future loan losses will be higher than those suggested by current news and bank's characteristics. Hence, we assume optimist CEOs keep lower reserves than those suggested by our estimations coming from current news, and pessimists keep higher reserves than the estimated value.

Hence, to measure confidence first we estimate the impact of the news and bank characteristics on loan loss reserves. To this aim, we test the following equation:

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

in which Δ denotes absolute variation, *LOG* denotes natural logarithm, *(-1)* indicates the previous year, and ε is the error term. Table 3.1 in the Appendix gives the definitions of the variables. In equation 1, regressors 1-14 are the internal, balance-sheet determinants (e.g., non-performing loans, uncollectable loans, profits, tier 1 regulatory capital, size); the remaining variables are external, macroeconomic determinants (real GDP growth, current leading indicators, stock market performance and the Federal Funds rate).

A rise in NPLs increases expected loan losses and leads managers to expand loan loss reserves. Bad news on the performance of the economy has a similar effect.[5] By contrast, a gain in profits reduces loan loss reserves. But Liu and Ryan (2006), Fonseca and González (2008), Kanagaretnam, Lobo, and Mathieu (2003), and Leventis, Dimitropoulos and Anandarajan (2011), among others, provide evidence on the income smoothing effect in banking, although this latter is admittedly more likely to affect provisioning than total loan loss reserves. Hence, we expect that an increase in profitability may actually lead to an expansion of loan loss reserves, if the banks use the latter for purposes of income smoothing. Table 2 reports the results of the estimation of equation 1.

[5] Pain (2003) and Bikker and Metzemakers (2005) have shown that faster real GDP growth reduces banks' provisioning. Laeven and Majnoni (2003) and Black and Gallemore (2013) report that in business expansions banks tend to defer the recognition of expected losses, entering them in the accounts only with the onset of adverse cyclical conditions.

Table 2. Estimation of the determinants of loan loss reserves.

Years: 2001-2013. Method: Quantile Regression (Median), Huber Sandwich Standard Errors and 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% probability respectively.

Dependent Variable:	Δ LLR	LLR	Δ LLR	LLR	LLR	LLR	LLR	LLR
Type of sample	Open	Open	Closed	Closed	Open	Closed	Open	Closed
Observations	all	all	all	all	Banks > 4 obs		Banks > 4 obs	
Fixed effects	No	No	no	no	Yes	Yes	yes	yes
Estimation method	QREG	QREG	QREG	QREG	QREG	QREG	QREG with IV	QREG with IV
Equation	(1)	(1bis)	(2)	(2bis)	(3)	(4)	(5)	(6)
C	2.35245***	2.35245***	1.86402***	1.86402***	-0.02001***	-0.01785***	-0.04038***	-0.02562***
LLR(-1)	-0.08363***	0.91636***	-0.08258***	0.91742***	0.75964***	0.77330***	0.78785***	0.94760***
Δ (LLR(-1))	0.01575**	0.01575**	0.03324***	0.03324***	0.12179***	0.11280***	-0.15212**	-0.27042***
100* UNC	-0.00001***	-0.00001***	-0.00001***	-0.00001***	-0.00000	-0.00000	0.00000*	0.00001***
Δ GL	-0.03025***	-0.03025***	-0.17258***	-0.17258***	-0.08898***	-0.17495***	-0.21514***	-0.33770***
Δ (NPL)	0.00242***	0.00242***	0.00273***	0.00273***	0.00021	0.00049*	0.00121**	0.00178***
NPL(-1)	-0.00013	-0.00013	0.00131***	0.00131***	-0.00275***	-0.00180***	-0.00407***	-0.00253***
LOGTA (-1)	0.00495***	0.00495***	0.00381***	0.00381***	0.09014***	0.07693***	-0.06780***	-0.11245***
Δ LOGTA	0.00360***	0.00360***	0.00195***	0.00195***	0.00664***	0.00509***	0.01292***	0.00869***
LOG(GLTA(-1))	-0.00316***	-0.00316***	-0.00161	-0.00161	0.07562***	0.06566***	-0.09119***	-0.12789***
IMPTE	-0.00000	-0.00000	-0.00001	-0.00001	0.00038***	0.00037***	0.00069**	0.00061***
TIER1	-0.00032***	-0.00032***	-0.00083***	-0.00083***	0.00101***	0.00051***	0.00156***	0.00108**
OP(-1)	-0.01398***	-0.01398***	-0.00970***	-0.00970***	-0.00922***	-0.00770***	-0.02537***	-0.02176***
OPBT	0.01299***	0.01299***	0.01389***	0.01389***	0.00544***	0.00664***	0.02619***	0.02319***
Δ(OPBT)	-0.00909***	-0.00909***	-0.00906***	-0.00906***	-0.00630***	-0.00645***	-0.02222***	-0.01876***
GDP	-0.03584***	-0.03584***	-0.02588***	-0.02588***	-0.02421***	-0.01875***	-0.05965***	-0.05937***
CLIF	-0.00690***	-0.00690***	-0.00426***	-0.00426***	-0.00293***	-0.00096	-0.02393***	-0.02791***
LOG(SMK(-1))	-0.21686***	-0.21686***	-0.18455***	-0.18455***	-0.19597***	-0.16885***	-0.21111***	-0.27120***
ΔLOG(SMK)	0.06925***	0.06925***	0.01089	0.01089	0.04243***	0.01447	0.59487***	0.58034***
FEDFUND	-0.00257***	-0.00257***	-0.00386***	-0.00386***	-0.00891***	-0.00889***	-0.01492***	-0.00582**
No. observations:	103215	103215	76204	76204	82203	65052	73338	59095
Adj, Pseudo R-squared	0.04019	0.55255	0.04885	0.58682	0.36010	0.39194	0.07389	0.08129

In the QREG estimations with instrumental variables, in the case of fixed effects the IVs are applied to the lagged variables.

First, notice that the dynamics in our regressions derives from an error correction scheme:

$\Delta y_t = a + b_0 y_{t-1} + b_1 x_{t-1} + c_{01}\Delta x_{t-1} + c_{10}\Delta y_{t-1} + c_{11}\Delta x_{t-1} + \ldots$, equivalent to: $y_t = a + \beta_0 y_{t-1} + b_1 x_{t-1} + c_{01}\Delta x_{t-1} + c_{10}\Delta y_{t-1} + c_{11}\Delta x_{t-1} + \ldots$ (With $\beta_0 \equiv 1+b_0$), where we considered only a few relevant lags; *y* denoting the dependent variable and x the vector of regressors.

The results indicate that an increase in NPLs increases loan loss reserves. By contrast, high operating profits (OP) in t-1, as well current increases in "pre-provision operating profit", reduce the amount of loan loss reserves. However, in order to stabilize profits, high amounts of current "pre-provision operating profits" determine an increases in loan loss reserves. Macroeconomic variables, such GDP growth, current leading indicators, and stock market index, lower the loan loss reserve ratio. In addition, a rise in the fed funds rate lowers reserves, since as the cost of loans rises, lending remuneration improves. The results do not vary greatly between the open and the closed sample, with instrumental variables estimations[6] employed for the lagged dependent variable in case of "fixed effect".

We also estimated equation 1 including future uncollectable loans and non-performing loans among the regressors. The parameters of the equations with and without these two regressors are quite similar, as are the residuals. Finally, the results are not altered by taking the variation rather than the level of loan loss reserves as the dependent variable (see Table 2) or adding risk-weighted assets over total assets to the set of regressors.[7]

Notice that the residuals in the estimation of equation (1) reflect the unexplained components, i.e. determinants of loan loss reserves not included in the regressors plus idiosyncratic factors. The latter include the CEO's confidence about future losses.

However, if current news and bank's characteristics are the only determinants of loan loss reserves, the residuals of the estimates of equation 1 should be unrelated to future values of non-performing loans and uncollectable loans. But, Table 3 shows a positive and significant correlation of the future values of non-performing loans and uncollectable loans with the current values of the unexplained components of loan loss reserves (U[LLR]). Moreover, U[LLR] is more important than the explained component of loan loss reserves E[LLR] - resulting from the estimate of equation 1 - in determining future uncollectable loans (UNC) and non-performing loans (NPL).

Table 3. The relationship between the explained and unexplained components of loan loss reserves and banks' future performance of the loans.

Dependent variable	UNC(t+1)	NPL(t+1)
Estimation method	QREG	QREG
Variable	coefficients	coefficients
	All banks	All banks
Const	-0.02492***	0.41122***
U[LLR]	0.08130***	0.30077***
E[LLR]	0.04981**	0.26358***

[6] Notice that in these regressions the lagged dependent variable produces biased estimations if there are a large number of banks and a small number of observations per bank. When fixed effects were considered, therefore, we always used instruments for the lagged dependent variable.

[7] To save on space, we do not present these additional results, but they are available upon request.

Obs	59,435	59,440

Therefore, we take the unexplained component of loan loss reserves as a proxy of CEOs' confidence about future performance. That is, we assume that the more confident the CEO is, the lower the value of the residuals of the estimated equation 1 will be. Hence, our proxy of confidence is the negative of U[LLR] (i.e., conf ≡ - U[LLR]).

However, the error term reflects current objective data unobservable to the researchers (i.e. idiosyncratic factors and variables not included among the regressors). As an example, residuals may reflect managerial efficiency, so that banks with more efficient managers need to keep lower reserves, and the opposite holds for banks with inefficient managers. On the other hand, it is reasonable to expect that efficient managers are also more optimists than inefficient ones.[8] Thus to assess how well the residuals reflect confidence, we compared our proxy with some other proxies of bank's confidence existing in the literature that are not affected by this potential distortion.

First, we compared our indicator of confidence with the more straightforward one from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices, covering up to 60 large domestic commercial banks and 24 large branches and agencies of foreign banks in the U.S. The Fed survey offers a more direct indicator of confidence, asking senior loan officers whether their bank's loan quality is likely to improve or deteriorate substantially or somewhat or to stabilize around current levels (Board of Governors of the Federal Reserve System, 2013). To derive the Fed's aggregate confidence index, we assigned scores of +2, +1, 0, -1, -2 from the most optimistic to the most pessimistic answer and computed an aggregate weighted index for each year. Unfortunately, this survey is not available before 2005.

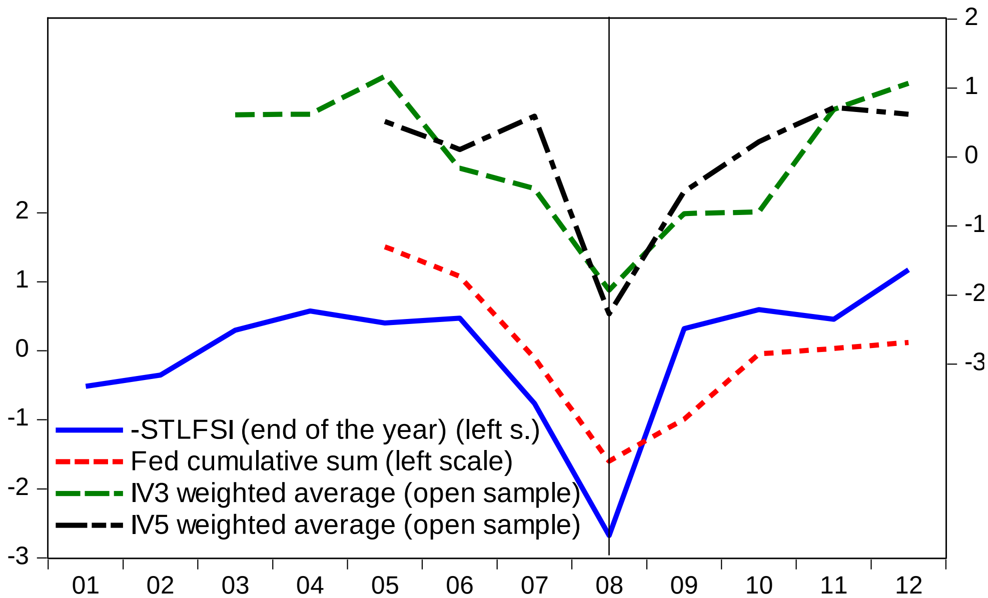
In addition, we have compared our index with the St. Louis Fed's Financial Stress Index (STLFSI), which is constructed using 18 weekly data series: seven interest rate series, six yield spreads and five other indicators of financial market volatility (Federal Reserve Bank of St. Louis, 2010). Each of these variables captures some aspect of financial stress, so as the financial stress in the economy changes, the data series are likely to move together. The index begins in late 1993 and is designed to have an average value of zero, indicating normal financial market conditions. Negative values suggest less than normal

[8] Chen and Lin (2013) find that a CEO who has a higher level of managerial optimism can improve the firm's investment efficiency.

financial market stress, positive values above-average stress. We assume that the greater the stress in financial markets, the lower bank managers' confidence will be. Consequently, higher confidence in Figure 1 corresponds to the opposite of the STLFSI.

Figure 1 reports the aggregate values of the last two confidence indexes, in addition to our own aggregate proxy of confidence.

Figure 1 Comparison between confidence indexes.



Normalized scale; left s. = left scale, otherwise right scale; IV3 = three year rolling IV, IV5 = five year rolling IV.

The red line is the aggregate value of confidence computed using the FED survey. So, it is a direct indicator of the degree of confidence of the bank's managers. The blue line is the opposite of the St. Louis Fed's Financial Stress Index. Higher values of the blue line correspond to greater confidence in the financial markets. The green line IV3 is the weighted average of our indicator of confidence using IV three years rolling estimation (Shanken, 1992) of the residuals of our LLR estimations (with changed sign), and the black line reports the same indicator using five-years rolling estimations (IV5).

It is remarkable to notice that, despite the different sources of data, our aggregate indicators of confidence are highly correlated to both the indicator of confidence constructed by the FED using bank-level data, and the stress indicator built up by the St. Louis Fed using aggregate variables. However, our indicator of confidence is built up out of bank's balance sheet data, instead of surveys or macroeconomic data.

Confidence can be measured along two dimensions: cross-sectional and temporal. At any point in time bank managers may differ in their confidence about the future. And of course, confidence may change over time. Figure 1 shows the evolution of confidence from 2001 to 2013: it rose until 2007, plummeted in 2008-09, and turned back up thereafter (see also Table 6 below).

One concern about using the residuals from estimation of equation 1 as an indicator of confidence is the determinants of the distribution of those residuals. Our analysis (see the appendix to Section 4) finds a particularly large number of outliers, so in our case the distribution depends more on fat tails than on Kurtosis with only a relative few outliers. This justifies the use of the quintile regression method.

5. Confidence, incentives and banking behavior

a) The hypotheses

In the account of such authors as Akerlof and Shiller (2009), Geanakoplos (2009), and Danielsson and Shin (2009), rational behavior implies that good news builds confidence among all economic agents and leads banks to be more risk-prone and to expand their balance sheets. In this view, an increase in risk-taking is not the product of behavioral bias but of greater confidence, fueled by good economic performance. Kindleberger (2005), Minsky (1992), Shleifer and Vishny (2010), De Grauwe (2012) and Thakor (2015) have shown that financial intermediaries in markets influenced by investor sentiment display cyclical behavior as regards both credit and investment, and both are unstable. Following this approach, we assume that increases in confidence among all economic agents spur risk-taking, lending and leverage. Specifically, we state:

Hypothesis 1. *The higher confidence of the bank's managers the greater the riskiness of the portfolio.*

This hypothesis rests on the assumption that more confident CEOs have better expectations about the future and take more risk because they feel better equipped to handle it. Goel and Thakor (2008) and Eisenbach and Schmalz (2015), among others, argue that overconfident managers underestimate risk and so engage in excessive risk-taking.

Hypothesis 2: *More confident banks expand lending, leverage and total assets more strongly.*

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, Gallmeyer, Johnson, Rutherford, and Stanley, 2011; Ben-David, Graham, and Harvey, 2013) and to grant credit to higher-risk borrowers (Hirshleifer and Luo, 2001; Thakor, 2015). Both these effects lead these banks to lend more and to loosen lending standards (Ma, 2014; Eisenbach and Schmalz, 2015). In addition, more confident banks expand their balance sheets more and consequently are more likely to face capital constraints. It follows that they have greater resort to external funding.

Adrian and Shin (2011) prove that the size of the bank or financial intermediary (its asset volume) is determined by the degree of leverage permitted by market conditions; Malmendier, Tate, and Yan (2011) find that banks prefer debt to equity when there are good opportunities for growth during a credit boom. Empirically, Beltratti and Stulz (2012) and Fahlenbrach, Prilmeier, and Stulz (2012) show that a rise in leverage beforehand played an important role in the global financial crisis of 2007-08.

An alternative explanation blames the excessive risk that ultimately triggered the financial crash of 2007-08 on the structure of incentives for bank CEOs (see Section 2). This structure founds managers' remuneration on the relative performance of the bank (see Rajan, 2005).[9]

So, we assume:

Hypothesis 3: *Banks' managers undertake more risk in order to get higher profits than their peers.*

The intuition is that if the CEO fails to make more profits than peers at competitor banks, this lowers the value of the bank, so that investors as well as depositors will find it less attractive. Consequently, the manager is threatened with the loss of a good portion of income or even dismissal and replacement by a more efficient manager. In this framework, excessive risk-taking is the outcome of the fierce competition among banks and between banks and other financial institutions.

[9] Cai et al. (2010), among others, examine the relationship between executive compensation and banks' profitability in US. They find that total compensation in 2005, and four of its main components—salary, bonuses, restricted stocks, and stock options—all had fairly strong, positive correlations (0.3-0.5) with net income and market value. On the other hand, correlations were very low (less than 0.1) between compensation and return on assets and return on equity. This kind of pay structure may have encouraged "short-termism" and excessive risk-taking.

We proxy managerial incentives with the difference between bank *i*'s profit in year *t* and the average weighted value (AWV) of the other banks' profits. In formal terms, the incentive to undertake more risk (I) is determined by:

$$\mathbf{I} = \mathbf{\Pi}_{it} - \text{AWV } \mathbf{\Pi}_t$$

with **Π** denoting return on equity (ROE), return on assets (ROA), or net operating profits (OP$). Indeed, in the following analysis we use the difference in the ranking of operating profits between bank *i* and the average ranking of banks in year *t* (*Rank(OP$)(t) - Av[Rank(OP$)](t)*). Considering rank instead of absolute profit value avoids problems of heteroskedasticity and high data variance.

Finally, it is reasonable to assume that our two motivations for risk-taking, confidence and incentives, are independent. Confidence, in fact, increases during the cyclical upswing and decreases in the downswing, whereas competition produces more or less the same effect throughout, inducing bank CEOs to undertake more risk in both phases of the business cycle.

In fact, the correlation between confidence and incentives is very low (Table 4).

Table 4. Correlation between proxies of confidence and incentives

	Confidence	ROA_{it} – $AWVROA_t$	ROE_{it} – $AWVROE_t$	$Rank(OP\$)_{it}$ - $Av[Rank(OP\$)]_t$
Confidence	1	0.02048	-0.00261	-0.01720
ROA_{it} – $AWVROA_t$	0.02048	1	0.87047	0.54197
ROE_{it} – $AWVROE_t$	-0.00261	0.87047	1	0.53533
$Rank(OP\$)_{it}$ - $Av[Rank(OP\$)]_t$	-0.01720	0.54197	0.53533	1

b) The results

To analyze the effects of confidence, we consider the impact of the explained and the unexplained values of loan loss reserves separately. However, splitting a variable (LLR in our case) into expected values and residuals by means of an estimated regression creates a problem of "error in variables" when they are introduced as independent variables in a regression, and this generates biased coefficient estimates. To attenuate this bias, following Shanken (1992), we estimate a h-years rolling equation ending in year t-1 and we apply the parameters so obtained to establish the explained and unexplained values in year t. When this procedure is employed and h=3, the period under examination shortens to 2003-2013. Tables 6-9 below report the results.[10]

To start with, we report in the Table 5 the average level of banks' managers confidence, change in gross loans over total loans (Δln(GL/TA)), leverage (Δln(Y_L1), uncollectable loans (UNC)and the Z-score (ΔZ-Score) of the American commercial, cooperative and saving banks before, during and after the crisis of 2007-2008. Aggregate confidence is obtained using the three years rolling window.

Table 5. Indicators of banking behaviour and performance by period

	Before crisis	During crisis	After crisis
Confidence	0.04565	-0.09518	-0.01646
Δln(GL/TA) (t)	0.00810	-0.14804	0.01335
Δln(Y_L1) (t+1)	-0.00904	0.01252	0.00392
UNC	6.25498	11.90660	11.79770
Δ Z-Score (t+1)	-1.47100	-14.45165	1.44628

In the boom period before the crisis confidence was high and lending increased, heightening also the fragility of the bank's balance sheet (in the same period the probability of default of the bank increased significantly). Confidence, lending and the Z-Score plummeted during the crisis; by contrast, uncollectable loans peaked. Finally, after the crisis, confidence recovered weakly and the probability of default shrunk, but loan losses remained high.

Table 6 shows how managerial confidence and incentives affect the size (Total assets, TA) and riskiness (Risk-weighted assets/Total assets, RWATA) of the portfolio before, during and after the last financial crisis.[11] We consider also Z-score as an alternative indicator of risk.

Table 6. The impact of confidence and incentives on portfolio size and riskiness

Δln(TA) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.09426***	0.08449***	0.09828***	-0.01166
Δln(TA) (t)	-0.39884***	-0.33992***	-0.42654***	-0.39928***
Confidence (t)	0.01294**	0.03015***	-0.00923	-0.00013
E[ΔLLR] (t)	-0.02883***	-0.02027***	-0.00552	-0.02374***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.01593***	-0.00562***	-0.01736***	-0.04871***
Obs.	76,143	32,581	15,411	28,151
Adj Pseudo R2	0.07379	0.04666	0.07704	0.10110

[10] However, we employed also 5-year rolling, and the results (reported in Appendix) are similar to the three-years rolling window case.

[11] Specifically, "crisis period" designates independent variables referring to the years t=2007 and t=2008 and dependent variables to the years t+1=2008 and t+1=2009 respectively.

ΔRWATA (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.24374***	0.14099***	0.34815***	0.39450***
RWATA (t)	-0.35070***	-0.18936***	-0.50448***	-0.59455***
Confidence (t+1)	0.00952***	0.01946***	0.00041	0.00380**
E[ΔLLR] (t+1)	-0.00375***	-0.00619***	-0.00322*	0.00481***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00237***	0.00074***	0.00200***	0.00479***
Obs.	79,591	36,031	13,440	28,115
Adj Pseudo R2	0.07086	0.04236	0.10505	0.12154

Δ Z-Score (t+1)	All years	Before crisis	During crisis	After crisis
Constant	6.06725***	5.00174***	9.25825***	6.75903***
Z-Score (t)	-0.19960***	-0.16163***	-0.33032***	-0.18950***
Confidence (t)	-0.02032	-0.76860***	1.85892***	-0.11897
E[ΔLLR] (t)	-0.07453	-0.04256	-0.51405	-0.33810***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.03885**	-0.03776	-0.11434***	-0.02651
Obs.	73,128	31,228	14,499	27,401
Adj Pseudo R2	0.05201	0.04149	0.11432	0.04116

Confidence does have a positive impact on changes in portfolio size, but this result is due to only the impact of before the crisis: during and after the crisis confidence has not a significant effect on portfolio size and its riskiness. A higher relative performance of the bank (in terms of net operating profits) to its peers instead, always reduces the future portfolio size of the bank. It seems that the incentive to expand the portfolio size operates only when the bank underperforms relative to the peer group.

By contrast, both greater confidence and higher relative performance heightens portfolio riskiness, but with differential effects through the business cycle. While the impact of relative performance is significant in all the stages of the business cycle, the effects of confidence on risk-taking differ substantially between the pre- and post-crisis periods, being weaker in the last period. In addition, confidence loses its significance during the crash, supporting the thesis that the explanation of banking behavior in this period must lie in other factors, such as the panic effect documented by Gorton (2008). Finally, as expected, E[ΔLLR] (i.e. the component of loan loss reserves explained by present balance-sheet items and macroeconomic variables) exerts a negative effect on the variables considered above. Similar results holds in the five-year rolling estimations (see Appendix). The alternative indicator of risk (Z-score) supports the conclusion on the greater role of confidence before the crisis. Moreover, it indicates that confidence contributed more to the increase in risk tails before the crisis.

Since the above analysis suggests that both confidence and incentives are relevant in determining risk taking of the bank before the crisis of 2007-2008, we asked what is the most important factor in determining the conditions that led to the crash. To estimate the relevance of confidence and incentives on risk taking, we used standard deviation (SE) of each variable multiplied by its correspondent parameter. However, a similar result holds using median absolute variable (MAV) instead of standard deviation (see Table 5.1 in Appendix).

Table 7. The relevance of confidence and incentives in risk-taking, lending and leverage

Relevance of confidence and incentives on change in TA

Based on:	Δlog (TA) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.00700	0.01352	(-0.00454)	(-0.00008)
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.05168	-0.01728	-0.05705	-0.16600

Relevance of confidence and incentives on change in RWATA

Based on:	Δ RWA/TA (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t+1)	0.00556	0.00897	(0.00031)	0.00237
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00761	0.00225	0.00651	0.01632

Relevance of confidence and incentives on changes in loans/total assets

Based on:	Δln(GL/TA) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.03595	0.01443	0.02391	0.06310
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.07484	0.03788	0.06556	0.16490

Relevance of confidence and incentives on change in leverage

Based on:	Δln(Y_L1) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.01019	0.00243	(0.01142)	(0.02494)
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00509	0.00412	0.01019	-0.00051

There are reported in parenthesis the values when the impact of the variable is not significant.

The results reported in Table 7 indicate that, before crisis, confidence was more important than incentives in building the risk that eventually produced the financial crash of 2007-08. After the crisis, by contrast, the main determinant of portfolio risk becomes relative performance. Thus, the crisis period produced a structural change in the impact of confidence and incentives on banks' risk taking. The intuition of this result is that while incentives operate in a similar way all the time, confidence is more dependent from the up and down of the business cycle. The bigger the crash the longer it takes for confidence to restore. Next, we consider whether the results extend to other aspects of the banking behaviour.

Table 8 reports the results of the effects of confidence and of managerial incentives on lending (Gross loans/Total assets, GL/TA), leverage (Y_L1), deposits and short-term funding (DEP) before, during and after the financial crash of 2007-08.

Table 8. The effects of confidence and incentives on lending, leverage and deposits and short term funding

Δln(GL/TA) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	-0.12336***	-0.08574***	-0.11101***	-0.13710***
Δln(GL/TA) (t)	-0.38167***	-0.33687***	-0.38121***	-0.39032***
Confidence (t)	0.06643***	0.03220***	0.04861***	0.09748***
E[ΔLLR] (t)	-0.02754***	-0.02816***	-0.05427***	-0.01456**
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.02307***	0.01232***	0.01995***	0.04839***
Obs.	76,143	32,581	15,411	28,151
Adj Pseudo R2	0.09052	0.07616	0.08220	0.10993

Δln(Y_L1) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	1.07213***	0.56358***	1.26239***	1.71876***
ln(Y_L1) (t)	-0.45720***	-0.23981***	-0.53414***	-0.74188***
Confidence (t)	0.00568**	0.01596***	-0.00102	0.00376
E[ΔLLR] (t)	-0.01429***	-0.01373***	-0.02395***	-0.00240
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00468***	0.00235***	0.00249***	0.00625***
Obs.	76,086	32,577	15,388	28,111
Adj Pseudo R2	0.09531	0.04585	0.12614	0.17543

Δ DEP (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.47203***	0.57276***	0.33821***	0.53488***
DEP (t)	-0.54591***	-0.66316***	-0.40005***	-0.60458***
Confidence (t)	0.01883***	0.00542**	0.02321***	0.03853***
E[ΔLLR] (t)	-0.00278**	0.00042	-0.00168	-0.01386***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00157***	0.00134***	0.00310***	-0.00015
Obs.	76,142	32,581	15,411	28,150
Adj Pseudo R2	0.15988	0.18184	0.16817	0.16279
Δ DEP (t+1)	All years	Before crisis	During crisis	After crisis

Results in Table 8 confirm that incentives are significant in determining lending and leverage in all the phases of the business cycle. However, also confidence is significant in determining change in lending al through the period and affects leverage before the crash of 2007. So, it is interesting to investigate the relevance of confidence and incentives in determining lending and leverage. Results reported in table 8 offer clear cut conclusions with respect to lending: incentives are always more relevant than confidence in determining lending, and these results are confirmed using the five years rolling window method (see Appendix). The relevance of the two determinants on leverage is less clear cut, but both SE and MAV methods suggest that incentives were more relevant than confidence in determining leverage before the crisis (see Table 8 and 5.1).

Interestingly, the impact of confidence on lending is always higher than on deposits and short term funding. Notice that lending is more related to decisions of the bank's managers than deposits and short term funding, which depend to a greater degree from savers' decisions.

Among other things, Table 5 and the results reported in Table 8 also offer some insight into the determinants of the credit crunch documented by Ivashina and Scharfstein (2008). The decline in confidence was a significant factor in the plunge in lending during the crisis. By contrast, a better bank's relative performance had a countervailing effect, increasing the proportion of lending in the balance sheet even during the crisis.

An interesting question is whether also future loans performance depend on confidence and perverse incentives. We expect, in fact, that this should be the case. In this analysis, non-performing and uncollectable loans capture loan performance.

Table 9. The impact of confidence and incentives on loan performance and probability of default

Δ NPL (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.12365***	0.06516***	0.54429***	0.25718***
NPL(t)	-0.58609***	-0.53931***	-0.72531***	-0.60751***
Confidence (t)	-0.05725***	-0.03791***	-0.01730	-0.00569
E[ΔLLR] (t)	0.09060***	0.02310***	-0.03114***	0.09723***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.03223***	0.01991***	0.03261***	0.02784***
Obs.	76,102	32,545	15,406	28.151
Adj Pseudo R2	0.15919	0.14634	0.22206	0.16067

100*UNC (t+1)	All years	Before crisis	During crisis	After crisis
Constant	-0.03681***	-0.04948***	-0.00628	0.00539
NPL(t)	0.01237***	0.01038***	0.01074***	0.01763***
Confidence (t)	-0.07631***	-0.05503***	-0.08707***	-0.06850***
E[ΔLLR] (t)	0.04782***	0.03886***	0.05190***	0.03641***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00899***	0.00631***	0.01395***	0.01420***
Obs.	76,119	32,564	15,407	28,148
Adj Pseudo R2	0.00050	0.00045	0.00018	0.00038

Results reported in Table 9 show that more confident banks did have the best performance of the loans in the short run. In addition, consistent with the previous results, confidence has a higher impact than incentives in determining loan performance before the crisis (see Table 5.2 in the Appendix). It seems that more confident bank's managers fulfil their expectations in the short run. Is this true also in the long run?

To study this question, we consider the impact of confidence before the crisis on loans performance during and after the crisis. The results reported in Table 10 indicate that the impact of confidence on loan performance in the long run is opposite to those of the short run: i.e., the banks more confident before the crisis were also those that suffered the greatest loan losses and failed more during the crisis. This evidence suggests that overconfident bank's managers may underestimate farther outcomes of their behaviour, with the consequence that they may take too much risk in good time and too little risk in bad time.

Table 10. The effects of average confidence and incentives before the crisis on loans performance and the Z-score of the bank during and after the crisis.

	Years≥2007	Years≥2007	Years≥2007
Dependent variable	**Δ NPL (t+1)**	**UNC (t+1)**	**z-score (t+1)**
Constant	0.11320***	-0.06650***	26.62359***
NPL(t)	-0.82883***	0.00914***	-2.12140***
Conf before 2007	0.05220***	0.02747***	-1.69520***
E[ΔLLR] before2007	-0.04824***	-0.02605***	3.04020***
Inc before 2017	0.01111***	0.00457***	-0.27041***
Conf (t)	-0.03763***	-0.02008***	2.83051***
E[ΔLLR] (t)	0.07453***	0.02011***	-2.77031***
Inc (t)	0.02316***	0.00571***	-0.32085***
Adj Pseudo R2	0.47296	0.00034	0.02126
Obs.	40,959	40,952	40,832
Relevance	**Δ NPL (t+1)**	**UNC (t+1)**	**z-score (t+1)**
Conf before 2017	0.015418	0.008113	-0.500659
Inc before 2017	0.028525	0.011728	-0.693969

The impact of the incentives before the crisis on loan performance and Z-score during and after the crisis are similar to the incentives. Hence, we estimated their relevance, by multiplying each coefficient by the standard deviation of the correspondent variable. The results indicate that incentives contributed more than confidence, even though the difference in the contribution to loan performance and Z-score after 2007 is negligible.

Similar results are obtained if we consider confidence and incentives in the last year before the crisis (2006) instead of their average values before the crisis period.

Notice that the highest values of confidence correspond by definition to overconfident bank's managers, and the lowest values of the confidence distribution identify the underconfident managers. The rest of the managers may be classified as mid confidents. Therefore, from the previous analysis we can infer the relative contribution of these three categories of managers to the financial crash of 2007-2008. Overconfident banks before the crisis did have the highest loan losses and the highest reduction of the Z-score during and after the crisis. Finally, the results reported in Table 11 confirm previous conclusions on the opposite effects of confidence in the short and the long run. Indeed, the impact of the increase in confidence in the short term is negative and opposite the effect in the medium-long run.

Finally, Table 10 shows that the higher E[LLR] (i.e. the component of loan loss reserves explained by present balance-sheet items and macroeconomic variables), the greater the future increase in non-performing and uncollectable loans. Current adverse signals on the performance of the bank and the economy lead banks to increase loan loss reserves, to face losses that will materialize at *t+1.* And the direct correlation between LLR and future loan performance is confirmed when the sample is split into the three sub-periods.

The foregoing results provides also some insight on the role of confidence and incentives in the recovery from a financial crisis. The spur for risk-taking and lending after the crisis is due to more the profit incentive effect than to the increase in confidence (see Tables 7-9). Indeed, after the crisis, confidence is not significant (in the increase in portfolio size) or less relevant (in risk-taking and lending) than the incentive effect.

We performed a series of checks to gauge the extent to which these results may depend on our particular regressors and methodology. First, we substituted return on assets or return on equity for operating income as proxy for managerial incentives; the main difference using these alternative indicators of relative performance is that incentives are most of the time no longer significant in risk-taking: confidence is the sole significant factor (see Tables 5.3 and 5.4 in the Appendix), before, during and after the crisis. However, the more striking result of these robustness checks is the impact of confidence on the expansion and contraction of loans in the portfolio during the business cycle (see Tables 5.6-5.9 in the Appendix).[12]

6. Concluding remarks

We have inquired into the role of confidence and managerial incentives in shaping the behavior and performance of US commercial, cooperative and savings banks before, during and after the

[12] Similar results hold if we substitute change in loans to loans over total assets as dependent variable. To save on space, we do not report these results, but they are available from the authors upon request.

financial crash of 2007-08, developing a new proxy for confidence and overconfidence that can gauge confidence for all banks at once and over time. According to this indicator confidence should change over the business cycle. Concretely, we should find that it increased up until 2007, plummeted between 2007 and 2009, and recovered thereafter, with opposite effects on banking behavior. By contrast, incentives should operate similarly in upswing and downswing alike, always inducing managers to undertake more risk, in the effort to improve their bank's performance by comparison with their peers.

The empirical results confirm these predictions. Whereas the impact of relative performance is similar throughout the period, the effects of confidence on risk taking, lending and leverage differ very markedly. Confidence increases risk-taking and leverage only before 2007-08, and loses most of its effects thereafter. Hence, prior to the crisis confidence was a more important factor in risk-taking whereas after it incentives played a greater role.

In other words, our findings suggest that managerial overconfidence before 2007 was a major factor in the excessive risk-taking that led to the financial crash, and that the resulting credit crunch may be ascribed to the plunge in confidence triggered by the crash. On the other hand, the recovery from the crash is likely to be supported more from the incentive of the managers to perform better than their peers than from the recovery of their confidence. Finally, during the crisis confidence loses its significance in determining the size and the riskiness of the portfolio, again supporting Gorton's thesis that the best explanation of the banks' behaviour in this period was panic (Gorton, 2008).

However, excessive confidence was the most important factor building up the risk tail that eventually triggered the financial crisis of 2007-2008 and the subsequent banking failures, By contrast, the incentive to perform better than their peers was the driving force of the recovery after the crisis.

An important topic for further research is whether there are specific banks or financial institutions that play a leading role in determining the level of confidence and incentives, both in the boom and the burst. However, this paper shows that the spread of confidence among small and medium-size banks is an important determinant of the 2007-2008 financial crash and its aftermaths.

In terms of policy, our findings strongly suggest that for purposes of crisis prevention, it is more important to curb overconfidence among banks, other financial institutions and investors than it is to restrict perverse incentives by capping executive remuneration.

References

Adrian, T., Shin, H. S., 2011. Financial Intermediary Balance Sheet Management. Annual Review of Financial Economics, 3, p. 289-307.

Akerlof, G. A., Shiller, R. J., 2009. Animal Spirits. Princeton University Press, pp. 230.

Altunbas, Y., Manganelli, S., Marques-Ibanez, D., 2011. Bank Risk During The Financial Crisis Do Business Models Matter? European Central Bank, Working paper N. 1394.

Bebchuk, L.A., Cohen, A., Spamann, H. (2010). The Wages of Failure: Executive Compensation at Bear Stearns and Lehman 2000-2008. Yale Journal on Regulation, 27 (2).

Bannier, C.E., Feess, E., Packham, N. (2013). Competition, Bonuses, and Risk-taking in the Banking Industry. Review of Finance, 17 (2), p. 653‑690.

Barberis, N., 2013. Psychology and the financial crisis of 2007—2008. In M. Haliassos (ed.), Financial innovation: Too much or too little? MIT Press.

Beltratti A., Stulz, R., 2012. The credit crisis around the globe: Why did some banks perform better? Journal of Financial Economics 105, 1–17.

Ben-David, I., Graham, J. R., Harvey, C. R., 2013. Managerial miscalibration. Quarterly Journal of Economics 128, 15.

Bhagat, S., Bolton, B. (2014). Financial crisis and bank executive incentive compensation. Journal of Corporate Finance 25, p. 313–341.

Bikker, J., Metzemakers, P., 2005. Bank provisioning behavior and procyclicality. International Financial Market, Institutions, and Money 15 (2), 141–157.

Black, D. E., Gallemore, J. (2013). Bank Executive Overconfidence and Delayed Expected Loss Recognition. Available at SSRN: https://ssrn.com/abstract=2144293.

Board of Governors of the Federal Reserve System (2013). Senior Loan Officer Opinion Survey on Bank Lending Practices (FR 2018; OMB No. 7100-0058). https://www.federalreserve.gov/boarddocs/SnLoanSurvey.

Brunnermeier, M. K., 2009. Deciphering the Liquidity and Credit Crunch 2007-08. Journal of Economic Perspectives 23, 77-100.

Cai, J., Cherny, K., and Milbourn, T. (2010). Compensation and Risk Incentives in Banking, Economic Commentary, June, 21.

Campbell, T.C., Gallmeyer, M., Johnson, S.A., Rutherford, J., Stanley, B.W., 2011. CEO optimism and forced turnover. Journal of Financial Economics 101 (3), 695–712.

Daniel, K., Titman, S., 1999. Market Efficiency in an Irrational World. Financial Analysts Journal 55 (6), 28-40.

De Grauwe, P., 2012. Booms and busts in economic activity: A behavioral explanation. Journal of Economic Behavior and Organization 83, 484– 501

Delis, M. D., Hasan, I., Tsionas, E. G., 2014. The risk of financial intermediaries. Journal of Banking and Finance 44, 1–12.

Demirguc—Kunt, K., Huizinga, H., 2010. Bank activity and funding strategies: The impact on risk and returns. Journal of Financial Economics 98, 626–650.

Demyanyk, Y., Van Hemert, O., 2011. Understanding the Subprime Mortgage Crisis. Review of Financial Studies 24, 1848-1880.

DeYoung, R., Peng, E. Y., Yan, M. (2010). Executive Compensation and Business Policy Choices at U.S. Commercial Banks. Federal Reserve Bank of Kansas City. RWP 10-02. Efing, M., Hau, H., Kampkötter, P., Steinbrecher, J. (2015). Incentive Pay and Bank Risk-Taking: Evidence from Austrian, German, and Swiss Banks. Journal of International Economics, 96 (1), p. 123-140.

Eisenbach, T. M., Schmalz, M. C., 2015. Anxiety, Overconfidence, and Excessive Risk-Taking. Federal Reserve Bank of New York, Staff Report No. 711.

El Sood, H.A., 2012. Loan loss provisioning and income smoothing in US banks pre and post the financial crisis. International Review of Financial Analysis 25, 64–72.

Fahlenbrach, R., Prilmeier, R., Stulz, R., 2012. This time is the same: using bank performance in 1998 to explain bank performance during the recent financial crisis. Journal of Finance 67, 2139–2185.

Fahlenbrach, R., and Stulz, R. M. (2011). Bank CEO incentives and the credit crisis. Journal of Financial Economics, 99(1), 11-26.

Federal Reserve Bank of St. Louis (2010), National Economic Trends, January 2010. Fonseca, A.R., González, F., 2008. Cross-country determinants of bank income smoothing by managing loan-loss provisions. Journal of Banking and Finance 32 (2), 217-228.

Geanakoplos, J., 2009. The Leverage Cycle. Cowles Foundation Discussion Paper n. 1715R.

Gennaioli, N., Shleifer, A., Vishny, R., 2015. Neglected Risks: The Psychology of Financial Crises. American Economic Review 105(5), 310–314.

Goel, A. M., Thakor, A. V., 2008. Overconfidence, CEO selection, and corporate governance. Journal of Finance 63, 2737–2784.

Gorton, G. B., 2008. The Panic of 2007. NBER Working Paper No. 14358.

Hirshleifer, D.A., Luo, G.Y., 2001. On the Survival of Overconfident Traders in a Competitive Securities Market. Journal of Financial Markets 4(1): 73–84.

Ho, P., Huang, C., Lin, C., Yen, J., 2016. CEO overconfidence and financial crisis: Evidence from bank lending and leverage. Journal of Financial Economics 120, 194-209.

International Monetary Fund, 2014. Global Financial Stability Report: Risk-taking, Liquidity, and Shadow Banking—Curbing Excess while Promoting Growth, Ch 3.

Kanagaretnam, K., Lobo, G., Mathieu, R., 2003. Managerial incentives for income smoothing through bank loan loss provisions. Review of Quantitative Finance and Accounting 20 (1), 63–80.

Kindleberger, C. P., 2005. Manias, Panics, and Crashes. John Wiley and Sons, pp. 355.

Ivashina, V., Scharfstein, D., 2010. Bank lending during the financial crisis of 2008. Journal of Financial Economics, 97 (3), 319-338.

Laeven, L., Majnoni, G., 2003. Loan loss provisioning and economic slowdowns: too much, too late? Journal of Financial Intermediation 12, 178–197.

Leventis, S., Dimitropoulos, P.E., Anandarajan, A., 2011. Loan Loss Provisions, Earnings Management and Capital Management under IFRS: The Case of EU Commercial Banks. Journal of Financial Service Research 40, 103–122.

Liu, C., Ryan, S., 2006. Income smoothing over the business cycle: Changes in banks' coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom. The Accounting Review 81(2), 421–441.

Ma, Y., 2014. Bank CEO Optimism and the Financial Crisis. Harvard University, Working paper.

Malmendier, U., Tate, G., 2005. Ceo overconfidence and corporate investment. Journal of Finance 60 (6), 2661–2700.

Malmendier, U., Tate, G., Yan, J., 2011. Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies. Journal of Finance 66 (5), 1687–1733.

Massa, M., and Patgiri, R. (2009). Incentives and Mutual Fund Performance: Higher Performance or Just Higher Risk Taking? Review of Financial Studies, 22(5), 1777-1815.

Merkle, C., 2013. Financial Overconfidence Over Time: Foresight, Hindsight, and Insight of Investors. University of Mannheim. Working paper.

Minsky, P. H., 1982. Can "It" Happen Again? M.E. Sharpe Inc., New York, pp. 290.

Minsky, P. H., 1992. The Financial Instability Hypothesis. The Levy Economics Institute of Bard College, Working Paper N. 74.

Niu, J., 2010. The effect of CEO overconfidence on bank risk-taking. Economics Bulletin 30, 3288–3299.

Pain, D., 2003. The provisioning experience of the mayor UK banks: a small panel investigation, Bank of England, London, Working Paper N. 177.

Palumbo, M. G., Parker, J. A., 2009. The integrated financial and real system of national accounts for the United States: does it presage the financial crisis? American Economic Review 99, 80–86.

Rajan, R.G. (2005). Has Financial Development Made the World Riskier? NBER Working Paper n. 11728.

Reinhart, C.M., Rogoff, K.S., 2009. This Time is Different. Princeton University Press, pp. 463.

Shanken, J., 1992. On the Estimation of Beta-Pricing Models. The Review of Financial Studies 5 (1), 1-33.

Shleifer, A., and Robert W Vishny, R. W., 2010. Unstable Banking. Journal of Financial Economics 97 (3): 306-318.

Sironi, A., Suntheim, F., 2012. CEO Overconfidence in Banking, Working Paper. Available at SSRN: https://ssrn.com/abstract=2250344.Thanassoulis, J. (2012) "The case for intervening in bankers' pay", The Journal of Finance , 67 (3), p. 849-895.

Thakor, A., 2015. Lending Booms, Smart Bankers and Financial Crises. American Economic Review, 105 (5):305-09.

Appendix

Appendix to Section 3

Table 3.1 describes the variables used in the econometric analysis and their sources, Table 3.2 reports the summary statistics, and Table 3.3 reports the correlation matrix. We opted for rank correlations instead of the traditional Pearson r correlation, considering the high Kurtosis value of all the balance-sheet data.

Table 3.1 Variables and data sources

Definition	Symbol	Source
Bank-specific variables:		
Deposits and short-term funding/Total assets	DEP	Bankscope
Size (log of total assets)	LOGTA	Bankscope
Gross loans/Total assets	GLTA	Bankscope
Gross Loans (log)	GL	Bankscope
Impaired loans/Gross loans	IMP	Bankscope
Impaired Loans/Total Equity	IMPTE	Bankscope
Liquid assets / Total assets	LIQU	Bankscope
Loan loss provisions/Gross loans	100*LLP	Bankscope
Loan loss reserves/Gross loans	LLR	Bankscope
Total_long_term_funding /Total_liabilities	LTF	Bankscope
Non-performing Loans/Gross Loans	NPL	Bankscope
Non-performing Loans/Total Equity	NPLTE	Bankscope
Net_interest_margin	NIM	Bankscope
Operating profits / Total assets(-1)	OP	Bankscope
(Operating profits +Loan Loss Provisions)/Total assets	OPBT	Bankscope, Bondware
Return on assets	ROAA	Bankscope
Return on equity	ROAE	Bankscope
Risk-weighted assets/Total assets	RWATA	Bankscope
Tier1 Regulatory capital ratio	TIER1	Bankscope
Uncollectable loans/Gross loans(-1).	100*UNC	Bankscope
Leverage (Total assets / Total equity)	Y_L1	Bankscope
Macro variables:		
Real annual GDP growth	GDP	World Bank
Composite leading indicator (end year)	CLIF	OECD
Stock market index (log) (year 2000=100)	LOGSMK	Yahoo Finance
Official interest rates	FED_FUND	Fed
Treasury bond long-term rate	LTTB	Fed
R3,three-month unsecured interbank rate	R3M	Fed
Three-month interbank RISK	RISK3	Fed

Table 3.2 Summary statistics. American commercial, cooperative and savings banks, 2001-2013. Open sample.

	All banks							
	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	N obs

100*DEP	715.345	86.585	2794026	0	17289.8	81.196	9369.752	103854
GL	4.545	4.431	14.146	0	1.436	0.89	5.547	103862
ΔGL	14.728	5	19200	-99.896	131.36	58.058	5925.354	103862
GLTA (%)	523.874	63.675	1554733	0.002	11250.04	71.225	6990.643	103862
IMPTE	1.008	0.031	5110.265	0	36.26	95.061	10738.67	103544
100*LIQU	135.533	7.473	940101.2	0	6233.097	101.384	12432.91	103861
100*LLP	0.415	0	60	-40	1.24	9.605	277.486	103862
LLR (%)	1.508	1.29	32.2	0	1.028	6.234	95.902	103840
Δ(LLR)	0.041	0	24.36	-30.09	0.587	1.183	221.027	103834
LOGTA	5.033	4.875	14.708	0.693	1.357	1.162	6.372	103862
Δ LOGTA	0.078	0.057	10.441	-11.08	1.301	-0.021	10.218	103862
100*LTF	3.68	0.571	99.145	-12.785	6.366	3.647	27.584	103806
NIM	4.081	4.01	70.58	-21.11	1.261	8.313	213.317	103862
NPL	1.681	0.61	84.27	0	3.069	5.047	50.896	103544
Δ (NPL)	0.136	0	78.83	-81.98	3.378	0.171	43.856	103408
NPLTE	1.008	0.031	5110.265	0	36.26	95.061	10738.67	103544
OP	0.994	1.1	78.2	-52.8	1.555	1.579	163.579	103860
OPBT	1.284	1.3	78.2	-52.8	1.45	5.735	229.294	103860
Δ (OPBT)	0.053	0	144.9	-45.2	1.735	12.32	851.393	103821
ROAA	0.78	0.89	28.95	-26.79	1.276	-1.408	59.971	103862
ROAE	7.493	8.46	199.58	-702.48	13.231	-6.093	150.407	103862
RWATA	0.677	0.685	3.151	0	0.14	0.047	7.49	97737
TIER1	16.697	13.9	695.2	-16.5	13.308	17.895	576.328	103741
100*UNC	7.77	0.019	-	-	286.569	89.581	9933.867	103833
Y_L1	10.283	10.091	418	1	4.9	23.918	1275.949	103862
CLIF	99.657	100.191	101.396	95.647	1.574	-1.162	3.718	103862
FED_FUND	1.93	1.346	5.05	0.125	1.781	0.583	1.921	103862
GDP	0.881	1.5	2.9	-3.6	1.637	-1.439	4.693	103862
LOGSMK	7.088	7.097	7.41	6.855	0.155	0.213	2.389	103862
LTTB	3.824	4.014	5.021	1.803	0.936	-0.667	2.384	103862
R3M	2.236	1.55	5.319	0.281	1.742	0.545	1.879	103862
R3M-RISK3	1.993	1.572	5.179	0.169	1.777	0.614	1.968	103862

Table 3.3 Spearman's rank correlations (American commercial, cooperative and savings banks**, 2001-2013,** open sample)

	100*DEP	GL	ΔGL	GLTA	IMPTE	100*LIQU	100*LLP	LLR (%)	Δ(LLR)	LOGTA	Δ LOGTA	100*LTF	NIM	NPL	Δ (NPL)	NPLTE	OP
100*DEP	1000	339	130	795	354	653	-137	-056	-032	-371	-421	-264	-010	164	023	354	-157
GL	339	1000	125	503	491	070	372	-041	042	597	001	231	-072	412	036	491	-046
ΔGL	130	125	1000	242	-166	-015	-024	-299	-286	-053	146	-015	093	-082	030	-166	-078
GLTA	795	503	242	1000	399	507	-058	-115	-026	-277	-372	-026	085	189	033	399	-130
IMPTE	354	491	-166	399	1000	232	229	254	112	141	-252	100	-032	734	136	1000	-147
100*LIQU	653	070	-015	507	232	1000	-193	059	-004	-481	-378	-259	043	069	021	232	-160
100*LLP	-137	372	-024	-058	229	-193	1000	113	094	500	198	183	-012	392	170	229	-218
LLR (%)	-056	-041	-299	-115	254	059	113	1000	215	037	-043	-014	091	197	-001	254	-000
Δ(LLR)	-032	042	-286	-026	112	-004	094	215	1000	072	-010	027	-005	069	075	112	-009

LOGTA	-371	597	-053	-277	141	-481	500	037	072	1000	405	335	-097	227	-006	141	118
Δ LOGTA	-421	001	146	-372	-252	-378	198	-043	-010	405	1000	128	012	-086	-053	-252	055
100*LTF	-264	231	-015	-026	100	-259	183	-014	027	335	128	1000	-076	081	-019	100	007
NIM	-010	-072	093	085	-032	043	-012	091	-005	-097	012	-076	1000	008	012	-032	158
NPL	164	412	-082	189	734	069	392	197	069	227	-086	081	008	1000	385	734	-304
Δ (NPL)	023	036	030	033	136	021	170	-001	075	-006	-053	-019	012	385	1000	136	-199
NPLTE	354	491	-166	399	1000	232	229	254	112	141	-252	100	-032	734	136	1000	-147
OP	-157	-046	-078	-130	-147	-160	-218	-000	-009	118	055	007	158	-304	-199	-147	1000
OPBT	-184	080	-081	-126	-059	-207	159	045	027	262	105	061	166	-147	-125	-059	880
Δ (OPBT)	-108	-010	075	-061	-095	-109	103	-022	019	089	221	011	001	-123	-189	-095	368
ROAA	-124	-079	-065	-117	-148	-131	-238	-004	-015	061	035	-010	158	-301	-192	-148	945
ROAE	-084	-027	-045	-101	-095	-164	-199	-034	-005	122	066	060	144	-296	-205	-095	873
RWATA	-066	236	132	206	126	-174	269	007	007	214	110	194	154	064	-004	126	065
TIER1	000	-283	-091	-110	-200	208	-296	037	-022	-322	-151	-283	-076	-090	010	-200	028
100*UNC	-205	214	-170	-190	164	-216	680	090	-111	406	134	131	-027	357	117	164	-127
Y_L1	133	159	041	053	180	-078	142	-062	014	174	065	185	002	052	-003	180	-096
CLIF	041	005	088	055	-112	-018	-050	-089	-159	-042	-032	-021	034	-038	-041	-112	-012
FED_FUND	052	-075	258	104	-249	-026	-119	-213	-099	-166	029	-038	069	-146	014	-249	026
GDP	049	-029	078	031	-118	000	-058	-037	-157	-060	-047	-026	073	-046	-038	-118	017
LOGSMK	011	064	019	009	046	014	013	-008	-161	058	-033	002	-023	036	-013	046	-021
LTTB	-062	-179	063	-031	-201	-054	-177	-081	-039	-133	025	048	045	-391	-146	-201	243
R3M	-069	-148	058	-026	-179	-064	-147	-080	-042	-104	024	066	028	-357	-143	-179	194
R3M-RISK3	-070	-151	058	-028	-182	-066	-159	-080	-043	-103	023	063	028	-364	-148	-182	201

	OPBT	Δ (OPBT)	ROAA	ROAE	RWATA	TIER1	UNC	Y_L1	CLIF	FED_FUND	GDP	LOGSMK	LTTB	R3M	R3M-RISK3
100*DEP	-184	-108	-124	-084	-066	000	-205	133	041	052	049	011	-062	-069	-070
GL	080	-010	-079	-027	236	-283	214	159	005	-075	-029	064	-179	-148	-151
ΔGL	-081	075	-065	-045	132	-091	-170	041	088	258	078	019	063	058	058
GLTA	-126	-061	-117	-101	206	-110	-190	053	055	104	031	009	-031	-026	-028
IMPTE	-059	-095	-148	-095	126	-200	164	180	-112	-249	-118	046	-201	-179	-182
100*LIQU	-207	-109	-131	-164	-174	208	-216	-078	-018	-026	000	014	-054	-064	-066
100*LLP	159	103	-238	-199	269	-296	680	142	-050	-119	-058	013	-177	-147	-159
LLR (%)	045	-022	-004	-034	007	037	090	-062	-089	-213	-037	-008	-081	-080	-080
Δ(LLR)	027	019	-015	-005	007	-022	-111	014	-159	-099	-157	-161	-039	-042	-043
LOGTA	262	089	061	122	214	-322	406	174	-042	-166	-060	058	-133	-104	-103
Δ LOGTA	105	221	035	066	110	-151	134	065	-032	029	-047	-033	025	024	023
100*LTF	061	011	-010	060	194	-283	131	185	-021	-038	-026	002	048	066	063
NIM	166	001	158	144	154	-076	-027	002	034	069	073	-023	045	028	028
NPL	-147	-123	-301	-296	064	-090	357	052	-038	-146	-046	036	-391	-357	-364
Δ (NPL)	-125	-189	-192	-205	-004	010	117	-003	-041	014	-038	-013	-146	-143	-148
NPLTE	-059	-095	-148	-095	126	-200	164	180	-112	-249	-118	046	-201	-179	-182
OP	880	368	945	873	065	028	-127	-096	-012	026	017	-021	243	194	201
OPBT	1000	450	822	764	175	-072	128	-058	-029	-010	-004	-018	179	140	141
Δ (OPBT)	450	1000	343	330	120	-011	033	-067	001	-006	001	-023	082	065	065
ROAA	822	343	1000	924	046	042	-152	-091	-004	022	019	-010	210	170	177

ROAE	764	330	924	1000	092	-180	-138	201	-014	020	013	-014	238	191	198
RWATA	175	120	046	092	1000	-638	113	122	026	004	-000	028	099	144	143
TIER1	-072	-011	042	-180	-638	1000	-149	-701	024	015	019	007	-121	-129	-127
100*UNC	128	033	-152	-138	113	-149	1000	075	-021	-117	-039	036	-197	-167	-173
Y_L1	-058	-067	-091	201	122	-701	075	1000	-018	002	004	-022	072	050	053
CLIF	-029	001	-004	-014	026	024	-021	-018	1000	303	696	318	020	088	097
FED_FUND	-010	-006	022	020	004	015	-117	002	303	1000	006	220	464	470	469
GDP	-004	001	019	013	-000	019	-039	004	696	006	1000	014	-076	-074	-058
LOGSMK	-018	-023	-010	-014	028	007	036	-022	318	220	014	1000	-026	078	080
LTTB	179	082	210	238	099	-121	-197	072	020	464	-076	-026	1000	917	918
R3M	140	065	170	191	144	-129	-167	050	088	470	-074	078	917	1000	990
R3M-RISK3	141	065	177	198	143	-127	-173	053	097	469	-058	080	918	990	1000

Correlations are multiplied by 1000.

Appendix to Section 4

Table 4.1 Estimation of the determinants of loan loss reserves/gross loans: comparison of regression methods.

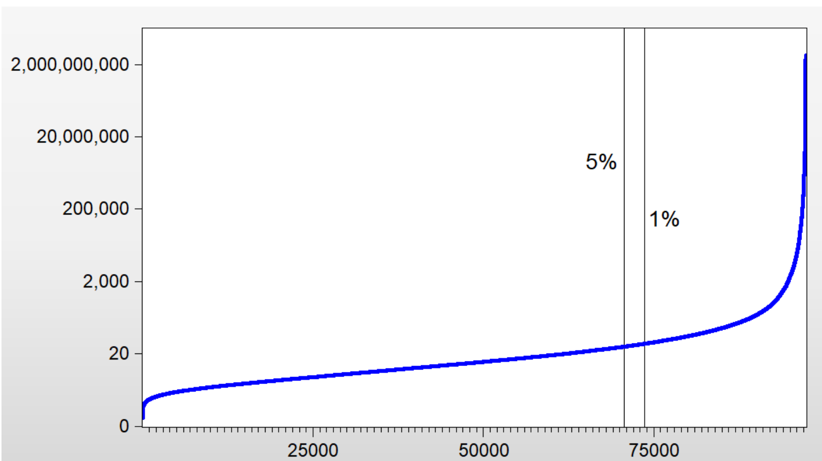
Years: 2001-2013; */**/*** indicate significance at 10/5/1% respectively. *N.B.: a higher value for the dependent variable corresponds to a lower level of confidence. Hence (apart from the lagged dependent variable), a negative coefficient corresponds to an increase in confidence.*

Original equations		Eq (1) Table 2			
Estimator	QREG	OLS	Robust LS	1-99% winsorized OLS	LS cleared of outliers
Type of sample	open	open	open	open	open
Regressors / Eqs	(1)	(2)	(3)	(4)	(5)
const	2.35245***	6.38949***	2.43334***	5.13582***	1.94195***
LLR(t-1)	-0.08364***	-0.13823***	-0.09469***	-0.09393***	-0.08669***
ΔLLR(t-1)	0.01575**	0.01234***	0.00851***	0.05100***	0.01227***
100* UNC	-0.00001***	-0.00000	-0.00001***	-0.00116***	-0.00001***
Δ GL	-0.03025***	-0.03020***	-0.11905***	-0.05349***	-0.13826***
Δ (NPL)	0.00242***	0.00706***	0.00268***	0.01043***	0.00238***
NPL(t-1)	-0.00013	0.00136*	-0.00055***	0.00243***	-0.00054**
LOG(TA(t-1))	0.00495***	0.02067***	0.00404***	0.02030***	0.00290***
ΔLOG(TA)	0.00360***	0.00943***	0.00410***	0.01155***	0.00360***
LOG(GLTA (t-1))	-0.00316***	0.00170	-0.00299***	0.00153	-0.00316***
IMP	-0.00000	0.00014***	-0.00017***	0.00000	-0.00007***
TIER1	-0.00032***	0.00150***	-0.00034***	0.00033	-0.00045***
OP(t-1)	-0.01398***	-0.03681***	-0.01336***	-0.02183***	-0.01122***
PBT	0.01299***	0.03808***	0.00724***	0.02562***	0.00610***
Δ(PBT)	-0.00909***	-0.03743***	-0.00381***	-0.01503***	-0.00247***
GDP	-0.03584***	-0.07513***	-0.02745***	-0.05641***	-0.02134***
CLIF	-0.00690***	-0.02762***	-0.00856***	-0.02261***	-0.00636***
LOG(SMK(t-1))	-0.21686***	-0.48975***	-0.20157***	-0.39323***	-0.16482***
ΔLOG(SMK)	0.06925***	0.29153***	0.04394***	0.20892***	0.01348*
Fed_fund	-0.00257***	0.00115	-0.00114***	0.00238***	-0.00150***
No. observations:	103215	103215	103215	80263	84880
Residual kurtosis	218.13	206.59	220.47	9.35	2.85

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 I Standard Errors & Covariance. 1-99% winsorized OLS = OLS applied to subsamples containing only data between the 1st and 99th percentile of every variables; LS cleared of outlier residuals = regression contains only observations whose residuals are not classified as outliers

A problem in the estimations was the exceptionally high residual Kurtosis (fat tails). This might be a consequence of non-normal residual distribution or the presence of outliers. The application of an MMM chi-squared test to all the variables in the previous table suggests that the number of outliers is particularly high (Figure 4.1), so this seems more likely to be a case of fat tail distribution than of Kurtosis due to a few outliers.

Figure 4.1 – MMM chi-squared test for outliers applied to the variables of Table 4.1



In order to check whether our preference for the QREG estimator was well motivated, we compared the goodness of fit of the following five estimators: OLS, robust LS, QREG, winsorized 1-99% OLS, and OLS of the regression cleared of outlier residuals. We employed a Montecarlo simulation, with the starting point Eq. 1 above. "Winsorized 1-99% OLS" are obtained by applying OLS to a subsample containing only data between the 1st and 99th percentile of every variable. "LS cleared of outlier residuals" are OLS applied to a regression containing observations whose residuals are not classified as outliers, identified by the so-called interquartile range method (IQR).[13] The equation was first estimated by OLS and the correspondent outliers were found. After dropping all observations corresponding to the most extreme outliers, OLS were estimated again, and the new correspondent outliers identified. The procedure is repeated until no outlier emerges.
First, we took as "true" parameters β_i* of our simulation the average of the parameters β_{ih} obtained by the five estimators, and employed these β_i*s to compute both ΔLLR^*, the corresponding estimations of the dependent variable ΔLLR, and the residuals $u^*=\Delta LLR-\Delta LLR^*$. The kurtosis of u^* was 213.6, where the value consistent with normal distributions is 3.

[13] If IQR is the interquartile range of residuals, the lower and upper bounds for outliers are defined respectively as: =0.25 quantile - 1.5*IQR and =0.75 quantile + 1.5*IQR. Residuals outside these bounds are considered outliers.

Second, on the basis of those values, we started our simulation by adding to *ΔLLR** the residuals *u'* obtained by bootstrapping *u**, in order to get our simulated dependent variable *ΔLLR'=ΔLLR*+u'*. We then regressed *ΔLLR'* on our 20 explanatory variables with the four different methods. This procedure was repeated 10,000 times.
The goodness of fit of the parameters was related to the deviation between the "true" parameters β_i^* and their 10,000 simulations $\beta_i'h$ corresponding to each of the four methods. The statistics taken as measure of dispersion are: MAD (median absolute deviation), SE, interquartile range, 2.5%-97.5% range, and 0.5%-99.5% range.
Table 4.2 reports the main results of the simulations. In the left side of the table, the goodness of fit is measured by the ranking of the dispersion between β_i^* and the 10,000 $\beta_i'_h$: rank 1 corresponds to the smallest dispersion, i.e. the greatest precision, and rank 4 to the highest dispersion. The numbers reported here for any estimator are the average rank of the 20 parameters. The right-hand side of Table 4.2 is similar, but it relates to the dispersions of $(\beta_i^* - \beta_i'_h)$ of every estimator and the average dispersion $\Sigma(\beta_i^* - \beta_i'_h)/5$. Of course, the lower the value, the better the fit. The data in Table 4.2 report for any estimator its corresponding 20 parameter means.

Table 4.2 Classification of estimator goodness. 10.000 simulations of equations in Table 4.1 (bootstrap method).

	Ranking						Values / average values (%)					
	OLS	Robust LS	QREG	1-99% winsored LS (a)	1-99% winsored LS (b)	LS cleared of outliers	OLS	Robust LS	QREG	1-99% winsored LS (a)	1-99% winsored LS (b)	LS cleared of outliers
MAD	5.05	1.60	1.40	4.35	5.60	3.00	128.95	48.65	48.34	141.26	180.81	52.00
SE	5.10	1.55	1.45	4.25	5.65	3.00	130.75	48.61	48.46	140.47	179.74	51.97
25%-75%	5.05	1.65	1.35	4.35	5.60	3.00	128.97	48.64	48.34	141.28	180.76	52.02

(a): for every variable, values outside 1-99% interval are substituted by their correspondent 1 and 99% quantiles (b) for every variable, values outside 1-99% interval are dropped.

It is apparent that the most efficient estimator is QREG (quantile regression), closely followed by Robust LS and "cleared of outliers" LS, while OLS and winsorized LS are far worse. Hence, our decision to use the QREG estimation method seems to be well grounded.

Appendix to Section 5

Table 5.1. Relevance of confidence and incentives in determining risk-taking using median absolute variable (MAV) (Confidence: Shanken's procedure, 3-year rolling)

Relevance of confidence and incentives on change in TA					
Based on:	Δlog (TA) (t+1)	All years	Before crisis	During crisis	After crisis
MAV	Confidence (t)	0.00172	0.00309	-0.00104	-0.00003
MAV	Rank(OP\$) (t) - Av[Rank(OP\$)] (t)	-0.04430	-0.01440	-0.04966	-0.14214
Relevance of confidence and incentives on change in RWATA					
Based on:	Δ RWA/TA (t+1)	All years	Before crisis	During crisis	After crisis
MAV	Confidence (t+1)	0.00130	0.00207	0.00009	0.00060
MAV	Rank(OP\$) (t) - Av[Rank(OP\$)] (t)	0.00650	0.00185	0.00563	0.01398
Relevance of confidence and incentives on changes in loans/total assets					
Based on:	Δln(GL/TA) (t+1)	All years	Before crisis	During crisis	After crisis

MAV	Confidence (t)	0.00881	0.00331	0.00546	0.01911
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.06415	0.03157	0.05707	0.14120

Relevance of confidence and incentives on change in leverage

Based on:	Δln(Y_L1) (t+1)	All years	Before crisis	During crisis	After crisis
MAV	Confidence (t)	0.00250	0.00056	0.00261	0.00755
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00437	0.00343	0.00887	-0.00044

Table 5.2. Relevance of confidence and incentives on loan performance and probability of default (Confidence: Shanken's procedure, 3-year rolling).

Effects of confidence and incentives on NPL

Based on:	Δ NPL (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	-0.03098	-0.01699	(-0.00851)	(-0.00368)
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.10455	0.06121	0.10716	0.09487
MAV	Confidence (t)	-0.00760	-0.00389	-0.00194	-0.00112
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.08963	0.05102	0.09328	0.08124

Effects of confidence and incentives on uncollectable loans

Based on:	100*UNC (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	-0.04129	-0.02467	-0.04283	-0.04434
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.02916	0.01940	0.04584	0.04839
MAV	Confidence (t)	-0.01012	-0.00565	-0.00977	-0.01343
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.02500	0.01617	0.03991	0.04144

Effects of confidence and incentives on Z-score

Based on:	Δ Z-Score (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	(-0.01100)	-0.34455	0.91444	(-0.07701)
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.12603	-0.11609	-0.37572	-0.09034
MAV	Confidence (t)	(-0.00270)	-0.07889	0.20868	(-0.02332)
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.10804	(-0.09677)	-0.32708	-0.07736

There are reported in parenthesis the values when the impact of the variable is not significant.

Table 5.3 The impact of confidence and incentives on portfolio size and riskiness (Confidence: Shanken's procedure, 5-years rolling)

Δln(TA) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.08466***	0.08300***	0.09241***	-0.01166
Δln(TA) (t)	-0.41194***	-0.38572***	-0.42725***	-0.01038
Confidence5 (t)	-0.00494	0.01466	-0.00778	-0.39944***
E[ΔLLR] (t)	-0.03087***	-0.01748***	-0.00485	-0.01272
Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.02116***	-0.00726***	-0.01723***	-0.02766***
Adj Pseudo R2	0.08229	0.05511	0.07712	0.10126
Obs.	59,450	15,888	15,411	28,151

Dep. Var.: Δ RWATA t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.29118***	0.15975***	0.35518***	0.39419***
RWATA (t)	-0.41996***	-0.21135***	-0.51824***	-0.59424***
Confidence5 (t+1)	0.00582***	0.01658***	0.00046	0.00339*
E[ΔLLR] (t+1)	-0.00286***	-0.00703***	-0.00106	0.00495***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00281***	0.00078***	0.00232***	0.00481***
Adj Pseudo R2	0.08472	0.05027	0.10809	0.12149
Obs.	63,979	21,857	14,007	28,115

Table 5.4 The effects of confidence and incentives on lending, leverage and deposits and short term funding (Confidence: Shanken's procedure, 5-year rolling)

Δln(GL/TA) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	-0.11888***	-0.07626***	-0.10284***	-0.12450***
Δln(GL/TA) (t)	-0.38378***	-0.31689***	-0.37706***	-0.39030***
Confidence5 (t)	0.06894***	0.01730	0.08153***	0.09236***
E[ΔLLR] (t)	-0.03018***	-0.03307***	-0.04738***	-0.01769***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.02734***	0.01236***	0.01967***	0.04846***
Adj Pseudo R2	0.09267***	0.07034	0.08279	0.10972
Obs.	59,450	15,888	15,411	28,151

Δln(Y_L1) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	1.25583***	0.61825***	1.25666***	1.72126***
ln(Y_L1) (t)	-0.54036***	-0.26794***	-0.53591***	-0.74230***
Confidence5 (t)	0.00209	0.01069*	0.00599	0.00156
E[ΔLLR] (t)	-0.01029***	-0.01523***	-0.02020***	-0.00333
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00535***	0.00246***	0.00278***	0.00621***
Adj Pseudo R2	0.11841	0.05589***	0.12599	0.17543
Obs.	39,385	15,886	15,388	28,111

Δ DEP (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.48331***	0.59866***	0.34235***	0.53656***
DEP (t)	-0.55504***	-0.69766***	-0.40006***	-0.60458***
Confidence5 (t)	0.02089***	0.00121	0.00886***	0.04253***
E[ΔLLR] (t)	-0.00495***	0.00185	-0.00358**	-0.01259***
Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00155***	0.00191***	0.00298***	0.00013
Adj Pseudo R2	0.16149	0.21294	0.16815	0.16279
Obs.	59,449	15,888	15,411	28,150

Table 5.5* The relevance of confidence and incentives in risk-taking, lending and leverage *(Confidence: *Shanken's procedure, 5-year rolling)*

Based on:	Δln(TA) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	-0.00328	0.00643	-0.00589	-0.26276
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.06983	-0.02261	-0.05662	-0.09426
MAV	Confidence (t)	-0.00094	0.00166	-0.00436	-0.07344
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	-0.06048	-0.01897	-0.04929	-0.08071

Based on:	Δ RWATA (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence5 (t+1)	0.00408	0.00740	0.00039	0.00211
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00916	0.00239	0.00755	0.01639
MAV	Confidence (t+1)	0.00110	0.00213	0.00020	0.00056
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.00788	0.00198	0.00653	0.01404

Based on:	Δln(GL/TA) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.04574	0.00758	0.06174	0.06076
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.09022	0.03850	0.06464	0.16514

MAV	Confidence (t)	0.01308	0.00196	0.04570	0.01698
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.07814	0.03229	0.05627	0.14141

Based on:	Δln(Y_L1) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.00139	0.00469	0.00454	0.00103
SE	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.01766	0.00766	0.00914	0.02116
MAV	Confidence (t)	0.00040	0.00121	0.00336	0.00029
MAV	Rank(OP$) (t) - Av[Rank(OP$)] (t)	0.01529	0.00643	0.00795	0.01812

Table 5.6. The impact of confidence and incentives on portfolio size and riskiness using ROAE as indicator of profitability (Confidence: Shanken's procedure, 3-year rolling)

Δln(TA) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.08684***	0.07803***	0.09736***	0.08042***
Δln(TA) (t)	-0.41338***	-0.34528***	-0.44365***	-0.43551***
Confidence (t)	0.00919**	0.02299***	-0.00703	0.00610
E[ΔLLR] (t)	-0.01810***	-0.01585***	0.00276	-0.02733***
ROAE (t) - Av[ROAE] (t)	0.00044***	0.00075***	-0.00101	-0.00065
Adj Pseudo R2	0.07048	0.04604	0.07339	0.08804
Obs.	76143	32,581	15,411	28,151

Dep. Var.: Δ RWATA (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.23841***	0.14154***	0.35391***	0.37938***
RWATA (t)	-0.34412***	-0.19040***	-0.51475***	-0.57410***
Confidence (t+1)	0.00942***	0.01958***	-0.00022	0.00419***
E[ΔLLR] (t+1)	-0.00359***	-0.00637***	-0.00183	0.00575***
ROAE (t) - Av[ROAE] (t)	0.00017***	0.00025***	-0.00004	0.00016**
Adj Pseudo R2	0.06907	0.04283	0.10659	0.11519
Obs.	79,591	37,469	14,007	20,115

Table 5.7. The effects of confidence and incentives on lending, leverage and deposits and short term funding using ROAE as indicator of profitability (Confidence: Shanken's procedure, 3-year rolling)

Δln(GL/TA) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	-0.11404***	-0.06974***	-0.11192***	-0.24375***
Δln(GL/TA) (t)	-0.39097***	-0.33371***	-0.39198***	-0.43182***
Confidence (t)	0.06659***	0.03754***	0.05457***	0.09842***
E[ΔLLR] (t)	-0.04000***	-0.03619***	-0.06428***	-0.00304
ROAE (t) - Av[ROAE] (t)	-0.00064***	-0.00112***	-0.00151***	-0.00000
Adj Pseudo R2	0.08295	0.07223	0.07800	0.09705
Obs.	76,143	32,581	15,411	28,151

Δln(Y_L1) (t+1)	All years	Before crisis	During crisis	After crisis
Constant	1.06410***	0.58666***	1.24800***	1.70966***
ln(Y_L1) (t)	-0.45421***	-0.25052***	-0.52808***	-0.73708***
Confidence (t)	0.00416	0.01673***	-0.00330	0.00140
E[ΔLLR] (t)	-0.01311***	-0.01390***	-0.02454***	-0.00169
ROAE (t) - Av[ROAE] (t)	0.00199***	0.00281***	0.00080***	0.00141***
Adj Pseudo R2	0.09733	0.05335	0.12657	0.17383
Obs.	76,076	32,577	15,388	28,111

Δ DEP (t+1)	All years	Before crisis	During crisis	After crisis
Constant	0.47155***	0.57322***	0.33748***	0.53483***
DEP (t)	-0.54598***	-0.66317***	-0.40006***	-0.60458***
Confidence (t)	0.01890***	0.00569**	0.01804***	0.03948***
E[ΔLLR] (t)	-0.00313***	-0.00030	-0.00294**	-0.01454***
ROAE (t) - Av[ROAE] (t)	0.00025**	0.00023**	0.00056**	-0.00047*
Adj Pseudo R2	0.15988	0.18184	0.16815	0.16279
Obs.	76,142	32,581	15,411	28,150

Table 5.8. The relevance of confidence and incentives in risk-taking, lending and leverage using ROAE as indicator of profitability (Confidence: Shanken's procedure, 3-year rolling)

Based on:	Δln(TA) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.00497	0.01031	-0.00346	0.00395
SE	ROAE (t) - Av[ROAE] (t)	0.00591	0.01010	-0.01476	-0.00819
MAV	Confidence (t)	0.00122	0.00236	-0.00079	0.00120
MAV	ROAE (t) - Av[ROAE] (t)	0.00196	0.00330	-0.00451	-0.00279

Based on:	Dep. Var.: Δ RWATA (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t+1)	0.00551	0.00903	-0.00017	0.00261
SE	ROAE (t) - Av[ROAE] (t)	0.00232	0.00350	-0.00018	0.00202
MAV	Confidence (t+1)	0.00128	0.00208	-0.00005	0.00066
MAV	ROAE (t) - Av[ROAE] (t)	0.00076	0.00110	-0.00057	0.00069

Based on:	Δln(GL/TA) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.03603	0.01683	0.02684	0.06371
SE	ROAE (t) - Av[ROAE] (t)	-0.00860	-0.01508	-0.02207	0.00000
MAV	Confidence (t)	0.00884	0.00385	0.00613	0.01929
MAV	ROAE (t) - Av[ROAE] (t)	-0.00286	-0.00492	-0.00674	0.00000

Based on:	Δln(Y_L1) (t+1)	All years	Before crisis	During crisis	After crisis
SE	Confidence (t)	0.00225	0.00750	-0.00162	0.00091
SE	ROAE (t) - Av[ROAE] (t)	0.02674	0.03782	0.01169	0.01777
MAV	Confidence (t)	0.00055	0.00172	-0.00037	0.00027
MAV	ROAE (t) - Av[ROAE] (t)	0.00888	0.01235	0.00357	0.00606