Money, Credit, Monetary Policy, and the Business Cycle in the Euro Area: What Has Changed Since the Crisis?*

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This paper studies the relationship between the business cycle and financial intermediation in the euro area. We establish stylized facts and study their stability during the global financial and the European sovereign debt crises. Long-term interest rates have been exceptionally high, and long-term loans and deposits exceptionally low, since the Lehman collapse. Instead, short-term interest rates and short-term loans and deposits did not show abnormal dynamics in the course of the financial and sovereign debt crises.

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

1. Introduction

In the autumn of 2008, the United States and the euro area were in a recession (see, respectively, the results of the NBER and the CEPR dating committees at www.nber.org and www.cepr.org). At that stage, the collapse of Lehman Brothers triggered a banking crisis and major disruptions in global financial markets, which many

^{*}This paper builds on a framework that the authors developed for policy analysis at the European Central Bank. We wish to thank the editor, Boragan Aruoba, and two anonymous referees for their constructive comments. We also thank Brandyn Bok, Antonello D'Agostino, Rujun Han, Marco Del Negro, Björn Fischer, Fabio Fornari, Jordi Gali, Romain Houssa, Alberto Musso, Huw Pill, Giorgio Primiceri, and Julian Von Landesberger. The views expressed in this paper are those of the authors and do not necessarily reflect those of the European Central Bank, the Eurosystem, the Federal Reserve Bank of New York, or the Federal Reserve System.

believe to have amplified the downturn leading to the deepest recession since the thirties. The euro area, after a brief and relatively weak recovery, in 2011 plunged into a new recession and sovereign debt crisis of some of its member states. During this period of prolonged instability of the real economy and the financial sector, the volume of funds intermediated by the financial sector sharply declined, accompanied by large fluctuations in the associated interest rates. Do these unprecedented developments reveal the emergence of anomalies in the transmission mechanisms, in the nature of the shocks or in their relative importance? Or do they just reflect unusually large but otherwise standard business cycle shocks? Are potential anomalies concentrated only in some specific segments of financial intermediation? These are the main questions that we explore in this paper.

Our strategy to address these questions consists of two steps. First, we establish stylized facts about the cyclical behavior of a rich set of euro-area macroeconomic, monetary, and financial variables before the prolonged period of turmoil starting in 2008. Then, we explore whether the developments in the course of the recent crises are characterized by a significant break in the relation between financial intermediation and the rest of the economy.

We assess financial intermediation by focusing on bank loans and deposits. Although these variables describe only the activity of banks, excluding market financing, they capture a relevant part of financial intermediation because banks play a very relevant role in the euro-area financial system (European Central Bank 2008). 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, i.e., overnight deposits, saving deposits, and time deposits with maturity up to two years. These categories exclude interbank deposits as well as deposits with maturity longer than two years and they represent approximately 30 percent 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 flexible linear dynamic model, a large vector autoregressive (VAR) model, which allows us to analyze simultaneously the dynamics of the variables in the data set.

Inference is conducted using a Bayesian approach with informative priors, to address the potentially severe problem of overfitting arising from the large dimension of our model, as suggested in Doan, Litterman, and Sims (1984); Banbura, Giannone, and Reichlin (2010); and Giannone, Lenza, and Primiceri (2015). The methodology provides a framework for the analysis of the joint dynamics of a large panel of time series without relying on the so-called marginal approach, which consists of estimating a small system and then adding one variable at a time (for examples of the latter modeling 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 it complicates the interpretation of the results across models.

In order to establish stylized facts, we study the cyclical characteristics of our variables in the pre-crisis period (January 1992 to September 2008). We perform this analysis by means of impulse response functions to "cyclical" shocks, constructed as the linear combination of shocks that explain the bulk of the cyclical variation of variables describing real economic activity. This should not be thought of as a structural identification but, rather, as a statistical device, which provides a summary description of contemporaneous, leading and lagged correlations at business cycle frequencies over the typical cycle. Indeed, we find that the response to an adverse cyclical shock reflects the narrative of typical recessions: economic activity and prices decline, and so do interest rates, as monetary policy becomes more accommodative.

We also compare the impulse responses to "cyclical" shocks with the impulse responses of the system to an exogenous increase in the short-term interest rate, i.e., a monetary policy shock. This comparison provides additional insights on the relative importance of portfolio and transaction effects. Generally, the empirical results show that the monetary policy shocks have contractionary effects and, hence, they imply a negative correlation between short-term interest rates and economic activity. Instead, as mentioned above, in a typical downturn this correlation is positive, due to the systematic monetary policy reaction. This difference in conditional correlations in typical and in policy-induced downturns allows us to qualitatively assess the relative importance of real effects and changes in the interest rates for the financial intermediation dynamics along the business

cycle. Broadly speaking, the comparison of the responses to the two shocks provides some information about the elasticities of different variables to economic activity and interest rates. Specifically, marked differences of the responses of a specific aspect of financial intermediation in the two different types of contraction indicate that cyclical shocks propagate primarily through interest rate effects.

With the historical regularities at hand, we address the question of 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 ranging from October 2008 to February 2018. The 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 economic activity and consumer prices in the course of 2008–18. The pre-crisis historical 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. Hence, relevant deviations of the estimated counterfactual path from actual realizations reveal anomalies in the transmission mechanisms, in the nature of the shocks or in their relative importance, specific to the recent financial crisis.

Our results reveal a dichotomy between short- and long-term loans and deposits. While the developments in overnight deposits, saving deposits, and corporate loans with maturity up to one year appear to reflect historical regularities, the post-crisis dynamics in deposits and loans (both to firms and households) at longer maturity is characterized by a "significant break." In particular, already in the early phases of the financial crisis, loans to households have contracted more than expected. The unusual decline of long-term loans to firms is more pronounced during the sovereign crisis, reflecting the process of financial fragmentation emerging in euro-area countries. Interestingly, the observed path of the three-month 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 is due also to the

non-standard monetary policy of the ECB, which has kept the spread between interbank and policy rates under control during the crises.

Our paper is related to a growing literature that studies the euroarea 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. 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 in euroarea data before the crisis. In particular, the ECB 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 U.S. data, the papers by Bernanke and Blinder (1992), Bernanke and Gertler (1995), Christiano, Eichenbaum, and Evans (1996), and 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 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 et al. 2009; and Stark and Papademos 2010).¹

Although our focus is mainly on the business cycle characteristics of the euro-area variables, some of the results of the paper are

¹The model developed in this paper is the basis of regular policy briefing at the European Central Bank and has been part of a project enhancing monetary analysis in that institution.

also related to the debate on the effects of unconventional monetary policy actions on the United Kingdom, the United States, and the euro area (see, for example, Lenza, Pill, and Reichlin 2010; Chen, Curdia, and Ferrero 2011; Del Negro et al. 2011; Gambacorta, Hofmann, and Peersman 2011; Peersman 2011; Ciccarelli, Maddaloni, and Peydro 2012; Giannone et al. 2012; and Kapetanios et al. 2012).

The structure of the paper is as follows. Section 2 describes the database and the model specification. Section 3 describes the stylized facts on the functioning of the euro area 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 twenty-eight monthly macroeconomic, financial, monetary, and credit variables in the sample January 1992 to February 2018. We also include selected variables for the United States, in order to capture international linkages. The appendix provides precise variables definitions.

The macroeconomic block includes measures of real activity (industrial production and the unemployment rate) and prices for the euro area. We also include U.S. industrial production and consumer prices. The three-month EURIBOR and the U.S. federal funds rates are our proxies for the policy rate in the euro area and the United States, respectively. The rest of the financial block includes interest rates on government bonds at different maturities, euro-area stock prices, and the U.S. dollar/euro exchange rate.

Turning to financial intermediation, our focus in this paper is on bank deposits and loans, which 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. Regarding the monetary block, the database includes the three main euro-area monetary aggregates, time deposits and saving deposits. The narrowest aggregate, M1, is the sum of currency in circulation and overnight deposits. M2 consists of M1 plus time deposits (i.e., deposits with an agreed maturity of up to two years) and saving deposits (i.e., deposits redeemable with a notice of up to three

months), which we also include individually in the database. Finally, M3 consists of M2 plus repurchase agreements (repos), money market funds shares, and debt securities issued with a maturity of up to two 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 with maturity 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, mortgages, 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.²

2.2 The Model

Let X_t be a vector including the n variables just described (all variables enter the empirical model in terms of log-levels, except for variables expressed in rates or with negative levels, which enter in levels). We estimate a VAR model with p (=7) lags:

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

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

The large dimension (n=28 and p=7) of our VAR model implies that we face an issue of over-fitting, due 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, 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

 $^{^2}$ We thank Christoffer Kok Sorensen for sharing with us the data on the lending rates used in Kok Sorensen and Werner (2006).

offers a parsimonious but reliable estimate of the complex dynamic interactions among the macro, monetary, and financial variables in the data set.

More specifically, we use a normal-inverse-Wishart prior centered on a random-walk model. For Σ , the covariance matrix of the residuals, we use an inverse-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 prior and two priors on the sum of coefficients, as originally proposed by Litterman (1979), Doan, Litterman, and Sims (1984), and Sims (1996).

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 $E(A_2) = \cdots = E(A_p) = 0_{n,n}$,

where $Cov[(A_s)_{i,j}, (A_r)_{h,m} \mid \Sigma] = (\frac{\lambda^2 \Sigma_{i,h}}{s^2 \Psi_{j,j}})$ 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 $1/s^2$ 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 two priors on the sum of the VAR coefficients were introduced as refinements of the Minnesota prior to further "favor unit roots and cointegration, which fits the beliefs reflected in the practices of many applied macroeconomists" (see Sims and Zha 1998, p. 958). These additional priors tend to reduce the importance of

the deterministic component implied by VARs estimated conditioning on the initial observations (see Sims 1996; Giannone, Lenza, and Primiceri 2019). The first of these two priors is known as the no-cointegration (or, simply, sum-of-coefficients) prior. To understand what this prior entails, we rewrite the VAR equation in an error-correction form:

$$\Delta X_{t} = A_{0} + (A_{1} + \dots + A_{p} - I_{N})X_{t-p}$$

+ $B_{1}\Delta X_{t-1} + \dots + B_{p}\Delta X_{t-p} + \epsilon_{t},$

where $B_s = -A_{s+1} - \cdots - A_p$.

A VAR in first differences implies the restriction $\Pi = (A_1 + \cdots + A_p - I_N) = 0$. Doan, Litterman, and Sims (1984) introduced the no-cointegration prior which centered at 1 the sum of coefficients on own lags for each variable, and at 0 for the sum of coefficients on other variables' lags. This prior also introduces correlation among the coefficients on each variable in each equation. The tightness of this additional prior is controlled by the hyperparameter μ . As μ goes to infinity, the prior becomes diffuse while, as it goes to 0, it implies the presence of a unit root in each equation.

Notice that, in the limit, the prior just discussed is not consistent with cointegration. This motivates the use of an additional prior on the sum of coefficients that was introduced by Sims (1996) and is known as the dummy-initial-observation prior. This prior states that a no-change forecast for all variables is a good forecast at the beginning of the sample. The hyperparameter δ controls the tightness of this prior. As δ tends to 0, the prior becomes more dogmatic and all the variables of the VAR are forced to be at their unconditional mean, or the system is characterized by the presence of an unspecified number of unit roots without drift. As such, the dummy-initial-observation prior is consistent with cointegration.

The setting of these priors depends on the hyperparameters λ , μ , δ , and Ψ , 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 Giannone, Lenza, and Primiceri (2015). This involves treating the coefficients of the prior as additional parameters, in the spirit of hierarchical modeling. As hyperpriors (i.e., prior distributions for the hyperparameters), we

use proper but almost flat distributions. In this setup, the marginal likelihood evaluated at the posterior mode of the hyperparameters is close to its maximum. Given the draws of the hyperparameters, the VAR coefficients can then be drawn from their posterior distribution, which is normal/inverse Wishart.

2.3 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–September 2008.

2.3.1 Pre-crisis Stylized Facts

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. The cyclical (or, alternatively, business cycle) shock is defined as the linear combination of orthogonal shocks that captures the maximum variance of industrial production at business cycle frequencies (i.e., those related to cycles with a period of length between two and eight years).³ More in detail, our VAR(p) model can be rewritten as

$$X_t - A_0 - A_1 X_{t-1} - A_2 X_{t-2} - \dots - A_p X_{t-p} = \varepsilon_t \quad \varepsilon_t \sim WN(0, \Sigma)$$

and, using filter notation,

$$A(L)X_t = A_0 + \varepsilon_t \quad \varepsilon_t \sim WN(0, \Sigma).$$

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

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

where $A(z) = I_n - A_1 z - A_2 z^2 - \cdots - A_p z^p$ for all complex numbers z. Notice that since the variables are in (log)-levels, the spectral

³This identification strategy has also been used by Di Cecio and Owyang (2010) and more recently by Angeletos, Collard, and Dellas (2018). Uhlig (2004) and Giannone, Reichlin, and Sala (2005) adopt similar identification strategies in the time domain.

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

$$X_{t} - A_{0} - A_{1}X_{t-1} - A_{2}X_{t-2} - \dots - A_{p}X_{t-p} = Cu_{t},$$

$$u_{t} \sim WN(0, I_{n}),$$

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

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

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

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

In the objective function, in order to focus on conventional business cycle frequencies, we set $\underline{\omega} = \frac{2\pi}{32}$ (frequency of thirty-two quarters, i.e., eight years) and $\overline{\omega} = \frac{2\pi}{8}$ (frequency of eight quarters, i.e., two years). In practice, we perform the maximization for all draws from the posterior of the VAR coefficients A_0, A_1, \ldots, A_p and the residuals covariance matrix Σ .

Notice that this is not an economic identification but rather a statistical identification that we use as a device to study dynamic correlations over the business cycles. The impulse response functions to this shock should reflect the unconditional correlations over the "typical" business cycle. In other words, this "statistical identification" approach allows us to extract information on the cross-correlations of the series of interest at business cycle frequencies, also preserving information on lead-lag relations.

We also study the impulse responses of the system to an exogenous increase in the short-term interest rate, i.e., a monetary policy shock. Generally, as the empirical results will show, these shocks have contractionary effects and, hence, they imply a negative correlation between short-term interest rates and economic activity. Instead, in a "typical downturn" this correlation is positive, due to the systematic monetary policy reaction. This difference in conditional correlations in "typical" and in policy-induced downturns allows us to qualitatively assess the relative importance of real effects and changes in the interest rates for the financial intermediation dynamics along the business cycle. Broadly speaking, the comparison of the responses to the two shocks provides some information about the elasticities of different variables to economic activity and interest rates. Indeed, marked differences of the responses of a specific aspect of financial intermediation in the two different types of contraction indicate that cyclical shocks propagate primarily through interest rate effects. This should not be confused with the importance of the shocks, which is instead assessed using the variance decomposition.⁴

⁴It is important to notice that this method provides only a qualitative inspection of transmission mechanisms. A fully fledged analysis, able to precisely disentangle all the different features of the shock propagation, can only be conducted with more structural models such as, for example, dynamic stochastic general equilibrium models. However, the advantage of our modeling strategy is that it provides an empirically robust characterization of the dynamics of a large and

For the identification of the monetary policy shocks, we rely on two alternative strategies, both considering the three-month EURI-BOR as a good proxy for the policy rate, before the crises. 5 Our first strategy is based on a recursive scheme (see Christiano, Eichenbaum, and Evans 1999 for a discussion of this identification scheme) which implies that the indicators of euro-area economic activity and prices and the U.S. variables (these are the seven variables ordered above the EURIBOR in the VAR and in table 1 in the appendix) can react to the monetary policy shock only after one month. Financial variables, instead (these are the variables ordered under the EURIBOR in the VAR and in table 1 in the appendix), can react instantaneously to the monetary policy shock. Our second identification scheme is based on sign restrictions (Uhlig 2005; Arias, Rubio-Ramirez, and Waggoner 2014). The sign restrictions are imposed for three months and assume a negative correlation of the EURIBOR with M1, industrial production, and the harmonized index of consumer prices and a positive correlation of the EURIBOR with the unemployment rate, bond rates, and lending rates. We find that the choice of the identification scheme is immaterial for the purpose of interpreting the dynamics ensuing to cyclical shocks (although some differences emerge in the impulse responses to the monetary policy shocks themselves) and we consider the recursive scheme as our baseline in the rest of the paper.⁶

2.3.2 The Crisis

After having established the pre-crisis facts, we ask whether the prolonged period of crisis has induced changes in the structure of

detailed set of monetary and credit variables, among others, which would still be difficult to achieve for the current generation of structural models.

⁵The EONIA (overnight interbank rate) may be a better proxy for the policy rate, in principle. We have used the three-month EURIBOR, since the EONIA is available only on a shorter sample than ours. However, results are robust to this choice, since the parameters are estimated before the crisis when the EURIBOR and the EONIA were almost perfectly collinear. The analysis of the stability in the aftermath of the crisis is also not affected, since, as discussed in the next section, our counterfactual paths are constructed by conditioning only on business cycle developments and not on interest rates.

⁶Figure A1 in the online appendix (available at http://www.ijcb.org) shows both sets of impulse responses to a monetary shock.

correlations among the variables in our system. To this end, we compare the observed developments in monetary and credit markets with those implied by the pre-crisis correlations and the observed developments in the real economy and in consumer prices. To assess the latter, we perform a counterfactual scenario analysis for the period ranging from October 2008 until February 2018. The counterfactuals are constructed as follows:

- (i) We use the same coefficients estimated in the previous section, i.e., using the sample January 1992–September 2008.
- (ii) We assume that the euro-area industrial production, the euroarea unemployment rate, the U.S. industrial production, and consumer prices in the euro area and in the United States are known for the whole sample, while all other variables are only observed until September 2008.
- (iii) We compute the conditional expectations for all variables and for the period October 2008–February 2018 based on the precrisis VAR coefficients (see step (i)) and the knowledge of euro-area and U.S. real activity developments and consumer prices in the whole sample (see step (ii)).⁷

Notice that the coefficients of the model are kept fixed at the pre-crisis value. Therefore, our conditional forecasts capture the most likely shocks that could generate the Great Recession under the assumption of no change in the average features of the shocks (because the covariance matrix of the forecast errors is kept fixed) and in the dynamic interdependence among the variables (because the autoregressive coefficients are kept fixed), compared with the pre-crisis period. Hence, we would identify a large difference between observed and counterfactual dynamics only if the crisis had induced substantial structural changes or it had been generated by shocks of unprecedented nature.

⁷The conditional expectations are computed by means of the simulation smoother described in Banbura, Giannone, and Lenza (2015) and based on Carter and Kohn (1994) and Durbin and Koopman (2001).

From a methodological point of view, this paper relates to the literature on time variation in macrofinancial linkages. Some of this literature (see, for example, Prieto, Eickmeier, and Marcellino 2016) takes the route of estimating VAR models with continuous changes in shock volatilities, autoregressive dynamics, and contemporary relationships among variables, as developed and refined in Primiceri (2005) and Del Negro and Primiceri (2015). Other papers (see, for example, Nason and Tallman 2015) assume instead that the variation evolves in a Markov-switching fashion. One advantage of the two approaches above would be to make breakpoints endogenous, rather than imposing them on specific dates. We rely on the methodology based on a time-invariant VAR and counterfactuals on the crisis period for two main reasons. First, a potential disadvantage of the time-varying approaches above is that they can aggravate the curse of dimensionality, in particular given our purpose to gauge the stability of the relationships of relatively rich monetary and credit blocks with the rest of the economy. Moreover, the focus of this paper is not to identify breaks over the euro-area sample; rather, we ask precisely whether the recent financial and sovereign crises disrupted the macrofinancial linkages in the euro area. An alternative to the BVAR model for high-dimensional systems is the dynamic factor model (DFM). DFMs and large VARs are intimately related: they are not competing models but, rather, complementary approaches to econometrics with big data. Specifically, recent theoretical analysis and empirical evidence shows that Bayesian shrinkage and dynamic factor models produce similar results in terms of (i) structural identification of shocks, (ii) unconditional forecasts, and (iii) conditional forecasting (see De Mol, Giannone, and Reichlin 2008; Banbura, Giannone, and Reichlin 2010; and Banbura, Giannone, and Lenza 2015). We use the BVAR methodology since it allows us to take into account the uncertainty associated with all the modeling decisions, from the degree of shrinkage to the degree of "differencing" (see Giannone, Lenza, and Primiceri 2015). In the dynamic factor model, instead, the decision on the number of factors and the differencing of the data is based on pre-testing, and the uncertainty associated with these choices is not easy to account for. Stock and Watson (2012) use a DFM to investigate the stability of the cyclical characteristics of many U.S. variables during the financial crisis in a similar vein to our study.

3. Results

3.1 Stylized Facts Before the Crisis: 1992–2008

In this section, we analyze the historical correlations between financial intermediation and business cycle developments over the period from January 1992 to September 2008.

Figure 1 reports the median (dashed line) and the 16 percent and 84 percent quantiles of the distribution (shaded area) of the impulse responses to a one-standard-deviation cyclical shock.⁸ The results are cast in terms of the log-levels of the variables (or of the levels for the variables expressed in rates) over a horizon of up to twenty-four months after the shocks. We also report the median impulse response to a monetary policy shock (dotted line).⁹

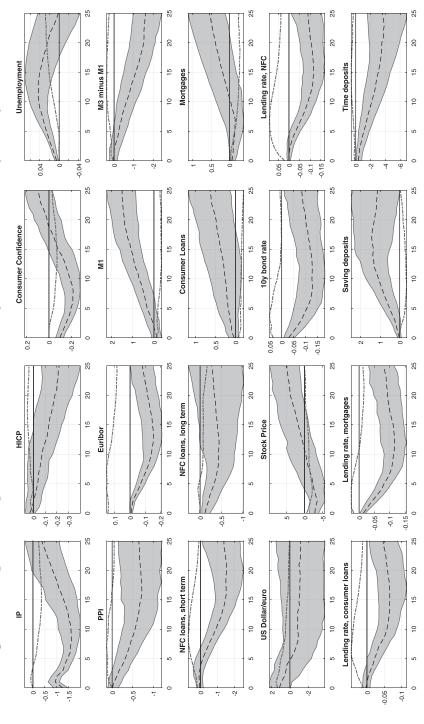
We find that the results on the cyclical shock reflect the narrative of typical recessions: industrial production declines and so do consumer confidence, production prices, and stock prices. Unemployment is anticyclical and HICP declines with a delay. The euro/dollar exchange rate is quite unresponsive. Perhaps surprisingly, the effects of monetary policy shocks in the euro area are similar, at least in qualitative terms, to those found for the United States. In particular, in response to a monetary contraction, we estimate a protracted decline in real activity associated with a similar development in consumer confidence, an appreciation of the euro with respect to the dollar, and a decline in stock prices. We also find that consumer prices (HICP) hardly move, although the median response shows evidence of a price puzzle (for early findings on some of these features, see Peersman and Smets 2003).

We now turn to the responses of interest rates, loans, and deposits, on which we focus in the analysis of the crisis period in

 $^{^8}$ A one-standard-deviation cyclical shock decreases industrial production, on impact, by 1.2 percent, with a trough at -1.6 percent over the horizon in which we estimate the impulse response functions. For the sake of readability, we report only the result for the main twenty variables. The full set of results is available upon request.

⁹For comparability, we rescale the impulse response to a monetary policy shock to match the peak impact of the cyclical shock on unemployment. The full set of unscaled impulse responses to a monetary policy shock is available in the online appendix, together with a robustness check in which we identify the effects of the monetary policy shock by means of sign restrictions.

Figure 1. Impulse Responses of All Variables: Cyclical and Monetary Policy Shocks



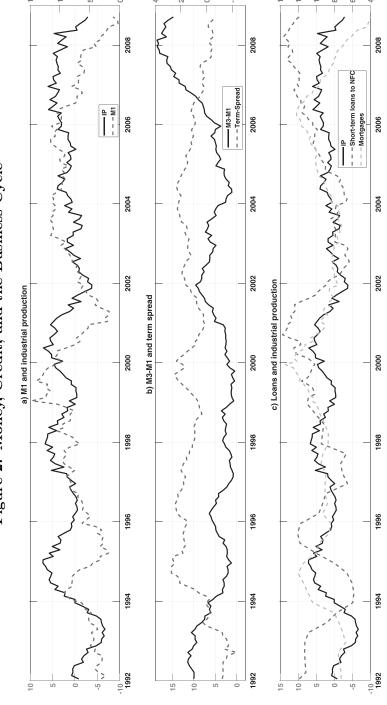
Notes: One-standard-deviation cyclical shock. The shaded area reports the range between the 16th and 84th quantiles, while the dashed line refers to the median response. The dashed-dotted line refers to the median response to a monetary policy shock, rescaled to match the absolute value of the peak in the response of the EURIBOR obtained with the cyclical shock.

the next section. In response to a cyclical contraction, we observe a negative and slightly lagged response of the short-term interest rate (three-month EURIBOR), reflecting the systematic response of monetary policy. 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 similar magnitude as the decline in short-term interest rates and the shape of the yield curve is unaffected while, in a monetary tightening, long-term rates move in the same direction as the policy rate, but considerably less. Hence, in the aftermath of a monetary tightening, the spread between long and short rates declines, while it is unaffected in a cyclical contraction. These different responses of short-term interest rates and the term spread in the two different types of contraction, cyclical and monetary, can help to interpret our results on the cyclical features of the variables. If the dynamics of a given variable are mainly driven by real economic developments, then we should expect it to behave similarly in the cyclical and the monetary contractions, which are both characterized by a decline in economic activity. Conversely, if interest rate effects are prominent in explaining the dynamics of such variables, we should expect marked differences in the response to the two shocks.¹⁰

The narrow monetary aggregate, M1 (which includes currency and overnight deposits) increases in the course of a cyclical contraction, i.e., it shows an anticyclical behavior. Instead, it decreases in response to a monetary tightening (the so-called liquidity effect), suggesting that interest rate effects dominate the effects from economic activity in determining its behavior. In fact, M1 is negatively correlated with the policy rate, conditionally on both shocks. Hence, narrow money is mainly driven by liquidity effects. These results explain the negative unconditional correlation between the growth rate of M1 and industrial production (see figure 2, panel A). When economic activity weakens, the short-term interest rate responds negatively, with a lag. Contemporaneously to the drop in short-term interest rates, M1 increases due to the liquidity effect, which

¹⁰For a similar analysis on U.S. data, using a different technical approach, see den Haan, Sumner, and Yamashiro (2007).

Figure 2. Money, Credit, and the Business Cycle



Notes: Money, credit, and industrial production: year-on-year growth rates. Term spread: ten-year bond rates minus three-month EURIBOR. Left axis: IP (panel A), M3 – M1 (panel B), IP and short-term loans to non-financial corporations (NFC) (panel C). Right axis: M1 (panel A), term spread (panel B), mortgages (panel C).

explains the negative unconditional correlation between economic activity and M1 growth.

As for M1, the response of M2 - M1 and M3 - M1 to a cyclical contraction is different from the response to a monetary contraction. 11 This suggests that the changes in economic activity are not the predominant force also to account for the developments in broader monetary aggregates. However, the cyclical behavior of M2 - M1 and M3 - M1 is the opposite of that of M1: the response in a cyclical contraction is negative while it is positive in a monetary contraction. Moreover, the correlation with the interest rate is always positive, independently from the nature of the shock. These results suggest that portfolio considerations are important drivers of broad money. In fact, in a monetary tightening, the positive spread opening up between short-term rates and long-term bond rates implies that short-term monetary assets (especially time deposits) earn a higher return than non-monetary assets with longer maturity (e.g., government bonds), boosting M2-M1 and M3-M1. Instead, in response to a cyclical contraction, the shape of the yield curve is not affected.

The implication of these findings is that, while M1 is countercyclical, M3 and M2 are not very correlated with the cycle and they are inversely related to the term spread (see figure 2, panel B). To further interpret these findings, we now look at saving and time deposits. ¹²

 $\mathrm{M3}-\mathrm{M1}$ and $\mathrm{M2}-\mathrm{M1}$ appear to mainly reflect the dynamics of time deposits. In fact, as $\mathrm{M3}-\mathrm{M1}$ and $\mathrm{M2}-\mathrm{M1}$, time deposits are positively correlated with the short-term interest rates. Saving deposits, instead, are mainly driven by the liquidity effect. Indeed, saving deposits have shorter maturity than time deposits and, hence, behave very similarly to the overnight deposits in $\mathrm{M1}$. Instead, the decision of holding time deposits, which have longer maturities than saving deposits, is dominated by portfolio considerations:

 $^{^{11}}$ M2 – M1 is of about the same magnitude of M1 and accounts for between 40 and 48 percent of the whole M3 while the M3 – M2 component is smaller, i.e., between 11 and 15 percent of M3.

 $^{^{12}}$ Saving deposits and time deposits have more or less equal share in M2 – M1 and saving deposits are more liquid.

higher short-term rates imply higher returns for time deposits which, everything else equal, should induce substitution from other, non-monetary, asset holdings.

Loans are generally procyclical. However, short-term corporate loans show a delayed response. This explains why loans to nonfinancial corporations lag the business cycle (see figure 2, panel C). This result has important implications for the debate 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: they are procyclical whether or not the rates decline (non-monetary contraction) or increase (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 U.S. data by Gertler and Gilchrist (1993) 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 rebalance 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, facing the upward pressure on their cost of lending induced by a monetary tightening, firms may be encouraged to draw down their precommitted credit lines with banks. Finally, Gertler and Gilchrist (1993) argue that the demand of loans may increase in an economic recession due to the need of firms to address the squeeze in their cash flows.

The comparison between a monetary and a cyclical contraction sheds 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 1993) with a negligible role for interest rate effects, we would expect it to materialize also in the case of a cyclical contraction, which is contrary to our findings.

Finally, we find that the responses of lending rates in both types of contractions bear some similarity to those of the short-term

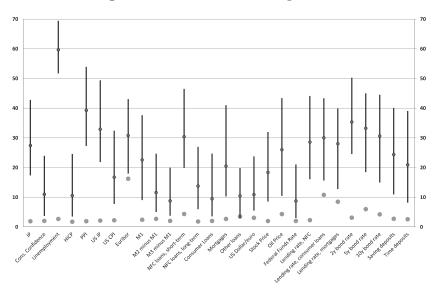


Figure 3. Variance Decomposition

Notes: Median share of variance explained by the monetary policy shock, large dots; median share of variance explained by the cyclical shock, small dots; 16th and 84th quantiles of the distribution of the share of variance explained by the cyclical shock, solid lines. Horizontal axis: variables. Vertical axis: percentage of variance explained.

interest rates, but they are stickier, in particular those for consumer loans. 13

Figure 3 reports the percentage of the variance at business cycle frequencies accounted for by the cyclical shocks. In particular, we report the median (small dots) and the 16th and 84th quantiles (lines) of the distribution of the share of variance accounted for by the cyclical shock. As a comparison, we also report the median of the distribution of the share of variance accounted for by the monetary policy shock (large dots).

The cyclical shock explains, on average across variables, about 25 percent of the variance at business cycle frequencies. Among categories of loans, short-term loans to non-financial corporations and

¹³For a survey of studies on the stickiness of lending rates, see Kok Sorensen and Werner (2006).

mortgages are the most cyclical variables. Among monetary aggregates, the share of the variance of M1 explained by the cyclical shock is slightly more than 20 percent, while it is considerably lower for broader monetary aggregates.

The monetary policy shock does not appear to be an important driver of business cycle fluctuations. On average, it explains less than 5 percent of the variance at business cycle frequencies and it accounts for about 10 percent only for the short-term interest rate and lending rates. This result might also be due to the specific sample on which we estimate our model (1992–2008).¹⁴

4. The Financial and Sovereign Crises in the Euro Area

Do the relationships we established in the previous section remain robust once we control for the unprecedented size of the shocks experienced over the course of the crises? For the analysis over the period of the financial and sovereign crises, we focus on loans, deposits, and interest rates. 15

In practice, we compute conditional expectations of the variables of interest on the basis of historical (pre-crisis, the VAR model is estimated with data until September 2008) correlations and the realized path of variables representing business cycle conditions and consumer prices. ¹⁶ By conditioning on macroeconomic variables, we capture the size of the shocks that would have caused the recent recessions if they were due to the sources of fluctuations that have typically generated recessions in the euro area. For example, if exogenous financial shocks were traditionally associated with a recession in the euro area, we would be implicitly conditioning also on those shocks.

To assess whether the variables of interest developed according to historical regularities, we compare their conditional expectations

¹⁴For example, Mojon (2008) shows that, for the United States, "unsystematic monetary policy" played a very small role in the sample 1985 to 2008, while it was much more prominent in earlier samples.

¹⁵The complete set of results is available upon request.

¹⁶See Giannone, Lenza, and Reichlin (2010) for an application of this idea to identify the effects of the inception of the euro on per capita GDP in the euro-area countries.

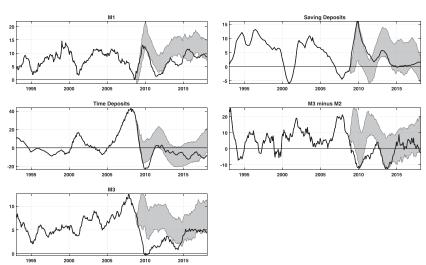


Figure 4. Actual and Counterfactual Year-on-Year Growth Rates of M3 and Components

Note: Solid line: actual year-on-year growth rates; shaded areas: counterfactual distribution, 16th to 84th quantile range.

with the actual developments from October 2008 onward. Significant discrepancies would signal either the materialization of different shocks from those traditionally prevailing to explain the dynamics of the variables of interest, or a change in the relationship between the latter variables and the conditioning set during the crisis.

Figure 4 reports the actual and counterfactual decomposition of the year-on-year growth rate of M1, savings deposits, time deposits, M3 - M2, and M3.

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. M3, instead, has strongly declined during the crises, and its evolution is much more difficult to reconcile with the historical regularities captured in our empirical model. Only recently, starting in 2015, the M3 growth rates are again in line with historical regularities. The analysis by components indicates that the collapse in M3 growth is mainly explained by the

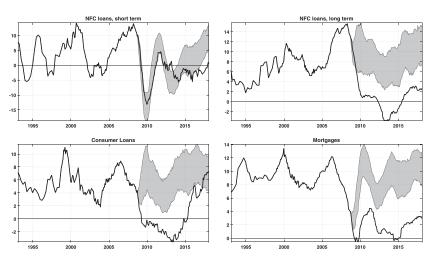


Figure 5. Actual and Counterfactual Year-on-Year Growth Rates of Retail Loans

Note: Solid line: actual year-on-year growth rates; shaded areas: counterfactual distribution, 16th to 84th quantile range. NFC stands for non-financial corporations.

less liquid time deposits and M3-M2 components, while the saving deposits, which have a shorter maturity than time deposits, move more in line with M1.

Figure 5 reports the actual and counterfactual paths of the year-on-year growth rates of short- and long-term loans to non-financial corporations, consumer loans, and mortgages.

Short-term loans to non-financial corporations evolved in line with past regularities, except maybe in the very recent part of the sample. Long-term loans to non-financial corporations, consumer loans, and mortgages, on the other hand, show an exceptional decline. As for the monetary aggregates, it is the long-term segment of loans which is particularly weak during the crisis period.¹⁷

¹⁷In figure A2 (in the online appendix), we show that the exceptional weakness of loans to households—i.e., consumer loans and loans for house purchases in the aftermath of the Lehman collapse—can be rationalized by conditioning on the post-crisis developments of house prices and the euro-area budget-to-GDP

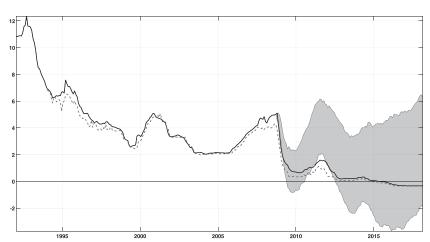


Figure 6. Counterfactual Exercises on Three-Month ${\bf EURIBOR}$

Note: Solid line: three-month EURIBOR; shaded area: 16th to 84th quantile of the distribution of the conditional forecasts of the EURIBOR; dashed line: EONIA rate.

Figure 6 reports the observed path of the three-month EURI-BOR and the distribution of its counterfactual path (median and 16th and 84th quantiles). We also include the path of the EONIA rate, for reference.

The counterfactual path for the EURIBOR reflects the stance of monetary policy that would materialize had the ECB conducted its standard monetary policy according to the regularities observed before the crisis. Since no constraint is imposed on the counterfactual path, nothing prevents it from crossing the zero line and stepping

ratio. The latter variables are available at the quarterly frequency and were interpolated to be included in our monthly VAR. We also find that the inclusion of house prices and the deficit-to-GDP ratio do not change the pre-crisis results. Hence, we can conclude that the weakness in household loans during the Great Recession is at least partly due to the specific financial shocks reflected in the two additional conditioning variables. However, in the episode of the sovereign debt crisis, such weakness emerges again, and it cannot be rationalized by the inclusion of house prices and the deficit-to-GDP ratio. The source for the data on the deficit-to-GDP ratio is Paredes, Pedregal, and Perez (2009).

into negative territory. In practice, our counterfactual EURIBOR path can be interpreted as a sort of shadow rate, capturing the stance of monetary policy "according" to historical regularities.

Interestingly, the observed path of the three-month EURIBOR is, over the full horizon under analysis, well inside the 16th and 84th quantiles of the counterfactual forecast distribution, i.e., the interbank market rates have roughly behaved according to historical regularities with respect to the business cycle in the euro area. ¹⁸

Moreover, in the course of the last decade, the probability that the counterfactual interest rate remains positive was always quite high. In this probabilistic sense, the zero lower bound was not too strongly binding in the euro area. This contrasts with the U.S. case for which Stock and Watson (2012), on the basis of a similar approach, find that the zero lower bound was binding very early into the crisis period. This different assessment of the two areas, particularly for the period of the global financial crisis of 2007–09, is also confirmed by back-of-the-envelope calculations based on a simple Taylor rule, since during that episode the increase in unemployment rates was larger in the United States than in the euro area. ¹⁹

In the figure, we also report the EONIA rate, which is a better proxy of the policy rate for the euro area. The EONIA and the three-month EURIBOR were almost undistinguishable before the long period of crisis facing the euro area. The spread between the two rates became more sizable in the first phase of the crisis, but it was still quite limited relative to the uncertainty surrounding our counterfactuals and, after 2012, it markedly decreased, reaching its historical lows. The latter dynamics are also due to the non-standard monetary policy of the ECB which, providing ample liquidity to the

¹⁸Stock and Watson (2012) find a breakdown of the relationship of the U.S. federal funds rate. We find that our result on the EURIBOR remains robust also if we condition on the post-crisis developments in the U.S. federal funds rate. The results are available upon request. We thank an anonymous referee for suggesting this additional exercise.

¹⁹According to the Organisation for Economic Co-operation and Development (OECD), the unemployment gap in that period was 1 percent in the euro area and 4 percent in the United States. Based on these estimates, Nechio (2011) found that a simple Taylor rule based on the euro area is able to accurately predict the observed behavior of the short-term interest rate.

monetary and financial institutions in the euro area, contributed to stabilize the money market rates.

In figure 7, we report the ten-year bond rates and the associated spread with respect to the three-month EURIBOR.

Uncertainty around bond rates is quite large. However, relative to short-term rates, it emerges that long-term rates have been less reactive to cyclical conditions than what has been historically observed. The stickiness of long-term rates has also been observed in other countries and periods (for the United States, for example, see Backus and Wright 2007). Combined with the sharp decline in short-term rates during the first phase of the crisis, it implies an unusually steep yield curve. This finding can help to explain the unusual weakness of broad monetary aggregates since, as we have seen in the previous section, their 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.²⁰ although it cannot account for the full extent of the unusual reduction in broad monetary aggregates.

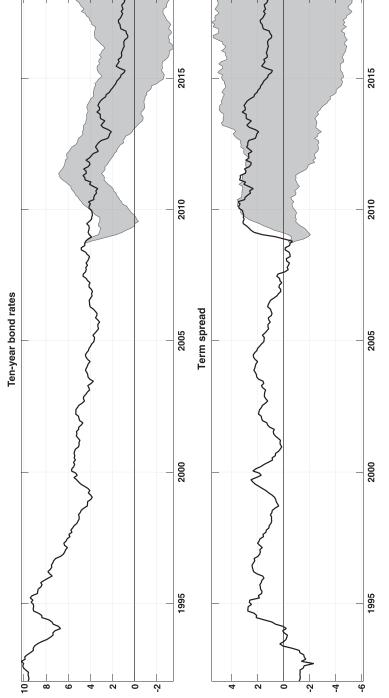
Finally, in order to provide some indications of the mechanisms explaining the weakness of some categories of loans, we match the findings on quantities with results on the associated lending rates.

Figure 8 shows that, consistent 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, lending rates on mortgages have been stickier, particularly in the 2008–09 period. This result suggests that the unusual weakness in certain categories of loans seen above may have been due, at least partly, to the restriction of supply by banks which has affected riskier and less profitable categories such as long-term loans.²¹

²⁰The growth rates of M3 would have been between 2 and 3 percent higher in 2010 had the steepness of the yield curve behaved in line with past regularities.

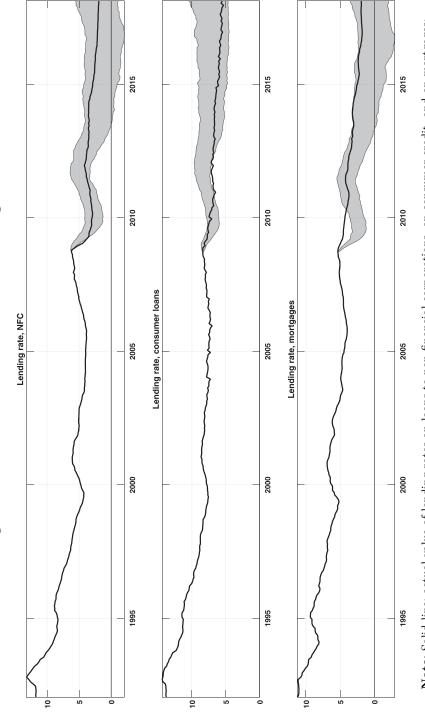
²¹Ciccarelli, Maddaloni, and Peydro (2012) and De Santis and Darracq Paries (2013), using data from the Bank Lending Survey, provide more evidence on the relevance of supply factors to explain the tightness of euro-area credit markets.

Figure 7. Counterfactual Exercises on Ten-Year Bond Rates and Term Spread



Note: Solid line: actual value of ten-year bond rates and term spread (ten-year bond rates minus EURIBOR); shaded area: 16th to 84th quantile of the distribution of the conditional forecasts.

Figure 8. Counterfactual Exercises on Lending Rates



Note: Solid line: actual value of lending rates on loans to non-financial corporations, on consumer credit, and on mortgages; shaded area: 16th to 84th quantile of the distribution of the conditional forecasts.

5. Conclusions

This paper provides stylized facts 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 then identify breaks in historical regularities after the crisis 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 United States in a large body of empirical literature.

As for the post-crisis developments, 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 display a stable relationship with the business cycle, the latter do not. Long-term interest rates are higher than suggested from the precrisis association with cyclical variables, while long-term loans and deposits are lower. One implication of these findings is that while systematic monetary policy in the euro area did not deviate from the implicit pre-crisis rule, the transmission from short-term rates to long rates was impaired.

The heterogeneity between the short and the long end of the maturity structure of euro-area bank assets and liabilities, and corresponding interest rates, suggests some promising directions to improve economic modeling. Such heterogeneity emerges both in the analysis of the pre-crisis stylized facts and in the post-crisis dynamics, revealing a market segmentation that is not just a feature of specific shocks or economic regimes. Despite the progress in the modeling of macrofinancial linkages stimulated by the extended period of financial turmoil of the last decade, the characterization of the banking sector has remained quite stylized, largely failing to capture some of the relevant aspects of the segmentation highlighted in this paper. For example, among other things, the portfolio effects that turn out to be important drivers of the long end of bank liabilities play generally a small role, if any, in macroeconomic models with banking.

Appendix. Database

Table 1. Database

Variables	Transformation	Units
Industrial Production	Log-Levels	Ind.
HICP	Log-Levels	Ind.
Unemployment Rate	Levels	Ppt.
Producer Prices Index	Log-Levels	Ind.
U.S. Industrial Production	Log-Levels	Ind.
U.S. Consumer Prices Index	Log-Levels	Ind.
U.S. Federal Funds Rate	Levels	Ppt.
EURIBOR Three Months	Levels	Ppt.
Consumer Confidence	Levels	Bal.
Oil Price (Euro)	Log-Levels	Ind.
U.S./Euro Exchange Rate	Log-Levels	\$/€
Stock Prices	Log-Levels	Ind.
Two-Year Bond Rate	Levels	Ppt.
Five-Year Bond Rate	Levels	Ppt.
Ten-Year Bond Rate	Levels	Ppt.
M1	Log-Levels	€Bl.
M2	Log-Levels	€Bl.
M3	Log-Levels	€Bl.
Loans to Non-financial Corporations up to One Year	Log-Levels	€Bl.
Loans to Non-financial Corporations over One Year	Log-Levels	€Bl.
Consumer Loans	Log-Levels	€Bl.
Loans for House Purchases	Log-Levels	€Bl.
Other Loans	Log-Levels	€Bl.
Lending Rate, Loans to NFC up to One Year	Levels	Ppt.
Lending Rate, Consumer Loans	Levels	Ppt.
Lending Rate, Loans for House	Levels	Ppt.
Purchases		
Saving Deposits	Log-Levels	€Bl.
Time Deposits	Log-Levels	€Bl.

Notes: HICP: Harmonized Index of Consumer Prices; NFC: Non-financial corporations; Bl: billions; Ppt: percentage points; Ind: index number; Bal: balance of positive and negative replies to surveys on economic conditions in the euro area. The data on financial intermediation (loans, deposits, and monetary aggregates) are defined in terms of notional stocks. For details, see Colangelo and Lenza (2013).

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