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Does monetary policy affect bank risk-taking?

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Abstract: This paper investigates the relationship between short-term interest rates and bank risk. Using a unique database that includes quarterly balance sheet information for listed banks operating in the European Union and the United States in the last decade, we find evidence that unusually low interest rates over an extended period of time contributed to an increase in banks' risk. This result holds for a wide range of measures of risk, as well as macroeconomic and institutional controls.

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"John Bull can stand many things but can not stand two percent" (Walter Bagehot, 1873).

Introduction

In the aftermath of the burst of the dotcom bubble, many central banks lowered interest rates to ward off recession. Prior successes in taming higher levels of inflation strengthened the support for a large number of monetary authorities to lower interest rates, keeping them below the levels suggested by historical experience (Taylor, 2009). While excessive liquidity could encourage bank risk-taking, this financial stability aspect was not seen as particularly threatening for two main reasons. First, most central banks around the world have progressively shifted towards tight inflation objectives as their best contribution to fostering economic growth (Svensson and Woodford, 2004). Second, financial innovation had, for the most part, been regarded as a factor that would strengthen the resilience of the financial system by resulting in a more efficient allocation of risks (Greenspan, 2005). In this context, the financial stability implications of monetary policy actions were deemed of minor importance.

Although it is difficult to state that monetary policy has been the main cause of the current crisis, it could have contributed to its build-up. There are two main ways in which low interest rates may influence bank risk-taking. First, low interest rates affect valuations, incomes and cash flows, which in turn can influence how banks measure risk (Adrian and Shin, 2009a; 2009b; Borio and Zhu, 2008). Second, low returns on investments, such as government (risk-free) securities, may increase incentives for banks, asset managers and insurance companies to take on more risk for behavioral, contractual or institutional reasons, for example to meet a nominal return target (Brunnermeier, 2001; Rajan, 2005).

In this paper we analyze empirically the relationship between monetary policy and risk-taking by banks. Using a unique database of quarterly balance sheet information and risk measures for listed banks operating in the European Union and the United States in the last decade, we find evidence that unusually low interest rates over an extended period of time contributed to an increase in banks' risk-taking. The paper is innovative and relevant in two respects: first, it analyzes the effectiveness of the risk-taking channel at the international level using a wide range of publicly available indicators for bank risk; second, it relies on an in-depth analysis of the possible determinants of banks' risk prior and during the financial turmoil. In order to disentangle the effects of monetary policy from other factors, we have to delve into other possible causes of changes in banks' risk. Hence we also account for bank-specific characteristics (size, liquidity, capitalization, lending portfolios, profitability), macroeconomic factors (*GDP*, housing and equity prices, structure of the yield curve), and institutional characteristics at the national level (competition, risk appetite, intensity of regulation).

The remainder of this paper is organized as follows. The next section discusses how monetary policy can have an impact on banks' risk-taking. Section III describes the data used in the analysis, while Section IV presents the econometric model and main results. Section V verifies the robustness of the findings considering: i) a more complete term structure for bank risk; ii) non-linear models including explicitly business expectations, differences in the levels of bank regulation and competition; iii) a model that evaluates the probability for a bank to belong to the last quartile of the riskier banks during the crisis. The last section summarizes the main conclusions.

Monetary policy and risk-taking: theory and evidence

From a historical perspective, easy monetary conditions are a classical ingredient in boom-bust type business fluctuations (Fisher, 1933; Hayek, 1939; Kindleberger, 1978). Low interest rates could indeed induce financial imbalances by means of a reduction in risk aversion of banks and other investors. This part of the monetary transmission mechanism has been recently referred to as the risk-taking channel and relates to how changes in monetary policy rates affect either risk perceptions or risk-tolerance (Borio and Zhu, 2008).

There are a number of ways in which low interest rates can influence bank risk-taking. The first is through their impact on valuations, incomes and cash flows and measured risk.[4] A reduction in the policy rate boosts asset and collateral values, which in turn can modify banks' estimates of probabilities of default, loss given default and volatilities. For example, low interest rates by boosting asset prices tend to reduce asset price volatility and thus measured risk: since a higher stock price increases the value of equity relative to corporate debt, a sharp increase in stock prices reduce corporate leverage and could thus decrease the risk of holding stocks. This example can be applied to the widespread use of Value-at-Risk methodologies for economic and regulatory capital purposes (Danielsson et al (2004)). As volatility tends to decline in rising markets, it releases risk budgets of financial firms and encourages position-taking. A similar argument is provided by Adrian and Shin (2009b) who stress that changes in measured risk determine adjustments in bank balance sheets and leverage conditions and this, in turn, amplifies business cycle movements.[5]

The second way the risk-taking channel may operate is through the 'search for yield' (Rajan, 2005). Low interest rates may increase incentives for asset managers to take on more risks for a number of factors. Some are psychological or behavioral in nature such as the so-called money illusion: investors may ignore the fact that nominal interest rates may decline to compensate for lower inflation. Others may reflect institutional or regulatory constraints. For example, life insurance companies and pension funds typically manage their assets with reference to their liabilities. In some countries, liabilities are linked to a minimum guaranteed nominal rate of return or returns reflecting long-term actuarial assumptions rather than the current level of yields. In a period of declining interest rates, they may exceed the yields available on highly-rated government bonds. The resulting gap can lead institutions to invest in higher-yielding, higher-risk instruments. More generally, financial institutions regularly enter into long-term contracts committing them to produce relatively high nominal rates of return. And a similar mechanism could be in place whenever private investors use short-term returns as a way of judging manager competence and withdraw funds after poor performance (Shleifer and Vishny, 1997; Brunnermeier and Nagel, 2004). More broadly, the link between low interest rates and excessive risk-taking is also influenced by competition, the structure of managerial bonus schemes and deficiencies in supervision and regulation (Ackerman et al., 1999; Salas and Saurina, 2003; Kouwenberg and Ziemba, 2007).

A third possible set of effects of monetary policy on risk-taking may operate through habit formation. In their work on the equity risk premium, Campbell and Cochrane (1999) show that investors become less risk-averse during economic expansions because their

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[4] This is close in spirit to the familiar financial accelerator, in which increases in collateral values reduce borrowing constraints (Bernanke et al, 1996). Adrian and Shin (2009b) claim that the risk-taking channel is distinct but complementary to the financial accelerator because it focuses on amplification mechanisms due to financing frictions in the lending sector. Fostel and Geanakoplos (2009) link the leverage cycle with contagion.

[5] Lower interest rates may reduce the incentives to screen borrowers, thereby effectively encouraging banks to relax their credit standards. From a modeling perspective, this mechanism is equivalent to the impact of increased competition on lending standards (Ruckes, 2004; Dell'Ariccia and Marquez, 2006).

consumption increases relative to normal levels. An easing of monetary policy may, by increasing real economic activity, decrease the degree of investors’ risk aversion. This mechanism is in line with the findings from literature on asset-pricing models, which predict higher credit spreads in the long run after periods of lower interest rates (Longstaff and Schwartz, 1995; Dufresne et al., 2001).

Finally, risk-taking may also be influenced by the communication policies of a central bank and the characteristics of policymakers’ reaction functions. For example, a high degree of central bank predictability with regard to future policy decisions can reduce market uncertainty and thus lead banks to take on more risks. In this way agents’ perception that the central bank will ease monetary policy in the event of bad economic outcomes could lower the probability of large downside risks, thereby producing an insurance effect. This is a typical moral hazard problem. For this reason, Diamond and Rajan (2009) argue that in good times monetary policy should be kept tighter than strictly necessary based on current economic conditions, in order to diminish banks’ incentive to take on liquidity risk. In a forward looking manner agents can also choose to increase their interest rate exposure to macroeconomic conditions making monetary policy time inconsistent not because of an inflation bias in the preference of policy makers but rather to the higher macroeconomic sensitivity to interest rates (Farhi and Tirole, 2009).

Turning to the empirical evidence, there are only a handful of studies that try to test directly for the existence of a risk-taking channel. The paper by Jiménez et al (2009) uses micro data of the Spanish Credit Register over the period 1984–2006 to investigate whether the stance of monetary policy has an impact on the level of risk of individual bank loans. They find that low interest rates affect the risk of the loan portfolio of Spanish banks in two conflicting ways. In the short term, low interest rates reduce the probability of default of the outstanding variable rate loans, by reducing interest burdens of previous borrowers. In the medium term, however, due to higher collateral values and the search for yield, banks tend to grant more risky loans and, in general, to soften their lending standards: they lend more to borrowers with a bad credit history and with more uncertain prospects.

Ioannidou et al (2009) take a different, perspective and analyze whether the risk-taking channel works not only on the quantity of new loans but also on their interest rates. The authors investigate the impact of changes in interest rates on loan pricing using Bolivian data over the period 1999–2003. They find that, when interest rates are low, not only do banks increase the number of new risky loans but they also reduce the rates they charge to riskier borrowers relative to what they charge to less risky ones. Interestingly, the reduction in the corresponding spread (and the extra risk) is higher for banks with lower capital ratios and more bad loans. Data on individual loan and borrower characteristics is however confidential in most occasions and available only for a handful of countries who maintain a credit register.

Our approach is complementary. We take an international perspective and focus on the banking sector by relying on publicly available information to most central banks and supervisors. We use an extensive and unique database which matches balance sheet data at a quarterly frequency for listed banks in the European Union and US with an array of individual proxies of bank risk. In order to insulate the effects of monetary policy we control for a wide set of alternative factors that could impact on risk-taking attitude including bank-specific characteristics, macroeconomic conditions, differences in the intensity of bank supervision, investors' risk aversion, changes in bank competition perception, the housing price boom-bust cycle and excessive lending growth.

Data

The sample comprises quarterly balance sheet information taken from Bloomberg over the period 1998-2008. Unlike the overwhelming majority of international banking studies which employ annual data, this research uses quarterly data which are more appropriate for measuring the short-term impact of monetary policy changes on bank risk. The initial sample includes information from an unbalanced panel of more than 1,100 listed banks from 16 countries: Austria, Belgium, Denmark, Germany, Greece, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, the United Kingdom and the United States. In order to ensure as much comparability as possible in accounting standards, we included only listed banks (which are usually very large and often cross-listed in several stock exchanges) and focused on standard indicators (i.e. balance sheet size, capital to asset ratio, liquidity ratio, total lending, return on assets).

The variable accounting for bank risk is an important element of the analysis. Hence, the data on individual bank financial statements have been matched with a wide array of publicly available and widely used measures accounting for bank risk.

The first one is given by the expected default frequency (*EDF*). *EDF* is the probability that a company will default within a given time horizon (typically one year).[6] *EDF* is a well-known, forward-looking indicator of credit risk, computed by Moody's KMV, which builds on Merton's model to price corporate bond debt (Merton, 1974).[7] The *EDF* value, expressed as a percentage, is calculated combining banks' financial statements with stock market information and a default database.

EDF figures are regularly used by financial institutions, investors, central banks and regulators to monitor the health of the financial system (IMF, 2009a; ECB, 2009). The evolution of the one-year *EDF* for the countries in the sample is reported in Chart 1.

Even if *EDF*s have done quite well as a predictor of default during the recent credit crisis with respect to other measures (see, for instance, Munves et al., 2009), Chart 1 shows that risk had probably been underpriced in the pre-crisis period.[8] This means that prior to the crisis banks were taking risks which were not fully accounted for by financial market indicators at the time. Indeed, one key element of the risk-taking channel works through the impact of interest rates on measured risk. This implies that the risk was not fully apparent at the time the loans or other activities were made. The panel approach undertaken in this study allows us to solve, at least in part, this problem by analyzing not only the time dimension but also the cross section dimension among banks. By means of the latter we are able to analyze relative changes in bank risk-attitude (i.e. comparing risky versus less risky banks as perceived by the market) and link these changes to monetary policy even in a period of subdued risk perception. In addition, the use of microeconomic data allows us to rule out the assumption that the increase in banks' *EDF*s during the crisis period is simply caused by the realization of a negative systemic shock and to control for the impact on risk-taking of bank-specific characteristics.

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6 "Default" refers to the failure to make a scheduled debt payment.

7 More specifically the calculation of EDF builds on Vasicek and Kealhofer's extension of the Black-Scholes-Merton option-pricing framework to make it suitable for practical analysis and on the proprietary default database owned by KMV (Dwyer and Qu, 2007). For an empirical application of *EDF*s see, for instance, Garlappi et al. (2007).

8 This bias is likely to be smaller than in the case of other indicators of bank risk (such as bond spreads) as *EDF* includes both leverage and volatility which tends to grow also in periods prior to banking problems.

In general the identification strategy used in this paper is the following: since monetary policy conditions are different across countries, the hypothesis of the risk-taking channel would suggest that bank risk (*EDF*) increases by more in those countries where the level of interest rate has been relatively low (below both the Taylor rule and the natural rate reflecting national economic conditions). Given that the main estimation specifications (see Section IV) involve only one quarter lag between the monetary policy indicators and the *EDF*s, we have also extended our analysis studying the probability of being a risky bank during the crisis conditional of a number of pre-crisis factors (see Subsection V.III).

As further robustness checks, the analysis of *EDF* is supplemented by including additional measures to account for bank risk derived from stock market information. The objective is to decompose bank risk into two measures accounting for *idiosyncratic* (individual) and *systemic* (market wide) elements. Thus we can ascertain whether monetary policy influences each individual bank's risk position on top of systemic considerations. More specifically this helps clarify bank attitudes towards risk-taking, independent of the developments in the banking system as a whole, which might be due to shocks common to all financial intermediaries. To tackle this, two complementary approaches have been used. The first is based on a simple Capital Asset Pricing Model (*CAPM*). This allows for the calculation of specific beta coefficients for each bank in the sample for each specific quarter, using daily data. The idiosyncratic component is then simply given by the unexplained component of each regression for bank *i* over each quarter *t (IDSC1)*.[9] The second approach follows Campbell et al. (2001), who build on Merton (1980) and decompose historical stock market movements into total market, banking sector and individual bank level volatility. As in Campbell et al. (2001), the latter is interpreted as the idiosyncratic risk of each individual bank for each given quarter (*IDSC2*).[10] The top left hand side of Table 1 shows the correlation between the different measures of bank risk used in this paper. The correlation is always positive and significant, but in many cases is significantly less than one.

Turning to the macroeconomic variables, the monetary policy rate is the three-month interbank rate. This measure, unlike the interest rate on main refinancing operations, is able to capture the effect of the recent credit crisis on the actual cost of bank refinancing.[11] The

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[9] The *CAPM* model is based on the following equation: $R_{i,k,t=}\ \beta_{i,t}+\ R_{m,k,t}\ +\varepsilon_{i,t}$ where $R_{i,k,t}$ and $R_{m,k,t}$ are the individual bank *i* and market wide *m* logarithmic returns calculated for each country *k* at quarter *t*. The term $\varepsilon_{i,t}$ is the bank specific residual. We use bank-level return data at daily frequency, including all traded banks represented in the Datastream broad banking index for each country. We included banks which were traded at one point during our period of study (for instance, so-called 'dead' banks resulting from acquisitions are also included). The broad Datastream indices are used as they are comparable across countries and have a very wide coverage. For the sake of simplicity, we follow Campbell et al. (2001) and assume that the zero-intercept assumption is reasonable in this context. We also rerun all calculations including a bank specific intercept with no changes in the main results. All estimations are available upon request.

[10] Campbell et al. (2001) calculate the decomposition of stock market volatility without imposing a parametric model to describe its evolution over time. By assuming that the different components (market, sector and individual) of stock market returns are orthogonal to one another, a simple variance decomposition can be undertaken to calculate each of these components of risk. Therefore individual bank idiosyncratic risk can be calculated as:

$$\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{t=1}^{T}\frac{(R_{i,k,q,t}-R_{B,k,q,t})^2}{obs}$$

where $R_{i,t}$ and $R_{B,t}$ are, respectively, the individual bank *i* and banking sector *B* returns for each country *k* at time *t*. The variable *obs* refers to the number of daily observations for each quarter available for bank *i*. All results are available upon request.

[11] We also tried other measures of monetary policy rates with a lower maturity (overnight, one-month) and results remain unchanged.

seasonally adjusted nominal *GDP* was obtained from the OECD Economic Outlook database, while Datastream is the source of stock market returns and interest rates. The slope of the yield curve is calculated as the difference between the ten-year government bond yields and the short term rate. Housing index nominal returns have been obtained from the Bank for International Settlements.

The initial sample consisted of more than 1,100 banks in 16 industrialized countries. Unfortunately, not all of the bank risk measures used in the study were available for all of these banks so it was decided to restrict the analysis to the 643 banks for which all the necessary information was available. Table 2 gives some basic information on the final dataset. From a macroeconomic point of view, this dataset is still extremely relevant because it represents around two-thirds of the total lending provided by banks in the European Union and the US. The average size of the banks in the sample is the largest in the United Kingdom, Belgium and Sweden, and smallest in Finland and Greece. Equally, the average size of US banks is not very large because there is more information available for this country and many small banks are also listed. The averages of individual bank characteristics differ across countries. There are also differences in terms of capital and liquidity ratios, probably reflecting different competitive and institutional conditions, as well as different stages of the business cycle.

In Table 3, banks are grouped depending on their specific risk position, using one-year *EDF*s. A 'high-risk' bank has the average *EDF* of banks in the fifth quintile (i.e. EDF_H is equal to 2.02%); a 'low-risk' bank has the average *EDF* of the banks in the first quintile (EDF_L is equal to 0.09%). The first part of the table shows that high-risk banks are smaller, less liquid and less capitalized. The lower degree of liquidity and capitalization appears to be consistent with the higher risk of these banks. Additionally, low-risk banks make relatively fewer loans than high-risk banks, but the difference is not so remarkable.

The econometric model and results

Empirically, the main difficulty in measuring the impact of low interest rates on bank risk-taking is to separate the effects of changes in monetary policy rates on two key areas: first, the risk of outstanding loans and, second, banks' incentives to take on new risk. As already discussed in Section II, a reduction of interest rates causes a positive direct effect on lending portfolios (since households and firms pay a reduced interest rate on variable rate mortgages, the probability of their going into default declines) while a reduction of the interest rate below the benchmark causes a negative effect as the 'search for yield' gives way to an overall increase in new risk-taking.

To tackle this identification problem, we have considered both the quarterly change in the monetary policy rate and the deviation of the interest rate from a benchmark level that evaluates the relative stance of monetary policy. In particular, the following country-specific benchmark measures have been calculated:

a) the difference between the actual nominal short-term interest rate and that generated by a 'Taylor rule' with interest rate smoothing *(TGAP)*;[12]

[12] The Taylor rule suggests a simple way of setting monetary policy (Taylor, 2001). In particular, the money market interest rate (i.e. federal funds rate in the US) is a positive function of both the difference between inflation (π_t) and its target level (π^*), and the output gap: the gap between *GDP* (y_t) and its long-term potential non inflationary level (y_t^*). Algebraically, this can be written as $i_t=(1-\gamma)[\alpha+\beta_\pi(\pi_t - \pi^*)+\beta_y(y_t - y_t^*)] + \gamma\ i_{t-1}$, where

b) the difference between the actual nominal short-term interest rate and that generated by a standard "Taylor rule", using equal weights on output and inflation and no interest rate smoothing *(TGAP2)*;[13]

c) the difference between the real short-term interest rate and the "natural interest rate" *(NRGAP)*, calculated using the Hodrick-Prescott filter.

Chart 2 shows the three measures for the United States. In general, it was found that using a Taylor rule of type (a), with interest rate smoothing, tends to reduce the gap with respect to the nominal interest rate. This measure is also much less strongly correlated with bank *EDF* than the other measures (-0.10 against -0.20 and -0.18)[14]. In this paper, *TGAP* is used as the main measure of relative monetary policy, with the aim of applying a more stringent criterion for testing for the existence of a risk-taking channel. In other words, since smoothing tends to reduce the magnitude of the channel that is being tested, if a risk-taking channel is detected using the *TGAP* measure, the strength of this channel would be expected to be even more significant using a standard Taylor rule *(TGAP2)* or the natural interest rate *(NRGAP)*.

The baseline empirical model is given by the following equation:

$$\begin{aligned}\Delta EDF_{i,t} = \alpha\Delta EDF_{i,t-1} + \sum_{j=0}^{1}\beta_j \Delta MP_{k,t-j} + \sum_{j=0}^{1}\gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1}\delta_j \Delta GDPN_{k,t-j} + \\ + \sum_{j=0}^{1}\varphi_j SLOPE_{k,t-j} + \sum_{j=1}^{4}\phi_j SD + \varepsilon_{i,t}\end{aligned} \tag{1}$$

with i=1,…, N , k= 1, …,15 and t=1, …, T where N is the number of banks, k is the country and T is the final quarter. Table 4 reports the summary statistics for the variables used.

In the baseline equation (1) the quarterly change of the Expected Default Frequency (ΔEDF) for bank i in quarter t, is regressed on changes in the monetary policy indicator (ΔMP), the Taylor Rule Gap (*TGAP*), nominal *GDP* growth rate ($\Delta GDPN$), the steepness of the yield curve (*SLOPE*). Seasonal dummies *(SD)* have also been included in this specification. One lag of all the variables has been introduced in order to obtain white noise residuals.

We relate changes in bank *EDFs* to country-specific macro-variables because intermediation activity, which is the most important part of banks' business, is done principally towards residents. Nevertheless we are aware that a part of bank activities takes place on international markets and national conditions could be less important for a number of big European banks located in small countries. However, if this were the case we should observe a less significant link between changes in individual bank risk and low interest rates in the country where the bank is headquartered. In other words, if a risk-taking channel is

the γ represents the degree of interest rate smoothing and α is the real rate prevailing when output and inflation are at target levels ($r^*=i^*-\pi^*=\alpha-\pi^*$). We set $\beta_\pi=1.5$ and β_y =0.5. The interest rate smoothing parameter γ has been set to 0.85. The target inflation (π^*) has been set to 2%.

13 Following the standard set-up for a Taylor rule, we set $\beta_\pi=\beta_y$=0.5 and $\gamma=0$. Also in this case the target inflation (π^*) has been set to 2%.

14 All the three correlations are significantly different from zero at 1% significance level (see the p-values in the first column of Table 1).

detected using our identification strategy, the strength of this channel would be expected to be even more significant when controlling for multinational activity.

The main results of the analysis are reported in Table 5. The introduction of a lagged dependent variable among the predictors creates substantial complications in the estimation as the lagged dependent variable is correlated with the disturbance. Hence the models have been estimated using the GMM estimator developed for dynamic panel models by Arellano and Bover (1995) and Blundell and Bond (1998). This estimator ensures efficiency and consistency, provided that the models are not subject to serial correlation of order two and that the instruments used are valid (which is checked using the Sargan test).

Table 5 shows that, ceteris paribus, the effects of changes in the short term monetary policy rate on banks' risk are positive. The overall quality of a loan portfolio indeed increases (banks' *EDFs* decrease) if interest rates are lowered. This is consistent with the finding of Jiménez et al. (2009) that lower interest rates reduce the credit risk of outstanding loans and the predictions of Dubecq et al. (2009). The drop in the *EDF* is probably reinforced by the reduction in bank funding liquidity cost after the decrease in short-term monetary interest rates (Diamond and Rajan, 2009; Adrian and Shin, 2009a).

The coefficient related to the *TGAP* variable is negative and significant, confirming the effect of a risk-taking channel: if the interest rate is below the benchmark rate, banks do take more risks. For example, taking the results from the baseline model in the first column, if the interest rate is 100 basis points below the value given by the Taylor rule, the average probability for a bank to go into default increases by 0.6 % after a quarter and by 0.8% in the long run. This is a very rough estimate of such a probability and - since the model does not include controls for asset price dynamics and individual bank-specific characteristics (to be discussed below) - it represents an upper limit of the effect.

The coefficients for Δ*GDPN* are negative. Better economic conditions increase the number of projects becoming profitable in terms of expected net present value, thereby reducing the overall credit risk of the bank (Kashyap et al., 1993). Higher output growth reduces credit risk on both new and outstanding loans, in stark contrast to the differential effects of monetary policy.

Furthermore, the coefficients for the slope of the yield curve are negative. A steeper yield curve determines an increase in bank profits (a decrease in the *EDF*) because of the typical maturity transformation function performed by banks, since their assets have a longer maturity than liabilities. This is consistent with the findings of Albertazzi and Gambacorta (2009).

Since the Taylor rule gap could, in principle, give different indications with respect to other measures, the reliability of these baseline results have been tested using the natural rate gap; that is, the difference between the real short-term interest rate and the natural interest rate (*NRGAP*). As shown in the second column of Table 5, results are very similar: the only difference is the magnitude of the coefficient for *NRGAP*, caused by the different average level of the two variables. As discussed at the beginning of this section, results are even more in favor of the existence of a risk-taking channel when using a simple Taylor rule with no interest rate smoothing and equal weights.

Improvements in borrowers' net worth and collateral are taken into account by introducing into the specification the evolution of asset prices:

$$\Delta EDF_{i,t} = \alpha\Delta EDF_{i,t-1} + \sum_{j=0}^{1}\beta_j \Delta MP_{k,t-j} + \sum_{j=0}^{1}\gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1}\delta_j \Delta GDPN_{k,t-j} + \\ + \sum_{j=0}^{1}\varphi_j SLOPE_{k,t-j} + \sum_{j=0}^{1}\mu_j \Delta HP_{k,t-j} + \sum_{j=0}^{1}\kappa_j \Delta SM_{k,t-j} + \sum_{j=1}^{4}\phi_j SD + \varepsilon_{i,t} \quad (2)$$

where ΔHP and ΔSM are the quarterly changes in housing and stock market returns, respectively. Both asset returns are demeaned and adjusted for inflation. The introduction of these variables accounts for the effects of the standard 'financial accelerator' mechanism, through which financing frictions on firms and households amplify or propagate exogenous disturbances (Bernanke and Gertler, 1989). With a given bank risk aversion (or tolerance), the coefficients of both variables should be negative: a boost in asset prices increases the value of collateral and reduces overall credit risk.

However, the results presented in the third column of Table 5 show that only the coefficients for changes in stock market returns have the expected negative sign, while the opposite is the case for housing prices. This calls for further investigation into the relationship between changes in housing prices and bank risk.

Ellis (2008) points out that the recent credit crisis was triggered by credit losses on US mortgages. In the period under consideration, the United States seems to have built up a larger excess of housing supply, experienced a greater easing in mortgage lending standards, and ended up with a household sector that is more vulnerable to falling house prices. Some of these outcomes seem to have been driven by tax, legal and regulatory systems that encouraged households to increase their leverage and permitted banks to enable that development. Apart from the United States, there are other countries in the sample that experienced a boom-bust housing price cycle, namely Denmark, Ireland, Spain, Sweden and the United Kingdom (IMF, 2009b). Given this fact, we have included in the model (see below equation (3)) two interaction variables between each asset price and a dummy (*HPBB*) that takes the value of 1 if the bank is based in one of the countries that experienced a boom-bust housing cycle and zero elsewhere.

$$\Delta EDF_{i,t} = \alpha\Delta EDF_{i,t-1} + \sum_{j=0}^{1}\beta_j \Delta MP_{k,t-j} + \sum_{j=0}^{1}\gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1}\delta_j \Delta GDPN_{k,t-j} + \\ + \sum_{j=0}^{1}\varphi_j SLOPE_{k,t-j} + \sum_{j=0}^{1}\mu_j \Delta HP_{k,t-j} + \sum_{j=0}^{1}\kappa_j \Delta SM_{k,t-j} + \\ + \sum_{j=0}^{1}\mu^*_j \Delta HP_{k,t-j} * HPBB + \sum_{j=0}^{1}\kappa^*_j \Delta SM_{k,t-j} * HPBB + \sum_{j=1}^{4}\phi_j SD + \varepsilon_{i,t} \quad (3)$$

The fourth column of Table 5 shows that the positive link between housing prices and trends in bank risk is accounted for by developments in the housing market of those countries that experienced a boom-bust cycle. The coefficient μ_j for the remaining European countries, where the housing price bubble did not materialize (or was less pronounced), is indeed negative.

The link between bank risk and accommodative monetary policy could also be influenced by balance sheet characteristics that summarize the ability and willingness of banks to supply additional loans (Ehrmann et al., 2003). We have, therefore, introduced into the specification *SIZE* (the log of total assets; Kashyap and Stein, 1995), *LIQ* (securities and other liquid assets over total assets; Stein, 1998); and *CAP* (the capital-to-asset ratio; Kishan and Opiela, 2000; Van den Heuvel, 2002). The econometric model is therefore modified in the following way:

$$\Delta EDF_{i,t} = \alpha\Delta EDF_{i,t-1} + \sum_{j=0}^{1}\beta_j \Delta MP_{k,t-j} + \sum_{j=0}^{1}\gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1}\delta_j \Delta GDPN_{k,t-j} + \\ + \sum_{j=0}^{1}\varphi_j SLOPE_{k,t-j} + \sum_{j=0}^{1}\mu_j \Delta HP_{k,t-j} + \sum_{j=0}^{1}\kappa_j \Delta SM_{k,t-j} + \\ + \varpi\, SIZE_{i,t-1} + \tau\, LIQ_{i,t-1} + \zeta\, CAP_{i,t-1} + \sum_{j=1}^{4}\phi_j SD + \varepsilon_{i,t} \tag{4}$$

where all bank-specific characteristics refer to *t-1* in order to avoid endogeneity bias.

The results are reported in the fifth column of Table 5. The effects of liquidity (*LIQ*) and capitalization (*CAP*) on bank risk are negative. All other things being equal, liquid and well-capitalized banks are considered less risky by the market. The effect on size is contrary to the 'too big to fail' paradigm.

During the recent credit crisis not all banks have been equally affected and responsible. The banks which were predominantly affected were large institutions which moved away from traditional retail banking activities towards a business model that principally relied on the creation, distribution and trading of new and complex securities (Panetta et al., 2009). Moreover, it has often been pointed out that these big banks in financial difficulties could have been "too big to be saved by their national governments alone" (Stiglitz, 2009). In order to check if the result on the size variable is driven by these effects during the crisis, the model has been adapted by including an interaction between the variable *SIZE* and a crisis dummy (*CRISIS*), which takes the value of 1 from 2007Q3 to 2008Q4 and zero elsewhere.

$$\Delta EDF_{i,t} = \alpha\Delta EDF_{i,t-1} + \sum_{j=0}^{1}\beta_j \Delta MP_{k,t-j} + \sum_{j=0}^{1}\gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1}\delta_j \Delta GDPN_{k,t-j} + \\ + \sum_{j=0}^{1}\varphi_j SLOPE_{k,t-j} + \sum_{j=0}^{1}\mu_j \Delta HP_{k,t-j} + \sum_{j=0}^{1}\kappa_j \Delta SM_{k,t-j} + \\ + \varpi\, SIZE_{i,t-1} + \varpi * SIZE_{i,t-1} * CRISIS + \tau\, LIQ_{i,t-1} + \zeta\, CAP_{i,t-1} + \sum_{j=1}^{4}\phi_j SD + \varepsilon_{i,t} \tag{5}$$

Interestingly, the log of total assets (*SIZE*) now has the expected negative impact on bank riskiness in the pre-crisis period, while the interaction with the dummy for the crisis period is positive and significant (see the sixth column of Table 5). The sign of the *TGAP* variable is still negative and significant, confirming the fact that if the interest rate is below the benchmark rate, banks do take more risks. In this more complete specification, however, if the short-term interest rate is 100 basis points below the rate given by the Taylor rule, the average probability for a bank to default increases by 0.4% after a quarter, which is significantly lower than the baseline estimation (0.6% in the first column of Table 5).

Historically, most systemic banking crises have been preceded by periods of excessive lending growth (Reinhart and Rogoff, 2008; Borio and Drehmann, 2009). Therefore, it would be interesting to test whether the risk-taking channel continues to work at the level of individual banks, even when controlling for the effect on banking risk due to excessive lending, which is more systemic in nature. We have, therefore, computed a bank-specific measure for excessive credit expansion by subtracting from the individual bank lending growth at a given point in time the mean of the growth for all the other banks over that specific quarter. Since the impact of excessive credit expansion on bank risk could be non-linear (see Section III), the quadratic term was also added.[15]

$$\begin{aligned}\Delta EDF_{i,t} &= \alpha \Delta EDF_{i,t-1} + \sum_{j=0}^{1} \beta_j \Delta MP_{k,t-j} + \sum_{j=0}^{1} \gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1} \delta_j \Delta GDPN_{k,t-j} + \\ &+ \sum_{j=0}^{1} \varphi_j SLOPE_{k,t-j} + \sum_{j=0}^{1} \mu_j \Delta HP_{k,t-j} + \sum_{j=0}^{1} \kappa_j \Delta SM_{k,t-j} + \\ &+ \varpi\, SIZE_{i,t-1} + \tau\, LIQ_{i,t-1} + \zeta\, CAP_{i,t-1} + \\ &+ \theta_1 EXLEND_{i,t-1} + \theta_2 EXLEND^2_{i,t-1} + \sum_{j=1}^{4} \phi_j SD + \varepsilon_{i,t}\end{aligned} \qquad (6)$$

The results reported in the last column of Table 5 show a U-shaped relationship between the deviation of lending growth from the mean value and bank risk. Banks that have a very low growth rate (that probably do not reach economies of scale), as well as those that have a high one (that may have a very aggressive price policy and supply a risky segment of the market), are considerably riskier than average (see Chart 3).[16] The sign of the *TGAP* variable, which monitors the risk-taking channel, remains negative and significant. The levels of the coefficients are predictably lower, because they capture only the part of the risk-taking channel that is dependent on non-traditional bank activities such as investment banking, securitization, derivatives and negotiation activity. The fact that a substantial part of the risk in bank balance sheets was not linked to traditional lending is amply documented (see, for instance, Shin, 2009).

Robustness tests

Different measures for bank risk

The robustness of the results has been checked by considering a more complete term structure for bank risk. The reason for this test is that the one-year horizon for the *EDF* may not be sufficient to capture certain properties of risk that build up over a longer time frame. In order to address this, equation (1) was rerun using the *EDF* as a dependent variable with horizons of both five and ten years. Unfortunately, these data have only been officially available since 2004, thereby reducing the number of observations in the sample. Despite this, the results presented in the second and third columns of Table 6 are consistent with those for the baseline model that uses the *EDF* over a one-year horizon (reported again for convenience in the first column of Table 6).

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[15] See Kwan and Eisenbeis (1997).

[16] The result still holds if we consider a bank-specific measure for excessive lending lagged 4 quarters instead of one quarter under the hypothesis that the market needs at least one year to detect a significant deviation of the credit portfolio of a given bank with respect to the industry average (Jiménez and Saurina, 2006). Similar results are obtained using the loan to total asset ratio instead than the lending growth rate. Estimations are available from the authors upon request.

It is worth noting that the increase of the *EDF* horizon does not change the sign and the significance of the coefficients attached to the monetary policy indicator (ΔMP) or the Taylor Rule Gap (*TGAP*). It does, however, produce some effects on the absolute value of the β and γ coefficients. In particular, a drop in the monetary policy rate still reduces a bank's *EDF* by lowering the credit risk on outstanding loans, although the magnitude of this effect is reduced for a longer-term horizon, probably because a substantial number of credit positions opened today will be closed at a future date. On the contrary, the strength of the risk-taking channel increases because it probably takes some time for banks to adjust their portfolios towards a more risky composition. Very similar results are obtained using the natural interest rate gap or other specifications of the Taylor rule as measures of accommodative monetary policy.

The second robustness test consists of calculating the impact of monetary policy on the idiosyncratic component of bank risk. In particular, it is necessary to test whether monetary policy influences an individual bank's attitude toward risk, independently of the developments of the banking system as a whole, a common driver for all intermediaries. In other words, we recognize that the banking sector is a highly interlinked industry subject to systemic shocks, which could operate regardless of individual bank risk attitude. With this in mind, our goal is to capture only individual bank risk, independent of developments in the banking market as a whole. In order to tease out systemic risk and obtain the idiosyncratic component of bank risk, two approaches, based on stock market information, were used: first, a simple *CAPM* model; second, the approach used by Campbell et al. (2001), who separate stock market risk into broad index, industrial sector and idiosyncratic components (see Section III for more details). The results for the baseline equation (1), when the two alternative measures for idiosyncratic risk are used, are reported in columns IV and V of Table 6. The use of idiosyncratic measures for bank risk does not change the sign and the significance of the monetary policy indicator (ΔMP) and the Taylor Rule Gap (*TGAP*). This confirms that bank risk-taking is not completely due to common factors emerging from the banking sector.

The third robustness test is the use of spreads on the credit default swap as an alternative variable for bank risk positions. This measure, which accounts for the cost of buying credit risk insurance subject to a certain credit event (usually a default), has been widely used during the recent credit crisis as the barometer of financial health and an early indicator of banks' problems (Blanco et al, 2005; Longstaff et al, 2005). Results for an unbalanced sample of more than 100 large banks over the period 2002-2009 obtained from Bloomberg were also consistent with those obtained by using the *EDF* and idiosyncratic measure of banks risk. Results are not reported for the sake of brevity.

The fourth robustness test was to use changes in bank ratings as a dependent variable, in order to see whether our results hold when these ratings are considered as a proxy for bank risk. This test is interesting because downgrades in ratings are sluggish and take a long time to occur. This, for example, seems to have been the case for the rating of securitized products during the recent credit crisis (Benmelech and Dlugosz, 2009). The robustness test, therefore, used the banks' standard long-term senior unsecured rating history and ratings outlook, calculated by Moody's and available for a sub-sample of 149 banks, as a dependent variable in equation (1). In this case, the effect of the risk-taking channel is not strongly detected (i.e. the coefficients associated with ΔMP and the *TGAP* measure have the correct sign, but are no longer always significant). This could be due to the implementation of ratings downgrades, as observed during the Asian crisis (Ferri et al., 1999).

Testing for non-linear effects, business expectations and regulatory differences

The recent crisis has reminded us of the fact that the manifestation of risk may be sudden and not linear. This section, therefore, provides a number of tests to verify whether the risk-taking channel is still in place when specific non-linear interactions between monetary policy and bank risk are taken into account.

The first aspect to consider is that the effect of monetary policy on bank risk may be influenced not only by the *TGAP* but also by two other aspects: firstly, the nominal level of the interest rate; secondly, how many consecutive quarters the interest rate has been below the benchmark. The baseline equation has, therefore, been modified to include terms that represent the interaction between the *TGAP* variable and, respectively, the level of the interest rate (*MP)* and the number of consecutive quarters the interest rate has been below the level implied by the Taylor rule (*BEL*).[17]

$$\Delta EDF_{i,t} = \alpha \Delta EDF_{i,t-1} + \sum_{j=0}^{1} \beta_j \Delta MP_{k,t-j} + \sum_{j=0}^{1} \gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1} \delta_j \Delta GDPN_{k,t-j} + \sum_{j=0}^{1} \varphi_j SLOPE_{k,t-j} + \sum_{j=0}^{1} \psi_j TGAP_{k,t-j} MP_{k,t-j} + \sum_{j=0}^{1} \rho_j TGAP_{k,t-j} BEL_{k,t-j} + \sum_{j=1}^{4} \phi_j SD + \varepsilon_{i,t} \tag{7}$$

The first column of Table 7 shows that the negative link between *ΔEDF* and *TGAP* is reinforced if the level of interest is particularly low (ψ_j>0), in line with the search for yield hypothesis. Financial intermediaries typically commit themselves to producing relatively high nominal rates of return in the long term. When interest rates become unusually low, independently of their relative distance with respect to the Taylor rule, the contractual returns can become more difficult to achieve and this can put pressure on banks to take on more risk in the hope of generating the return needed to remain profitable. Moreover, the coefficient ρ_j is negative, confirming that the effects of monetary policy on bank risk are amplified in the case of an extended period of low interest rate. To sum up, it is not only the size of the deviation of the interest rate with respect to a benchmark that matters but also the length of time this deviation persists.

How can we be sure that what we are capturing are the effects of a risk-taking channel rather than heightened expectations of the economic conditions? Banks could indeed take on more risk simply because they anticipate better prospects rather than because interest rates are low. In order to control for this effect, we have included forward values of nominal growth in *GDP*, derived from Consensus Forecast Indicators (*ΔGDPCF*).[18] The results reported in the second column of Table 7 show that the effects on bank risk of a long period of low interest rates are still in place.

These results could also be influenced by the distorting impact of the global level of risk aversion on the signals of bank risk. This does not seem to be the case as similar results are obtained when we also include into the specification the State Street Investor Confidence Index (*SSICI*), a measure of global investors' attitude to risk (see the third column of Table 7). The variable *SSICI* controls for elements of structural irrationality or other behavioral attitudes on the side of investors, such as herding behavior (Barberis et al., 1998; Brunnermeier and Nagel, 2004).[19]

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[17] The variables *MP* and *BEL* were also initially included in isolation in equation (7) but turned out not to be significant. Therefore we have decided to drop them from the model also taking into account the fact that *MP* is highly correlated with the variable *SLOPE* (see Table 1).

[18] We thank Steven Cecchetti for this useful suggestion.

[19] The State Street Investor Confidence Index focuses on expectations for future prices and returns and provides a quantitative measure of the actual and changing levels of risk contained in investment portfolios

The above results may also be influenced by differences in the intensity of bank supervision, which could have had an impact on the amount of risk undertaken (Beltratti and Stulz, 2009). In particular, it is necessary to verify whether more permissive legislation on bank activities could have led financial intermediaries to take more risks. Following the approach in Barth et al. (2004), a regulation variable (*REG*) was introduced into the baseline equation. This variable takes into account the extent to which banks may engage in securities, insurance and real estate activities. For the countries analyzed in this study, the variable *REG* takes a value from 5 to 12, where the latter value represents the maximum level of activity in which banks may engage. The results in the fourth column of Table 7 indicate a positive and significant value for this variable, supporting the idea that banks took more risk in those countries where specific institutional factors allowed them to be involved in more non-traditional banking activities. Also, in this case, the coefficients for the monetary policy indicator (ΔMP), Taylor Rule Gap (*TGAP*), and their interactions with *MP* and *BEL* remain basically unchanged, pointing to the fact that the effects of long-standing low interest rates on bank risk are still at work. Very similar results are obtained replacing the variable *REG* with a complete set of country dummies to take into account other institutional characteristics.

Modeling the probability of banks becoming risky

In this section, the probability of a bank becoming among the riskier institutions during the crisis period is modeled. In particular, those financial intermediaries that experienced the highest increase in their default probability after the 2007 summer are considered as risky. We have, therefore, created a binary variable (*risky*) that takes the value of 1 if the bank is in the top quartile of the distribution in terms of changes in the expected default probability in the period of financial crisis (2007Q2 – 2008Q4), and 0 elsewhere. Starting from a sample of 588 banks, whose median increase in default probability during the crisis was 0.7%, banks considered as risky are those for which the increase was higher than 2.1% that delimit the last quarter of the distribution.

The probability of a bank becoming risky during the crisis is considered as a function of a combination of factors that developed prior to the crisis. On the one hand, this probability is determined by macro factors, such as the health of the economy, the evolution of asset prices, the level of interest rates and the structure of the yield curve; on the other hand, it is affected by bank specific characteristics, such as size, liquidity, capitalization, the use of securitization instruments, lending activity.

The baseline empirical model is given by the following probit equation:

$$P\left[risky_{ik} = 1 \middle| X\right] = \Phi(X'\beta) \tag{8}$$

where P is the probability, Φ is the standard cumulative normal probability distribution, X is a vector of regressors that include macro-variables of country k where bank i has its main seat and specific characteristics of the same bank i over the five years prior to the crisis (2002Q2 – 2007Q2). As usual, β parameters are estimated by maximum likelihood.

Table 8 summarizes the results of the estimation. The pseudo-R^2 of the regression model, as in similar exercises, is not very high (14%) and reflects the fact that the Probit model only

representing about 15% of the world's tradable assets. Further information is available at: http://www.statestreet.com/industry_insights/investor_confidence_index/ici_overview.html.

captures some of the underlying long-term causes of the financial turmoil and does not use any information from the crisis period. This means that the model neglects all those factors such as expectations of negative changes, difficulties in financial markets, liquidity interventions and, most importantly, bank idiosyncratic shocks that unfolded after the summer of 2007.

Consistently with the risk-taking channel hypothesis, the coefficient for the *BEL* variable is positive and significant. This result confirms that if the interest rate is well below the benchmark rate for an overly extended period of time, banks do take more risks.[20]

The probit analysis aimed to take into consideration two additional factors, not analyzed so far, that could have influenced the evolution of bank risk prior to the crisis, namely, securitization activity and bank profitability.

The trigger of the crisis was the subprime mortgage segment in the US that highlighted the limitations of the Originate-to-Distribute (*OTD*) model. This means that it is interesting to check if the effectiveness of the risk-taking channel still holds controlling for the fact that most of the banks in the sample have relied heavily on the securitization market and might have simply reduced monitoring and screening on their loan portfolios (Parlour and Plantin, 2007). Drucker and Puri (2007) show that securitized loans tend to be less informationally sensitive than loans held by banks, i.e. banks sell loans such as mortgages for which screening and monitoring are less important than for commercial and industrial loans. In the specification, we included, therefore, a bank-specific ratio of securitization activity to assess whether banks that were more active in the securitization market experienced a higher increase in their default probability during the crisis. The results show that banks that securitized increased their default probability during the period of crisis, even if this effect is only marginally significant.

Profitability could have also played a role in bank risk-taking. It could be argued that certain banks which have done exceptionally well and achieved higher levels of profits prior to the crisis could be those who took the highest amounts of risk, for example, by expanding into segments of business with higher volatility of cash flows or by lowering their credit standards. Berger et al. (2000) and Goddard et al. (2004) find evidence that there is significant year-to-year persistence in the profitability of US and European banks. To control for the possible impact of performance on bank risk, we have also included the average return on assets (*ROA*) as a measure of profitability. Unlike the return on equity, the return on total assets is a measure of banks' profits which does not include the influence on profits of leverage, which is already controlled by means of the capital-to-asset ratio.

There is also a long established literature arguing that increases in competition could lead to greater (and possibly excessive) risk-taking by banks. This is because increased competition reduces the market power of banks, thereby decreasing their charter value. The decline in charter value, coupled with the existence of limited liability and the application of flat rate deposit insurance, could encourage banks to take on more risk (Matutes and Vives, 2000). To take this into account, we have used the responses from the Bank Lending Survey for euro area banks and Senior Loan Officer Survey for US banks regarding the effect of competition on credit conditions to construct a net percentage index (see Ciccarelli et al., 2010). This index, representing the difference between the number of banks that reported a tightening in credit conditions due to competition and the number that reported an easing, was used in the regression. The results indicate a positive link between the competition index

[20] Similar results are obtained using a *LOGIT* model or a simple *OLS* where the dependent variable is simply the change in the bank *EDF* over the crisis period. Estimations are available from the authors upon request.

(*COMP*) and risk-taking, but with no statistical significance. This result is in line with Boyd and De Niccoló (2005), who argue that the theoretical basis for linking more competition with increased incentives towards bank risk-taking is fragile.[21]

Conclusions

The current credit crisis has drawn the attention of researchers and policy makers back to the link between monetary policy and bank risk-taking. Low short-term interest rates may influence banks' perceptions of, and attitude towards, risk in at least two ways: (i) through their impact on valuations, incomes and cash flows which in turn can modify how banks measure risk; (ii) through a more intensive search for yield process, especially when nominal return targets are in place. These two ways may be amplified if agents perceive that monetary policy will be relaxed in the case of decreasing asset prices in a financial downturn (the so-called insurance effect) causing a classic moral hazard problem.

The economic expansion that began in 2002 was characterized in many instances by the coexistence of low monetary policy rates, financial innovation and booming asset prices, three conditions that may have amplified the effectiveness of the risk-taking channel.

We contribute to the debate and analyze the link between monetary policy and bank risk using a unique database of listed banks operating in 16 developed countries during and prior to the period of the financial crisis. We find that subdued short-term low interest rates over an extended period of time contributed to an increase in banks' risk. This central insight is of interest to both monetary and supervisory authorities and has two main corollaries. First, it suggests that central banks would need to consider the possible effects of monetary policy actions on bank risk. The potential impact of risk-taking by banks may have implications for longer term macroeconomic outlook including output growth, investment and credit. Second, banking supervisors should strengthened the macro-prudential perspective to financial stability by intensifying their vigilance during periods of protracted low interest rates, particularly if accompanied by other signs of risk-taking, such as rapid credit and asset price increases.

[21] See Carletti and Hartmann (2002) for a useful survey of the literature linking competition and stability.

Correlation matrix

Table 1

	EDF	*EDF5*	*EDF10*	IDSC1 (2)	IDSC2 (3)	LNRATE	*MP*	*TGAP*	*TGAP2*	*NRGAP*	*ΔGDPN*	*SLOPE*	*ΔHP*	*ΔSM*	*SIZE*	*LIQ*	*CAP*	*EXLEN*	*BEL*	*REG*	*SSICI*
EDF	1.000																				
EDF5	0.968	1.000																			
	0.000																				
EDF10	0.850	0.930	1.000																		
	0.000	*0.000*																			
IDSC1 (2)	0.089	0.084	0.092	1.000																	
	0.000	*0.000*	*0.000*																		
IDSC2 (3)	0.506	0.347	0.216	0.030	1.000																
	0.000	*0.000*	*0.000*	*0.000*																	
LNRATE	0.166	0.196	0.247	0.272	0.079	1.000															
	0.000	*0.000*	*0.000*	*0.000*	*0.000*																
MP	-0.009	-0.183	-0.165	0.074	-0.007	-0.016	1.000														
	0.009	*0.000*	*0.000*	*0.000*	*0.381*	*0.269*															
TGAP	-0.098	-0.126	-0.266	0.091	-0.031	-0.066	0.456	1.000													
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*														
TGAP2	-0.203	-0.197	-0.259	0.024	-0.047	-0.047	0.356	0.627	1.000												
	0.000	*0.000*	*0.000*	*0.002*	*0.000*	*0.001*	*0.000*	*0.000*													
NRGAP	-0.183	-0.268	-0.310	0.035	-0.056	-0.020	0.667	0.708	0.857	1.000											
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.174*	*0.000*	*0.000*	*0.000*												
ΔGDPN	-0.138	-0.272	-0.279	0.090	-0.017	-0.025	0.115	0.255	0.131	0.289	1.000										
	0.000	0.000	0.000	0.000	0.026	0.083	0.000	0.000	0.000	0.000											
SLOPE	0.024	0.165	0.131	-0.011	0.005	0.010	-0.893	-0.342	-0.327	-0.640	-0.105	1.000									
	0.001	*0.000*	*0.000*	*0.143*	*0.503*	*0.467*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*										
ΔHP	-0.155	-0.352	-0.332	0.136	-0.096	-0.028	0.070	0.439	0.264	0.285	0.477	-0.048	1.000								
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.049*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*									
ΔSM$_t$	-0.131	-0.345	-0.306	0.121	-0.094	-0.030	0.038	0.195	0.186	0.206	0.375	-0.092	0.641	1.000							
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.038*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*								
SIZE	-0.065	-0.069	-0.109	-0.522	-0.027	-0.498	-0.004	0.042	0.054	0.045	-0.031	-0.042	-0.029	-0.030	1.000						
	0.000	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*	*0.447*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*							
LIQ	0.003	-0.080	-0.045	-0.077	-0.016	-0.067	-0.048	0.078	0.064	0.027	0.022	0.062	0.072	0.041	0.137	1.000					
	0.646	*0.000*	*0.000*	*0.000*	*0.049*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*						
CAP	-0.024	-0.066	-0.113	0.113	-0.001	0.156	0.005	0.037	0.045	0.034	-0.016	-0.010	0.005	-0.001	-0.282	0.249	1.000				
	0.001	*0.000*	*0.000*	*0.000*	*0.857*	*0.000*	*0.314*	*0.000*	*0.000*	*0.000*	*0.003*	*0.047*	*0.355*	*0.888*	*0.000*	*0.000*					
EXLEND	-0.006	-0.022	-0.025	0.041	-0.001	-0.037	-0.006	-0.016	-0.066	-0.042	0.000	-0.001	-0.030	0.002	-0.011	-0.033	-0.020	1.000			
	0.383	*0.010*	*0.001*	*0.000*	*0.906*	*0.019*	*0.224*	*0.003*	*0.000*	*0.000*	*0.944*	*0.808*	*0.000*	*0.722*	*0.046*	*0.000*	*0.000*				
BEL	0.005	0.144	0.128	-0.204	0.019	0.111	-0.496	-0.372	-0.340	-0.356	-0.117	0.316	-0.176	-0.075	-0.160	-0.196	-0.068	0.007	1.000		
	0.447	*0.000*	*0.000*	*0.000*	*0.015*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.191*			
REG	0.066	0.027	0.000	0.067	0.014	0.236	0.123	-0.115	-0.115	-0.095	0.037	-0.031	0.015	-0.011	-0.354	-0.200	-0.106	0.022	0.145	1.000	
	0.000	*0.002*	*0.998*	*0.000*	*0.061*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.014*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*		
SSICI	-0.034	-0.303	-0.228	0.241	-0.072	-0.078	0.240	0.248	0.214	0.176	0.304	0.001	0.320	0.262	-0.052	0.113	-0.010	0.000	-0.696	0.128	1.000
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.909*	*0.000*	*0.000*	*0.000*	*0.000*	*0.060*	*1.000*	*0.000*	*0.000*	

Source: Authors' calculations.
Notes: (1) P-values in italics. (2) Obtained from a *CAPM* model. (3) Obtained following the approach used in Campbell et al. (2001). For more details see Section III. The meaning of the symbols is reported in Table 4.

Descriptive statistics by country: 1999-2009

(mean values)

Table 2

	Nominal *GDP*	Money market rate	Bank size, total assets	Loan growth	Capital	Liquidity	*EDF*	Idiosyn-cratic risk (1)	Stock market return (2)	Housing price changes (2)	Slope of yield curve	Number of banks (3)	Weight inside sample (4)
Country	(Annual growth rate)	(Annual interest rate)	(USD millions)	(Annual growth rate)	(% of total assets)	(% of total assets)	(1 year ahead)	(%)	(Average quarterly changes)	(Average quarterly changes)	(%)	(Final dataset))	(%)
Austria	3.99	3.11	37,912	14.89	6.21	31.35	0.43	0.04	0.55	1.77	1.34	9	1.65
Belgium	4.13	3.13	222,456	11.35	7.27	46.17	0.10	0.06	-1.66	1.25	1.39	5	0.94
Denmark	4.19	3.48	11,370	14.03	11.89	25.41	0.32	0.11	0.51	0.64	1.08	32	6.36
Finland	4.78	3.14	8,984	10.58	7.26	21.57	0.07	0.04	-0.15	2.47	1.28	2	0.17
France	3.94	3.11	123,158	7.74	11.30	19.38	0.44	0.04	-0.11	1.60	1.30	22	3.80
Germany	2.40	3.11	139,145	4.22	6.79	29.96	0.83	0.06	-0.43	-0.01	1.22	24	3.63
Greece	7.60	4.94	20,436	21.18	7.91	26.45	1.12	0.07	-1.27	1.87	0.15	9	1.44
Ireland	9.59	3.34	74,902	20.15	4.64	26.34	0.19	0.08	-2.00	0.84	1.29	4	0.81
Italy	3.73	3.30	45,400	14.61	9.51	27.40	0.22	0.04	-1.13	0.89	1.50	24	4.13
Netherlands	5.03	3.10	173,784	11.35	8.29	24.18	1.04	0.04	-1.58	0.69	1.31	5	0.80
Portugal	4.56	3.33	290,065	15.18	5.06	21.25	0.24	0.04	-1.03	0.80	0.06	5	0.97
Spain	7.34	3.21	81,173	18.34	8.52	20.23	0.12	0.05	0.07	1.66	1.35	13	2.61
Sweden	4.91	3.36	180,368	12.73	5.26	26.28	0.09	0.02	0.10	0.34	1.23	4	0.82
UK	3.70	4.97	373,507	11.52	7.90	30.34	0.26	0.03	-0.49	0.18	0.03	6	1.00
USA	4.90	3.65	14,946	11.02	9.77	23.17	0.70	0.09	-0.68	-0.55	1.21	479	70.89
Total	4.99	3.49	119,840	11.33	9.60	23.64	0.61	0.05	-0.62	0.96	1.00	643	100.00

Sources: Bloomberg, OECD, Eurostat, Datastream, Moody's KMV, Creditedge and BIS. Data for Luxembourg turned out to be available for only one bank and were not used for confidentiality reasons.

Notes: (1) Idiosyncratic risk is calculated following the estimation suggested by Campbell et al. (2001). For more details, see Appendix. (2) Adjusted for inflation. (3) Banks analyzed in this table refer to the final dataset after the filtering process and other corrections. (4) As a percentage of the number of observations.

Balance sheet characteristics and bank risk profile[1] Table 3

Distribution by bank risk (one year ahead EDF)	**Size**	**Liquidity**	**Capitalization**	**Lending**
	(USD millions)	(% total assets)	(% total assets)	(Annual growth rate)
High-risk banks (EDF=2.02%) (a)	20,405	21.3	8.9	13.5
Low-risk banks (EDF=0.09%) (b)	94,746	26.0	10.9	11.3
Δ=(a)-(b)	-74,341	-4.7	-2.0	2.2

Note: [1] A low-risk bank has an average ratio of the *EDF* in the first quintile of the distribution by bank risk; a high-risk bank an average *EDF* in the last quintile. Since the characteristics of each bank could change with time, percentiles have been calculated on mean values.

Summary statistics of the variables used in the regressions Table 4

(1999Q1-2008Q4)

Variable	Number of observations	Mean	Median	Std. Dev	Min	Max	1st quartile	3rd quartile
EDF_t	19,796	0.61	0.17	1.9	0.01	29.98	0.08	0.43
$\Delta\ EDF_t$	19,796	0.07	0.00	0.83	-28.0	27.0	-0.03	0.03
ΔMP_t	19,796	-0.08	0.00	0.56	-3.75	1.53	-0.27	0.34
$TGAP_t$	19,796	-0.44	-0.27	0.57	-3.6	1.37	-0.76	-0.07
$NRGAP_t$	19,796	-0.3	-0.21	1.41	-5.1	3.62	-1.1	0.63
$\Delta GDPN_t$	19,796	1.09	1.15	0.96	-5.97	11.46	0.86	1.54
$SLOPE_t$	19,796	1.09	0.88	1.29	-2.25	3.69	-0.09	2.26
ΔHP_t	19,796	0.00	0.84	4.95	-22.98	79	-1.45	2.52
ΔSM_t	19,796	0.00	1.92	10.2	-47.63	63.72	-4.99	6.42
$SIZE_t$	19,796	7.15	6.55	2.25	-4.61	15.43	5.66	8.25
LIQ_t	19,796	23.62	22.61	10.7	0.00	49.99	15.72	30.54
CAP_t	19,796	9.6	8.75	5.03	1.03	74.90	6.99	10.89
$EXLEND_t$	19,796	0.00	-0.62	7.8	-85.8	94.7	-3.35	2.64
$EXLEND_t^2$	19,796	60.00	9.12	290.2	0.00	8968.1	1.95	31.6
BEL	19,796	8.99	10.00	6.00	0.00	20.00	3.00	14.00
REG	19,796	10.32	11.00	1.85	4.00	12.00	10.00	11.00
SSICI	19,796	114.70	114.2	11.77	83.10	134.33	107.05	122.12

where:

EDF_t	=	expected default frequency (1 year ahead)
ΔEDF_t	=	change in the *EDF* (1 year ahead)
ΔMP_t	=	changes in the money market rate
$TGAP_t$	=	Taylor Rule gap
$NRGAP_t$	=	natural interest rate gap
$\Delta GDPN_t$	=	changes in nominal *GDP*
$SLOPE_t$	=	changes in the slope of the yield curve
ΔHP_t	=	quarterly changes in the housing price index (demeaned)
ΔSM_t	=	quarterly changes in stock market returns (demeaned)
$SIZE_t$	=	log of total assets (USD millions)
LIQ_t	=	liquidity-to-total assets *100
CAP_t	=	capital-to-total asset ratio *100
$EXLEND_t$	=	excessive credit expansion (demeaned)
$EXLEND_t^2$	=	square term of excessive credit expansion (demeaned)
BEL	=	number of consecutive quarters with interest rate below the benchmark
REG	=	regulatory index
SSICI	=	State Street Investor Confidence Index

Regression results

Table 5

Dependent variable: quarterly change of the expected default frequency (EDF) over a 1 year horizon	(I) Baseline model (Taylor GAP)		(II) Baseline model (Natural rate GAP)		(III) The financial accelerator (house and stock market returns)		(IV) The financial accelerator (different behaviour in countries with boom-bust housing cycle)		(V) Bank specific characteristics (size, liquidity, capitalization)		(VI) Bank size effect during the crisis		(VII) Excessive lending expansion	
	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error
ΔEDF_{t-1}	0.222 ***	0.006	0.216 ***	0.006	0.223 ***	0.007	0.224 ***	0.007	0.302 ***	0.007	0.278 ***	0.007	0.299 ***	0.008
ΔMP_{t}	0.114 **	0.050	0.064 **	0.030	0.185 ***	0.065	0.191 ***	0.069	0.080 **	0.041	0.082 ***	0.018	0.080 **	0.041
ΔMP_{t-1}	0.425 ***	0.047	0.094 ***	0.011	0.344 ***	0.051	0.281 ***	0.052	0.216 ***	0.043	0.185 ***	0.027	0.148 ***	0.033
$TGAP_{t}$	-0.111 **	0.050			-0.142 ***	0.052	-0.185 ***	0.055	-0.078 *	0.043	-0.202 ***	0.028	-0.090 **	0.036
$TGAP_{t-1}$	-0.497 ***	0.056			-0.447 ***	0.060	-0.408 ***	0.060	-0.262 ***	0.046	-0.156 ***	0.017	-0.194 ***	0.037
$NRGAP_{t}$			-0.048 ***	0.011										
$NRGAP_{t-1}$			-0.111 ***	0.013										
$\Delta GDPN_{t}$	-0.095 ***	0.013	-0.056 ***	0.013	-0.106 ***	0.014	-0.152 ***	0.017	-0.080 ***	0.010	-0.092 ***	0.010	-0.101 ***	0.009
$\Delta GDPN_{t-1}$	-0.140 ***	0.008	-0.111 ***	0.008	-0.124 ***	0.008	-0.158 ***	0.008	-0.102 ***	0.008	-0.112 ***	0.007	-0.088 ***	0.006
$SLOPE_{t}$	-0.011 **	0.005	-0.021 **	0.010	-0.027 **	0.012	-0.019 *	0.010	-0.053 ***	0.013	-0.030 **	0.013	-0.054 ***	0.010
$SLOPE_{t-1}$	-0.068 ***	0.020	-0.099 ***	0.021	-0.084 ***	0.023	-0.077 ***	0.024	-0.050 ***	0.011	-0.031 ***	0.011	-0.055 ***	0.010
ΔHP_{t}					0.010 ***	0.002	-0.004 *	0.002	0.011 ***	0.002	0.011 ***	0.002	0.010 ***	0.001
ΔHP_{t-1}					0.002 *	0.001	-0.110 ***	0.001	0.002 *	0.001	0.002 *	0.001	0.002 *	0.001
ΔSM_{t}					-0.010 ***	0.001	-0.009 ***	0.001	-0.011 ***	0.001	-0.007 ***	0.001	-0.010 ***	0.001
ΔSM_{t-1}					-0.011 ***	0.001	-0.007 ***	0.001	-0.007 ***	0.001	-0.004 ***	0.001	-0.004 ***	0.001
ΔHP_{t}*HPBB							0.016 ***	0.004						
ΔHP_{t-1}*HPBB							0.014 ***	0.004						
ΔSM_{t}*HPBB							-0.004 ***	0.001						
ΔSM_{t-1}*HPBB							-0.005 ***	0.001						
$SIZE_{t-1}$									0.060 ***	0.009	-0.033 ***	0.011	0.039 ***	0.009
LIQ_{t-1}									-0.008 ***	0.001	-0.004 ***	0.001	-0.012 ***	0.001
CAP_{t-1}									-0.013 ***	0.001	-0.016 ***	0.001	-0.019 ***	0.001
$SIZE_{t-1}$*CRISIS											0.030 ***	0.002		
$LEND\_GROWTH_{t-1}$													0.0013	0.003
$LEND\_GROWTH_{t-1}$^2													0.0001 ***	0.000
Sample period	1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4	
No of banks, No of observations	643	19,796	643	19,796	643	19,796	643	19,796	643	19,796	643	19,796	588	18,303
Sargan test (2nd step; pvalue)		0.293		0.198		0.247		0.225		0.275		0.277		0.258
MA(1), MA(2) (p-value)	0.000	0.695	0.000	0.696	0.000	0.631	0.000	0.759	0.000	0.374	0.000	0.741	0.000	0.723

Notes: Robust standard errors. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficients for the seasonal dummies are not reported. In the GMM estimation, instruments are the second and further lags of the dependent variable, the macro-variables and of the bank-specific characteristics included in each equation.

Different measures for bank risk

Table 6

Different measures of bank risk as dependent variable.	(I) ΔEDF 1yrs		(II) ΔEDF 5yrs		(III) ΔEDF 10yrs		(IV) Idiosyncratic measure (CAPM model)		(V) Idiosyncratic measure (Campbell et al. 2001)		(VI) ΔRating	
	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error
Dependent variable$_{t-1}$	0.222 ***	0.006	0.310 ***	0.006	0.291 ***	0.000	0.481 ***	0.007	0.393 ***	0.020	0.001	0.011
ΔMP_t	0.114 **	0.050	0.276 ***	0.052	0.202 ***	0.069	0.034 ***	0.008	0.052 ***	0.009	0.002	0.002
ΔMP_{t-1}	0.425 ***	0.047	0.091 ***	0.023	0.089 *	0.047	0.160 ***	0.007	0.155 ***	0.014	0.007 *	0.004
$TGAP_t$	-0.111 **	0.050	-0.176 ***	0.064	-0.684 ***	0.078	-0.027 ***	0.007	-0.185 ***	0.015	-0.007 **	0.003
$TGAP_{t-1}$	-0.497 ***	0.056	-0.592 ***	0.094	-0.254 **	0.110	-0.028 ***	0.002	-0.077 ***	0.008	-0.001	0.002
$\Delta GDPN_t$	-0.095 ***	0.013	-0.192 ***	0.029	-0.357 ***	0.035	-0.013 ***	0.001	-0.056 ***	0.004	-0.001	0.001
$\Delta GDPN_{t-1}$	-0.140 ***	0.008	-0.206 ***	0.018	-0.331 ***	0.026	-0.012 ***	0.001	-0.080 ***	0.004	-0.001	0.001
$SLOPE_t$	-0.011 **	0.005	-0.090 *	0.047	-0.092	0.058	-0.004 *	0.002	-0.024 ***	0.009	-0.001	0.002
$SLOPE_{t-1}$	-0.068 ***	0.020	-0.155 ***	0.050	-0.251 ***	0.054	-0.035 ***	0.002	-0.018 **	0.008	-0.001	0.001
Sample period	1999 Q1 - 2008 Q4		2004 Q1 - 2008 Q4		2004 Q1 - 2004 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4	
No. of banks, no. of observations	643	19,796	643	11,631	643	11,631	643	19,796	643	19,796	149	4,500
Sargan test (2nd step; pvalue)		0.211		0.175		0.222		0.296		0.211		0.311
MA(1), MA(2) (p-value)	0.000	0.695	0.000	0.202	0.000	0.599	0.000	0.400	0.000	0.695	0.000	0.364

Notes: Robust standard errors. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficients for the seasonal dummies are not reported.

In the GMM estimation, instruments are the second and further lags of the dependent variable, the macro-variables and of the bank-specific characteristics included in each equation.

Testing for non-linear effects, business expectations and differences in regulation

Table 7

Dependent variable: quarterly change of the expected default frequency (EDF) over a 1 year horizon	(I) Controlling for nominal level of interest rates and extended period of low interest rates		(II) Controlling for changes in business expectations (Consensus Forecast)		(III) Controlling for changes in risk appetite (State Street Investor Confidence Index)		(IV) Difference in regulation (Barth et al., 2004)	
	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error	Coeff.	S.Error
ΔEDF_{t-1}	0.203 ***	0.007	0.242 ***	0.008	0.244 ***	0.007	0.240 ***	0.007
ΔMP_{t}	0.070	0.068	0.262 ***	0.052	0.263 ***	0.057	0.241 ***	0.052
ΔMP_{t-1}	0.226 ***	0.054	0.125 ***	0.040	0.120 ***	0.044	0.142 ***	0.042
$TGAP_{t}$	-0.167 **	0.080	-0.322 ***	0.056	-0.318 ***	0.057	-0.146 **	0.058
$TGAP_{t-1}$	-0.057 *	0.030	-0.093	0.057	-0.065 *	0.037	-0.213 ***	0.078
$\Delta GDPN_{t}$	-0.017 **	0.008						
$\Delta GDPN_{t-1}$	-0.114 ***	0.008						
$SLOPE_{t}$	-0.043 *	0.025	-0.025	0.019	-0.031 *	0.018	-0.016	0.017
$SLOPE_{t-1}$	-0.081 ***	0.022	-0.042 ***	0.016	-0.042 ***	0.016	-0.080 ***	0.017
$TGAP_{t}*MP_{t}$	0.134 ***	0.017	0.025 **	0.011	0.025 **	0.011	0.011	0.011
$TGAP_{t-1}*MP_{t-1}$	0.024 *	0.014	0.020 *	0.012	0.020 *	0.012	0.050 ***	0.012
$TGAP_{t}*BEL_{t}$	-0.015 ***	0.001	-0.005 ***	0.001	-0.005 ***	0.001	-0.009 ***	0.001
$TGAP_{t-1}*BEL_{t-1}$	-0.045 ***	0.002	-0.013 ***	0.002	-0.003 **	0.001	-0.003 *	0.001
$\Delta GDPNCF_{t}$			-0.073 ***	0.008	-0.063 ***	0.008	-0.111 ***	0.008
$\Delta GDPNCF_{t+1}$			-0.011 *	0.006	-0.010 *	0.006	0.004	0.006
$SSICI_{t}$					0.002 *	0.001		
REG_{t}							0.119 ***	0.014
Sample period	1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4		1999 Q1 - 2008 Q4	
No of banks, No of observations	643	19,796	643	19,796	643	19,796	643	19,796
Sargan test (2nd step; pvalue)		0.687		0.825		0.333		0.261
MA(1), MA(2) (p-value)	0.000	0.849	0.000	0.871	0.000	0.863	0.000	0.928

Notes: Robust standard errors. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The coefficients for the seasonal dummies are not reported.In the GMM estimation, instruments are the second and further lags of the dependent variable, the macro-variables and of the bank-specific characteristics included in each equation.

Modelling the probability for a bank to become risky — Table 8

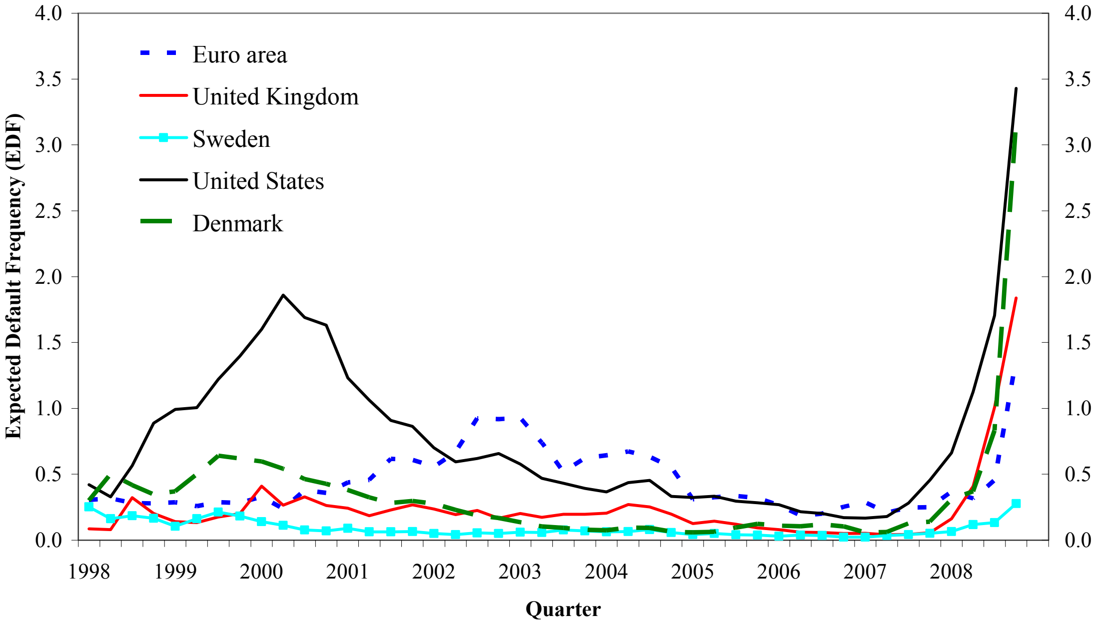
Dependent variable: P($risky_{ik}$=1)	(I) Baseline equation			(II) Bank profit			(III) Competition effect		
	Coef.	Sig	Robust Std. Err.	Coef.	Sig	Coef.	Coef.	Sig	Coef.
BEL	0.285	***	0.091	0.288	***	0.094	0.321	***	0.108
ΔGDPN	-1.178	**	0.575	-1.185	**	0.589	-1.541	**	0.763
SLOPE	-1.277	**	0.517	-1.317	**	0.531	-1.726	**	0.748
ΔHP	0.836	***	0.209	0.899	***	0.217	1.239	***	0.458
ΔSM	0.758	***	0.274	0.803	***	0.283	0.879	***	0.309
EDF	0.276	***	0.101	0.256	**	0.114	0.269	**	0.116
SIZE	-0.023		0.038	0.001		0.040	0.004		0.040
LIQ	-0.012	**	0.005	-0.013	**	0.005	-0.013	**	0.005
CAP	-0.046	***	0.017	-0.033	*	0.018	-0.034	*	0.018
SEC	0.198	*	0.113	0.196	*	0.111	0.204	*	0.115
EXLEND	0.146	***	0.025	0.157	***	0.026	0.158	***	0.026
REG	0.064		0.103	0.088		0.105	0.056		0.109
ROA				-0.270	**	0.126	-0.279	**	0.127
COMP							0.041		0.046
constant	-5.947	***	2.004	-6.499	***	2.078	-7.122	***	2.256
Number of obs		588			588			588	
LR $chi^2(14)$		94.32			96.86			97.66	
Prob > chi^2		0.000			0.000			0.000	
Pseudo R^2		0.1417			0.1476			0.1488	

The equation models the probability for a bank i with head office in country k to become risky during the crisis (to be in the last quartile of the distribution). All explanatory variable except *BEL* are expressed as average values over the period 2002 Q2- 2007 Q2. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

Chart 1

Expected default frequency of banks

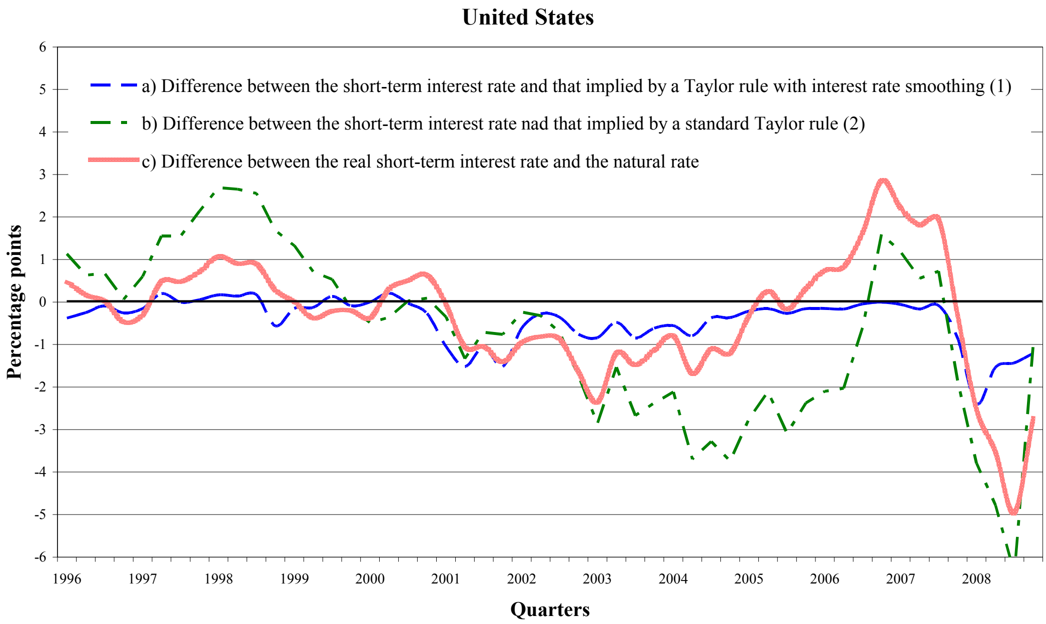
(over a 1 year ahead horizon; averages by country and groups of countries)



Source: Moody's KMV.

Chart 2

Alternative measures to evaluate monetary policy stance



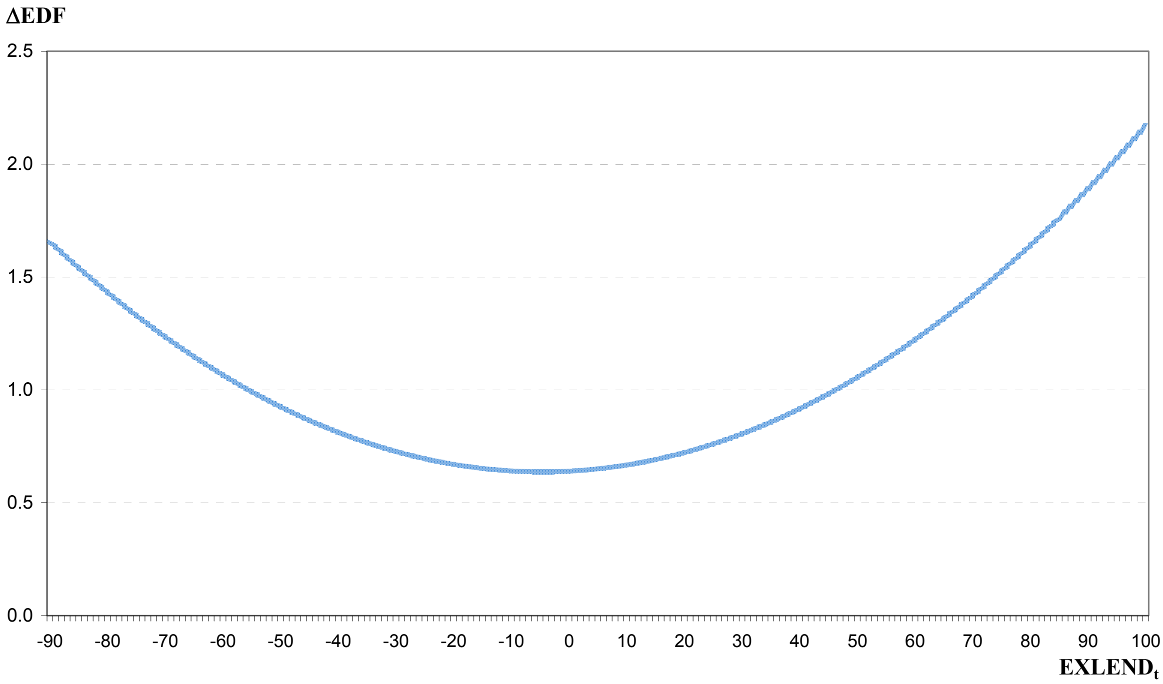
Source: Authors' calculation.

Notes: The Taylor rule is given by the formula $i_t=(1-\gamma)[\alpha+\beta_\pi(\pi_t-\pi^*)+\beta_y(y_t-y_t^*)]+\gamma\, i_{t-1}$, where the natural rate α is calculated by means of a Hodrick and Prescott filter. (1) β_π=1.5; β_y =0.5; γ=0.85; (2) β_π=0.5; β_y =0.5; γ=0.

Chart 3

Excessive lending expansion and bank risk

(quarterly changes of EDF one year ahead; percentages)



Source: Authors' calculations. The variable EXLEND represents excessive credit expansion (demeaned).

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