



EUROPEAN CENTRAL BANK  
EUROSYSTEM

## Working Paper Series

Carlo Altavilla, Matthieu Darracq Paries  
and Giulio Nicoletti

Loan supply, credit markets and  
the euro area financial crisis

No 1861 / October 2015



**Note:** This Working Paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB

## Abstract

We use bank-level information on lending practices from the euro area Bank Lending Survey to construct a new indicator of loans' supply tightening controlling for both macroeconomic and bank-specific factors. Embedding this information as external instrument in a Bayesian vector autoregressive model (BVAR), we find that tighter bank loan supply to non-financial corporations leads to a protracted contraction in credit volumes and higher bank lending spreads. This fosters firms' incentives to substitute bank loans with market finance, producing a significant increase in debt securities issuance and higher bond spreads. We also show that loans' tightening shocks explain a large fraction of the contraction in real activity and the widening of credit spreads especially over the recession which followed the euro area sovereign debt crisis.

**JEL:** E51, E44, C32

**Keyword:** Credit Supply, Lending standards, Bank Lending Survey, External Instruments

## **Non-technical summary**

This paper focuses on the macroeconomic impact of credit supply shock in the euro area. Given the prominent role played by the financial intermediaries in financing euro area firms, it is very important to correctly assess the macroeconomic impact of changes in the supply of loans extended by banks to non-financial corporations (NFCs).

In order to identify loan supply shocks we make use of unique bank-level information on credit standards in the ECB's Bank Lending Survey (BLS) to construct a new indicator of bank credit supply conditions for the euro area, labelled Loan Supply Indicator (LSI). The indicator is derived from changes in bank credit standards which are not due to bank-specific demand factors and macro-financial conditions. We show that the LSI sheds new light on the relative tightness of bank loan supply across time.

This indicator is then used as external instrument in a Bayesian VAR model to identify credit supply shocks. The results suggest that adverse loan supply shocks lead to a protracted contraction in credit volumes and higher bank lending spreads, which fosters firms' incentives to substitute bank loans for market finance, producing a significant increase in debt securities issuance and higher bond spreads. Moreover, tighter bank loan supply to non-financial corporations explains a large fraction of the recession following the euro area sovereign crisis. During this period, banks' supply tightening is also able to explain both the increases in credit spreads and the substitution between loans and bonds issued by firms.

Finally, we complement our analysis by constructing an indicator of Excess Bond Premia from corporate bond level data to extract a signal from the risk attitude of financial market participants. We shed light on how much information from bank credit supply disruptions, as indicated by our loan supply indicator, differs from the information available from financial market, as indicated by the EBP. We investigate the impact an unanticipated shock in EBP and its relative ability to explain macroeconomic developments, above and beyond the bank-related supply shock. Our results show that during the Great Recession, the information from financial markets not explained by the tightening of euro area banks credit explains a large fraction of macroeconomic developments.

# 1 Introduction

This paper analyses the macroeconomic impact of credit supply shocks in the euro area. The eurozone has recently experienced two severe recessions. The first recession, usually referred to as the “Great Recession”, started in 2008 and took place in the context of the post-Lehman global financial crisis. The second recession started in 2011 and was instead mainly determined by euro area specific events following the so called “Euro area sovereign debt crisis”. Over the course of both economic downturns, bank loans rapidly decelerated, recording an extended period of contraction, and lending rate spreads substantially widened. Given the prominent role played by the financial intermediaries in financing the euro area firms, we attempt to assess the macroeconomic consequences of changes in the supply of loans extended by banks to non-financial corporations (NFCs).

The contraction in bank-intermediated credit and the surge in firms’ borrowing cost observed over the recessionary periods might be consistent with a change in the supply of loans. What is less clear, however, is how much the change in credit supply have contributed to the developments in the real economic activity, as many confounding factors mostly associated to general economic conditions were at play. In a context of falling aggregate demand and poor macroeconomic performance, for example, banks might be induced to protect their balance sheet by tightening the conditions at which credit is granted. Moreover, in periods of financial distress banks might optimally react to the increased level of perceived counterparty (borrower) risk by raising the price on new (wholesale and retail) credit lines. In this circumstances, banks could be seen as responding to already existing adverse economic conditions rather than generating them. These examples suggest that in order to assess the macroeconomic impact of credit supply shock it is crucial to correctly identify the change in credit univocally stemming from the banks’ lending behaviour not related to other confounding factors.

In order to identify loan supply shocks we make use of unique bank-level information on credit standards in the ECB’s Bank Lending Survey (BLS) and construct a new indicator of bank credit supply conditions for the euro area, labelled Loan Supply Indicator (LSI). This indicator is derived from changes in bank credit standards which are not due to bank-specific demand factors and macro-financial conditions. We show that the LSI sheds new light on the relative tightness of bank loan supply over time and in particular across the two recessionary episodes.

The indicator of supply condition is then used as external instrument in a Bayesian VAR model to identify loan supply shocks. Results suggest that adverse loan supply shocks lead to a protracted contraction in credit volumes and higher bank lending spreads, which fosters firms’ incentives to substitute bank loans for market finance, producing a significant increase in debt securities issuance and higher bond spreads. Moreover, tighter bank loan supply to non-financial corporations explains

a large fraction of the recession following the euro area sovereign crisis. During this latter period, banks' supply tightening is also able to explain both the increases in credit spreads and the substitution between loans and bonds issued by firms.

Finally, we complement our analysis by constructing an indicator of Excess Bond Premia (EBP, as in Gilchrist and Zakrajšek, 2012a) from corporate bond level data to extract a signal from the risk attitude of financial market participants. We shed light on how much information from bank credit supply disruptions, as indicated by our loan supply indicator, differs from the information available from financial market, as indicated by the EBP. Expanding on the seminal contributions of Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012a, 2012b, 2013), we investigate the impact of unanticipated shocks to the EBP and their relative ability to explain macroeconomic developments, above and beyond the bank-related supply shocks. Our results show that during the Great Recession, the information from financial markets not explained by the tightening of euro area banks credit explains a large fraction of macroeconomic developments.

Our paper relates to three main strands of literature. The first one focuses on the identification of the macroeconomic effects of credit supply shocks identified by bank lending standards as reported in surveys. Bassett et al. (2014) use information from the Senior Loan Officer Opinion Survey collected by the Federal Reserve to construct a credit supply indicator. Lown and Morgan (2006) studied the macroeconomic impact of a shock to lending standards using information contained in the same survey. Ciccarelli et al. (2013, 2014) estimate a panel-VAR including variables from the BLS aggregated at country level and found that, especially in financially distressed countries, the credit channel (both the bank lending and the non-financial borrower balance-sheet channel) might act as an amplification mechanism for the impact of monetary policy on real economy. Darracq Pariès and De Santis (2015) use a similar econometric framework and identify credit supply shocks using aggregated BLS information.

The second strand of literature focuses on the alternative financing sources of non-financial firms and their choice between bank and market financing in periods of financial distress. Early studies on the endogenous choice between banks versus market finance (Holmstrom and Tirole, 1997; Repullo and Suarez, 2000) argue that a contraction in firms' net worth, as observed during the crisis, should lead to a shift from bond to more bank finance. More related to our work, Becker and Ivashina (2014) highlight, instead, that banks' credit tightening can induce firms to substitute bank credit with stronger issuance of corporate bonds.. A theoretical rationale for this evidence is proposed by Adrian et al. (2012). In their model, banks follow a "Value-at-Risk" approach. Under this constraint, when the default risk of NFCs increases, the bank's optimal choice is to deleverage sharply and thus contract lending. Given that the demand for credit from NFCs has limited elasticity, risk-averse bond investors need to be encouraged to increase their credit supply. This requires a widening of the spreads on corporate bonds. The substitution between bonds and loans

is also found in De Fiore and Uhlig (2011) where the shift from bank loans to bonds can be the result of NFCs optimal financing choices in the face of a negative bank supply shock. In this model, firms have heterogeneous risks of default and can optimally choose the source of financing. Loans differ from bonds as banks can acquire information on a firm's default risk, while dispersed bond holders cannot. In this context, a shock that reduces the screening efficiency of banks relative to the market induces a shift from loans to bonds. However, bond financing becomes more costly, as the average risk of default for the larger pool of market-financed firms is higher. Regarding the macroeconomic impact, the effects of a bank supply shock are greatly amplified when firms cannot substitute bank finance with bond finance.

The final group of studies related to our paper focuses on the role of corporate bond market indicators in predicting macroeconomic developments and identifying credit supply shocks. Gilchrist and Zakrajšek (2012a) introduced an indicator of Excess Bond Premium (EBP), interpreted as a credit supply shock, without distinction between bank lending and market financing. In a different paper, Gilchrist and Zakrajšek (2012b) explore in more details the transmission of a positive EBP shock to bank lending. Based on euro area data, Gilchrist and Mojon (2014) conduct an exercise similar to Gilchrist et al. (2009), estimating a factor-augmented VAR model where they identify a credit supply factor summarising the information on credit spreads (both for banks and non-financial corporations) that is orthogonal to the factors summarising the other variables.

The rest of the paper is organized as follows. Section 2 reviews some empirical facts observed during the recent recessions. Section 3 constructs a bank credit standards indicator (Loan Supply Indicator or 'LSI') from bank-level survey information and section 4 reviews our identification methodology using external instruments. Section 5 provides evidence on the effect of the LSI indicator as external instrument from a BVAR model. Section 6 documents the excess bond premium using euro area security-level data from corporate bond markets and its effects, residually from our bank credit standard indicator (LSI). Section 7 provides concluding remarks.

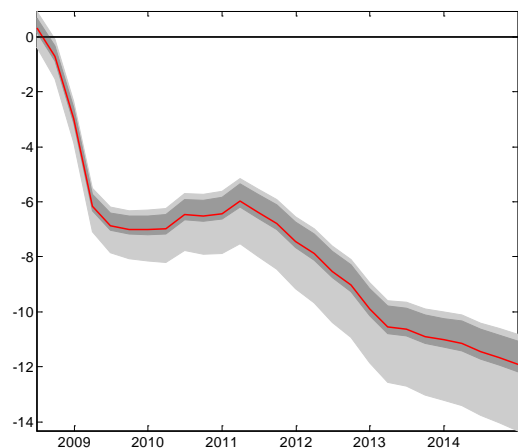
## 2 Stylized facts

In this section we review some empirical facts related to key euro area macroeconomic variables since the onset of the Great Recession. In order to compare the observed historical outcomes with plausible estimates of trend growth that would have realised in absence of the crises we follow Christiano, Eichenbaum and Trabandt (2014). The uncertainty surrounding the trend output estimates is accounted for by computing several (Log-) linear trends of variables starting at different points in time from 1990Q1 and within the time interval (1990Q1-2003Q1) up to 2008Q2. We then

extrapolate each of these trends till 2014Q4. Gaps are then constructed as the percentage difference between the projected trend value of the variable and its observed realisation.

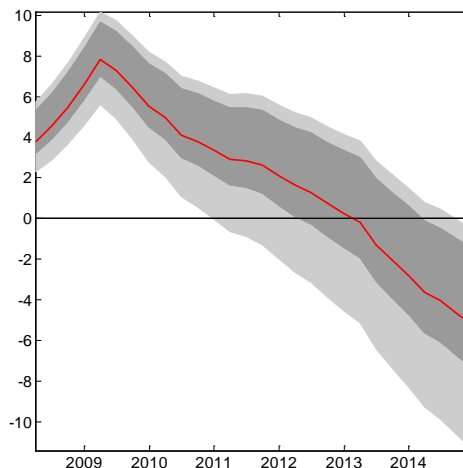
**Figure 1: Detrended macro variables and correlation between Real GDP and NFC loan growth**

**(A)** Real GDP– detrended (gap from trend in percentage)



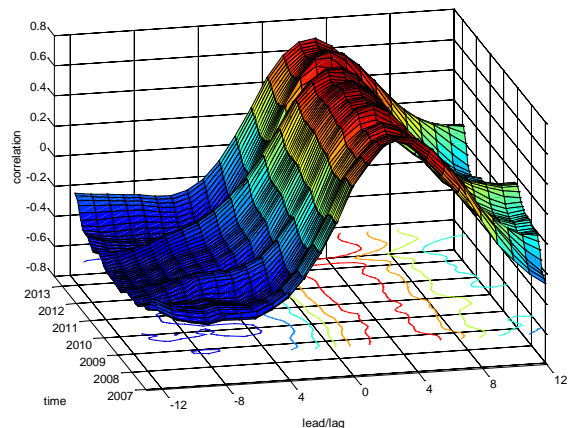
Note: the figure reports the median (solid red line), the 95th-5th (light grey) and the 84th-16th (dark grey) range of the detrended data.

**(B)** Loans to NFCs relative to GDP– detrended (gap from trend in percentage)



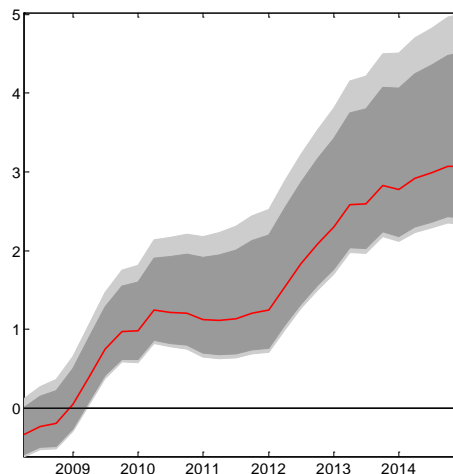
Note: the figure reports the distribution of the detrended Loans to NFCs to nominal GDP ratio. The figure reports the median (solid red line), the 84-16 percentile (dark grey) and the 95-5 percentile (light grey) range of the detrended data.

**(C)** Dynamic cross-correlation between real GDP growth and NFC loan growth (percent)



Note: The figure shows the cross-correlation between GDP growth at time “t” and NFC loan growth at time “t+k”.

**(D)** Debt security issuance – detrended (gap in percentage)



Note: the figure reports the distribution of the detrended Debt security issuance. The figure reports the median (solid red line), the 84-16 percentile (dark grey) and the 95-5 percentile (light grey) range of the detrended data.

Starting with economic activity, real GDP losses associated with the recent recessionary episodes appear to be substantial. Panel A of Figure 1 suggests that in absence of the two recessionary periods the real GDP would have been about 12% higher by the end of 2014. The reduction in economic activity was however smaller than the associated fall in credit to non-financial

corporations, suggesting that a strong deleveraging process occurred. Panel B in Figure 1 shows such deleveraging process in terms of loans to (nominal) GDP ratio, which fell considerably since the start of the financial crisis.

The historical correlation between GDP and credit growth is shown in panel C of Figure 1 in terms of the lead/lag relationship between the real output and loans. The figure reports the cross-correlation between GDP growth at time “ $t$ ” and loan growth at time “ $t+k$ ” obtained by using different leads and lags (the analysis considers 12 lags and 12 leads) over different sample periods. More precisely, the sample starts in 1990Q1 and recursively ends in each quarter from 2007Q1 to 2014Q4. The figure highlights that growth rate in loans to firms positively correlates with real GDP growth albeit with a four quarters delay and that this feature did not break-up after the onset of the Great Recession.

Finally, security issued by non-financial corporations increased substantially (Panel D), especially around the recessionary episodes.

Stylised facts are, of course, of limited value when trying to give a causal interpretation to the dynamics followed by credit aggregates. The statistical association between banks’ provision of credit and real activity that arises in the data, for example, might potentially mask a severe endogeneity problem. Moreover, whether the buoyant bond issuance activity observed through the crisis might be interpreted as a relief factor for firms capable of accessing to market financing is also not clear (Becker and Ivashina, 2014; Adrian et al., 2012). The following sections cope with these issues by identifying the macroeconomic impact of credit supply restrictions.

### 3 A Loan Supply Indicator (LSI)

In this section we construct an indicator of credit tightening which captures loan supply conditions from the euro area banking sector using granular bank-level information available from the Bank Lending Survey (BLS) maintained at the European Central Bank. Similar surveys are produced by other central banks such as the Federal Reserve and the Bank of England and are routinely used to extract soft information on the banking sector behaviour. In the BLS a representative sample of euro area banks<sup>1</sup> are asked, among other things, about the credit standards they apply for the provision of loans to non-financial firms. Answers are typically displayed in the form of a net diffusion index. A visual comparison between the credit standards’ net diffusion index and the corresponding index on credit demand factors<sup>2</sup> shows that the two indices are highly (negatively) correlated (Figure 2, left panel). This feature is common also to the surveys conducted

<sup>1</sup> See Appendix 1 for a more detailed description of the Bank Lending Survey.

<sup>2</sup> Changes in the demand for loans or credit lines to enterprises as expressed by the question: “Over the past three months, how has the demand for loans or credit lines to enterprises changed at your bank, apart from normal seasonal fluctuations?”

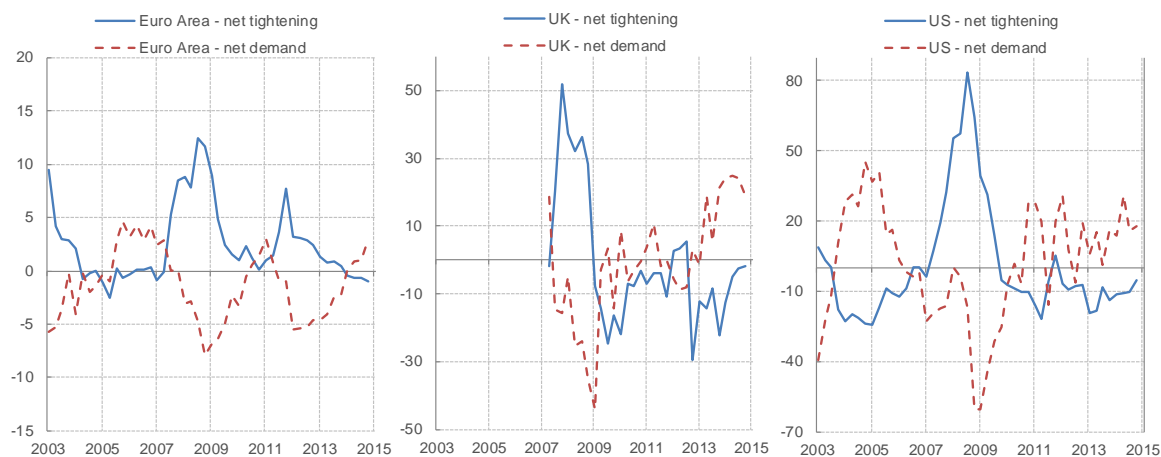


in the UK and US (Figure 2, middle and right panels): the fall (increase) in the net demand for loans to enterprises is associated with the net tightening (easing) of credit standards. This evidence suggests that the macroeconomic effect of credit supply shocks might be difficult to identify as many factors simultaneously influence both the demand and the supply of credit.

To deal with this endogeneity issue, we exploit bank-level individual information in the BLS. The Loan Supply Indicator we propose “cleans” the information retrieved from the BLS on credit standards from the information contained in the prevailing economic conditions and non-credit supply factors.

Soft information from surveys has been used in previous studies (see Ciccarelli et al., 2013, 2014 for the euro area and Bassett et al., 2014, for the US) to disentangle credit supply from demand. Unlike in Ciccarelli et al. (2013) this paper uses granular information (i.e. bank-level responses) contained in the BLS to identify the effects of credit supply disturbances on the euro area economy. Similar to our study, Bassett et al. (2014) use individual data on the Senior Loan Officer Opinion Survey. However, as the BLS is fully anonymised at bank level, we cannot match banks’ balance sheet items to our individual bank lending survey’s responses as proposed in Bassett et al. (2014).

**Figure 2: Net tightening of credit standards and net demand for loans to enterprises according to the surveys in the euro area, UK and US (*percentages of banks, inverted scale for demand*)**



Note: The figure reports the results on credit supply and demand contained in the Bank Lending Survey for the euro area, the Credit Conditions Survey in UK, and the Senior Loan Officer Opinion Survey on Bank Lending Practices for the US. The blue solid line depicts the change in overall bank lending standards; the red dashed line depicts the diffusion index in overall loan demand. Positive value of the diffusion index indicates a net tightening/increase in credit standards/demand, while a negative value indicates a net easing/decrease in credit standards/demand. Sample period goes from 2003Q1 to 2014Q4.

To disentangle the possible causal effect of a tightening in credit standards, we borrow from the literature on treatment effects (see Imbens, 2004) and use a propensity score method. We formulate a model explaining how likely is for each bank to tighten credit based on prevailing economic

conditions. This information is then used to reweight each bank’s response so as to mimic the conditions of a randomised experiment. The measure obtained by reweighting the individual credit standards responses is labelled Loan Supply Indicator measure for each individual bank “ $i$ ”, i.e.  $LSI_i$ . Finally, the  $LSI_i$  for all banks are aggregated across banks and across countries to obtain a measure of Loan Supply Indicator for the euro area. The aggregation method employed is the same as the one used to obtain the credit standards’ net diffusion index for the BLS.

In our methodology, the number of categorical answers in the BLS is reduced to two cases, down from the original five. Although the BLS’ answers range from “strong easing” to “strong tightening”, most of the individual responses concentrate in practice either on “neutral” or on “tightening” responses (see Figures A.1 and A.2 in the Appendix 1). We then group the BLS’s answers according to only two large categories. The first one, called “tight”, is composed by jointly considering the answers of “tightening” and “strong tightening”. The second one, labelled “non-tight”, considers the answers of “neutral”, “easing” and “strong easing”.<sup>3</sup>

We can then consider “tightening” versus “non-tightening” of bank credit as reported in the BLS as a dichotomous treatment. The methodology we choose borrows from the literature on treatment effects (see for a survey Imbens 2004). More specifically, “tightening” of credit is assimilated to the treatment a patient receives and whose causal effect we aim at estimating. The indicator variable  $D = (tight, non - tight)$ , denotes whether there is treatment (tight) or no treatment (non-tight). When considering the credit standard extended by banks (CS), for example, the two “potential outcomes” are  $CS_t(tight), CS_t(non - tight)$ . The average treatment effect (ATE) we would like to estimate is the difference between the two counterfactual paths:

$$ATE = CS_t(tight) - CS_t(non - tight) \quad (1)$$

The lack of treatment randomization leads to selection bias. Indeed, if the selection of treated and non-treated units were made as in a fully randomised experiment, no endogeneity issue would arise and the net diffusion index of credit standards would resemble a measure of Average Treatment Effect. However, as banks are likely to tighten credit in a way which is driven by determinants that also influence the potential outcomes, the assumption valid for a randomised experiment cannot hold. To overcome this problem, as usually done in this literature, the key assumption we make is that the experiment is random conditional on a set of observable factors  $Z_t$ . This is called “selection on observables” condition:

$$D_t \perp (CS_t(tight), CS_t(non - tight)) \mid Z_t \quad (2)$$

<sup>3</sup> When trying to extent to three categories, tightening (“tightening” and “strong tightening”), neutral (“neutral”) and easing (“easing” and “strong easing”), results do not change significantly. However, given the limited amount of easing responses the handling of the associated limited dependent variable model becomes rather complex, so that we present simpler and meaningful results in the paper.

The treatment (or no treatment) is orthogonal to the potential outcomes, once we controlled for factors  $Z_t$ . When the equation (2) holds, one can use the inverse propensity score estimator to recover the causal effect of treatment on observed variables.<sup>4</sup>

We denote as  $LSI_i$  (Loan Supply Indicator of bank  $i$ ) the inverse propensity weighted estimator of each bank response (see Imbens, 2004) and it corresponds to:

$$LSI_i = \frac{i(\mathit{tight} = 1)}{P(\mathit{tight} = 1 | Z)} \quad (3)$$

where  $i(\mathit{tight} = 1)$  is the indicator function of a (single) bank declaring tightening and  $P(\mathit{tight} = 1 | Z)$  is the probability (or propensity score) that the bank declares tightening given a set of conditioning variables  $Z$ .

To estimate the propensity score we use a simple probit as a model for the probability distribution of treatment or no treatment. The main determinants  $Z$  of individual credit standards considered in the estimation are the lag of the BLS credit standards, the bank-level demand factor from the BLS, GDP growth and unemployment of the country of the reporting bank, expectations on economic activity as reported in Consensus Economics, VSTOXX (i.e. the Dow Jones EURO STOXX 50 Volatility measured on euro area), a proxy for the monetary policy stance (as consistent with the risk taking channel, see discussion in Maddaloni and Peydro (2013)) both in terms of actual component (EONIA) and in terms of the expected component (3-month in 1-year OIS forward). Finally, we incorporate a measure of market perception of risk of non-financial corporations above and beyond fundamentals: an Excess Bond Premium for euro area non-financial corporations as discussed for the United States by Gilchrist et al. (2012a) (we describe its construction in the next section).

Table 1 provides the estimates of the marginal effects of our determinants with standard errors clustered at bank level. Model (1) shows that past credit supply developments and bank individual demand factors are a significant determinant of credit standards. Demand conditions contribute to increasing the probability of having a tightening by some 5 p.p., while past (bank-specific) tightening conditions provide a stronger contribution (about 20 p.p.) to the probability of having a further tightening.

The richer specification in column (2) shows that both actual and expected economic conditions also significantly contribute to explain credit tightening. When a country experiences adverse economic conditions unemployment is high (or GDP consensus forecasts are low) and banks also tend to reduce their credit supply. If such macroeconomic factors are omitted, the effects of credit

<sup>4</sup> The inverse propensity score estimator is a more general case of the linear framework used by Bassett et al. (2014) for the US and it was used in the context of monetary policy shocks by Angrist and Kuersteiner (2011).

supply tightening can be polluted by confounding factors. Financial risk factors also influence credit standards: as already suggested by Gilchrist et al. (2012b) financial markets spreads (proxied by the excess bond premium for non-financial corporations) significantly explain credit tightening; the volatility of euro area stock markets (VSTOXX)<sup>5</sup> is rarely significant in our estimates once the excess bond premium is included. Finally, model (3) shows includes monetary policy variables: the Eonia (a proxy for the policy rate in the euro area) and the 3-month in 1-year forward rate of the OIS rate. The latter is a measure of the expected path of monetary policy 1-year ahead. Gertler and Karadi (2015) use a similar measure for the US to capture both standard and non-standard monetary policy. In line with the results obtained by Maddaloni and Peydro (2013), the contribution of monetary policy to credit standards is significant. This evidence corroborates at a more micro-level the ‘risk taking channel of monetary policy’ for the euro area. In a nutshell, when interest rates are low, banks are induced to take on more risk thereby relaxing credit supply standards. A tightening of credit conditions is much easier to explain in an environment of tight monetary policy, rather than when policy rates are extremely low.

Specifications (4), (5) and (6) provide some robustness checks of our probit. In (4) we include country dummies: results are broadly unchanged. In (5) we test for sample robustness and estimate the model up to 2011Q2: estimates are mostly unchanged when the post-2011Q3 sample is dropped. This shows that results are not driven by the euro area sovereign crisis.

Model (6) includes bank-level random effects. As marginal effects are not computed for such case, model (7) reports estimates of the full specification without random effects<sup>6</sup>: model (6) and (7) display very similar estimates, irrespective of including bank-level random effects.

The main results are also robust when a different measure of credit standards is used. In particular they are confirmed when we consider the BLS sub-questions on capital, liquidity positioning and market funding used by Ciccarelli et al. (2013).<sup>7</sup>

<sup>5</sup> We do not enter here in the discussion on whether uncertainty or the excess bond premium are causal for economic conditions (see for example Caldara et al (2015) and Gilchrist, Jae and Zakrajšek (2014), where they show that financial frictions are able to explain uncertainty), but we simply add both measures to our probit regressions. However, using only the excess bond premium does not change results substantially.

<sup>6</sup> The main results are also robust to generalising the LSI to include the easing of credit standards (not included in the paper).

<sup>7</sup> More specifically, the subquestions are the followings: “Over the past three months, how have the following factors affected your bank's credit standards as applied to the approval of loans or credit lines to enterprises (as described in question 1 in the column headed "Overall")? i) Costs related to your bank's capital position; ii) Your bank's ability to access market financing (e.g. money or bond market financing); iii) Your bank's liquidity position.

**Table 1: Factors affecting changes in banks' credit standards**

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Marginal effects	Marginal effects	Marginal effects	Marginal effects	Marginal effects	Base coefficients	Base coefficients
Lag Credit Standard	0.278*** (0.0121)	0.234*** (0.0131)	0.220*** (0.0132)	0.197*** (0.0111)	0.251*** (0.0149)	1.239*** (0.0725)	1.428*** (0.0853)
Demand factor	0.0667*** (0.0127)	0.0419*** (0.0127)	0.0416*** (0.0124)	0.0516*** (0.0114)	0.0479*** (0.0160)	0.346*** (0.0724)	0.270*** (0.0818)
GDP Growth		-0.0132*** (0.00394)	-0.00646 (0.00407)	-0.00642* (0.00384)	-0.00483 (0.00541)	-0.0446* (0.0259)	-0.0419 (0.0264)
Changes in Unemployment		0.0526*** (0.0137)	0.0504*** (0.0145)	0.0409*** (0.0127)	0.0517*** (0.0173)	0.347*** (0.0841)	0.327*** (0.0933)
GDP Forecast (Consensus)		0.00718 (0.00481)	-0.0138*** (0.00481)	-0.00940** (0.00478)	-0.0137** (0.00607)	-0.0913*** (0.0341)	-0.0899*** (0.0309)
Lag EONIA			0.0309*** (0.00347)	0.0322*** (0.00374)	0.0415*** (0.00645)	0.237*** (0.0278)	0.201*** (0.0216)
Lagged change in 3m-in-1y OIS Forward			0.00557 (0.0108)	-0.00491 (0.0107)	0.0258** (0.0131)	-0.0131 (0.0716)	0.0362 (0.0705)
Change in VSTOXX			-0.00175 (0.00121)	-0.00148 (0.00122)	-0.00198 (0.00163)	-0.0129 (0.00789)	-0.0114 (0.00789)
Change in EBP		0.000895*** (0.000149)	0.000639*** (0.000224)	0.000659*** (0.000226)	0.000533 (0.000325)	0.00461*** (0.00166)	0.00415*** (0.00147)
Lag VSTOXX		0.00254*** (0.000448)					
Constant							-1.777*** (0.0763)
Country fixed effect	NO	NO	NO	Yes	NO	NO	NO
Observations	4,354	4,354	4,273	4,273	2,846	4,273	4,273

Note: Sample period: 2003:Q1–2014:Q4; No. of banks 137. Dependent variable in the probit regression is a discrete variable  $\Delta CS_{it}$  = (tight, neutral), representing the change in credit standards reported by bank  $i$  in quarter  $t$ . Lag Credit Standard is the lagged dependent variable (i.e.  $\Delta CS_{it-1}$ ); VSTOXX is the Dow Jones EURO STOXX 50 Volatility measured on euro area; EBP is the excess bond premium; 3m-in-1y OIS Forward is the forward rate retrieved from the 3-month in 1-year OIS rate. GDP Forecast is taken from Consensus Forecasts. Robust asymptotic standard errors are clustered at the bank level and are reported in parentheses. \*\*\* Statistical significance at 1%, \*\* statistical significance at 5%, \* statistical significance at 10%.

As we show in Table 2, using our granular approach, the group of questions at hand shall not be considered as “pure”, as each of the three components responds to past bank-level demand with a marginal effect that is only slightly smaller than with the baseline credit standards. Economic determinants are also significant, albeit less strongly so than in our baseline case. Even the LSI derived from the capital positioning sub-question (which is the one that seems to be the least endogenous) is quite similar to our baseline LSI (results available upon request).

**Table 2: Marginal effects in probit regression with different dependent variables**

VARIABLES	(1) Capital Position	(2) Market Funding	(3) Liquidity Position
Lag Capital Position	0.229*** (0.0190)		
Demand factor	0.0284** (0.0139)	0.0245* (0.0126)	0.0226* (0.0120)
GDP Growth	-0.00289 (0.00346)	-0.0145*** (0.00363)	-0.0102*** (0.00327)
Changes in Unemployment	0.0147 (0.0128)	0.0151 (0.0108)	0.0145 (0.0103)
GDP Forecast (Consensus)	-0.0133** (0.00679)	-0.00784* (0.00455)	-0.00179 (0.00449)
Lag EONIA	0.0104*** (0.00391)	0.00908** (0.00389)	-0.00180 (0.00376)
Lagged change in 3m-in-1y OIS Forward	-0.00586 (0.0117)	-0.00333 (0.0104)	0.00165 (0.0100)
Change in VSTOXX	0.000715 (0.00136)	0.00126 (0.00110)	-0.00123 (0.00100)
Change in EBP	0.000201 (0.000253)	4.78e-05 (0.000236)	0.000643*** (0.000218)
Lag Market Funding		0.217*** (0.0137)	
Lag Liquidity position			0.193*** (0.0153)
Observations	3,042	3,042	3,042

Note: Sample period: 2003:Q1–2014:Q4; No. of banks 137. Coefficients refer to average marginal effects on the dependent variable. Dependent variable in the probit regressions are discrete variable  $\Delta CS_{it}$  = (tight, neutral), referring respectively to the Capital Position, Market Funding and Liquidity Position of the question “factors affecting credit standards” and it represents the change in credit standards reported by bank  $i$  in quarter  $t$ . Lag Capital Position, Lag Market Funding and Lag Liquidity position are the lagged dependent variable (i.e.  $\Delta CS_{it-1}$ ) in each respective regression; VSTOXX is the Dow Jones EURO STOXX 50 Volatility measured on euro area; EBP is the excess bond premium; 3m-in-1y OIS Forward is the forward rate retrieved from the 3-month in 1-year OIS rate. GDP Forecast is taken from Consensus Forecasts. Robust asymptotic standard errors are clustered at the bank level and are reported in parentheses. \*\*\* Statistical significance at 1%, \*\* statistical significance at 5%, \* statistical significance at 10%.

Finally, we need to aggregate bank-individual LSI measures into a euro area measure of loan supply. In order to do that we use weights that reflect how much each country in the euro area weights in terms of loans' composition. This is the same aggregation method as the one used to compute the BLS net diffusion index. The LSI is plotted against the net percentage change of credit standards in Figure 3. The time profile of the two indicators appears to differ over the sample. The financial developments during the last decade through the lens of both indicators could be structured by the following sub-periods.

First, from 2005 to mid-2007, credit standards were almost systematically easing in net terms. The LSI displayed a broadly similar profile with at the margin a relatively more pronounced loosening in the run-up to the crisis.

Second, from summer-2007 to the third quarter of 2008, the financial crisis erupted initially as interbank liquidity tensions and culminated with the Lehman-Brothers default. Through this episode, credit standards were continuously tightened reaching a peak over the sample. By contrast, the LSI indicator jumped to its highest level over the sub-period, right after the summer 2007, moderating somewhat thereafter as the first batch of non-standard monetary policy measures was introduced. From this standpoint, the LSI anticipated bank vulnerabilities and contrary to the net percentage change of credit standards did not reach its maximum in 2008Q3.

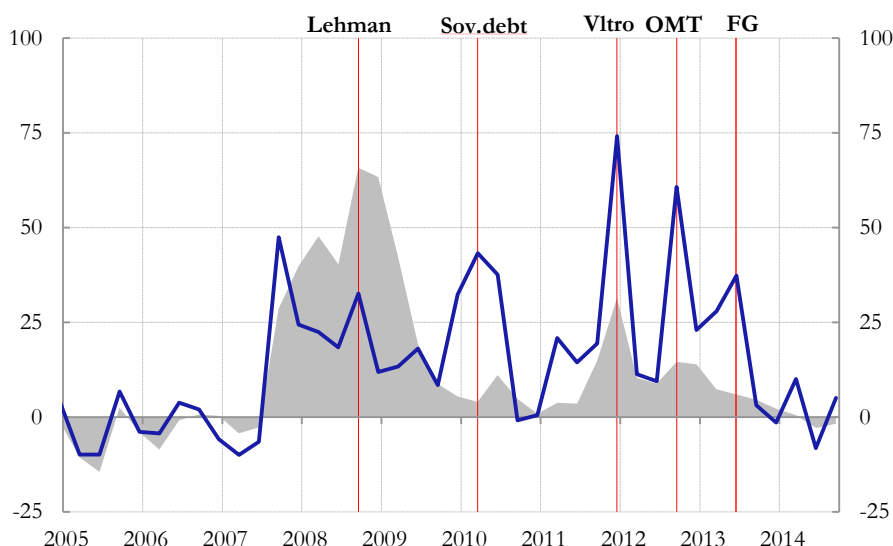
Third, from end-2008 to the beginning of 2010, the net tightening of credit standards moderated continuously, ending at mild levels by historical standards. Conversely, the LSI depicted the resurgence of financial tensions by end-2009, along with the first signs of the European sovereign debt crisis affecting smaller member countries. The LSI actually peaked in the first quarter of 2010 at the time the ECB started its Sovereign Market Programme (SMP).

Fourth, from mid-2010 to end 2011, credit standards pictured negligible impact of financial tensions in the first part of the sub-period but increased afterwards significantly up until 2011Q4, which coincided with the exceptional liquidity measures taken by the ECB: two very long-term refinancing operations (VLTROs). In relative terms, the tightening of credit standards appeared then much smaller than the one recorded around end-2008. By comparison, the LSI displays a qualitatively similar picture but a much more accentuated pattern. In the fourth quarter of 2011, the LSI jumped to its highest reading over the last decade, reverting suddenly in the next quarter. The acute tensions experienced by the euro area financial sector across almost all large member countries and the subsequent relief brought by the VLTROs are well-captured by the indicator.

Fifth, from 2012 to mid-2013, the moderation of the net tightening of credit standards which started after the VLTROs was only temporarily interrupted in the summer-2012 before the decision of the ECB to introduce an Open Market Transaction (OMT) programme. Like in the previous

sub-period, the LSI depicts a much sharper reaction, indicating heightened financial tensions at time of the OMT, which receded somehow but persisted till the second half of 2013.

**Figure 3: Loan Supply Indicator (LSI) (*blue line*) vs. BLS net tightening of credit standards on loans to enterprises (*shaded area*) - net percentage changes**



Note: Individual BLS responses are corrected by taking into account bank-specific loan demand (BLS), macroeconomic conditions (actual and expected) at country level, the riskiness conditions of non-financial corporations in the euro area and monetary policy conditions (Eonia and forward rates). Correction is obtained using an Inverse Propensity Score Method; probit model estimated on pooled BLS data. Latest observation: October 2014 BLS.

Finally, from mid-2013 onwards, the credit standards tightened by less and less, ultimately turning to net easing. Comparatively, the LSI declined much more strongly in the second half of 2013, alongside with the normalisation witnessed in various financial market segments and further easing of the monetary policy stance, notably through forward guidance.

Overall, the LSI index tends to be higher in historical episodes of bank-related stress that were less likely to be driven by pre-existing economic conditions. The time profile of the LSI seems to provide an accurate dating of the main events of the financial crisis and sheds new light on the relative tightness of loan supply across the various sub-periods. In summary, when correcting the credit standards for bank-specific and country-wide demand factors, the LSI signals that the waves of financial distress that occurred from 2011 to 2013 were more related to loan supply conditions than the ones experienced from 2007 to 2009. In comparison, a face value interpretation of the net percentage change of credit standard would reach an opposite conclusion.

In the following section we use the LSI as external instrument in a BVAR mode to identify the macroeconomic impact of a bank-related credit supply tightening.



## 4. Assessing the macroeconomic impact

### 4.1 The dataset and the estimation method

We use a BVAR model to analyse the dynamics of a set of macroeconomic variables, which summarise real, credit and financial markets. In particular, the model includes firms' costs of financing measures derived from both bonds and bank loans (BBB-AA spreads and lending margins respectively); volumes of bank lending to new business (adjusted for sales and securitisation) and corporate securities (as notional stocks), as well as the policy interest rate, the GDP and the GDP deflator<sup>8</sup>. The model is estimated in log-levels for real GDP, GDP deflator, loans to NFCs, and debt issuance by NFCs. Short-term interest rate, composite lending rate to NFCs and the spread between the NFCs' BBB bonds and the AAA government bond are instead taken in level. The autoregressive order used in the estimation is five.

For the estimation of the VAR, we address the curse of dimensionality problem by using Bayesian shrinkage as suggested in De Mol, Giannone and Reichlin (2008). More in details, we use Normal-Inverse Wishart prior distributions: we impose the so-called Minnesota prior, according to which each variable follows a random walk process, possibly with drift (due to Litterman, 1979). Moreover, we impose two sets of prior distributions on the sum of the coefficients of the VAR model: the “sum-of-coefficients” prior, originally proposed by Doan, Litterman, and Sims (1984) and an additional prior that was introduced by Sims (1993), known as “dummy-initial-observation” prior.

The hyper-parameters controlling for the informativeness of the prior distributions are treated, as suggested in Giannone, Lenza and Primiceri (2015), as random variables and are drawn from their posterior distribution, so that we also account for the uncertainty surrounding the prior setup in our evaluation. The sample period goes from 1996Q1 to 2014Q4. Results are similar when restricting the sample to the euro area period only, i.e. after the 1999Q1.

### 4.2 The identification strategy

Identification of credit supply shock is achieved by using the LSI as external instrument in the VAR. Simple identification schemes based, for example, on Choleski decomposition have been widely criticised in the literature on financial frictions and on monetary policy for being typically misspecified with respect to generic data generating processes.<sup>9</sup>

<sup>8</sup> Results are robust to considering HICP instead of GDP deflator. The EONIA is taken as policy interest rate, results are similar using the 3 months euribor measure.

<sup>9</sup> A recent discussion on the US case on how identification with external instruments can deliver more reliable results compared to other identification schemes can be found in Mumtaz et al. (2014).

The external instrument methodology we use follows recent contributions by Stock and Watson (2012), and Mertens and Ravn (2013). In this approach, a credit supply constraint is identified using the additional information of the instrument with respect to variables already contained in the VAR, without imposing pre-defined sign-restrictions on the rotation matrix of the variance-covariance matrix, nor directly including a possibly mis-measured variable such as the BLS in the VAR. These aspects of the methodology are important for our analysis. First, the method allows the sample over which the LSI is calculated (i.e. the BLS sample) to be much shorter than the sample used for the estimation of the BVAR. In this way, we can still estimate the BVAR using longer macroeconomic data series, while focusing on the panel information for the BLS. A second advantage, compared to other methods that also use BLS information, is that external instruments are more robust to possible measurement error, which is a likely issue when using information from surveys.

We can now enter more into the details of the external instrument methodology. The BVAR model produces reduced form residuals  $\eta_t$  of dimension  $N$ . They are linear combination of structural shocks  $\epsilon_t$ , including the credit supply, using a rotation matrix:

$$\epsilon_t = H \eta_t \quad (4)$$

where  $H$  is the  $N \times N$  identification matrix. Without loss of generality we consider the credit supply as the first shock. Calling then  $\epsilon_{1t}$  the credit supply shock, its identification is achieved once the first row of  $H$ , say  $H_1$  of  $H = [H_1 \dots H_N]$ , is determined.

Consider now for simplicity having a single valid instrument  $Z$  for the credit supply shock. In order to be valid,  $Z$  should satisfy three conditions:

$$E[\epsilon_j \times Z] = 0 \text{ if } j > 1, \quad (5)$$

$$E[\epsilon_j \times Z] = \alpha \text{ if } j = 1, \quad (6)$$

$$\Sigma_{\epsilon\epsilon} = D, D = \begin{bmatrix} \sigma_{\epsilon_1}^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_{\epsilon_N}^2 \end{bmatrix}, \quad (7)$$

Condition (5) states that the chosen instrument should be orthogonal with respect to the structural shocks different from the one we want to identify; condition (6) specifies the chosen instrument should be correlated to the shock we want to identify and that their covariance is  $\alpha \neq 0$ . Finally, condition (7) states that structural shocks should not be cross-correlated.

Under assumptions (5-7) it can be shown that the structural shock can be estimated by regressing the reduced form innovations  $\eta_t$  onto the instrument  $Z$ . After some substitutions we obtain:

$$\begin{aligned}
E[\eta_t Z_t] \Sigma_{\eta}^{-1} \eta_t &= E[\eta_t Z_t] (H' D H)^{-1} \eta_t = \\
&= \alpha H_1 (H' D H)^{-1} \eta_t = \\
&= \left( \frac{\alpha H_1}{\sigma_{\varepsilon_1}} \right) \eta_t = \frac{\alpha}{\sigma_{\varepsilon_1}} \varepsilon_{1t},
\end{aligned} \tag{8}$$

where the last result follows condition the orthogonally condition of the instrument with respect to the structural shocks that are different from the credit supply one. Importantly, the identification of  $\varepsilon_{1t}$  is obtained up to a normalisation constant  $\frac{\alpha}{\sigma_{\varepsilon_1}}$ . Once one structural shock  $\varepsilon_{1t}$  has been identified from expression (8),  $H_1$  can be singled out by regressing the identified structural shock  $\varepsilon_{1t}$  on the reduced form innovations  $\eta_t$ . In this way we compute impulse responses and historical decomposition for the identified structural shock. The case of multiple instruments used to identify a single shock can also be handled by substituting the OLS regression in equation (8) by a reduced rank regression.

## 5 Macroeconomic effects of banks' credit restrictions

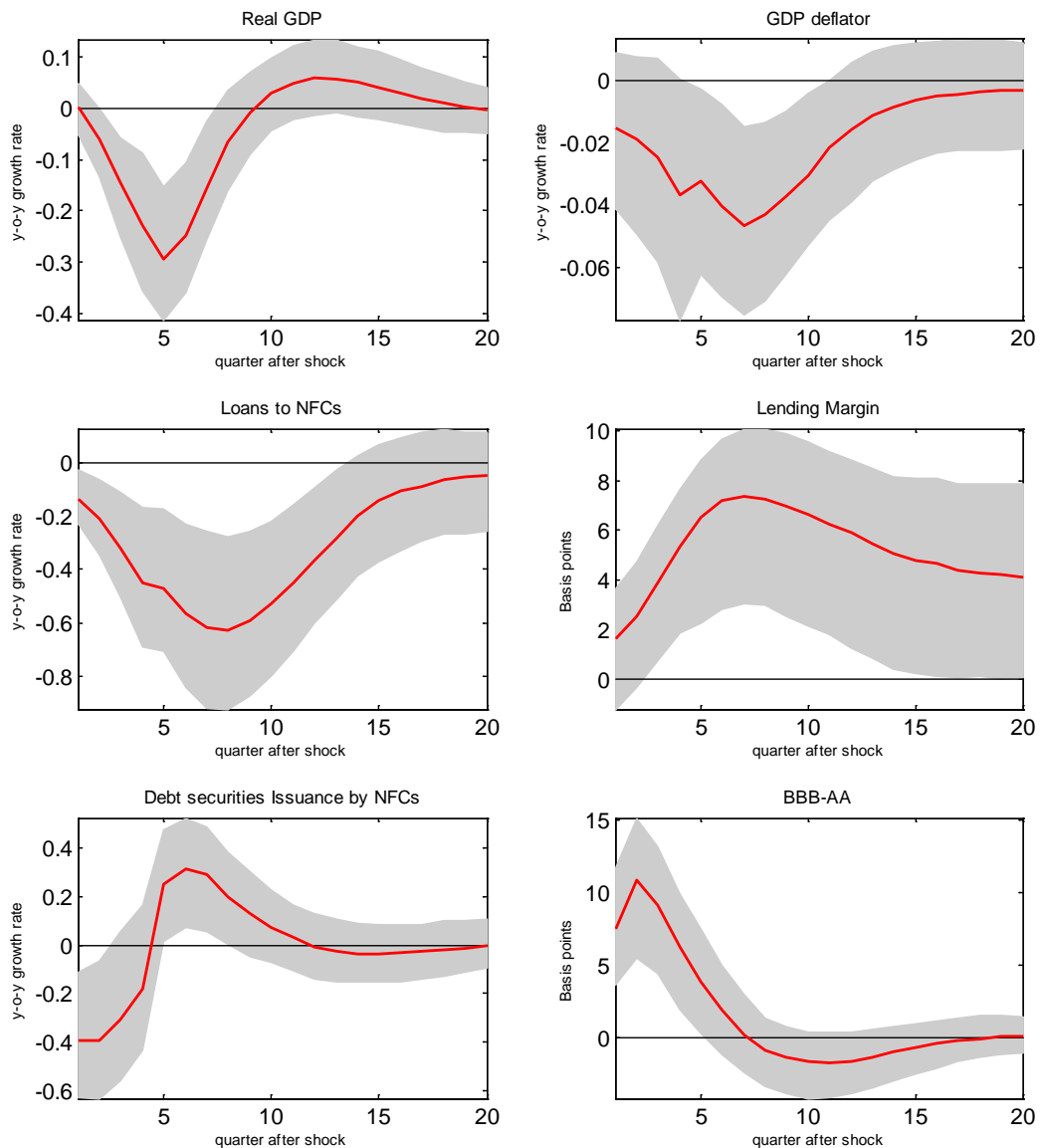
### 5.1 Impulse response functions

The impulse response functions of a loan supply shock corresponding to tighter LSI are presented in Figure 4. Real GDP growth declines for about 2 years with a peak loss of 0.3 in y-o-y terms. The associated loss for the GDP level is of about 0.6 percentage points at the trough. The impact on GDP deflator inflation rate is also negative, but comparably small. Regarding all other variables related to bank intermediation, the loan supply shock leads to gradually higher bank lending rate spreads and lower outstanding amounts of loans. The impact of the shock on loans is more gradual and persistent than on output. This feature suggests that loan supply disturbances contribute to explain the lead-lag relationship between loan and activity observed in our sample. Loan supply factors take some time to affect loan dynamics while the impact on economic activity materializes more rapidly. Differently from a Choleski identification scheme, where the recursive ordering of variables is predefined, in the external instruments methodology possible zero restrictions on the impact of variables are endogenously determined. For example, in the same quarter of the LSI shock, GDP growth remains substantially unaffected (as for the zero restrictions), but all other variables respond within the same quarter of the shock.

In terms of relative magnitudes, the peak effect on loans is much stronger than on the GDP: the maximum impact on real GDP is around 0.5 percentage points compared with 2 percentage points on loans. Finally, the lending rate spreads react relatively little compared with the contraction in GDP and loans. Such a mild response indicates that the identification of the credit supply shocks

through the BLS answers on credit standards is likely to gear the transmission towards quantitative bank lending channels related to non-price terms and conditions. Here, the benefits of relying on BLS information to identify credit supply shocks seem to material.

**Figure 4: Response to an adverse loan supply shock**



Note: the figure reports the impact of a tightening to loan supply indicator on selected macroeconomic variables. Red solid line represents the posterior median. The shaded are represent the 95-percent confidence intervals based on 2000 MCMC draws from the posterior distribution.

The lagged impact of credit standards on bank loans confirms previous findings on euro area data (Cicarelli et al. 2014). For the US, Lown and Morgan (2006) identify a credit standard shock to the Federal Reserve’s Loan Officer Opinion Survey by applying a recursive identification scheme. The

typical credit standards shock would also imply a delayed and more pronounced response for loan volume compared with GDP. In Bassett et al. (2014) the loan supply shock also leads to output decline in the US which precedes a much stronger and protracted loan contraction.

Turning to the transmission of loan supply shocks to market-based financing variables, the contraction in loan volumes and the higher bank lending spreads impact firms' incentives to substitute bank loans for market finance. On impact, firms reduce their recourse to both loans and securities' financing. However, after about one year, loans and economic activity continue being depressed, but non-financial corporations start to substitute loans' financing with bonds' financing, producing a significant increase in debt securities issuance. The overall effect on the level of securities issuance tends to die out in about three years.

Consistently with the underlying transmission mechanism, the BBB-AA corporate bond spread also increases, by about 10 basis points and, looking at the relative dynamics of bond spreads compared to lending margins, the surge in bond spreads is relatively short-lived, whereas the lending rate spread increase is more persistent.

The transmission of the loan supply shock to bank and market-based financing appears in line with theoretical explanations of the corporate financing decisions (see Adrian et al., 2012; De Fiore and Uhlig, 2011; and Becker and Ivashina, 2014). At time of bank fragilities, one may expect some substitution of bank loans with debt securities: access to debt markets provides a financial buffer to firms against the tightening of bank lending conditions but investors will require some risk compensation to step-in and fill the external financing gap.

With respect to previous studies, we add a more detailed description on how substitution between loans and bonds operates over time: bond issuance of non-financial corporations does not increase contemporaneously with respect to banking distress, but only after some delay.

## 5.2 Historical decomposition

Having identified and described the propagation mechanism of shocks to loan supply, we now turn to the historical decomposition of macroeconomic and financial variables in order to assess the role of loan supply structural shocks in the euro area macroeconomic developments during the financial crises. Figure 5 displays the contribution of shocks to output, inflation and credit variables since 2005.

Through the pre-crisis period, loan supply shocks contributed to annual GDP growth positively from 2005 to 2007, peaking at around 1 percentage points in the course of 2006 and receding thereafter. The associated effects on price dynamics reached 0.3 percentage points. Turning to

credit variables, up to 3 p.p. of annual loan growth was explained by supportive loan supply factors by end-2007 while lending rate spreads were compressed by almost 30 basis points.

From 2008 to 2010, the positive contribution of loan supply factors to GDP growth was rapidly reabsorbed and turned negative. In mid-2009, the contribution reached -1 p.p. getting back to a neutral contribution by the end of 2010. While significant, the loan supply effects do not explain the overall contraction in GDP over this period.

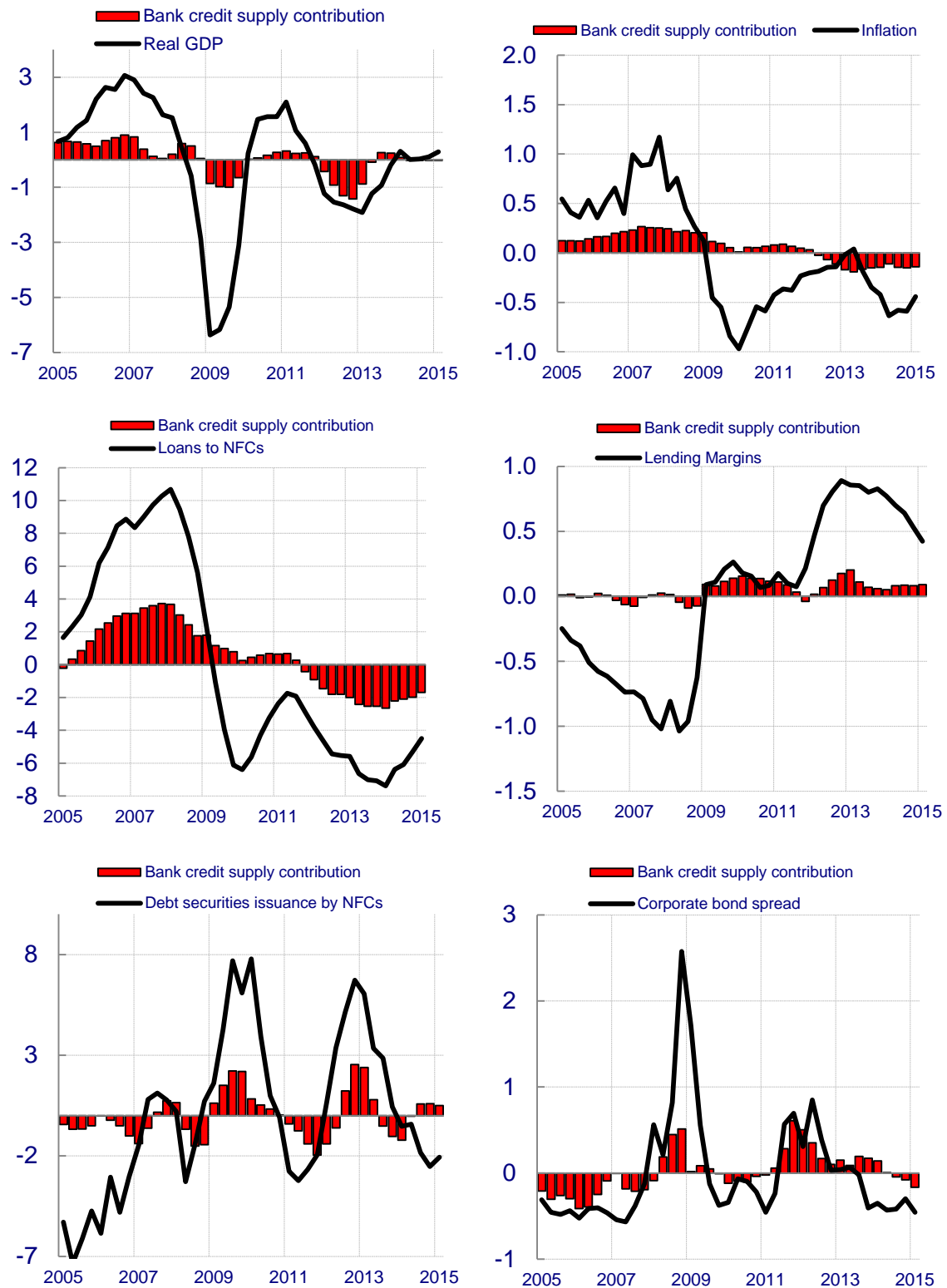
Overall, the positive contribution to annual loan growth receded from 3% in the beginning of 2008 to almost zero in 2010 while the negative contribution to lending rate spreads halved, reaching -15 basis points. Regarding market-based finance, the loan supply shocks explains 30 basis points of the sharp increase in corporate bond spreads during the turn of the year 2009, and more than 2 percentage points of the surge in bond issuance recorded in 2009-2010.

Thereafter, the resurrection of financial tensions, since mid-2011, led to some turn around in the contribution of the loan supply shocks weighting on annual GDP growth by -1.5 p.p. in 2012.

The drag on loan dynamics reached 3 p.p. and the contribution to lending rate spreads increased up to 30 basis points. The loan supply shocks also explains a significant part of the corporate bond spread increases recorded in 2011 and 2012 with its contribution reaching 60 basis points at the peak. Similarly, the rebound of debt securities issuance was supported by the contribution of the loan supply shocks recovering from -3 percentage points in mid-2011 to 2.5 percentage points in mid-2013. By comparison with the initial phases of the crisis, the contributions of loan supply disturbances are much stronger for the last part of the sample, in line with the picture portrayed by the narrative description of the LSI.

Overall, the ability of loan supply shocks to explain the BBB-AA spreads appears to be limited over the 2008-2009 recessionary period. This might suggest that the rise in credit spreads for euro area non-financial corporations might have been driven by other sources additional to tightening of loan supply. With this result in mind, we analyse whether the Great Recession can be explained by other factors not related to our measure of bank credit tightness. This is done in two steps. First, we construct a measure of Excess Bond Premium (EBP) for non-financial corporations in the euro area, similar to what already done for the US by Gilchrist et al (2012a). Second, we assess the macroeconomic impact associated with the EBP dynamics not explained by loans supply tightening.

Figure 5: Historical decomposition of selected macroeconomic variables



Note: The panels of the figure depict the contribution of the credit supply shock (red bars) and excess bond premium shock (light blue bars) to the historical developments of selected macroeconomic variables.

## 6. Excess Bond Premium indicator for the euro area non-financial corporate sector

This section presents a measure of excess bond premium (EBP) for euro area NFCs bonds. The EBP measures the premium requested by investors additional to what available information on bonds and their issuers would be able to explain in normal times (see Gilchrist and Zakrajšek, 2012a).

In terms of dataset, we select euro-denominated investment-grade bonds with the minimum size of issuance of 250 million euros. Bonds which embedded options such as asset-backed, callable, puttable, floating rate, perpetual or sinking fund are excluded. Moreover, bonds with less than one year to maturity are excluded as they become illiquid and not representative. Finally, we concentrate only on bonds of countries-of-risk which have at least 5 bonds on average among all monthly time intervals.

Our EBP broadly follows Gilchrist and Mojon (2014) for the underlying dataset and Gilchrist and Zakrajšek (2012a) for the methodology.<sup>10</sup> Individual corporate bond spreads are computed as the difference between the effective yield on the security and the Overnight Indexed Swap (OIS) rate with the same maturity as the residual maturity of the respective bond. Gilchrist and Mojon (2014) instead, use the German Bund zero coupon interest rates. The euro area sovereign debt crisis led to a strong fragmentation of the sovereign markets across the region with significant “safe haven” flows especially towards German sovereign bonds. In this respect, the OIS curve may provide better benchmark risk free interest rates for the euro area and avoid contaminating the corporate bond spreads with specific factors related to liquidity premia in the German sovereign market.

Turning to the econometric specification, we employ pooled linear<sup>11</sup> regressions explaining credit spreads  $S_{it}$  by individual bond characteristics, ratings and a set of time, country and sector dummies:

$$S_{it} = \alpha + \beta Z_{it} + \gamma rating_{it} + \sum_j \delta_j country[j] + \sum_k \zeta_k sector[k] + \epsilon_{it}, \quad (9)$$

Where  $i$  refers to the individual bond, and  $t$  to the time period. The vector  $Z_{it}$  represents two bond-specific characteristics: time-to-maturity and coupon. To capture possible country effects we add country dummies  $j$ , adopting the nationality of the parent company issuer to define the country of issuance.<sup>12</sup> We apply similar rules for the sector of the issuer  $k$ , with  $k$  being either a financial or

<sup>10</sup> The dataset used in this part of the analysis is similar to the one used in Krylova (2015) and Gilchrist and Mojon (2014). See Appendix 2 for a more detailed description of the dataset.

<sup>11</sup> No relevant difference is found when using a log-normal distribution for the error term in (9).

<sup>12</sup> Euro area is considered as an aggregation of seven countries: Austria, Belgium, Germany, Spain, France, Italy and The Netherlands.



non-financial parent company.<sup>13</sup> Coefficients  $\delta_j$  and  $\zeta_k$  are estimated for generic country  $j$  and sector  $k$  corresponding to country and sector dummies. The variable *rating* represents a proxy for credit risk and financial health of the issuer: ten rating categories are considered, including subdivisions to distinguish between plus and minus-rated bonds<sup>14</sup> and monitor changes in rating over time. We do not rely on single ratings, but on the composite measure of Moody's and Standard & Poors ratings. Several studies indicate that ratings are not perfectly correlated with actual defaults and may not have the same predictive performance as market-based measures of credit risk. But overall, evidence is quite mixed as ratings embody the judgemental assessments of long-term credit quality of an issue and capture different aspects of credit quality as market-based measures of default risk. Our choice for ratings was ultimately guided by data availability. The rating variable is based on a logistic transformation of the rating scale.

The regression is performed for the whole sample of bonds, including both financial and non-financial sectors. The sample period goes from July 1999 to December 2014. Table 3 shows the results.

Regarding the bond characteristics  $Z_{it}$ , *time-to-maturity* is statistically significant at 1%. The level of a *coupon* paid by a bond also significantly affects corporate bond spreads. Ratings also have a sizeable and significant effect.

To construct the *Excess Bond Premium (EBP)* for the non-financial sector, we first compute for each bond  $i$  the residual  $S_{it} - \hat{\beta}Z_{it} - \hat{\gamma}rating_{it}$ . We then aggregate residuals using as weights the value of the outstanding amount of bond  $i$  over total bonds outstanding at time  $t$  ( $w_{it}^{NFC}$ ).

$$EBP_t = \sum_{i \in NFC} w_{it}^{NFC} (S_{it} - \hat{\beta}Z_{it} - \hat{\gamma}rating_{it}) \quad (10)$$

Figure 6 plots the Excess Bond Premium for the non-financial sector: we also provide the 10<sup>th</sup> to 90<sup>th</sup> percentile of the term in (10) to gauge an idea of the dispersion in bonds' markets evaluations.

The EBP tracks the main events of financial stress for non-financial corporations in the euro area: starting from 1999. First, financial conditions for NFCs deteriorated in the early 2000s; this was in the context of a slowdown of economic activity in the euro area. The environment of very low risk perception between 2004 and 2007 is also captured by the EBP indicator. Finally, the EBP peaks the month after the Lehman event and during the Sovereign Crisis in the euro area, both in the summer of 2011 and then in 2012.

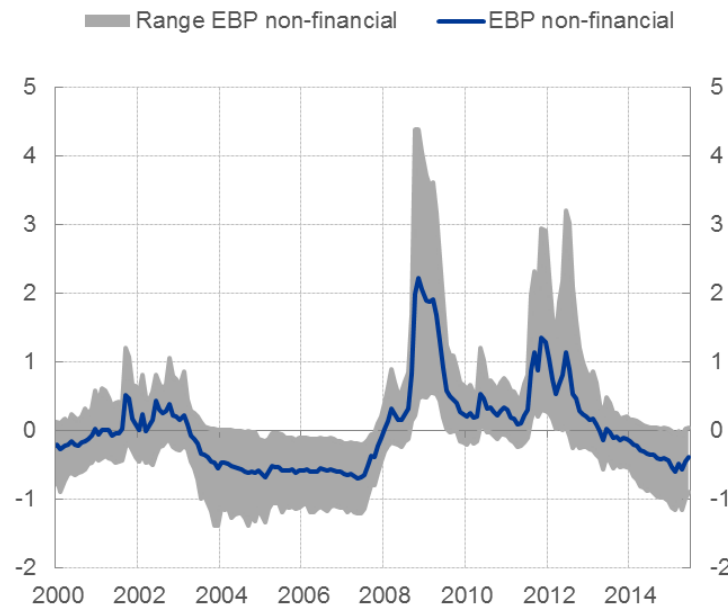
<sup>13</sup> We pool together financial and non-financial corporations mainly to increase the number of bonds available to estimation: results for do not differ substantially when only non-financial corporations are included in our sample although we obtain less precise estimates.

<sup>14</sup> We discriminate between 10 subcategories: AAA, AA1 (AA+), AA2 (AA), AA3 (AA-), A1 (A+), A2 (A), A3 (A-), BBB1 (BBB+), BBB2 (BBB) and BBB3 (BBB-) rated bonds.

**Table 3: Pooled corporate bond regression**

Variable	Parameter estimates
Time-to-maturity	2.4***
Coupon	-1.7***
Rating	32.3***
Fin sector dummy	40.0***
Country Dummies	
Austria	72.7***
Belgium	86.8***
Germany	65.1***
Spain	108.9***
France	80.0***
Italy	132.1***
Netherlands	70.0***
Effective observations	154444

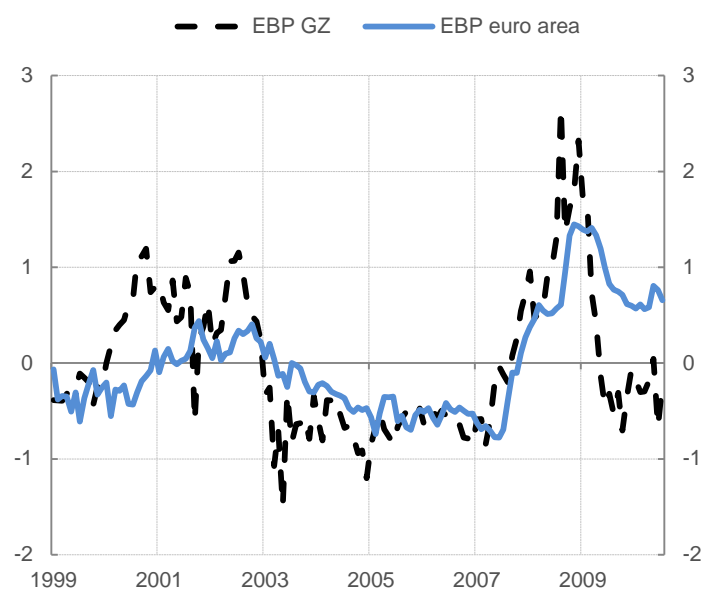
Note: Sample period: 1999:m1– 2014:m12; Total No. of bonds: 3785. \*\*\* Statistical significance at 1%, \*\* statistical significance at 5%, \* statistical significance at 10%.

**Figure 6: Excess bond premium for NFCs in the euro area (*basis points*)**

Source: Bank of America Merrill Lynch and Bloomberg, authors' calculations. Last observation: 2014M12. Note: black dashed line is the EBP, the shaded area represents the 90th-10th quantile interval of the EBP's underlying components.

We constructed the EBP by using a linear regression approach which we found to be more interpretable as it can be immediately translated into basis points (i.e. a spread concept). However, following the original contribution by Gilchrist and Zakrajšek (2012a), the EBP was computed using a specification in logs for the spreads. This change in specification has very little impact on the rest of the results in the paper, using a log-specification allows us to compare the European EBP with the original US EBP. Figure 7 presents such comparison: the two indices appear to be substantially similar, which is not fully surprising given the extent of integration in financial markets.

**Figure 7: Log-Excess bond premium for NFCs in the euro area versus US**



Source: Bank of America Merrill Lynch and Bloomberg, authors' calculations. Last observation: 2010M9. Note: black dashed line is the EBP for the US as in Gilchrist et al (2012) (EBP GZ), the blue solid line is the EBP we compute for the euro area.

## 6.1 Impulse response functions

In this section we add the excess bond premium as an additional external instrument in our BVAR model to gauge financial markets disruptions. When adding the EBP to the model, we ideally would like it capture financial frictions that have not been measured by bank loan supply indicator. This seems to be the case as the EBP has a correlation of only 0.3 with the LSI and its effects have been removed from the LSI measure by controlling for it in the probit analysis. This observation is also consistent with our finding that over the great recession (2008-2009), the ability of banking distress to capture surges in financial spreads was limited.

When dealing with the EBP, we impose a temporal structure on how it can interact with the LSI<sup>15</sup>: the EBP is allowed to be influenced contemporaneously by the LSI. This is consistent with the fact that we cleaned the LSI from the effects of the EBP when constructing it. It is also consistent with the theory by Adrian et al (2012), according to whom a tightening in the bank credit would induce households to step in the market to provide funds and thereby, given the larger risk aversion compared to banks this would induce a rise in the bond yields. In practice this is implemented by using the residual of the following equation as instrument:

$$EBP_t = \alpha + \beta EBP_{t-1} + \gamma LSI_t + \delta LSI_{t-1} + \eta_t^1 \quad (11)$$

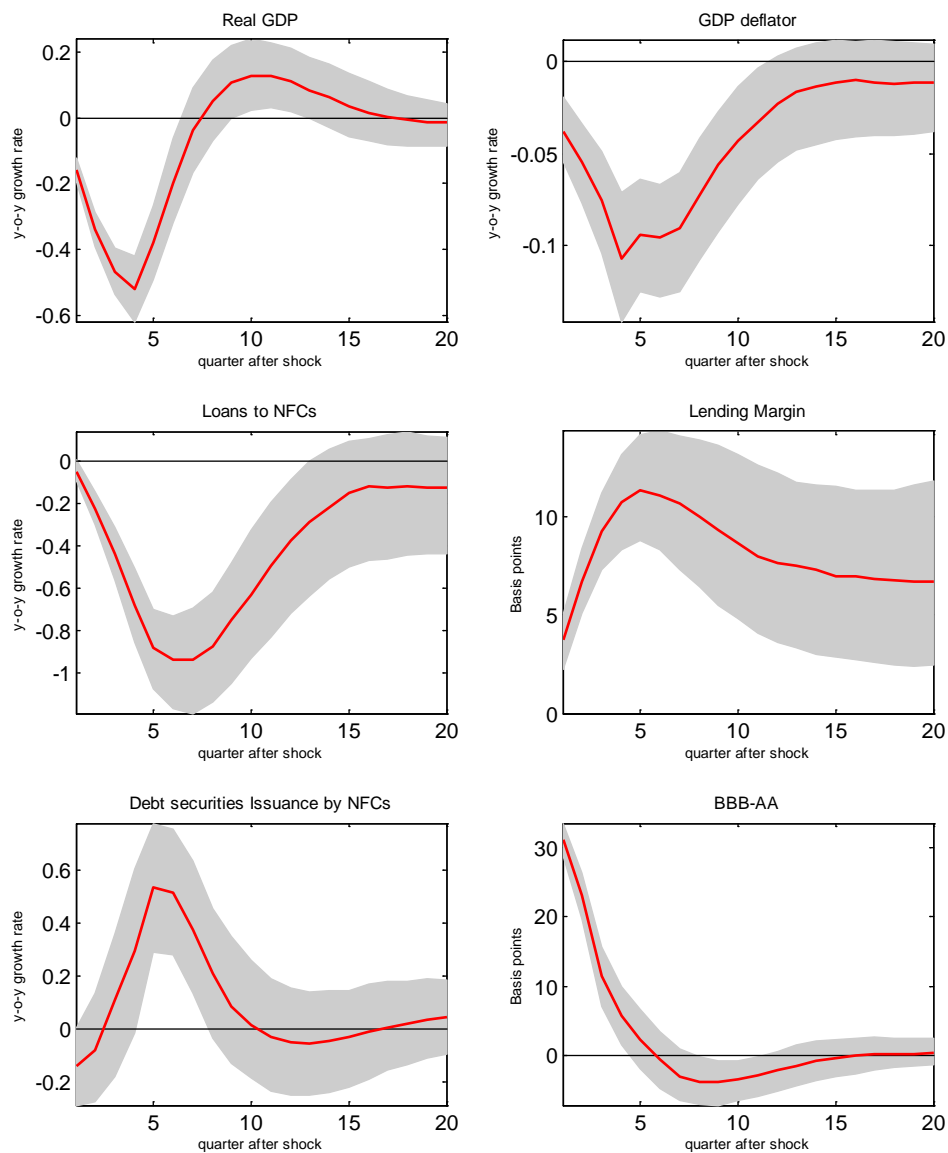
Then the residual  $\eta^1$  is used as instrument. The impulse response functions corresponding to an increase in the Excess Bond Premium (EBP) are plotted in Figure 8. The results point to a short-lived negative impact on annual real GDP growth, declining by -0.2 p.p. in the first quarter. After two years (compared to the three years of the LSI shock), the GDP significantly rebounds and starts expanding. Compared with the loan supply shock and for a given effect on output, the EBP shock has a stronger propagation on inflation as the annual inflation remains at around 0.1 p.p. below baseline for the first three quarters following the shock. Differently from the LSI shock, in the case of the EBP the impact of loans is roughly zero while the GDP drops already in the quarter following the shock. GDP and loans' growth tend also to be more coincident, compared to the LSI shock.

Comparing loans' with securities dynamics, annual loan growth is around 0.7 p.p. below baseline during the first year after the shock while the annual growth of market debt issued increases by about 0.4 p.p. after the first year. The EBP shock drives a significant substitution from bank lending to debt securities issuance: after about one year non-financial corporations start issuing significantly more securities. Differently from the LSI shock, the EBP has a permanent effect on the level of securities issued by non-financial corporations.

Besides, the EBP shock leads a sharp rise in corporate bond spreads while bank lending rate spreads increase persistently but to a lesser extent. The transmission of the EBP shock to the credit variables displays a stronger increase in the relative cost of market debt, compared with the propagation of the loan supply shock.

<sup>15</sup> This is also consistent with the treatment of two instruments in Mertens and Ravn (2013).

**Figure 8: Response to an Excess Bond Premium shock**

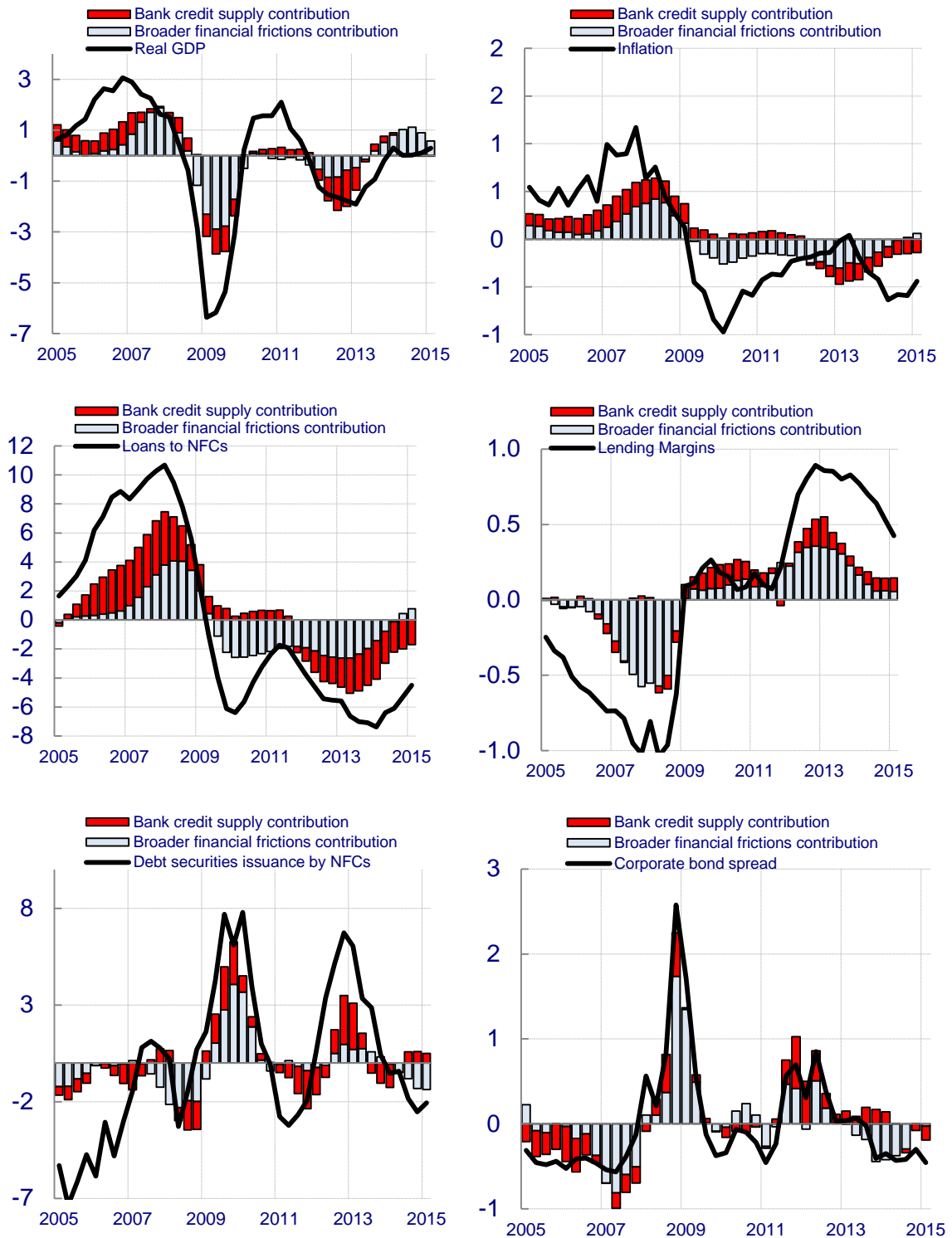


Note: the figure reports the impact of a rise to Expected Bond Premium of euro area non-financial corporations measure on selected macroeconomic variables. Red solid line represents the posterior median. The shaded are represent the 95-percent confidence intervals based on 2000 MCMC draws from the posterior distribution.

## 6.2 Historical decomposition

This section quantifies the contribution to macroeconomic developments of credit supply shocks, measured by loan supply shocks (LSI) and broader financial conditions (EBP). Figure 9 puts together the effects of loan supply (red bars) as estimated in the previous section with the historical decomposition obtained using the Excess bond premium (blue bars).

Figure 9: Historical decomposition of selected macroeconomic variables



Note: The panels of the figure depict the contribution of the credit supply shock (red bars) and excess bond premium shock (light blue bars) to the historical developments of selected macroeconomic variables.

Financial frictions measured by the EBP have a strong role in the initial phases of the crisis. From mid-2007 to mid-2009, the contribution to annual GDP growth went from 2 p.p. to -2.5 p.p. and drove corporate bond spreads almost 200 bps higher. For the other variables, a similar pattern is observed with two to three quarters lag: the EBP shock explains 0.5 p.p. of the moderation in annual inflation from the beginning of 2008 to end-2009, more than 5 p.p. of the decline in the annual growth rate of loans, around 5 p.p. of the increase in the annual growth rate of debt issuance and 70 bps in the rise of lending rate spreads.

Overall, our results suggest two shocks (bank credit supply and EBP) are important to explain credit market developments in the euro area. This result is consistent with the counterfactual analysis of De Fiore and Uhlig (2014) showing that, in a DSGE with micro-founded corporate financing choices between bank loans and market debt, two sets of shocks are needed to match the changes in credit variables. The first shock is related to bank efficiency, which might resemble our loan supply shock. The second shock is instead related to uncertainty or risk, which would correspond more to our Excess Bond Premium shock.

## 7 Conclusions

This paper have analysed the macroeconomic impact of credit supply shocks in the euro area. The relevance of this issue relates to the prominent role played by the banks in financing euro area businesses. Loan supply shocks are identified by using a new indicator of bank credit supply conditions, labelled Loan Supply Indicator (LSI), derived from bank-specific responses on credit standards in the Bank Lending Survey maintained at the ECB. Augmenting a Bayesian VAR model with this indicator as external instrument to identify credit supply shocks suggest that adverse shocks to bank loans lead to a contraction in real activity and credit volumes and to a widening in bank lending spreads. The model also highlights that following a credit tightening firms' tend to substitute bank loans by issuing debt securities. Moreover, tighter bank loan supply to non-financial corporations explains a large fraction of the recession following the euro area sovereign crisis. During this period, banks' supply tightening is also able to explain both the increases in credit spreads and the substitution between loans and bonds issued by firms.

Finally, the analysis is complemented by constructing an indicator of financial market condition. Corporate bond level data are used to construct an indicator of the risk attitude of financial market participants, i.e. the excess bond premia. We show that a shock in the EBP leads to a significant contraction in real activity with credit volumes declining and lending spreads widening. Assessing the ability of this shock to explain macroeconomic developments above and beyond the bank-related supply shock, we show that it explains a large fraction of macroeconomic developments during the Great Recession.

## References

- Adrian Tobias, Paolo Colla, and Hyun Song Shin, (2012) Which Financial Frictions? Parsing the Evidence from the Financial Crisis of 2007 to 2009, NBER Chapters, in: *NBER Macroeconomics Annual 2012*, Volume 27, pages 159-214 National Bureau of Economic Research, Inc.
- Angrist, Joshua D., and Guido D Kuersteiner (2011) Causal Effects of Monetary Shocks: Semiparametric Conditional Independence Tests with a Multinomial Propensity Score, *Review of Economics and Statistics* 93(3): 725-47
- Bassett, William F., Chosak, Mary Beth, Driscoll, John C. and Zakrajšek, Egon (2014) Changes in bank lending standards and the macroeconomy, *Journal of Monetary Economics*, Elsevier, vol. 62(C), pages 23-40
- Becker Bo and Ivashina Victoria (2014) Cyclicalities of credit supply: Firm level evidence, *Journal of Monetary Economics*, Volume 62, March 2014, Pages 76–93
- Caldara, D., Fuentes-Albero C., Gilchrist S., Zakrajšek E (2015): The Macroeconomic Impact of Financial and Uncertainty Shocks, *mimeo*
- Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno (2014) Risk Shocks, *American Economic Review*, 104(1): 27-65.
- Christiano, Lawrence J. Martin S. Eichenbaum, Mathias Trabandt (2014) Understanding the Great Recession, *NBER Working Paper* No. 20040
- Ciccarelli M., Maddaloni A. and José-Luis Peydró (2013) Heterogeneous Transmission Mechanism: Monetary Policy and Financial Fragility in the Euro Area, *Economic Policy*, vol 28-75, 459-512.
- Ciccarelli M., Maddaloni A. and José-Luis Peydró (2014) "Trusting the Bankers: A New Look at the Credit Channel of Monetary Policy," *Review of Economic Dynamics*, (forthcoming)
- Darracq Pariès, M. and Roberto De Santis (2015) A Non-Standard Monetary Policy Shock: The ECB's 3-Year LTROs and the Shift in Credit Supply, *Journal of International Money and Finance* forthcoming
- De Fiore, Fiorella and Harald Uhlig (2011) Bank Finance versus Bond Finance, *Journal of Money, Credit and Banking*, Blackwell Publishing, vol. 43(7), pages 1399-1421.
- De Fiore, Fiorella and Harald Uhlig (2014) Corporate Debt structure and the financial crisis. ECB Working Paper, forthcoming.
- De Mol, C., D. Giannone, and L. Reichlin (2008) Forecasting using a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components?, *Journal of Econometrics*, 146(2), 318–328.



Doan, T., R. Litterman, and C. A. Sims (1984): “Forecasting and Conditional Projection Using Realistic Prior Distributions,” *Econometric Reviews*, 3, 1–100.

Giannone, D., M. Lenza, and G. Primiceri (2015) Priors for Vector Autoregressions, *The Review of Economics and Statistics*, MIT Press, vol. 2(97), pages 436-451, May.

Gertler Mark and Peter Karadi (2015) Monetary Policy Surprises, Credit Costs and Economic Activity, *American Economic Journal: Macroeconomics*, 7(1): 44-76.

Gilchrist, S. and Benoit Mojon (2014) Credit Risk in the Euro Area, *NBER Working paper* N.20041, National Bureau of Economic Research, Inc

Gilchrist, S, Jae W. Sim and E Zakrajšek, 2014: Uncertainty, Financial Frictions, and Investment Dynamics, NBER Working Papers 20038, National Bureau of Economic Research, Inc.

Gilchrist, S. Yankov V. and E. Zakrajšek (2009) Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets, *Journal of Monetary Economics*, Elsevier, vol. 56(4), pages 471-493, May

Gilchrist, S. and E. Zakrajšek (2012a) Credit Spreads and Business Cycle Fluctuations, *American Economic Review*, 102(4): 1692-1720.

Gilchrist, S. and E. Zakrajšek (2012b) Bank Lending and Credit Supply shock, The Proceedings of the 16th World Congress of the International Economic Association Vol. III: *The Global Macro Economy and Finance*. Edited by Franklin Allen, Masahiko Aoki, Nobuhiro Kyotaki, Richard Gordon and Joseph Stiglitz, 2012.

Gilchrist, S. and E. Zakrajšek (2013) The Impact of the Federal Reserve's Large-Scale Asset Purchase Programs on Corporate Credit Risk, *Journal of Money, Credit and Banking*, Blackwell Publishing, vol. 45(s2), pages 29-57

Krylova, E. (2015) Leading indicator properties of euro-denominated corporate bond spread indices and excess bond returns, ECB WP forthcoming

Holmstrom, Bengt & Tirole, Jean (1997) Financial Intermediation, Loanable Funds, and the Real Sector, *The Quarterly Journal of Economics*, MIT Press, vol. 112(3), pages 663-91, August.

Imbens, Guido (2004) Non parametric Estimation of Average Treatment Effects under Exogeneity: A Review , *The Review of Economics and Statistics*, Vol 86 No 1 pp 4-29

Litterman, R. (1979): “Techniques of forecasting using vector autoregressions,” *Federal Reserve of Minneapolis Working Paper* 115.

Lown, Cara and Morgan, Donald P. (2006) The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey, *Journal of Money, Credit and Banking*, Blackwell Publishing, vol. 38(6), pages 1575-1597, September.

Maddaloni A. and J.-L. Peydro (2013) Monetary Policy, macroprudential Policy, and Banking Stability: Evidence from the Euro Area, *International Journal of Central Banking*, vol. 9(1), pages 121-169, March.

Mertens Karel and Morten O. Ravn (2013) The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States, *American Economic Review*, American Economic Association, vol. 103(4), pages 1212-47, June.

Mumtaz H. and G. Pinter and Theodoridis K (2014) What do VARs Tell Us about the Impact of a Credit Supply Shock? An Empirical Analysis," Working Papers 716, Queen Mary University of London, School of Economics and Finance. Repullo, Rafael and Suarez, Javier (2000) Entrepreneurial moral hazard and bank monitoring: A model of the credit channel, *European Economic Review*, Elsevier, vol. 44(10), pages 1931-1950.

Repullo, Rafael and Suarez, Javier, (2000): Entrepreneurial moral hazard and bank monitoring: A model of the credit channel," *European Economic Review*, Elsevier, vol. 44(10), pages 1931-1950, December.

Sims, C.A. (1993) A Nine-Variable Probabilistic Macroeconomic Forecasting Model, in *Business Cycles, Indicators and Forecasting*, NBER Chapters, pp. 179–212. National Bureau of Economic Research, Inc.

Stock James H. and Mark W. Watson (2012) Disentangling the Channels of the 2007-2009 Recession, *NBER Working Papers* 18094, National Bureau of Economic Research, Inc.

## Appendix 1: Bank Lending Survey

The BLS is addressed to senior loan officers of a sample of euro area banks and is conducted four times a year. The survey is representative of the banking sector in the euro area as it collects individual answers from 137 banks and takes into account the characteristics of national banking structures. The survey contains 17 specific questions on past and expected credit market developments. The former covers developments over the past three months, while the latter focus on the next three months. Questions are classified according to the two borrower sectors that are the central focus of the survey, i.e. enterprises and households. The definitions and classifications used in the survey are consistent with other ECB statistics. For both enterprises - i.e. non-financial corporations - and households, the questionnaire covers both loan demand and loan supply factors.

Among the supply factors, attention is given to credit standards and credit conditions and terms, as well as to the various factors that may be responsible for their changes. Credit standards are the internal guidelines or criteria that guide a bank's loan policy. The terms and conditions of a loan refer to the specific obligations agreed upon by the lender and the borrower, such as the interest rate, collateral required and maturity. All in all, ten questions centre on supply factors, of which seven look at credit standards and three at terms and conditions. Of the questions on credit standards, three refer to banks' liquidity position, access to market funding and capital position, which are the most acute sources of bank vulnerabilities during the financial crisis affecting credit supply. Seven questions focus explicitly on loan demand, of which three look at demand from enterprises and four at demand from households.

Table A.1: representativeness of the BLS sample

Country	Loans to euro area resident non-financial enterprises					Loans to euro area resident households for house purchase					Loans to euro area resident households for consumer credit and other lending					Total main assets					Number of banks in the BLS sample*
	2014	2013	2012	2011	2010	2014	2013	2012	2011	2010	2014	2013	2012	2011	2010	2014	2013	2012	2011	2010	
euro area	<b>56.2</b>	56.2	54.7	54.0	51.7	<b>64.3</b>	64.9	63.8	63.8	61.0	<b>47.4</b>	47.4	46.1	45.5	40.0	<b>57.0</b>	55.7	59.6	53.8	137	
BE	<b>79.3</b>	78.1	77.5	78.6	78.3	<b>54.5</b>	52.8	54.5	51.0	45.9	<b>55.7</b>	57.3	57.5	56.3	56.9	<b>60.0</b>	60.4	63.5	68.2	73.4	4
DE	<b>37.3</b>	37.1	36.6	34.8	34.6	<b>33.2</b>	33.5	33.8	34.4	34.2	<b>31.4</b>	31.3	31.1	30.4	30.6	<b>38.2</b>	38.2	37.3	43.8	39.1	34
EE	<b>84.4</b>	85.2	86.1	88.5		<b>97.4</b>	97.7	97.5	97.6		<b>85.0</b>	85.8	75.2	90.4		<b>86.1</b>	87.8	87.3	89.4		4
IE	<b>72.9</b>	69.0	67.2	67.8	68.7	<b>84.6</b>	82.4	79.4	83.7	74.3	<b>74.0</b>	59.9	58.5	67.7	76.5	<b>51.4</b>	49.9	49.6	51.4	59.1	5
GR	<b>86.8</b>	80.6	64.3	61.5	62.4	<b>90.7</b>	80.3	66.8	66.8	67.4	<b>91.5</b>	85.7	67.2	66.3	65.3	<b>90.8</b>	84.4	73.0	70.6	71.0	4
ES	<b>63.0</b>	61.8	54.6	50.3	44.1	<b>62.7</b>	62.4	57.6	54.0	48.5	<b>53.9</b>	54.9	49.3	45.1	40.6	<b>59.8</b>	57.6	52.9	54.1	50.2	10
FR	<b>53.0</b>	54.2	55.6	56.1	55.8	<b>85.6</b>	86.5	86.3	86.4	86.0	<b>58.3</b>	57.6	57.4	57.5	50.0	<b>67.5</b>	67.5	65.4	65.3	68.1	15
IT	<b>60.3</b>	59.7	60.7	61.8	61.5	<b>61.8</b>	62.4	63.3	64.8	66.5	<b>44.0</b>	44.6	46.4	47.1	47.1	<b>54.4</b>	55.3	57.1	58.9	62.4	8
CY	<b>81.7</b>	79.4	78.3	84.0	81.8	<b>89.0</b>	88.8	87.7	88.0	87.9	<b>93.6</b>	93.2	91.0	91.5	91.8	<b>72.6</b>	70.2	69.6	71.2	59.9	4
LV	<b>72.5</b>					<b>84.7</b>					<b>63.5</b>					<b>49.5</b>					4
LU	<b>42.8</b>	44.6	45.5	41.8	42.2	<b>88.6</b>	88.4	88.9	75.2	75.0	<b>32.2</b>	30.5	30.8	26.8	32.2	<b>18.9</b>	17.5	18.1	18.8	19.4	7
LU (domestic)	<b>66.5</b>	67.8	69.0	55.6	60.8	<b>90.2</b>	90.1	89.7	75.3	75.2	<b>82.8</b>	85.0	86.0	73.7	73.0	<b>18.9</b>	17.5	18.1	18.8	19.4	7
MT	<b>69.4</b>	68.5	92.5	74.4	73.6	<b>94.7</b>	94.7	95.2	96.3	97.9	<b>91.8</b>	93.3	94.6	95.7	97.0	<b>32.1</b>	26.1	26.4	53.6	60.0	4
NL	<b>69.7</b>	69.8	71.8	71.8	60.5	<b>93.8</b>	96.1	97.0	97.1	93.1	<b>81.6</b>	81.0	80.7	79.3	70.0	<b>92.4</b>	80.8	81.1	83.7	73.6	8
AT	<b>43.4</b>	43.8	32.3	32.2	34.2	<b>29.0</b>	29.5	27.7	27.3	27.9	<b>22.1</b>	22.7	20.5	17.9	19.0	<b>41.2</b>	41.3	32.7	30.5	32.5	7
PT	<b>69.3</b>	68.7	68.1	69.7	68.7	<b>75.4</b>	75.4	75.4	78.8	80.0	<b>47.9</b>	48.8	49.3	52.0	53.2	<b>69.7</b>	69.5	69.5	73.4	76.5	5
SI	<b>47.6</b>	55.0	56.4	56.2	56.8	<b>61.8</b>	62.5	62.8	64.4	64.7	<b>55.4</b>	55.4	56.5	57.8	60.0	<b>53.5</b>	54.2	56.9	56.7	58.4	5
SK	<b>68.2</b>	68.6	46.0	46.5	46.1	<b>76.0</b>	76.1	61.7	61.0	61.5	<b>78.9</b>	80.9	70.6	72.2	72.0	<b>70.4</b>	70.3	57.0	54.5	55.9	5
FI	<b>73.7</b>	73.9	74.9	76.5	77.1	<b>90.5</b>	90.8	91.1	90.8	90.6	<b>86.8</b>	87.9	87.9	88.0	88.1	<b>83.4</b>	80.7	79.8	86.2	81.6	4

Source: Eurosystem. \*Number of banks in the October 2014 survey round.

The cross-sectional analysis focuses on the individual responses of banks to questions related to changes in credit standards and loan demand. Given BLS data availability with the first wave of the survey taking place in 2003Q1, we only consider the 11 countries that joined the euro area as of 2003Q1 with the exclusion of Luxemburg: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain.

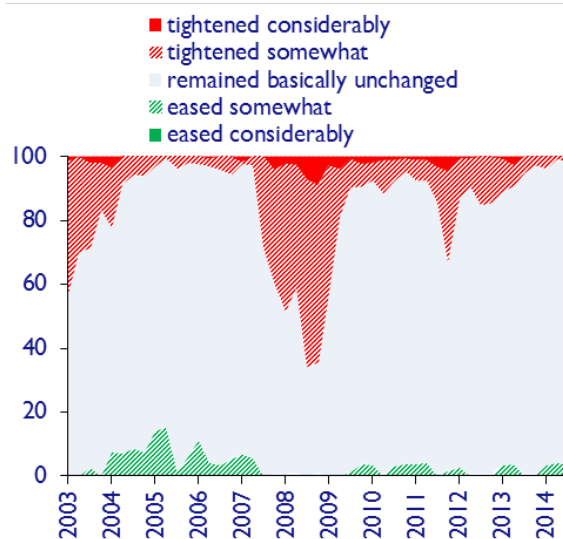
The analysis focuses on the following two questions.

The first one relates to changes in credit standards applied to the approval of loans or credit lines to enterprises and is expressed by the question: “Over the past three months, how have your bank’s credit standards as applied to the approval of loans or credit lines to enterprises changed?”

The second one relates changes in the demand for loans or credit lines to enterprises, is expressed by the question: “Over the past three months, how has the demand for loans or credit lines to enterprises changed at your bank, apart from normal seasonal fluctuations?”

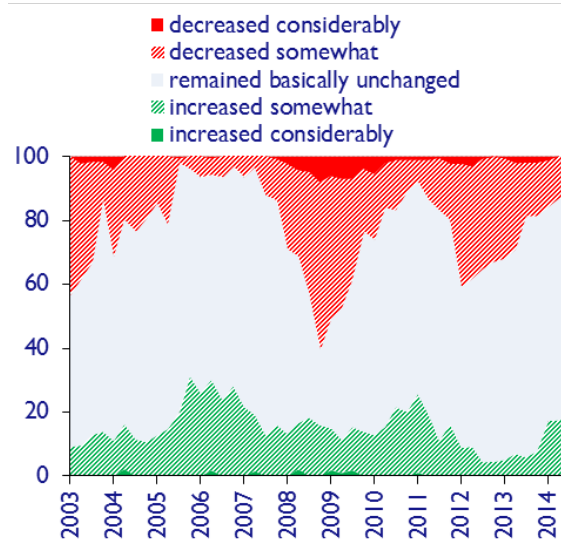
Figure A.1 and A.2 report the distributions of *i)* changes of credit standards for loans to euro area NFCs, and *ii)* changes in net demand for loans to euro area NFCs.

Figure A.1: Distribution of changes of credit standards for loans to euro area NFCs (*percentages of banks*)



Source: ECB (BLS)

Figure A.2: Distribution of changes in net demand for loans to euro area NFCs (*percentages of banks*)



Source: ECB (BLS)

## Appendix 2: Corporate bond dataset

We use information on all available euro-denominated bonds contained in the Merrill Lynch EMU corporate bond index. Although the index does not cover the entire corporate euro-denominated bonds market, it includes the most liquid and representative bonds for the market. Afterwards, we exclude bonds without investment grade and with embedded special features (asset-backed, callable, putable, floating rate, perpetual and sinking fund) from our sample as their pricing is contaminated by different category of risk. Some of remaining bonds in our sample have the explicit government guaranties, but we assume that this special feature is already reflected in the rating of these bonds. Additionally, a few bonds without the proper attribution of country-of-risk or volume-of-issuance are excluded from the list. We use the country-of-risk attribution of underlying bonds as the country-specification, provided by agencies, could be misleading and expose the country of domicile or the country of issuance, and not the country of risk for some bonds. We assume that the performance of a particular bond is representative for the market as long as it is included in the index, and, therefore, we keep this bond in our data sample only for the abovementioned period. We distinguish between 10 rating categories including subdivisions to differentiate plus and minus-rated bonds and monitor changes in rating over time. For cross-sectional and time series analysis we have to shrink our dataset in order to obtain reliable parameter estimates. First, we make sure that all bonds with less than one year to maturity are excluded from the sample as their pricing becomes illiquid and not representative. Second, we concentrate only on bonds of countries-of-risk, which have not less than 5 bonds on average among all monthly time intervals. These results in the following country decomposition of our dataset: Austria (AT), Australia (AU), Belgium (BE), Switzerland (CH), Germany (DE), Denmark (DK), Spain (ES), France (FR), Great Britain (GB), Italy (IT), Japan (JP), the Netherlands (NL), Sweden (SE) and the United States (US). For measure corporate spreads with respect to the euro-area risk-free rate, namely the Overnight Indexed Swap (OIS) curve and will construct the maturity-matched corporate spreads for each security. As an additional filter, we eliminate outliers having corporate spreads higher than 2000 basis points from our data sample.

### Acknowledgements

We would like to thank Martin Bodenstein, Karel Mertens, Haroon Mumtaz and participants at internal seminar, 30th Annual Congress of the European Economic Association (Mannheim), International Conference on Computational and Financial Econometrics in Pisa (IT), the 2nd Annual Conference of the International Association for Applied Econometrics (IAAE) Thessaloniki (GR) for their comments and suggestions. Anca-Mihaela Paraschiv provided excellent research assistance. All errors and omissions are our own responsibility. The opinions in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank and the Eurosystem. Please address any comments to the authors listed below.

### Carlo Altavilla

European Central Bank, Frankfurt am Main, Germany;  
e-mail: [carlo.altavilla@ecb.int](mailto:carlo.altavilla@ecb.int)

### Matthieu Darracq Paries

European Central Bank, Frankfurt am Main, Germany;  
e-mail: [matthieu.darracq\\_paries@ecb.int](mailto:matthieu.darracq_paries@ecb.int)

### Giulio Nicoletti

European Central Bank, Frankfurt am Main, Germany;  
e-mail: [Giulio.Nicoletti@ecb.int](mailto:Giulio.Nicoletti@ecb.int)

### © European Central Bank, 2015

Postal address 60640 Frankfurt am Main, Germany  
Telephone +49 69 1344 0  
Website [www.ecb.europa.eu](http://www.ecb.europa.eu)

All rights reserved. Any reproduction, publication and reprint in the form of a different publication, whether printed or produced electronically, in whole or in part, is permitted only with the explicit written authorisation of the ECB or the authors.

This paper can be downloaded without charge from [www.ecb.europa.eu](http://www.ecb.europa.eu), from the Social Science Research Network electronic library at <http://ssrn.com> or from RePEc: Research Papers in Economics at <https://ideas.repec.org/s/ecb/ecbwps.html>.

Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website, <http://www.ecb.europa.eu/pub/scientific/wps/date/html/index.en.html>.

ISSN 1725-2806 (online)  
ISBN 978-92-899-1674-5  
DOI 10.2866/83401  
EU catalogue No QB-AR-15-101-EN-N