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Managerial Beliefs and Banking Behavior

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Abstract
We use a large sample of US banks to construct a new indicator of managerial beliefs based on bank provisioning. This indicator does not only anticipate a future charge-off but also explains future loan growth and other variables. In particular, the indicator shows that an increase in managerial optimism (pessimism) leads to expanded (tight) lending, leverage, and a riskier (less risky) portfolio. Our findings confirm that widespread managerial optimism (pessimism) prevailed before (during) the 2007-2008 financial crisis and that changes in managerial beliefs played an important role in the lending and leverage cycles.

Keywords Managerial optimism and pessimism · Banking behavior · Bank's risk · 2007-2008 financial crisis/crash

JEL Classification G010 · G020 · G021

1 Introduction

Several authors have pointed out the relevance of managerial sentiments in shaping banking behavior. Keynes (1936), and more recently Akerlof and Shiller (2009), have stressed the role of "animal spirits" in managerial behavior; and Minsky (1982) has explained how during normal times success spurs confidence that can set the stage for a subsequent

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financial crisis. Along the same line, Bordalo et al. (2018) points out that good news causes excessive optimism and bad news causes excessive pessimism among bank managers; and Geanakoplos (2009) explains how an endogenous increase in optimism or pessimism generates a leverage cycle. Danielsson et al. (2011) and Thakor (2015) provide models in which over a long period of sustained profitability, banks invest in increasingly riskier assets since all agents become more tolerant of risk-taking. This strand of literature relates excessive risk-taking in the upswing of a business cycle to the spread of optimism, and a credit crunch to the prevailing pessimism that occurs during a crisis.

Despite theoretical models and historical evidence (e.g., Kindleberger 2005; Reinhart and Rogoff 2009) that have pointed out the role of confidence in banking, the literature offers surprisingly little evidence on the effect of either managerial optimism or pessimism on the behavior of banks. One reason is the difficulty in detecting managerial beliefs. Bank managers may differ in their expectations because they hold private information about the nature of their customers and loans. In addition, the over- or undervaluation of future loan losses may be due to the subjective feeling of the bank managers, and determining whether expectations are due to private information or managerial beliefs is difficult. Therefore, bank managers may react in different ways to the same news, and consequently they may set aside lower or higher reserves for the same amount of loans (Plosser and Santos 2018).

The first goal of our paper is to provide an indicator of managerial beliefs (i.e., managerial optimism and pessimism). We measure managerial beliefs about the future performance of the bank with the difference between the actual and estimated values of the loan loss reserves.

Banks set aside loan loss reserves to prepare for future loan losses. In this paper, we divide the total allowances for loan losses of each bank into two components. The first (the estimated value of loan loss reserves) is the amount explained by public information, that is, balance-sheet items, macroeconomic data (includes some public outlooks and macroeconomic uncertainty), and indicators obtained by combining some balance-sheet data that represent bank and managerial characteristics (ability and risk tolerance). This component is obtained with a pool regression of the allowances on those variables. If bank managers hold better or worse expectations about future loan losses than those indicated by current news and balance-sheet conditions, then the actual reserves will differ from the estimated loan loss reserves. Further, the residuals of the estimated loan loss reserves – the second component of allowances – are of a particular relevance to future loan losses since they reflect either managerial optimism or pessimism. The reasoning behind the connection between residuals and future charge-offs is that optimism and pessimism are mainly grounded in the bank's private information about the riskiness of its customers and projects, and their future economic situations.

Even if residuals are connected to future loan losses, the latter are far from perfectly consistent with the amount of reserves. Therefore, we posit that if optimism and pessimism are more reflective of the subjective feelings of the bank managers, then their forecasts of future loan losses will be characterized by errors; that is, the realized charge-offs at t+h will differ from the expected charge-offs relative to t+h. This difference means that bank managers often find themselves too optimistic or too pessimistic ex post in forecasting their losses, and we posit that these errors in evaluating future losses are persistent over time. On the other hand, forecasting errors may also be due to unexpected events, but they are less likely to be systematic.

Indeed, we show that managerial beliefs are significant determinants of future charge-offs, and they change during the business cycle. On average, optimism in banking prevailed before 2007. The 2007-2008 financial crisis turned managerial optimism into pessimism. However, as soon as the economy moved away from the crisis, a new wave of optimism began. Moreover, during the 2007-2008 financial crisis the forecasting errors of future loan losses spiked that indicated the financial crisis came as a surprise to bank managers. Our proxy for managerial beliefs is highly correlated to the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices that has estimates on the managerial expectations about the future performance of loans. In addition, we argue that not only does the unexplained component of loan loss reserves have a significant impact on future loan losses of the bank but is particularly relevant in determining the future paths of other important variables (such as future loans and leverage) that are sensitive to bank managers' optimism or pessimism.

Ho et al. (2016) show that the persistence of overconfidence (banks with overconfident CEOs before the Russian crisis of 1998 had significantly overconfident CEOs in 2006), and Fahlenbrach et al. (2012) find that a culture of risk is persistent (a bank that performed poorly in 1998 also performed poorly in the 2007-2008 crisis). By contrast, we provide evidence that the persistence of optimism is very low, and the bank's optimism before 2007 does not have any explanatory power on the resurrection of optimism after 2011.

Our results support Keynes (1936) and Akerlof and Shiller's (2009) arguments about the instability of animal spirits. In addition, we find that managerial beliefs play an important role in lending, leverage, and risk-taking. Managerial optimism (pessimism) leads to increased (decreased) lending and leverage as well as higher (lower) risk-taking. We provide evidence of increased optimism in lending, leverage, and risk-taking before the 2007-2008 financial crisis but pessimism in these activities during the crisis. Our findings support the view that widespread changes in managerial beliefs are more relevant than the behavioral biases of a relatively small number of CEOs in determining the lending and leverage cycles.

The rest of our paper is organized as follows: Section 2 has a survey of the recent literature on the determinants of discretionary provisioning. Section 3 has descriptions of the data and the method used in the econometric analysis. Section 4 presents our indicator of managerial optimism or pessimism, and in Section 5 we study the relationship between managerial beliefs and the forecasting errors in future charge-offs. Section 6 provides some robustness checks and a comparison of our indicator of managerial beliefs with a Fed survey addressing similar issues. Section 7 gives the results of several exercises that estimate the effects of managerial beliefs on bank lending and risk-taking that uses the method of local projections. Section 8 concludes the paper.

2 Review of the Literature

The starting point of the paper is that despite the regulatory requirements, bank managers have discretionary power to determine the allowances for loan losses. During the sample period, regulators required US banks to provision for loan losses under the incurred loss method. No. 5 and No. 114 of the Statement of Financial Accounting Standards (SFAS) require firms to provision for an estimated credit loss from a loss contingency when an asset becomes impaired or a liability is incurred by the date of the financial statements and when they can reasonably estimate the amount of the loss. In 2001, the SEC issued new requirements for the provisioning process in which banks should estimate loan losses for groups of loans through the application of loss rates to the aggregate loan balances of each group. Such loss rates reflect the bank's historical loan loss experience for each group of loans, and the bank can adjust the loss for relevant environmental factors over a specific period. However, the imprecise wording in the FASB standards and interpretations that the estimated loss is "probable" and "can be reasonably estimated" induces discretion in accounting for loan loss provisions. In addition, even after the issuance of the SEC Staff Accounting Bulletin No. 102 (2001) there are factors that magnify the discretion inherent in the provisioning process. The first factor is how banks decide to group and assess loans for collectability based on their type, past due status, and degree of risk. Second, it is how bank managers establish the appropriate time frames over which to evaluate the loss experience. Finally, there are qualitative factors (e.g. industry, geographical, economic, and political factors) that bank managers use to assess loss rates (see SAB, No. 102). Indeed, Collins, et al. (1995), Liu and Ryan (2006), Kanagaretnam et al. (2003, 2004), El Sood (2012), Hegde and Kozlowski (2015), among others, have shown the use of loan loss provisions for income smoothing or for tax reasons; and BIS (2015), Wall and Koch (2000), Ahmed et al. (1999), have pointed to the regulatory capital incentive to manage provisions. In this paper, we propose another reason for discretional provisioning related to managerial beliefs.

In principle, bank managers should set up loan loss reserves equal to the forecast of future charge-offs because if they provision too much, they forgo profitable lending opportunities; and if they provision too little, they risk having to cut back dividend distributions or having to bolster capital to cover the loan losses. However, a great deal of evidence (Balboa et al. 2013, Laeven and Majnoni 2003; Fonseca and Gonzales, 2008; Black and Gallemore 2013) exists that bank managers also use loan loss reserves for income smoothing; that is, they may also increase reserves when the expected loan losses are low, or they may delay recognition of future loan losses. Therefore, loan loss reserves may have objectives other than just covering the expected loan losses (Ozili and Outa 2017; Beatty and Liao 2014; Wall and Koch 2000).

Even though the principles that underlie US banks' loan loss accounting emphasize the importance of maintaining "prudent" reserves that are sufficient to offset expected losses, the lack of definitive standards on what "prudent" means leaves managers with substantial discretion in determining provisioning. In addition, bank managers possess private information regarding the true health of their loan portfolio (Wahlen 1994; Collins et al. 1995; Kanagaretnam et al. 2004), and they may hide that information at any time if it is in their own interests to do so (Plosser and Santos 2018). Indeed, there is a great deal of evidence that provisioning is largely discretionary (Hasan and Wall 2004; El Sood 2012; Huizinga and Lauven 2012).

The baseline model that studies often use to investigate bank provisioning (e.g., Ahmed et al. 1999; Hasan and Wall 2004; Laeven and Majnoni 2003; Wahlen 1994) distinguishes among nondiscretionary and discretionary determinants, relevant bank-specific factors, institutional factors, and country or regional factors.

As an example, Hasan and Wall (2004) distinguish between the nondiscretionary (i.e., nonperforming loans and total loans) and the discretionary determinants (earnings) of loan loss reserves for a large number of countries. They find evidence that the discretionary determinants are generally significant: the coefficients for the earnings ratio have a positive sign with lower values for US banks than for non-US banks. El Sood (2012) uses a sample of 878 US bank holding companies over the period from 2001–2009 and finds strong evidence of the use of provisioning for income smoothing. Banks smooth income when they (1) hit the regulatory minimum target, (2) are in non-recessionary periods, and (3) are more profitable. Further, Balboa et al. (2013) examine 15,268 US banks during the period from 1996–2011 and find that US banks use loan loss provisions to smooth reported earnings when they are positive and substantial. On the other hand, Huizinga and Lauven (2012) find that weak US banks manipulated their loan loss provisioning during the 2007-2008 financial crisis to manage their regulatory capital.

However, the bulk of the literature does not consider the determinants of allowances for loan losses related to managerial traits. Indeed, bank managers may differ in ability, risk aversion, and degree of confidence; all of which affects the provisioning and risk-taking in banking.

There is evidence that the managerial propensity for risk played an important role in the excessive risk-taking that instigated the 2008-2009 financial crisis (International Monetary Fund 2014; Fahlenbrach et al. 2012; Ho et al. 2016; Beltratti and Stulz 2012; Andreou et al. 2015). In addition, Demerjian et al. (2012) provide evidence that more capable bank managers are more likely to intentionally smooth earnings. Further, Black and Gallemore (2013) and Ahmed and Duellman (2012) find that overconfident bank managers recognize lower loan loss provisions and delay recognition of expected loan losses. Indeed, managerial traits are likely to also affect the expectations about future loan losses. High-ability managers may possess superior skills in estimating accruals (Demerjian et al. 2012) and in forecasting earnings (Baik et al. 2011). In addition, Hribar and Yang (2016) provide evidence that overly optimistic managers overestimate future outcomes and underestimate uncertainty when predicting uncertain events (miscalibration). Therefore, managers who are overly optimistic or who overvalue their capabilities are more likely to make forecasting errors. However, forecasting errors may occur not only for reasons related to a manager's personality but also to their feelings about the future. In turn, the latter may change during the business cycle. The aim of this paper is to address these issues.

3 Data and Method

We use quarterly data on US banks from the Federal Deposit Insurance Corporation (FDIC).[1] The dataset contains more than 11,000 US depository institutions that the FDIC insured over the period from the first quarter of 2000 to the third quarter of 2019. These banks fall into the following categories: national banks, state-chartered banks, trust companies, savings banks, national or state-chartered commercial banks, and other financial institutions that operate under general banking codes or are specifically authorized by law to accept deposits. However, in our analysis we use only those banks which provide loans and set aside reserves to face future loan losses. The common feature of these banks is that they are subject to the same supervisory rules for operational safety and soundness.

After eliminating banks with missing data and outliers (see below), we have 8,890 banks and 471,734 observations. For the econometric analysis, we deleted banks with insufficient lags to perform the econometric analysis, and in the estimations that use fixed effects we only included banks with at least 12 quarters of observations.

Table 1 presents the summary statistics of the data, and Table 6 in the appendix has descriptions of the variables used in the study.

From now on, ln indicates the natural logarithm of the variable, and Δ indicates the absolute change in the value of the variable. Tables 7 and 8 in the appendix present respectively the correlation matrix and the persistency of the variables. We also used rank correlations in addition to the traditional Pearson r-correlations because of the high kurtosis value of all the balance-sheet data (see Table 1), but the results were similar. The persistence of the absolute values of the variables is quite high, while the persistence of the variation is low. In addition, there is seasonality in the data (the correlation is higher for the period of four lags). Hence, to reduce collinearity among the variables, we perform the estimations using the level of the regressors at t-1 and their variation in the other lags.

[1] Statistics on Depository Institutions, SDI. Available at: https://www7.fdic.gov/sdi/download_large_list_outside.asp.

Table 1 Summary statistics for the banks' balance-sheet variables; for the macroeconomic variables; and for the magnitudes of the banks' expected allowances, residuals, and forecast errors.

Panel A: Bank's balance-sheet variables used in the estimation of equations 1 and 2
Number of banks: 8,890. Observations: 471734. Period: 2000-2019.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
lnT_ALLOWANCES	7.17	7.06	16.88	1.10	1.42	0.74	5.07
lnT_ALLOWANCES-lnLOANS	-4.40	-4.39	-1.55	-6.76	0.43	-0.51	4.95
lnT_ASSETS	12.04	11.90	21.58	7.14	1.32	1.07	6.12
ln(RWA/T_ASSETS)	4.19	4.22	5.16	2.26	0.22	-1.03	4.93
lnTIER_1	2.32	2.28	4.50	0.40	0.27	0.90	4.91
CHARGE_OFFS%	0.14	0.05	1.11	-0.83	0.24	1.42	6.09
NONPERFORMING%	1.02	0.66	5.95	0.00	1.10	1.67	5.86
NET_INCOME%	0.87	0.77	3.43	-1.79	0.62	0.67	3.66
ROA%	0.99	0.96	11.06	-6.82	0.64	0.08	6.62
RANK_OP/1000	46.81	46.20	100.00	0.01	26.91	0.07	1.87
ΔALLOWANCES	0.02	0.01	2.78	-1.85	0.09	1.77	32.54
ΔlnLOANS	0.02	0.01	2.11	-1.60	0.06	2.52	42.32
ΔlnT_ASSETS	0.02	0.01	1.67	-0.91	0.05	3.18	43.90
Δln(RWA/T_ASSETS)	0.00	0.00	1.28	-1.21	0.05	-0.31	23.46
ΔlnTIER_1	0.00	0.00	1.99	-1.60	0.06	0.54	47.64
ΔNONPERFORMING%	-0.00	-0.00	1.99	-1.99	0.47	0.19	6.70
ΔROA%	0.01	0.01	10.79	-6.49	0.29	0.89	53.94
Δ (RANK_OP/1000)	-0.22	-0.16	99.63	-99.53	7.01	0.32	51.05

Panel B: Macroeconomic variables used in the estimation of the equations 1 and 2
Observations: 2600. Period: 2000-2019.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
GDP_GROWTH%	2.05	2.21	4.33	-3.92	1.53	-1.78	7.48
lnS&P_INDEX	7.94	7.78	9.04	7.18	0.50	0.67	2.39
FED_FUND%	1.23	1.20	5.26	-2.91	2.20	0.17	2.26
EXP_GDP-GROWTH%	2.90	2.87	4.17	1.64	0.56	0.01	2.60
ΔGDP_GROWTH%	-0.01	-0.07	3.23	-2.76	0.78	0.35	6.19
ΔlnS&P_INDEX	0.01	0.03	0.15	-0.36	0.08	-1.56	7.09
ΔFED_FUND%	-0.06	-0.00	0.73	-1.42	0.48	-1.10	4.18
ΔEXP_GDP-GROWTH%	-0.03	-0.02	0.92	-0.72	0.28	0.50	4.41

Panel C: Magnitude of the expected allowances, residuals, and forecast errors shown in Figures 2 and 3
u[…] is the component of the variable not explained by the estimation of equation 1 or 2.
E[…] is the component of the variable explained by the estimation of equation 1 or 2.

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
CHARGE_OFFS(t+1)%	0.110	0.045	1.138	-0.733	0.185	242424
CHARGE_OFFS(t+2)%	0.114	0.046	1.138	-0.851	0.194	245267
CHARGE_OFFS(t+3)%	0.117	0.045	1.222	-1.046	0.203	245048
CHARGE_OFFS(t+4)%	0.124	0.048	1.325	-1.046	0.213	244461
E[CHARGE_OFFS(t+1)]%	0.110	0.067	0.958	-0.630	0.151	242424
E[CHARGE_OFFS(t+2)]%	0.114	0.091	0.796	-0.443	0.114	245267
E[CHARGE_OFFS(t+3)]%	0.117	0.099	0.700	-0.406	0.096	245048

Table 1 (continued)

E[CHARGE_ OFFS(t+4)]%	0.124	0.106	0.736	-0.330	0.094	244461
u[CHARGE_OFFS(t+1)]%	0.000	-0.020	0.617	-0.595	0.107	242424
u[CHARGE_OFFS(t+2)]%	0.000	-0.027	0.992	-0.864	0.158	245267
u[CHARGE_OFFS(t+3)]%	0.000	-0.035	1.158	-1.138	0.179	245048
u[CHARGE_OFFS(t+4)]%	0.000	-0.040	1.173	-1.170	0.192	244461
u[ΔALLOWENCES]	0.0016	-0.0008	1.5192	-12.2560	0.0652	244300
E[ΔALLOWENCES]	-0.0041	-0.0026	0.5238	-11.9788	0.0496	244300

We estimated the optimal number of lags and leads of the variables. The most appropriate number of lags is eight, while the future values of charge-offs are significant up to 12 leads. Further, we estimated the loan loss reserves with an ordinary least squares, a quantile regression, and the GMM model.

We assume that the total allowances for the loan losses (T_ALLOWANCES$_i$) of each bank are the sum of the estimated values of loan loss reserves (E[ALLOWANCES$_i$]) and the residuals of the estimated loan loss reserves (u[ALLOWANCES$_i$]). Allowances for loan losses are estimated with a pool equation that uses an OLS. We use a GMM for the lagged dependent variable to avoid a biased coefficient only when we estimate fixed effects (see Nickell 1981). For every regression we drop all observations corresponding to the outlier residuals. We use Cook‘s distance "D(i)" for observation i (i=1, .., n) to detect them. As a cutoff for D(i), we use 15; while this is a very high level, the residual kurtosis remains particularly high even when outliers are eliminated.[2] Its advantage with respect to winsorizing is that it facilitates the finding of highly influential data for each variable, while winsorizing consigns outliers on the base of the same quantiles (e.g. 1%) for each variable. A comparison of Cook's distance and winsorizing while using equation 1 shows that Cook's distance generates more observations with a better shaped residual distribution.

We also add lagged dependent and independent variables to the regressors. Lagged variables may be important in determining the allowances for loan losses; because in determining their amount, banks may also account for the recent history of the reserves and of the explanatory variables. This is confirmed by the usual tests of the optimal number of lags, among them the Schwarz criterion, and the fact that many of the coefficients for the lagged variable are significant.

In addition, the residuals of the estimations of loan loss reserves that used different specifications and estimation methods are all strongly correlated; therefore, the choice between those various alternatives is not so crucial when we describe the behavior of managers with respect to the allowances for loan losses.

4 Estimating Optimism and Pessimism in Banking

Our aim is to understand the effect of either managerial optimism or pessimism on the risk-taking of banks. First, we provide a proxy for managerial beliefs. Optimism or pessimism is likely to affect the way bank managers react to current news when setting their loan

[2] The procedure of eliminating outliers is recursive: OLS estimation, drop worse outliers, new OLS estimation, drop worse outliers, etc. until no outliers remain. Our Eviews code is available on request. We also checked other measures, in particular RStudent(i), but the results were similar.

loss reserves. Optimistic (pessimistic) managers have better (worse) expectations about the future, and they set aside lower (higher) loan loss reserves than warranted by current news and bank and managerial characteristics. Hence, we represent managerial optimism or pessimism with the deviation in actual reserves from their estimated value based on the current news as well as bank and managerial characteristics.[3] Following the literature (Ozili and Outa 2017; Beatty and Liao 2014; Hasan and Wall 2004), we first assume that managers determine "normal" loan loss reserves according to the current news about the performance of the bank while considering the economy, bank characteristics, and institutional factors as well as their attitudes and abilities. CEOs are more likely to make decisions on loan loss allowances in small banks, and most of the processes surrounding loan loss accounting are likely to be made by CFOs in large banks. However, Chava and Purnanandam (2010) study the managerial risk-taking incentives for the CEOs and CFOs of the corporation, and they find common driving forces behind the managerial decision-making as well as similar effects on leverage, cash balances, and earnings-smoothing. On the other hand, Baker et al. (2019) examine the effect of the CEO's or CFO's power on both accruals (AEM) and real earnings management (REM), and they show that this power mitigates the effect of one another on the AEM and REM. Similar results are obtained by Florackis and Sainani (2021). In the same vein, we can infer that managerial behavior in banking may reflect the CEO's or CFO's managerial beliefs depending more on their relative knowledge and power.

Using this set of regressors, we estimate the amount of loan loss reserves with the following equation:

$$y_{it} = \alpha_i + \beta X_{it} + \gamma Z_t + \delta D_t + \epsilon_{it} \tag{1}$$

The y_{it} is bank i's allowances for loans at time t when expecting loan losses; X is the vector of the bank's performance indicators, and managerial and bank characteristics; Z is the vector of macroeconomic variables at the state level (X and Z also have lags of the regressors and of the dependent variable y_{it}); and D indicates a set of dummy variables. For equation 1, we use up to date information to establish the amount of allowances to set aside at time t for loan losses expected at time t + h for $1 \leq h \leq 4$. Supplementary Table A4 in the online appendix [4] has a summary of the regression results from the equation (1) estimations for h=1. Similar results hold for h>1.

If the above factors are the only determinants of loan loss reserves, the estimated reserves should be equal to the actual reserves, and no residual can have any explanatory power for future loan losses. By contrast, optimistic (pessimistic) bank managers are likely to set aside less (more) reserves for future loan losses than those warranted by the current news or by managerial and bank characteristics.

On the other hand, the residuals of equation 1 may be determined by private information about the riskiness of their loans to clients or managerial beliefs about future loan losses. However, disentangling optimism and pessimism is very difficult. We argue that if either managerial optimism or pessimism reflect only private information about the riskiness of the loans, and the riskiness is correctly estimated, our indicator of optimism or

[3] In contexts other than banks, Puri and Robinson (2007), Goel and Thakor (2008), and Campbell et al. (2011) measure optimism as the miscalibration of expectancy and find different effects for low, moderate, and high levels of CEO optimism.

[4] Available at:https://www.unical.it/portale/strutture/dipartimenti_240/disesf/servizi/silipo/ricerca/Online%20Appendix.pdf

pessimism should have a high predictive power for future loan losses. By contrast, if managerial expectations are grounded in the subjective feelings of bank managers about future loan losses, they are likely to be characterized by persistent forecast errors. Hence we claim that forecast errors are an ex post measure of the subjective feelings of bank managers. Indeed, we show that bank managers make significant forecasting errors when determining the amount of reserves for future loan losses, and these errors are persistent over time (see Section 5). However, managerial subjective beliefs are not the only determinants of the forecast errors. As an example, bank managers may differ in risk aversion and their ability to predict loan losses or to assess the riskiness of the loans (see Baik et al. 2011, Demerjian et al. 2013, Choi et al. 2014). In addition, small and large banks may differ in their tools and capacities to assess the riskiness of the loans. Indeed, we show that more capable and less risk-averse bank managers face lower loan losses, and larger banks face more loan losses in the future. On the other hand, forecasting errors on future loan losses are likely to be higher when there is greater information asymmetry between borrowers and lenders because banks more randomly select borrowers. However, residuals may reflect other managerial or bank characteristics as well as unobservable omitted variables that affect both the loan loss reserves and their determinants. Therefore, we estimate loan loss reserves with and without bank fixed effects and with and without dummy variables for each quarter. The degree of correlation among the residuals in the case of the Pearson correlations is 80%. In addition, the effect of the determinants of the loan loss reserves is similar in the two cases. These results indicate that the problem of omitted variables may not be relevant.

Next we estimate the predictive power of our indicator of managerial beliefs on future loan losses and forecast errors. Indeed, if idiosyncratic managerial optimism and pessimism are significant determinants of the expectations about the future, the residuals of the estimated loan loss reserves should have predictive power for future loan losses.

To test this hypothesis, we use the following model:

$$\begin{aligned}\mathrm{CHARGE\_OFFS}_{i,t+h} &= a_{0t} + a_{1t}u[ALLOWANCES]_{it} + a_{2t}E[ALLOWANCES]_{it} + a_{3t}T\_ALLOWANCES_{it} + a_{4t}VIX_{it} \\ &+ a_{5t}CHARGE\_OFFS_{it} + a_{6t}RANK\_OP_{it} + a_{7t}\left(\frac{RWA}{T\_ASSET}\right)_{it} + a_{8t}lnT\_ASSET_{it} + a_{9t}GDP\_GROWTH_{s,t} + \epsilon_{i,t+h}\end{aligned} \tag{2}$$

where $u[ALLOWANCES]$ are the residuals of equation 1, and $E[ALLOWANCES]$ are the estimated values of allowances using equation 1; h= quarters 1,2,3, and 4 that are the forecasting horizons. i refers to the bank and s to the state of the United States of America.

A summary of the results from the estimations of equation 2 are reported in Table 2.

The results reported in Table 2 indicate that the residuals of equation (1) have a highly significant effect on future loan losses for h=1,…,4, and similar results hold for a longer time horizon.[5]

As mentioned in footnote 4, a problem with equations of Table 2 is that a couple of regressors, as u[ΔALLOWANCES], are the output of another regression, and this might create a so-called problem of "error in variable", leading to bias OLS estimated parameters.

[5] However, splitting a variable (allowances for loan losses (T_ALLOWANCES in our case)) into its expected value and residuals and then adding them as explanatory variables in other regressions may create a bias due to "errors in variables." To mitigate this bias, we follow Shanken (1992) and use a rolling window to estimate equation 1. In addition, we use the method recommended in Inoue et al. (2017) to compute the optimal rolling window (see also Clark and McCracken 2009). Although the difference between the recursive and rolling estimations is low, four years is the optimal rolling window. However, in a rolling window not all macroeconomic variables can be used, since they are the same for all banks and their number may be excessive compared to the observations entering each window.

Table 2 The effect of managerial optimism or pessimism on future charge-offs**.** This table presents the results on the effect from changes in optimism or pessimism as well as of the estimated value of loan loss reserves on future charge-offs at h=1,…,4 quarters ahead. In addition, we control for managerial ability (RANK_OP/1000), risk tolerance (RWA/T_ASSET), and the size of the bank (LOG_T_ASSET) as well as *GDP_GROWTH* and VIX_M. The VIX_M is the average previous quarter value of the Chicago Board Options Exchange Volatility Index. The estimation method is an OLS applied to a pool of data with heteroskedastic- and autocorrelation-consistent (HAC) standard errors and covariance (Bartlett kernel, Newey-West fixed bandwidth). The regression does not contain outliers. Dummies 3, 6, and 9 are the first, second, and third quarter seasonality effects. The u[…] is the component of the loan loss reserves not explained by the estimation of equation 1, and E[…] is the component of the loan loss reserves explained by estimation of equation 1. The sample period runs from the second quarter of 2006 to the fourth quarter of 2018. Standard errors are in brackets. Coefficients and standard errors are multiplied by 100.

CHARGE_OFFS%	h=1	h=2	h=3	h=4
C	-6.795***	-5.949***	-7.326***	-3.280***
	(0.502)	(0.889)	(1.114)	(1.245)
Dummy3	5.425***	4.105***	4.862***	-5.386***
	(0.080)	(0.079)	(0.083)	(0.096)
Dummy6	6.602***	7.513***	-1.113***	-1.292***
	(0.076)	(0.096)	(0.085)	(0.086)
Dummy9	8.224***	-0.673***	0.506***	-0.745***
	(0.083)	(0.074)	(0.068)	(0.071)
$u[\Delta ALLOWANCES]$	15.217***	26.371***	28.459***	32.251***
	(0.358)	(0.532)	(0.588)	(0.634)
$E[\Delta ALLOWANCES]$	22.046***	33.858***	44.526***	39.218***
	(0.477)	(0.723)	(0.880)	(0.865)
$T\_ALLOWANCES)(-1)$	1.335***	1.971***	1.849***	1.521***
	(0.051)	(0.090)	(0.112)	(0.125)
VIX_M	0.105***	0.206***	0.269***	0.317***
	(0.003)	(0.005)	(0.006)	(0.007)
CHARGE_OFFS%	71.943***	49.405***	38.041***	35.137***
	(0.175)	(0.283)	(0.332)	(0.358)
$GDP\_GROWTH_{s,t}\%$	-0.132***	-0.269***	-0.310***	-0.344***
	(0.008)	(0.014)	(0.018)	(0.020)
RANK_OP/1000	-5.205***	-12.39***	-14.56***	-27.75***
	(1.526)	(2.700)	(3.392)	(3.853)
RWA/T_ASSET	0.027***	0.057***	0.084***	0.109***
	(0.002)	(0.003)	(0.004)	(0.005)
LOG_T_ASSET	0.576***	0.896***	1.015***	0.709***
	(0.032)	(0.057)	(0.071)	(0.079)
Adjusted R-squared	0.668	0.343	0.224	0.194
Durbin-Watson stat	1.958	1.156	0.881	0.769
Obs	242,424	245,267	245,048	24,4461
C(5)=c(6) Wald test	Pr = 0.000	Pr = 0.000	Pr = 0.000	Pr = 0.000

The ***,**, and * represent significance at the 1%, 5%, and 10% levels of probability respectively.

Actually, one of the OLS assumption is that E[ε|X]=0, for each regressor X and the residual ε: in other terms, the correlation between any independent variable and the equation residuals must be zero, otherwise coefficients are biased. Unfortunately, these correlations cannot be measured by employing OLS residuals, since, in OLS estimation, the measured correlation is always zero even if the true correlation is not. In the case of Table 2, the problem related to u[ΔALLOWANCES] involves also E[ΔALLOWANCES], since E[ΔALLOWANCES] ≡ ΔT_ALLOWANCES - u[ΔALLOWANCES]. A solution is to use the estimated residuals coming from an estimator method not suffering from this problem, e.g. GMM. We used as instruments for GMM estimator the rank u[ΔALLOWANCES] and ΔT_ALLOWANCES, which is a balance sheet item and not an estimated variable. The correlation between GMM residuals and the explanatory variable u[ΔALLOWANCES] was found to be very low (-0.016), and also the GMM estimation of the coefficients of u[ΔALLOWANCES] is similar to the correspondent OLS estimation (OLS = 15.06, GMM = 17.74 in case of one-quarter forecasts): the bias is therefore small and OLS results are acceptable. Hence on average u[ΔALLOWANCES] is an unbiased measure of correct managerial expectations.

More pessimistic (optimistic) bank managers have more (less) loan losses in the future that supports the view that managerial beliefs are to some extent grounded in the managers' private information about the nature of the loans and their customers. However, public information is more relevant than managerial beliefs in determining future loan losses. Further, more capable and more risk-averse bank managers face lower loan losses in the future. Moreover, managerial beliefs determine future loan losses even when we add the VIX, the Chicago Board Options Exchange's volatility index that is a measure of the stock market's expectation of volatility based on the S&P 500's index options, to the regressors.[6] Moreover, the correlations of the residuals from estimating equation 1 without using the VIX as a regressor, using the values of the VIX on the last day of the previous quarter (VIX_F) and with the average values of the previous quarter VIX (VIX_M) are close to one (see Supplementary Table A8 in the online appendix). Overall, the results reported in Table 2 indicate that the VIX improves the forecasting of future charge-offs but that the VIX only marginally changes the explanatory power of the residuals as well as that of the estimated loan loss reserves. Specifically, the values of the coefficients for *u*[Δ*ALLOWANCES*] decrease between 2% and 6% and those of E [Δ*ALLOWANCES*] between 10% and 12%, but the values of the coefficients for *T_ALLOWANCES* increase between 15% and 50% relative to the estimates of equation 2 without the VIX among the regressors (see Supplementary Table A15 in the online appendix).[7] In addition, by adding the VIX to the regressors in equation 2, the adjusted R-squared is very similar to those without this regressor (see Supplementary Tables A11,A12,A13 in the online appendix).

[6] The results in Table 2 are based on the average values of the VIX in the previous quarter (VIX_M). However, they are very similar when we use the values for the last day of the previous quarter (see Supplementary Tables A11-A14 in the online appendix). The daily VIX values are available at https://www.macrotrends.net/2603/vix-volatility-index-historical-chart.

[7] The results of the estimates of equation 1 with and without the VIX as the explanatory variable indicate that the adjusted R-squared is 0.508056 when we use the quarterly average values of the VIX and 0.508048 when we use the values for the last day of the quarter. The adjusted R-squared is 0.507850 without adding the VIX (see Supplementary Table A7 in the online appendix). We also regress the VIX on the residuals obtained by estimating equation 1 without adding the VIX, and the adjusted R-squared is 0.000031 (see Supplementary Tables A9-A10 in the online appendix).

Finally, we recall that among the regressors in equation 1 there is the consensus forecast provided by the FRED. So, we can conclude that our indicator of managerial beliefs does not reflect either consensus forecasts or macroeconomic uncertainty.

With the following figure, we show the impulse responses of charge-offs in the next h=1,2, and 4 quarters on managerial beliefs, and the average effects of the latter through the entire period. The confidence bands are 2σ and 3σ (Fig. 1).

5 Managerial Beliefs and Forecasting Errors

In this section, we address whether bank managers' forecasts of future loan losses are characterized by errors, and if the latter persist over time. First, we summarize the evolution of managerial believes through time.

Figure 2 shows the mean and median values of the residuals from equation 1 as well as the 5% and 25% highest and lowest values over time.

The median values of the residuals indicate that before the 2007-2008 financial crisis, bank managers were on average optimistic, and they became pessimistic during the 2007-2008 financial crash. Starting in 2012, optimism among American banks again prevailed.

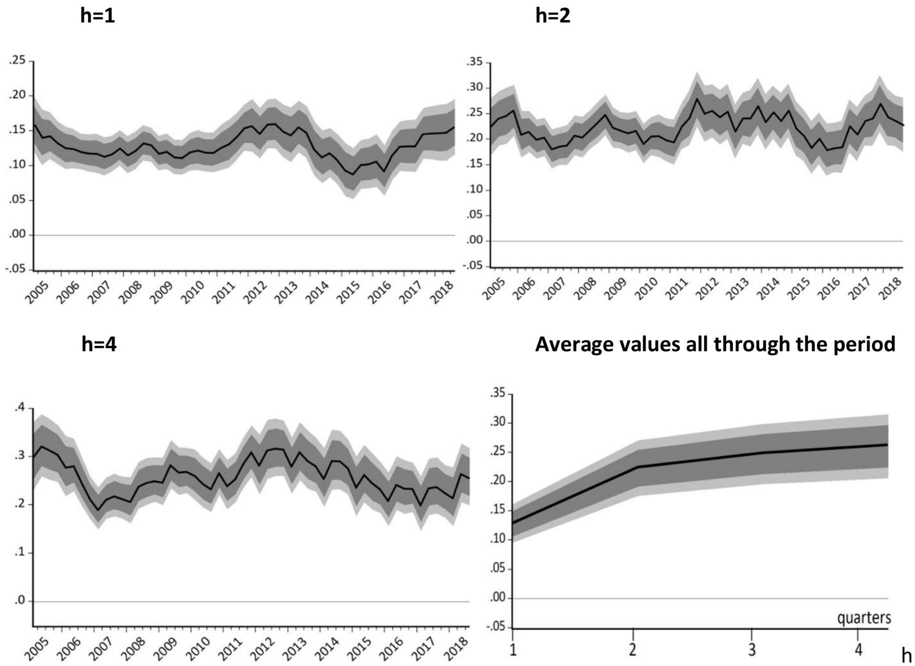

Fig. 1 Impulse responses of charge-offs on u[ALLOWANCES]. Panels h=1, 2, and 4 indicate the effects of managerial beliefs on the average value and the variance of loan losses 1, 2 and 4 quarters ahead. The last panel displays the variance in loan losses related to the forecasting horizon. The confidence bands of the figures are 2σ and 3σ.

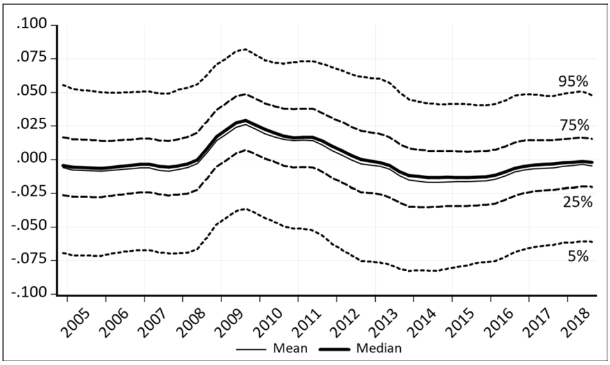

Fig. 2 Managerial optimism and pessimism (*u[ALLOWANCES]*) over time. The figure displays the median and mean values of the ex-ante estimated residuals as well as the 5%, 25%, 75% and 95% quintiles. The residuals are obtained by a four-quarter moving rolling estimations of Equation 1.

We measure forecasting errors by the difference between future charge-offs at t+h ($CHARGE\_OFFS_{i,t+h}$) and the expected value of future loan losses estimated using equation 2 ($E[CHARGE\_OFFS_{i,t+h}]$). Theoretically, we expect that all things being equal, forecasting errors on future loan losses are more likely to occur if expectations better reflect the subjective feelings of the bank managers, which induces them to systematically undervalue or overvalue future loan losses, than private information. It follows that when the residuals of the estimated value of the loan loss reserves of the bank wrongly reflect subjective managerial optimism or pessimism that forecast errors on future loan losses will be persistent and highly correlated over time. On the other hand, if forecasting errors are due to unexpected events, they are likely to be uncorrelated between subsequent periods.[8]

Figure 3 shows the forecasting errors made by the banks at time t related to the next t+h quarter, h=1,2,3,4

Overall, the average value of the forecasting errors is around zero before 2007, and it increases during the financial crisis of 2007-2008. That increase indicates that the crisis came as a surprise to many bank managers. In addition, the crisis induced more bank managers to become pessimistic about the future (the median value increased). However, during the crisis forecasting errors increased for both optimistic and pessimistic managers, and the distribution of the residuals became skewed toward pessimism. The results in Figure 3 (see the last panel) also indicate that forecasting errors are higher the longer the forecasting horizon.

A comparison of Figures 2 and 3 shows that the forecasting errors on average are higher in periods when bank managers are more pessimistic. Specifically, the period of average moderate optimism before the crisis had few forecasting errors, while the very pessimistic mood during the 2007-2008 financial crisis saw a spike in the levels of forecasting errors. The latter declined as soon as pessimism turned into a new wave of optimism in 2012.

[8] In a similar way, Kapinos et al. (2016) decompose the effect of predictable and unpredictable movements in housing prices and find that unexpected housing price changes have particularly large effects on small businesses' balance sheets.

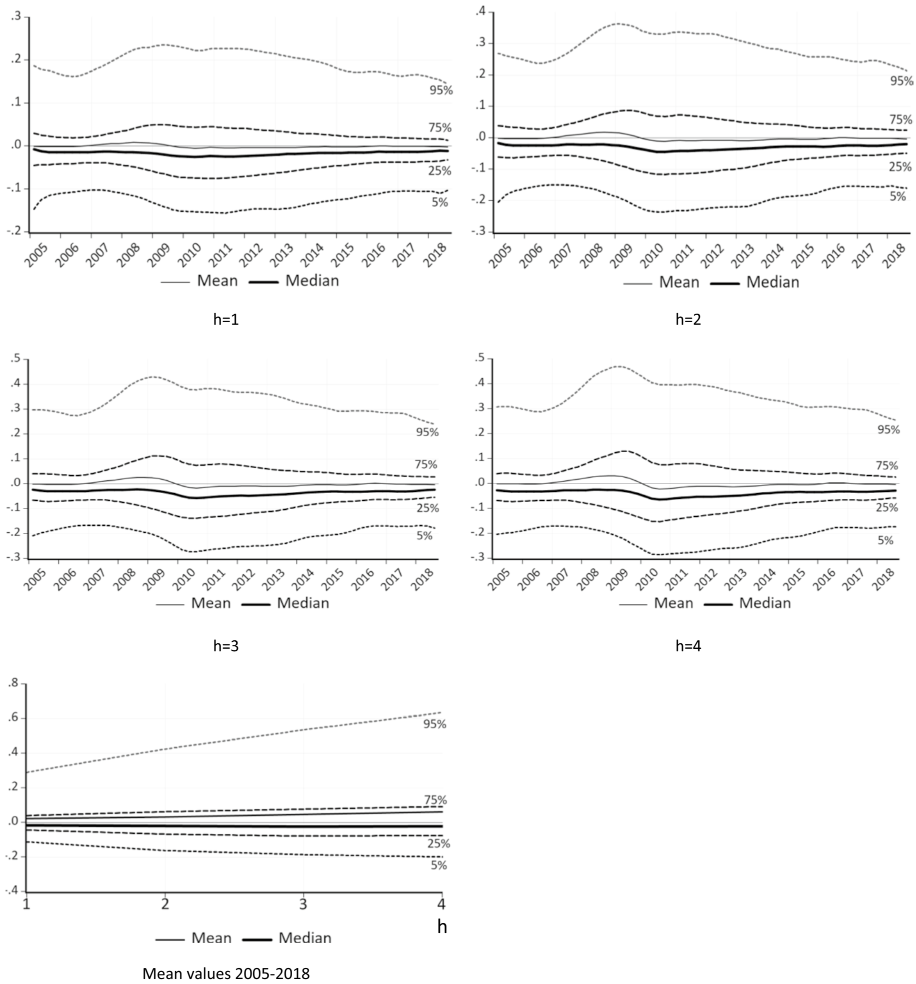

Fig. 3 Forecasting errors of future loan losses in the period from 2005-2018. This figure displays the median and mean values of the forecasting errors as well as the 5%, 25%, 75% and 95% quintiles of the forecasting errors over each quarter. Panels h=1…4 display the means, medians, and the distributions of the forecasting errors 1, 2, 3, and 4 quarters ahead. The last panel shows how forecasting errors relate to the forecasting horizon.

We posit that the wrong expectations result in an inappropriate amount of reserves that are likely to persist for several quarters. To test this hypothesis, we compute the coefficient correlation among subsequent forecasting errors at the same bank. The average value of the coefficient for forecasting errors correlations are reported in Table 3.

Specifically, the correlation between forecasting errors of future loan losses in t+1 and t+2 is 43%, and that between t+1 and t+3 is 27%. In addition, the correlation coefficient between t+2 and t+3 is 52%, and that between t+3 and t+4 is 58%. Overall, the

Table 3 Correlation between our index and forecasting errors.The forecasting errors of bank *i* are the difference between the CHARGE_OFFS% at t+h and the ESTIMATED CHARGE OFFS at t+h using equation 2. $u[ALLOWANCES]_{it}$ is the value of the residuals (excluding outliers) obtained from estimating equation 1. *i* refers to the bank, *t* to the time, and *h* is the quarter ahead relative to *t*. The table provides the correlations among forecasting errors in different periods and between our index of the optimism or pessimism of bank *i* at time *t* and the forecasting errors in subsequent periods.

		$Forecasting\ errors_{i,t+h}$			
		h=1	h=2	h=3	h=4
$Forecasting\ errors_{i,t+h}$	h=1	1.00	0.43	0.27	0.20
	h=2	0.43	1.00	0.52	0.35
	h=3	0.27	0.52	1.00	0.58
	h=4	0.20	0.35	0.58	1.00
$u[ALLOWANCES]_{it}$		-0.00	-0.02	-0.02	-0.01

correlations between forecasting errors in subsequent periods are quite high that support the hypothesis that optimism and pessimism are not random events but persist over time.

On the other hand, the correlation between our indicator of optimism or pessimism and forecasting errors on loan losses at t+h, h=1,2,3,4 at the bank level is very low that reflects the fact that our indicator is a good predictor of future loan losses (see Table 2). That correlation confirms the hypothesis that managerial beliefs are grounded more in the private information about the quality of their clients than on subjective feelings of bank managers about future loan losses. However, if this is true for the banks included in Table 2, that is, belonging to the sample free of outliers, then the conclusions are different for banks not included in that sample. When we apply the coefficients from our OLS or GMM estimations to the banks belonging to outlier residuals obtained by estimating equation 1 with the ΔALLOWANCES, then the results show that the most optimistic and pessimistic bank managers strongly underestimate their future loan losses (see Table 4) (the hypothesis of equality between means is rejected at zero probability based on Welch F-test, and the hypothesis of equality between the medians is rejected at zero probability based on Wilcoxon/Mann-Whitney (tie-adj.), Med. Chi-square, Adj. Med. Chi-square, Kruskal-Wallis, Kruskal-Wallis (tie-adj.), and van der Waerden tests).

Table 4 Forecast errors for one-quarter ahead CHARGE_OFFs% with and without outlier residuals. This table presents the results on the impact of the residuals u[ΔALLOWANCES] at time *t* on the mean and median values of the forecast errors of charge-offs at t+1 using both OLS and GMM estimators. In one estimation outliers are included among the residuals, in the other not.

Method	OLS			GMM		
Outliers	No	Yes		No	Yes	
Sign of $u[\Delta ALLOWANCES]_t$	+/-	+ (pessimist)	-(optimist)	+/-	+ (pessimist)	-(optimist)
Mean	0.00	27.28	24.51	0.02	26.61	25.41
Median	-2.03	4.69	3.01	-2.05	4.09	3.56

Specifically, the most pessimistic (optimistic) managers on average underestimate their future loan losses by about 27% (24%) in the OLS estimation and 26% (25%) when we use GMM estimations. Similar results hold with two, three and four quarters ahead forecast errors.

6 Robustness Checks

To assess the validity of our indicator, first we compare the aggregate weighted average values of managerial optimism and pessimism over time to the FED Senior Loan Officer Opinion Survey on Bank Lending Practices. The Federal Reserve conducts the survey quarterly with up to 80 large domestic banks and 24 US branches and agencies of foreign banks. Among other things, the survey asks senior loan officers whether the quality of future loans is likely to improve or deteriorate substantially or somewhat, or to stabilize around its current level. Panel 4.a of Figure 4 displays the net percentage of respondents that indicates the tightening standards for C&I loans (lower percentage= higher optimism). Their pessimism spiked in 2008, and forecasts again became optimistic in 2010.

Despite the different sources of data, our aggregate indicator of managerial optimism or pessimism (Panel 4.b) is highly correlated with the Federal Reserve's indicator (Panel 4.a) that denotes how this indicator captures similar phenomena. However, our indicator of optimism or pessimism is based on banks' balance-sheet data not survey data. In addition, comparing Panels 4.a and 4.b, managers of large banks seem to be more worried than other managers during the financial crisis.

We assume that optimism and pessimism are characteristics of the bank managers that affect the amount of allowances they set aside for future loan losses as well as other balance-sheet variables. An event in which managerial beliefs are likely to change is

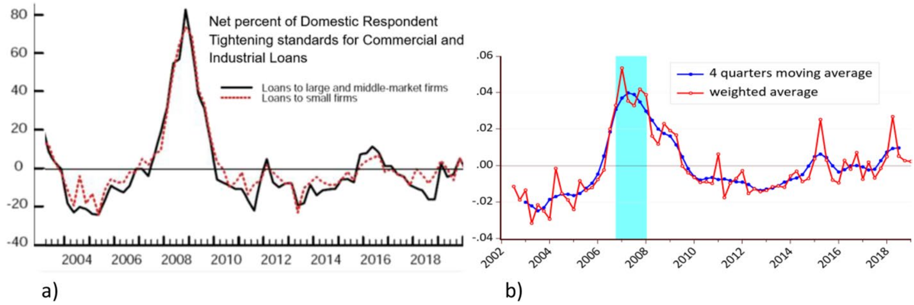

Fig. 4 Comparison of our aggregate measure of managerial optimism or pessimism with the aggregate value of FED Senior Loan Officer Opinion Survey on Bank Lending Practices. Panel a displays the net percentage of the banks' senior loan officers that indicated tightened standards for commercial and industrial Loans. Positive values denote the tightening and negative values the loosening of the lending conditions. Panel b displays the moving average and the weighted average of managerial beliefs over four quarters. The positive values correspond to the prevalence of pessimism and negative values to the prevalence of optimism.

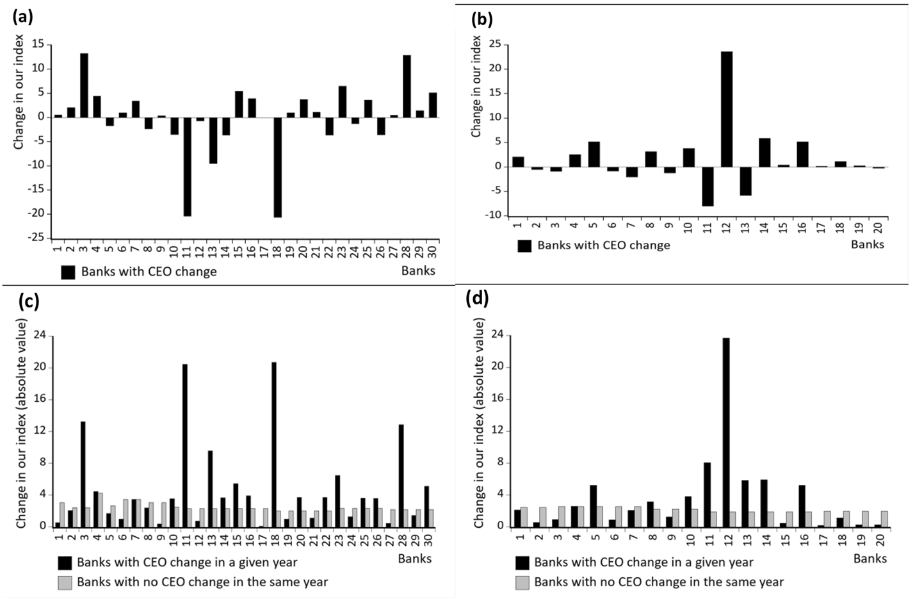

Fig. 5 CEO turnover and change in managerial beliefs in large and small banks. Panel a displays the changes in our index of managerial beliefs between the quarter before and after the CEO turnover for a sample of the 30 largest American banks that changed CEOs between 2000 and 2019. Panel b does the same for a sample of 20 small American banks that changed CEOs after 2013. Panel c compares the change in managerial beliefs for the largest 30 banks that changed CEOs with similar banks that did not change CEOs, and Panel d compares the change in managerial beliefs for the 20 small American banks that changed CEOs with similar banks that did not change CEOs in the same period.

managerial turnover. So, we construct a sample of 50 banks which changed CEOs in the period from the first quarter of 2000 to the third quarter of 2019 to check the impact of turnovers on managerial beliefs.[9]

We report the evidence separately for large and small US banks in Figure 5. Changes in managerial beliefs refer to the difference in $u[ALLOWANCES]$ for the same bank between the quarter before and after the turnover.

Panels 5.a and 5.b show respectively for large and small banks whether the new CEOs were more optimistic or pessimistic relative to the old one. First, the turnover has a greater impact on the change in managerial beliefs for the bulk of the banks in our sample. In addition, even though new CEOs overall are more pessimistic than the old ones, there are more optimistic new CEOs among large than small banks.

Panels 5.c and 5.d in Figure 5 show the absolute values of changes in our index, respectively, for large and small banks between the quarter before and after the turnover as well as the median value of $u[ALLOWANCES]$ of the banks which did not change their CEO in the

[9] The sample comprises 30 of the 100 largest US banks which changed CEOs in the sample period and 20 small banks which changed CEOs after 2013. The latter come from Y-6 forms that were not available before 2013. There were not too many changes in banks' CEOs: e.g., Rajgopal et al. (2019), based on a sample of 97 US banks in the years from 2007-2015, find that 81% of bank CEOs were also the chairmen of their boards before and after the crisis, which supports our finding.

same year of the turnover. The absolute variation in the value of the residuals shows that overall managerial beliefs change more for banks which experienced a managerial turnover than those that did not. In addition, managerial turnover has a greater impact on large than small banks. These results provide additional evidence in favour of our hypothesis that the residuals from estimated loan loss reserves are likely to capture managerial beliefs in banking.

7 Managerial Sentiments and Risk-taking in Banking

In this section, we use our measures of managerial sentiments to estimate the effects of managerial optimism and pessimism on lending, leverage, and risk-taking.

Thus, we propose the following hypothesis:

7.1 Hypothesis 1. Optimistic bank managers lend and leverage more.

Optimistic bank managers have stronger expectations that borrowers will be able to repay, and therefore they are more willing to lend (see, e.g., Malmendier and Tate 2005; Goel and Thakor 2008; Campbell et al. 2011; Ben-David et al. 2013). Further, more optimistic bank managers expand their balance sheets more, and they are likely to face higher capital constraints and to resort to more external funding. Adrian and Shin (2011) show that the asset level of financial intermediaries is determined by the degree of leverage that is permitted by market conditions, and Malmendier et al. (2011) find that banks prefer debt to equity when there are good opportunities for growth during a credit boom. In addition, Beltratti and Stulz (2012) and Fahlenbrach et al. (2012) show that the preceding rise in bank leverage played an important role in the 2007-2008 financial crisis. Hence, we hypothesize:

7.2 Hypothesis 2: Optimistic bank managers build riskier portfolios.

This hypothesis applies to greater optimism in bank managers both across banks and over time. It relies on the assumption that optimistic managers deal with better quality borrowers and projects and have higher trust in the possibility of making profitable investments. Both these effects spur the incentive to expand their activity and to take more risk.

To test the above hypotheses, we use the following model:

$$\mathrm{DEP}_{it+h} = \mathrm{a}^{h} u[ALLOWANCES]_{it} + \mathrm{OtherTerms} \tag{3}$$

where DEP represents alternative measures of managerial behavior (lending, leverage, or risk-taking), and $u[ALLOWANCES]_{it}$ denotes the measures of managerial sentiment.

We use the local projections method in Jorda (AER 2005) to map the impulse response function captured by a^h of the dependent variable to different measures of managerial sentiment.

To estimate the effect of managerial optimism and pessimism on lending, leverage, and risk-taking, we estimate the following specification of equation 3:

$$\begin{aligned}\mathrm{DEP}_{i,t+h} = &\sum\nolimits_{j=0}^{8} b_{oj} u[ALLOWANCES]_{i,t-j} + \sum\nolimits_{j=0}^{8} b_{1j} \Delta E[ALLOWANCES]_{i,t-j} \\ &+ \sum\nolimits_{j=0}^{8} b_{2j} DEP_{i,t-j} + b_{1t} T\_ALLOWANCES_{i,t-1} \\ &+ b_{2t}\mathrm{RANK\_OP}_{i,t} + b_{3t}(\mathrm{TIER\_1/RWA})_{i,t} + b_{4t}\mathrm{lnT\_ASSET}_{i,t} + \epsilon_{i,t}\end{aligned} \tag{4}$$

DEP is the dependent variable; and h alternatively takes the values of 1, 2, 3, and 4 quarters; as before, *u*[*ALLOWANCES*] are the residuals of equation 1. Hence, the data related to the effects of managerial optimism and pessimism refer to 2002–2019.

Following hypotheses 1 and 2, we assume that the higher the optimism is, then the higher the increase in risk-taking, lending, and leverage in the subsequent quarters. The results of the estimations of (4) are reported in Figure 6. This figure shows the impulse responses of risk-taking, lending, and leverage to managerial beliefs at different horizons h=1,2,3,4 quarters.

Panel a shows the impulse responses of lending on managerial beliefs (*u*[*ALLOWANCES*]) and Panel b shows the impulse responses of risk-weighted assets over total assets on managerial beliefs. They are negative; hence, optimistic bank managers (negative residuals of equation 1) increase lending and risk-taking in the subsequent periods. The opposite holds for pessimistic bank managers (positive residuals of equation 1). Panel c shows the impulse responses of Tier_1/total assets (the inverse of leverage) to managerial beliefs. They are positive. It follows that pessimistic managers (residuals of equation 1 are positive) reduce leverage in subsequent periods. On the other hand, optimistic managers return to more debt in subsequent periods to finance banking activity. Panel d of Figure 6 shows the impulse responses of nonperforming loans to managerial beliefs. The results indicate that pessimistic managers face more nonperforming loans in the future, although with a decreasing effect over time. Overall, Figure 6 provides support for both hypotheses: more optimistic bank managers build up riskier portfolios by lending and leveraging more.

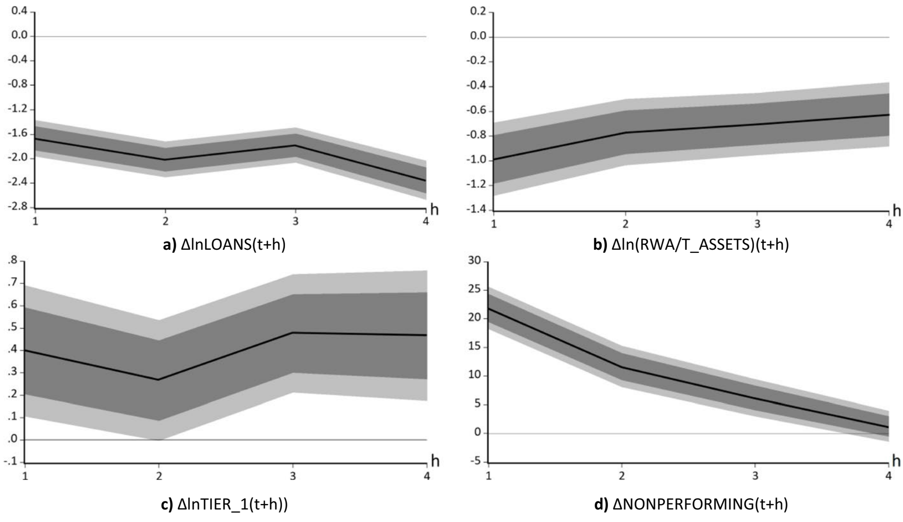

Fig. 6 The effects of managerial beliefs on risk-taking, lending, leverage, and nonperforming loans. The vertical axes show the impulse responses on managerial beliefs and the horizontal axes the time horizon of 1,2,3,4 quarters. The reported confidence bands are 2σ and 3σ. Panel a displays the impulse responses of LOANS on managerial beliefs, Panel b the impulse responses of RWA/T_ASSETS on managerial beliefs, Panel c the impulse responses of TIER_1 (the inverse of leverage) on managerial beliefs, and Panel d displays the impulse responses of NONPERFORMING on managerial beliefs. Negative values indicate that optimists (pessimists) react by increasing (decreasing) the value of the variable. The opposite holds with positive values.

Table 5 The effects of managerial beliefs and public information on lending and charge-offs. A negative sign on the coefficient means that an increase in pessimism (u[…] increases) at time t leads to a reduction in loans and charge offs in subsequent periods. A similar effect exists for E[…]. Row c and row f measure the contribution of our proxy of managerial beliefs respectively on the change in loans and net charge-offs to loans in subsequent periods. Standard errors are in the brackets.

		∆lnLOANS(t+h)			
		h=1	h=2	h=3	h=4
a	$u[\Delta ALLOWANCES]_t$	-1.66***	-2.00***	-1.77***	-2.35***
		(0.10)	(0.10)	(0.09)	(0.10)
b	$E[\Delta ALLOWANCES]_t$	-0.65**	-0.16	-1.90***	-2.63***
		(0.30)	(0.30)	(0.31)	(0.30)
c	a/(a+b) %	71.63	92.62	48.17	47.15
		CHARGE_OFFS(t+h)%			
		h=1	h=2	h=3	h=4
d	$u[\Delta ALLOWANCES]_t$	14.65***	27.44***	27.05***	29.94***
		(0.31)	(0.85)	(0.50)	(0.54)
e	$E[\Delta ALLOWANCES]_t$	23.09***	35.82***	45.46***	41.16***
		(0.40)	(0.86)	(0.74)	(0.73)
f	d/(d+e) %	38.81	43.37	37.30	42.10

The ***, **, and * represent significance at the 1%, 5%, and 10% probability levels respectively.

Most important, the regression results summarized in Table 5 show that the effects of managerial sentiments on lending are greater than those based on public information (i.e., estimated loan loss reserves). More precisely, managerial sentiments explain on average more than 60% of change in loans and about 40% of future charge offs.

These findings support the view, pointed out by Keynes and Akerlof and Shiller, among others, that animal spirits play a relevant role in lending decisions.

The joint results that more optimistic bank managers take more risk and lend more while they face less loan losses indicates that optimism or pessimism may have some basis in the private information about the quality of their clients. As a robustness check, we test whether the last result extends also to the outlier banks. Indeed, in this case we get the opposite result; the most optimistic banks also have the largest loan losses in the future as well as the most pessimistic ones. This result means that overly optimistic bank managers are likely to base their decisions more on subjective beliefs than private information about their clients.

8 Conclusion

Although optimism and pessimism are normal aspects of managerial and non-managerial behavior, the evidence on bank managers refers only to the existence of behavioral biases (i.e., overconfidence).

In this study, we provide a proxy for optimism or pessimism, and we analyze its ability to forecast certain balance-sheet items. Our proxy is related to the determinants of allowances for loan losses. As explanatory variables of allowances, we have used financial statement data, some macroeconomic variables, and two indicators of managerial efficiency and risk aversion. The residuals of the regressions are attributable to the whole set of variables not included in the regressions and, in particular, the managers' private information on the quality of loans. These components are certainly relevant because the residuals are very much connected to the future performance of the uncollectable loans of the corresponding banks. We therefore interpret these residuals as a proxy for managers' optimism or pessimism regarding future losses coming from their confidential information.

In other words, while one component essentially represents the expectations that come from public information, the residual represents a proxy for the subjective component that is linked to the private information that managers have on their banks. Therefore, it is a proxy for their optimism or pessimism about the future that is not detectable in public information. Further, optimistic or pessimistic bank managers are more likely to make forecasting errors about future charge-offs. Indeed, the most optimistic bank managers also have the largest loan losses in the future as well as the most pessimistic ones that means overly optimistic bank managers are likely to base their decisions more on subjective beliefs than private information about their clients.

We have estimated the allowances for loan losses with different econometric methods and with different specifications, and the correlation of the corresponding residuals is always very high. Therefore, our results are robust. They indicate that banks were more optimistic before the 2007-2008 financial crisis and after 2011, while they were pessimistic during the crisis.

Furthermore, our aggregate measure of managerial beliefs is highly correlated with the Federal Reserve's indicator of managerial expectation on the quality of future loans. Further, for a sample of large and small banks we show that our indicator of managerial beliefs changes more when there is managerial turnovers in banks.

Our clear cut results on the effect of managerial beliefs show that an increase in optimism leads to expanded lending, leveraging, and risk-taking, and the opposite effect occurs when pessimism prevails. The effect of managerial beliefs on lending, leveraging, and risk-taking was particularly strong during and after the crisis up to 2013. Indeed, widespread pessimism among bank managers during the crisis determined the contraction of the loans in subsequent periods.

Our results provide evidence that widespread optimism occurred before the 2007-2008 financial crisis, which led to increasing lending, leverage, and risk-taking, followed by pessimism during the crisis. By contrast, overconfidence and risk aversion are persistent personality traits that generate behavioral biases. Ho et al. (2016) find that overconfident CEOs bore excessive risk before the 2007-2008 financial crisis and were subject to more losses during it, and Fahlenbrach et al. (2012) show that the persistence of the risk culture is a determinant of that crisis. Our empirical evidence shows that the leverage and lending cycles documented in the literature are determined by the waves of optimism and pessimism that occur during the business cycle. From a policy perspective, our work indicates that to prevent excessive lending, leverage, and risk-taking in the upswing, and the credit crunch in the downswing of the cycle, a deep understanding of what fuels the broad-based spread of optimism and pessimism is important. Finally, we argue that our measure of managerial beliefs opens up new avenues for future research, such us the analysis of the impacts of optimism and pessimism on the business cycle as well as on the allocation of loans between sectors and firms that may differ in managerial beliefs as well or in the risk-return combination.

Appendix

Table 6 Variables used in the econometric analysis

Name	*Form FFIEC 041 name* Original name	xls file	Definition
1.Bank-specific variables:			
T_ALLOWANCES	Lnatres		**Loan loss allowance** Allowance for loan and lease losses
LOANS	Idlnls	Net Loans and Leases	**Loans and leases, gross:** Loans and lease financing receivables of the institution, including unearned income
	Lnatresr	Assets and Liabilities	**Loss allowance to loans:** Allowance for loan and lease losses as a percent of the total loan and lease financing receivables, excluding unearned income
ALLOWANCES = ln(T_ALLOWANCES/LOANS) = ln(lnatresr/100)			Ln(**Loss allowance/loans**)
T_ASSETS	Asset	Assets and Liabilities	**Total assets:** The sum of all assets owned by the institution including cash, loans, securities, bank properties, and other assets. This total does not include off-balance-sheet accounts
RWA	RWAJT	Assets and Liabilities	**Total risk-weighted assets adjusted:** Total risk-weighted assets are assets adjusted for risk-based capital definitions that include on-balance-sheet as well as off-balance-sheet items multiplied by specified risk-weights. A conversion factor is used to assign an equivalent amount to the balance sheet for selected off-balance-sheet accounts. As of March 2015, all institutions began reporting the amended CALL schedule RC-R Part I and Part II that incorporated the risk-based capital rules based on the Basel III framework and section 939A of the Dodd-Frank Act. Some designated as Advanced Approaches institutions began reporting RC-R Part 1a based on the updated requirements as of March 2014. (See: FDIC Financial Institutions Letter FIL-24-2012) RIS data note: Prior to March 2014, this variable was the same as the RIS variable RWAJ

Table 6 (continued)

Name	*Form FFIEC 041 name* Original name	xls file	Definition
RWA/T_ASSETS = 100*RWAJT/T_ASSETS			Risk-weighted assets over total assets; proxy for managerial risk tolerance
TIER_1 Corresponds to: Rbc1aaj only if its value is positive and <100, otherwise it is not considered	Rbc1aaj	Performance and Condition Ratios	**Core capital (leverage) ratio:** Tier 1 (core) capital as a percent of average total assets minus ineligible intangibles. Tier 1 (core) capital includes common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. The amount of eligible intangibles (including mortgage servicing rights) included in core capital is limited in accordance with supervisory capital regulations. Average total assets used in this computation are an average of the daily or weekly figures for the quarter. As of March 2015, all institutions began reporting the amended CALL schedule RC-R Part I and Part II that incorporated risk-based capital rules based on the Basel III framework and section 939A of the Dodd-Frank Act. Some designated institutions began reporting based on the updated requirements as of March 2014. (See: FDIC Financial Institutions Letter FIL-24-2012)
CHARGE-OFFS If its value is <-2000 it is not considered	Ntlnlsr	Performance and Condition Ratios	**Net charge-offs to loans:** Gross loan and lease financing receivable charge-offs, less gross recoveries, (annualized) as a percent of average total loans and lease financing receivables
NONPERFORMING	Nclnlsr	Noncurrent loans to loans	Noncurrent loans to loans: Total noncurrent loans and leases, loans and leases 90 days or more past due plus loans in nonaccrual status, as a percent of gross loans and leases

Table 6 (continued)

Name	*Form FFIEC 041 name* Original name	xls file	Definition
ROA	Roa	Performance and Condition Ratios	**Return on assets (ROA):** Net income after taxes and extraordinary items (annualized) as a percent of the <u>average total assets</u>
NET_INCOME = 100* (ibefxtr+elnatr+itax) / (Asset(t)+Asset(t-1))/2)	Ibefxtr	Income and Expense	**Income before extraordinary items:** Income (loss) before security transactions, extraordinary items, and other adjustments
	Elnatr	Income and Expense	**Provision for loan and lease losses:** The amount needed to make the allowance for loan and lease losses adequate to absorb expected loan and lease losses (based upon management's evaluation of the bank's current loan and lease portfolio). <u>Call Reporters:</u> Prior to 2001 and after 2002, an allowance for transfer risk was also included to cover losses on international assets. Additionally, from 1997 to 2000, it included a provision for credit losses on off-balance-sheet credit exposures <u>TFR Reporters:</u> Reflects net provision for losses on interest-bearing assets
	Itax	Income and Expense	**Applicable income taxes:** Applicable federal, state, local, and foreign income taxes
			Quarterly rank of bank's *i* income less average rank of all banks in the same quarter (high rank = lowest income)
$u[\Delta ALLOWANCES]$			Change in ALLOWANCES not explained by four-year rolling estimation of equation 1
$E[\Delta ALLOWANCES]$			Change in ALLOWANCES explained by four-year rolling estimation of equation 1.
$E[ALLOWANCES]$= $\mathrm{ALLOWANCES}_{t-1}+E[\Delta ALLOWANCES]$			Level of ALLOWANCES at quarter t explained by four-year rolling estimations of equation 1

Table 6 (continued)

Name	*Form FFIEC 041 name* Original name	xls file	Definition
u[*ALLOWANCES*]			Level of ALLOWANCES at quarter t not explained by the four-year rolling estimations of equation 1 (Residuals of estimated equation 1)
RANK_OP/1000			Rank of profit for bank *i* relative to the average profit of all the banks. The rank is divided by its maximum and multiplied by 100. Proxy of managerial ability
2. Macroeconomic variables:			
GDP_GROWTH			Annual percentage GDP growth
S&P_INDEX			Standard and Poor's stock index
FED_FUND			Effective federal funds rate (% p.a.) on last business day of month. From 01/01/2009 to 01/12/2015 we use the Atlanta Fed Wu-Xia shadow federal funds rate
EXP_GDP_GROWTH			Expected future GDP growth provided by the Fed of Philadelphia
VIX			The daily level of the CBOE Volatility Index. The VIX index measures the expectation of stock market volatility over the next 30 days as indicated by the S&P 500's index options

Table 7 Correlation among the variables. Panel a displays the correlations for the levels of the variables and panel b the correlations for the variations in the variables.

Panel a Correlations for the levels of the variables

	ALLOW-ANCES	ln(LOANS/T_ASSETS)	lnT_ASSETS	ln(RWA/T_ASSETS)	lnTIER_1	CHARGE-OFFS	NONPER-FORMING	NET_INCOME	ROA	RANK_OP	GDP_GROWTH	lnS&P_INDEX	FED_FUND	EXP_GDP-GROWTH
ALLOWANCES	1.000	-0.149	-0.102	0.080	0.043	0.087	0.226	0.063	0.074	0.029	0.012	0.023	-0.137	0.003
ln(LOANS/T_ASSETS)	-0.149	1.000	0.135	0.751	-0.165	0.055	0.006	0.127	0.045	-0.161	-0.017	0.010	0.093	-0.037
lnT_ASSETS	-0.102	0.135	1.000	0.203	-0.214	0.116	0.005	0.134	0.065	-0.764	0.020	0.190	-0.068	-0.133
ln(RWA/T_ASSETS)	0.080	0.751	0.203	1.000	-0.159	0.076	-0.003	0.186	0.132	-0.239	-0.016	0.023	0.100	-0.053
lnTIER_1	0.043	-0.165	-0.214	-0.159	1.000	-0.102	0.018	0.009	0.053	0.162	0.015	0.168	-0.042	-0.125
CHARGE-OFFS	0.087	0.055	0.116	0.076	-0.102	1.000	0.284	0.102	-0.109	-0.053	-0.108	-0.109	-0.101	-0.005
NONPERFORM-ING	0.226	0.006	0.005	-0.003	0.018	0.284	1.000	-0.083	-0.145	0.069	-0.106	0.002	-0.190	-0.076
NET_INCOME	0.063	0.127	0.134	0.186	0.009	0.102	-0.083	1.000	0.629	-0.427	0.045	-0.091	0.104	0.053
ROA	0.074	0.045	0.065	0.132	0.053	-0.109	-0.145	0.629	1.000	-0.454	0.097	-0.022	0.096	0.081
RANK_OP	0.029	-0.161	-0.764	-0.239	0.162	-0.053	0.069	-0.427	-0.454	1.000	0.050	0.034	0.022	0.013
GDP_GROWTH	0.012	-0.017	0.020	-0.016	0.015	-0.108	-0.106	0.045	0.097	0.050	1.000	0.216	0.067	0.435
lnS&P_INDEX	0.023	0.010	0.190	0.023	0.168	-0.109	0.002	-0.091	-0.022	0.034	0.216	1.000	-0.269	-0.553
FED_FUND	-0.137	0.093	-0.068	0.100	-0.042	-0.101	-0.190	0.104	0.096	0.022	0.067	-0.269	1.000	0.102
EXP_GDP-GROWTH	0.003	-0.037	-0.133	-0.053	-0.125	-0.005	-0.076	0.053	0.081	0.013	0.435	-0.553	0.102	1.000

Panel b Correlations for the variations in the variables

	ΔALLOW-ANCES	Δln(LOANSLOANS/T_ASSETS)	ΔlnT_ASSETS	Δln(RWA/T_ASSETS)	ΔlnTIER_1	ΔCHARGE-OFFS	ΔNONPER-FORMING	ΔNET_INCOME	ΔROA	ΔRANK_OP	ΔGDP_GROWTH	ΔlnS&P_INDEX	ΔFED_FUND	ΔEXP_GDP-GROWTH
ΔALLOWANCES	1.000	-0.303	-0.154	-0.190	-0.022	-0.354	0.130	-0.117	-0.096	0.131	0.005	-0.037	-0.050	0.044
Δln(LOANS/T_ASSETS)	-0.303	1.000	-0.497	0.702	0.179	0.006	-0.019	0.160	0.058	-0.048	-0.002	0.037	0.040	-0.080
ΔlnT_ASSETS	-0.154	-0.497	1.000	-0.399	-0.204	-0.003	-0.001	-0.003	-0.042	-0.020	-0.013	-0.039	-0.035	0.027
Δln(RWA/T_ASSETS)	-0.190	0.702	-0.399	1.000	0.146	0.005	-0.006	0.110	0.045	-0.037	0.010	0.037	0.043	-0.056
ΔlnTIER_1	-0.022	0.179	-0.204	0.146	1.000	-0.028	-0.000	0.040	0.159	-0.045	0.024	0.035	0.052	-0.016
ΔCHARGE-OFFS	-0.354	0.006	-0.003	0.005	-0.028	1.000	-0.069	0.191	-0.105	0.073	-0.018	-0.026	-0.040	-0.045

Table 7 (continued)

ΔNONPER-FORMING	0.130	-0.019		-0.001	-0.006	-0.000	-0.069	1.000	-0.037	-0.045	0.041	-0.022	-0.037	-0.063	0.000
ΔNET_INCOME	-0.117	0.160		-0.003	0.110	0.040	0.191	-0.037	1.000	0.163	-0.205	0.023	0.089	0.034	-0.181
ΔROA	-0.096	0.058		-0.042	0.045	0.159	-0.105	-0.045	0.163	1.000	-0.514	0.043	0.023	0.051	-0.012
ΔRANK_OP	0.131	-0.048		-0.020	-0.037	-0.045	0.073	0.041	-0.205	-0.514	1.000	0.066	0.083	0.098	0.076
ΔGDP_GROWTH	0.005	-0.002		-0.013	0.010	0.024	-0.018	-0.022	0.023	0.043	0.066	1.000	0.578	0.277	0.095
ΔlnS&P_INDEX	-0.037	0.037		-0.039	0.037	0.035	-0.026	-0.037	0.089	0.023	0.083	0.578	1.000	0.400	0.251
ΔFED_FUND	-0.050	0.040		-0.035	0.043	0.052	-0.040	-0.063	0.034	0.051	0.098	0.277	0.400	1.000	0.161
ΔEXP_GDP-GROWTH	0.044	-0.080		0.027	-0.056	-0.016	-0.045	0.000	-0.181	-0.012	0.076	0.095	0.251	0.161	1.000

Table 8 Persistency of the variables. Panel a displays the persistency in the auto- and partial correlations of the absolute values of the variables up to four quarters, and panel b the persistency in the variations in the variables.

	Lags	ALLOWANCES	ln(LOANS/T_ASSETS)	lnT_ASSETS	ln(RWA/T_ASSETS)	lnTIER_1	CHARGE-OFFS	NONPERFORMING	NET_INCOME	ROA	RANK_OP	GDP_GROWTH	lnS&P_INDEX	FED_FUND	EXP_GDP-GROWTH
Panel a: Persistency in the levels of the variables															
Auto-corr.elation	1	0.867	0.877	0.907	0.883	0.875	0.535	0.721	0.363	0.747	0.874	0.776	0.885	0.914	0.760
	2	0.814	0.83	0.868	0.837	0.823	0.369	0.608	0.125	0.679	0.821	0.589	0.817	0.858	0.634
	3	0.774	0.796	0.837	0.802	0.784	0.28	0.534	0.28	0.628	0.781	0.398	0.763	0.788	0.509
	4	0.741	0.768	0.809	0.772	0.751	0.262	0.479	0.717	0.597	0.748	0.216	0.717	0.71	0.384
Partial Correlation	1	0.867	0.877	0.907	0.883	0.875	0.535	0.721	0.363	0.747	0.874	0.776	0.885	0.914	0.76
	2	0.251	0.265	0.261	0.259	0.242	0.116	0.184	-0.008	0.272	0.243	-0.035	0.16	0.137	0.132
	3	0.121	0.133	0.114	0.123	0.118	0.061	0.094	0.274	0.136	0.113	-0.12	0.069	-0.083	-0.025
	4	0.074	0.083	0.058	0.074	0.073	0.095	0.062	0.657	0.106	0.071	-0.115	0.041	-0.119	-0.068
	Lags	ALLOWANCES	ln(LOANS/T_ASSETS)	lnT_ASSETS	ln(RWA/T_ASSETS)	lnTIER_1	CHARGE-OFFS	NONPERFORMING	NET_INCOME	ROA	RANK_OP	GDP_GROWTH	lnS&P_INDEX	FED_FUND	EXP_GDP-GROWTH
Panel b Persistency in the variations of the variables															
Auto-correlation	1	0.016	-0.105	-0.022	-0.158	-0.049	-0.118	-0.116	-0.258	-0.103	-0.1	0.256	0.2	0.2	-0.13
	2	-0.002	-0.115	0.046	-0.074	-0.054	-0.03	-0.029	-0.311	-0.038	-0.034	0.084	-0.075	-0.075	-0.032
	3	0.015	-0.054	0.03	-0.04	-0.038	-0.045	-0.016	-0.264	-0.06	-0.042	0.002	0.005	0.005	-0.019
	4	0.132	0.246	0.198	0.132	0.102	0.078	0.012	0.763	0.04	0.041	-0.358	-0.088	-0.088	0.139
Partial Correlation	1	0.016	-0.105	-0.022	-0.158	-0.049	-0.118	-0.116	-0.258	-0.103	-0.1	0.256	0.2	0.2	0.2
	2	-0.002	-0.128	0.046	-0.101	-0.056	-0.045	-0.043	-0.405	-0.05	-0.034	0.02	-0.12	-0.12	-0.12
	3	0.015	-0.083	0.032	-0.071	-0.044	-0.055	-0.025	-0.617	-0.07	-0.04	-0.026	0.049	0.049	0.049
	4	0.131	0.222	0.198	0.11	0.095	0.065	0.006	0.509	0.024	0.041	-0.38	-0.115	-0.115	-0.115

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Declarations

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