Does Monetary Policy Affect Bank Risk?*

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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 suggesting 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 suggest that monetary policy is not neutral from a financial stability perspective.

JEL Codes: E44, E52, G21.

*The opinions expressed in this paper are those of the authors only and do not necessarily reflect those of the European Central Bank (ECB) or the Bank for International Settlements (BIS). We would like to thank Itai Agur, Geert Bekaert, Claudio Borio, Santi Carbo, Steven Cecchetti, Bob DeYoung, Philipp Hartmann, Gabriel Jimenéz, Alexandros Kostakis, Bartosz Mackowiak, Phil Molyneux, Stefano Neri, Kalin Nikolov, Steven Ongena, Huw Pill, Rafael Repullo, Klaus Schaeck, Sami Vähämaa, Kenneth West, John Wilson, and, in particular, one anonymous referee for useful comments and discussions. We are also grateful for their comments to participants at the European Finance Association annual meeting in Frankfurt, at the CEPR/University of Tilburg conference on "Procyclicality and Financial Regulation," at the BIS/ECB workshop on "Monetary Policy and Financial Stability," at the ECB workshop "Monetary Policy Transmission Mechanism in the Euro Area in its First 10 Years," as well as to participants at seminars held at the University of Munich, the Deutsche Bundesbank, and Banque de France. Corresponding author: Leonardo Gambacorta, Bank for International Settlements, Centralbahnplatz 2, 4002 Switzerland. E-mail address: Leonardo.Gambacorta@bis.org.

1. Introduction

In the aftermath of the dot-com 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 buildup. There are at least two main 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. For example, low interest rates would normally boost the price of financial assets, which in turn can modify banks' estimates of the probability of default, loss given default, and volatilities. This would lead to an expansion of banks' balance sheets due to an increase in their risk tolerance (Borio and Zhu 2008; Adrian and Shin 2009a, 2009b). Second, relatively subdued costs of short-term funding coupled with low returns on government bonds may increase incentives for financial institutions to "search for yield" due to behavioral, contractual, or institutional reasons (Rajan 2005). For example, life insurance companies and pension funds could have minimum returns fixed by statute or contractually. More generally, financial institutions regularly enter into long-term contracts with a significant percentage of their borrowers and investors involving a commitment to produce certain levels of nominal rates of return. The same 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.

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 accounts for country-related factors—other than monetary policy—that could affect bank risk contemporaneously. Second, it analyzes the impact of monetary policy on a broad concept of bank risk that is captured by the expected default frequency (EDF). It also relies on an in-depth analysis of the possible determinants of banks' risk prior to 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 in many ways, under the assumption that it is difficult to ascertain banks' risk taking in real time.

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 3 describes the identification strategy and the data used in our analysis, while section 4 presents the main results. Section 5 verifies the robustness of the findings. The last section summarizes the main conclusions.

[1] For an overview of the existing empirical evidence on the risk-taking channel, see Buch, Eickmeier, and Prieto (2011).

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

2. 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 perception 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; Borio and Zhu 2008; Adrian and Shin 2009a).

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 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, Shin, and Zigrand 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

[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, Gertler, and Gilchrist 1996). Adrian and Shin (2009a) 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.

[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, Estrella, and Shin 2010).

banks. A similar argument is provided by Adrian and Shin (2009a), 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.

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 judge bank managers' competence, forcing them to shift risks and increase their exposure in periods of low interest rates. This 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.[6]

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. (2014) 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

[6]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 policymakers but rather due to the higher macroeconomic sensitivity to interest rates (Farhi and Tirole 2009).

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

Ioannidou, Ongena, and Peydró (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 (2012) analyze the effect of monetary policy on the sensitivity of debt holders 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 Peydró (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, Eickmeier, and Prieto (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 to 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 United States 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.

3. Model, Identification Strategy, and Data

3.1 The Model

The baseline empirical model is given by the following equation:

$$\Delta EDF_{i,k,t} = \alpha \Delta EDF_{i,k,t-1} + \beta \Delta EDF\_NF_{k,t} + \gamma NRGAP_{k,t-1} + \psi MC_{k,t-1} + \lambda BSC_{i,k,t-1} + \sum_{j=1}^{4} \phi_j SD + \varepsilon_{i,t} \qquad (1)$$

with $i = 1, \ldots, N, k = 1, \ldots, 15$, and $t = 1, \ldots, T$, 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 headquartered in country k in quarter t is regressed on its own lag and EDF change for the non-financial sector in country $k(\Delta EDF\_NF)$. This variable aims at filtering out the effects of changes in the market price of risk due to the business cycle. The measure of the stance of monetary policy is $NRGAP$, while 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. Variables are taken with one lag to mitigate possible endogeneity problems. Seasonal dummies (SD) have also been included in this specification.

3.2 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

Table 1. Summary Statistics of the Variables Used in the Regressions (1999:Q1–2008:Q4)

Variables	Number of Observations	Mean	Median	Std. Dev.	Min.	Max.	1st Quartile	3rd Quartile	Sources
ΔEDF	19,796	0.07	0.00	0.83	−28.0	27.0	−0.03	0.03	Moody's KMV
ΔEDF_NFS	19,796	0.12	0.04	0.65	−1.32	3.39	−0.12	0.21	Moody's KMV
IR	19,796	3.28	3.06	1.62	1.00	10.45	1.95	4.90	IMF
$NRGAP$	19,796	−0.32	−0.21	1.41	−5.10	3.62	−1.1	0.63	Authors' calculations
$TGAP$	19,796	−0.44	−0.27	0.57	−3.60	1.37	−0.76	−0.07	Authors' calculations
$\Delta GDPN$	19,796	1.09	1.15	0.96	−5.97	11.46	0.86	1.54	OECD
ΔHP	19,796	0.00	0.84	4.95	−22.98	31.75	−1.45	2.52	BIS
ΔSM	19,796	0.00	1.92	10.2	−47.63	63.72	−4.99	6.42	Datastream
$SLOPE$	19,796	1.09	0.88	1.29	−2.25	3.69	−0.09	2.26	BIS
SEC	19,796	1.70	0.00	1.30	0.00	510.0	0.00	34.52	Bloomberg
DEP	19,796	76.09	80.7	18.2	0.02	99.00	67.8	97.1	Bloomberg
CTI	19,796	70.79	63.1	35.0	1.03	2.00	55.4	72.5	Bloomberg
$SIZE$	19,796	7.15	6.55	2.25	−4.61	15.43	5.66	8.25	Bloomberg
CAP	19,796	9.6	8.75	5.03	1.03	74.90	6.99	10.89	Bloomberg
ROA	19,796	0.95	0.92	1.77	−58.17	39.70	0.57	1.26	Bloomberg
$RESCUE$	19,796	0.005	0.00	0.08	0.00	1.00	0.00	0.00	BIS

(continued)

Table 1. (Continued)

Variables	Number of Observations	Mean	Median	Std. Dev.	Min.	Max.	1st Quartile	3rd Quartile	Sources
EXC_LEN	19,796	0.25	0.00	0.43	0.00	1.00	0.00	1.00	Authors' calculations
BEL	19,796	4.05	3.00	4.97	0.00	17.0	0.00	6.00	Authors' calculations
SPI	19,796	11.7	13.0	1.89	7.00	13.0	11.00	13.0	Barth et al. (2004)
COMP	11,525	−50.8	−53.8	31.7	−100.0	50.0	−73.7	0.00	Bank Lending Survey

Notes:
ΔEDF = change in the *EDF* at the bank level (one year ahead)
ΔEDF_NFS = *EDF* change for the non-financial sector at the country level (one year ahead)
IR = money-market rate
$NRGAP_t$ = natural interest rate gap
$TGAP$ = Taylor-rule gap
$\Delta GDPN_t$ = changes in nominal *GDP*
ΔHP = quarterly changes in the housing price index (demeaned)
ΔSM = quarterly changes in stock market returns (demeaned)
$SLOPE$ = changes in the slope of the yield curve
SEC = securitization ratio*100
DEP = deposit-to-total-liability ratio*100
CTI = cost-to-income ratio*100
$SIZE$ = log of total assets (USD millions)
CAP = capital-to-total-asset ratio*100
ROA = return on assets*100
EXC_LEN = dummy for banks with excessive lending expansion
$RESCUE$ = dummy for banks that received government support
BEL = number of consecutive quarters with interest rate below the natural rate
SPI = official supervisory power index
$COMP$ = competition index

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 in 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 on bank risk, we include in the set of macroeconomic controls (MC) both changes in the broad stock market indices for non-financial corporations and changes 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 perception (or tolerance), these variables aim to capture the effects of changes in asset prices on banks' risk positions via changes in the value of borrowers' collateral.

A related factor is that general economic conditions and future expectations of economic activity can also have an 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 not only by means of change in the EDF for the non-financial sector (ΔEDF_NF) but also by including in the vector of macroeconomic controls (MC) the slope of the yield curve ($SLOPE$). The latter is calculated for every country as the difference between the ten-year government bond yields and the three-month interbank rate. Due to the maturity transformation role of banks, there is a close relationship between the shape of the yield curve and bank profits (Viale, Fraser, and Kolari 2009).

3.3 The Bank Lending Channel and the Risk-Taking Channel

The risk-taking channel also has some overlaps 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 across banks. This strategy relies on the hypothesis that certain bank-specific characteristics (for example, access to securitization or the wholesale market) only influence loan supply movements, while bank's loan demand is largely independent of these factors. Broadly speaking, this approach assumes that after a monetary tightening the drop in the availability of total funding (which affects banks' availability to make new loans) or the ability to shield loan portfolio is different among banks.

We have therefore included three bank-specific characteristics that could influence bank funding ability in case of monetary policy movements: (i) the ratio of securitization activity over total assets (SEC), (ii) the share of deposits over total liabilities (DEP), and (iii) an efficiency indicator, the cost-to-total-income ratio (CTI).

The use of securitization shelters banks' loan supply from the effects of monetary policy; banks that securitize their assets to a larger extent have, on average, a higher capacity to liquidate their loans and get additional funding to finance new investment projects independently of monetary policy changes (Altunbas, Gambacorta, and Marques-Ibanez 2009). Moreover, the use of securitization techniques (especially if the equity tranche is not totally retained) may reduce banks' credit risk.

The share of deposits over total liabilities is a measure of bank contractual strength. Banks with a large amount of deposits will adjust their deposit rates by less (and less quickly) than banks whose liabilities are mainly composed of variable-rate bonds that are directly affected by market movements (Berlin and Mester 1999). Intuitively, this should mean that, in view of the presence of menu costs, it is more likely that a bank will adjust its terms for passive deposits if the conditions relating to its own alternative form of refinancing (i.e., bonds) change. Moreover, a bank will refrain from changing deposit conditions because, if the ratio of deposits to total liabilities is high, even small changes to their price will have a huge effect on total interest rate costs. In contrast, banks which use relatively more bonds than deposits for financing purposes come under greater pressure because their costs increase contemporaneously with and to a similar extent as market rates. Finally, the ratio of bank deposits over total liabilities is also influenced by the existence of deposit insurance, which makes this form of funding more stable and less exposed to the risk of a run. Acharya and Mora (2012) report that banks may actively manage the deposit-to-total-funding ratio by changing deposit rates.

The third indicator (cost-to-total-income ratio) measures the efficiency of the bank. This ratio captures bank profitability and therefore its income-generation capabilities. More efficient banks are also considered less risky by investors and have a higher capacity to tap funds in the market. Recent evidence also shows that bank balance sheet characteristics are important drivers of bank performance during the financial crisis (Demirgüc-Kunt and Huizinga 2010; Beltratti and Stulz 2012).

As additional controls, we have also included bank size, proxied by the logarithm of the bank's total assets ($SIZE$), and the capital-to-asset ratio (CAP). These bank-specific characteristics not only give insightful information on a bank's ability to insulate loan supply from monetary policy shocks (Kashyap and Stein 2000; Kishan and Opiela 2000) but also control for "too-big-to-fail" considerations, differences in business models, and capital regulation effects.

3.4 Quarterly versus Annual Data and Macroeconomic Coverage of the Data Set

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 data set from quarterly consolidated balance sheet information taken from Bloomberg (a commercial data provider) over the period 1999–2008. This mitigates also the problem of lags in losses recognition and represents an important novelty of our work because the overwhelming majority of cross-country banking studies have resorted to annual data. Our data set initially includes more than 1,100 listed banks from fifteen countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, the United Kingdom, and the United States.[7] To ensure broad comparability in accounting methodologies, we include in the final data set only listed banks (which typically adhere to international accounting standards) for which all necessary information were available.[8]

Table 2 gives some basic information on the final data set that include 643 banks. From a macroeconomic point of view, this data set is highly representative, as it comprises around two-thirds of the total lending provided by banks in the European Union and the United States. The average size of the banks in the sample is largest in the United Kingdom, Belgium, and Sweden and smallest in Finland and Greece. Equally, the average size of U.S. banks is not very large, because small U.S. 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.

3.5 The Measurement of Bank Risk

We measure bank risk with the expected default frequency (EDF), the probability that a bank will default within a given time horizon (typically one year). EDF is a well-known, forward-looking

[7]Although twelve 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 natural rates and Taylor rules at the country level; see section 3.6) was different across countries.

[8]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 the minimum differences in accounting standards between the United States, where U.S. GAAP is mostly used, and the International Accounting Standards (IAS) applied in the European Union.

Table 2. Descriptive Statistics by Country: 1999–2008 (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 (One Year Ahead)	ROA[a] (%)	Stock Market Return[b] (Average Quarterly Changes)	Housing Price Changes[b] (Average Quarterly Changes)	Slope of Yield Curve (%)	Number of Banks[c] (Final Data Set)	Weight Inside Sample[d] (%)
Austria	3.99	3.11	37,912	14.89	6.21	31.35	0.43	1.33	0.55	1.77	1.34	9	1.65
Belgium	4.13	3.13	222,456	11.35	7.27	46.17	0.10	2.26	−1.66	1.25	1.39	5	0.94
Denmark	4.19	3.48	11,370	14.03	11.89	25.41	0.32	1.33	0.51	0.64	1.08	32	6.36
Finland	4.78	3.14	8,984	10.58	7.26	21.57	0.07	0.82	−0.15	2.47	1.28	2	0.17
France	3.94	3.11	123,158	7.74	11.30	19.38	0.44	1.13	−0.11	1.60	1.30	22	3.80
Germany	2.40	3.11	139,145	4.22	6.79	29.96	0.83	0.11	−0.43	−0.01	1.22	24	3.63
Greece	7.60	4.94	20,436	21.18	7.91	26.45	1.12	1.04	−1.27	1.87	0.15	9	1.44
Ireland	9.59	3.34	74,902	20.15	4.64	26.34	0.19	0.97	−2.00	0.84	1.29	4	0.81
Italy	3.73	3.30	45,400	14.61	9.51	27.40	0.22	0.65	−1.13	0.89	1.50	24	4.13
Netherlands	5.03	3.10	173,784	11.35	8.29	24.18	1.04	0.83	−1.58	0.69	1.31	5	0.80
Portugal	4.56	3.33	290,065	15.18	5.06	21.25	0.24	0.67	−1.03	0.80	0.06	5	0.97
Spain	7.34	3.21	81,173	18.34	8.52	20.23	0.12	1.19	0.07	1.66	1.35	13	2.61
Sweden	4.91	3.36	180,368	12.73	5.26	26.28	0.09	0.68	0.10	0.34	1.23	4	0.82
UK	3.70	4.97	373,507	11.52	7.90	30.34	0.26	0.63	−0.49	0.18	0.03	6	1.00
USA	4.90	3.65	14,946	11.02	9.77	23.17	0.70	0.89	−0.68	−0.55	1.21	479	70.89
Total	4.99	3.49	119,840	11.33	9.60	23.64	0.61	0.92	−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.

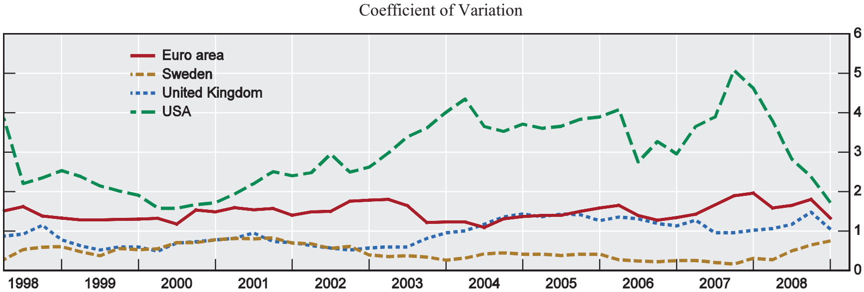
[a] Return on activity: Profit before taxes over total assets.

[b] Adjusted for inflation.

[c] Banks analyzed in this table refer to the final data set after the filtering process and other corrections.

[d] As a percentage of the number of observations.

Figure 1. Cross-Sectional Dispersion of Banks' EDF



Source: Authors' calculations.
Notes: 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.

indicator of risk, computed by Moody's KMV, which builds on Merton's model to price corporate bond debt (Merton 1974).[9] 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 (European Central Bank 2009; International Monetary Fund 2009). Figure 1 shows that the cross-sectional dispersion of banks' EDF (measured by means of the coefficient of variation) started to increase well before the period of financial crisis, especially in the United States and the United Kingdom. This means that there were already significant differences in bank risk at the cross-sectional level prior to the crisis. More importantly, while during the financial crisis the materialization of risk was—on aggregate—quite sudden, EDF has done relatively well with respect to other measures as a predictor of default prior to the crisis, particularly on a cross-sectional

[9]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, Uppal, and Wang (2007).

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, Hamilton, and Gokbayrak 2009 and Harada, Takatoshi, and Takahashi 2010). In this respect, the panel 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' EDFs 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 five- and ten-years-ahead EDFs, which provide accumulated expectations of default further in time.[10]

In table 3, banks are grouped depending on their specific risk position, using one-year EDF values. A "high-risk" bank has the average EDF of banks included in the fifth quintile (i.e., in the 20 percent of the riskier banks with an average EDF_H equal to 1.7 percent); a "low-risk" bank has the average EDF of the banks in the first quintile (EDF_L is equal to 0.03 percent). 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, securitize by more their lending portfolio, and are more efficient (have a lower cost-to-income ratio).

[10] A possible criticism to the 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. However, the statistical correlation between the EDF and the short-term rate is not statistically different from zero. This means that the proprietary KMV formula does not seem to be systematically affected by such mechanism.

Table 3. Balance Sheet Characteristics and Bank Risk Profile†

Distribution by Bank Risk (One-Year-Ahead EDF)	Lending (Annual Growth Rate)	Size (USD Mill.)	Liquidity (% Total Assets)	Capitalization (% Total Assets)	Securitization (% Total Assets)	Cost-to-Income Ratio (%)	ROA (%)	ROA Variability‡ (Coefficient of Variation)
High-Risk Banks (EDF = 1.7%) (a)	15.0	15,206	25.7	8.7	0.6	69.4	0.7	1.4
Low-Risk Banks (EDF = 0.03%) (b)	10.6	92,996	26.9	9.5	0.8	60.3	1.1	0.9
Δ = (a) − (b)	4.4	−77,791	−1.2	−0.8	−0.2	9.0	−0.4	0.5

†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 has an average EDF in the last quintile.
‡The coefficient of variation of the return on assets is calculated for the four quarters ahead (*ROA*).

Bank profitability, measured by return on assets (ROA), is higher and more stable for low-risk banks. The coefficient of variation of the ROA calculated using information for the four quarters ahead for low-risk banks is indeed 40 percent lower than that for high-risk banks (0.9 and 1.4, respectively). As the ROA variability is not directly affected by (general) changes in the market price of risk, we have used it as an alternative measure for bank risk taking.[11]

3.6 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.[12] This strategy, however, needs to address which benchmark to use in order to assess the stance of monetary policy at any point in time.

In this paper we measure the monetary policy stance as the deviation of the real policy rate (money-market rate minus CPI inflation) from the "natural interest rate" *(NRGAP)*, calculated using the Hodrick-Prescott filter.[13] Similar results are obtained using alternative measures of the Taylor rule (see section 4). The

[11]The analysis has been supplemented with other measures of bank risk derived from stock market information: (i) a simple capital asset pricing model (CAPM) and (ii) the Campbell et al. (2001) approach that decomposes stock market volatility into total market, banking sector, and individual bank-level volatility. Using these measures instead of the EDF provides very similar results. For more details, see the working paper version of the study, available at www.bis.org/publ/work298.pdf.

[12]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 multi-national activity.

[13]The Hodrick and Prescott (1997) filter breaks down a time series y_t into a smooth path g_t and remaining deviations (residuals or shocks) ε_t, respectively.

correlation between the *NRGAP* and a Taylor rule with interest rate smoothing is 0.75^{***}, and that with a standard Taylor rule is 0.85^{***}.[14]

Figure 2 shows the dispersion of the monetary policy stance across the fifteen countries analyzed in this study. The chart reports the median, the first quintile, and the last quintile of the distribution of the *NRGAP*. The dispersion is quite high, although eleven of the countries included belong to the euro area, which has a single monetary policy. The dispersion indeed does not decrease by excluding non-euro-area countries from the sample: the standard deviation of the *NRGAP* is around 1 percent both for the whole sample and including only euro-area countries. The figure indicates that in the period ranging from 2003 to 2006, monetary policy has been generally accommodative (real interest rate below the natural rate, $NRGAP < 0$) in most countries (Taylor 2009).

3.7 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 monetary policy decisions. That is, we 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

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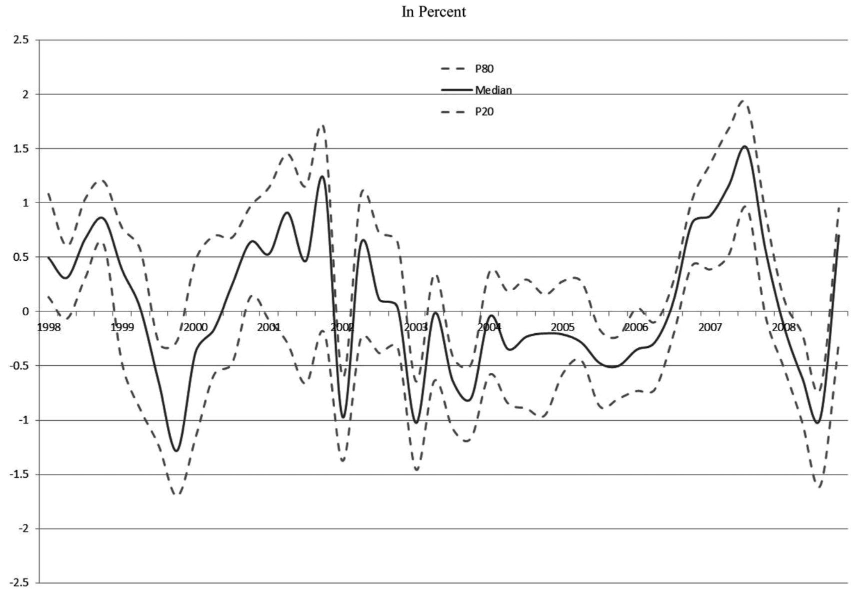
To achieve smoothness, a penalty is imposed on g_t such that second-order differences are penalized. The application requires the specification of a penalized parameter λ, say, which steers the "smoothness" of the fitted path for g_t. We use a smoothing parameter λ equal to 1,600 as suggested by Ravn and Uhlig (2002).

[14]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 United States) is a positive function of 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 $\beta_\pi = 1.5$ and $\beta_y = 0.5$. The interest rate smoothing parameter γ has been set to 0.85. The target inflation (π^*) has been set to 2 percent. In the case of the standard setup for a Taylor rule, we set $\beta_\pi = \beta_y = 0.5$ and $\gamma = 0$.

Figure 2. Dispersion of the Monetary Policy Stance Indicator



Source: Authors' calculations.
Notes: The figure reports the median, the first quintile (P20), and the last quintile (P80) of the monetary policy stance measure in the fifteen countries included in the sample. The monetary policy stance measure is given by the difference between the real short-term interest rate and the "natural interest rate" (*NRGAP*), calculated using the Hodrick-Prescott filter with a smoothing parameter $\lambda = 1{,}600$.

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 before the occurrence of the financial crisis (Bernanke and Woodford 2005). This could arguably have changed from the last quarter of 2008 onwards, as the failure of Lehmann Brothers intensified the credit crisis considerably as well as central banks' concerns about the situation of the banking sector. For this reason, we stop our sample period in 2008 and insert a dummy for those banks that received government assistance in the last quarter of 2008.

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, Newey, and Rosen (1988) and Arellano and Bond (1991) and was 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.[15] As a final precaution, we consider all macro-variables and bank-specific characteristics at $t-1$.

4. The Results

The main results of the analysis are reported in table 4. 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).[16]

Table 4 shows that, ceteris paribus, changes in the EDF of the non-financial sector are positively linked to banks' EDF. This implies that the EDF of both financial and non-financials are driven by general movements in the stock market. The coefficient related to the

[15] 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 Beck, Levine, and Loayza (2000) apply it to investigate the relation between financial development and economic growth.

[16] We cluster standard errors ($\varepsilon_{j,k}$) at the country level. In this way we are able to control for the fact that, due to the presence of different institutional settings, probably financial conditions of each bank in a country are not independent of one another. We have also rerun all models with clusters at the bank level and with double-clustered standard errors (country and bank/time and country) with no substantial change in results. For a general discussion on different approaches used to estimating standard errors in finance panel data sets, see Petersen (2009).

Table 4. Regression Results

Dependent Variable: Quarterly Change of the Expected Default Frequency over a One-Year Horizon	(1) Baseline Model (Natural-Rate Gap)	(2) Alternative MP Stance Measure (Taylor Gap)	(3) The Financial Accelerator (Collateral Value)	(4) Non-Linear Effects	(5) Bank-Specific Characteristics (Bank Lending Channel)
$\Delta EDF_{t\text{-}1}$	0.3719**	0.3517***	0.3492**	0.3496**	0.6402***
	(0.1367)	(0.1361)	(0.1363)	(0.1364)	(0.0237)
ΔEDF_NFS_t	0.3567***	0.3709***	0.3316***	0.3325***	0.2706***
	(0.0307)	(0.0335)	(0.0290)	(0.0282)	(0.0238)
$NRGAP_{t\text{-}1}$	−0.0741***		−0.0695***	−0.0673***	−0.0585***
	(0.0054)		(0.0110)	(0.0104)	(0.0062)
$TGAP_{t\text{-}1}$		−0.1244***			
		(0.0339)			
$SLOPE_{t\text{-}1}$			−0.0364***	−0.0435***	−0.0212***
			(0.0107)	(0.0111)	(0.0029)
$\Delta HP_{t\text{-}1}$			−0.3992**	−0.4231**	−0.7067***
			(0.1950)	(0.2136)	(0.0948)
$\Delta SM_{t\text{-}1}$			0.4324	0.4140	0.4823
			(0.2189)	(0.2840)	(0.3454)
$NRGAP_{t\text{-}1}{*}IR_{t\text{-}1}$				0.0050***	
				(0.0017)	
$NRGAP_{t\text{-}1}{*}BELOW_{t\text{-}1}$				−0.0042***	
				(0.0014)	
$SEC_{t\text{-}1}$					−1.0219**
					(0.4755)
$DEP_{t\text{-}1}$					−0.0691*
					(0.0394)

(continued)

Table 4. (Continued)

Dependent Variable: Quarterly Change of the Expected Default Frequency over a One-Year Horizon	**(1) Baseline Model (Natural-Rate Gap)**	**(2) Alternative MP Stance Measure (Taylor Gap)**	**(3) The Financial Accelerator (Collateral Value)**	**(4) Non-Linear Effects**	**(5) Bank-Specific Characteristics (Bank Lending Channel)**
$CTI_{t\text{-}1}$					0.5119^{***}
					(0.0523)
$SIZE_{t\text{-}1}$					0.0066
					(0.0055)
$CAP_{t\text{-}1}$					-0.0037^{***}
					(0.0003)
Bank Rescue and Seasonal Dummies	Yes	Yes	Yes	Yes	Yes
Sample Period	1999:Q1–2008:Q4	1999:Q1–2008:Q4	1999:Q1–2008:Q4	1999:Q1–2008:Q4	1999:Q1–2008:Q4
Observations	19,796	19,796	19,796	19,796	19,796
Number of Banks	643	643	643	643	643
Test for AR(1) Pr > z =	0.000	0.000	0.000	0.000	0.000
Test for AR(2) Pr > z =	0.956	0.923	0.958	0.956	0.253
Hansen Test Prob > Chi2 =	0.989	0.899	0.952	0.998	0.880

Notes: Robust standard errors (clustered at the country level) are reported in parentheses. The symbols *, **, and *** represent significance levels of 10 percent, 5 percent, and 1 percent, respectively. The coefficients for the dummies are not reported.

NRGAP variable is instead negative and significant, indicating that an accommodative monetary policy ($NRGAP < 0$) has a positive effect on bank risk. For example, taking the results from the baseline model in the first column, if the real interest rate is 100 basis points below the natural rate, the average probability for a bank to go into default increases by around 0.07 percent after a quarter and by 0.12 percent in the long run.

Since the natural-rate gap could, in principle, give different indications with respect to other measures, the reliability of the baseline result has been tested using the Taylor gap (*TGAP*)—that is, the difference between the actual nominal short-term rate and that generated by a standard "Taylor rule."[17] As shown in the second column of table 4, results are very similar: the only difference is the magnitude of the coefficient for *TGAP*, caused by the different average level of the two variables.

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) and the slope of the yield curve (*SLOPE*). Both asset returns are demeaned using their long-term averages of the last twenty 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 4 show that only the coefficients for changes in housing price have the expected negative sign, while those for stock market changes are not statistically different from zero. This could be due to the fact that the effect of changes in the stock market are already picked up by the evolution of the EDF for non-financial corporations.

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

[17] For more details on the results obtained using Taylor rules, see the working paper version of the study, available at www.bis.org/publ/work298.pdf.

instance, Albertazzi and Gambacorta 2009; Viale, Fraser, and Kolari 2009).

The recent credit crisis has illustrated that the manifestation of risk may be sudden and not linear. The effect of monetary policy on bank risk may be influenced not only by the *NRGAP* but also by two other major elements: first, the nominal level of the interest rate; second, the number of consecutive quarters in which the interest rate has been below the natural rate. In order to account for these two factors, the baseline equation has been modified to include terms that represent the interaction between the *NRGAP* variable and, respectively, the level of the interest rate (*IR)* and the number of consecutive quarters the interest rate has been below the natural rate (*BEL*).[18]

$$\begin{aligned}\Delta EDF_{i,k,t} = {} & \alpha\Delta EDF_{i,k,t-1} + \beta\Delta EDF\_NF_{k,t} + \gamma NRGAP_{k,t-1} \\ & + \psi NRGAP_{k,t-1}IR_{k,t-1} + \rho NRGAP_{k,t-1}BEL_{k,t-1} \\ & + \psi MC_{k,t-1} + \sum_{j=1}^{4}\phi_j SD + \varepsilon_{i,t}\end{aligned} \tag{2}$$

The fourth column of table 4 shows that the negative link between ΔEDF and *NRGAP* is reinforced if the level of interest is particularly low ($\psi_j > 0$), in line with the "search for yield" hypothesis. As discussed, financial intermediaries often commit themselves contractually to produce relatively high nominal rates of return in the long term (Rajan 2005). 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 expected return. Moreover, the coefficient ρ 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 during which this deviation persists.

[18] The variables *IR* and *BEL* were also initially included in equation (2) in isolation but turned out to be not significant. We have therefore decided to drop them from the model, also taking into account that *IR* is highly correlated with the variable *SLOPE* (-0.893^{***}).

The link between bank risk and accommodative monetary policy could also be influenced by banks' balance sheet characteristics that summarize the 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 (i) the ratio of securitized loans over total assets (SEC), (ii) the share of deposits over total liabilities (DEP), (iii) the cost-to-total-income ratio (CTI), (iv) the logarithm of bank's total assets ($SIZE$), and (v) the capital-to-asset ratio (CAP). All bank-specific characteristics refer to $t-1$ in order to avoid endogeneity bias.

The results are reported in the fifth column of table 4. As expected, there is a negative correlation between securitization activity and bank risk, which is in line with the bank lending channel literature. Banks with greater access to the securitization market are better able to buffer their lending activity against shocks related to the availability of external finance. Also, the link between bank risk and deposit strength is negative. Banks that have a large amount of deposits are less affected by market movements, especially during periods of financial stress (Gambacorta and Marques-Ibanez 2011). Finally, all other things being equal, less efficient and less capitalized banks are considered more risky by the market.

5. Robustness Tests

5.1 Different Measures of Bank Risk

The robustness of the results has been checked by considering a more complete term structure for the expected default frequency. 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 as a dependent variable the EDF with horizons of both five and ten years. Unfortunately, these data are only available from 2004, thereby reducing the number of observations in the sample. Despite this, the results presented in the first two columns of table 5 are consistent with those for the baseline models that use the EDF over a one-year horizon (see columns 1 to 4 of table 4).

Table 5. Different Measures for Bank Risk

Different Measures of Bank Risk as Dependent Variable	**(1) Δ*EDF 5yrs***	**(2) Δ*EDF 10yrs***	**(3) Δ*Rating***	**(4) CV_ROA**
Lagged Dependent Variable	0.4773***	0.3429***	0.0042	0.0018***
	(0.0649)	(0.0283)	(0.0053)	(0.0006)
ΔEDF_NFS_t	0.2952***	0.6757***		
	(0.0421)	(0.2011)		
$\Delta GDPN$			−0.0007	−0.7619
			(0.0014)	(0.7452)
$NRGAP_{t\text{-}1}$	−0.0990***	−0.1416***	−0.0029**	−2.8401***
	(0.0041)	(0.0305)	(0.0012)	(0.4248)
$SLOPE_{t\text{-}1}$	−0.0311***	−0.1198***	−0.0039***	−2.1384***
	(0.0070)	(0.0299)	(0.0011)	(0.3321)
$\Delta HP_{t\text{-}1}$	−2.6411***	−9.5190***	0.0101	−32.794***
	(0.4032)	(1.1974)	(0.0226)	(4.3477)
$\Delta SM_{t\text{-}1}$	0.0830	2.0909***	0.0085	1.6656
	(0.2069)	(0.7321)	(0.0074)	(1.2772)
$SEC_{t\text{-}1}$	−0.5816	−2.2356	−0.0154	−5.0624
	(0.7466)	(3.0601)	(0.1067)	(4.9616)
$DEP_{t\text{-}1}$	−0.0615	−0.1534	−0.0081*	−13.932
	(0.0721)	(0.2036)	(0.0043)	9.3615
CTI_{t-1}	0.4082***	1.1741***	0.0233**	1.0295
	(0.0546)	(0.1833)	(0.0094)	(0.9634)

(continued)

Table 5. (Continued)

Different Measures of Bank Risk as Dependent Variable	**(1) Δ*EDF 5yrs***	**(2) Δ*EDF 10yrs***	**(3) Δ*Rating***	**(4) CV_ROA**
$SIZE_{t\text{-}1}$	−0.0002	−0.0209	0.0005	0.3133
	(0.0066)	(0.0217)	(0.0004)	(0.2539)
$CAP_{t\text{-}1}$	−0.0076***	−0.0266**	−0.0001	−0.0491***
	(0.0023)	(0.0120)	(0.0002)	(0.0167)
Bank Rescue and Seasonal Dummies	Yes	Yes	Yes	Yes
Sample Period	2004:Q1–2008:Q4	2004:Q1–2008:Q4	1999:Q1–2008:Q4	1999:Q1–2008:Q4
Observations	11,631	11,631	4,500	19,796
Number of Banks	643	643	149	643
Test for AR(1) Pr > z =	0.000	0.000	0.000	0.000
Test for AR(2) Pr > z =	0.144	0.337	0.263	0.901
Hansen Test Prob > Chi2 =	0.999	0.965	0.910	0.944

Notes: Robust standard errors (clustered at the country level) are reported in parentheses. The symbols *, **, and *** represent significance levels of 10 percent, 5 percent, and 1 percent, respectively. The coefficients for the dummies are not reported.

The increase of the *EDF* horizon does not change the sign and the significance of the coefficients attached to the monetary policy stance (*NRGAP*). It does, however, produce some effects on the absolute value of the γ coefficient. In particular, 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 Taylor gap as a measure of accommodative monetary policy.

The second 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 2010). 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).[19] Looking at the third column of table 5, the effect of the risk-taking channel is less strongly detected (i.e., the coefficients associated with the *NRGAP* measure have the correct sign, but its significance is reduced). This could be due to the implementation of ratings downgrades, as observed during the Asian crisis.[20]

In the third robustness test we used, as an additional measure of bank risk, the coefficient of variation of the return on assets (*ROA*) calculated from developments on this variable on the four quarters

[19] In particular, the dependent variable $\Delta Rating$ has been calculated in the following way. First, we computed the variable *Rating* by assigning Moody's ratings (from AAa to C) to eight different buckets, where 1 is the safest bank and 8 the riskiest. We then calculated the first difference of the variable rating. This means, for example, that a $\Delta Rating$ value of +1 is equivalent to the downgrade of a bucket of a bank in a given quarter.

[20] As an additional robustness test, we also used the spreads on the credit default swap for each individual bank as a 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, Brennan, and Marsh 2005). Results for an unbalanced sample of more than 100 large banks over the period 2002–9 obtained from Bloomberg were also consistent with those obtained by using the *EDF*. Results are not reported for the sake of brevity.

ahead (i.e., forward). *ROA* is a complementary indicator of bank profitability that is not directly affected by (general) changes in the market price of risk. Also, in this case the effect of the risk-taking channel is visible on the estimations (the coefficient on the *NRGAP* measure is negative and significant; see the fourth column of table 5), while the balance sheet characteristics that influence bank funding ability lose their statistical significance in many cases.

Finally, we have checked the robustness of our results controlling for the banks' starting level of risk. In particular, we have included in the specifications the *lagged level* of the bank *EDF* in addition to the *lagged change in EDF*. The additional variable expressed in *level* turned out to be not significant and left the results unchanged.[21]

5.2 Testing for Excessive Lending, Institutional Differences, and Data Issues

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, by nature, more systemic. In order to select those banks that supplied lending in excess, we have, first, run a standard lending equation over our estimation period 1999–2008.[22] Second, for

[21] Results are not reported for the sake of brevity but are available from the authors upon request.

[22] The specification is taken from the first column of table 3 in Gambacorta and Marques-Ibanez (2011). In particular, the model is given in the following equation:

$$\Delta \ln(loans)_{ikt} = \mu_i + \alpha \Delta \ln(loans)_{ikt-1} + \mathrm{B}CD_k + \mathrm{H}TD_t + \delta X_{ikt-1} + \Gamma\Theta_t + \varepsilon_{ikt}$$

with $I = 1, \ldots, N, k = 1, \ldots, 15$, and $t = 1, \ldots, T$, where N is the number of banks, k is the country, T is the final quarter, μ_i is a vector of fixed effects, and Θ_t are the seasonal dummies. The growth rate in nominal bank lending to residents (excluding interbank positions), $\Delta\ln(loans)$, is regressed on country and time dummies (*CD* and *TD,* respectively). These variables are very important to take into account different country-specific institutional characteristics and loan demand shifts through time. Bank-specific characteristics included in vector X are *SIZE*, the log of total assets; *LIQ*, cash and securities over total assets; and *CAP*, the standard capital-to-asset ratio. Also, in this case bank-specific characteristics refer to $t-1$ in order to mitigate a possible endogeneity bias.

each quarter we have ordered banks according to the residuals (the difference between actual loan changes and the change in loans predicted by the regression). Third, we have constructed a dummy for excessive lending (*EXC_LEND*) that takes the value of 1 if a bank k in a given quarter t is in the first quartile of the distribution of the residuals.

The results reported in the first column of table 6 show a positive coefficient for *EXC_LEND*. Banks that have a very high lending growth increase their riskiness by more than their peers. The sign of the *NRGAP* 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).

The above results may also be influenced by differences in the intensity of bank supervision, unrelated to monetary policy, which could have had an impact on the amount of risk undertaken (Beltratti and Stulz 2012). 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, Caprio, and Levine (2004), we introduce in the model the official Supervisory Power Index (*SPI*). This indicator could in principle take a value ranging from 0 (no supervision) to 14 (maximum supervision).[23] The results in the third column of table 6 indicate a negative but only slightly significant value for this variable, supporting the idea that banks took less risk in those countries where supervisory activities were more stringent. Also, in this case, the coefficients for the natural-rate gap (*NRGAP*), and its interactions with *IR* and *BEL*, remain basically unchanged, suggesting that the

[23]The official Supervisory Power Index is given by the sum of World Bank guide questions 5.5, 5.6, 5.7, 6.1, 10.4, 11.2, 11.3.1, 11.3.2, 11.3.3, 11.6, 11.7, 11.9.1, 11.9.2, and 11.9.3 on the Financial Services Authority's relation to auditors, management, and shareholders. Yes = 1, No = 0. Higher values indicate greater supervisory power. For the countries analyzed in this study, the variable *SPI* takes a value from 7 to 13. For more information, see Barth, Caprio, and Levine (2004).

Table 6. Excessive Lending, Institutional Differences, and Data Issues

Dependent Variable: Quarterly Change of the Expected Default Frequency over a One-Year Horizon	(1) Excessive Lending	(2) Supervisory Strength	(3) Competition	(4) Reduced Sample	(5) Database Collapsed at the Country-Quarter Level
Lagged Dependent Variable	0.4864***	0.6404***	0.6240***	0.5183***	0.1003**
	(0.1192)	(0.0238)	(0.0036)	(0.0016)	(0.0479)
ΔEDF_NFS_t	0.1883***	0.2707***	0.2470***	0.1209***	0.1016**
	(0.0525)	(0.0234)	(0.0068)	(0.0104)	(0.0422)
$NRGAP_{t-1}$	−0.0499***	−0.0583***	−0.0617***	−0.0500***	−0.0070**
	(0.0036)	(0.0061)	(0.0027)	(0.0057)	(0.0028)
$SLOPE_{t-1}$	−0.0233***	−0.0212***	−0.0193***	−0.0290***	−0.0055
	(0.0013)	(0.0026)	(0.0010)	(0.0025)	(0.0035)
ΔHP_{t-1}	−0.4195*	−0.6990***	−0.3261***	−0.3666***	−0.1619
	(0.2267)	(0.0939)	(0.0633)	(0.0489)	(0.1597)
ΔSM_{t-1}	0.3075	0.4816	0.5909	0.2610	0.0472
	(0.2076)	(0.3490)	(0.4838)	(0.1817)	(0.0419)
SEC_{t-1}	−0.9619**	−1.0244**	−1.0766**	−0.8470**	−2.9179*
	(0.4066)	(0.4806)	(0.5425)	(0.4169)	(1.5159)
DEP_{t-1}	−0.0682***	−0.0650***	−0.1252***	−0.0691***	−0.0064
	(0.0255)	(0.0251)	(0.0055)	(0.0243)	(0.0148)
CTI_{t-1}	0.3050***	0.5115***	0.4700***	0.3105***	0.0076
	(0.0686)	(0.0505)	(0.0544)	(0.0581)	(0.0070)

(continued)

Table 6. (Continued)

Dependent Variable: Quarterly Change of the Expected Default Frequency over a One-Year Horizon	**(1) Excessive Lending**	**(2) Supervisory Strength**	**(3) Competition**	**(4) Reduced Sample**	**(5) Database Collapsed at the Country-Quarter Level**
$SIZE_{t-1}$	0.0043	0.0072	0.0070	0.0058	0.0041*
	(0.0045)	(0.0056)	(0.0050)	(0.0043)	(0.0025)
CAP_{t-1}	−0.0019*	−0.0030***	−0.0041***	−0.0016***	−0.0016***
	(0.0010)	(0.0004)	(0.0002)	(0.0001)	(0.0001)
EXC_LEND_{t-1}	0.0148*				
	(0.0085)				
$SPI_{t\text{-}1}$		−0.0019*			
		(0.0010)			
$COMP_{t\text{-}1}$			0.0008***		
			(0.0001)		
Bank Rescue and Seasonal Dummies	Yes	Yes	Yes	Yes	Yes
Sample Period	1999:Q1–2008:Q4	1999:Q1–2008:Q4	2002:Q4–2008:Q4	1999:Q1–2008:Q3	1999:Q1–2008:Q4
Observations	19,796	19,796	11,525	19,153	600
Number of Banks/Countries	643	643	607	643	15
Test for AR(1) Pr > z =	0.000	0.000	0.000	0.000	0.000
Test for AR(2) Pr > z =	0.803	0.254	0.233	0.512	0.190
Hansen Test Prob > Chi2 =	0.978	0.988	0.972	0.669	0.889

Notes: Robust standard errors (clustered at the country level) are reported in parentheses. The symbols *, **, and *** represent significance levels of 10 percent, 5 percent, and 1 percent, respectively. The coefficients for the dummies are not reported.

effects of long-standing low interest rates on bank risk are still at work. Very similar results, not reported for the sake of brevity, are obtained replacing the variable *SPI* with a complete set of country dummies to take into account other institutional characteristics.

An increase in competition could lead to greater (and possibly excessive) bank risk (Jiménez, Lopez, and Saurina 2007; Cihak, Wolfe, and Schaeck 2009). 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, the Senior Loan Officer Survey for U.S. banks, and the Credit Condition Survey for UK banks regarding the effect of competition on credit conditions to construct a net percentage index (see Maddaloni and Peydró 2011 for a similar application). This index, which 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. Due to data limitation, the estimation starts in the last quarter of 2002 (2007:Q2 for UK banks). Danish and Swedish financial intermediaries have been excluded from the sample. In line with the existing traditional literature (Keeley 1990), we find a positive link between the competition index ($COMP$) and bank risk. This result is, however, in contrast with recent empirical evidence that detect that more competition reduces the probability of bank failure (Boyd and De Nicoló 2005).

A possible concern could be the inclusion in the sample period of the last quarter of 2008, when many central banks started to adopt unconventional monetary policies to avoid a financial meltdown (Gambacorta, Hofmann, and Peersman 2012). For this reason, we have rerun the baseline equation on a reduced sample that excludes 2008:Q4 (fourth column of table 6). The results remain unchanged.

Our database is biased towards U.S. banks that represent around 70 percent of the observations. Therefore, we have also checked the robustness of the results by modifying the model weighting each country in the analysis equally. To this end we have first collapsed the panel into one observation per country-quarter and then run the following modified version of model (1):

$$\Delta EDF_{k,t} = \alpha\Delta EDF_{k,t-1} + \beta\Delta EDF\_NF_{k,t} + \gamma NRGAP_{k,t-1} + \psi MC_{k,t-1} + \lambda BSC_{k,t-1} + \sum_{j=1}^{4}\varphi_j SD + \varepsilon_{i,t} \qquad (1')$$

with $k = 1, \ldots, 15$ and $t = 1, \ldots, T$, where k is the country and T is the final quarter. By collapsing the panel country-quarter level, we don't have observations at the bank level anymore: *EDF* and bank-specific characteristics (*BSC*) are simple averages of national banking sectors. The results are reported in the last column of table 6. Due to the reduction in the number of observations (from 19,796 to 600) and the impossibility to exploit the cross-sectional variability across banks, the significance of many coefficients is drastically reduced, especially those associated with bank-specific characteristics. However, the coefficient related to the *NRGAP* variable is still negative and significant, indicating that an accommodative monetary policy ($NRGAP < 0$) has a positive effect on (average) bank risk.

6. Conclusions

The credit crisis has drawn the attention of researchers and policymakers 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; and (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 fifteen 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, investors' risk perception, 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.

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