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FINANCIAL CONDITIONS INDEX AND CREDIT SUPPLY SHOCKS FOR THE EURO AREA

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ABSTRACT

We implement a two-step approach to construct a financing conditions index (FCI) for the euro area and its four larger member states (Germany, France, Italy and Spain). The method, which follows Hatzius *et al.* (2010), is based on factor analysis and enables to summarise information on financing conditions from a large set of financial indicators, controlling for the level of policy interest rates, changes in output and inflation. We find that the FCI tracks successfully both worldwide and euro area specific financial events. Moreover, while the national FCIs are constructed independently, they display a similar pattern across the larger euro area economies over most of the sample period and varied more widely since the start of the sovereign debt crisis in 2010. Focusing on the euro area, we then incorporate the FCI in a VAR model comprising output, inflation, the monetary policy rate, bank loans and bank lending spreads. The credit supply shock extracted with sign restrictions is estimated to have caused around one fifth of the decline in euro area manufacturing production at the trough of the financial crisis and a rise in bank lending spreads of around 30 basis points. We also find that adding the FCI to the VAR enables an earlier detection of credit supply shocks.

Keywords

Euro area, financial conditions index, credit supply shocks, large dataset, factor models, structural VAR, sign restrictions

JEL Classification

E17, E44, E50

NON-TECHNICAL SUMMARY

The international financial crisis of 2008-09 and the euro area sovereign debt crisis have brought to the fore the importance of financial conditions to the macro-economy. Stress in financial markets impairs through different channels the normal flow of lending to consumers and corporations, depressing economic activity and inflation. Increasing borrowing costs and falling asset prices weight on consumption through both wealth and inter-temporal substitution effects. Higher external finance premium penalises capital expenditures. Consumption and investment are also affected by changes in risk perceptions and risk tolerance, that alter market risk premia, and by constraints in the supply of credit.

Because of the complexity of the financial sector, a wide range of financial variables is needed to fully characterise its functioning in real time. Combining these variables into a summary statistic of the financial environment for economic agents as well as the degree of strains in the financial system, namely a financing conditions index (FCI), is analytically challenging but operationally appealing for monetary policy. An FCI can also be useful to assess the success of policy measures aimed at alleviating financial market tensions or impairments in the transmission channel of monetary policy.

In this paper, we construct an FCI for the euro area and its larger economies. By construction, the indicator is broadly independent from the level of policy interest rates. It could therefore be interpreted as summarising the financial shocks which affect the economy over and beyond monetary policy impulses. In this sense, the indicator may also measure, through the crisis, the degree of impairment in the monetary policy transmission mechanism.

Country-specific panels of large datasets are setup for the euro area and its four larger member states (Germany, France, Italy and Spain). In each case, the bulk of the series capture conditions in financial markets for the three sources of firm's external finance, namely the banking sector, the fixed income market, and equity markets. Variables considered include: bank lending rates, MFI loans to households and NFCs, money growth, spreads between government bond yields of different maturities, bank capital and liquidity, equity and securities issuance by MFIs and NFCs, bank and corporate bond yields, stock market returns of financial and non-financial institutions, volatility in equity and exchange rate markets, and correlations among different financial variables, among others. Moreover, given the degree of external openness of euro area economies, the foreign exchange rate and the price of raw materials are also included in the dataset, along with the financial variables.

We implement a two-step approach to construct the FCI. This approach follows the methodology recently implemented in Hatzius *et al.* (2010). *First*, each financial variable is purged from its response to developments in demand, prices and monetary policy to capture exogenous shifts in the financial environment. *Second*, the FCI is constructed as the common component of the movements in the large set of variables from the first step, using Principal Component Analysis (PCA).

The FCIs track successfully both worldwide and euro area specific financial events. More precisely, financial conditions deteriorated sharply during the financial crisis in 2008-09, following the collapse of Bear Sterns in early 2008 and particularly after Lehman Brothers filed for bankruptcy in September 2008. The FCIs also point to significant tightening at the beginning of 2010, amid concerns on some euro area sovereigns, but the announcement of the Securities Market Programme by the ECB in May 2010 brought this deterioration to a halt. Triggered by renewed fiscal concerns, further tightening is recorded between mid-2011 and October 2011 which receded after the announcement and implementation of the VLTROs by the ECB. Finally, the FCI tightened again in the second and the third quarters of 2012 due to the re-intensification of tensions in some euro area sovereign debt markets, but announcement of OMTs by the ECB in the summer of 2012 has led to tangible signs of improvements.

The FCI for the euro area as a whole is finally used to identify bank lending supply shocks from a VAR model comprising output, inflation, the monetary policy rate, bank loans and bank lending spreads. The historical shock decomposition shows that at the trough of the financial crisis, in the middle of 2009, credit supply conditions are estimated to have weighed on manufacturing production by up to 4 p.p. on an annual basis, *i.e.*, about one fifth of the recorded decline. The impact of credit supply shocks on bank lending spreads is estimated to account for about one half of the observed increase in bank lending spreads and for about one third of the decline in the rate of growth of bank lending to NFCs.

I INTRODUCTION

The international financial crisis of 2008-09 and the euro area sovereign debt crisis have brought to the fore the importance of financial conditions to the macro-economy and the construction of related quantitative indicators. Financial conditions characterise the functioning of financial markets and access to credit by non-financial agents. To be operational for policy makers, they are often synthesised in one or a few indicators, computed either as a weighted average of several standardised variables or as latent variables contributing to explain the dynamics of observable variables related to the financial side of the economy. In the first case, the index runs the risk of missing important information or spillovers. In the second case, specification and identification play a crucial role to prevent opaque estimation.

Financial markets frictions impair through different channels the normal flow of lending to consumers and corporations, depressing economic activity and inflation. Increasing borrowing costs and falling asset prices depress consumption through both wealth and inter-temporal substitution effects. The user cost of capital becomes more expensive and demand for new physical capital contracts. Consumption and investment are also impaired by changes in risk perceptions and risk tolerance, that alter market risk premia, and by imperfections in credit supply (such as information asymmetries between lenders and borrowers). Changes in the real exchange rate have also a burden on activity through their impact on net exports.

Because of the complexity of the financial sector, a wide range of financial variables is needed to fully characterise its functioning in real time. Although individual financial indicators can prove to be useful as predictors of economic activity and inflation at specific points in time, their relevance is likely to change over time. As shown by Stock and Watson (2002a), the use of large information sets produces more robust signals. In the case of the United States, where a large part of the economy is financed through bond markets, Gilchrist and Zakrajsek (2011) show that a large number of corporate spreads provides a good measure of financing conditions. In the case of the euro area, where the external financing of non-financial corporations operates primarily via bank finance, the information set needed is likely to be wider and to incorporate more than price variables. Indeed, variables needed to capture adequately financing conditions in the euro area include various asset prices and quantities, such as short and long-term bank lending rates, bank lending volumes, securities and equity issuance, stock prices, credit conditions and exchange rates, among others. Combining these variables into a summary statistic of the financial environment for economic agents as well as the degree of strains in the financial system, namely a financing conditions index (FCI), is analytically challenging but operationally appealing for monetary policy. Among a broad set of factors, the assessment of financing conditions can help to guide the implementation of monetary policy measures, both conventional and unconventional. As documented below, financial stress appears to have increased preceding the implementation of such policies in the euro area. At the same time, an FCI can also be useful to assess the success of policy measures aimed at alleviating financial market tensions or impairments in the transmission channel of monetary policy (see below).

In this paper, we construct an FCI for the euro area and its larger economies (Germany, France, Italy and Spain). Ideally, financing conditions indices (FCIs) should measure financial shocks, *i.e.*, exogenous shifts in financial conditions. Hence, by construction, the indicator should be orthogonal to the level of policy interest rates and to developments in demand and prices. It should reflect financial tensions summarising dysfunctions in financial market segments and the degree of impairment in the monetary policy transmission mechanism. Indeed, we implement a two-step approach to construct the FCI. This approach follows the methodology recently implemented in Hatzius *et al.* (2010). *First*, each financial variable is purged from its response to developments in demand, prices and monetary policy to capture exogenous shifts in the financial environment. *Second*, the FCI is constructed as the common component of the movements in the large set of variables from the first step, using Principal Component Analysis (PCA).

The FCIs track successfully both worldwide and euro area specific financial events. More precisely, the FCI points to significant deterioration during the financial crisis in 2008-09, at the beginning of 2010, amid concerns on some euro area sovereigns, between mid-2011 and October 2011, as well as in the second and the third quarters of 2012. At the same time, the indicator seems to capture well the relief brought by ECB's non-standard measures, like the Securities Market Programme in May 2010, the Very Long Term Refinancing Operations (VLTROs) in December 2011 and February 2012, as well as the announcement of Outright Monetary Transactions (OMTs) in secondary markets for sovereign bonds in the euro area.

The FCI is also used to improve on the identification of credit supply shocks within a standard Structural VAR estimated on euro area data. This exercise shows that, at the trough of the financial crisis, in the middle of 2009, credit supply conditions are estimated to have weighed on manufacturing production by up to 4 p.p. on an annual basis, *i.e.*, about one fifth of the recorded decline. The impact of credit supply shocks on bank lending spreads is estimated to account for about one half of the observed increase in bank lending spreads and for about one third of the decline in the rate of growth of bank lending to NFCs.

The remainder of the paper consists of four Sections, as well as three appendices. The paper first reviews various aspects of the indices that have been developed in the literature. It then presents the methodology and data to construct the index for the euro area and the larger economies and presents the corresponding results (Section 3). In Section 4, SVAR models are estimated in order to identify credit supply shocks and estimate their impact on manufacturing production, bank loans to corporations and bank lending spreads. Annex 1 includes the tables and charts referred to in the main text. Annex 2 develops the literature review. Annex 3 details the data used and the statistical transformation performed prior to the estimation.

2 LITERATURE REVIEW

Research on financial conditions was preceded by extensive analysis on the impact of monetary conditions on the macro-economy. The original idea behind monetary conditions indices was that interest rates set by central banks may give an incomplete picture of the impulses imparted by monetary policy on economic activity. Particularly, in the case of small open economies, the exchange rate was seen to amplify the effect of changes in policy rates. Hence, measuring monetary conditions through a weighted index of both the short-term interest rate and the exchange rate was expected to give a more accurate picture of the overall monetary policy stance. In the 1990s, these indices became widely used to assess the stance of monetary policy.[1] Later on, a number of authors extended the idea of the monetary conditions index to other asset prices equally relevant for economic activity (such as long-term interest rates, equity prices and house prices, among others). These measures were called financial conditions indices and they intended to provide a broader measure of financial conditions than monetary conditions indices.

Several international organisations, central banks, investment banks and academics have developed Financing Conditions Indices (FCI) to assess the prospects of economic activity and inflation, the appropriateness of the macroeconomic policy stance, and to guide financial investment decisions. Extensive work has been done to analyse financial conditions in the United States, and to a lesser extent in the euro area. Some work has been done also on Japan, the United Kingdom, and groups of developed countries. In what follows, we review several FCIs developed in the literature, including: the St. Louis Fed's Financial Stress Index, the Chicago Fed National Financial Conditions Index (Brave and Butters, 2011), the ECB Global Index of Financial Turbulence (ECB, 2009), three indices constructed at the International Monetary Fund (IMF, 2008; Swiston, 2008; and Matheson, 2012); the OECD Financial Conditions Index (Guichard *et al.*, 2009), the Goldman Sachs FCI, the Deutsche Bank FCI (Hooper *et al.*, 2007 and 2010), the Bloomberg FCI (Rosenberg, 2009) and the Citi FCI (D'Antonio, 2008) and three indices developed in the academic literature (Hatzius *et al.,*2010; Hollo *et al.,* 2011; and van Roye, 2011).

Financing conditions indices are constructed in general as a weighted average of a number of financial variables, as follows:

$$FCI_t = \sum_{i=1}^{p} a_i x_{i,t} \qquad \text{EQ. 1}$$

[1] Monetary conditions indices were pioneered by the Bank of Canada and the Reserve Bank of New Zealand. The idea was to construct a weighted index of the short-term interest rate and the exchange rate, where the weights reflected the relative impact of those monetary conditions on an intermediate or final target variable, such as the output gap, output growth or inflation.

where FCI_t is the overall financing conditions index at time t and $x_{i,t}$ are p financial variables at time t, such as short and long-term interest rates, bank lending volumes, securities and equity issuance, stock prices, credit conditions, exchange rates, etc.[2] The a_i's are weights attached to each of the variables.

Financing conditions indices in the literature differ in several respects. The three most important differences lie in the methodology used to compute the weights attached to the variables, the control for endogeneity of the financial variables, and whether or not they include the policy interest rate among the financial indicators. We address each of these issues in turn.

2.1 THE THREE BASIC METHODS TO COMPUTE THE WEIGHTS

In the first method, the index is built as a simple average of the variables included. The studies that use this method are ECB (2009), IMF (2008) and Bloomberg FCI. Because of its simplicity, this method allows using an intermediate number of variables (the studies mentioned before use between 6 and 10 variables).

In the second method, each variable in the index is weighted using estimates of its relative impact on real GDP growth or inflation. These weights are generated using simulations from large-scale macroeconomic models (such as the FRB Macro Model, the MUSE model of the Bank of Canada, or the OECD Global Model), or from econometric models (such as vector autoregression models or reduced-form demand equations). The studies that use this method are the Goldman Sachs FCI, Deutsche Bank FCI, Citi FCI, Swiston (2008), Beaton *et al.* (2009), the OECD FCI and Hollo *et al.* (2011). Because the analysis requires an econometric estimation of the impact of financial conditions on macroeconomic outcomes, the number of variables has been kept to the minimum (usually between 4 and 7 variables).

In the third method, the index is computed as the common component of several financial variables. The common component captures the greatest common variation in the variables and it is traditionally interpreted as the FCI. It is usually estimated via principal component analysis (PCA). This method has the advantage that it allows summarising a large information set into a single indicator (the literature surveyed here uses between 18 and 100 indicators). Studies that use this method include the St. Louis Fed's Financial Stress Index, the Chicago Fed National Financial Conditions Index, Deutsche Bank, Matheson (2012), Hatzius *et al.* (2010) and van

2 In some cases, these variables are included in levels, while in others they are included as a difference with respect to a long-term average.

Roye (2011).[3] From these indices, only the Chicago Fed National Financial Conditions Index and Hatzius *et al.* (2010) purge financial variables from cyclical and monetary policy influences.[4]

2.2 CONTROL FOR POTENTIAL ENDOGENEITY

As mentioned before, FCIs should capture only exogenous shifts in the financial environment, that is, movements in financial variables unrelated to other cyclical or policy-determined macroeconomic variables. Hence the need to build an index that measures the impact of financial variables on macroeconomic outcomes *over and above* the direct effect of monetary policy and the economic cycle (Hatzius *et al.*, 2010). The indices surveyed here that purge financial variables from cyclical and monetary policy influences are the Chicago Fed National Financial Conditions Index, Swiston (2008), the Goldman Sachs FCI, and Hatzius *et al.* (2010).

2.3 INCLUSION OF INTEREST POLICY RATES

Some of the indices include the interest policy rate or a short-term interest rate along with a larger set of financial indicators. This is the case of the St. Louis Fed's Financial Stress Index, the Goldman Sachs FCI, the OECD FCI and Swiston (2008). These indices can be interpreted as an extension of monetary conditions indices to account for more complex transmission mechanisms than those subsumed by policy interest rates and exchange rate changes only. By contrast, other indices exclude interest rates on the ground that these are set by central banks with a view to maintaining price stability, while financial conditions are determined endogenously by the financial sector in reaction to economic policies and macro-economic developments. Hence, they focus only on transmission channels unaccounted for by the traditional monetary policy transmission mechanism. In this respect, the indices that exclude interest policy rates can be considered a complement to monetary conditions indices. The indices that exclude interest policy rates from the set of indicators are the Chicago Fed National Financial Conditions Index, the ECB Global Index of Financial Turbulence, the Deutsche Bank FCI, the Bloomberg FCI, the Citi FCI, IMF (2008), Matheson (2011), Hatzius *et al.* (2010), van Roye (2011) and Hollo *et al.* (2011).

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[3] The Deutsche Bank FCI mixes methods 2 and 3. In a first step, principal component analysis is applied to a set of variables to extract a common factor. Then, weights for this common factor and policy interest rates are computed according to their contribution to GDP growth.

[4] These methodological differences have to be borne in mind when interpreting the various FCIs. For example, changes in the indices derived from the second method will have a direct interpretation in terms of future macro-economic outcomes. In contrast, using methods one and three allow only comparing current and past levels of financing conditions.

The indices surveyed before also differ in other respects, such as the frequency of the data used to construct the FCI and the control for missing data (see Annex 2 for a detailed comparison of the indices).

Data frequency: Most of the indices use monthly or quarterly data. Only a limited number of studies use higher frequency data (St. Louis Fed's Financial Stress Index; Bloomberg FCI; Hollo *et al.*, 2011). Because high frequency data tend to benefit from short publication lags, using daily or weekly data allows the analyst to assess financial conditions in real time. The disadvantage is, however, that focusing on high frequency data may blur the information received by the policy-maker, usually with a higher horizon. An alternative to effectively deal with this issue is to use econometric methods that mix data with different frequencies in the same indicator (like in the Chicago Fed National Financial Conditions Index). While these methods improve the in-sample explanatory power of the FCI, they provide volatile estimates at the end of the sample until the low frequencies indicators are known. The resulting gain has to be benchmarked in real-time.

Missing data: Some of the financial conditions indices surveyed here (Chicago Fed National Financial Conditions Index; Hatzius *et al.,* 2010; van Roye, 2011) control for the presence of missing observations at the beginning of the sample due to data availability.[5] Because the analysis is not restricted to a balanced data set, this strategy maximises the number of usable observations. Other indices (Chicago Fed National Financial Conditions Index; Matheson, 2012; van Roye, 2011) also control for missing observations at the end of the sample, due to publication lags. A key advantage of these indices is that they allow the analyst to assess financial conditions in real time, making them highly valuable for policy analysis.

[5] For example, some financial market instruments, such as credit default swaps (CDS), were inexistent until relatively recently.

3 COMPUTING THE FCI FOR THE EURO AREA AND THE LARGER ECONOMIES

As detailed above, the construction of FCIs involves several methodological choices to summarise the information stemming from a large dataset into a single indicator. We implement a two-step approach to estimate the financing conditions index for the euro area and the larger economies. This approach follows the methodology recently implemented in Hatzius *et al.* (2010). *First*, each financial variable is purged from its response to developments in demand, prices and monetary policy to capture exogenous shifts in the financial environment. *Second*, the financing conditions index is constructed as the common component of the movements in financial variables unrelated to cyclical and policy-determined macroeconomic variables from a large set of variables using Principal Component Analysis (PCA).

After a description of the dataset used, the steps are detailed below, focusing on three sets of results: the share of the variance of each financial indicator explained by non-financial factors, the response of each financial indicator to a change in financing conditions, and the FCI *per se*. We then analyse the correlation between the FCI and the spread between the overall cost of financing and the EURIBOR 3-months.

3.1 DATASET AND PRELIMINARY TRANSFORMATION

Given the complexity of modern financial systems and the difficulty in clearly defining and measuring financial stress, the analyst has to limit attention to only a few aspects of the financial system (Hollo *et al.*, 2011). These aspects have to be selected from a broad array of largely imperfect measures of the level of strains in the respective market segment. The number of variables that capture the level of strains in financial markets in the euro area depends on data availability. A panel of 62 variables is used in the euro area and the bulk of the series capture conditions in financial markets of the three sources of firm's external finance, namely the banking sector, the fixed income market and equity markets. Variables considered include: bank lending rates, MFI loans to households and NFCs, money growth, spreads between government bond yields of different maturities, bank capital and liquidity, equity and securities issuance by MFIs and NFCs, bank and corporate bond yields, stock market returns of financial and non-financial institutions, volatility in equity and exchange rate markets, and correlations among different financial variables, among others. Moreover, given the degree of external openness of the euro area, the foreign exchange rate and the price of raw materials are also included in the dataset, along with the financial variables.[6]

To our knowledge, the dataset used in this paper is the largest that has been used ever in the construction of an FCI for the euro area.[7] The estimation sample covers the period from January 2003 to January 2013. Prior to estimation, each variable is transformed to make it stationary (see the third column of the Table in Annex 3). The country datasets built for the four larger euro area economies try to mimic the euro area dataset to the extent possible. In terms of number of variables, they are comparable but smaller, as equivalent series are not always available over the full period.[8]

3.2 FIRST STEP: ISOLATING THE IMPACT OF NON-FINANCIAL FACTORS ON EACH FINANCIAL SERIES

As in Hatzius *et al.* (2010), we control for the potential endogeneity of financial variables stemming from changes in demand, HICP inflation and monetary policy, so that changes in financial variables reflect exogenous shifts in the financing environment rather than the impact of macroeconomic conditions or monetary policy. The transformed series are de-meaned and standardised and then purged from macroeconomic conditions based on the following regression:

$$x_{it} = C + A(L)x_{it-1} + B(L)Y_{t-1} + v_{it} \qquad \text{EQ.2}$$

where x_{it} denotes the financial indictor *i* at time *t*, Y_t is a vector of macroeconomic indicators (the 3-month growth rate of manufacturing production, 12-month HICP inflation, and the 3-month EURIBOR rate in level, C is a constant, $A(L)$ and $B(L)$ are lag polynomials and v_{it} is a residual uncorrelated with past values of Y_t. This residual component represents the financial

6 Guichard *et al.* (2009) show that an exchange rate shock has a stronger impact in the euro area than in Japan or the United States.

7 An advantage of the FCI developed here over that of Hollo *et al.* (2011) is the use of an extensive set of quantities (such as bank loans and issuance of securities and equities). Compared with van Roye (2011), who also computes a financing conditions index for the euro area, we use a larger and longer dataset.

8 Annex 3 provides a more detailed description of the variables considered in the analysis as well as the transformation implemented. The number of variables for each country is as follows: Germany (31), France (35), Italy (32) and Spain (34).

variables purged from macroeconomic influences.[9] The number of lags, one or two depending on the indicator, is selected by minimising the Akaike Information Criteria.[10]

Note that we keep the policy determined interest rates separate from the financial variables. This is because the former are set by central banks with a view to maintaining price stability, while the latter are determined endogenously by the financial sector in reaction to economic policies and macro-economic developments. Various arguments make the 3-month EURIBOR rate key for the transmission of monetary policy in the euro area. First, EURIBOR is of crucial importance for the efficient functioning of the euro area financial system. Monetary policy decisions and market expectations of the future path of policy rates are directly reflected in EURIBOR, which serves as a reference for highly liquid and standardised derivative products and also for the pricing of various, usually less liquid, marketable debt instruments. Hence, EURIBOR has a direct bearing on financing and credit conditions. Second, there is broad consensus that the main reference rate underlying other euro interest rates is EURIBOR. Given the crucial role of EURIBOR in the formation of both euro money market interest rates and market expectations regarding the future values of short-term interest rates, it plays an essential role in the interest rate channel, which transmits changes in policy interest rates along the yield curve. Finally, a large share of loans to non-financial corporations and households in the euro area are issued at a floating rate. These floating rate loans are referenced mostly to EURIBOR.[11]

Including the 3-month EURIBOR rate in Equation (2) also accounts for a large part of non-standard measures, to the extent that those measures affect liquidity in the banking system. In particular, because of the importance of the banking sector in the euro area, a large part of non-standard measures were designed to address tensions in banks' funding conditions and money markets in particular. In this respect, measures taken included the provision of larger allotment amounts in the main refinancing operations (MROs), switching from variable rate tenders to fixed rate tenders with a full allotment of the liquidity demanded by counterparties, a lengthening of the maturity of the refinancing operations and a broadening of the collateral framework. The aim of these policies was to reduce the spread between EURIBOR and the rate on the main refinancing operations and secured market rates, thus helping to restore the normal functioning of the transmission of monetary policy. Empirical evidence for the euro area shows that these measures were effective in addressing disruptions in the money market and were

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9 Note that no specific assumption is needed regarding the behaviour of the residual, apart from it being stationary.

10 Hatzius et al. (2010) do not include the lagged dependent variable in equation (2). However, we decided to include them because financial variables might be persistent over time. These lagged dependent variables proved to be significant in the estimated equations. Hence, excluding such variables would have induced an omitted variable bias, resulting in an over persistent FCI.

11 See ECB (2013) for a review of the usefulness of EURIBOR and other reference rates.

instrumental for stabilising the financial system and the economy (see ECB, 2011; Lenza *et al.* 2010; Abbassi and Linzert, 2012).

Chart 1 reports the share of the variance explained by Equation (2), when isolating exogenous shifts in financial indicators from changes in macroeconomic conditions. As can be seen from the Chart, more than 75% of the variation in bank bond yields, in the term spread of government bonds and in the correlation between stock market returns of financial institutions and overall stock markets (beta financials) is explained by macroeconomic conditions, monetary policy and persistence. In the case of the volatility of stocks of financial and non-financial corporations and the foreign exchange rate, the correlation between stock markets and government bond yields, money growth, bank lending rates and bank loans to households and non-financial corporations, the regressors have an intermediate level of explanatory power (between 20% and 70%, depending on the variable). Other variables tend to be less cyclical and less responsive to monetary policy, such as the liquidity and capital ratio, issuance of equities by non-financial corporations, stock prices and the cost of equity, the foreign exchange rate and the world price of raw materials. In terms of ranking, similar results are obtained at the country level.[12]

[CHART 1]

3.3 SECOND STEP: POOLING THE INFORMATION VIA FACTOR MODEL TECHNIQUES

The residuals in Equation (2) can be decomposed as follows:

$$v_{it} = \lambda_t' F_t + \mu_{it} \qquad \text{EQ. 3}$$

where F_t is a set of unobserved financial factors, common to all financial variables, λ_t' is a row vector of coefficients, and μ_{it} is the idiosyncratic variation in v_{it}, unrelated to F_t and Y_t. The unobserved common factors, F_t, that capture the co-movement among the financial variables, is the financing conditions index (FCI).

Several techniques have been proposed in the literature to estimate the unobserved factors F_t. However, available studies on the relative performance of the various methods implemented using US data, like Stock and Watson (2004) or Darracq and Maurin (2009) have not reached a clear consensus on the best method. In this paper, we consider the static principal components method of Stock and Watson (2002a and 2002b).

12 Charts 1 and 2 at the country level for Germany, France, Italy and Spain are available upon request.

Before estimating the FCI, one has to select the optimal number of factors that are needed to capture adequately the co-movement in the data. In the case of the estimation of static factors, Bai and Ng (2002) propose to minimize an information criterion to determine the optimal number of static factors, as follows:

$$r = Arg\min_{r}\left(\ln\left(\hat{V}_r\right) + r.g\left(N,T\right)\right) \quad Where \;\; \hat{V}_r = \frac{1}{NT}\sum_{i,t}\hat{\xi}_{t,i}^{2} \qquad \text{EQ. 4}$$

Where r is the optimal number of factors, $\hat{V}_r$ is the average residual variance when r factors are estimated, g is a penalty function and N and T are the cross section and the time dimensions of the panel, respectively. Bai and Ng (2002) propose three penalty functions which define three information criteria. As usual, the criteria depend on the trade-off between good fit and parsimony. These criteria have different properties in finite samples but are asymptotically equivalent:

$$\begin{aligned} g_1(N,T) &= \frac{N+T}{NT}\ln\left(\frac{NT}{N+T}\right) \\ g_2(N,T) &= \frac{N+T}{NT}\ln\left(\min\left(\sqrt{T},\sqrt{N}\right)\right) \\ g_3(N,T) &= \frac{\ln\left(\min(T,N)\right)}{\min(T,N)} \end{aligned} \qquad \text{EQ. 5}$$

Table 1 reports these criteria, computed over the datasets of financial variables for the euro area and the largest economies, for 1 to 6 factors. Empirical evidence presented in that Table shows that the optimal number of factors to retain is one for all the criteria and all of the economies under consideration.

[TABLE 1]

Given the selected number of factors, the response of each financial indicator to a change in financing conditions (the vector λ in EQ. 4) is reported in Chart 2. The coefficient lambda is positive in about half of the cases, indicating that the indicator increases when financial conditions loosen. This is generally the case for quantities, such as bank loans to households (for consumption and house purchase) and non-financial corporations, issuance of equities and securities, money growth, etc. Negative lambdas generally prevail among corporate bond yields, indicating that deterioration in the financing environment is associated with an increase in corporate bond yields.

[CHART 2]

In what follows, we use the static principal components method of Stock and Watson (2002a and 2002b) to summarise the information on the remaining part of each financial indicator into a single index. Using this method, the unobserved factor can be written as:

$$F_t = \lambda' v_t \qquad \text{EQ. 5}$$

where λ is the vector grouping the λ_i's and v_t is the vector containing the purged financial variables. From this equation, it can be seen that the weight that each financial indicator has in the index is proportional to its lambda coefficient.[13]

3.4 ANALYSING THE RESULTS

Charts 3a and 3b present the FCI computed for the euro area and the four larger economies, respectively, since the beginning of 2007. In both charts, a higher value of the FCI represents an improvement in the financial environment, *i.e.* less frictions in financial markets while a lower value of the FCI represents deterioration in the financial environment. The FCIs are de-meaned and standardised over the period. The FCIs track successfully both worldwide and euro area specific financial events.[14]

It can be seen that the FCIs vary across time and, to a much lesser extent across countries, possibly reflecting the integration of financial markets. Financial conditions are found to be exceptionally tight in the wake of the financial crisis, in 2008 and in 2009, as well as more recently in the wake of sovereign debt tensions in some countries in the euro area. In particular, financing conditions were relatively loose in 2007, above their average over the estimation period. They deteriorated sharply during the financial crisis in 2008 and in 2009, following the collapse of Bear Sterns in early 2008 and particularly after Lehman Brothers filed for bankruptcy in September 2008. The index for the euro area and the four larger economies reached a historical minimum in the beginning of 2009, when financial conditions started to

[13] As signalled by Hatzius *et al.* (2010), the least squares estimator of F_t (principal components) is sufficiently accurate that can be used in subsequent regression analysis, with no first-order loss in efficiency or modification of standard regression inference procedures.

[14] As with other financing conditions indices in the literature, a higher value of the FCI may be capturing also to some extent the presence of unsustainable dynamics in credit and stock market prices. For example, the FCI of Hatzius *et al*. (2010) improves before the stock market crash of 1987 and before the sub-prime crisis that erupted at the end of 2008. However, the construction of an FCI which abstracts from potential credit and stock price bubbles requires the identification of such bubbles in real time, which is not straightforward and subject to strong debate. All in all, we consider this feature to be a strength of the FCI in that it allows for testing whether loose financing conditions resulted in the build-up and subsequent burst of bubbles in credit and stock markets.

loosen, following a worldwide relaxation in monetary policy. Financing conditions started to tighten again at the end of 2009 and the beginning of 2010, amid concerns on some euro area sovereigns, but the announcement of the Securities Market Programme by the ECB in May 2010 brought this deterioration to a halt. Triggered by renewed fiscal concerns, financing conditions tightened again between mid-2011 and October 2011. The announcement of further non-standard measures by the ECB in the last of quarter of 2011 led to a clear improvement in financial market conditions. The financial environment appears to have tightened again in the second quarter of 2012, following the intensification of turmoil in euro area sovereign debt markets. However, the announcement of OMTs by the ECB in the summer of 2012 has led to tangible signs of improvements in financing conditions. Overall, these results support the view that non-standard measures have succeeded in alleviating financial market frictions in the euro area, thus helping to restore the functioning of the monetary policy transmission mechanism. At the same time, our FCI compares favourably with other financing conditions indices available for the euro area. In particular, our FCI co-moves considerably with the OECD indicator and the Goldman Sachs indicator over the longer term. All of the indices track successfully both worldwide and euro area-specific financial events. However, our FCI appears to vary much more strongly over the crisis period (from 2009 to 2011), reflecting that the important role played by financial factors over this period is, by construction, better captured in our FCI.[15]

[CHARTS 3a and 3b]

A large body of literature uses an average of spreads between corporate bond yields and a risk-free interest rate as a measure of the tightness in financing conditions (Ghilchrist and Zakrajcek, 2011; Ghilchrist and Mojon, 2013). The FCI is by construction more complex than a weighted average of several spreads, as it reflects both price and quantitative supply conditions. We follow the literature and project the FCI for the euro area and the four larger economies on bank lending rate spreads, using country specific equations. The spread is computed as the difference between a composite cost of bank lending to non-financial corporations (NFCs) and the three-month EURIBOR. The composite cost of bank lending to NFCs is a weighted average of loan rates on short term and long term loans, with the weights representing the new business volumes for each loan. Hence, by construction, the composite cost is country specific.

15 Unlike the other two indicators, our FCI encompasses a large range of financial series. For more details see ECB (2012).

Based on the auxiliary regressions of the FCI on lending rate spreads (not shown here), we compute the dynamic contribution of the FCI to the bank lending rate spread.[16] Such "dynamic scaling" enables to interpret directly the indicator as a financing cost.

Focusing on the euro area as a whole, NFCs lending rate spreads have increased persistently since the beginning of 2009 despite a reduction in the short-term market rates. This suggests that the gradual pass-through of the monetary policy stance into bank lending rates has been impaired (see Chart 4a). The FCI could then be used to quantify such impairments. Indeed, the dynamic contribution of the FCI to the lending rate spread is shown in Chart 4b. The FCI contributed to narrow bank lending spreads until the end of 2008 but the contribution turned positive just after the eruption of the financing crisis. Later on, in 2010, the contribution increased again, reaching up to 50 b.p. at the beginning of 2012.

[CHARTS 4a and 4b]

[16] The monthly change in the spread is projected on the lag level of the spread, a constant, the contemporaneous value of the FCI and its lagged value. The long run elasticity between the FCI and the spread can be computed as the sum of the coefficient on the FCI divided by 1 minus the coefficient on the lagged level of the spread. A permanent, one-unit change in the FCI is associated with a reduction in the level of the spread by between 10 and 16 basis points on an annual basis.

4 IDENTIFYING CREDIT SUPPLY SHOCKS WITH THE FCI

The estimated FCI does not have a structural interpretation and a more encompassing model is required to estimate better the transmission and the impact of shocks in the financial system to the real economy. In this section, we use the information content of the FCI to identify credit supply shocks.

Since the beginning of the financial crisis, there has been an important debate on the contribution of financing conditions to business cycles in the euro area. While there is widespread agreement that shocks originating in the financial system have been important in shaping economic activity, their exact quantification remains an open issue (Adrian, Colla and Shin, 2012). In this context, the quantification of the stimulus provided by monetary policy has also attracted a lot of interest. Since Bernanke *et al.* (2005) it is well known that monetary policy "shocks" and the implied dynamic responses of the economy as estimated within small scale VAR models comprising typically activity, prices and interest rates tend to be mismeasured by the econometrician.[17] By definition, the FCI, which filters information from many financial variables can be expected to ameliorate the shock extraction of monetary policy. Including an FCI into the small scale VAR reduces the risk of omitting a subset of information used by the monetary policy maker while not imposing their appropriate nature, as usually done when approximating financing environment by spreads.

In this section, we provide an estimate of credit supply shocks for the euro area as a whole. The estimation requires first the estimation of a VAR and, second, the identification of the structural shocks hitting the economy. Only two shocks are identified, monetary policy shocks and credit supply shocks. We estimate a vector autoregression model (VAR) as follows:

$$\begin{bmatrix} Y_t \\ FCI_t \end{bmatrix} = C + \begin{bmatrix} \Phi(L) \\ \beta(L) \end{bmatrix} Y_{t-1} + \begin{bmatrix} \mathrm{B}(L) \\ C(L) \end{bmatrix} FCI_{t-1} + \mu_t \qquad \text{EQ. 6}$$

Where Y_t is the vector of macro-economic variables and monetary policy used in the first step to extract from each financial series the impact of demand, prices and monetary policy, to which we append bank loans to NFCs and the spread between a composite cost of bank lending to NFCs and the 3-month EURIBOR. FCI_t is the financing conditions index, C is a column

[17] A possible example of the effects of shock mismeasurement is the "price puzzle".

vector of constants, $\Phi(L)$, $\beta(L)$, $\mathrm{B}(L)$ and $C(L)$ are matrices of lag polynomials, and μ_t is a vector of multivariate normal shocks to the system.

Standard VAR models estimated for the purpose of monetary policy analysis comprise typically a monetary policy indicator, a real-activity measure and a price index. In order to identify credit supply shocks, these models have been augmented by including other series related to corporate bond yields, monetary base, or answers to the Bank Lending Surveys (Peersman, 2012; Darracq and De Santis, 2013). In our model, to estimate credit supply shocks, we augment the standard monetary policy VAR with bank loans to NFC and bank lending spreads on loans to NFCs.

To illustrate the changes resulting from the inclusion of the FCI, we estimate two versions of the VAR described by EQ. 6: one excluding the FCI, called benchmark, where the coefficients of the lag polynomial matrix B(L) are all set to zero, and one including the FCI as an endogenous variable in the VAR. By comparing the results with and without the FCI, it is then possible to determine the marginal contributions of the information contained in the FCI. Although it can be argued that the financing conditions index is exogenous to some of the variables already included in the VAR (as it is purged from the impact of demand, prices and monetary policy), it is not necessarily independent from loans and bank lending spreads. Hence, we enable the index to enter endogenously in the VAR. This implies that the FCI reacts to the other variables in the VAR and is therefore the product of a combination of shocks among which only the credit supply shock is identified. In turn, part of the FCI is left unexplained.

The VAR is estimated using monthly data over the period from January 2003 until January 2013. The composite cost of bank lending to NFCs used to compute the spread over the 3-month EURIBOR rate is based on an aggregation of interest rates on short-term loans and long term loans weighted by new business volume of loans. The number of lags retained is selected on the basis of the Akaike information criterion.

4.1 SHOCK IDENTIFICATION AND IMPULSE RESPONSE ANALYSIS

The typical framework for the identification of monetary policy shocks is ill-equipped to identify credit supply shocks. In particular, a traditional Cholesky decomposition for monetary policy shocks assumes the following standard ordering in the VAR: prices first, activity second and EURIBOR third. Hence, monetary policy shocks and demand shocks affect prices with a lag, while activity reacts contemporaneously to demand and nominal shocks but with a lag to unexpected changes in monetary policy. Such decomposition does not disentangle properly a monetary policy shock from a credit supply shock, as it seems difficult to envisage variables that would be hit more quickly by the former than by the later. Hence, to identify the credit supply shock, we use sign restrictions instead of the typical recursive decomposition. We follow the approaches of Canova and de Nicolo (2002) and Uhlig (2005) to identify the two shocks.

We do not aim at identifying all the shocks in the economy but only at disentangling monetary policy shocks from credit supply shocks. For this purpose, we compare the outcome of two VAR models, one consisting of five variables: inflation, activity, loans, bank lending spreads on loans to NFCs, and EURIBOR; and the same VAR including a financing conditions index. To identify the shocks, we follow similar constrains as Busch *et al*. (2010), Gambetti and Musso (2012) and Peersman (2012), among others. A positive monetary policy shock, *i.e.* an unexpected increase in short-term interest rate, depresses activity, prices and loans. A positive credit supply shock associated with a softening of the financing environment boosts activity and triggers a tightening of the monetary policy rate. The impact on prices is left unrestricted as the positive effect on demand can be mitigated by a positive effect on supply. Both a positive monetary policy shock and a negative credit supply shock depress loans and activity. In order to dissociate a positive credit supply shock from an expansionary monetary policy shock, we impose a different sign on the monetary policy rates and impose that the bank lending spread declines in the case of a positive credit supply shock (Table 2). In the model incorporating the FCI, the sign restriction also applies to the indicator, with an increase being associated with a negative credit supply shock.

[TABLE 2]

In this identification scheme, the time profile of the responses is an issue, especially when using monthly data. It is well documented in the literature that prices are sluggish in the euro area. Loan growth may also take some time to adjust to shocks. To solve the issue, we consider the average response over four months and impose the sign restriction starting one month after the shock to activity, prices and loans.[18] The prior and posterior distributions of the reduced form VAR belong to the Normal-Wishart family. To draw the 'candidate truths' from the posterior, we take a draw from the unrestricted Normal-Wishart posterior of the possible decomposition of the variance-covariance matrix of residuals, which allows the construction of impulse response functions. If the impulse response functions from a particular draw satisfy the imposed restrictions, the draw is kept.[19] Each draw is required to satisfy simultaneously the restrictions of the two identified shocks.

Chart 5 reports the response of the endogenous variables (the median estimate of the accepted draws) to a one standard deviation shock in the credit supply shock for the model augmented

[18] See Montford and Uhlig (2009) for a generalisation of this approach using a criterion function.

[19] 10000 draws are computed.

with the FCI. The median of the accepted draws is plotted, together with the confidence band at 15% and 85% level, symmetrically distributed and delimited by the dotted lines. Overall, the confidence bands remain relative large especially for the responses of the variables left unrestricted. Beyond the sign restrictions, the responses are generally of the expected magnitude and time profile.

A credit supply shock leads to a slowdown in industrial production and to a later decline in inflation in the euro area. Indeed, as the reaction of inflation is not restricted, some of the draws accepted incorporate a positive reaction, but these remain marginal as shown by the upper confidence band (Chart 5). The impact on loans is even more delayed. All three responses display a hump-shape, with the impact on activity peaking four to eight months after the shock, that on prices 12 to 14 months after and that on loans 15 to 17 months after. The peak effect on manufacturing production, 0.6% is 50% higher than on loans – 0.4% and ten times stronger than on HICP inflation (0.06 p.p.). Bank lending spreads rise after the shock and reach a peak of around 5 basis points (b.p.) eight months after the shock. To result in a lower bank lending rate, the decline in the monetary policy rate must be above the rise in the spread and it is what we found, with a peak decline of 15 b.p. in the 3-months EURIBOR. The effects of the credit supply shock are more persistent on loans, spread and the monetary policy rate, and disappear around two years after the shock. Overall, when comparing the time profile of the responses and the relative magnitude at the peak of each effect, the effect are largely plausible, especially between activity, loans and bank lending spreads, even though being on the low side between activity and prices.

[CHART 5]

4.2 SHOCKS CONTRIBUTION

Based on the orthogonalized impulse responses and the estimated structural shocks, one can compute the contribution of credit supply shocks to the observables. This is shown in Chart 6 using the model augmented with the FCI. At the trough of the financial crisis, in the middle of 2009, credit supply conditions are estimated to have exerted an adverse effect on manufacturing production amounting to about 4 p.p. This impact represents about one fifth of the recorded decline. While this may not appear as high, one has to bear in mind the role played by the demand shock during this period and also the impact of the collapse in world trade. The peak effect on inflation is reached toward the end of 2009 and is of around -0.3 p.p. of annual price inflation.

Regarding MFI loans to non-financial corporations the contribution of credit supply shocks in 2009 amounts to about 2.5%, one fifth of the decline recorded at that time, a contribution which is again reached at the end of 2011, on the back of the sovereign debt crisis, also associated with major impairments in the European financial system. A similar profile is observed for the contribution of credit supply shocks to bank lending spreads, amounting to around 30 b.p. in the middle of 2009, resorbing thereafter and again contributing to the same amount at the end of 2011. Prior to the start of the financial crisis, from 2003 to 2008, credit supply shocks are estimated to have pushed up bank loans by more than 1% each year and compressed bank lending spreads by up to 30 b.p.

Interestingly, it is worth noting that a large part of the variance in the FCI does not reflect what we identify as a credit supply shock. At the peak of the financial crisis at the end of 2008 and early 2009, around one third of the tightening in financial conditions reflected bank-lending shocks. Moreover, the relevance of this shock for activity and inflation is much lower than in the case of Peersman (2012). Indeed, there is more in the FCI than the shock we identify, shocks originating in the financial sphere and transmitted to the economy without passing-through the banking sector. Indeed, in his estimation, the author identifies three sub-shocks: lending demand, lending supply shocks caused by monetary policy shifts and lending multipliers shocks. In what follow, we compare the credit supply shocks estimated in both models, the benchmark and the augmented with the FCI.

[CHART 6]

4.3 COMPARING THE RESULT OF THE BENCHMARK AND AUGMENTED MODEL

Chart 7 plots the difference between the augmented and the benchmark model in the estimated contribution of credit supply shocks to the observables. A negative value suggests a more negative (or less positive) impact in the model identified with the FCI compared with the model identified without it. The estimated impact of credit supply shocks appears to change substantially between the two models.

In particular, when using the FCI, bank lending conditions are estimated to have been tighter during the period from the middle of 2007 to the beginning of 2009 than in the model that excludes the FCI. During that period, on average, the adverse impact on manufacturing production and on loans is higher by 1 p.p. while the impact on spreads is higher by around 10 b.p. Hence in the first stage of the financial crisis, the FCI enables to detect the adverse impact earlier. In the second stage of the financial crisis, starting with the sovereign debt crisis, the adverse impact of credit supply shocks is lower when identified with the FCI. Indeed, from

2010 to the end of 2012, the benchmark model suggests that loans would be more adversely affected by credit supply shocks, for 0.5 to 1.0 of annual growth and bank lending spread would be pushed up by 5 to 10 b.p.

[CHART 7]

Other than shock contributions, another exercise typically performed to compare shocks or models in a standard VAR context is variance decomposition. This exercise consists in determining the fraction of the forecast error of a variable that is attributable to a particular shock.[20] Tables 3 reports the contribution of credit supply shocks to the variables included in the VAR. The first line reports the result obtained from the benchmark model while the second line reports the results obtained from the model augmented with the FCI. The contribution to the variance is reported at various forecast horizons: on impact, one quarter after the shock, and one, two and three years after the shock.

Two observations stand out from Table 3. First, the credit supply shock explains a sizeable fraction of the forecast error of the variables. For example, at a horizon of one year, the share of the variance explained by this shock is between 23% and 44% for all the variables in the benchmark model and between 23% and 39% in the augmented model. For most of the variables, the peak is reached between 1 quarter and 1 year ahead. In the case of the financing condition index, bank-lending shocks explain a relatively small share of the variance, around 15% of its forecast error. These results confirm that bank-lending shocks are important drivers of business cycles at high frequencies. However, the relatively smooth profile of the macroeconomic series is difficult to match with the high volatility of the FCI and only a part of the FCI results from credit supply shocks identified mostly based on macroeconomic series. Second, the discrepancies between the results obtained from the two models are not very noticeable, apart from being slightly stronger at short horizons for manufacturing production, loans and bank lending spreads when estimated with the benchmark model. These results show that the FCI encompasses more shocks that the credit supply shock identified here, shocks transmitted to the economy without passing-through the banking sector or shocks not impacting the real economy.

[TABLE 3]

[20] Variance decomposition results follow immediately from the coefficients of the MA representation of the VAR system and the variance of the structural shocks.

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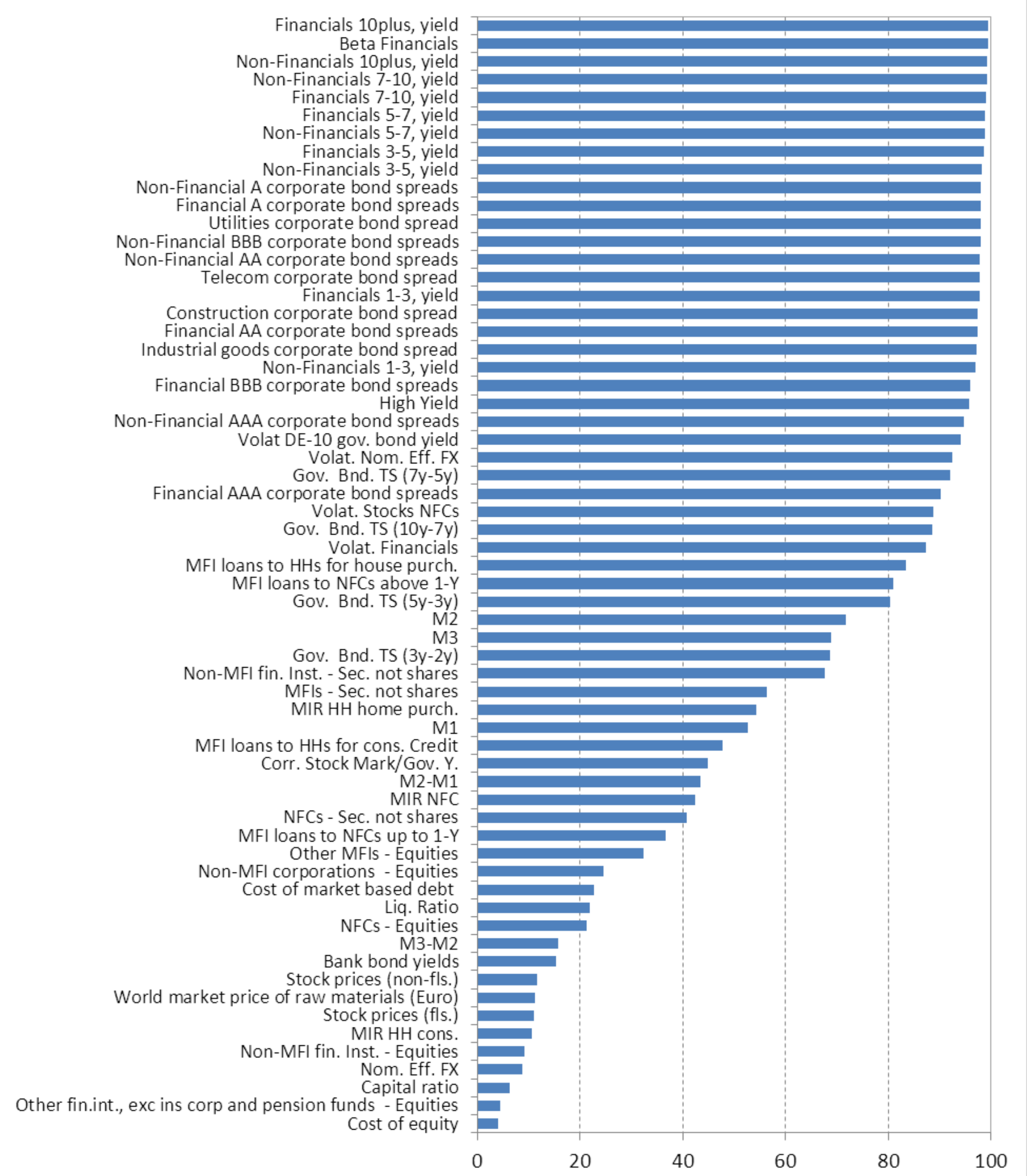
ANNEX I TABLES AND CHARTS

Chart 1 Share of the variance of each financial indicator explained by macroeconomic conditions, monetary policy and lagged values of the dependent variable

(euro area as a whole)



Note: R-square of the estimated EQ. 2 for each financial indicator in the euro area dataset. Country results available upon request.

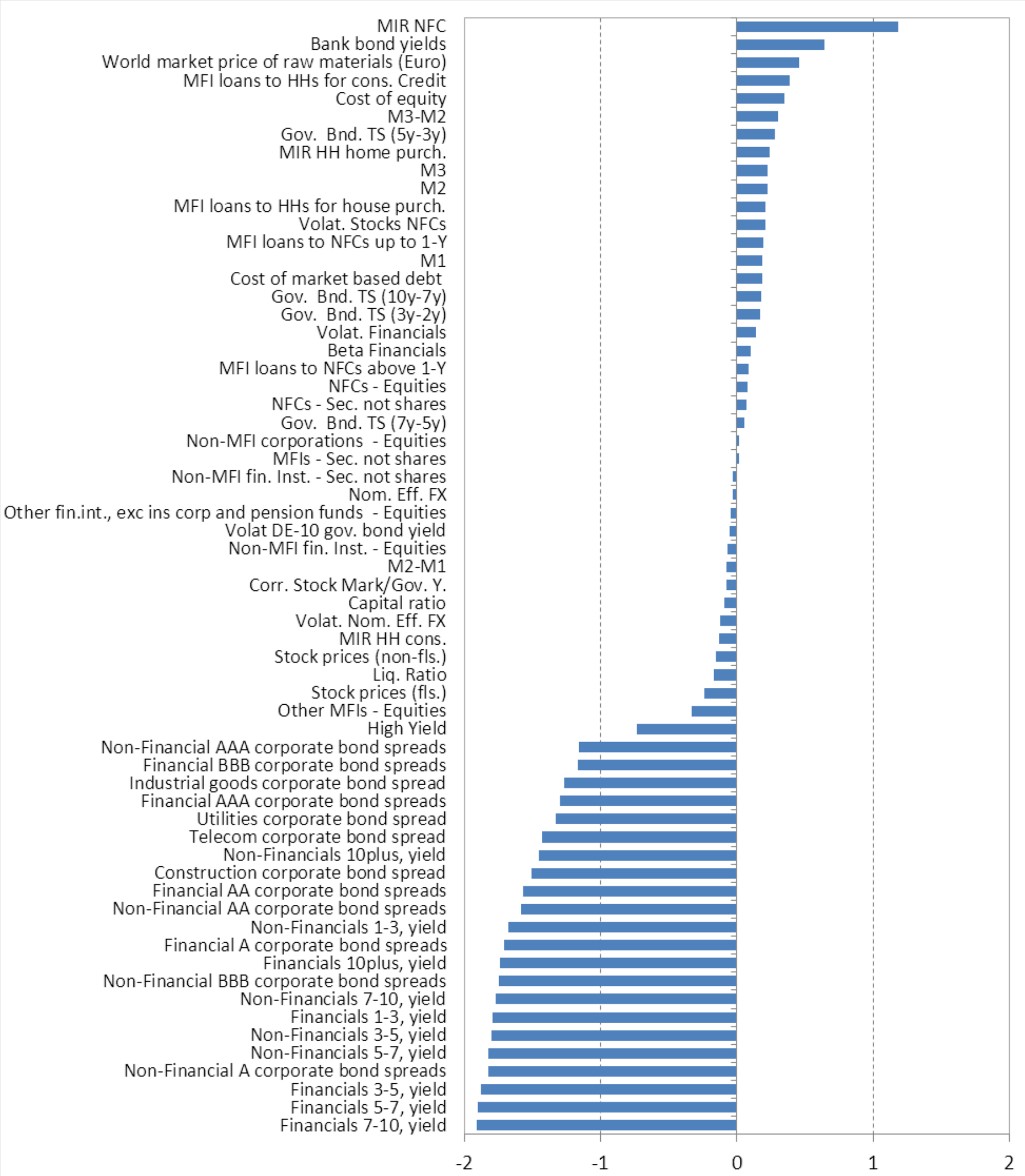
Table 1 **Bai and Ng (2002) criteria to select the number of factors**

		1	2	3	4	5	6
Euro area	*ICp1*	**0.87**	0.88	0.90	0.93	0.97	1.01
	ICp2	**0.88**	0.90	0.92	0.96	1.01	1.06
	ICp3	**0.85**	0.84	0.84	0.85	0.87	0.90
Germany	*ICp1*	**0.97**	1.00	1.05	1.11	1.17	1.24
	ICp2	**0.97**	1.01	1.07	1.14	1.21	1.28
	ICp3	**0.95**	0.97	1.00	1.04	1.09	1.14
France	*ICp1*	**0.97**	1.00	1.05	1.11	1.17	1.24
	ICp2	**0.98**	1.01	1.07	1.14	1.20	1.28
	ICp3	**0.96**	0.97	1.00	1.04	1.09	1.14
Italy	*ICp1*	**0.98**	1.01	1.05	1.11	1.18	1.25
	ICp2	**0.99**	1.02	1.07	1.14	1.21	1.30
	ICp3	**0.97**	0.98	1.01	1.05	1.10	1.16
Spain	*ICp1*	**0.99**	1.01	1.06	1.13	1.19	1.27
	ICp2	**0.99**	1.03	1.09	1.16	1.23	1.31
	ICp3	**0.97**	0.98	1.02	1.06	1.11	1.17

Note: The table reports the criteria described in EQ. 4 and 5. Each criterion is reported on a row with the columns indicating the number of factor assumed. The bold fonts isolate the number of factor retained in each case.

Chart 2 Response to a unit change in financing conditions

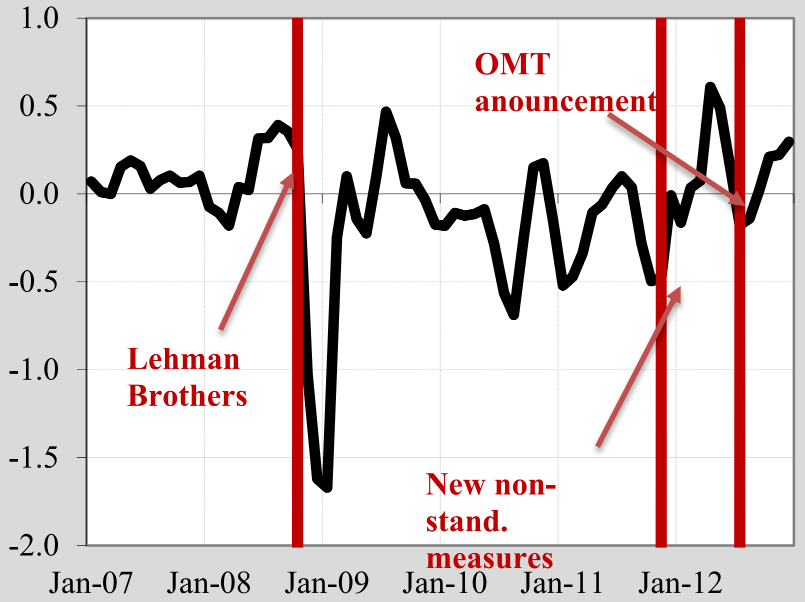
(euro area as a whole)



Note: See Equation EQ. 3 for the definition of Lambdas. Responses are reported as a ratio to the variance of the residual in EQ. 2. A positive response signifies that the variable decreases with a loosening of financing conditions. Country results available upon request.

Chart 3a Financing conditions index in the euro area since 2007

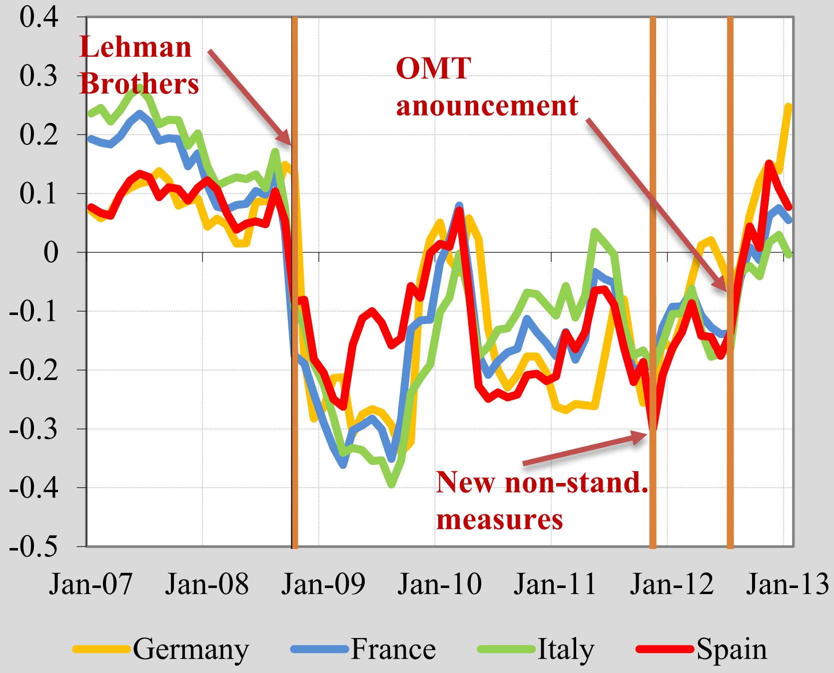
(three months moving sum)



Note: A decline in the FCI signifies a tightening of financial conditions. By construction, the mean of the indices is zero and the standard deviation is one over the estimation period. Last observation is January 2013.

Chart 3b Financing conditions index for the four larger economies

(twelve months moving sum)



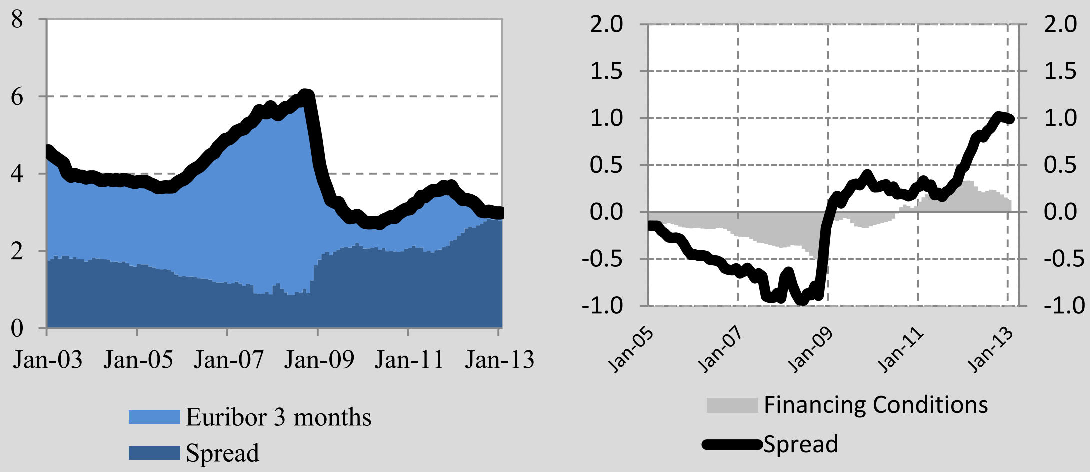
Note: A decline in the FCI signifies a tightening of financial conditions. By construction, the mean of the indices is zero and the standard deviation is one over the estimation period. Last observation is January 2013.

Chart 4 Spread between cost of lending and EURIBOR and contribution of financing conditions

(euro area as a whole)

a) ***Cost of bank lending and spread to the EURIBOR***

b) ***Estimated contribution of financing conditions to the spread (% and p.p.)***



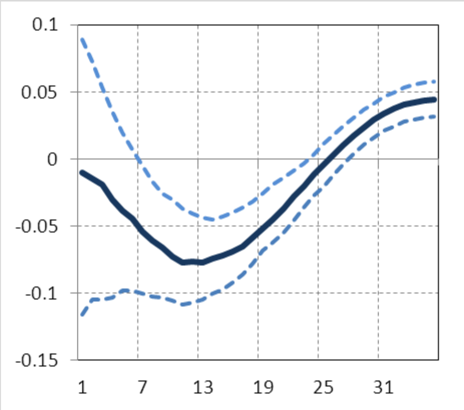
Note: The spread is derived as the difference between a composite cost of MFI lending to NFCs and the EURIBOR 3 months. On the right hand panel, the spread and the contribution are initialised to zero at the beginning of 2005. Last observation is January 2013.

Table 2 Sign restrictions enabling the identification of shocks

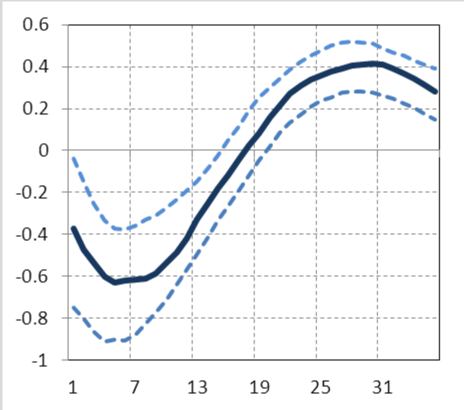
	HICP	Industrial production	Loans	bank lending spreads on NFC loans	monetary policy	Financing condition
Monetary policy shock	-	-	-		+	
Credit supply shock		-	-	+	-	-

Chart 5 Impulse response function of endogenous variables to a one standard deviation shock in credit supply conditions corresponding to a tightening

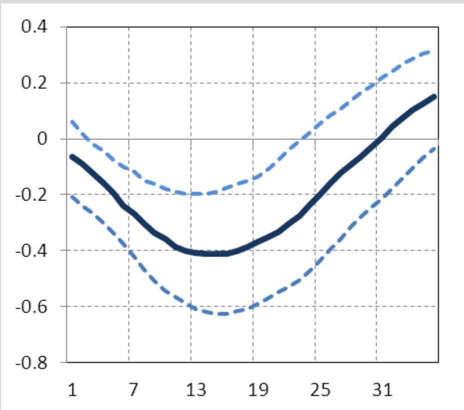
a) HICP



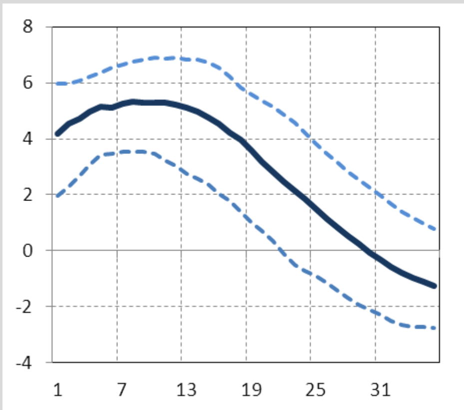
b) Manufacturing production



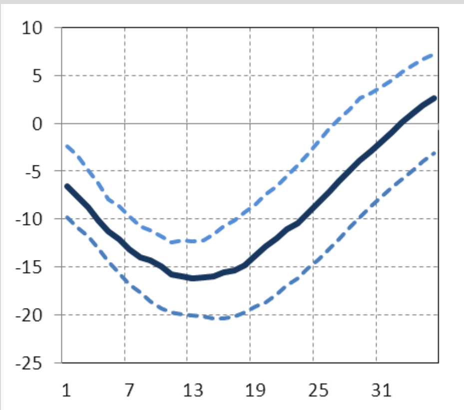
c) MFI loans to NFCs



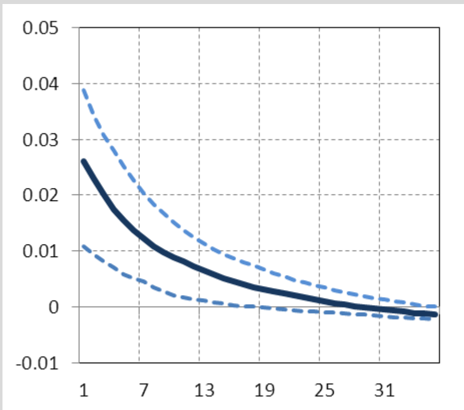
d) Bank lending spreads



e) EURIBOR 3 months



f) Financing Condition Index

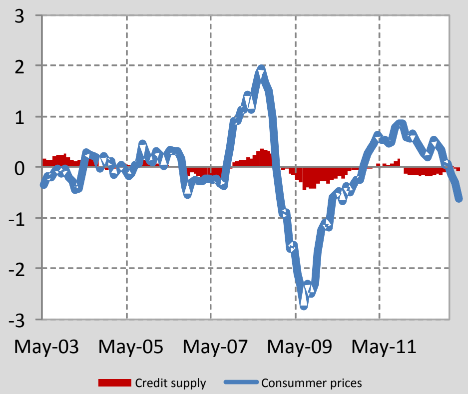


Note: Based on a VAR comprising the annual growth rate of manufacturing production, HICP, and bank loans to NFCs, as well as bank lending spreads on loans to NFCs, the 3-month EURIBOR, and the FCI. The shocks are identified with sign restrictions (see Table 2). The response of HICP inflation, manufacturing production and loans are expressed in percentage points of annual growth while the EURIBOR and the bank lending spreads are reported in basis points.

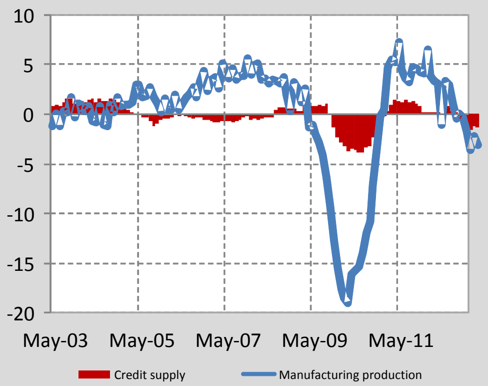
Chart 6 Contribution of credit supply shocks

(de-meaned variables)

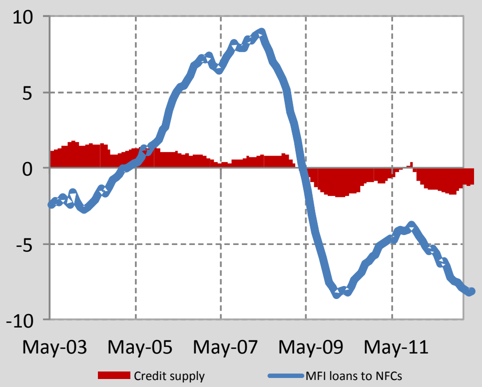
a) HICP



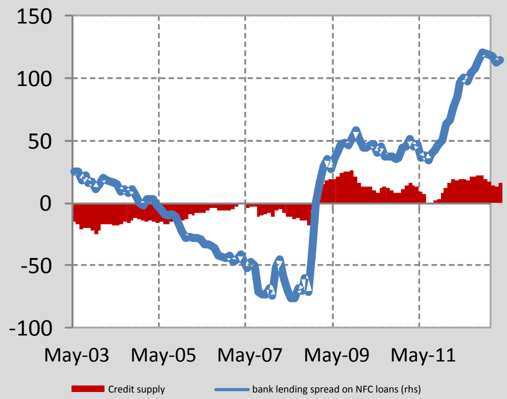
b) Manufacturing production



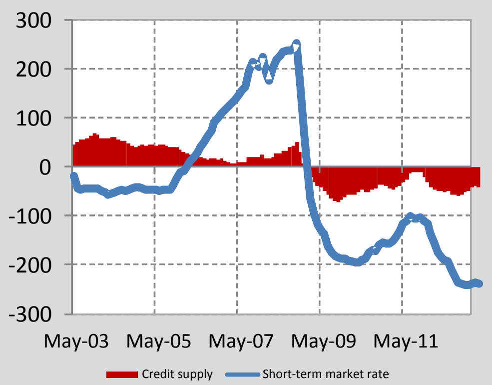
c) MFI loans to NFCs



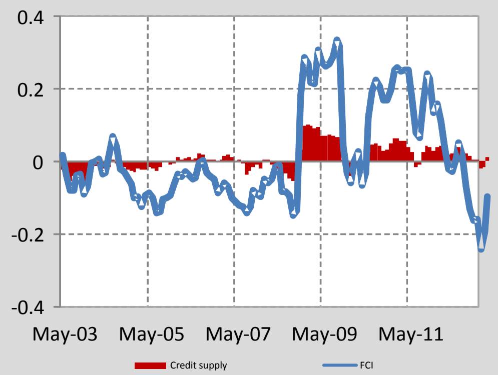
d) Bank lending spreads



e) EURIBOR 3 months

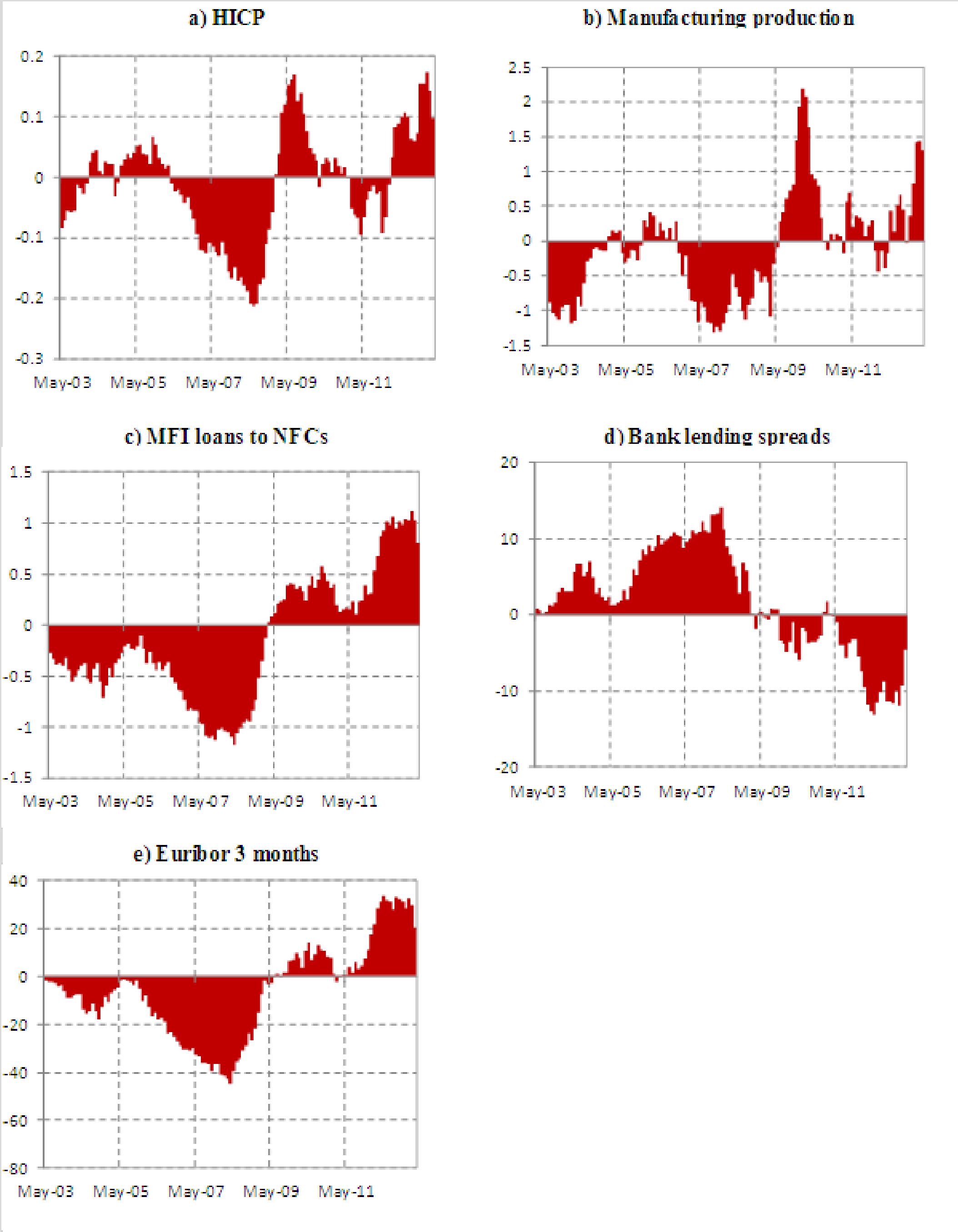


f) Financing condition index



Note: Credit supply shocks are based on a VAR comprising manufacturing production, HICP inflation, bank loans to NFCs, the 3-month EURIBOR, the bank lending spreads on loans to NFCs and the FCI. The shocks are identified with sign restrictions (see Table 2). In the charts, all the variables are de-meaned. HICP inflation, manufacturing production and loans are expressed in percentage points while the EURIBOR and the bank lending spreads are reported in basis points.

Chart 7 **Difference in the contribution of credit supply shocks between the model identified with and without the FCI**



Note: Based on a VAR comprising manufacturing production, HICCP, 3-month EURIBOR, bank loans to NFCs, bank lending spreads on loans to NFCs and the FCI. The shocks are identified with sign restrictions (see Table 2). In the charts, all the variables are de-meaned. HICP inflation, manufacturing production and loans are expressed in percentage points while the EURIBOR and the bank lending spreads are reported in basis points.

Table 3	Contribution of credit supply shocks to the variance of the forecast error (%)					
	HICP	Manuf. prod.	NFC loans	bank lending spread	EURIBOR 3 month	FCI
t=0	19	22	20	30	34	0
	19	19	16	24	36	17
1 qtr ahead	21	28	26	39	43	0
	21	26	21	33	42	15
1 year ahead	23	26	28	37	44	0
	23	23	23	32	39	15
2 years ahead	22	26	21	25	30	0
	22	24	18	21	27	15
3 years ahead	23	26	19	21	24	0
	22	23	17	19	22	15

Note: For every forecast horizon, the first line reports the results corresponding to the model excluding the FCI while the second line is based on the model incorporating financing conditions among the regressors.

ANNEX 2 LITERATURE REVIEW

Authors	St. Louis Fed's Financial Stress Index (STLFSI)	Chicago Fed National Financial Conditions Index (NFCI)	ECB global index of financial turbulence (GIFT)
Countries	United States	United States	The world's 29 main economies.
Period	Since 1993	The longest time series extends back to 1971, while the shortest begins in 2008.	Since 1994
Frequency	Weekly data	Mixed frequency: uses weekly, monthly and quarterly data to construct weekly index.	Monthly data
Variables	Interest rates (effective fed funds rate, treasury yields, corporate bond yields), yield spreads (yield curve, corporate bond spreads, counterparty risk, TED spread) and other Indicators (emerging market bond index, stock and bond market volatility, breakeven inflation rate, stocks of financial institutions). 18 weekly data series in total. Each variable is first standardised.	Money markets (interest rate spreads, implied volatility, trading volumes of money market products), debt and equity markets (equity and bond price measures capturing volatility and risk premium, residential and commercial real estate prices, municipal and corporate bonds, stocks, asset-backed securities, and credit derivative market volumes) and the banking system (survey-based measures of credit availability, accounting-based measures for commercial and shadow banks, interest rate spreads). 100 financial indicators in total.	Fixed income (term spread, TED spread and international spread), equity (stock market returns and time-varying stock return volatility) and foreign exchange markets (time-varying exchange rate volatility). Each variable is first standardised and subsequently filtered to minimise noise stemming from the highest frequencies. To ensure that the index is restricted to values in the range of 0 (low stress) to 100 (high stress), the filtered standardised time series is converted through a logistic transformation.
Methodology	The FCI is computed as the first common factor of a Principal Component Analysis implemented over the previously mentioned set of financial variables. The coefficients are scaled so that the index has a unit standard deviation.	The index is derived from a large approximate dynamic factor framework estimated with the Kalman Filter. Because of the varying frequencies of the data the Kalman filter is modified to deal with missing values and includes additional state variables that evolve deterministically to adjust for the temporal aggregation issues caused by the varying frequencies of data. The index itself is standardised.	The index is constructed as a variance-weighted average of sub-indices associated with stress in the corresponding market sub-segment. For each market and economy, regional market-specific indices are calculated by taking the average of the converted components. The corresponding world index is a weighted average of the individual country and market-specific indices.
Missing data	No	Yes, due to data availability at the beginning of the sample and to publication lags.	No
Control for endogeneity	No	The underlying series that make up the financial conditions index were purged of cyclical influences.	No

Authors	IMF FSI	IMF FCI	IMF US FCI	OECD FCI
Countries	17 advanced economies	US and euro area	US	US, euro area, Japan and the UK
Period	Since 1980	Since 1994	Since 1990	Since 1990
Frequency	Monthly data	Monthly data	Quarterly data	Quarterly data
Variables	Time varying beta of bank shares, interbank-treasury spread, inverted yield gap, corporate bond spread, stock market decline and volatility, exchange rate volatility.	Spreads (government bond yield, corporate bond spread, yield curves), prices (exchange rates, stock prices, oil price), and quantities (money, NFCs' debt, securities issuance, bank credit, bank lending surveys, market capitalisation). Indicators that are not available for the entire period, such as survey data for the euro area, are backdated using the Dynamic Factor Model (see below). Each variable is first standardised.	Short term interest rates, corporate bond yields (investment grade and high yield), bank lending standards, equity prices and real exchange rate.	Bank lending standards, high yield corporate bond spread, financial and housing wealth, real short and long term interest rates and exchange rate.
Methodology	The index is constructed by taking the average of the variables after adjusting for the sample mean and standardising by the sample standard deviation. The index is then rebased so that it ranges from 0 to 100. Finally, it is converted into quarterly frequency by taking the average of the monthly data.	The FCI is computed as the first common factor of a Dynamic Factor Model (DFM) estimated over the previously mentioned set of financial variables.	A VAR model is estimated with these variables and real GDP, the GDP deflator and oil prices. The FCI is computed based on the IRFs of GDP to these variables and accounts for the timing of lagged transmission effects. The four quarter moving average of the FCI is reported.	For the United States, the weight of each variable was estimated from a reduced form econometric model (estimated over the sample 1990Q4 to 2007Q3), supplemented in some cases with coefficients calibrated from large-scale macroeconomic models. The weight of the other countries is based on judgemental calibration, using the existing US indicator as a reference point. Each FCI is calibrated so that a unit decline in the index implies a 1% reduction in the level of GDP after 4-6 quarters.
Missing data	No	Yes, due to publication lags.	No	No
Control for endogeneity	No	No	Yes, the VAR framework captures the endogenous response of financial variables to economic activity and vice versa. Shocks are identified through a Cholesky decomposition.	No

Authors	Goldman Sachs FCI	Deutsche Bank FCI	Bloomberg FCI	Citi FCI
Country	Euro area	US, euro area and Japan	US	US
Period	Since 1999	Since: 1990 (US), 1999 (euro area), 1992 (Japan)	Since 1991	Since 1984
Frequency	Quarterly data	Quarterly data	Daily data	Monthly data
Variables	Real 3-month EURIBOR, real long-term corporate bond yield, real effective exchange rate and stock market capitalisation ratio.	Changing composition across economies. For the euro area: yield curve, growth in credit to corporate and the household sector, M1 growth, stock prices, house prices, nominal trade weighted EUR. All series are standardised and defined such that an increase corresponds a tightening in financial conditions.	Three groups (sub-indices): 1) money market indicators; 2) bond market indicators; and 3) equity market indicators. Ten variables in total. Each variable (indicator) is standardised using data for the period from 1991 to mid-2008.	Corporate spreads, money supply, equity values, mortgage rates, the trade-weighted dollar and energy prices. Nominal values are deflated. Variables are normalised to have zero mean and a unit standard error.
Methodology	The change in the FCI is computed as a weighted sum of changes in the previously mentioned financial variables. The weights are computed from a regression of year-on-year GDP growth on the first difference of the previously mentioned variables.	The FCI is computed in two steps: 1) the first common factor is extracted from the previously mentioned set of financial variables using Principal Component Analysis; and 2) The FCI is computed as a weighted average of policy interest rates and the common factor of financial variables. The weights are determined according to the contributions of these two variables to real GDP growth from a single regression model that includes inflation as an additional regressor.	Each variable (indicator) in the three groups receives a weight that adds up to 1/3. An overall index (FCI) is computed as an equally weighted sum of the three sub-indices. The overall FCI is also standardised.	Weighted sum of the previously mentioned financial variables. The weights are computed as follows: 1) a reduced-form forecasting equation is estimated using a coincident indicator as a measure of economic activity and the previously mentioned financial variables as regressors; and 2) the weights are computed as the respective coefficients divided by their sum.
Missing data	No	No	No	No
Control for endogeneity	It partly controls for endogeneity, because past values of the financial variables in the regression are expected to be relatively less affected by future GDP growth.	No	No	No

Authors	Hatzius *et al.* (2010)	van Roye (2011)	Hollo *et al.* (2011)
Countries	US	Germany and euro area	Euro area
Period	Since early 1970s, depending on the variable	Since 1981 for Germany and since 1999 for the euro area, depending on the variable	Since 1999 originally, extended backwards until 1987.
Frequency	Quarterly data	Monthly data. Quarterly data interpolated to get monthly values	Weekly data, restricted to variables with a short publication lag.
Variables	45 financial variables grouped into five categories: 1) interest rate levels and spreads; 2) asset prices; 3) stock and flow quantities; 4) surveys; and 5) second moment or risk measures. The variables are made stationary and standardised.	Three groups of variables: banking sector, securities market and foreign exchange market. 23 variables for Germany and 22 for the euro area	The composite indicator of systemic stress (CISS) is build up from five sub-indices: bank and non-bank financial intermediaries, money markets, equity market, bond market and foreign exchange markets. 3 variables per group including measures of realised volatility, spreads, correlations, maximum cumulated loss, etc. Each variable is first transformed into a quintile statistics based on its cumulative distribution function. The index is extended twelve years backwards on the basis of proxy variables.
Methodology	The FCI is computed as the first principal component of the previously mentioned set of financial variables. The methodology ("approximate dynamic factor model") is implemented over an unbalanced data set. The FCI is itself standardised.	The FCI is computed as the first principal component of the previously mentioned set of financial variables. The model is an "approximate dynamic factor model" with dynamic behaviour of the common latent factor. The model is estimated over an unbalanced data set.	The FCI is computed in two steps: 1) the three variables are aggregated by taking their arithmetic mean to form each sub-index; 2) The sub-indices are aggregated on the basis of weights which reflect their time-varying cross-correlation (based on standard portfolio theory) and their average relative impact on economic activity. The resulting composite indicator of systemic stress is unit free and rests on an ordinal scale.
Missing data	Yes, due to data availability at the beginning of the sample.	Yes, due to data availability at the beginning of the sample and to publication lags.	No. The use of daily and weekly data with a short publication lag intends to make the index available in real time.
Control for endogeneity	The underlying series that make up the financial conditions index were purged of cyclical influences.	No	No

Note: STLFSI: http://research.stlouisfed.org/publications/net/NETJan2010Appendix.pdf ; Chicago Fed National Financial Conditions Index (NFCI): Brave and Butters (2011); ECB: ECB (2009); IMF FSI: IMF (2008); IMF FCI: Matheson (2012); IMF US FCI: Swiston (2008); OECD FCI: Guichard and Turner (2008) and Guichard *et al.* (2009); Goldman Sachs FCI: Bahaj *et al.* (2007); Deutsche Bank FCI: Hooper *et al.* (2007 and 2010); Bloomberg FCI: Rosenberg (2009); Citi FCI: D'Antonio (2008).

ANNEX 3 VARIABLES AND STATISTICAL TREATMENT BEFORE ESTIMATION

Banking sector				
Variable	**Description**	**Transf.**	**Source**	**Countries**
Beta Financials	Monthly average of the rolling 60-business days covariance of the daily percentage change of a country's banking sector equity index and its overall stock market index, divided by the rolling 60-business days variance of the daily percentage change of the overall stock market index.	Level	Own calculations based on data from Thompson Financial Datastream	Euro area, Germany, Italy, Spain.
Government bond term spread 1	Difference between 3-year and 2-year benchmark government bond yield.	Level	ECB	Euro area, Germany, Italy, Spain.
Government bond term spread 2	Difference between 5-year and 3-year benchmark government bond yield.	Level	ECB	Euro area, Germany, Italy, Spain.
Government bond term spread 3	Difference between 7-year and 5-year benchmark government bond yield.	Level	ECB	Euro area, Germany, Italy, Spain.
Government bond term spread 4	Difference between 10-year and 7-year benchmark government bond yield.	Level	ECB	Euro area, Germany, Italy, Spain.
Bank bond yield	Nominal bank bond yields.	Change	ECB	Euro area
Stock market return, financial institutions	Monthly stock market return of financial institutions.	Growth	Thompson Financial Datastream	Euro area, Germany, Italy, Spain.
Stock market return volatility, financial institutions	Realised volatility of stock market returns of financial institutions. Monthly average of absolute daily returns.	Level	Own calculations based on data from Thompson Financial Datastream	Euro area, Germany, Italy, Spain.
MFI loans to HHs for house purchase	MFIs loans to households for house purchase, total maturity, all currencies combined. Data are working day and seasonally adjusted.	Growth	ECB	Euro area, Germany, Italy, Spain
MFI loans to HHs for consumer credit	MFIs loans to households for consumer credit, total maturity, all currencies combined. Data are working day and seasonally adjusted.	Growth	ECB	Euro area, Germany, Italy, Spain
Short-term loans to NFCs	MFIs loans to non-financial corporations of up to 1 year maturity, all currencies combined.	Growth	ECB	Euro area, Germany, Italy, Spain
Long-term loans to NFCs	MFIs loans to non-financial corporations of over 1 year maturity, all currencies combined.	Growth	ECB	Euro area, Germany, Italy, Spain

Banking sector (cont.)				
Variable	**Description**	**Transf.**	**Source**	**Countries**
Capital ratio	Capital ratio of the banking sector, defined as total capital plus reserves over total assets	Change	ECB	Euro area, German, Spain
Liquidity ratio	Liquidity ratio of the banking sector, defined as securities plus cash over total assets	Change	ECB	Euro area, German, Spain
Stock of money 1	Euro area aggregate stock of money, M1.	Growth	ECB	Euro area, Germany, Italy, Spain
Stock of money 2	Euro area aggregate stock of money, M2.	Growth	ECB	Euro area
Stock of money 3	Euro area aggregate stock of money, M3.	Growth	ECB	Euro area, Germany, Italy, Spain
Change stock of money	Difference between stock of money M3 and M2 for euro area, and M3 and M1 in Germany and Italy	Growth	ECB	Euro area, Germany, Italy, Spain
Securities issuance of MFIs	Securities issuance by monetary financial institutions excluding shares, seasonally adjusted.	Growth	ECB	Euro area, Germany, Italy, Spain
Securities issuance of financial institutions other than MFIs	Securities issuance by non-monetary financial institutions excluding shares, seasonally adjusted.	Growth	ECB	Euro area
Equity issuance by MFIs	Equity issuance by monetary and financial institutions.	Growth	ECB	Euro area, Germany, Italy, Spain
Equity issuance by non-MFIs corporations	Equity issuance by non-MFIs corporations.	Growth	ECB	Euro area
Equity issuance by non-MFI financial institutions	Equity issuance by non-MFI financial institutions	Growth	ECB	Euro area
Equity issuance by other MFIs	Equity issuance by other MFIs	Growth	ECB	Euro area
Equity issuance by other fin. inst.	Equity issuance by other financial institutions, excluding insurance corporations and pension funds.	Growth	ECB	Euro area
Bank lending rates to NFCs	Euro area (changing composition), annualised lending rate (total maturity) by monetary and financial institutions to non-financial corporations.	Change	ECB	Euro area, Germany, Italy, Spain
Bank lending rates to households for house purchase	Euro area (changing composition), annualised lending rate (total maturity) by monetary and financial institutions to households for house purchase.	Change	ECB	Euro area, Germany, Italy, Spain
Bank lending rates to households for consumption	Euro area (changing composition), annualised lending rate (total maturity) by monetary and financial institutions to households for consumption.	Change	ECB	Euro area, Germany, Italy, Spain

Fixed income markets				
Variable	**Description**	**Transf.**	**Source**	**Countries**
Bond market volatility	Realised volatility of benchmark 10-year government bond yield. Monthly average of the absolute value of daily yield changes. The German Bund is used for the euro area and Germany. National benchmark bond yields are used in the other cases.	Level	Own calculations based on data from Thompson Financial Datastream	Euro area, Germany, Italy, Spain
Securities issuance by NFCs	Securities issuance by non-financial corporations, annual rate of change	Growth	ECB	Euro area, Germany, Italy, Spain
Nominal cost of market–based debt	Nominal cost of issuing debt by non-financial corporations.	Change	ECB	Euro area
Equity markets				
Stock market return, non-financial institutions	Monthly stock market return of non-financial institutions.	Growth	Thompson Financial Datastream	Euro area, Germany, Italy, Spain.
Correlation between stock market returns and government bond yields	Monthly average of the rolling 60-business days correlation of the daily percentage change of the equity index and government bond yields.	Level	Own calculations based on data from ECB and Thompson Financial Datastream	Euro area, Germany, Italy, Spain.
Stock market volatility	Realised volatility of stock market return of non-financial institutions. Monthly average of absolute daily return.	Level	Own calculations based on data from Thompson Financial Datastream	Euro area, Germany, Italy, Spain.
Nominal cost of equity	The nominal cost of equity is calculated based on their respective amounts outstanding.	Change	ECB	Euro area
Equities issuance by NFCs	Issuance of equities by non-financial corporations.	Growth	ECB	Euro area, Germany, Italy, Spain
Foreign exchange market				
Nominal effective exchange rate	Euro area nominal effective exchange rate vis-a-vis 12 trading partners.	Growth	ECB	Euro area, Germany, Italy, Spain.
Foreign exchange rate volatility	Realised volatility of nominal effective exchange rate vis-a-vis 12 trading partners. Monthly average of absolute daily return.	Level	Own calculations based on data from ECB	Euro area, Germany, Italy, Spain.
Other variables				
Raw materials	World market price of raw materials in Euro.	Growth	ECB	Euro area, Germany, Italy, Spain.

Note: In the column Transf. “growth” is the one-month percentage change in the variable, whereas “change” is the one month change in the variable. “Level” means that the variable is included without transformation.