Money, credit, monetary policy and the business cycle in the euro area: what has changed since the crisis?

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Abstract

This paper provides VAR based evidence of the response of a large set of euro area macroeconomic and financial variables to cyclical and monetary policy shocks. It then uses the model to analyze the stability of financial intermediation after the 2008 crisis. Our key finding is that the cyclical dynamics of short-term interest rates, deposits and loans is not significantly different from that identified in the pre-crisis sample while long-term interest rates have been exceptionally high and long-term loans and deposits exceptionally low.

JEL Classification: E32, E51, E52, C32, C51.

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1 Introduction

In this paper, we establish the stylized facts about the cyclical behavior of a rich set of euro area macroeconomic, monetary and financial variables before the prolonged period of turmoil started in 2008. Cyclical characteristics of financial variables in the euro area are only partly known and it is important to uncover them, among other things, to establish a benchmark with respect to which the subsequent crisis can be analyzed. Then, we explore whether the developments in the course of the recent crises reveal a significant break in the relation between financial intermediation and the rest of the euro area and the global economy.

We assess financial intermediation by focusing on bank loans and monetary aggregates. These variables capture a partial but essential aspect of financial intermediation. Partial, because they describe only the activity of banks and exclude market financing. Essential, because of the relevant role played by banks in the euro area financial system.[1] Loans and the corresponding lending rates are disaggregated by holding sector - corporate and household mainly - and maturity. Monetary aggregates include M1, M2 and M3. In addition, we distinguish among all the categories of deposits which are part of M3. The latter include overnight deposits, saving deposits and time deposits with maturity up to two years. The bulk of these deposits is represented by retail deposits from the household and corporate sectors and they exclude the inter-bank as well as deposits at maturity longer than two years. Overall, the deposits in our data set represent approximately 30 % of the liabilities of the banking sector. Loans, on the asset side, account for a similar percentage. We also abstract from international transactions (deposits and loans to non-residents).

The empirical analysis is based on a large vector autoregressive (VAR) model. This is a flexible and general reduced form model that enables us to analyse the joint dynamics of our large set of data. The model allows us to characterize the pre-crisis cyclical behaviour of all the variables of interest, by constructing impulse response functions, and also to assess what has changed during the crisis by means of counterfactual experiments.

For the specification of the VAR, we address the high dimensional data problem by means of bayesian shrinkage, as suggested in De Mol, Giannone, and Reichlin (2008) and Banbura, Giannone, and Reichlin (2010). We validate our modelling approach by studying its out-of sample forecasting performance. Overall, we find that the model performs quite well suggesting that, by means of bayesian shrinkage, we have been able to control for over-fitting and, at the same time, to extract the relevant sample information. The methodology we adopt provides a framework for the analysis of the joint dynamics of a large panel of time series without recurring to the so-called marginal approach, which consists in estimating a small system and then adding a variable at a time (for examples of the latter modelling strategy, see Christiano, Eichenbaum, and Evans, 1996; den Haan, Sumner, and Yamashiro, 2007). The latter approach has two drawbacks, it may suffer from an omitted variables problem and makes it difficult to interpret results across models.

On the basis of the bayesian VAR model, we analyze the cyclical characteristics of our large set of variables in the pre-crisis period (January 1992 to July 2007). We perform this analysis by means of impulse response functions to two types of shocks: a monetary policy shock (which we identify recursively) and a shock which we label "cyclical", constructed as the linear combination of shocks explaining the bulk of the cyclical variation of variables describing real economic activity. The responses to the cyclical shock describe contemporaneous, leading and lagged correlations at business cycle

[1] For evidence on this point and a comparison with the US, see ECB (2008)

frequencies over the typical cycle. The comparison between responses to the monetary and cyclical shocks allows us to partly "inspect the mechanisms" underlying those cyclical correlations. The main idea is that marked differences in the responses of a specific variable in a *contraction* generated by a monetary policy and a cyclical shock, suggest that the state of the business cycle is not a relevant factor to explain the dynamics of that variable. As an example, we find that in the typical recession (i.e. in response to a negative cyclical shock), M1 increases. In order to explain the mechanisms underlying this anti-cyclical behavior, we notice that M1 exhibits the opposite behavior in a recession generated by a monetary tightening (a contractionary monetary policy shock). Hence, it is unlikely that the state of the cycle is an important factor to explain the dynamics of M1. However, we find that short-term interest rates also behave differently in a monetary contraction (in which they increase) and in the typical cyclical contraction (in which they decrease). This suggests that the anti-cyclical behavior of M1 is mostly due to the "liquidity effect", i.e. to a negative response to the short-term interest rate (for a similar analysis on US data, using a different technical approach, see den Haan, Sumner, and Yamashiro, 2007).

Once we have established the stylized facts in normal times for the euro area, we can address the question whether the recent period of turmoil was characterized by a "significant break" in the dynamic interrelationships between financial intermediation and the rest of the economy. The analysis is carried out by constructing counterfactual paths for loans, deposits and interest rates in the period August 2007 to June 2013. Such counterfactual paths correspond to those we would have observed, given (i) the pre-crisis historical regularities in the euro area and (ii) the observed behavior of real and inflation data in the course of 2007-2013. Relevant deviations of the estimated counterfactual path from actual realizations reveal anomalies in the transmission process, specific to the recent financial crisis. The pre-crisis empirical regularities are established using a sample that includes two recessions: the one experienced in the early nineties and the early millennium slowdown. Crucially, these are not episodes of major financial disruption, as it is the case in the recent crisis.

Our results reveal an interesting dichotomy between short and long-term loans and deposits. While the developments in overnight deposits, saving deposits and corporate loans with maturity of one year do not appear to reflect any "significant break", this has not been the case for deposits and loans (both to firms and households) at longer maturity. More in details, loans to households have been weaker than expected since the early phases of the financial crisis, while weaknesses in long-term loans to firms are more associated with the financial fragmentation emerged in euro area countries during the sovereign crisis. Interestingly, the observed path of the three months Euribor (an interbank interest rate, often considered as a proxy of the policy rate in empirical studies) is quite close to the median of the distribution of its counterfactual path, i.e., the interbank market rates have roughly behaved according to historical regularities with respect to the business cycle in the euro area. This contrasts with exceptionally high long-term interest rates and suggests that while the monetary policy rule describing systematic policy has been stable, the transmission mechanism after 2008 was impaired.

Our paper is related to a growing literature that studies the euro area economy. However, to our knowledge, this is the first paper studying business cycle properties of a broad set of variables representing credit markets, monetary variables and interest rates in the euro area before and in the course of the prolonged period of turmoil associated with the financial and sovereign crises. A recent paper by Peersman (2013) also studies some aspects of financial intermediation in the euro area, with the aim of assessing the role of credit shocks and without distinction of pre and post-crisis developments.

Other papers have studied the monetary transmission mechanism on euro area data before the crisis. In particular, the European Central Bank promoted a set of studies providing many interesting results (see the collection of studies in Angeloni, Kashyap, and Mojon, 2003). However, those studies were based on a sample that included only a few years into the existence of the monetary union and none of the time series studies considered our level of detailed information (in particular, see the chapters by Peersman and Smets and Mojon and Peersman). More recently, Boivin, Giannoni, and Mojon (2009) have considered multi-country models but the focus has not been on financial intermediation. On US data, the papers by Bernanke and Blinder (1992); Bernanke and Gertler (1995); Christiano, Eichenbaum, and Evans (1996); den Haan, Sumner, and Yamashiro (2007) are close to the spirit of the first part of our paper. In particular, these authors used data on disaggregated loans and some components of flow of funds data in order to characterize the credit cycle and shed some light on the "credit channel" of monetary policy. Our study, however, has a broader scope. The analysis on deposits and the monetary aggregates is of a specific interest, given the importance that the ECB attributes to these variables both as indicators of inflationary pressures and of financial risk (see, for example, Ferrero, Nobili, and Passiglia, 2007; Fischer, Lenza, Pill, and Reichlin, 2009; Stark and Papademos, 2010).[2]

Although our focus is mainly on the business cycle characteristics of the euro variables, some of the results of the paper are also related to the debate on the effects of unconventional monetary policy actions on the UK, US and euro area (see, for example Lenza, Pill, and Reichlin, 2010; Del Negro, Eggertsson, Ferrero, and Kiyotaki, 2011; Chen, Curdia, and Ferrero, 2011; Gambacorta, Hofmann, and Peersman, 2011; Peersman, 2011; Giannone, Lenza, Pill, and Reichlin, 2012; Kapetanios, Mumtaz, Stevens, and Theodoridis, 2012; Ciccarelli, Maddaloni, and Peydro, 2012). For the US, Stock and Watson (2012) investigates the stability of the cyclical characteristics of many variables during the turmoil, in similar vein to our study.

The structure of the paper is as follows. Section 2 describes the database, the model specification and reports the results of our empirical validation exercise, based on an out-of-sample forecasting evaluation. Section 3 describes the stylized facts on the functioning of the euro area by looking at the responses to monetary policy and cyclical shocks in the pre-crisis period. Section 4 analyzes the crisis. Section 5 concludes.

2 Data and model specification

2.1 Data

The data-set includes 39 monthly macroeconomic, financial, monetary and credit variables in the sample January 1992 to June 2013. We also include selected variables for the US, in order to capture international linkages. Table 1 in the subsection 2.3 provides precise variables definitions.

The macroeconomic block includes measures of real activity (industrial production and the unemployment rate) and prices (consumer prices, HICP, and producer prices) for the euro area. We also include US industrial production and consumer

[2]The model developed in this paper is the basis of regular policy briefing at the European Central Bank and has been part of a project for the enhancing of monetary analysis in that institution.

prices.

The three-months Euribor and the FED funds rates are our proxies for the policy rate in the euro area and the US, respectively. The rest of the financial block includes interest rates on government bonds at different maturities, euro area stock prices and the US dollar/euro exchange rate.

Since, as mentioned in the introduction, the euro area financial system is mainly based on banks, bank deposits and loans represent an important component of financial intermediation and can be particularly informative about the role of the financial sector in the transmission of shocks. For this reason, we include rich monetary and credit blocks in our database.

For what concerns the monetary block, the database includes the three main euro area monetary aggregates. The narrowest aggregate, M1, includes currency in circulation and overnight deposits. M2 consists of M1 plus time deposits (i.e. deposits with an agreed maturity of up to 2 years) and saving deposits (i.e. deposits redeemable with a notice of up to 3 months). We also include (see the last eight variables in table 1) a disaggregation of time and saving deposits by holding category, i.e. we distinguish among saving and time deposits held by households (HH), non-financial corporations (NFC), insurance companies and pension funds (ICPF) and other financial institutions (OFI).[3] Finally, M3 consists of M2 plus repurchase agreements (repo), money market funds shares and debt securities issued with a maturity of up to 2 years.

Loans to the private sector are decomposed into those to non-financial corporations and those to households. Moreover, we distinguish between loans to non-financial corporations up to one year (short-term) and above one year (long-term). Loans to households, instead, are further decomposed according to their purpose: consumer loans, loans for house purchases and other loans. We also include the lending rates for different types of loans, whenever available, i.e. for short-term loans to non-financial corporations, loans for house purchases and consumer loans.[4]

2.2 The model

Let X_t be the vector including the n variables defined in table 1 (all variables enter the empirical model in terms of log-levels, except for variables expressed in rates or with negative levels, that enter in levels). We estimate a VAR model with p (=13) lags:

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} ... + A_p X_{t-p} + \epsilon_t$$

where ϵ_t is a normally distributed multivariate white noise with covariance matrix Σ.

The large dimension ($n = 39$ and $p = 13$) of our VAR model implies that we face an issue of over-fitting, owing to the large number of parameters (the so-called "curse of dimensionality"). We address this issue by shrinking the parameters toward those of the naïve and parsimonious random walk with drift model, $X_{i,t} = \delta_i + X_{i,t-1} + e_{i,t}$. De Mol, Giannone,

[3] OFI are financial institutions not classifiable as monetary and financial institutions (MFI; in practice, banks) or insurance companies and pension funds

[4] We thank Christoffer Kok Sorensen for sharing with us the data on the lending rates used in Kok Sorensen and Werner (2006).

and Reichlin (2008) and Banbura, Giannone, and Reichlin (2010) have shown that this approach reduces estimation uncertainty without introducing substantial bias. This is achieved thanks to the tendency for macroeconomic time series to co-move over the business cycle, which creates scope for the data to point "massively" in the same direction against a naïve prior model that does not allow for any dynamic interaction. The resulting model offers a parsimonious but reliable estimate of the complex dynamic interactions among the macro, monetary and financial variables included in the data set.

More specifically, we use a Normal-Inverted Wishart prior centered on a random walk model. For Σ, the covariance matrix of the residuals, we use an inverted Wishart prior distribution with scale parameter given by a diagonal matrix Ψ and $d = n + 2$ degrees of freedom. This is the minimum number of degrees of freedom that guarantees the existence of the prior mean of Σ, which is equal to $\Psi/(d - n - 1) = \Psi$.

For the constant A_0 term, we use a flat prior. For the autoregressive coefficients (A_1 ... A_p), we use the Minnesota and the sum of coefficients priors, as originally proposed by Litterman (1980) and Doan, Litterman, and Sims (1984), respectively.

As regards the Minnesota prior, conditional on the covariance matrix of the residuals, the prior distribution of the autoregressive coefficients is normal with the following means and variances:

$E(A_1) = I_n$ while $E(A_2) = ... = E(A_p) = 0_{n,n}$

$Cov[(A_s)_{i,j}, (A_r)_{h,m} \mid \Sigma] = (\frac{\lambda^2 \Sigma_{i,h}}{c^2 \ \Psi_{j,j}})$ if $m = j$ and $r = s$, zero otherwise.

Notice that the variance of these prior distributions decays with the lag, and that coefficients associated with the same variables and lags in different equations are allowed to be correlated. The key hyperparameter is λ, which controls the scale of all the prior variances and covariances, and effectively determines the overall tightness of this prior. For $\lambda = 0$ the posterior equals the prior and the data do not influence the estimates. If $\lambda \to \infty$, on the other hand, the posterior expectations coincide with the Ordinary Least Squares (OLS) estimates. The factor $1/c^2$ is the rate at which the prior variance decreases with increasing lag length and $\frac{\Sigma_{i,h}}{\Psi_{j,j}}$ accounts for the different scale and variability of the data.

The sum of coefficients prior, which we additionally impose on the autoregressive coefficients, is a simple modification of the Minnesota prior involving linear combinations of the VAR coefficients. More precisely, rewrite the VAR equation in error correction form:

$$\Delta X_t = A_0 + (I_n - A_1 - ... - A_p)X_{t-1} + B_1 \Delta X_{t-1} + \ + B_p \Delta X_{t-p+1} + \epsilon_t$$

.

A VAR in first differences implies the restriction $(I_n - A_1 - ... - A_p) = 0$. We follow Doan et al. (1984) and set a prior that shrinks $\Pi = (I_n - A_1 - ... - A_p)$ towards zero. This can be understood as "inexact differencing". In the literature it is usually implemented by adding dummy observations. The tightness of this additional prior is controlled by the hyperparameter μ. As μ goes to infinity the prior becomes diffuse while, as μ goes to 0, we approach the case of exact differencing which implies the presence of a unit root in each equation.

Summing up, the setting of these priors depends on the hyperparameters λ and μ, which reflect the informativeness of the prior distribution for the model's coefficients. These parameters are usually set on the basis of subjective considerations or rules of thumb. We follow a more formal approach proposed by Banbura, Giannone, and Lenza (2014). This involves treating the coefficients of the prior as additional parameters, in the spirit of hierarchical modeling. In this paper, we use improper flat distributions as hyperpriors and, for simplicity, do we do not account for uncertainty on hyperparameters and set them at their posterior mode. This strategy amounts to estimating hyperparameters by maximizing the marginal likelihood (i.e. their posterior under a flat hyperprior) and is an empirical Bayes method. Given the hyperparameters, the VAR coefficients can then be drawn from their posterior distribution, which is Normal/Inverse-Wishart.

2.3 Model performance: forecast evaluation

Before presenting our main empirical results, we run a recursive out-of-sample forecasting evaluation, for the purpose of model validation. Since the size of our model is very large, we want to make sure that we are not over-fitting the data. In that case, forecasting performance would be poor.

We start by estimating the model from January 1992 to December 1998, produce a forecast and then we iterate the procedure by recursively updating our estimation sample by one month until the end of the sample. We consider two forecasting horizons: three and twelve months for which the evaluation samples are, respectively, March 1999 - June 2013 and December 1999 - June 2013.[5]

Results are reported in terms of the ratio of the Mean Squared Forecast Errors (MSFE) of the VAR model versus the MSFE of the prior model, which is the random walk model in levels with drift. Numbers smaller than one imply that our model improves over the prior model, showing that our procedure is able to extract information from the sample.

Table 1 below reports, in each column, variable definition, transformations and the MSFEs ratios for the forecast horizon of three and twelve months ahead. The last three columns report the values of each series at the beginning of 1999, 2008 and in the last month of our sample.

Table 1. Database

[5]Define as X_t our generic variable and h the forecasting horizon. Our target variable in the forecasting exercise is the h-period annualized change $x_t^h = \frac{12}{h} \times (log(X_{t+h}) - log(X_t))$ for variables which enter the model in log-levels and $x_t^h = \frac{12}{h} \times (X_{t+h} - X_t)$, for variables that enter in levels.

Variables	Transformation	Ratio vs RW		Value			
		h=3	h=12	Units	Jan 99	Jan 08	Jun 13
1 Industrial Production	log-levels	0.71	0.85	ind	94.09	113.90	98.74
2 HICP	log-levels	1.15	1.88	ind	86.96	106.44	117.23
3 Unemployment rate	levels	0.30	0.45	ppt	9.91	7.35	12.11
4 Producer Prices Index	log-levels	0.85	1.41	ind	76.83	99.61	108.12
5 US Industrial Production	log-levels	0.53	0.59	ind	91.00	105.3	103.95
6 US Consumer Prices Index	log-levels	1.13	1.56	ind	84.34	108.64	119.28
7 US Federal Funds rate	levels	0.60	0.76	ppt	4.63	3.94	0.09
8 Euribor 3 months	levels	0.61	0.96	ppt	3.13	4.48	0.21
9 Consumer Confidence	levels	0.79	0.80	bal	-1.80	-11.4	-18.80
10 World price of raw materials (euro)	log-levels	1.15	1.57	ind	24.00	100.1	118.50
11 Oil price (euro)	log-levels	1.17	1.61	ind	16.50	103.3	126.80
12 US/euro exchange rate	log-levels	1.28	1.58	$\$/e$	1.14	1.49	1.31
13 Stock Prices	log-levels	0.98	0.91	ind	307.20	380.15	268.27
14 2 years bond rate	levels	1.45	2.31	ppt	3.00	3.74	1.05
15 3 years bond rate	levels	1.23	1.53	ppt	3.09	3.75	1.42
16 5 years bond rate	levels	1.33	1.63	ppt	3.30	3.86	1.88
17 7 years bond rate	levels	1.33	1.63	ppt	3.64	3.97	2.31
18 10 years bond rate	levels	1.20	1.54	ppt	3.82	4.23	3.07
19 M1	log-levels	1.04	1.34	€bl	1970	3854	5212
20 M2	log-levels	0.78	0.85	€bl	4028	7406	8261
21 M3	log-levels	0.63	0.72	€bl	4608	8756	9958
22 Own rate of return, M1	levels	0.32	0.89	ppt	0.61	0.89	0.08
23 Own rate of return, M3	levels	0.34	0.70	ppt	1.74	2.36	0.16
24 Loans to non-financial corporations up to 1 year	log-levels	0.41	0.36	€bl	820	1295	1171
25 Loans to non-financial corporations over 1 year	log-levels	0.25	0.28	€bl	1388	3163	3444
26 Consumer loans	log-levels	0.43	0.41	€bl	383	623	581
27 Loans for house purchases	log-levels	0.26	0.40	€bl	1557	3449	3815
28 Other loans	log-levels	1.13	1.12	€bl	641	759	809
29 Lending rate, loans to NFC up to 1 year	levels	0.47	0.98	ppt	4.94	5.76	3.44
30 Lending rate, consumer loans	levels	0.66	0.76	ppt	7.96	8.06	6.66
31 Lending rate, loans for house purchases	levels	0.69	1.18	ppt	5.44	5.11	3.01
32 Saving deposits of households	log-levels	0.51	0.78	€bl	1142	1464	1973
33 Saving deposits of NFC	log-levels	0.73	0.92	€bl	18	29.54	86
34 Saving deposits of ICPF	log-levels	1.07	0.87	€bl	1	1.48	6.2
35 Saving deposits of OFI	log-levels	1.16	1.50	€bl	2.3	12.84	7.74
36 Time deposits of households	log-levels	0.18	0.46	€bl	577	1064	915
37 Time deposits of NFC	log-levels	0.85	0.94	€bl	205	477	385
38 Time deposits of ICPF	log-levels	1.17	1.28	€bl	30.49	76.93	80.02
39 Time deposits of OFI	log-levels	0.82	0.76	€bl	85.09	337	209.2

Note: OFI: other financial institutions; NFC: non-financial corporations; ICPF: insurance companies and pension funds; bl: billions; ppt: percentage points; ind: index number; bal: balance of positive and negative replies to surveys on economic conditions in the euro area.

Overall, the model performs quite well suggesting that, by means of bayesian shrinkage, we have been able to control for over-fitting and, at the same time, to extract the relevant information from the data at our disposal. In particular, it improves on the random walk with drift for all real variables, loans, deposits, the euribor and lending rates. For consumer prices, commodity prices, exchange rates and financial prices (i.e. the yield curve and stock prices) the random walk forecasts are more difficult to outperform. This is not surprising, given the wide empirical evidence on the unpredictability of these variables (see, among others, Campbell, Lo, and MacKinlay, 1997; Kilian and Taylor, 2003; D'Agostino, Giannone, and Surico, 2006; Stock and Watson, 2006; Fischer, Lenza, Pill, and Reichlin, 2009).

These results give support to our approach of modeling the variables simultaneously within a single large model.

2.4 Empirical exercises

The VAR model is used to establish stylized facts for the period prior to the last crisis and, then, to identify anomalies during the crisis. The pre-crisis sample is January 1992 - July 2007.

Pre-crisis stylized facts

Stylized facts are established by the estimation of impulse response functions to two sets of identified shocks. We aim not only at *assessing* but also, to the extent possible, at *interpreting* business cycle features of key monetary and credit aggregates.

The main tools to describe the business cycle features of key monetary and credit aggregates are their impulse response functions to a "cyclical shock", i.e., the shock that accounts for the bulk of business cycle fluctuations. More precisely, we define the business cycle shock as the linear combination of orthogonal shocks that captures the maximum variance of unemployment at business cycle frequencies (i.e. those related to cycles with a period of length between two and eight years).[6] The impulse response functions to this shock describe the unconditional correlations over the "typical" business cycle. Essentially, a cyclical shock is a perturbation of the system by those combinations of shocks which have generated the bulk of business cycle correlations. This is a "statistical identification", a device for extracting information on the cross correlations of the series of interest at business cycle frequencies which also preserves information on lead-lag relations.

The "monetary policy shock" is identified by assuming a recursive (Choleski) structure (see Christiano, Eichenbaum, and Evans, 1999, for a discussion of this identification scheme) where the assumption is that, before the Lehman collapse, the three-months euribor was a good proxy for the policy rate. The recursive ordering we adopt is reported in Table 1 in the previous sub-section. The indicators of euro area economic activity and prices and the US variables, i.e., the seven variables ordered above the euribor in table 1, are assumed to react to the monetary policy shock only after one month. Financial variables, instead, ordered below the euribor in table 1, are allowed to react instantaneously to the monetary policy shock. Alternatively, this identification scheme can be seen as assuming that systematic monetary policy can react to financial markets only after one month, while no delay is imposed to the response to prices and economic activity.

The comparison between the two sets of impulse responses allows us to establish whether cyclical shocks propagate primarily through changes in the interest rates or whether they have pure real effects, as explained in the introduction.

In fact, anticipating some of the results, due to the systematic monetary policy, short-term interest rates are generally highly pro-cyclical while the the term-spread (i.e., the difference between long-term bond rates and the short-term interest rates) is unresponsive to the cycle. On the other hand, the monetary policy shock generates a counter-cyclical behaviour of the short-term interest rate and a cyclical behavior of the term-spread.

[6] See the technical appendix at the end of the paper for details on the implementation. Our approach is very similar to that of Di Cecio and Owyang (2010). Other popular procedures to identify business cycle shocks as those in Uhlig (2004) and Giannone, Reichlin, and Sala (2005) can be seen as special cases of our procedure in that they pick those shocks that maximize the explainable variance at *all* frequencies.

Hence, by comparing the responses of the variables in a cyclical contraction with those in a monetary contraction we can, at least partly, assess the sign and the magnitude of interest rates versus pure real effects in explaining their dynamics. For example, marked differences in the responses of a specific variable in the two different types of contraction, both characterized by a recessionary scenario, indicate that the state of the business cycle is not the most relevant variable to explain the dynamics of that variable.

The crisis

After having established the pre-crisis facts, we proceed to ask whether the crisis has induced changes in the structure of correlations among the variables in our system. To this end, we compare the observed developments in monetary and credit markets with those implied by pre-crisis correlations and the observed real economic developments. In order to assess the developments in monetary and credit market implied by pre-crisis correlations and the observed real economic developments, we perform a counterfactual scenario analysis for the period ranging from August 2007 until June 2013. The counterfactuals are constructed as follows:

1. We use the same coefficients estimated in the previous section, i.e. using the sample January 1992 - July 2007.
2. We assume that the euro area industrial production and unemployment and US industrial production are known for the whole sample, while all other variables are only observed until July 2007.
3. We compute the conditional expectations for all variables and for the period August 2007 - June 2013 based on the pre-crisis VAR coefficients (see step 1) and the knowledge of euro area and US real activity developments in the whole sample (see step 2).[7]

Notice that the coefficients of the model are kept fixed at the pre-crisis value. Therefore, by conditioning on the observed real economic activity behavior during the crisis, we are identifying the most likely shocks that could have generated the great recession under the assumption of no substantial change neither in the average features of the shocks (this is because the covariance matrix of the forecast errors is kept fixed) nor in the dynamic interdependence, as captured by the autoregressive coefficients. If the crisis had induced substantial structural changes or it had been generated by shocks of unprecedented nature, we would identify a large difference between observed and counterfactual dynamics.

3 Results

3.1 Stylized facts before the crisis: 1992-2007

In this section, we analyze the impulse response functions to the cyclical and monetary policy shocks for the period ranging from January 1992 to July 2007.

[7] The conditional expectations are computed by means of the simulation smoother described in **?** and based on Carter and Kohn (1994).

We report the responses to one standard deviation shocks corresponding to a cyclical contraction and a monetary policy tightening. Results refer to the median, 16% and 84% quantiles of the distribution of the impulse responses of the log-levels or, for the variables expressed in rates, of levels. We report results for an horizon of up to 24 months after the shocks.

Figure 1 reports the complete set of results for impulse responses to the business cycle and monetary policy shocks.

INSERT FIGURE 1 HERE

Perhaps surprisingly, the effects of monetary policy shocks in the euro area are very similar, at least in qualitative terms, to those found for the US. In particular, in response to a monetary contraction, we estimate a protracted decline in real activity associated to a similar development in consumer confidence, a drop in the narrow monetary aggregate M1 (defined as "liquidity effect"), an appreciation of the euro with respect to the dollar, while stock prices decline. Turning to prices, we find that consumer prices (HICP) hardly move, while production prices (PPI) decline after a few months (for early findings on some of these features, see Peersman and Smets, 2003).

Responses to the cyclical shocks cannot be directly compared with any study on the US, but results for macro-economic variables, interest rates, exchange rates and stock prices reflect the narrative of typical recessions: industrial production is pro-cyclical and so are consumer confidence, production prices and stock prices. Unemployment is anti-cyclical and so is the exchange rate (the euro depreciates in response to a cyclical contraction). HICP declines with a delay. Interestingly, stock prices decline in response to both a monetary and cyclical contraction while the euro appreciates in response to the former and depreciates in response to the latter.

Let us now turn to the responses of interest rates, loans and deposits, which are the variables we focus on in the analysis of the crisis provided in the next section.

Starting with interest rates, in response to a cyclical contraction, we observe a negative and slightly lagged response of the short-term interest rate (three-months euribor), reflecting the systematic response of monetary policy to the cyclical contraction. On the contrary, when the decline in industrial production is generated by an exogenous monetary tightening, we observe an increase in the short-term rates. In response to a cyclical contraction, the decline of long-term interest rates (government bond returns with maturities from two to ten years) is of the same magnitude as the decline in short-term interest rates and the shape of the yield curve is unaffected. On the contrary, the anticipated temporary nature of the increase in short-term interest rates in a monetary tightening implies that long-term rates move in the same direction as the policy rate, but considerably less. This implies that, in the aftermath of a monetary tightening, the spread between long and short rates *declines* while it is *unaffected* in a cyclical contraction. Figure 2 zooms on the responses of industrial production the short and the long-term interest rates.

INSERT FIGURE 2 HERE

Table 2 below summarizes, in a very stylized way, the prevailing signs of the response of industrial production (y_t, proxy for real economic activity), short-term interest rates (i_t, proxy for the policy rate) and the term-spread (s_t, defined as long-term interest rates minus short-term interest rates) to the two shocks. The sign = indicates that a variable does not move in reaction to a shock, + indicates an increase, − a decrease. The signs are reported for a normalization of the shocks corresponding to a contraction in real economic activity

Table 2: Signs of the reaction of selected variables to the two identified shocks

Variable	y_t	i_t	s_t
Cyclical shock	-	-	=
Monetary policy shock	-	+	-

Results show the different responses of short-term interest rates and the term-spread in the two different types of contraction, cyclical and monetary. We use this heterogeneity to interpret our results. If the dynamics of a given variable is mainly driven by real economic developments, then we should expect it to behave similarly in the cyclical and the monetary contractions, both characterized by a decline in economic activity. Conversely, if interest rate effects are prominent in explaining the dynamics of such variable, we should expect marked differences in the response to the two shocks.

Monetary aggregates

The response of narrow money, M1, which includes currency and overnight deposits, is not the same for the two shocks, suggesting that interest rate effects dominate cyclical effects in determining its behavior. In anticipation of a cyclical contraction, M1 declines in the very short run, but after few months it becomes counter-cyclical. In response to a monetary contraction, we observe a persistent decline. Hence, M1 is negatively correlated with the policy rate, conditionally on both shocks. This suggests that narrow money is mainly driven by interest rate changes with a strong liquidity effect. These results shed light on the otherwise puzzling fact that the unconditional correlation between the growth rate of M1 and that of industrial production is negative (see figure 3, panel *a*). When economic activity weakens, the short-term interest rate responds negatively and with a lag. Contemporaneously to that negative response, we have an increase in M1 growth due to a strong liquidity effect and, since the effect of the slow-down in activity on M1 is small, unconditionally we observe a negative correlation between activity and M1 growth.

INSERT FIGURE 3 HERE

M2-M1 includes saving and time deposits, an important component of liabilities of financial institutions. M3-M1 includes, in addition, repos, shares of money market funds and debt securities with maturity up to two years.[8]

[8] M2-M1 is of about the same magnitude of M1 and accounts for between 40 and 48 % of the whole M3 while the M3-M2 component is smaller, i.e. between 11 and 15% of M3.

As in the case of M1, the response of M2-M1 and M3-M1 to a cyclical contraction is different from the response to a monetary contraction. This, once again, may suggest that the state of the business cycle is not the enough to account for the developments in these variables. However, the cyclical behavior of M2-M1 and M3-M1 is very different from that of M1: the response to a cyclical contraction is almost muted in the first 10 months and then becomes negative while the correlation with economic activity is negative in response to a monetary contraction. Moreover, the correlation with the interest rate is always positive, independently from the nature of the shock. These results indicate that interest rate effects and portfolio considerations are the main drivers of broad money.

In fact, although the short-term rate we consider, the three-months Euribor, is only an imperfect proxy for the returns on M2 minus M1 and M3 minus M1[9], the positive spread opening up between short-term rates and longer-term bond rates, implies that short-term monetary assets (especially time-deposits) tend to earn a higher return than longer-term non-monetary assets (e.g. government bonds) in the aftermath of a monetary tightening. This may explain the increase in the holdings of M2-M1 and M3-M1 in the aftermath of an exogenous monetary tightening. Conversely, the shape of the yield curve is not affected in response to a cyclical contraction. Therefore, in this case, holding short-term monetary assets does not become particularly attractive with respect to alternative, longer term investments.

The implication of our finding is that unlike M1, which is counter-cyclical, M3 and M2 are not very correlated with the cycle, while they are inversely related to the term spreads (see figure 3, panel *b*). In order to understand which components of broad monetary aggregates explain this behavior and to interpret the findings, we extend our analysis to a higher degree of granularity and look at saving and time deposits, and, later, at the main determinants of their holdings.[10]

Results show that the M3-M1 and M2-M1 mainly reflect the dynamics of time deposits for all holders. In fact, as M3-M1 and M2-M1, time-deposits are positively correlated with the short-term interest rates. Saving deposits, instead, are mainly driven by the liquidity effect. This is explained by the fact that saving deposits have shorter maturity than time-deposits and, hence, behave very similarly to the overnight deposits in M1. Conversely, the decision of holding time deposits, which have longer maturities than saving deposits, are dominated by portfolio considerations: higher short-term rates imply higher returns for time deposits which, everything else equal, should induce substitution from other, non-monetary, asset holdings.

Loans and lending rates

All loans are pro-cyclical. However, short term corporate loans show a delayed response. This explains why loans to non financial corporations lag the business cycle (see figure 3, panel *c*). This result has important implications for the current discussion on banking regulation. Some of the leading proposals on financial reforms suggesting to use quantities based on loans as early warning for financial stability risks are likely to be ineffective, since loans provide a delayed signal for those risks (for a discussion on these issues, see Repullo and Saurina, 2011). Loans respond more to real variables than to lending rates since they are pro-cyclical whether or not the latter decline (non-monetary contraction) or increase

[9] M2 and M3 consist mainly of deposit and deposit rates are not available for the full sample we consider.

[10] Saving deposits and time deposits have more or less equal share in M2-M1 and saving deposits are more liquid. In terms of holding sectors, the most sizable components are deposits to households and non-financial corporations which account for 90-95% of total deposits in M2-M1.

(monetary contraction). However, there is a significant exception: short term loans to non financial corporations, on impact, react positively to a monetary contraction indicating that interest rate effects dominate in the short-run. This feature has also been found in US data by Gertler and Gilchrist (1995) and more recently by den Haan, Sumner, and Yamashiro (2007). One possible interpretation of this finding, in line with the discussion in den Haan, Sumner, and Yamashiro (2007), is that an increase in interest rates induces banks to re-balance their loans portfolio in favor of more profitable and less risky short-term corporate loans, reducing the stock of loans to households. Another explanation for this finding is that, faced by a monetary tightening which puts pressure on the cost of lending, firms may be encouraged to draw-down their credit lines with banks at a previously lower bargained cost. Finally, Gertler and Gilchrist (1995) argue that the demand of loans may increase in an economic recession due to the need of firms to make up for the squeeze in their cash flows.

Our identification strategy, based on the comparison between a monetary and a cyclical contraction, may help to shed light on the relative merits of the three interpretations. If the temporary increase in loans were due to demand effects (as advocated by Gertler and Gilchrist, 1995) while interest rate effects played no role, we would expect such temporary increase in loans to appear also in the case of a cyclical contraction, which contradicts our findings.

Finally, turning to the costs of lending, we find that the responses of lending rates in both types of contractions bear some similarity to those of the short-term interest rates, but they are stickier, in particular those for consumer loans.[11]

Variance decompositions

Figure 4 reports the percentage of the variance at business cycle frequencies accounted for by the two shocks just described. In particular, we report the median (red dots) and the 16th and 84th quantiles (black lines) of the distribution of the share of variance accounted for by the cyclical shock and the median of the distribution of the share of variance accounted for by the monetary policy shock (blue bars).

INSERT FIGURE 4 HERE

The monetary policy shock does not appear to be an important driver of business cycle fluctuations. On average across variables, it explains less than 5% of the variance at business cycle frequencies and it accounts for more than 10% only for the short-term interest rate and the rate of return on M3.

The cyclical shock, instead, explains, on average across variables, about 30% of the variance at business cycle frequencies (at the median). As highlighted already in figure 3, loans are very cyclical variables and, in fact, the median share of the variance accounted for by the cyclical shock lies between 40% and 50%. Among monetary aggregates, the share of the variance at business cycle frequencies accounted for M1 by the cyclical shock is about 30%, while it is considerably lower for broader monetary aggregates.

[11] For a survey of studies on the stickiness of lending rates, see Kok Sorensen and Werner (2006)

4 The financial and sovereign crises in the euro area

For the analysis of the financial and sovereign crises, we focus on loans, deposits and interest rates.[12] We use the facts we established in the previous section and assess whether the relationships we uncovered remain robust, once we control for the unprecedented size of business cycle shocks. We address this question by performing the counterfactual exercises described in section 2.

More precisely, we first compute conditional expectations of the variables of interest on the basis of historical (pre-crisis, the VAR model is estimated with data until July 2007) correlations and the realized path of variables representing business cycle conditions.[13] By conditioning on real economy variables, we capture the size of the shocks that would have caused the recent recessions *if they were due to the shocks that have typically generated recessions in the euro area.* For example, if exogenous shocks to credit supply were traditionally associated to a recession in the euro area, we would be implicitly conditioning also on those shocks.

Then, we compare the conditional expectations of the variables of interest with their actual developments from August 2007 onward, in order to assess whether the developments in such variables are in line with historical regularities. Significant differences between expected and observed developments may signal that either different shocks from those traditionally prevailing to explain the dynamics of the variables of interest have materialized, or the relationship between the latter variables and the conditioning set has changed during the crisis.

Monetary aggregates and loans

Figure 5 reports the actual and counterfactual decomposition of the year-on-year growth rate of broad money (M3) by instrument (panel a) and by holding sector (panel b).[14]

INSERT FIGURE 5 HERE

The counterfactual on monetary aggregates shows no particularly exceptional behavior of M1 implying that overnight deposits, an important component of banks' retail funding, have been relatively resilient during the last two crises. M2 and M3, instead, have strongly declined during the crises and their developments are out of line with the historical regularities captured in our empirical model.

[12] The complete set of results is available upon request.

[13] See Giannone, Lenza, and Reichlin (2010) for an application of this idea for identifying the effects of the inception of the euro on comovement of GDP across countries.

[14] Precisely, for each component (defined as d_t), its contribution (defined as C_t) to the year-on-year growth rate of M3 (defined as m_t) is defined as:

$$C_t = \frac{d_t - d_{t-12}}{m_{t-12}}$$

Notice that the contributions exactly sum up to the growth rate of M3.

The decomposition by instruments (panel 4a) indicates that the collapse in M2 and M3 is mainly explained by the time deposits component for both households and non-financial corporations while the shorter term saving deposits move more in line with M1. Panel 4b shows the decomposition by holding sector and indicates that this dynamics is relatively broad based across sectors.

Figure 6 reports the actual and counterfactual decomposition of the growth of retail credit (i.e. the sum of bank loans to households, firms, other financial institutions and insurance company and pension funds). The decomposition is constructed by means of the same method adopted for broad money.

INSERT FIGURE 6 HERE

Remarkably, short-term loans to non-financial corporations behaved in line with past regularities. Long-term loans to non-financial corporations and loans for house purchases, on the other hand, show an exceptional decline. As for the monetary aggregates, it is the long term segment of loans which is exceptionally weak during the crisis period.

Monetary policy: euribor

Figure 7 reports the observed path of the three months Euribor and its counterfactual distribution (median and 16th and 84th quantiles).

INSERT FIGURE 7 HERE

The counterfactual path for the Euribor reflects the stance of monetary policy that would materialize, had the ECB continued to conduct its systematic standard monetary policy according to the regularities observed before the crisis. Since no constraint is imposed on the counterfactual path, nothing prevents it to cross the zero line and step into negative territory.

Interestingly, the observed path of the three months Euribor is always inside the 16th and 84th quantiles of the counterfactual forecast distribution and, in general, quite close to the median, i.e., the interbank market rates have roughly behaved according to historical regularities with respect to the business cycle in the euro area.

More in details, in the course of the global financial crisis, the median of the counterfactual distribution lies briefly below zero. However, the probability that the counterfactual interest rate remains positive was always high, going only slightly below 50% in 2009. In this probabilistic sense, the zero lower bound was not binding in the euro area. This contrasts with the US case for which Stock and Watson (2012), on the basis of a similar approach, find that the zero lower bound was indeed binding.[15]

[15] Similarly, Lombardi and Zhu (2014) define the shadow Federal Fund Rate as the predicted rate conditional on a variety of microeconomic conditions. They find that for the United States the shadow interest rate has been markedly below the observed rate, which reached the zero lower bound after the aggressive cut of the FED in response to the financial turmoil in 2008.

Bond and lending rates

In Figure 8a and 8b, we report the ten-year bond rates and the associated spread with respect to the three-month euribor.

INSERT FIGURE 8 HERE

Uncertainty around bond rates is quite large. However, it emerges that long term rates have been relatively less reactive to cyclical conditions than what has been historically observed. The stickiness of long-term rates has also been observed in other countries (for the US, for example, see Backus and Wright, 2007) which, combined with the sharp decline in short-term rates during the first phase of the crisis, implies an unusually steep yield curve. This finding can help to explain the unusual weakness of time-deposits since, as we have seen in the previous section, time-deposits dynamics are tightly linked to portfolio considerations. Along this line, ECB (2010) provides a set of estimates of the impact of yield curve dynamics on the developments in broad monetary aggregates and shows that the impact of the unusual steepness of the yield curve on monetary aggregates is sizable[16], although it cannot account for the full extent of the unusual reduction in broad monetary aggregates.

Finally, in order to provide some indications of the mechanisms at work explaining the weakness of some categories of loans, it is interesting to match the findings on quantities with results on the associated lending rates.

INSERT FIGURE 9 HERE

Figure 9 shows that, consistently with the results on quantities, the observed path of lending rates for short-term loans to non-financial corporations is in line with the counterfactual path. Instead, mortgage rates have been excessively sticky. This result suggests that the unusual weakness in certain categories of loans seen in figure 6 may have been, at least partly, due to the restriction of supply by banks which has particularly affected riskier and less profitable categories such as long-term loans and loans to households.[17]

5 Conclusions

This paper provides VAR based findings on the cyclical dynamics of a rich set of variables including real and nominal macroeconomic variables, banks retail loans, deposits, interest rates at various maturities and key financial and monetary indicators for the euro area. We establish stylized facts for the sample 1992-2007 and we then identify breaks in historical regularities after the crisis (2008-2013 sample) on the basis of a counterfactual experiment.

Our findings show that, pre-crisis, the dynamics of the series considered correspond quite closely to what has been found for the US in a large body of empirical literature.

[16] The growth rates of M3 would have been between 2 and 3% higher in 2010, had the steepness of the yield curve behaved in line with past regularities.

[17] Ciccarelli, Maddaloni, and Peydro (2012) and De Santis and Paries (2013), using data from the Bank Lending Survey, provide more evidence on the relevance of supply factors to explain the tightness of euro area credit markets

As for post- crisis, our key result is the dissimilarity in the behavior of short-term interest rates, loans and deposits from their long-term counterparts. While the former variables are remarkably stable, the latter are not. Long-term interest rates are higher than what suggested from pre-crisis association with cyclical variables while long-term loans and deposits are lower.

One implication of these findings is that while systematic monetary in the euro area did not deviate from the implicit pre-crisis rule, the transmission from short-term rates to long rates was impaired.

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A Identification of the cyclical shock

The VAR(p) model presented in the text can be rewritten as

$$X_t - A_1 X_{t-1} - A_2 X_{t-2} + ... + A_p X_{t-p} = \varepsilon_t \quad \varepsilon_t \sim WN(0, \Sigma)$$

and, using filter notation:

$$A(L) y_t = \varepsilon_t = \quad e_t \sim WN(0, \Sigma).$$

The spectral density matrix associated to the model can be defined as

$$S(\omega) = A\left(e^{-i\omega}\right)^{-1} \Sigma \left(e^{-i\omega}\right)^{-1\prime},$$

where $A(z) = I_n - A_1 z - A_2 z^2 - ... - A_p z^p$ for all complex numbers z.

Notice that since the variables are in (log)-levels, the spectral density matrix may not be well defined for $\omega = 0$. For this reason, $S(\omega)$ is often defined as the pseudo spectrum.

Define the structural VAR as:

$$X_t - A_1 X_{t-1} - A_2 X_{t-2} + ... + A_p X_{t-p} = C u_t, \quad u_t \sim WN(0, I_n),$$

where $C = \Sigma^{1/2} R'$, $\Sigma^{1/2}$ is any version of the square root of Σ (for example the Cholesky) and R is a rotation matrix (i.e. $R'R = I$) to be chosen on the basis of the identifying assumptions. Finally, $u_t = R\Sigma^{-1/2}\varepsilon_t$ are the structural shocks. Notice that, given the properties of the rotation matrix R, the structural shocks are orthogonal to each other.

The conditional spectral density associated with the j-th structural shock is given by

$$S_j(\omega) = A\left(e^{-i\omega}\right)^{-1} \Sigma^{1/2} r_j r_j' \Sigma^{1/2} A\left(e^{-i\omega}\right)^{-1\prime}$$

where r_j is the j-th column of R, i.e. $r_j' r_j = 1$ for all j while $r_j' r_i = 0$ for all $i \neq j$.

The orthogonality of structural shocks implies:

$$S(\omega) = \sum_{j=1}^{n} S_j(\omega)$$

The cyclical shock (say, the m-th shock) is defined as the shock $u_{m,t} = r_m' \Sigma^{-1/2} \varepsilon_t$ that explains the maximum of the *variance of unemployment* (say, the k-th variable) *at the business cycle frequencies* $\omega \in [-\underline{\omega}, \overline{\omega}]$.

The spectral density of variable k conditional on shock m corresponds to the k-th diagonal element of $S_j(\omega)$ and, hence, the variance at business cycle frequencies $V_{k,m}^{bc}$ of variable k conditional on shock m can be computed as

$$V_{k,m}^{bc} = \left[2 \int_{\underline{\omega}}^{\overline{\omega}} S_j(\omega) d\omega\right]_{k,k}$$

As a consequence our objective is:

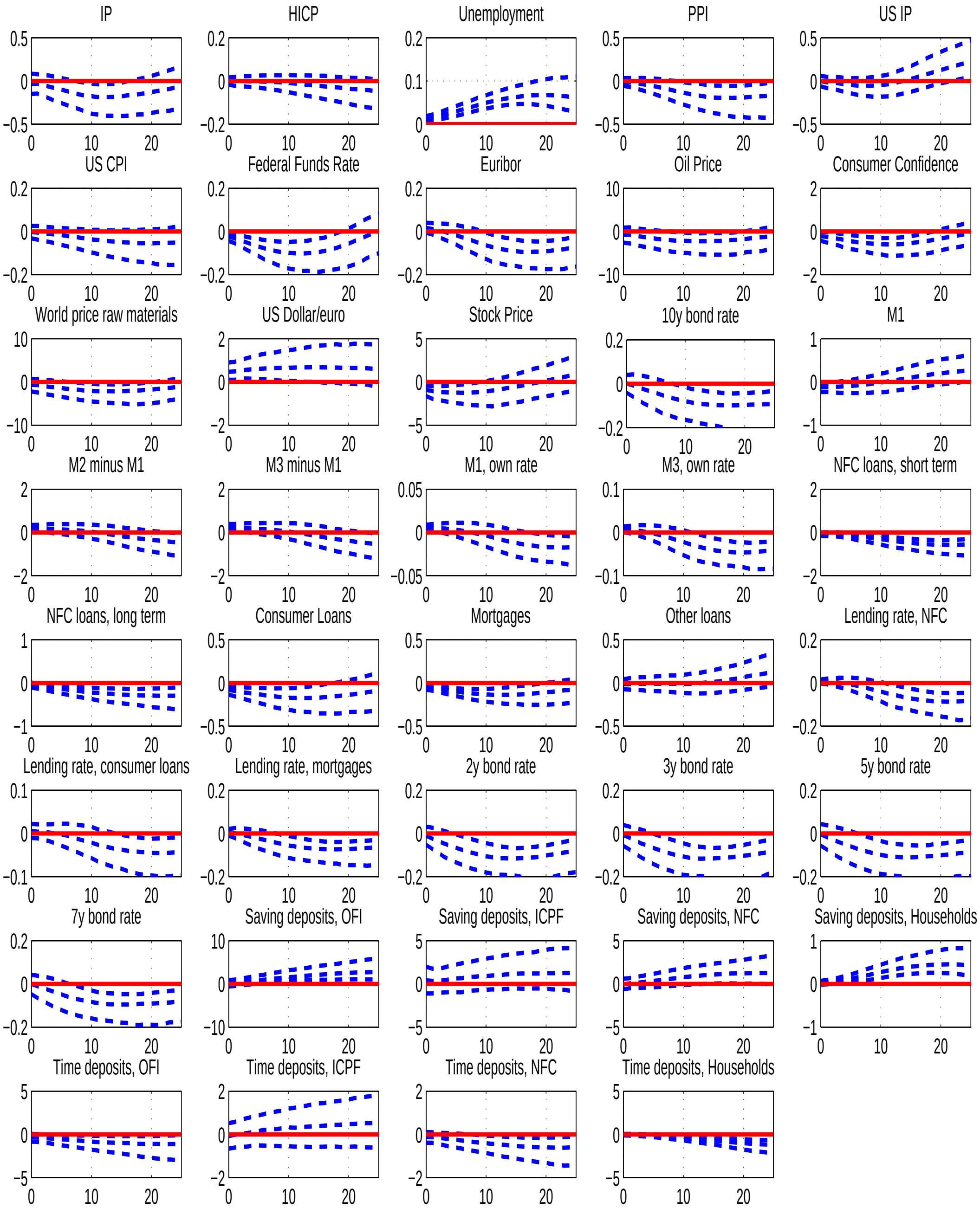
$$r_m^* = \arg \max_{r: r'r=1} \left[\int_{\underline{\omega}}^{\overline{\omega}} A\left(e^{-i\omega}\right)^{-1} \Sigma^{1/2} r r' \Sigma^{1/2} A\left(e^{-i\omega}\right)^{-1\prime} d\omega\right]_{k,k}$$

In the objective function, in order to focus on conventional business cycle frequencies, we set $\underline{\omega} = \frac{2\pi}{32}$ (frequency of 32 quarters, i.e. 8 years) and $\overline{\omega} = \frac{2\pi}{8}$ (frequency of 8 quarters, i.e. 2 years).

In practice, we perform the maximization for all draws from the posterior of the autoregressive coefficients $A_1, ..., A_p$ and the residuals covariance matrix Σ.

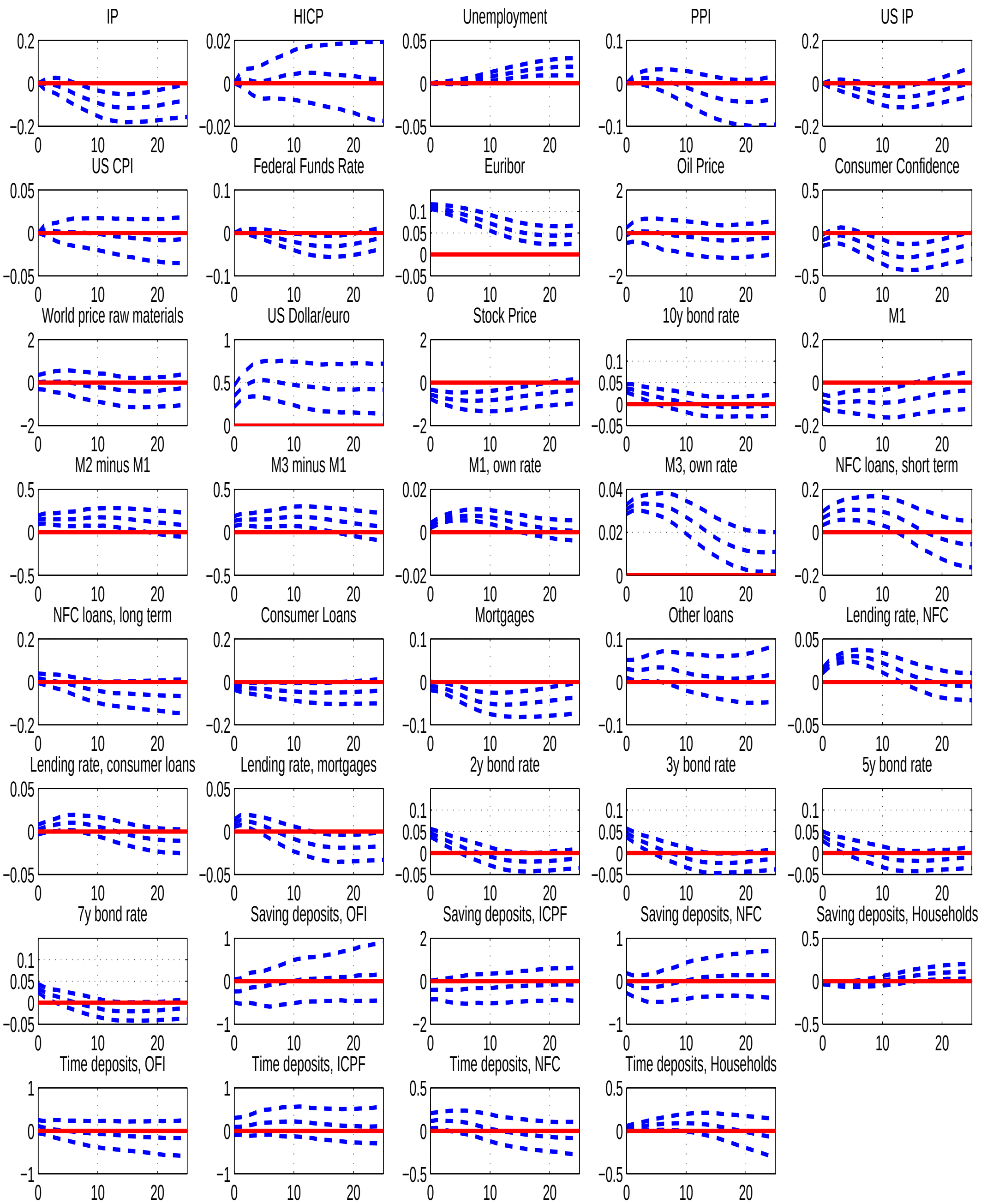
Figure 1: Impulse responses of all variables - Cyclical and monetary policy shocks

a) Cyclical shock



Note: One standard deviation shock. We report median, 16th and 84th quantiles. The red solid line represents the zero line.

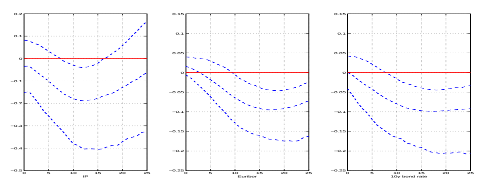
b) Monetary policy shock



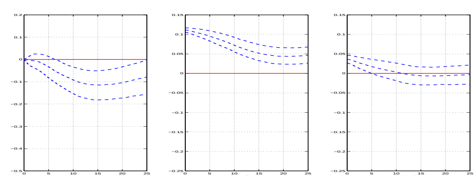
Note: One standard deviation shock. We report median, 16th and 84th quantiles. The red solid line represents the zero line.

Figure 2: Impulse responses of IP, short-term and long-term interest rates

(a)Cyclical shock



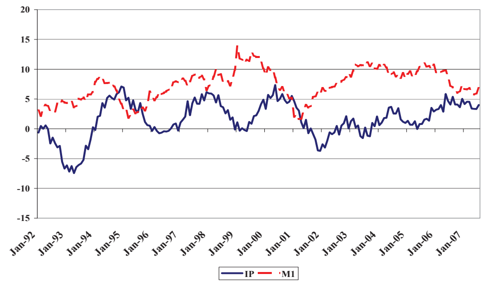
(b)Monetary policy shock



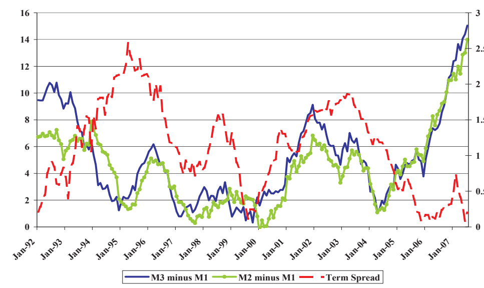
Note: Top panel: impulse responses to one standard deviation cyclical shock. Bottom panel: impulse responses to one standard deviation monetary policy shock. From left to right: industrial production, short-term interest rates and long-term interest rates. We report the median and the 16th and 84th quantiles of the distribution of impulse response functions

Figure 3: Money, credit and the business cycle

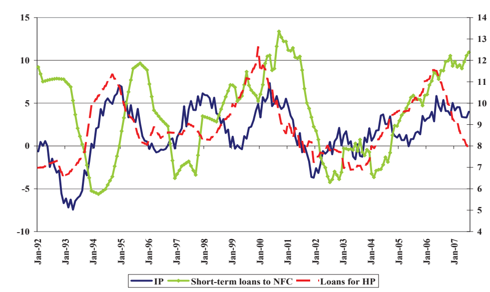
(a)M1 and industrial production



(b)M3-M1 and term spread

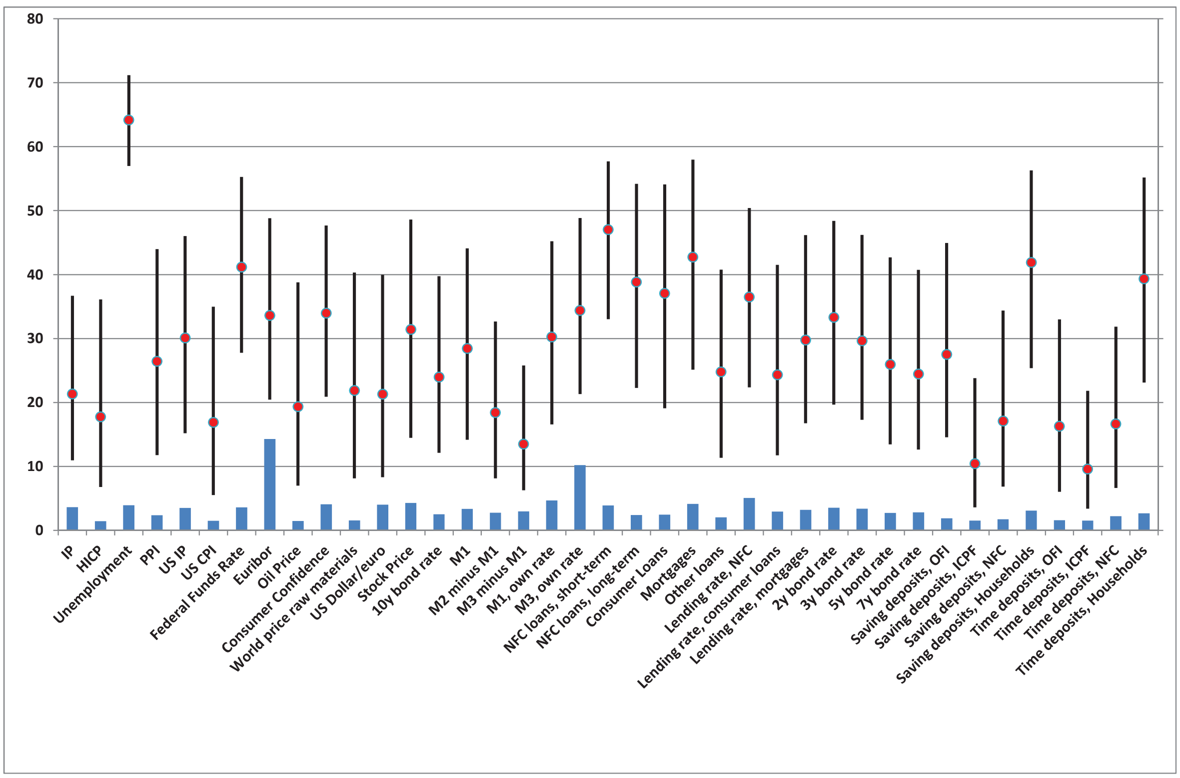


(c)Loans and industrial production



Note: Money and credit aggregates and IP are reported in terms of year-on-year growth rates. The term-spread is computed as the difference between ten years bond rates and the three months euribor.

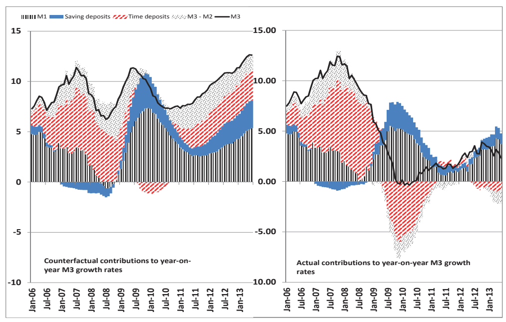
Figure 4: Variance decomposition



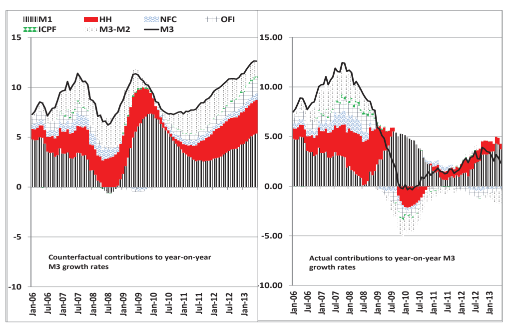
Note: share of variance explained by the monetary policy shock, blue bars; share of variance explained by the cyclical shock, red bars; 16th and 84th quantiles of the distribution of the share of variance explained by the cyclical shock, solid black lines. Horizontal axis: variables. Vertical axis: percentage of variance explained.

Figure 5: Actual and Counterfactual contributions to the year-on-year growth rates of M3

(a)Decomposition by instrument

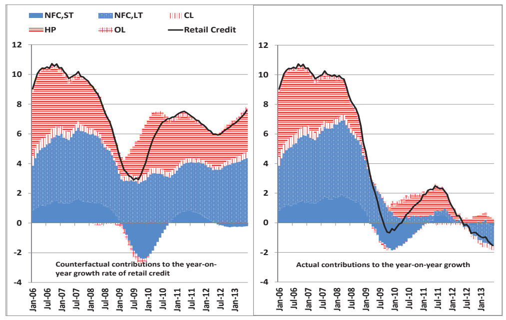


(b)Decomposition by holding sector



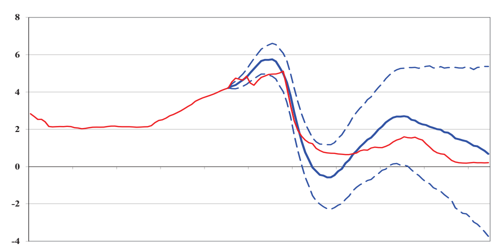
Note: The left panels report, from January 2006 to July 2007, the actual contributions and, from August 2007 onward, the median of the counterfactual contributions to the year-on-year growth rates of M3 (solid black line). The right panels report the actual contributions to the year-on-year growth rates of M3 in the sample January 2006 to August 2010.

Figure 6: Actual and Counterfactual contributions to the year-on-year growth rates of retail credit



Note: Retail credit is the sum of short and long-term loans to non-financial corporations, loans for house purchases, consumer loans and other loans to households. The left panel reports, from January 2006 to July 2007, the actual contributions and, from August 2007 onward, the median of the counterfactual contributions to the year-on-year growth rates of retail credit (solid black line). The right panels report the actual contributions to the year-on-year growth rates of M3 in the sample January 2006 to August 2010.

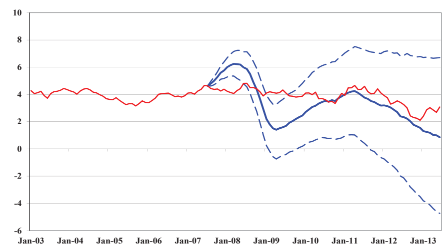
Figure 7: Counterfactual exercises on 3 months Euribor



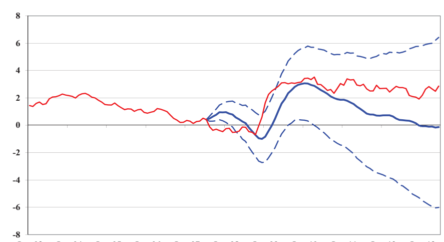
Note: we report the actual level of the 3 months euribor (red solid line) and the median (blue solid line) and the 16th and 84th quantiles of the distribution of the conditional forecasts (blue dashed lines).

Figure 8: Counterfactual exercises on 10 year bond rates and term-spread

(a) 10 year bond rates



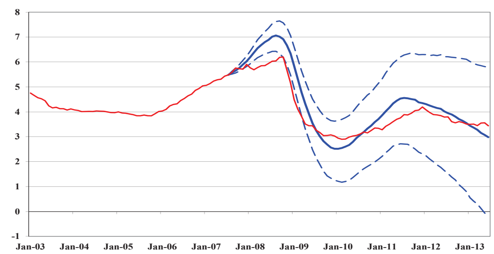
(b) Term-spread: 10 year bond rates minus Euribor



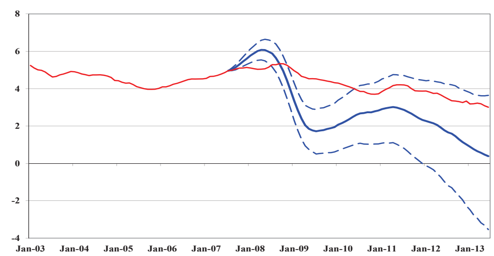
Note: we report the actual levels of the bond rates and the term-spread (red solid lines) and the median (blue solid line) and the 16th and 84th quantiles of the distributions of the conditional forecasts (blue dashed lines)

Figure 9: Counterfactual exercises on lending rates

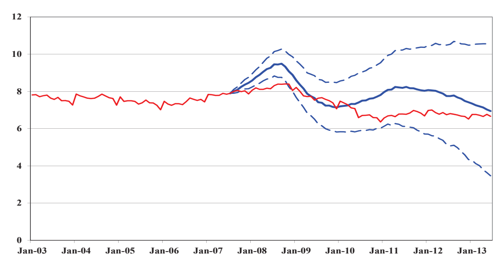
(a) Lending rates, short-term loans to non-financial corporations



(b) Lending rates, loans for house purchases



(c) Lending rates, consumer loans



Note: we report the actual levels of the lending rates (red solid lines) and the median (blue solid line) and the 16th and 84th quantiles of the distributions of the conditional forecasts (blue dashed lines)