Optimal versus realized bank credit risk and monetary policy

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Abstract

Standard banking theory suggests that there exists an optimal level of credit risk that yields maximum bank profit. We identify the optimal level of risk-weighted assets that maximizes banks' returns in the full sample of US banks over the period 1996–2011. We find that this optimal level is cyclical for the average bank, being higher than the realized credit risk in relatively stable periods with high profit opportunities for banks but quickly decreasing below the realized in periods of turmoil. We place this cyclicality into the nexus between bank risk and monetary policy. We show that a contractionary monetary policy in stable periods, where the optimal credit risk is higher than the realized credit risk, increases the gap between them. An increase in this gap also comes as a result of an expansionary monetary policy in bad economic periods, where the realized risk is higher than the optimal risk.

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1. Introduction

Bank managers make risky decisions about the transformation of liabilities to assets so as to produce profits. However, they can also produce large losses if they take on too much risk or if structural and macroeconomic conditions change unexpectedly.[1] This implies that the risk–return relationship is nonlinear and that there should be an optimal level of credit risk. Further, the inherent maturity mismatch between the asset and liability sides of the bank balance sheet causes a problem of time inconsistency: banks might alter their optimal risk decisions in different times. Despite the fundamental role of this idea in any theoretical model of bank risk and default, the empirical literature has largely neglected distinguishing between the realized and optimal (equilibrium) credit risk for the average bank and over time. Thus, the important implications of this distinction for the monetary and macroeconomic environment have not been studied. In this paper, we aim to fill this gap in the literature.

Theoretical models of the banking firm operating under adverse selection, moral hazard, and/or incomplete contracting assume that banks choose between risky and less risky assets and manage liabilities to maximize their value or profits (e.g., John, Saunders, and Senbet, 2000; Agur and Demertzis, 2012). Thus, banks make optimal decisions in light of the variable microeconomic problems they face, mostly related to informational asymmetry, and the regulatory and macroeconomic conditions. In this framework, equilibrium bank behavior can be compared and endogenized with optimality conditions for other agents (e.g., consumers or regulators) to study more general equilibrium relationships.

In practice, however, the realized level of credit risk is not equal to the optimal one in the short term. There can be many interrelated reasons for this discrepancy and three of them seem to be the most important ones. First, banks, like any other firm, can simply be inefficient and operate below capacity. In this sense, banks may fail to choose the optimal

[1] In a recent paper Agur and Demertzis (2012) model a bank manager's investment decision as a choice between two projects, one of which has lower expected return and higher volatility than the other.

mix or level of risky assets, a situation exacerbated during periods of rising uncertainty (e.g., Berger, Hancock and Humphrey, 1993). Second, the banking sector is notoriously characterized by herding behavior, which is usually pegged to the choices of leading banks or to the changing perceptions about the regulatory and macroeconomic environment. The history of banking crises has shown that herding behavior can be an important element in suboptimal risk decisions of banks in both good and bad economic periods (e.g., Acharya and Yorulmazer, 2007). Third, and perhaps most important, the maturity mismatch between assets and liabilities that is inherent in the banking business implies that the quality of bank balance sheets can quickly deteriorate in light of adverse developments due to depositor behavior in a classic Diamond and Dybvig (1983) framework, credit rationing *á la* Stiglitz and Weiss (1981), and other well-established mechanisms. Thus, banks can find themselves in situations where in good times they take on less than the optimal credit risk, while in bad times they are exposed to higher than the optimal risk. The outcome of both these states is lower than optimal returns.

We identify deviations between the realized and optimal bank credit risk using a simple empirical setup. We assume that bank profits depend on the risk decisions of bank managers and bank managers want to maximize returns on assets (or returns on equity if there is no principal agent problem). To do so, they seek the optimal level of credit risk. If bank managers decide to take on too little credit risk and hold a large share of liquid assets in their portfolios, bank profits will not be maximized. Bank returns will also be sub-optimal if bank managers take on too much credit risk, leading for example to the accumulation of a high volume of nonperforming loans (e.g., Goddard, Molyneux, and Wilson, 2004). Thus, profit as a function of risk may be described better by an inverted U-shaped curve.

Another important element of this setup is that the level of optimal credit risk must be time-varying. For instance, consider the situation in the period 2001–2007. Perceptions about the stability of the banking system were really optimistic and credit risk decisions were paying high yields. This implies that the optimal bank credit risk is relatively high during prosperous periods. When the housing bubble burst, banks found themselves exposed to very risky positions that started yielding losses because of the surging nonperforming loans. Furthermore, bank managers could not adjust the level of credit risk in the very short term, mainly because of issues related to maturity mismatch. Thus, in periods of stress, the optimal credit risk should be lower than the actual credit risk held in the portfolio of the average bank.

Using quarterly panel data for virtually all banks that operated in the United States (US) during the period 1996–2011, we identify the time-varying optimal level of credit risk mainly in terms of the ratio of risk-weighted assets to total assets. We indeed find a cyclical movement of the optimal level of credit risk for the average bank, which peaks just before the eruption of the crisis in 2006. The optimal credit risk quickly deteriorates from 2007 onward and this leaves banks with a higher than optimal credit risk in the crisis period. This explicitly shows how the deviations between the realized and optimal credit risk, owing to the three main channels highlighted above, leave the average bank operating in a suboptimal way.

These deviations have interesting implications for the monetary and the macroeconomic environment. A recent literature examines the interplay between banks' risk, monetary policy, and macroeconomic outcomes, suggesting that a monetary expansion leads banks to take on higher risks (e.g., Ioannidou, Ongena, and Peydro, 2014; Delis, Hasan, and Mylonidis, 2011). Our analysis is not about identifying the potency of this mechanism, which is termed the risk-taking channel of monetary policy. Instead, we opt for identifying a relation between the macroeconomic and monetary conditions, and the deviations between the optimal and the realized actual risk in bank portfolios. To this end, we use a vector error correction model (VECM) and time-series data on the federal funds rate and the median risk-weighted assets of US banks. We show that the optimal monetary policy from a macroeconomic viewpoint increases the deviations between the realized and optimal credit of banks, thus pushing banks to a suboptimal disequilibrium situation. In line with our result, Agur and Demertzis (2013) use a relevant theoretical model and show that because bank risk is sticky, monetary policy should keep rate cuts short to prevent excessive risk buildup.

Specifically, in good economic periods, the Fed has incentives to increase the interest rates. In these periods, where the optimal level of banks' credit risk is higher than the realized risk, we show that a monetary contraction will not only decrease the realized credit risk (in line with the existence of a risk-taking channel) but also increase the optimal level of credit risk. Similarly, in periods of turmoil in the banking sector, where the optimal level of banks' credit risk is lower than the realized risk, we show that a monetary expansion will increase the realized credit risk and decrease the optimal level of credit risk. Therefore, in both good and bad periods, the "optimal" monetary policy choices by the Fed aiming at smoothing the business cycle, force the realized level of banks' credit risk out of equilibrium. We contend that this finding has important policy implications for both the conduct of monetary policy and the prudential regulation of banks.

The rest of the paper proceeds as follows. Section 2 describes the empirical model used to estimate the optimal level of credit risk on the basis of specific theoretical considerations. Section 3 discusses the data set and the estimation method. Section 4 presents the empirical results from the estimation of the optimal credit risk. Section 5 examines the macroeconomic relations between the optimal level of credit risk, the realized credit risk, and the monetary conditions. Section 6 concludes the paper.

2. Identification of the optimal credit risk

2.1. Profitability equation and risky assets

Most theoretical studies model the banking firm as a wealth- or profit-maximizing entity. The premise is that banks use a set of inputs to invest in risky assets with a high return and in less risky assets with a low return (e.g., John, Saunders, and Senbet, 2000). The bank is also required to hold a fair amount of reserves with the central bank, as well as capital to absorb losses. Thus, the basic banking model can consider the presence of reserve requirements, capital regulation, or other forms of intervention. The bank decides on the optimal allocation of resources of high- and low-risk assets given its budget constraint and the "safe and sound" banking constraint posed by the regulator (e.g., Kim and Santomero, 1988). One can also think that the bank has its own soundness constraint if its decision is to maximize wealth or profits subject to minimizing the probability of default. This relates to the notion of the market discipline of the banking firm (e.g., Flannery and Sorescu, 1996).

Hughes and Mester (1994; 1998) provide an influential empirical counterpart of this theoretical framework. The first of these studies tests whether bank managers are acting in the shareholders' interest and maximizing expected profits or a utility function that trades off risk for return. The findings rule in favor of the trade-off between profit and risk. The second study shows that in a similar model of the banking firm, banks of different size classes exhibit behavior consistent with risk aversion.

This basic modeling of the banking firm yields a profit equation of the form (or similar to):

$$\Pi = p_1 y_1 + p_2 y_2 + p_3 y_3 - C(\textstyle\sum_{n=1}^{3} y\, , w) - p_k K \tag{1}$$

In this profit function, y_1 is the quantity of the risky asset (credit risk), which earns an average interest rate p_1. The interest rate on the risk-free asset y_2 is p_2 and p_3y_3 is the revenue from other sources not directly related with credit risk. We can consider that $y_1 + y_2$ represents the total assets of bank *i* used to generate profits, while p_3y_3 represents the noninterest income. Bank outputs are produced using input prices *w* and the bank draws capital *K* (at some rate p_k), which can be of the form of equity capital or debt-based capital.

2.2. Empirical model and the distinction between the short- and the long-run

In the empirical banking literature (e.g., Berger, Hasan, and Zhou, 2010), the identification of the factors explaining profits comes from a specification where the returns on assets or equity are regressed on a number of bank characteristics including those of equation (1). As profits are normalized with respect to the total assets or equity, it is usual practice to normalize the rest of the bank characteristics, including the variable used as a measure of credit risk *y*. Further, John, Saunders, and Senbet (2000), among others, assume that the representative bank maximizes expected profits by deciding on the optimal mix of risky and riskless assets, while standard microeconomic theory suggests that the profit function will be concave in y_1 if the cost function is convex (Hughes and Mester, 1994).

These considerations point to a non-linear relationship between profits and credit risk. The intuition of such an empirical modelling choice comes from quadratic objective functions in portfolio management that first appeared in Markowitz (1959). In our paper, the assumption on the non-linear relation between credit risk and profits is mostly based on the fact that banks must take credit risks to maximize their profits, but taking too much credit risk might result in losses. Empirical equations with squared terms are commonly used to describe maximization problems in the literature (e.g., Dell' Ariccia, Laeven and Marquez, 2014, for a recent example). Simplicity facilitates our aim, which is to estimate a risk-return relationship in terms of portfolio management and not to provide a general equilibrium model for bank profits. The latter would require taking into account the price setting behavior of a bank as a competitive firm and the informational problems that exist between borrowers and lenders; such a model is significantly more complicated and beyond the scope of this paper.

To identify the global maximum point, where the marginal impact of credit risk (i.e., the risky assets) turns negative, we estimate the following profit equation:

$$\Pi_{it} = a_0 + b\Pi_{i,t-1} + a_1 r_{it} + a_2 r_{it}^2 + a_3 c_{it} + u_{it}, \tag{2}$$

where Π is the return on assets (or equity) of bank i at time t; $r \equiv y_1$ denotes credit risk, c is a vector of control variables observed at the bank level that include, *inter alia*, the risk-free asset; and u is the disturbance. Here u_{it} can be analyzed as

$$u_{it} = \lambda_t + v_i + e_{it}, \tag{3}$$

where λ_t denotes time fixed effects, v_i denotes bank fixed effects, and e_{it} is the remainder disturbance. The presence of the lagged dependent variable among the explanatory variables is in line with the evidence that bank profits persist (Goddard, Liu, Molyneux, and Wilson, 2011). From equation (2), we identify the level of r that maximizes Π by setting the partial derivative of Π with respect to r equal to zero, i.e.,

$$\frac{\partial \Pi}{\partial r} = 0 => r = -\frac{a_1}{2a_2}. \tag{4}$$

Equation (2) also implies an unconstrained maximization problem for the managers. A major factor which is against this assumption is bank regulation. Regulation may either reduce (ceteris-paribus) the desired risk by a requirement in capital, i.e. the Basel Accord requires banks to hold capital of at least 8% of risk-weighted assets, or may increase the risk taken by providing implicit protection to “systemic” or “too-big-to-fail” banks (Kaufman, 2014). However, regulation constraints are time invariant and individual specific, i.e. the capital constraints apply ever since the first Basel Accord and very few banks show a dramatic change in status, thus are captured by the bank fixed effects v_i.

Also, bank herding behaviour, which may come from information contagion, can be described by cross section dependence and is captured by λ_t which is common across banks.

In this way, bank limited liability is also captured given its correlation with herding behaviour (e.g., Acharya and Yorulmazer, 2007).

An important distinction should be made here between the short- and the long-run objectives of the bank. Even though the distinction is somewhat blurry, most theoretical work on the objectives of the banking firm assumes a financial soundness constraint in place that implies long-term value maximization (e.g., Valencia, 2011). However, the majority of this work includes models that are static and have a short-term horizon based on expected profits, reflecting the idea of informational asymmetries due to agency problems (e.g., Jensen and Meckling, 1976). For example, because of information asymmetries between bank managers and owners or investors, the bank value can be driven by short-term results on profits, thus providing incentives to the bank managers to focus on these results at the expense of the long-term value-related targets of the bank.[2]

In line with the short-term profit-maximization literature, in our study we focus on the estimation of the optimal short-run bank credit risk. Thus, we do not provide any implications on the long-run equilibrium credit risk (where markets would clear) that maximizes value given a financial wealth constraint. We just provide inference on the potential short-run disequilibrium credit risk that bank managers would take to maximize short-term profits.

3. Data and estimation method

3.1. Data

We obtain bank-level quarterly data from the Federal Deposit Insurance Corporation (FDIC) Call reports. We start with the full sample of US commercial banks for the period 1996Q1 to 2011Q4, but we drop a number of observations where the values of our main variables are

[2] Clearly, short-term profit maximization does not necessarily increase shareholder value in the long run, a result that is well-documented also in the banking literature (Livne, Markarian, and Mironov, 2013, and Davies et al., 2014). However, studies like Keeley (1990) and Matutes and Vives (1996) suggest that in fairly competitive banking systems, such as the US one after the liberalization process in the late 1980s, the tradeoff between short- and long-term profit behavior favors the former.

quite unreasonable (e.g., negative values of bank assets). The reason our sample starts in 1996 is that data on risk-weighted assets, our main measure of risky assets, are unavailable before this date. Our final sample consists of 574,532 observations. Table 1 provides formal definitions for the variables used in the empirical analysis and Table 2 reports summary statistics.

[Insert Tables 1&2 about here]

We measure bank profits using the return on assets and equity in alternative specifications. While deciding on the risk strategy of banks, most bank managers consider the return on assets as the most important measure of bank profits (e.g., Hughes and Mester, 1994). In turn, a high return on equity is the primary objective of bank shareholders. Given that we are primarily interested in risk decisions, which are made by bank managers, we use the return on assets as our main dependent variable and provide sensitivity analysis on the basis of the return on equity.

Concerning the measures of high- and low-risk assets, we follow the regulatory definition of risky and riskless assets from the FDIC (2012). In particular, we use the ratio of risk-weighted assets to total assets (named *risk-weighted assets*) as our main proxy for the risky decisions of bank managers. In calculating this ratio different weights are assigned to different types of bank assets under the guidelines of the Basel Accord (e.g., Basel, 2011) and, thus, this ratio also encompasses information on the risk of the mix of different types of assets as in most theoretical banking models (e.g., John, Suanders, and Senbet, 2000). Further, *risk-weighted assets* measures *ex ante* as opposed to *ex post* risk of banks and this is the main reason it is favored by bank regulators and used in our empirical analysis. Specifically, our theoretical propositions on the optimal level of risk refer to *ex ante* bank risk, i.e. the risk position that bank managers obtain in a speculative manner to maximize profits. Naturally, at this time bank managers do not know the realized level of risk *ex post*.

The Basel accord also explains why using a risk-weight approach is the preferred methodology for the calculation of the risk position of banks. First, this ratio provides an easier approach to compare the riskiness of banks within and across countries; second, off-balance-sheet exposures can be easily included in capital adequacy calculations; and third banks are not deterred from carrying low risk liquid assets in their books. One could further differentiate between the various risky assets to obtain a more complex picture of the risk decisions of bank managers. For example, we may consider separate categories of loans bearing different risk weights under Basel II (e.g. Barakova and Pavlia, 2014). However, the purpose of this study is to identify the optimal bank risk for the average bank in terms of total credit risk and not to provide a complex analysis of the shares of various risky assets in bank portfolios.

The risk-weighted assets ratio is, however, criticized by a recent strand of literature on the basis of manipulation by banks or minimal sensitivity to market risk (e.g., Mariathasan and Merrouche, 2014; Vallascas and Hagendorff, 2013; Acharya, Engle, and Pierret, 2014). To this end, we examine the sensitivity of our findings by using the ratio of 30-89 days delinquent loans to total loans (*delinquent loans*) as an alternative *ex ante* measure of credit risk. This measure has the advantage that is not subject to over-manipulation by banks. However, this measure does not reflect the entire gamut of the credit risk activities by banks and might be less useful in its forecasting ability if delinquencies are the result of systemic risk hitting the banking industry and not the idiosyncratic behavior of each bank (i.e., delinquencies start to rise simultaneously with the systemic problems of the whole banking sector).[3] Further, delinquencies arrive after the "risk-taking" decision of bank managers to maximize profits: if managers new that the loans would fall into this category, the profit-maximization principle would imply the avoidance of the specific loan contracts.

[3] See e.g. Delis, Hasan, and Tsionas (2014).

To control for the riskless assets in bank portfolios we use the ratio of liquid assets to total assets (*liquidity*). Further, to avoid associating *ex ante* bank risk with risk arising *ex post*, we also control for the level of problem loans and loan-loss provisions (see Table 1 for explicit definitions). The inclusion of the problem-loans variable (named *problem loans*) suggests that bank managers make risk decisions today while knowing the level of problem loans in their portfolios. Similar to *problem loans*, the provisions variable (named *provisions*) does not capture the level of risk-taking *per se*, but it relates to managers' expectations about future losses in case of adverse developments (e.g. Bouvatier and Lepetit, 2012). Given that these expectations may or may not be realized, *provisions* represents another aspect of credit risk reflecting the level of bank managers' risk aversion. Thus, we assume that *problem loans*, *provisions*, and *risk-weighted assets* should be simultaneously included in our model, while we confirm in sensitivity analysis that exclusion of the former two variables does not yield significantly different results. Table 3.1 reports the pairwise correlation coefficients between the variables used in our empirical analysis for the full sample (the one using *risk-weighted assets*) and Table 3.2 the equivalent ones for the sample including *delinquent loans*. Evidently, the correlation coefficients between all the risk-related variables are quite small.

[Insert Tables 3.1 and 3.2 about here]

For the empirical estimation of equation (2), we use a number of additional bank-level control variables. In particular, we control for (i) bank size using the natural logarithm of real total assets (deflated by the GDP deflator), (ii) bank capital using the ratio of equity capital to the total assets (and/or the ratio of the risk-based capital to risk-weighted assets), and (iii) other sources of bank income using the ratio of the noninterest income to total income. The use of bank size and capital allow controlling for the profits arising from economies of scale and imperfections in capital markets, respectively. The noninterest income variable captures profits generated from nontraditional bank activities and is controlled for to prevent the risk-weighted assets variable from capturing the impact of these activities on bank profits (e.g. Karim, Liadze, Barrell, and Davis, 2013). All these are in line with the discussion of equation (2).[4]

An important feature of the data from the Call reports is that many of the variables display high seasonality. This is mostly the case with bank profits. Within each year, the lowest profits are observed on average in quarter 1 and the highest profits are observed in quarter 4. A similar pattern is observed to a different degree with many other of our bank-level variables. To avoid introducing a bias in our results because of the differences in the level of seasonality between the dependent and explanatory variables, we seasonally adjust the data. Specifically, we estimate equations of the form

$$x_{it} = b_0 + b_1 D_2 + b_2 D_3 + b_3 D_4 + \varepsilon_{it}, \tag{5}$$

where x_{it} is one of Π_{it}, r_{it}, c_{it} and D_2, D_3, D_4 are equal to 1 in quarters 2, 3, and 4, respectively, and zero otherwise. The estimation method for equation (5) is OLS on the fixed effects model. Then, we calculate the seasonally adjusted variables as

$$x_{it}^{adj} = \hat{\varepsilon}_{it}. \tag{6}$$

In some of the estimated equations, where we do not use time effects as in equation (3), we include a number of variables common to all banks that characterize the macroeconomic environment. First, we capture the changing macroeconomic conditions using the GDP growth rate. Second, we use the ratio of the dollar value of loans provided by commercial banks over GDP. This variable captures changes in the average credit conditions nationally.[5] These variables drop out when using time effects; thus, we employ them only to check the robustness of our results. Our data source for these variables is the Federal Reserve.

[4] We experiment with many other bank-specific control variables, such as the ratios of loans to assets, loans to deposits, and cost to income. The main results remain unaffected.
[5] We experiment with many other macroeconomic variables as well as with regional dummies, etc. The results remain unaffected and are available on request.

3.2. Estimation of the profitability equation

It is widely recognized in the banking literature that bank characteristics like risk and capital are endogenous in the profitability equation. A first concern, which is the most important in our case, relates to reverse causality. For example, a profitable bank will use part of the profits made at time *t* as loanable funds and another part as capital, creating an obvious reverse causality mechanism between banks' returns and risk and equity capital. The richness of the data set (especially the quarterly time dimension) allows us to mitigate problems arising from reverse causality by using the first lags of the explanatory variables instead of their contemporaneous values. Thus, we assume that the bank characteristics at quarter *t*-1 determine profits at time *t*.[6] In this sense, we can rewrite equation (2) as

$$\Pi_{it} = a_0 + b\Pi_{it-1} + a_1 r_{it-1} + a_2 r_{it-1}^2 + a_3 c_{it-1} + u_{it}. \tag{7}$$

Equation (7) is in line with the theoretical suggestion that bank managers decide on the level of credit risk today to materialize returns in a future date (e.g., Agur and Demertzis, 2012). To capture a different time pattern, where credit risk today materializes in returns at another quarter in the future, we also experiment with the fourth time lag on *r* and we show that this does not affect the results. Assuming no other source of endogeneity for the right-hand-side variables, we can estimate equation (7) with OLS on the fixed effects model with robust standard errors (e.g., Berger, Hasan and Zhou, 2010).[7]

However, another source of endogeneity can arise from omitted variables bias. For example, risk-weighted assets and bank profits can move in the same direction owing to changes in the structural and macroeconomic conditions common to all banks. Further, it

[6] It would be more problematic to establish causality if we had annual data. In that case, profits would have been determined by the bank's characteristics in the previous year. However, in empirical banking studies, one year can be a time period within which major changes can occur that affect bank performance.

[7] As is well-known in the econometrics literature, estimation of an equation like (7) with a fixed effects model is, in general, inconsistent because of the correlation between the fixed effects and the lagged dependent variable. However, for panels with large time and cross-sectional dimensions, the estimates from different methods converge (Baltagi, 2008). We confirm this in the empirical analysis below.

could be the case that the relationship between risk-weighted assets and banks' returns is affected by certain bank characteristics that are not controlled for in the empirical model. However, note that the empirical model includes both bank and time fixed effects, and these should lessen such a bias. To confirm that this type of endogeneity does not drive our results, we also use instrumental variables procedures such as the limited information maximum likelihood (LIML) for panel data with robust standard errors or the two-stage system generalized method of moments (GMM) of Blundell and Bond (1998) with robust standard errors (correction of Windmeijer, 2005).

LIML is a two-stage procedure that requires at least one instrumental variable that does not have a direct effect on bank profitability or an effect running through omitted variables (i.e., validate the exclusion restriction). To this end, we use the implications of the recent literature on the risk-taking channel of monetary policy (e.g., Ioannidou, Ongena, and Peydro, 2014; Delis, Hasan, and Mylonidis, 2011). This literature shows that low interest rates increase the average risk-taking behavior of banks for three main reasons. First, a shift from a high to low interest rate environment could leave financial institutions with long-term fixed rate contracts, seeking out riskier investments in an attempt to meet their liabilities (search-for-yield effect). Second, low rates boost asset and collateral values and tend to reduce price volatility, which in turn downsize bank estimates of probabilities of default and encourage higher risk positions (Borio and Zhu, 2008). Third, the commitment, for example, of a central bank for lower (future) interest rates in the case of a threatening shock reduces the probability of large downside risks, thereby encouraging banks to assume greater risk (transparency effect). Given the above, there should be a direct impact of monetary policy on banks' credit risk.

In addition, the exclusion restriction is validated if there is no significant correlation between the monetary policy variable and the stochastic term u in (7). One may argue that bank profits could in fact react to a change in monetary policy (i) if this change is correlated with the general structural and macroeconomic conditions and (ii) through the noninterest income that is excluded from the risk-weighted assets. Concerning the first argument and in addition to the use of time fixed effects, we consider the exogenous monetary policy shocks. These are estimated using the so-called Taylor rule residuals obtained from the OLS regression of the federal funds rate on GDP growth and inflation (e.g., Maddaloni and Peydro, 2011; Brissimis, Delis, and Iosifidi, 2012). Concerning the second argument, the inclusion of noninterest income among the control variables reassures that the exogenous monetary shocks are not correlated with profits through their impact on sources of bank profits other than interest income.

For the estimation of equation (7) using GMM, we augment the Taylor rule residuals with the second lags of all explanatory variables as instruments. By including the second lags as instruments (and not the first), we assume that all explanatory variables might be, to some extent, endogenous regressors in equation (7). This set of instruments produces acceptable values for the test for second-order autocorrelation and for the Hansen test for overidentifying restrictions (for details on these issues, see Roodman, 2009).

However, before moving on to the analysis of the estimation results, we should note that what we seek is the robust estimation of the optimal level of credit risk from equation (4) given (2). We will show below that all three estimators considered (OLS on the fixed effects model, LIML, and GMM) yield more or less the same values for the optimal credit risk. We primarily attribute this to the fact that *in very large panels* such as ours, *the results from all estimators converge* and the fixed effects estimator becomes consistent as the time dimension of the panel increases (Baltagi, 2008). Therefore, in our setting, even the simplest estimation methods, such as OLS, seem to produce robust estimates of the optimal credit risk.

4. Estimation results for the optimal credit risk

4.1. Baseline estimation results and robustness

Table 4 reports the results from the estimation of alternative specifications of equation (7). In all regressions, the dependent variable is the *return on assets*, except from that in column (10), where we use the *return on equity*. In line with the discussion in Section 2.1, all the results verify that the relationship between credit risk and bank profitability is an inverted U-shape. In column (1), we start with a very simple model, which is estimated by OLS and fixed effects. In column (2), we add quarter fixed effects. The results from these first two specifications yield values for the optimal level of credit risk equal to 0.666 and 0.717, respectively (we report the optimal point in the line below the results for the coefficient estimates). The first value is approximately equal to the mean value of *risk-weighted assets* in our sample (see Table 2), and the second is slightly higher, showing that the average bank in our panel could benefit by taking on a slightly higher amount of credit risk.

[Insert Table 4 about here]

In columns (3) and (4), we introduce a number of bank-level control variables in the equations with and without quarter fixed effects, respectively. The results show a slight decrease in the value of the optimal credit risk in the model without quarter effects, while the optimal point in the model with quarter effects is about the same as the equivalent in column (2). We feel that this pattern in the results comes from the importance of including quarter fixed effects in reducing the omitted variables bias. Moreover, in column (5), we drop the quarter effects and add year effects among the explanatory variables, and this yields very similar results to those in column (4). Further, in columns (6) and (7), we introduce the two macroeconomic variables, named *Growth* and *Credit by banks*. To do this, we drop the quarter effects (due to collinearity) and only add year effects in column (7). Evidently, both the coefficient estimates and the level of optimal bank credit risk remain practically unaffected.

So far, we have estimated equation (7) using OLS. We now relax the assumption that there is no endogeneity arising from omitted variables bias and use LIML and GMM for dynamic panels. We present the results from these regressions in columns (8) and (9). The results from the LIML and GMM estimates show that the optimal level of credit risk is 0.7 and 0.727, respectively. Thus, the optimal level of credit risk is not significantly driven by the estimation method. We also confirm this finding for the other specifications of equation (7). This is an expected finding because for large panels the results from all estimators converge (Baltagi, 2008). Thus, the OLS model with bank fixed effects and quarter fixed effects seems to be sufficient to robustly estimate the optimal level of credit risk, and is the one favored in the rest of the specifications owing to its simplicity and asymptotic efficiency.

In column (10) we examine the sensitivity of the results to the use of the *return on equity* as the dependent variable. We find that the optimal level of credit risk is equal to 0.715, which is almost equal to the equivalent specification with the return on assets as the dependent variable, i.e., that in column (4). Further, in column (11) we control for the bank regulatory capital ratio instead of the total capital ratio and in column (12) we control for both ratios. The reason is that safety and soundness might not be based only on total equity capital but also on regulatory capital. The two ratios have a correlation coefficient equal to 0.82 (see Table 3.1) and the results in columns (10) and (11) of Table 4 are a clear indication of collinearity. Importantly, however, the optimal level of risk remains at levels approximately equal to those of the previous regressions.

In Table 5 we examine the sensitivity of our results to the use of *delinquent loans* as our measure for bank credit risk. The inverted U-shaped relation between risk and returns continues to hold. Also, the optimal points on the delinquent loans are somewhat above the average of delinquent loans (equal to 0.013), irrespective of whether we control for the major loan categories (see column 2) or whether we use the return on equity instead of the return on assets.

[Insert Table 5 about here]

As a final sensitivity analysis of these baseline results, we consider whether the optimal level of credit risk changes when we assume a different time structure for our data or a different lag structure for *risk-weighted assets*. We first use annual and bi-annual averages of our data, instead of quarterly data. This allows examining whether bank managers have a longer-term horizon in their decision-making on credit risk.[8] We report the results in columns (1) and (2) of Table 6 and we find that the results are equivalent to those of Table 4.

Next, we report the results from a model where the lagged dependent variable is excluded from the analysis (column 3 of Table 6). The coefficient estimates on *risk-weighted assets* and its squared term gain somewhat in economic significance, but the optimal point is not significantly affected. Further, we simultaneously use the first three lags of *risk-weighted assets* and its squared term in column (4). This specification implicitly assumes that the risk decisions of bank managers in quarters t-1 to t-3 affect bank performance at time t. Adding up the coefficients from the three lags and taking the derivative as in equation (4) yields an optimal level of credit risk very similar to that reported in Table 4.

Finally, in column (5), we report the results from the specification where *risk-weighted assets* and its squared term are lagged four times (i.e., we use the annual lag). In this specification, we assume that the risk decisions of banks at quarter t-4 affect the profitability at quarter t. Under this assumption, the level of the optimal credit risk equals 0.67, which is only 0.04 points lower than the one identified in column (4) of Table 4. We consider many other variants for the lag structure of the risk-weighted assets, including the simultaneous

[8] Using annual and bi-annual data also allows reducing our sample size and examining the sensitivity of the main regression coefficients and the optimal point of credit risk.

inclusion of the first four, first eight, and first 16 lags. Changes in the optimal level of credit risk are not significant and these results are available on request.

[Insert Table 6 about here]

In Table 7 we extend our analysis by using subsamples of banks based on their size and capitalization. The first regression is based on a subsample of banks with total assets above the 90th percentile of the full sample, while the second regression on banks with total assets below the 50th percentile (a summary of these percentiles with the corresponding cut-off values is given in Table 8). The results show that the large banks have a lower optimal point compared to the small banks, which is intuitive given their more complex organizational structure, the wider array of products, and the increasing holdings of short-term assets that bear lower risk weights.[9] In turn, columns (3) and (4) report the equivalent results for the well-capitalized and the poorly-capitalized banks, respectively. In line with our expectations, we find that poorly capitalized banks have a lower optimal level of credit risk (these banks have a lower capacity to take on credit risk).

[Insert Table 7 & Table 8 about here]

So far, we have identified that the optimal level of credit risk for the average bank in our sample is between 0.69 and 0.71 for the most prominent specifications of equation (7). These values are somewhat higher than the actual value of risk-weighted assets for the average bank, showing that banks could on average gain in their short-term profitability by increasing their risk. The coefficient estimate in column (4) of Table 4 shows that a one standard deviation increase in *risk-weighted assets* will increase the *return on assets* of the average bank by approximately 0.04 points (up to the point where *risk-weighted assets* equals 0.71). Thus, for example, a 0.04 increase in *risk-weighted assets* from 0.67 to 0.71 will raise the *return on assets* by approximately 0.0016. Considering that the return on assets for the

[9] We carry out the same analysis using the 50bn USD as the threshold for large banks (instead of the 90th percentile). The results are very similar to those reported in column (1) of Table 6.

average bank equals 0.007, this is a very large increase (approximately equal to 23%). Of course, this result is valid under the assumption that the optimal point is constant across time and banks with different characteristics. We relax this assumption below.

4.2. Time-varying optimal credit risk

In this section, we consider whether the optimal level of credit risk varies with time. To identify this time-varying optimal level, we consider estimating the equation

$$\Pi_{it} = a_0 + b\Pi_{i,t-1} + a_1 r_{i,t-1} + a_2 r_{i,t-1}^2 + a_3 c_{i,t-1} + \sum_{j=3}^{T} f_j\, q_j r_{i,t-1} + \sum_{j=3}^{T} g_j\, q_j r_{i,t-1}^2 + \sum_{j=3}^{T} h_j q_j + u_{it}\,, \qquad (8)$$

where q_j are quarter dummies. Therefore, in equation (8), we obtain time-varying coefficients for r and r^2 by interacting these variables with the quarter fixed effects.[10] Subsequently, we calculate the optimal level of credit risk at each quarter t from the equation

$$\frac{\partial \Pi_t}{\partial r_{t-1}} = 0 => r_{t-1} = -\frac{a_1 + f_j}{2(a_2 + g_j)}\,. \qquad (9)$$

In Table 9, we present the estimation results from three different specifications of equation (8).[11] In the first two columns, we present the results from equations with the return on assets and the return on equity as dependent variables. In column (3), we present the equivalent results when we use *delinquent loans* instead of *risk-weighted assets*.

[Insert Table 9 about here]

In Figure 1, we plot the time-varying coefficient estimates (solid line), along with associated confidence intervals, against the quarterly average of *risk-weighted assets* (realized credit risk). Clearly, the two are not equal, reflecting a short-term disequilibrium in the handling of risk-weighted assets by bank managers. The quarterly trend of the optimal

[10] One could instead consider a time-varying model (e.g., Swamy, 1970). However, this class of models does not run for a panel with a size such as ours using a CORE i7vPro processor and 6.00 GB of RAM.
[11] Owing to space considerations, we do not replicate the full set of results in Tables 4 to 7. We rely on the equivalent specifications to the ones presented in columns (4) and (10) of Table 4 and of column (1) of Table 5. Similar to the findings in Section 3.1, changes in the results from using the other specifications are insignificant.

risk reveals an interesting pattern. During the relatively good periods for the economy, the optimal level of credit risk is above the average credit risk, while the opposite is true after relatively bad periods. For example, consider the period before the attack on the World Trade Centre in 2001. For about two years after the attack, the optimal level of credit risk remained below its average value. Subsequently, in most of the period 2003–2007, which is a period of considerable expansion in risk-weighted assets, the optimal credit risk is again higher than the average. Finally, since 2008, the optimal credit risk remains at the lowest level of our sample period, well below the realized level of credit risk.

[Insert Figure 1 about here]

This observed pattern has a number of economic implications. First and most obvious, the optimal level of credit risk leads the business cycle, while the realized credit risk follows the business cycle closely. Second, during good economic periods, the average bank has clear incentives to take on higher credit risk to maximize profits. However, this optimal bank behavior changes very quickly when adverse shocks hit the economy, leaving banks exposed to higher than optimal levels of risk. This stems from (i) the standard issue of maturity mismatch between bank assets and liabilities, (ii) the changing informational asymmetry (moral hazard and adverse selection) over the business and credit cycles, which cause changes in the efficient intermediation of funds (e.g. Duran and Lozano-Vivas, 2014), and (iii) the herding behavior of banks, which can cause by itself a disequilibrium situation in the risk-taking behavior of the banking sector. It is fairly obvious from Figure 1 that banks could not lower the level of credit risk close to the optimal level when the depth of the financial crisis became apparent in 2008. This is most probably owing to the fact that banks could not lower the volume of long-term loans, many of which were in fact nonperforming.

There are two more implications emerging from Figure 1. On the one hand, the average bank has clear economic incentives to take on higher credit risk during good economic times in search for yield. Yet, what is optimal from the micromanagerial perspective is far from optimal from the macroprudential perspective. Phrased differently, the level of credit risk that maximizes bank profits can be unsustainable in the long run, either because of the inability of banks to adjust their portfolios quickly in case of adverse developments or because of myopic behavior attributed to herding. On the other hand, the average bank does not have to be the one causing the crisis. It can take only a small number of very risky players to increase systemic risk to very high levels. Therefore, the fact that the optimal credit risk is higher than the realized one for some time before 2007 does not necessarily mean that this average bank behavior caused the subprime meltdown. Clearly, this requires additional analysis.

We can check this latter hypothesis by examining the risky behavior of the banks that failed in the period 2008–2009. In Figure 2, we replicate Figure 1, but we also add the quarterly average of risk-weighted assets of the banks that failed. Evidently, these banks have an average ratio of risk-weighted assets higher than the optimal level in almost the entire 2001–2008 period. This observation makes a case for bad managerial decisions for the involved banks, lack of private monitoring and market discipline, as well as inefficient supervision.

[Insert Figure 2 about here]

In Figure 3 we examine the time path of the optimal credit risk using *delinquent loans* as our credit-risk measure (coefficients obtained from column 3 of Table 9). Even though *delinquent loans* have only increased contemporaneously with the eruption of the crisis in 2007 (i.e., this measure does not capture the increase in bank risk in the period 2002-2006), we do find evidence (with a lag) for a similar cyclical pattern for the optimal credit risk. Specifically, in the period 2005-2007 the optimal credit risk is above the mean delinquent loans, while from 2008 onward the optimal value falls below the mean *delinquent loans*. The lag in this cyclicality vis-à-vis the findings on *risk-weighted assets* reflects the fact that the latter measure of credit risk better proxies, for the goals of our study, the *ex ante* risk-management decisions of bank managers.

[Insert Figure 3 about here]

In Figures 4 to 7 we plot the time-varying coefficient estimates from the results of Table 10. Figure 4 shows the optimal credit risk for the large banks and reveals that this optimal level fares very close to the average level of *risk-weighted assets*. In contrast, Figure 5 shows that it is the medium and smaller banks that mostly generate the cyclical behavior of optimal credit risk shown in Figure 1. Similarly, we find a major difference between the time paths of optimal credit risk for the well- and the poorly-capitalized banks (Figures 6 and 7, respectively). For the well-capitalized banks, the time path looks quite similar to the one of Figure 4. In contrast, for the poorly-capitalized banks the optimal credit risk is lower than their average in the period 2005Q3 to 2008Q1.

[Insert Table 10 & Figures 4-7 about here]

These findings have some important implications. First, the large, systemically important banks seem to have the technological expertise to operate closer to their risk-taking capacity in both good and bad economic periods. However, this also reveals that they are on average more risky compared to the smaller banks that have a substantial gap between the optimal and the realized credit risk in normal economic periods. Second, the poorly-capitalized banks "gamble for resurrection" in the period before the eruption of the crisis. This finding is in line with the theoretical implications of Murdock, Hellmann and Stiglitz (2000) and calls for better regulatory monitoring of the risk-taking behavior of the banks with low levels of capital.[12]

[12] On the same line, Delis, Staikouras, and Tsoumas (2013) show that high risk-weighted asset ratios tend to attract supervisory intervention, albeit in a rather delayed manner that amplifies the risk of insolvency.

5. Optimal credit risk and the macroeconomic environment

5.1. Theoretical considerations

The subprime financial and the subsequent euro-area crises recalled, in the most emphatic way, the importance of the banking sector in shaping macroeconomic outcomes. In Figure 1 we infer that the cyclicality of the optimal bank credit risk is a leading indicator of the business cycle and that realized credit risk is procyclical. Thus, the two indicators allow drawing some new insights into the interplay between banks' risk and the monetary and macroeconomic environment.

In Section 3.2, we highlight the main mechanisms through which low interest rates can increase bank risk and show that the empirical literature rules in favor of a negative relation between monetary policy rates and bank risk. The theory behind the risk-taking channel of monetary policy provides more mixed results. The models typically assume that banks choose their asset mix and leverage to maximize profits (e.g., Agur and Demertzis, 2012; Dell' Ariccia, Laeven, and Marquez, 2014). This setup allows banks to choose between a continuum of risky assets and different risk profiles. In either way, these theoretical frameworks predict that the nexus between monetary policy and bank risk depends on many factors, including the relative health of the banking system, the efficiency level of banks, and the state of the macroeconomic environment.

From our viewpoint, the studies by Agur and Demertzis (2012; 2013) are quite important in that banks choose their asset profile according to their efficiency. This is relevant to our empirical model in that inefficient banking can cause deviations from the optimal level of risk. Thus, by affecting both the cost of debt financing (thus also the realized credit risk) and the optimal debt choice of the bank, monetary policy can affect the gap between the realized and the optimal credit risk. The issue here is that an expansionary monetary policy positively affects asset and collateral values, and banks appear to have less risky portfolios. In other words, this mechanism is about the risk already present in bank portfolios and not solely about new risk. Our measures of realized and optimal credit risk correspond exactly to this theoretical interpretation of the nexus between monetary policy and bank risk, making our variables ideal to study the macroeconomic implications of optimal *vs.* realized credit risk.

In this framework, our analysis is concerned with testing macroeconomic equilibrium relationships among the monetary conditions, realized credit risk taken by banks, and optimal risk that maximizes bank profits within a time-series setting. This strategy has the obvious advantage of considering a limited number of variables and using all these variables as endogenous. With these issues in mind we proceed to the time-series empirical analysis.

5.2. Empirical analysis

We capture the complex interactions between the relevant variables with a system of equations approach, which allows for rich dynamics; namely, we apply an atheoretical VAR model. This model is used instead of the usual structural simultaneous equation model because the underlying theory dictating the variables in the structural system of equations for the subject at hand has not yet been well-established. In this way we avoid the *a priori* distinction between endogenous and exogenous variables and we do not have to impose arbitrary constraints to ensure identification. Given that many of the relevant variables are non-stationary, a variant of the VAR model will be used, namely the VECM (see also Granger, 2004).

The VECM takes the form

$$\Delta Y_t = c + FY_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + e_t \, , \tag{10}$$

where Y is the (4X1) vector of endogenous variables, F and Γ_i are (4X4) matrices, and p is the lag length of the corresponding VAR. The disturbances e_t are assumed to follow a four-dimensional Gaussian process with a zero mean and a nonsingular, finite, covariance matrix Ω. The four endogenous variables we use are (i) the federal funds rate (*ffr*) as our measure of the monetary conditions,[13] (ii) the series of the optimal bank risk (*optimal risk*), (iii) the series of the realized bank risk (*realized risk*), and (iv) real output (measured by the log of real GDP).

The results from two unit root tests, namely the Augmented Dickey Fuller (Said and Dickey, 1984) and the GLS Dickey Fuller (Elliott et al., 1996) tests, show that all four variables are stationary in first differences (Table 11). Thus, the above series are well-modeled by unit root processes and the use of the VECM model is necessary.

Two or more unit root processes may behave erratically at the individual level but there may be a surprising relationship that binds them together: their distance is never too big. This means that in the long run there is an equilibrium, which can be described from the model $y_t = \beta x_t + u_t$, where $y_t = \beta x_t$ is the relation between the two variables in equilibrium and u_t is the stationary error term describing the short-run deviations from this equilibrium. If such a long-run relationship exists then, in the time-series terminology, the variables are said to be cointegrated and $[1 \ \beta]'$ is called the cointegrating vector, which determines the long run equilibrium.

To test for cointegration, we employ Johansen's (1988) system approach. We consider all possible lag orders selected by the model selection criteria, namely the Akaike Information Criterion, the Schwarz-Bayesian Information Criterion, the Final Prediction

[13] Given that in the VECM, all variables are allowed to be endogenous by definition, we use the federal funds rate instead of the Taylor rule residuals that we used as an instrumental variable above (e.g., Buch, Eickmeier, and Prieto, 2010). Note that since the impact of policy shocks is through bank risk (either credit risk or noninterest income), the inclusion of the federal funds rate as an independent variable in equations (7) and (8) would not have any implications for the modelling choices in identifying the optimal level of bank risk. If anything, this would be owing to multicollineartiy, which we do not find to be present.

Error Criterion, and the Hannan-Quinn Information Criterion. These criteria are asymptotically equivalent but their results may vary in small samples. In theory, selecting the number of lagged differences to be smaller than the correct one will distort the size of the tests, while selecting orders greater than the correct one will result in loss of power. Given the sample size, the maximum possible lag order is set to four.

[Insert Table 11 about here]

When testing for the rank of the full system at the 5% level, the results show two cointegrating vectors if the selected lag length is one and one cointegrating vector if the selected lag length is two. We end up choosing a lag length equal to two, because selecting a lagged order smaller than the true results in inconsistent tests. Thus, our analysis considers the following (one) cointegrating relationship:

$$\begin{bmatrix} 1 & \beta_1 & \beta_2 & \beta_3 \end{bmatrix} \begin{bmatrix} output \\ ir \\ realized\ risk \\ optimal\ risk \end{bmatrix}. \tag{11}$$

The tests so far provide evidence in favor of a long-run equilibrium between the four variables; however, this equilibrium must be estimated. In other words, we need to estimate the cointegrating vector, i.e., the betas in equation (11). These betas exist inside the matrix F in model (10). Thus, we estimate the VECM using the reduced rank procedure of Johansen (1995) and provide the estimation results in Table 12. For the optimal lag order, we again consider all four information criteria. However, these criteria disagree, providing values equal to either zero (for the Schwartz criterion) or four (for the other three). We choose the most general order of four lags.

[Insert Table 12 about here]

Table 12 reports the estimation results of the cointegrating vector. Based on the estimation results we can rewrite the cointegrating relationship as:

$$output = -0.352*ffr - 15.982*realized\ risk + 22.819*optimal\ risk \tag{12}$$

The above coefficients can be interpreted in the following way: in the long run, where the system is in equilibrium, an increase by 1% in the federal funds rate will result in a 0.352% drop in output growth. All coefficients are statistically significant at conventional levels. The post-estimation Lagrange-multiplier tests by Johansen (1995) show that there is no autocorrelation in the residuals.[14] The Jarque-Bera test for normality does not reject the null hypothesis of normal residuals in any of the four equations.[15] Finally, we examine the stability of the coefficients of the model to guarantee that these are not affected by structural breaks. In Figure 8 we show the results for the recursive eigenvalue test of Hansen and Johansen (1999). The test does not reject the hypothesis of the long-run parameter stability of the eigenvalue at the 5% level.

[Insert Figure 8 about here]

Besides the long-run equilibrium, from the estimated VECM model we also infer the short-run adjustment mechanism that describes how the variables will react when they are pushed out of the long-run equilibrium by an exogenous shock or innovation. The following analysis uses the estimated VECM to examine how variables in the system respond to a shock (impulse) in one of them. We are primarily interested in the orthogonal impulse responses involving the theoretical considerations discussed in Section 5.1, which we present in Figures 9 to 11. Figure 9 shows that the realized credit risk responds positively and significantly to a positive change in the optimal credit risk. This effect is apparent even from Figure 1 and is intuitive: When banks view that their optimal strategy to maximize profits is to take on higher credit risks, they are willing to do so in the next quarter.

[Insert Figures 9-11 about here]

Figure 10 shows the response of the realized credit risk to a monetary policy shock. In the first five to six quarters, a monetary contraction (rise in the interest rate) reduces banks'

[14] The p-values for two additional lags are 0.076 and 0.41.
[15] The Jarque-Bera p-values for the four equations are 0.28, 0.06, 0.39, and 0.46.

risk and *vice versa*. This result confirms the findings of the empirical literature on the risk-taking channel of monetary policy (Ioannidou, Ongena and Peydro, 2009; Delis, Hasan and Mylonidis, 2011). However, Figure 11 shows that a negative monetary policy shock (rise in the interest rate) raises the optimal risk-weighted assets of banks. The response is a positive and statistically significant one, which lasts over the long-term. The level of the increase is also economically significant. A one standard deviation increase in the federal funds rate will increase the optimal risk-weighted assets by approximately 0.010 points in the first year and for each year thereafter. For a bank with an optimal level of risk-weighted assets, as given by specification (4) of Table 4, this will imply a rise of the optimal level from 0.711 to 0.723, which is indeed a large fluctuation for one year.

An explanation for this finding is that a reduction in the policy rate leads to lower deposit rates. Because the loan demand is negatively sloped, the reduction in deposit rates is only partially passed to the lending rates. This increases the intermediation margin and provides banks with incentives to take on higher risks, because expected profits will also be higher. Given the implications of Figure 10, banks will do so in the next period, and this diminishes the original negative shock presented in Figure 11 after period six. Thus, we offer an additional mechanism working along with the negative effect of monetary policy on banks' risk.

The most interesting implication of this case comes from the fact that a monetary policy shock tends to pull the realized and the optimal credit risk further apart in the short run. Phrased differently, the optimal monetary policy from a business-cycle perspective will always widen the gap between the realized and optimal credit risk of banks, pushing banks out of equilibrium. To see this, consider the following sequence of events. In good economic periods, interest rates are higher to prevent the economy from over-burning. Based on our impulse responses, the rise in interest rates will lower the realized credit risk (Figure 10) and increase the optimal credit risk (Figure 11). Given that in these periods, the optimal credit risk is usually higher than the realized credit risk (Figure 1), the gap between the two widens. A similar result emerges in bad economic periods, where the optimal monetary policy is to cut rates. This leads to an increase in the realized credit risk and a fall in the optimal credit risk. Given that in these periods, the realized risk is higher than the optimal risk, the result is again a widening in the gap between the two.

Another mechanism through which changes in the monetary policy rate distort the equilibrium risk behavior of banks relates to the interest-rate risk. This is the risk that the value of real assets will change owing to a change in the absolute level of interest rates, in the spread between two rates, in the shape of the yield curve, or in any other interest rate relationship. Naturally, all these interest rates are affected by the central bank rate. Our analysis is then consistent with the idea that following a monetary policy shock, it takes banks considerable time to adjust their valuation of assets and determine the optimal level of credit risk. In the meantime, the average bank either does not have the capacity to estimate the effect of interest-rate risk on its portfolio and determine its actual level of credit risk in the very short run or maturity mismatch does not allow the bank to quickly adjust in light of the monetary shock. This is also the essence of the theoretical model of Agur and Demertzis (2013) who show that because bank risk cannot be easily adjusted in the short run, monetary policy cuts should be short-lived to prevent excessive risk buildup.

In the VECM presented above, one can include a measure of bank capitalization or other macroeconomic variables, such as the inflation rate or a measure of monetary aggregates. This exercise yields very similar results, which are available on request. In addition, one can use the rest of the time series produced by the other specifications in Tables 8 and 9 or the equivalent ones in Tables 4-7. Again, the results are qualitatively and quantitatively similar. One can further infer on the effect of the monetary-policy-induced disequilibrium in banks' optimal risky strategy on real output. Our results show that the widening of the gap increases output in good economic times and decreases output in bad economic times. In other words, monetary policy can increase macroeconomic fluctuations through its impact on "disequilibrium banking." However, we should treat this result with caution as general implications for the real economy would probably need a more lengthy time series with additional business cycles.

6. Conclusions and policy considerations

This paper identifies for the first time the level of banks' credit risk that maximizes profits using the full sample of US banks over the period 1996Q1–2011Q4. This optimal (equilibrium) level of credit risk is different from the actual realized credit risk present in bank portfolios and reflects the level of credit risk a bank would take if it were to function in a fully-efficient profit-maximizing way and perfectly forecast the upcoming macroeconomic conditions, while prudential regulation would assist banks toward these goals. This "idyllic" situation would essentially reduce the probability of default to a minimum, primarily by reducing the effects of maturity mismatch and fluctuating asymmetric information on the probability of bank default.

We show that the optimal credit risk for the average bank leads the business cycle, while the realized credit risk closely follows the business cycle. In good economic periods, which are characterized by credit expansion, the optimal credit risk is higher than the realized risk, while this picture completely reverses in bad economic periods. Subsequently, using an error correction model, we demonstrate that the optimal monetary policy in smoothing the business cycle always leads to an increase in the gap between the equilibrium and realized credit risk of banks. This is because a contractionary monetary policy in good economic periods, where the optimal credit risk is higher than the realized risk, decreases the realized credit risk but increases the optimal credit risk. Similarly, an expansionary monetary policy in bad economic periods, where the optimal credit risk is lower than the realized risk, increases the realized credit risk but decreases the optimal credit risk.

In essence, our results offer another point in favor of the proponents of counter-cyclical bank regulation in the form of capital requirements and of those suggesting that monetary policy should lean against the wind. The obvious implication is that monetary policy and prudential regulation need to be closely linked to prevent the disequilibrium situation described in this paper. In fact, there are three choices: the conduct of monetary policy will incorporate elements of bank risk and financial stability or prudential bank regulation will be cyclical, or both. Strong steps toward the implementation of monetary policy within a framework that encompasses elements of prudent bank behavior have recently been enacted by the European Single Supervisory Mechanism. Within this mechanism, the prudent behavior of systemic European banks and the monetary tasks of the European Central Bank take place in the same body (the Governing council), awarding monetary policy a flavor of financial stability for the first time in the history of the European Monetary Union.

These suggestions have their own merits and drawbacks and the literature on this issue is flourishing. For example, Angeloni and Faia (2010) employ a standard dynamic stochastic general equilibrium framework extended to incorporate the banking sector and show that the best policy (out of a set of policies that they consider) for crisis prevention is the combination of mild anti-cyclical capital requirements and a monetary policy that reacts to inflation and “leans-against-the-winds.” Similar results are obtained by Gambacorta and Signoretti (2012). It is apparent that more work is required on the real outcomes of the pass-through of monetary policy through banks. It is also apparent that the implementation of the new banking regulation regime under Basel III should consider the effects of monetary policy in shaping equilibrium bank behavior.

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Table 1
Variable definitions and sources

Notation	Measure	Data source
A. Dependent variables		
Return on assets (ROA)	Total bank profits before tax/ total assets	Call reports
Return on equity (ROE)	Equity capital/ total assets	Call reports
B. Explanatory variables		
Risk weighted assets	Risk-weighted assets/ total assets	Call reports
Risk-based capital ratio	Total risk-based capital/ risk weighted assets	Call reports
Bank size	Natural logarithm of real total assets	Call reports
Capital	Equity capital/ total assets	Call reports
Liquidity	Liquid assets (cash and short-term government bonds)/ total assets	Call reports
Non-interest income	Non-interest income/ total income	Call reports
Problem loans	Non-performing loans (>90 days)/ total loans	Call reports
Provisions	Loan loss provisions/ total loans	Call reports
Growth	GDP growth rate (annual %)	Federal Reserve
Credit by banks	Loans provided by commercial banks/ GDP	Federal Reserve
Federal funds rate	The effective federal funds rate	Federal Reserve
CPI	Consumer Price Index	Federal Reserve
Delinquent loans	30-89 days delinquent loans/ total loans	Call reports
Commercial loans	Commercial loans/ total loans	Call reports
Loans to individuals	Loans to individuals/ total loans	Call reports
Real estate loans	Real estate loans/ total loans	Call reports
Other loans	Other loans/ total loans	Call reports

Table 2
Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
ROA	574,532	0.007	0.010	-0.257	0.488
ROE	574,532	0.077	0.103	-1.994	1.970
Risk-weighted assets	574,532	0.670	0.132	0.100	0.998
Risk-based capital ratio	574,532	0.178	0.136	-0.344	9.228
Bank size	574,532	11.786	1.367	6.889	21.584
Capital	574,532	0.107	0.053	-0.242	1.000
Liquidity	574,532	0.060	0.063	0.000	0.909
Non-interest income	574,532	0.111	0.087	0.000	1.000
Problem loans	574,532	0.008	0.017	0.000	0.748
Provisions	574,532	0.015	0.010	0.000	0.748
Growth	574,532	0.024	0.020	-0.046	0.052
Credit by banks	526,497	959.1	354.2	510.7	1,796.4
Federal funds rate	574,532	3.245	2.139	0.073	6.520
Consumer price index	574,532	0.610	0.529	-2.300	1.600
Delinquent loans	329,126	0.013	0.014	0.000	0.385
Commercial loans	99,820	0.142	0.089	0.000	0.929
Loans to individuals	99,820	0.077	0.074	0.000	0.966
Real estate loans	99,820	0.680	0.178	0.007	0.999
Other loans	99,820	0.100	0.132	0.000	0.855

Table 3.1
Full Sample Correlations matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1. Risk-weighted assets	1.000											
2. Risk-based capital ratio	-0.453	1.000										
3. Bank size	0.229	-0.252	1.000									
4. Capital	-0.174	0.822	-0.237	1.000								
5. Liquidity	-0.269	0.222	-0.203	0.121	1.000							
6. Non-interest income	0.007	-0.026	0.275	-0.013	0.095	1.000						
7. Problem loans	0.048	-0.046	0.001	-0.032	0.067	0.021	1.000					
8. Provisions	-0.053	0.172	-0.036	0.147	0.123	0.111	0.326	1.000				
9. Growth	-0.130	0.042	-0.153	0.004	-0.008	-0.052	-0.164	-0.021	1.000			
10. Federal funds rate	-0.065	0.051	-0.183	0.268	-0.089	-0.169	-0.201	-0.087	0.540	1.000		
11. Credit by banks	-0.153	0.049	-0.228	0.003	0.022	-0.158	-0.107	-0.021	0.437	0.696	1.000	
12. CPI	0.018	0.006	0.009	0.007	-0.042	0.008	-0.051	-0.018	0.281	0.169	-0.090	1.000

Table 3.2
Correlations matrix for the sample containing the delinquent loans data and controls

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Risk-weighted assets	1.000																
2. Risk-based capital ratio	-0.608	1.000															
3. Bank size	0.2548	-0.3049	1.000														
4. Capital	-0.2218	0.7801	-0.229	1.000													
5. Liquidity	-0.2285	0.2116	-0.2518	0.0949	1.000												
6. Non-interest income	0.0258	-0.1278	0.2736	-0.1345	0.0522	1.000											
7. Problem loans	0.0685	-0.0375	0.0242	-0.0115	0.0139	0.0108	1.000										
8. Provisions	-0.1502	0.3217	-0.1423	0.2409	0.1081	0.0005	0.3023	1.000									
9. Growth	-0.0594	0.043	-0.0464	0.0072	-0.0341	0.0586	-0.1808	0.0108	1.000								
10. Federal funds rate	0.0365	0.0113	-0.015	0.0097	-0.1092	-0.1156	-0.1573	-0.0589	0.2924	1.000							
11. Credit by banks	-0.0238	0.0015	-0.0471	-0.0144	-0.0153	-0.1152	-0.0532	-0.0212	-0.268	0.306	1.000						
12. CPI	0.0071	0.0143	-0.008	0.0108	-0.0458	0.0053	-0.0694	-0.0123	0.3903	0.2985	-0.1182	1.000					
13. Delinquent loans	-0.1131	0.1181	-0.1782	0.0835	0.0575	-0.0577	0.1974	0.1453	-0.0622	-0.0249	0.0394	-0.0328	1.000				
14. Commercial loans	0.0069	0.1151	-0.0237	0.0717	0.0599	0.0304	0.0021	0.1638	0.0126	0.005	0.0079	0.0019	-0.0072	1.000			
15. Loans to individuals	-0.2414	0.27	-0.1928	0.1256	0.1292	0.0696	-0.0559	0.1699	0.0451	0.0078	0.0691	0.0009	0.1707	0.557	1.000		
16. Real Estate loans	-0.0258	0.0906	0.043	0.0374	0.0464	0.0246	-0.0036	0.0867	0.0011	-0.0051	-0.016	0.001	-0.017	0.7826	0.4342	1.000	
17. Other loans	0.0008	0.1524	-0.3527	0.1814	0.0833	-0.1629	-0.0148	0.1727	-0.0041	-0.0032	0.001	-0.0017	-0.0164	0.168	0.0875	0.0551	1.000

Table 4
Optimal bank credit risk: Basic specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROE	ROA	ROA
ROA $_{t-1}$	0.566***	0.551***	0.513***	0.503***	0.488***	0.492***	0.483***	0.480***	0.882***		0.508***	0.503***
	(70.899)	(64.012)	(54.055)	(49.960)	(48.452)	(48.236)	(46.085)	(35.473)	(20.973)		(52.091)	(49.967)
ROE $_{t-1}$										0.521***		
										(78.613)		
Risk-weighted assets $_{t-1}$	0.048***	0.056***	0.033***	0.037***	0.040***	0.044***	0.043***	0.748***	0.186***	0.139***	0.035***	0.040***
	(15.107)	(16.675)	(10.726)	(11.846)	(12.784)	(11.913)	(11.736)	(5.981)	(3.270)	(7.361)	(10.469)	(12.860)
Risk-weighted assets^2 $_{t-1}$	-0.036***	-0.039***	-0.024***	-0.026***	-0.028***	-0.032***	-0.030***	-0.530***	-0.128***	-0.097***	-0.026***	-0.028***
	(-15.298)	(-16.187)	(-10.853)	(-11.500)	(-12.255)	(-11.758)	(-11.228)	(-6.014)	(-3.137)	(-6.858)	(-10.583)	(-12.572)
Bank size $_{t-1}$			-0.001***	0.001***	0.001***	0.000***	0.001***	-0.003***	0.005	0.005***	0.001***	0.001***
			(-14.341)	(11.999)	(12.680)	(4.269)	(11.459)	(-6.825)	(1.029)	(7.112)	(13.995)	(11.993)
Capital $_{t-1}$			-0.018***	-0.013***	-0.012***	-0.015***	-0.012***	0.013***	0.068**	-0.093***		-0.015***
			(-16.383)	(-11.323)	(-10.831)	(-12.456)	(-10.175)	(2.435)	(2.369)	(-15.836)		(-9.074)
Risk-based capital ratio $_{t-1}$											-0.004***	0.001*
											(-7.207)	(1.850)
Liquidity $_{t-1}$			-0.003***	-0.002***	-0.003***	-0.004***	-0.004***	0.020***	0.022	-0.027***	-0.002***	-0.002***
			(-6.118)	(-5.121)	(-7.738)	(-7.464)	(-8.271)	(4.684)	(0.608)	(-7.724)	(-4.201)	(-5.258)
Non-interest income $_{t-1}$			0.006***	0.008***	0.008***	0.008***	0.008***	0.003***	0.013	0.063***	0.008***	0.008***
			(9.214)	(12.308)	(11.755)	(11.781)	(11.416)	(4.070)	(0.624)	(12.501)	(12.160)	(12.348)
Problem loans $_{t-1}$			-0.079***	-0.069***	-0.072***	-0.076***	-0.074***	-0.087***	-0.094	-0.896***	-0.068***	-0.069***
			(-30.994)	(-28.153)	(-28.938)	(-28.655)	(-27.756)	(-27.757)	(-0.931)	(-28.057)	(-28.000)	(-28.182)
Provisions $_{t-1}$			0.005	0.000	-0.005	-0.004	-0.009	0.082***	0.443	-0.299***	0.002	-0.001
			(0.576)	(-0.022)	(-0.606)	(-0.456)	(-0.960)	(4.892)	(1.332)	(-4.937)	(0.276)	(-0.128)
Growth $_{t-1}$						0.032***	-0.007***					
						(38.715)	(-4.146)					
Credit by banks $_{t-1}$						0.000*	0.000***					
						(12.631)	(8.191)					
Optimal point	0.666***	0.717***	0.687***	0.711***	0.714***	0.687***	0.716***	0.700***	0.727***	0.715***	0.689***	0.710***
Quarter fixed effects	No	Yes	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	Yes	No	Yes	No	No	No	No	No
Observations	557,179	557,179	557,179	557,179	557,179	509,445	509,445	540,550	508,512	557,179	557,179	557,179
R-square (overall)	0.330	0.373	0.356	0.390	0.363	0.359	0.364			0.378	0.388	0.390
UIT (p-value)								0.000				
WIT (Wald statistic)								28.742				
OIT (p-value)								0.354	0.379			

Notes: The table reports coefficients and t-statistics (in parentheses) from the estimation of variants of equation (7). All variables are defined in Table 1. Regressions (1) to (7) and (10) to (12) are estimated with OLS on the fixed effects model with robust standard errors. Regression (8) is estimated with LIML on the fixed effects model with robust standard errors. Regression (9) is estimated with the Arellano and Bond (1991) first difference GMM for dynamic panels and robust standard errors. UIT is the p-value of the under-identification LM test by Kleibergen and Paap, which requires a value lower than 0.05 to reject the null hypothesis at the 5% level. WIT is the Wald F-statistic of the weak identification test by Kleibergen and Paap, which must be relatively high (higher than 10 as a rule of thumb) to reject the null. OIT is the p-value of the over-identification test by Hansen, which requires a value higher than 0.05 to reject the null hypothesis at the 5% level. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10 % level, respectively.

Table 5
Optimal bank credit risk: Risk measured by delinquent loans

	(1)	**(2)**	**(3)**
Dependent variable	ROA	ROA	ROE
ROA $_{t-1}$	0.932***	0.911***	
	(7.312)	(7.505)	
ROE $_{t-1}$			0.993***
			(7.793)
Deliquent loans $_{t-1}$	0.224*	0.238*	2.609**
	(1.806)	(1.715)	(2.019)
Deliquent loans^2 $_{t-1}$	-6.769*	-7.125*	-90.303**
	(-1.850)	(-1.755)	(-2.008)
Risk-weighted assets $_{t-1}$	-0.060**	-0.059**	-0.385
	(-2.243)	(-2.358)	(-1.592)
Bank size $_{t-1}$	0.011	0.007	0.082
	(0.929)	(0.636)	(0.748)
Capital $_{t-1}$	0.207**	0.183**	2.052**
	(2.563)	(2.302)	(2.474)
Liquidity $_{t-1}$	-0.047	-0.042	-0.336
	(-0.965)	(-0.959)	(-0.715)
Non-interest income $_{t-1}$	-0.004	0.003	-0.250
	(-0.065)	(0.063)	(-0.618)
Problem loans $_{t-1}$	-0.342	-0.315	-3.089
	(-1.590)	(-1.607)	(-1.391)
Provisions $_{t-1}$	-1.076	-0.811	-3.118
	(-0.908)	(-0.736)	(-0.269)
Commercial loans $_{t-1}$		0.005	0.011
		(0.735)	(0.137)
Loans to individuals $_{t-1}$		-0.018	0.014
		(-0.459)	(0.037)
Loans to real estate $_{t-1}$		0.000	0.002
		(0.160)	(0.214)
Optimal point	0.017***	0.017***	0.014***
Observations	170,973	170,973	170,973
OIT (p-value)	0.632	0.547	0.635

Notes: The table reports coefficients and t-statistics (in parentheses) from the estimation of variants of equation (7). Risk is measured by the delinquent-loans ratio. All variables are defined in Table 1. All regressions are estimated with the Arellano and Bond (1991) first difference GMM for dynamic panels and robust standard errors. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10 % level, respectively.

Table 6
Optimal bank credit risk: Other sensitivity analyses

Dependent variable	**(1)** ROA	**(2)** ROA	**(3)** ROA	**(4)** ROA	**(5)** ROA
ROA $_{t-1}$	0.378***	0.252**		0.489***	0.507***
	(3.295)	(2.209)		(47.470)	(46.743)
Risk-weighted assets$_{t-1}$	2.523***	0.870***	0.068***		
	(7.406)	(2.586)	(14.197)		
Risk-weighted assets$^2_{t-1}$	-1.837***	-0.610***	-0.047***		
	(-7.423)	(-2.755)	(-13.557)		
Risk-weighted assets $_{t-4}$					0.011***
					(4.256)
Risk-weighted assets^2 $_{t-4}$					-0.009***
					(-4.347)
Σ(Risk-weighted assets $_{t-1\ldots t-3}$)				0.036***	
				(10.288)	
Σ(Risk-weighted assets^2 $_{t-1\ldots t-3}$)				-0.026***	
				(-10.230)	
Bank size $_{t-1}$	-0.002***	-0.008**	0.003***	0.001***	0.000
	(-3.117)	(-2.087)	(17.571)	(11.061)	(1.448)
Capital $_{t-1}$	-0.001	0.024	-0.031***	-0.004**	-0.007***
	(-0.051)	(0.785)	(-16.059)	(-2.390)	(-8.561)
Liquidity $_{t-1}$	0.069***	0.045	-0.004***	-0.002***	-0.001
	(5.652)	(1.469)	(-5.526)	(-5.547)	(-1.499)
Non-interest income $_{t-1}$	0.004	0.048*	0.021***	0.008***	0.003***
	(0.302)	(1.886)	(15.578)	(12.829)	(4.708)
Problem loans $_{t-1}$	-0.073*	-0.108	-0.120***	-0.069***	-0.043***
	(-1.841)	(-1.388)	(-32.148)	(-27.390)	(-17.579)
Provisions $_{t-1}$	0.292***	0.511	-0.040***	-0.012	0.002
	(2.722)	(1.549)	(-2.819)	(-1.468)	(0.380)
Optimal point	0.686***	0.713***	0.721***	0.687***	0.668***
Observations	118,996	37,613	557,179	524,389	511,173
R-square (overall)			0.172	0.372	0.356
OIT (p-value)	0.485	0.601			

Notes: The table reports coefficients and t-statistics (in parentheses) from the estimation of variants of equation (7). Regressions (1) and (2) are estimated with the Arellano and Bond (1991) first difference GMM for dynamic panels and robust standard errors. Regressions (3) to (5) are estimated with OLS on the fixed effects model with robust standard errors. In regression (1) all variables are annual averages of quarterly observations and include annual fixed effects. In regression (2) all variables are bi-annual averages of quarterly observations and include bi-annual fixed effects. Regression (3) does not have a lagged dependent variable. Regressions (4) and (5) consider alternative lag structures. Regressions (3)-(5) include quarter fixed effects. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10 % level, respectively.

Table 7
Optimal bank credit risk: Specific bank groups

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable	ROA	ROA	ROA	ROA
ROA $_{t-1}$	0.558***	0.480***	0.483***	0.494***
	(20.031)	(36.105)	(23.219)	(57.114)
Risk-weighted assets $_{t-1}$	0.026	0.038***	0.045***	0.021***
	(1.494)	(9.249)	(8.238)	(4.215)
Risk-weighted assets^2 $_{t-1}$	-0.020	-0.027***	-0.031***	-0.015***
	(-1.597)	(-8.947)	(-8.088)	(-4.036)
Bank size $_{t-1}$	0.000	0.001***	0.002***	0.000*
	(1.254)	(10.589)	(7.659)	(1.714)
Capital $_{t-1}$	0.009	-0.015***	-0.009***	-0.002
	(1.215)	(-11.176)	(-4.901)	(-0.894)
Liquidity $_{t-1}$	-0.004**	-0.002***	-0.002**	-0.005***
	(-2.054)	(-3.683)	(-2.459)	(-5.415)
Non-interest income $_{t-1}$	0.008***	0.008***	0.014***	0.005***
	(4.193)	(7.196)	(7.207)	(8.533)
Problem loans $_{t-1}$	-0.060***	-0.070***	-0.059***	-0.066***
	(-6.195)	(-22.872)	(-11.863)	(-18.716)
Provisions $_{t-1}$	-0.001	0.012	0.027**	-0.119***
	(-0.038)	(1.190)	(2.262)	(-12.579)
Constant	-0.010	-0.015***	-0.012***	-0.004**
	(-1.639)	(-10.637)	(-6.810)	(-2.147)
Optimal point	0.640***	0.714***	0.710***	0.680***
Observations	55,345	279,334	139,143	138,854
R-square (overall)	0.441	0.375	0.352	0.461

Notes: The table reports coefficients and t-statistics (in parentheses) from the estimation of variants of equation (7). All variables are defined in Table 1. All regressions are estimated with OLS on the fixed effects model with robust standard errors and include quarter fixed effects. Regression (1) is based on a subsample of banks that have total assets above the 90% percentile. Regression (2) is based on a subsample of banks that have total assets below the 50% percentile. Regression (3) is based on a subsample of banks that have a total risk-based capital ratio above the 75% percentile. Regression (4) is based on a subsample of banks that have a total risk-based capital ratio below the 25% percentile. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10 % level, respectively.

Table 8
Percentiles for the sample splitting variables of Table 7.

Variable/Percentiles	5%	10%	25%	50%	75%	90%	95%
Total Assets	21,245.725	29,813.602	54,624.621	113,857.16	263,845.77	656,849.37	1,237,445.8
Risk-Based Capital Ratio	0.111	0.116	0.129	0.153	0.197	0.263	0.326

Notes: The table contains percentiles of per bank, across time, averages of total assets and risk-based capital ratios. Total assets are in thousands of dollars.

Table 9
Optimal bank credit risk: Time-varying models

	(1)	**(2)**	**(3)**
Dependent variable	ROA	ROE	ROA
ROA $_{t-1}$	0.511***		0.106***
	(51.009)		(2.597)
ROE $_{t-1}$		0.524***	
		(79.098)	
Risk-weighted assets $_{t-1}$	0.002***	0.003	
	(3.565)	(0.637)	
Risk-weighted assets^{2} $_{t-1}$	-0.016***	-0.132***	
	(-4.482)	(-5.374)	
Delinquent loans$_{t-1}$			41.416***
			(4.921)
Delinquent loans$^{2}_{t-1}$			267.396***
			(3.637)
Risk-weighted assets $_{t-1}$			-0.004
			(-0.453)
Bank size $_{t-1}$	0.001***	0.005***	-0.017**
	(11.915)	(6.880)	(-2.118)
Capital $_{t-1}$	-0.012***	-0.097***	0.024
	(-10.853)	(-16.261)	(1.108)
Liquidity $_{t-1}$	-0.002***	-0.027***	0.013
	(-5.874)	(-7.841)	(0.992)
Non-interest income $_{t-1}$	0.008***	0.063***	-0.103***
	(12.368)	(12.576)	(-5.938)
Problem loans $_{t-1}$	-0.068***	-0.890***	-0.100**
	(-28.224)	(-28.082)	(-2.406)
Provisions $_{t-1}$	-0.001	-0.305***	0.332***
	(-0.115)	(-5.027)	(3.477)
Constant	0.002***	0.020***	
	(30.818)	(29.218)	
Observations	557,179	557,179	184,059
R-square (overall)	0.407	0.385	

Notes: The table reports coefficients and t-statistics (in parentheses) from the estimation of variants of equation (8). All variables are defined in Table 1. In regressions (1) and (2) estimation method is OLS on the fixed effects model with robust standard errors. Regression (3) is estimated with the Arellano and Bond (1991) first difference GMM for dynamic panels and robust standard errors. All regressions include quarter fixed effects. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10 % level, respectively.

Table 10
Time-varying models: Specific bank groups

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable	ROA	ROA	ROA	ROA
ROA $_{t-1}$	0.555***	0.511***	0.494***	0.496***
	(21.212)	(51.009)	(24.034)	(57.475)
Risk-weighted assets $_{t-1}$	0.002	0.002***	0.002	0.002**
	(1.028)	(3.565)	(1.562)	(2.133)
Risk-weighted assets$^2{}_{t-1}$	-0.006	-0.016***	-0.012*	-0.013*
	(-0.581)	(-4.482)	(-1.881)	(-1.920)
Bank size $_{t-1}$	0.000	0.001***	0.002***	0.000
	(1.201)	(11.915)	(7.757)	(1.582)
Capital $_{t-1}$	0.010	-0.012***	-0.009***	-0.002
	(1.579)	(-10.853)	(-4.680)	(-0.865)
Liquidity $_{t-1}$	-0.004**	-0.002***	-0.002***	-0.005***
	(-2.288)	(-5.874)	(-3.162)	(-5.455)
Non-interest income $_{t-1}$	0.008***	0.008***	0.014***	0.005***
	(4.146)	(12.368)	(7.368)	(8.593)
Problem loans $_{t-1}$	-0.060***	-0.068***	-0.059***	-0.066***
	(-6.024)	(-28.224)	(-12.043)	(-18.807)
Provisions $_{t-1}$	-0.002	-0.001	0.026**	-0.118***
	(-0.075)	(-0.115)	(2.187)	(-12.509)
Constant	0.002***	0.002***	0.003***	0.001***
	(6.166)	(30.818)	(19.027)	(12.525)
Observations	55,345	557,179	139,143	138,854
R-square (overall)	0.451	0.407	0.380	0.466

Notes: The table reports coefficients and t-statistics (in parentheses) from the estimation of variants of equation (8). All variables are defined in Table 1. All regressions are estimated with OLS on the fixed effects model with robust standard errors and include quarter fixed effects. Regression (1) is based on a subsample of banks that have total assets above the 90% percentile. Regression (2) is based on a subsample of banks that have total assets below the 50% percentile. Regression (3) is based on a subsample of banks that have a total risk-based capital ratio above the 75% percentile. Regression (4) is based on a subsample of banks that have a total risk-based capital ratio below the 25% percentile. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10 % level, respectively.

Table 11
Unit root tests

	Augmented Dickey-Fuller		GLS Dickey-Fuller	
	Coefficient	5% critical value	Coefficient	5% Critical Value
Output (2)	-2.063	-2.921	0.828	-2.210
Federal funds rate (2)	-2.166	-2.921	-1.711	-2.210
Realized risk (6)	-1.612	-2.924	-1.245	-2.112
Optimal risk (2)	-1.766	-2.922	-1.269	-2.215

Notes: The table reports the augmented and GLS Dickey-Fuller unit root tests, along with their 5% critical values. The number of lags for each series is determined by information criteria and is in the parenthesis next to the variable.

Table 12
Cointegration vector

	Output	Federal funds rate	Realized risk	Optimal risk
Coefficient	1.000	0.352	15.982	-22.819
Standard deviation	0.000	0.061	5.470	4.776
P-value	0.000	0.000	0.003	0.000

Notes: The table reports the cointegration vector given by equation (11) of the VECM given by equation (10). The VECM is estimated using the one stage approach of Johansen (1995). The sample spans the period 1997Q3 to 2011Q4.

Figure 1: Evolution of the optimal bank credit risk vs. average credit risk

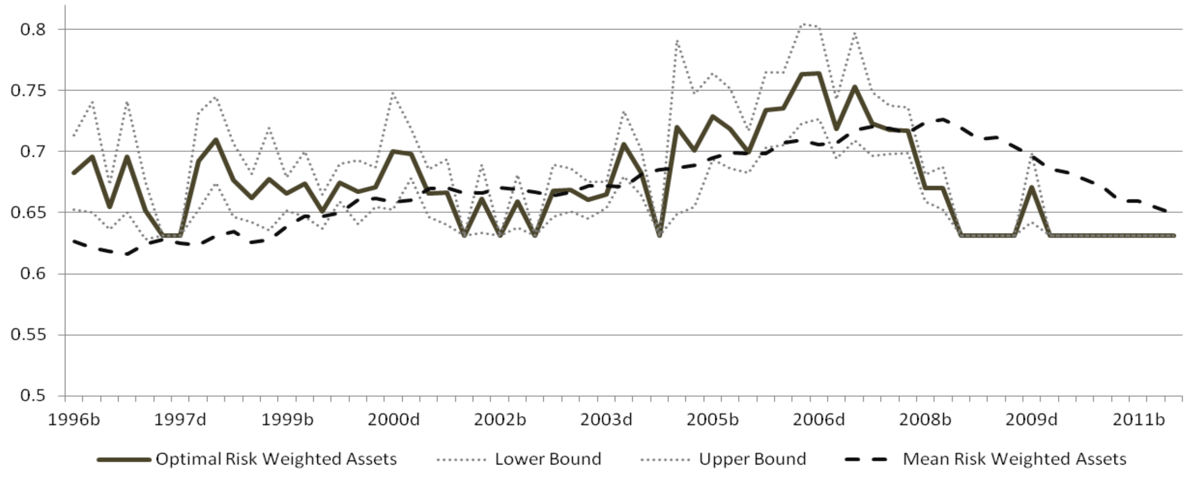


Figure 2: Evolution of the optimal bank credit risk vs. average credit risk of failed banks

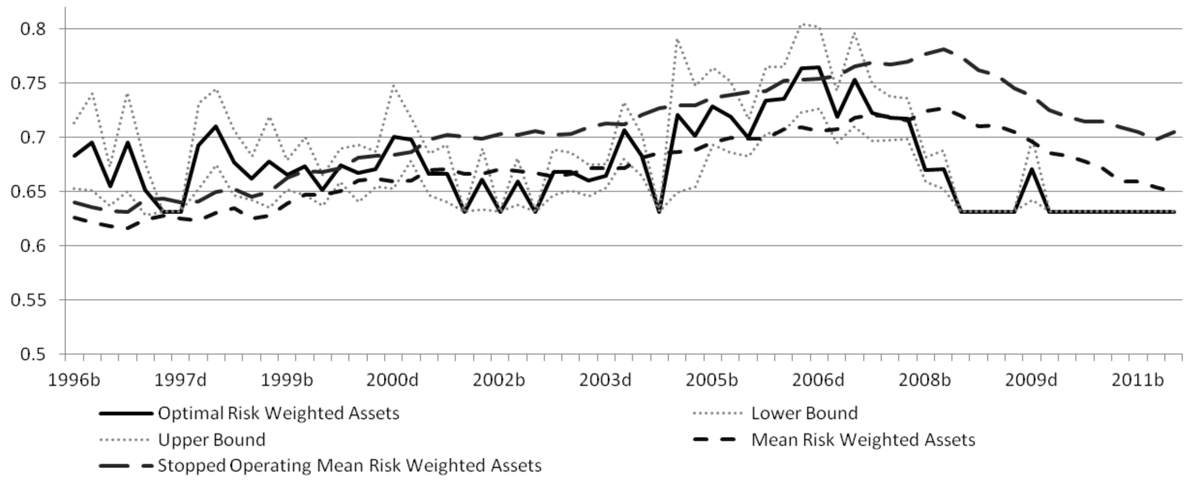


Figure 3: Evolution of the optimal bank credit risk vs. average credit risk based on delinquent loans

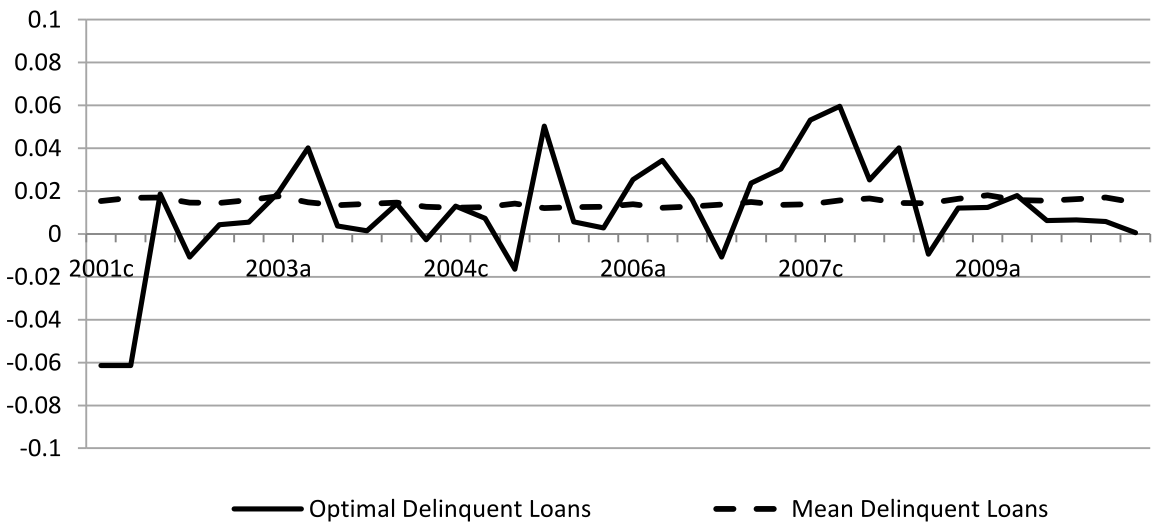


Figure 4: Evolution of the optimal bank credit risk of large banks (total assets>90% of sample average)

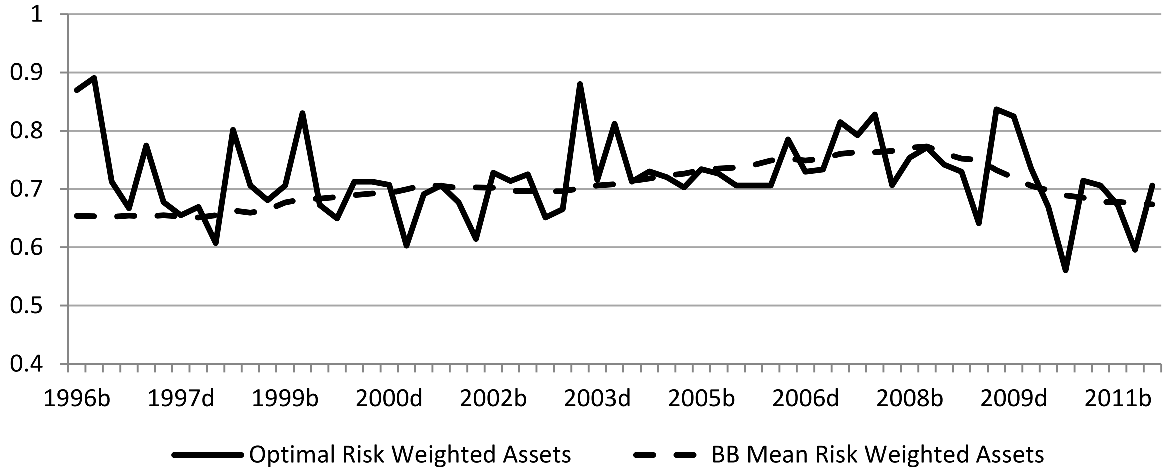


Figure 5: Evolution of the optimal bank credit risk of small banks (total assets<50% of sample average)

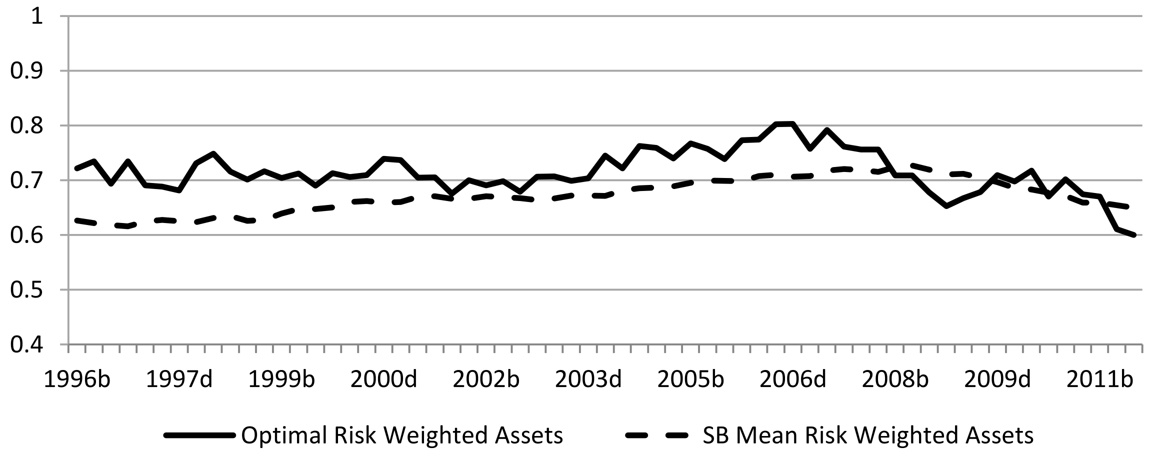


Figure 6: Evolution of the optimal bank credit risk of well-capitalized banks (capital>75% of sample average)

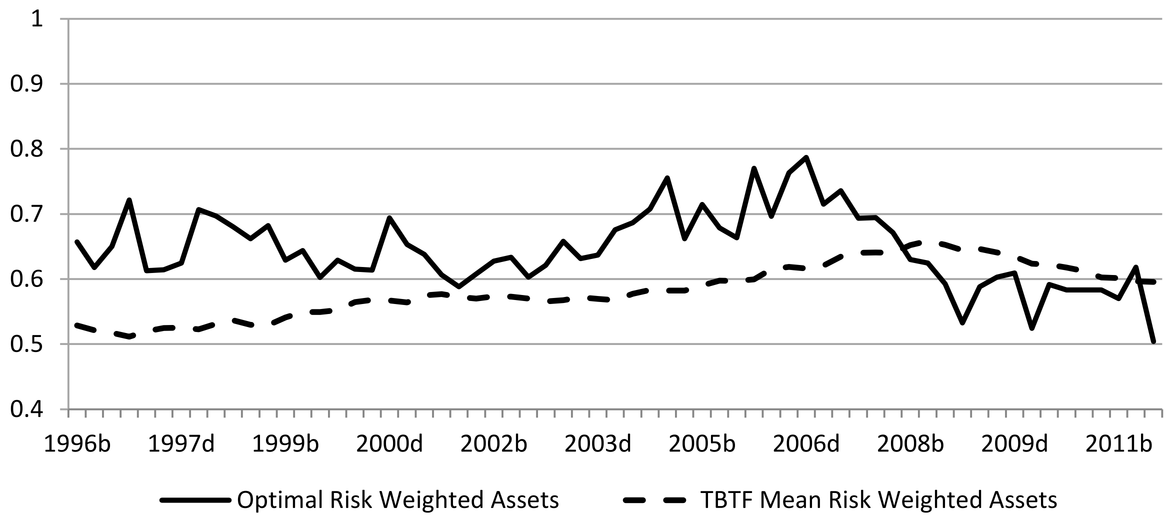


Figure 7
Evolution of the optimal bank credit risk of poorly-capitalized banks (capital<25% of sample average)

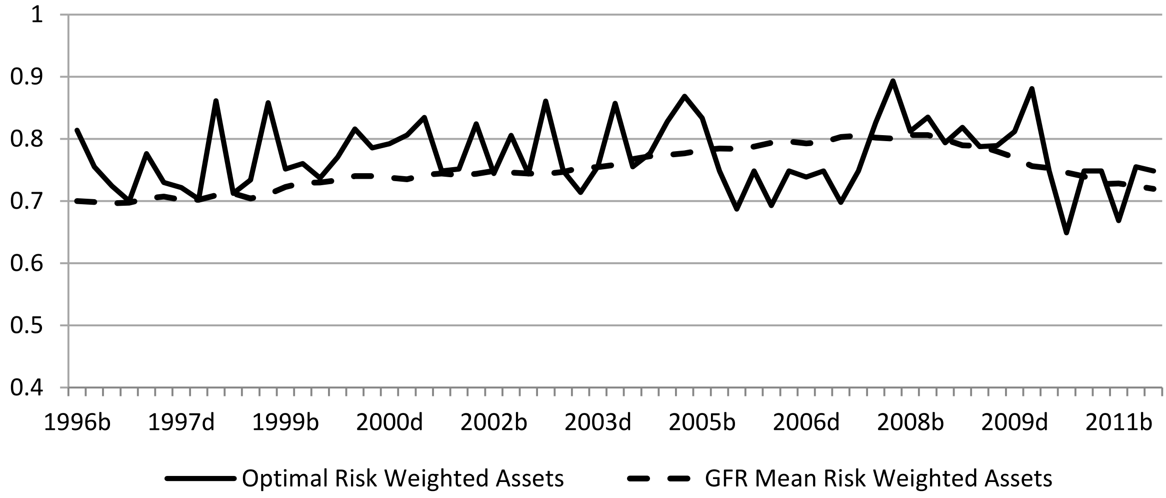
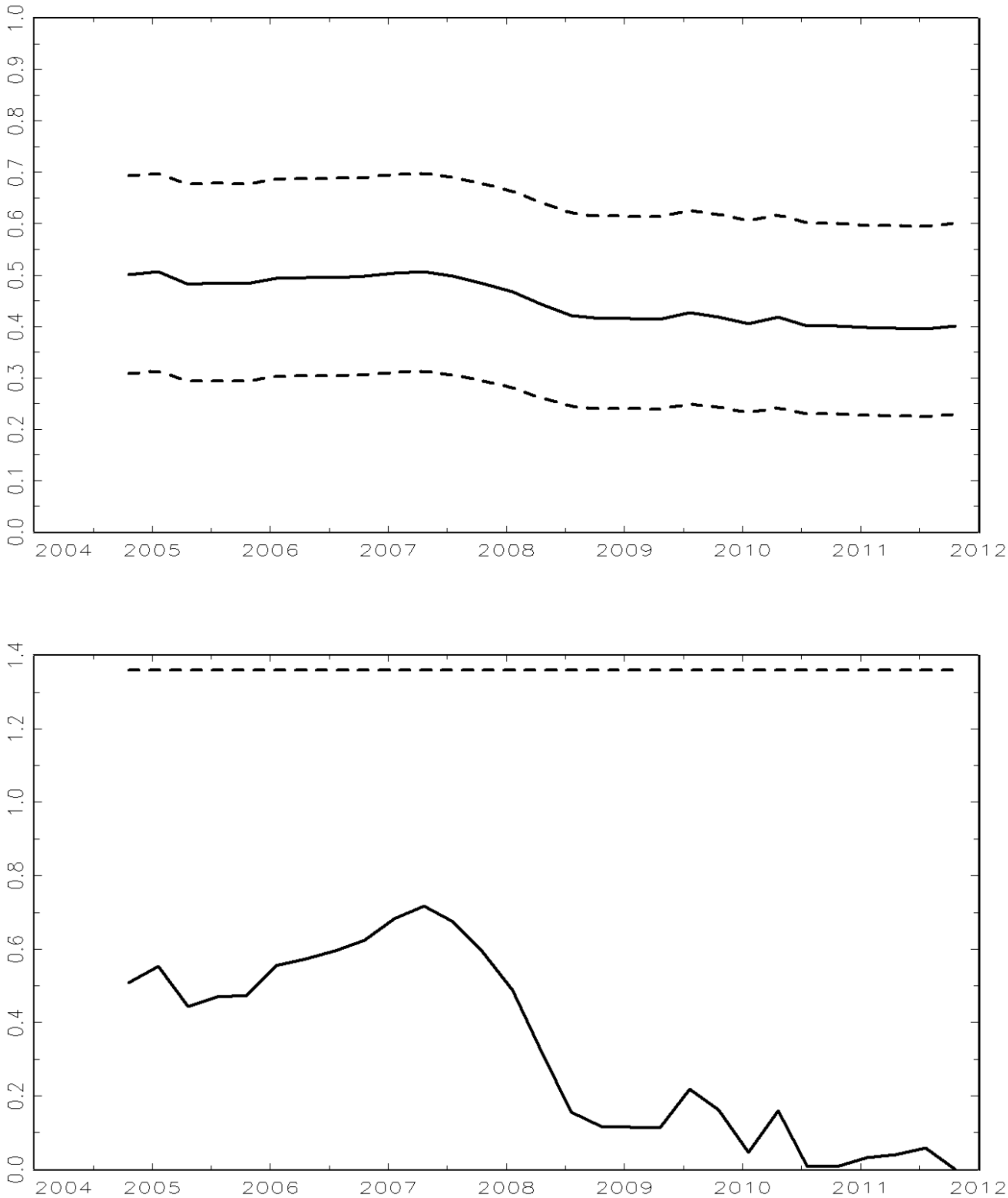


Figure 8
Stability of the time-series model



Notes: The upper part of the figure shows the recursively estimated largest eigenvalue (solid line), and its confidence interval (dashed lines), based on sample moments from an increasing fraction of the sample. The lower part of the figure shows that the recursive Tau statistics (solid line) never crosses the 95% critical value (dashed line) and, therefore, the null hypothesis of parameter constancy cannot be rejected.

Figure 9
Impulse response of risk-weighted assets to a shock in optimal risk-weighted assets

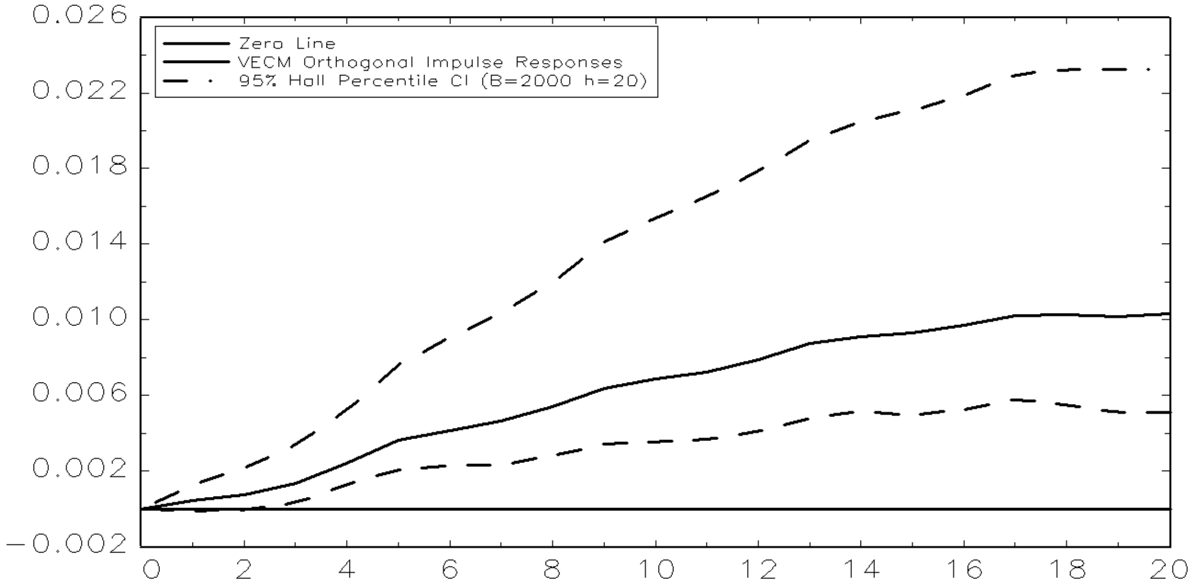


Figure 10
Impulse response of risk-weighted assets to a monetary policy shock

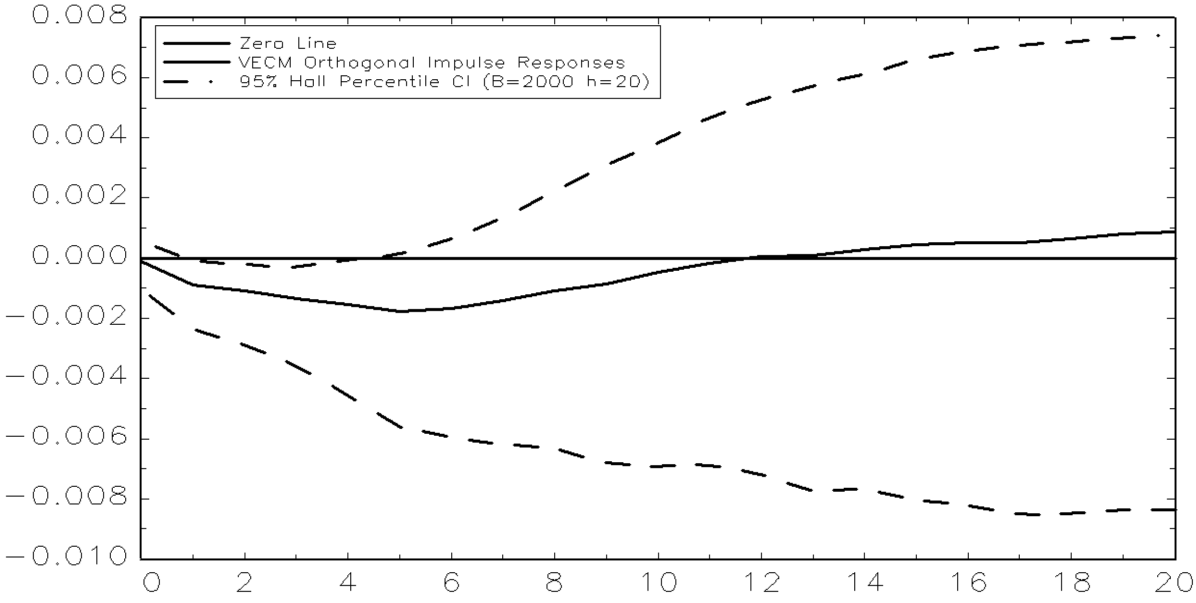


Figure 11
Impulse response of optimal risk-weighted assets to a monetary policy shock