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Abstract: We investigate the effect of relatively loose monetary policy on bank risk through a large panel including quarterly information from listed banks operating in the European Union and the United States. We find evidence that relatively low levels of interest rates over an extended period of time contributed to an increase in bank risk. This result holds for a wide range of measures of risk, as well as macroeconomic and institutional controls including the intensity of supervision, securitization activity and bank competition. The results also hold when changes in realized bank risk due to the crisis are accounted for. The results suggest that monetary policy is not neutral from a financial stability perspective.

Keywords: bank risk, monetary policy, credit crisis.
JEL classification: E44, E52, G21.

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I. INTRODUCTION

In the aftermath of the dotcom bust, 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, at the time this financial stability aspect was not seen as particularly threatening for two main reasons. First, a large number of central banks around the world had 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 contributing to 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 driver of the recent credit crisis, it could have contributed to its build-up. There are at least two ways in which low interest rates may influence bank risk. First, low interest rates affect valuations, incomes and cash flows, which in turn, have an influence on banks' estimations of expected risks. This would lead to an expansion of banks' balance sheet due to an increase in their risk tolerance (Adrian and Shin, 2009a; 2009b; Borio and Zhu, 2008). Second, relatively subdued costs of short-term funding coupled with low returns on government bonds may increase incentives for financial institutions to take on more risk for behavioral, contractual or institutional reasons (Rajan, 2005).

We examine empirically the relationship between monetary policy and bank risk by using an extensive database of quarterly balance sheet information and risk measures for listed banks operating in the European Union and the United States. We find evidence that unusually low levels of interest rates over an extended period of time contributed to an increase in banks' risk.

This paper complements other studies on the risk-taking channel.[1] First, it analyzes the existence of a risk-taking channel at the international level (through a cross-country analysis) while the existing literature has mostly analyzed this channel using detailed data from credit registers from single countries (i.e. Austria, Bolivia and Spain).[2] The international analysis of the risk-taking channel is useful as it contributes to account for country related factors - other than monetary policy - that could affect bank risk contemporaneously. It analyzes the impact of monetary policy on bank risk in a broad way by using a wide range of different publicly available indicators of bank risk. It also relies on an in-depth analysis of the possible determinants of banks' risk prior and during the credit crisis other than relatively loose monetary policy. Consequently, we try to disentangle the risk-taking channel from other monetary policy transmission mechanisms such as the financial accelerator and the bank lending channel. We control therefore for the impact on bank risk related to institutional characteristics such as competition, securitization activity and the intensity of regulation. Finally we control the robustness of our results under the assumption that it is difficult to ascertain banks' risk-taking in real time. This would imply that underlying risks would fully materialize only under the occurrence of an extreme event such as the crisis. Hence, using the crisis as a natural experiment, we also consider how realized bank risk during the recent financial crisis relates to monetary policy and a range of pre-crisis individual bank characteristics.

[1] For an overview of the existing empirical evidence on the risk-taking channel Buch et al. (2011).

[2] Delis and Kouretas (2011) who analyze the impact of interest rate levels on bank risk for euro area banks is an interesting exception.

The remainder of this paper is organized as follows. The next section discusses how relatively low interest rates for a prolonged period of time can have an impact on banks' risk. Section III describes the identification strategy and the data used in our analysis, while Section IV presents the main results. Section V verifies the robustness of the findings. The last section summarizes the main conclusions.

II. MONETARY POLICY AND BANK RISK: THEORY AND EVIDENCE

From a historical perspective, easy monetary conditions have been considered a classical ingredient in boom-bust type business fluctuations (Fisher, 1933; Hayek, 1939; Kindleberger, 1978). A prolonged period of relatively low interest rates (i.e. below the levels of monetary policy suggested by historical experience)[3] 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 informally referred to as the risk-taking channel and relates to how changes in monetary policy rates affect either risk perceptions or risk-tolerance of financial intermediaries (Rajan, 2005; Adrian and Shin, 2009b; Borio and Zhu, 2008).

There are a number of ways in which low interest rates can influence bank risk. The first is through their impact on valuations, incomes and cash flows that are typically used as an input in the risk management models employed by most financial institutions.[4] A reduction in the monetary policy rate boosts the prices and collateral

[3] In this paper we consider the Taylor rule and the natural rate of interest as the standard benchmarks to measure the stance of monetary policy as they are both regularly used by most central banks and analysts.
[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.

values of the assets on banks' balance sheets,[5] which in turn can modify banks' estimates of probabilities of default, loss given default and volatilities. That is, the increase in the price of financial assets coupled with the decline in their volatility translate into more benign (i.e. more contained) estimations of expected risks (Bernanke and Kuttner, 2005). This example can be applied to the widespread use of Value-at-Risk (VaR) methodologies regularly used by financial institutions for economic and regulatory capital purposes (Danielsson et al., 2004). Namely, in rising financial markets with lower volatility and improved banks' capital positions the use of VaR models tends to release risk budgets of banks. A similar argument is provided by Adrian and Shin (2009b) who stress that changes in measured risk by banks determine adjustments in their balance sheets and leverage conditions and this, in turn, amplifies business cycle movements.[6]

A second way in which monetary policy can influence bank risk is through increased 'search for yield' (Rajan, 2005). Low interest rates may increase incentives for financial institutions to take on more risks for a number of additional reasons. 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 constraints. For example, private investors often use short-term returns as a way to judging bank managers' competence forcing them to shift risks and increase their exposure in periods of low interest rates. This

[5] Also in this direction, as banks undertake a maturity transformation function, changes in the discount rate would affect more the value of banks' assets than of their liabilities (Adrian et al., 2010).

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

mechanism can be compounded due to herding behavior linked to predictable investor sentiment (Shleifer and Vishny, 1997; Brunnermeier and Nagel, 2004).

Finally, bank risk may also be influenced by the communication policies of a central bank and ex-ante perceptions of possible future policymakers' reaction functions. For example banks' perception that the central bank will ease monetary policy in bad economic outcomes could lower the expectations of large downside risks. This perceived insurance effect constitutes 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 economic conditions existing at the time, in order to diminish banks' incentives to take on liquidity risk.[7]

Turning to the empirical evidence, there are a handful of studies that directly test 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 loans. In the medium term, however, due to higher collateral values and the search for yield, banks tend to grant riskier loans and, in general, to soften their lending standards: they lend more to borrowers with a bad credit history and with more uncertain prospects. Using firm-bank data taken from the Bank of Austria's credit register, Gaggl and Valderrama (2010) show that the expected default

[7] 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 due to the higher macroeconomic sensitivity to interest rates (Farhi and Tirole, 2009).

rates within Austrian banks' business-loan portfolios increased during the period of low refinancing rates from 2003 to 2005.

Ioannidou et al (2009) take a different perspective and analyze whether the risk-taking channel works not only on the quantity and quality of new loans but also on their interest rates. The authors investigate the impact of changes in the monetary policy rates on loan pricing over the period 1999–2003 in Bolivia. They find that, when interest rates are low, banks increase the number of new risky loans and reduce the rates they charge to riskier borrowers relative to what they charge to less risky ones. Kishan and Opiela (2011) analyze the effect of monetary policy on the sensitivity of debt holder to perceptions of bank default risk. Their evidence is consistent with the existence of a risk pricing channel of monetary policy working via market discipline of debt holders.

Recent work has measured risk-taking by using evidence from surveys on credit standards. Maddaloni and Peydro (2011) found that low short-term interest rates soften credit standards. Interestingly, this softening is augmented by aggregate (calculated for each quarter and country) securitization activity and weak supervision for bank capital. Buch et al. (2011) resort to information provided in the Federal Reserve's Survey of Terms of Business Lending and found evidence for a risk-taking channel after a monetary policy loosening for small domestic banks.

Our approach is complementary. We take an international perspective and focus on the banking sector by relying on public information available to most central banks and supervisors prior and during the financial crisis. 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 proxies covering different perceptions on bank risk. In order to insulate the effects of monetary policy on bank risk we have to control for other more standard monetary policy transmission mechanisms such as the financial accelerator and the bank lending channel and to take into account institutional factors such as competition, securitization activity and the intensity of regulation.

III. MODEL, IDENTIFICATION STRATEGY AND DATA

III.1 The model

The baseline empirical model is given by the following equation:

$$\Delta EDF_{i,k,t} = \alpha \Delta EDF_{i,t-1} + \sum_{j=0}^{1} \beta_j \Delta IR_{k,t-j} + \sum_{j=0}^{1} \gamma_j TGAP_{k,t-j} + \sum_{j=0}^{1} \delta_j \Delta GDPN_{k,t-j} + \\ + \sum_{j=0}^{1} \varphi_j SLOPE_{k,t-j} + \psi\, MC_{k,t-j} + \lambda BSC_{i,k,t-j} + \sum_{j=1}^{4} \phi_j SD + \varepsilon_{i,t} \quad (1)$$

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 1 reports the summary statistics for the variables used and the relative sources.

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 short-term interest rate (ΔIR), a measure of the stance of monetary policy (*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 account for unobservables and obtain white noise residuals. *MC* and *BSC* represent, respectively, additional macro variables and bank-specific characteristics that we introduce to disentangle the risk-taking channel from other mechanisms at work.

III.2 The financial accelerator, collateral and the risk-taking channel

The analysis of the risk-taking channel implies a number of challenges. The first one is to disentangle the risk-taking channel from the standard ‘financial accelerator’ mechanism, through which financing frictions on firms and households amplify or propagate exogenous disturbances (Bernanke and Gertler, 1989).

The financial accelerator works through the borrowers' net worth: a monetary loosening increases borrowers' collateral values causing an overall improvement on their creditworthiness. In this situation there is a greater incentive for banks to ease financial constraints to borrowers and increase their lending (Matsuyama, 2007). The financial accelerator perspective implies therefore a credit driven amplification mechanism due to financial frictions on the side of borrowers'. In contrast, the risk-taking channel focuses on the amplification mechanisms related to financial frictions on the side on the bank.

In order to control for the impact of the borrowers' net worth we include in the set of macroeconomic controls (*MC*) both changes in the broad stock market indices for non-financial corporations and in the housing prices. These asset prices are demeaned from their long-term historical averages to capture abnormal changes in borrowers' collateral values. For a given level of bank risk aversion (or tolerance), these variables aim to capture the effects of changes in asset prices on banks' risk positions via changes on the value of borrowers' collateral.

A related factor is that general economic conditions and future expectations of economic activity can also impact on banks' risk. That is, banks could indeed take on more risk simply because of positive expected economic conditions. We control for this effect in two ways. First, we use in the baseline specification the slope of the yield curve calculated for every country as the difference between the 10-year government bond yields and the 3-month money market rate. Due to the maturity transformation role of banks, there is close relationship between the shape of the yield curve and bank profits (Viale et al., 2009). Second, as a robustness test we replace in some specifications nominal GDP growth rate with its 1-year ahead consensus forecast derived from Consensus Forecast Indicators (*ΔGDPCF*).

Finally, as our focus is on risk taking on the side of banks, we also include a proxy for global risk aversion from financial market investors. The idea is to account for bank incentives to take on risk (related to the stance of monetary policy) *on top of* the impact of global financial markets' risk appetite. For this we use the State Street Investor Confidence Index (*SSICI*), a measure of global investors' attitude to risk.[8] This variable helps to control for financial markets' risk aversion as well as elements of structural irrationality or other behavioral attitudes on the side of financial markets investors, such as herding behavior (Barberis et al., 1998). This is also in line with Bekaert et al. (2010) who decompose the low volatility in financial markets associated with periods of relatively loose monetary policy into a (lower) risk aversion and an (higher) uncertainty component. They found that loose monetary policy has mostly an impact on financial markets' risk aversion.

III.3 The bank lending channel and the risk-taking channel

The risk-taking channel has also some points of contact with the bank lending channel (Bernanke and Blinder, 1988; Ehrmann et al., 2003). According to the bank lending channel, a change in the short-term interest rate modifies bank funding conditions, which in turn affect the supply of bank lending.

In order to discriminate among loan supply and loan demand movements, the literature has focused on cross-sectional differences between banks. This strategy relies on the hypothesis that certain bank-specific characteristics (for example size, liquidity

[8] 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 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.

and capitalization) only influence loan supply movements while bank's loan demand is independent of these characteristics. Broadly speaking this approach assumes that after a monetary tightening the drop in the availability of total deposits (which affects banks' availability to make new loans) or the ability to shield loan portfolio is different among banks. In particular, small and less capitalized banks, which suffer a high degree of informational frictions in financial markets, face a higher cost in raising non-secured deposits and are constrained to reduce their lending by more; illiquid banks have less possibility to shield the effect of a monetary tightening on lending simply by drawing down cash and securities. To control for these effects we had to rely on micro data that allowed us to control for given bank-specific characteristics, in particular we introduce in the set of bank-specific characteristics: the log of total assets (*SIZE;* Angeloni et al. 1995; Kashyap and Stein, 1995, 2000), the liquidity to-total asset ratio (*LIQ*; Stein, 1998) and the capital-to-asset ratio (*CAP*; Kishan and Opiela, 2000; Van den Heuvel, 2002).[9] Recent evidence also shows that bank balance sheet characteristics are important drivers of bank performance during the financial crisis (Beltratti and Stultz, 2009; Demirgüc-Kunt and Huizinga, 2009).

III.4 Quarterly versus annual data and macroeconomic coverage of the dataset

An additional complication when trying to capture the risk-taking channel is that the impact of changes in short-term interest rates on banks' risk tolerance (or perceived risk) could be relatively brisk. Consequently the mechanism at work in the risk-taking channel cannot be fully captured by using annual financial statements. Hence we construct a dataset from quarterly consolidated balance sheet information taken from Bloomberg (a commercial data provider) over the period 1999-2008. This represents an

[9] More recently De Nicolò et al (2010) argue that the impact of monetary policy on banks' risk-taking incentives would depend on banks' capitalization and, more broadly, on the health of the banking system.

important novelty of our work because the overwhelming majority of cross-country banking studies have resorted to annual data. Our dataset initial includes 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.[10] To ensure broad comparability in accounting methodologies we include in the final dataset only listed banks (which typically adhere to international accounting standards) for which all necessary information were available.[11]

Table 2 gives some basic information on the final dataset that include 643 banks. From a macroeconomic point of view, this dataset is highly representative as it comprises 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 small US banks are listed. Bank specific 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.

[10] Although 12 countries in our sample belong to the euro area, the correlation of their business cycles is indeed relatively low. In around two thirds of the cases the bilateral correlation of GDP growth across the countries used in this study is not significantly positive. In one third of the cases, their business cycles are negatively correlated. It is also worth mentioning that while the monetary policy rate was shared in the euro area, the monetary policy stance (calculated by means of Taylor rules and natural rates at the country level, see Section III.6) was different across countries.

[11] In order to limit accounting changes that can introduce discontinuity in certain reported bank positions, we used broad accounting measures and definitions. This also limits to the minimum differences in accounting standards between the United States, where US Gaap is mostly used, and the International Accounting Standards (IAS) applied in the European Union.

III.5 The measurement of bank risk

The measurement of bank risk is particularly challenging because it is not directly and perfectly observable. Hence, the data on individual bank financial statements have been matched with a wide array of different measures which proxy for bank risk.

The first one is given by the expected default frequency (*EDF*). *EDF* is the probability that a bank will default within a given time horizon (typically one year). *EDF* is a well-known, forward-looking indicator of risk, computed by Moody's KMV, which builds on Merton's model to price corporate bond debt (Merton, 1974).[12] The *EDF* value, expressed as a percentage, is calculated by combining banks' financial statements with stock market information and Moody's proprietary 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). Figure 1 shows that the cross-sectional dispersion of banks' *EDF* (measured by means of the coefficient of variation) started to increase well ahead the period of financial crisis, especially in the US and the UK. This means that there were already significant differences in bank risk at the cross sectional level already prior to the crisis. More importantly, while during the financial crisis the materialization of risk was – on aggregate – quite sudden, *EDF* have done relatively well with respect to other measures as a predictor of default prior to the crisis particularly on a cross-sectional basis. In other words, the relative positions of banks ranked according to their *EDF* levels in the year before the crisis strongly helped to predict bank distress during the crisis period (see, for instance, Munves et al., 2009 and Harada et al, 2010). In this respect, the panel

[12] 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 see, for instance, Garlappi et al. (2007).

approach undertaken in this study allows us to bridge the sudden realization of bank risk by analyzing not only the time but also the cross-section dimension of the banks in our sample. By means of the latter we consider relative changes in bank risk-attitude (i.e. comparing riskier banks versus those perceived as less risky 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 individual bank risk over time. In order to account for possible variation in the maturity structure of credit risk expectations, we also complement our analysis by including the 5 and 10 years ahead *EDF*s which provides accumulated expectations of default further in time.

In Table 3, banks are grouped depending on their specific risk position, using one-year *EDF*s values. A 'high-risk' bank has the average *EDF* of banks included in the fifth quintile (i.e. in the 20% of the riskier banks with an average EDF_H 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 perceived risk of these banks. Additionally, low-risk banks make relatively fewer loans than high-risk banks, but the difference is not so remarkable.

As additional robustness checks, the analysis of *EDF* is supplemented by including measures of banks' risk derived from stock market information. This approach is particularly useful to decompose bank risk into two parts: *idiosyncratic* (individual) risk and *systematic* (market wide) risk. We calculate these two components for each bank over each quarter so that we are able to assess - through time - whether monetary policy influences individual banks' risk position independently of the developments in the financial system as a whole.

We use two complementary approaches to decompose bank risk in a systematic and an idiosyncratic element. First we follow a simple Capital Asset Pricing Model (*CAPM*). In our application, the *CAPM* model is based on the following equation: $R_{i,k,t=} \beta_{i,t*} R_{m,k,t} + \varepsilon_{i,t}$ where $R_{i,k,t}$ are the daily stock market logarithmic abnormal returns from each bank i from country k. $R_{m,k,t}$ are the daily stock market abnormal returns from the broad stock market index m from country k. The term $\varepsilon_{i,t}$ is the bank specific residual.

For each bank i we calculate our systematic component $\beta_{i,t}$ by running separate regressions on daily data for every quarter q from 1999Q1 to 2008Q4. In this way our risk proxies can be matched with the other individual banks' and macroeconomic variables which also enter into our equation at a quarterly frequency.

The idiosyncratic component *(IDSC*1*)* is then simply constructed as the average of the squared of the unexplained component of each regression for bank i over each quarter *q:* [13]

$$IDSC1 = \sum_{t=1}^{m} (\varepsilon_{i,t})^2 / m \qquad (2)$$

where m are the number of trading days in each quarter.

The second approach follows Campbell et al. (2001) who build on Merton (1980) and decompose stock market volatility into total market, banking sector and individual bank level volatility. In particular, by assuming that the different components

[13] We included banks which were actively traded for at least one year from 1999 to 2008 (for instance, so-called 'dead' banks due to mergers or acquisitions and which as a result are no longer traded at the end of our sample period are also included). We used the broad Datastream indices that 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.

(market, sector and individual) of stock market returns are orthogonal to one another, each risk component can be calculated by means of a simple variance decomposition. Therefore individual bank idiosyncratic risk for quarter q (in country k) can be calculated as:

$$IDSC2 = \sum_{t=1}^{m} \frac{(R_{i,k,q,t} - R_{B,k,q,t})^2}{m} \tag{3}$$

where for each time t, $R_{i,t}$ and $R_{B,t}$ are the individual bank i and the banking sector logarithmic returns respectively. The idiosyncratic measure of bank risk (*IDSC2*) is calculated for each quarter q where m refers to the number of daily observations for each quarter available for bank i.

The top left hand side of Table 4 shows the correlation between the different measures of bank risk used in this paper and the other variables. A possible criticism to *EDFs* as a measure of bank risk is related to their use of the Merton formula, where the probability of default could be mechanically inversely related to the level of the interest rate. The intuition is that lower interest rates make the present value of liabilities higher, ceteris paribus, which makes the probability of default correspondingly higher. We will see in section IV, however, that – when controlling for other factors – a reduction in interest rates is associated, in the short-term, with a reduction in bank's default probability. This means that the proprietary KMV formula does not seem to be systematically affected by such mechanism. We will get also similar indications by using *IDSC1* and *IDSC2* measures that are not significantly correlated with interest rate levels.

III.6 The measurement of monetary policy

The identification strategy takes into account that monetary policy conditions vary across countries and aims at exploiting the impact of heterogeneity of monetary conditions on banks' risk: other things being equal if the risk-taking channel is at work, bank risk (*EDF*) should increase by more in those countries where the interest rate level is relatively low.[14] This strategy however needs to disentangle the effects of changes in interest rates on outstanding loans from the influence of low interest rates on new bank risk. It will also have to address which benchmark to use in order to assess the stance of monetary policy at any point in time.

As discussed in Section 2, a reduction of interest rates increases the value of the amount of loans outstanding in banks' portfolios: low interest rates increase the value of the borrowers' collateral so the probability of their possible default declines. In contrast, a reduction of the interest rate below the benchmark triggers a 'search for yield' process that contributes to an increase in new bank risk-taking.

To tackle this identification problem, for each country we have considered both the quarterly change in the overnight rate (*IR*) and the deviation of the policy rate from a benchmark level that evaluates the relative stance of monetary policy.

In particular, for each of the countries included in our sample we calculate the following benchmark measures:

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[14] We relate changes in bank *EDFs* to country-specific macro-variables because domestic intermediation activity is the most important part of banks' business. Nevertheless we are aware that a part of bank activities takes place on international markets and that 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 detected using our identification strategy, the strength of this channel would be expected to be even more significant when controlling for multinational activity.

a) the difference between the actual nominal short-term interest rate and that generated by a 'Taylor rule' with interest rate smoothing *(TGAP)*;[15]

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)*;[16]

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 far less correlated with the banks' *EDF* than the other measures (-0.10 against -0.20 and -0.18).[17] Hence we decided to use *TGAP* 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 stronger when using a standard Taylor rule *(TGAP2)* or the natural interest rate *(NRGAP)*.

[15] 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), 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 $i_t = \gamma\ i_{t-1} + (1 - \gamma)\ [\alpha + \beta_\pi(\pi_t - \pi^*) + \beta_y(y_t - y_t^*)]$, where γ represents the degree of interest rate smoothing, and α is the real interest rate prevailing when output and inflation are at target levels ($r^* = i^* - \pi^* = \alpha - \pi^*$). We set β_π=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%.

[16] 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%.

[17] All the three correlations are significantly different from zero at 1% significance level (see the p-values in the first column of Table 4).

One possible criticism to the use of the *TGAP* measure together with the change in the short-term interest rate (ΔIR) is that the two measures tend to be positively correlated. The robustness of the results will be therefore checked by excluding from the specification (1) one variable (*TGAP* or ΔIR) at the time.

III.7 Possible identification limitations

One possible identification limitation of testing whether monetary policy does affect bank risk is that, in principle, the situation of the banking sector could also impact on monetary policy decisions. That is we also have to consider whether financial stability objectives can also determine monetary policy actions thereby biasing our estimations. We have considered this potential problem in a number of ways.

One first consideration is that we expect the endogeneity problem to be less important in the countries included in our sample as their monetary authorities have mostly an inflation targeting objective or a dual mandate also including economic growth or monetary aggregates. In general price stability was considered as a sufficient condition to reach macroeconomic and financial stability in the long run (Bernanke and Woodford, 2005).

This could arguably have changed in the last quarter of 2008 as the fail of Lehmann Brothers intensified the credit crisis spectacularly. As a result from this period onward it can be argued that financial stability considerations had an impact on the monetary policy actions. For this reason we stop our sample period in 2008 to avoid the effects of unconventional monetary policy actions.

A second way to mitigate endogeneity has been by the use of the dynamic Generalized Method of Moments (GMM) panel methodology to obtain consistent and unbiased estimates of the relationship between the monetary policy and bank risk. This methodology was first described by Holtz-Eakin et al. (1988) and Arellano and Bond (1991), and further developed by Blundell and Bond (1998). The use of this methodology reduces endogeneity bias that may affect the estimation of the regression parameters. It also takes into account the heterogeneity in the data caused by unobservable factors affecting individual banks.

We use the instruments as defined by Blundell and Bond (1998). According to these authors, in fact, exogenous variables, transformed in first differences, are instrumented by themselves, while endogenous regressors (also transformed in first differences) are instrumented by their lags in levels.[18]

Finally, we also consider whether the level of *EDF* attained during the crisis depends upon factors that developed slowly in the financial system prior to the eruption of the crisis. We tackle this problem in two ways. First, by distinguishing between systematic and idiosyncratic measures of banks' risk (see section III.3, above). Second, by means of a probit estimation that uses the crisis as a natural experiment. In particular we model the probability of a bank becoming risky during the crisis on a number of pre-crisis factors including monetary policy (see Section V.III below).

IV. THE RESULTS

The main results of the analysis are reported in Table 5. The GMM 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).

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[18] This approach has been applied in other areas of research in which the model was affected by possible endogeneity biases. For instance Blundell and Bond (1998) use it to estimate a labor demand model while and Beck et al. (2000) apply it to investigate the relation between financial development and economic growth.

Table 5 shows that, *ceteris paribus*, the effects of changes in the short-term monetary policy rate (ΔIR) 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 short-term 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 corresponding reduction in bank funding liquidity cost (Diamond and Rajan, 2009; Adrian and Shin, 2009a).

The coefficient related to the *TGAP* variable is instead negative and significant, confirming the effect of monetary policy on bank risk: 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.

As discussed in Section III.6 the variable ΔIR is – by construction – positively correlated with *TGAP* and the robustness of the results was double checked by including only one of the two variables at the time. When only one of the two variables is considered, the coefficients β and γ of equation (1) maintain their sign and statistical significance. The results – not reported for the sake of brevity but available from the authors upon request – confirm therefore that ΔIR and *TGAP* represent two different forces at work, as described above.

The coefficients for $\Delta GDPN$ 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 implies 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 most empirical findings (see for instance Viale et al., 2009).

Since the Taylor rule gap could, in principle, give different indications with respect to other measures, the reliability of these baseline results has 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 in Section III.6, results are also consistent with the existence of a risk-taking channel when using a simple Taylor rule with no interest rate smoothing and equal weights.

In order to control for the effects of the standard financial accelerator on borrowers' net worth and collateral, we also introduce in the specification quarterly changes in housing and stock market returns for each country (ΔHP and ΔSM, respectively). Both asset returns are demeaned using their long term averages of the last 20 years and adjusted for inflation. The coefficients of both variables should be expected to 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. We have further investigated the relationship between changes in housing prices and bank risk taking into consideration possible differences in the transmission in those countries in the sample that experienced a boom-bust housing price cycles, namely Denmark, Ireland, Spain, Sweden and the United Kingdom (IMF, 2009b). In particular, we include in the model 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.

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 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 banks' balance sheet characteristics that summarize their ability and willingness of banks to supply additional loans. In order to disentangle the effects of the risk-taking channel from those of the traditional bank lending channel we have, therefore, introduced into the specification *SIZE* (the log of total assets), *LIQ* (securities and other liquid assets over total assets); and *CAP* (the capital-to-asset ratio) 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 and capitalization 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 however contrary to the 'too big to fail' paradigm.

During the period of financial turmoil not all banks have been equally affected. The banks which were predominantly affected were large institutions which moved towards a business model that also relied on the creation, distribution and trading of new and complex securities. 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 is 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 (see the sixth column of Table 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. 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 (Tornell and Westermann, 2002). 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 therefore compute 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, a quadratic term was also added.

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 2). 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).

V. ROBUSTNESS TESTS

V.1 Different measures of 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 are available from 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).

It is worth noting that the increase of the *EDF* horizon does not change the sign and the significance of the coefficients attached to changes in the short-term interest rate (ΔIR) 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 short-term interest 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. We therefore rerun the baseline equation (1) using the two alternative measures for idiosyncratic risk described in Section III.6. The results reported in columns IV and V of Table 6 indicate that the use of idiosyncratic measures for bank risk as dependent variable 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 uses 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 ΔIR 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.[19]

V.2 Testing for non-linear effects, business expectations and regulatory differences

The recent credit 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,

[19] As an additional robustness test we also used the spreads on the credit default swap for each individual bank as dependent variable. 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 as the barometer of financial health and an early indicator of credit risk (Blanco 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.

respectively, the level of the interest rate (*IR)* and the number of consecutive quarters the interest rate has been below the level implied by the Taylor rule (*BEL*).[20]

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

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 rates. 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

[20] The variables *IR* 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).

(*ΔGDPCF*). 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. However, we obtain similar results even when we include in 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 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), we introduce in the model a regulation variable (*REG*) that 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 short-term changes in interest rates (Δ*IR*), the Taylor Rule Gap (*TGAP*), and their interactions with *IR* 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.

V.3 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 credit crisis (2007Q2 – 2008Q4), and 0 elsewhere. Starting from a sample of 588 banks, whose median increased 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 delimits 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:

$$P\left[risky_{ik} = 1 \middle| X\right] = \Phi(X'\beta) \tag{5}$$

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). The probit model is 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 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 risks.

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

First, 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 banks who relied more heavily on the securitization market might have lowered their monitoring and screening on their loan portfolios (Parlour and Plantin, 2008). Drucker and Puri (2009) 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.

Second, profitability could have also impacted on bank risk. It could be argued that certain banks which 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. 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 include 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.

Third, an increase in competition could lead to greater (and possibly excessive) banks risk (Cihak et al., 2009; Jimenez et al 2007). 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 Maddaloni and Peydrò, 2011 for a similar application). This index represents 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 (*COMP*) and bank risk 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.

V.4 Additional estimations

All results have been re-run including bank and country fixed effects to account for bank or country idiosyncratic — and persistent — factors not included in our main specification. However, the inclusion of these fixed effects has the cost of reducing the informational content of bank and country specific factors such as the regulatory index which does not change too much during the sample period.

The impact of monetary policy on bank risk can also vary depending on bank characteristics. Hence we also interacted our measures of monetary policy looseness certain key bank-specific characteristics used in this study (i.e. lending activity, liquidity and capitalization). These interactions allow us to verify whether bank specific factors lead to heterogeneity in bank risk related to changes in monetary policy. The results, available from the authors upon request, show that also in this case well-capitalized and highly liquid banks prior to the crisis were considered less risky during the crisis. However, this insulation effect produced by capital and liquidity buffers was lower in those countries that, prior to the crisis, experienced a particularly prolonged period of low interest rates.

VI. CONCLUSIONS

The credit crisis has drawn the attention of researchers and policy makers back to the link between monetary policy and bank risk. Low short-term interest rates for a prolonged period of time 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.

We 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 credit crisis. We find that low interest rates over an extended period of time contributed to an increase in bank risk. The results are robust to other factors that might have influenced bank-risk taking, including financial innovation, booming asset prices, the intensity of financial regulation, investor's risk aversion, bank-specific characteristics and competition policies.

The results of this paper are of interest to both monetary and supervisory authorities. First, they suggest that central banks would need to consider the possible effects of monetary policy actions on bank risk. The potential impact of bank risk by banks may have implications for longer term macroeconomic outlook including output growth, investment and credit. Second, banking supervisors should probably strengthen 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.

Table 1

SUMMARY STATISTICS OF THE VARIABLES USED IN THE REGRESSIONS
(1999Q1-2008Q4)

Variables	Number of observations	Mean	Median	Std. Dev	Min	Max	1st quartile	3rd quartile	Sources
EDF_t	19,796	0.61	0.17	1.9	0.01	29.98	0.08	0.43	Moody's KMV
ΔEDF_t	19,796	0.07	0.00	0.83	-28.0	27.0	-0.03	0.03	Moody's KMV
ΔIR_t	19,796	-0.08	0.00	0.56	-3.75	1.53	-0.27	0.34	IMF
$TGAP_t$	19,796	-0.44	-0.27	0.57	-3.6	1.37	-0.76	-0.07	Authors' calculations
$NRGAP_t$	19,796	-0.3	-0.21	1.41	-5.1	3.62	-1.1	0.63	Authors' calculations
$\Delta GDPN_t$	19,796	1.09	1.15	0.96	-5.97	11.46	0.86	1.54	OECD
$SLOPE_t$	19,796	1.09	0.88	1.29	-2.25	3.69	-0.09	2.26	BIS
ΔHP_t	19,796	0.00	0.84	4.95	-22.98	79	-1.45	2.52	BIS
ΔSM_t	19,796	0.00	1.92	10.2	-47.63	63.72	-4.99	6.42	Datastream
$SIZE_t$	19,796	7.15	6.55	2.25	-4.61	15.43	5.66	8.25	Bloomberg
LIQ_t	19,796	23.62	22.61	10.7	0.00	49.99	15.72	30.54	Bloomberg
CAP_t	19,796	9.6	8.75	5.03	1.03	74.90	6.99	10.89	Bloomberg
$EXLEND_t$	19,796	0.00	-0.62	7.8	-85.8	94.7	-3.35	2.64	Bloomberg
$EXLEND_t^2$	19,796	60.00	9.12	290.2	0.00	8968.1	1.95	31.6	Bloomberg
BEL	19,796	8.99	10.00	6.00	0.00	20.00	3.00	14.00	Authors' calculations
REG	19,796	10.32	11.00	1.85	4.00	12.00	10.00	11.00	Barth et al. (2004)
$SSICI$	19,796	114.70	114.2	11.77	83.10	134.33	107.05	122.12	State Street

where:

EDF_t	=	expected default frequency (1 year ahead)
ΔEDF_t	=	change in the *EDF* (1 year ahead)
ΔIR_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

Table 2

DESCRIPTIVE STATISTICS BY COUNTRY: 1999-2009

(mean values)

Country	Nominal *GDP* (Annual growth rate)	Money market rate (Annual interest rate)	Bank size, total assets (USD millions)	Loan growth (Annual growth rate)	Capital (% of total assets)	Liquidity (% of total assets)	*EDF* (1 year ahead)	Idiosyn-cratic risk (1) (%)	Stock market return (2) (Average quarterly changes)	Housing price changes (2) (Average quarterly changes)	Slope of yield curve (%)	Number of banks (3) (Final dataset))	Weight inside sample (4) (%)
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.

Table 3

BALANCE SHEET CHARACTERISTICS AND BANK RISK PROFILE [(1)]

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.

Table 4

CORRELATION MATRIX

	EDF	*EDF5*	*EDF10*	IDSC1 (2)	IDSC2 (3)	LNRATE	*IR*	*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*																
IR	-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.

Table 5

REGRESSION RESULTS

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
ΔIR_{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
ΔIR_{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
$\Delta HP_{t}*HPBB$							0.016 ***	0.004						
$\Delta HP_{t-1}*HPBB$							0.014 ***	0.004						
$\Delta SM_{t}*HPBB$							-0.004 ***	0.001						
$\Delta SM_{t-1}*HPBB$							-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.

Table 6

DIFFERENT MEASURES FOR BANK RISK

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
ΔIR_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
ΔIR_{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.

Table 7

TESTING FOR NON-LINEAR EFFECTS, BUSINESS EXPECTATIONS AND DIFFERENCES IN REGULATION

	(I)		(II)		(III)		(IV)	
Dependent variable: quarterly change of the expected default frequency (*EDF*) over a 1 year horizon	Controlling for nominal level of interest rates and extended period of low interest rates		Controlling for changes in business expectations (Consensus Forecast)		Controlling for changes in risk appetite (State Street Investor Confidence Index)		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
ΔIR_{t}	0.070	0.068	0.262 ***	0.052	0.263 ***	0.057	0.241 ***	0.052
ΔIR_{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
$TGAP_{t}*IR_{t}$	0.134 ***	0.017	0.025 **	0.011	0.025 **	0.011	0.011	0.011
$TGAP_{t-1}*IR_{t-1}$	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.

Table 8

MODELLING THE PROBABILITY FOR A BANK TO BECOME RISKY

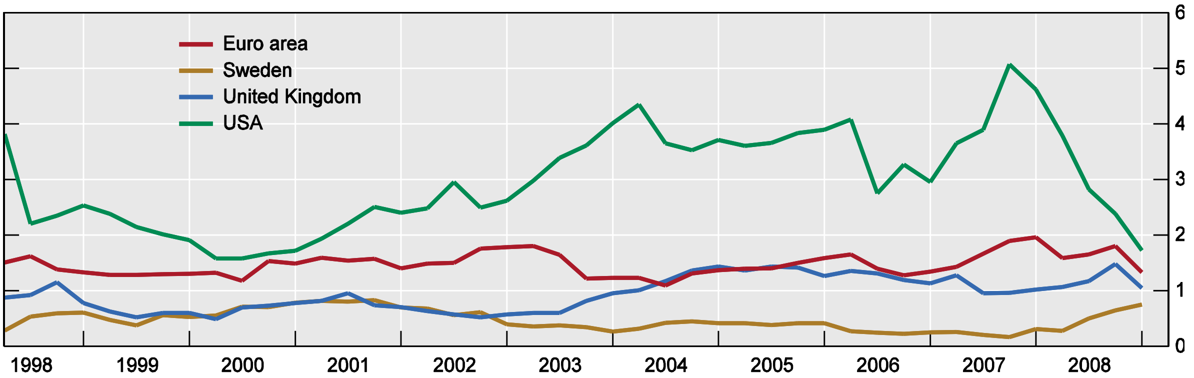
Dependent variable: P($risky_{ik}$=1)	(I) Baseline equation			(II) Bank profit			(III) Competition effect		
	Coef.	Sig	Robust Std. Err.	Coef.	Sig	Robust Std. Err.	Coef.	Sig	Robust Std. Err.
BEL	0.285	***	0.091	0.288	***	0.094	0.321	***	0.108
ΔGDPN	-1.178	**	0.575	-1.185	**	0.589	-1.541	**	0.763
SLOPE	-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

CROSS-SECTIONAL DISPERSION OF BANKS' EDF

Coefficient of variation



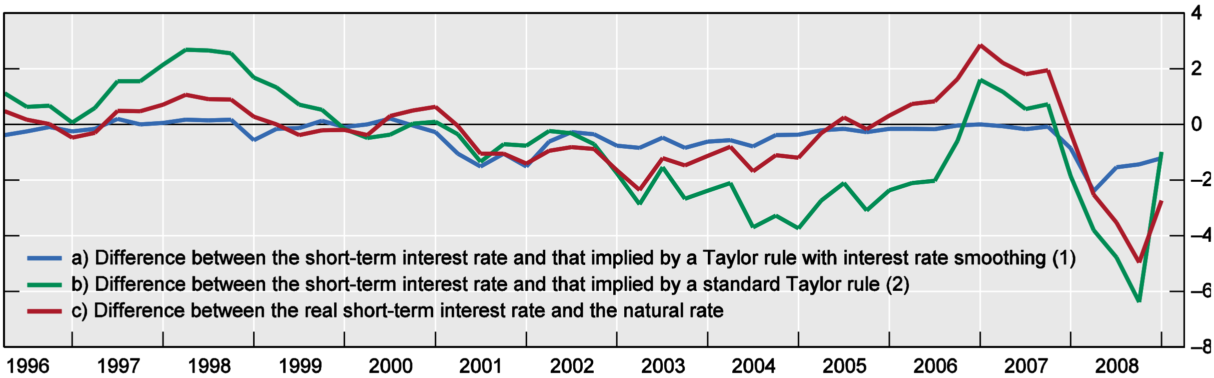
Source: Authors' calculations.

Note: The coefficient of variation is given by the ratio of the standard error to the mean. The series show the coefficient of variation of banks' expected default frequency in each quarter.

Chart 2

ALTERNATIVE MEASURES TO EVALUATE MONETARY POLICY STANCE IN THE US

In per cent



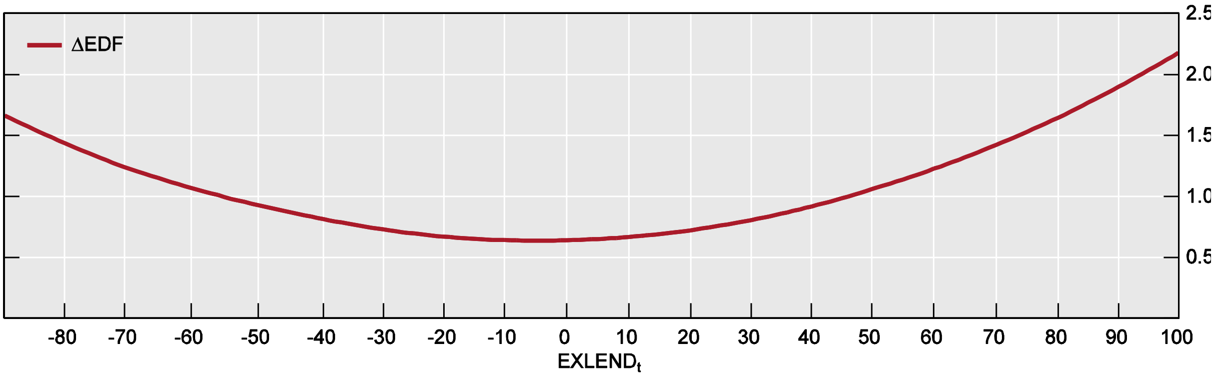
Source: Authors' calculation.

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

Chart 3

EXCESSIVE LENDING EXPANSION AND BANK RISK

(quarterly changes of EDF one year ahead; percentages)



Source: Authors' calculations.

Note: The variable *EXLEND* represents excessive credit expansion (demeaned).

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