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What does money and credit tell us about real activity in the United States?☆

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ABSTRACT

We analyse the forecasting power of different monetary aggregates and credit variables for US GDP. Special attention is paid to the influence of the recent financial market crisis. For that purpose, in the first step we use a three-variable single-equation framework with real GDP, an interest rate spread and a monetary or credit variable, in forecasting horizons of one to eight quarters. This first stage thus serves to pre-select the variables with the highest forecasting content. In a second step, we use the selected monetary and credit variables within different VAR models, and compare their forecasting properties against a benchmark VAR model with GDP and the term spread (and univariate AR models). Our findings suggest that narrow monetary aggregates, as well as different credit variables, comprise useful predictive information for economic dynamics beyond that contained in the term spread. However, this finding only holds true in a sample that includes the most recent financial crisis. Looking forward, an open question is whether this change in the relationship between money, credit, the term spread and economic activity has been the result of a permanent structural break or whether we might return to the previous relationships.

1. Introduction

Economists and forecasters alike were widely surprised by the sudden onset and the depth of the Great Recession of 2007–09. While the unprecedented scale of the recession was arguably quite challenging to be foreseen, the commonly held view is that most economic models failed to predict the financial crisis mainly because they were not taking sufficiently into account the interaction between financial variables and real activity. Moreover, against the background of modern monetary policy frameworks that have a substantial emphasis on inflation targeting, the analysis of monetary variables has lost some of its previous relevance (see for example, Carlstrom & Fuerst, 2004). Against this background, our aim is to revisit and explore the informational content of money and credit, in order to draw conclusions as to whether stronger attention should be set on such variables to improve the forecasting of US activity.

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The analysis of the role of money and credit for output has a long history. Empirical evidence on the money-output nexus for the United States is mixed.[1] On the one hand, Amato and Swanson (2001), Berger and Österholm (2009), Estrella and Mishkin (1997), Feldstein and Stock (1997) and Friedman and Kuttner (1992) tend to cast doubt on the role of money for predicting economic activity. In contrast, Aksoy and Piskorski (2005, 2006), Darrat, Chopin, and Lobo (2005), Favara and Giordani (2009), Hafer, Haslag, and Jones (2007), Nelson (2002), Swanson (1998) and Vilasuso (2000) find that there is information in money for predicting output. The latter authors often exclude certain monetary assets from the official aggregates or re-define money. For example, Darrat et al. (2005) emphasise that the forecasting power of money depends heavily on whether simple sum or Divisia measures of money are used, with positive results for money only holding for Divisia money; Aksoy and Piskorski (2005, 2006) exclude foreign holdings of cash in their analysis. In contrast, the older literature on the US economy usually found that official monetary aggregates play a causal role in output (see, e.g., Sims, 1972, 1980).

A large empirical literature has established statistically significant positive effects of credit growth to the non-financial sectors in the United States on (national and international) output growth (see, e.g. Gambetti & Musso, 2016; Lown & Morgan, 2006; Xu, 2012). Additionally, Schularick and Taylor (2012) demonstrate that credit growth is a powerful predictor of financial crises which, in turn, produce large output costs. Interestingly, and in contrast to the findings for the money-output relationship, the results for the United States with credit variables are not too different from those for the euro area (see, e.g., Gambetti & Musso, 2016). Den Haan, Sumner, and Yamashiro (2007) highlight the importance of distinguishing between different kinds of loans, especially between commercial and industrial loans on the one hand and real estate and consumer loans on the other.

Many authors have shown that interest rate spreads contain useful information for future real developments in the United States (see, e.g. Adrian & Estrella, 2008; Ang, Piazzesi, & Wei, 2006; Estrella & Trubin, 2006; Hamilton & Kim, 2002; Rudebusch & Williams, 2009).[2] This is especially true for the term spread – the difference between long-term and short-term rates. Many studies attribute the forecasting content of the term spread for activity to the impact that monetary policy has on both short- and long-term interest rates and thereby on output growth. A tightening of monetary policy undertaken to bring down inflation and stabilise the deviation of output growth around potential likely causes short term interest rates to rise by more than long term rates, leading to a flattening of the yield curve or a decline in the term spread. Adrian, Estrella, and Shin (2010) put forward another link between the term spread and economic activity, suggesting that when the term spread narrows, and since banks borrow short but lend long, the marginal loan becomes less profitable for the banks, leading to lower credit supply in the economy and consequently lower economic activity (the so-called risk-taking channel). However, the link between the term spread and activity seems to have become weaker or even disappeared since the mid-2000s (see De Pace & Weber, 2013, and the survey of Wheelock & Wohar, 2009).

In this paper, we use a comprehensive set of monetary and credit variables to investigate whether any of these helps to predict US GDP developments beyond the influence of interest rate spreads. Our results suggest that particularly narrow monetary aggregates as well as different credit variables do a good job in forecasting US GDP growth. In particular, our paper supports the view that for all forecasting horizons considered (up to 2 years), our small-scale VAR models with money or credit variables are able to outperform univariate AR models as well as a benchmark VAR with GDP growth and a term spread in rolling (and recursive) forecasting exercises over a sample that includes the most recent crisis period. In the pre-crisis sample, however, most of our selected VAR models with money or credit seem not to have additional information content for predicting GDP growth beyond the information contained already in the term spread.

Overall, our main findings suggest that money and credit variables together with the term spread should be taken into account when forecasting real activity in the United States. Nevertheless, these findings are mainly the result of the change in the relationship between money, credit, the term spread and economic activity since the 2007–09 financial crisis. Looking forward, an open question is thus whether the change in this relationship is permanent or whether we might go back to the previous trends.

The remainder of the paper is organised as follows. In the next section, we describe the data used in the paper, whereas in Section 3, we introduce a single-equation approach to help select the money and credit variables to be used in the following forecasting exercises. In Section 4, we first describe the benchmark model, which will be used as a reference when assessing the relative forecast accuracy of different VAR models and, subsequently, the forecast results stemming from these VAR specifications. Section 5 concludes.

2. Data

We use seasonally-adjusted quarterly data for the sample 1985Q1–2014Q4. US activity is measured by chain-linked real GDP (at 2009 prices). As the yield curve, and especially the term spread, has proven to be a good leading indicator in the

[1] The evidence in the euro area seems to suggest that especially narrow monetary aggregates, such as M1, outperform the yield spread in terms of its predictive content for cyclical movements in GDP (see Brand, Reimers, & Seitz, 2004).

[2] This holds also for many other countries (see, e.g., Ivanova, Lahiri, & Seitz, 2000 and Buchmann, 2011). Nevertheless, Ratcliff (2013) finds that while the term spread is useful in predicting whether there will be a recession or not, it does a poor job in capturing the probability of a recession.

United States, in general, we include a spread variable in our regressions. The different spreads tested are term spreads, bond spreads, lending spreads and the external finance premium (see Appendix A for details).

The models below with real GDP and one of the spread variables are augmented with one money or credit variable at a time, to yield a 3-variable regression framework. In total, we consider 30 monetary aggregates and 15 credit variables (see Appendix A). To calculate real variables, we deflate nominal variables with the personal consumption expenditures (PCE) deflator provided by the Bureau of Economic Analysis.[3] All variables have been transformed into logarithms, with the exception of the spread and the data from the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS), for which a level specification was taken into account.

We do not use real-time vintages of the data, but the revised and latest available figures because we are interested in what actually happens to the economy, not in an assessment of preliminary announcements of economic growth (see Ang et al., 2006). Charts of the main variables used are shown in Appendix B.

3. Single-equation approach

3.1. Econometric framework

Hamilton and Kim (2002) establish the importance of the yield spread for forecasting real output growth in the United States for the period 1953Q2–1998Q2. They use the following equation:

$$\Delta y_t^h = \alpha_0 + \alpha_1 spread_t + \alpha_2 x_t + \varepsilon_t, \tag{1}$$

where $\Delta y_t^h = \frac{400}{h}(\ln Y_{t+h} - \ln Y_t)$ is the annualised real GDP growth over the next h quarters (and Δ is the difference operator), $spread_t$ is the term spread (the 10-year Treasury Note yield minus the 3-month Treasury Bill yield), x_t is a vector of alternative explanatory variables (e.g. growth rates of M1, M2 and lagged growth rates of GDP) and ε_t is a white noise error term. Their general conclusion is that the term spread is especially useful in predicting real GDP growth up to two-years ahead. Whereas the coefficient on M1 is generally not statistically different from zero (and sometimes has the wrong negative sign), M2 exhibits statistically significant results with a positive sign for up to $h = 16$ quarters.

In order to present some preliminary evidence on the role of money and credit for real GDP and, at the same time, to pre-select variables, we update the results by Hamilton and Kim (2002) by using an analogous single equation approach with the term spread as a starting point. For x_t, we take the different monetary or credit variables in real terms mentioned above. We estimate (1) with OLS with the Newey-West correction for heteroscedasticity and autocorrelation. Our forecasting horizon ranges from $h = 1,\ldots,8$ quarters. In order to control for the 2007–09 international financial crisis, which might have created a structural break and changed the relationship between some of the variables, making it more challenging to forecast economic activity (see Ng & Wright, 2013), we distinguish between two different samples: the full sample goes from 1985Q1 to 2014Q4, while the shorter sample stops in 2007Q4.[4] This procedure should help to identify to which degree the results are distorted by the crisis period. Money and credit are judged to be helpful in forecasting GDP if α_2 is statistically significant (at least at the 10 percent level of significance).

3.2. Results

3.2.1. Monetary aggregates

Money (m) enters Eq. (1) in annual growth rates. Irrespective of the sample considered – including or excluding the crisis period – the results are generally promising, i.e. statistically significant, for all leads of M1 plus sweeps into money market deposit accounts, and currency in circulation, both with or without adjusting for currency abroad (see for the latter, Aksoy & Piskorski, 2005, 2006), as well as the Monetary Service Index M1 (see Table B1 in Appendix B with the R-squared of all equations for all forecast horizons and for the full sample). These are all transactions-oriented narrow monetary aggregates which highlight money's unique role for transactions purposes. Therefore, they should in principle have the closest relation to expenditures and real GDP, which turns out to be the case. The results for the narrow Divisia Index are in line with Gogas, Papadimitriou, and Takli (2013), but in contrast to Schunk (2001) who presents evidence supporting the broad Divisia monetary aggregates as the dominant predictors of real GDP. Some of the money variables are distorted by the crisis period, in the sense that they are only statistically significant up to 2007, such as currency plus demand deposits and the monetary base (adjusted or unadjusted). The latter result is not surprising, given the unprecedented large increase in banks' reserves at the Federal Reserve since the outbreak of the crisis, which has not pushed up US GDP growth as much as suggested by historical norms. For all other monetary aggregates, especially official simple-sum M1, M2 and MZM, the estimates are not statistically significant.

The results of the two best performing models, both in terms of the R-squared and statistical significance (for the full and the restricted sample), are shown in Table B2 in Appendix B. They refer to M1 plus sweeps into money market deposit accounts

[3] Bullard (2013) presents some reasons why the PCE should be preferred over the Consumer Price Index.

[4] Within the VAR setup presented in Section 4, we have conducted breakpoint tests to investigate empirically whether a break point exists due to the financial crisis. The results tentatively confirm the possibility of a structural break around the time of the 2007–09 financial crisis (Table B6 in Appendix B).

(*m1*) and currency in circulation (*cu*). These are the monetary aggregates which we include in the Vector Autoregressive Models (VAR) analysis in Section 4. The term spread (*Spread*) is generally not significant when taking money additionally into account. However, there is some (weak) evidence that the term spread is statistically significant in the longer leads ($h = 4, \ldots, 8$) when excluding the crisis period. This is surprising as most studies find that the term spread is a good predictor for output growth up to one year in advance (see Wheelock & Wohar, 2009). Using a comparable singe-equation exercise, Hamilton and Kim (2002) find that official M1 (however with the wrong sign) and M2 are significant together with the term spread for short and long leads in a sample from 1959 to 1998.

The fact that the term spread appears to be statistically more powerful in the sample that excludes the crisis period might be related to the nature of the 2007–09 financial crisis which appears to have made credit/corporate spreads more important than the term spread. Ng and Wright (2013) argue that, although the forecasting performance of the term and credit spread is somewhat episodic, the forecasting accuracy of credit spreads over the term spread has improved since the early-2000s due to two fundamental reasons. First, credit spreads are more useful in forecasting economic activity in the presence of a more highly leveraged economy, where developments in financial markets imply that credit spreads provide more information than before. Second, the Great Recession was rooted in excess leverage and the housing and credit market bubble, which have made credit spread developments central in trying to forecast economic activity. Our results for the term spread are also consistent with the literature, as several recent studies summarised in Wheelock and Wohar (2009) find that the term spread's forecasting power for US output has diminished in recent years.

3.2.2. Credit variables

Like with monetary aggregates, the credit aggregates are in annual growth rates. In contrast, the SLOOS survey data enter Eq. (1) in levels, and the sample begins in 1990Q3 due to data availability. Within credit variables, we distinguish between three main groups: credit growth, credit impulse, and credit standards. As regards the first group, in general all credit growth variables yield statistically significant results for all leads, with the exception of unadjusted real estate loans. Interestingly, the predictive power of credit to the private non-financial sector (particularly mortgage credit), and break-adjusted real estate loans before the crisis do not pass the conventional statistical significance levels, implying that the forecasting power of these variables is only due to the crisis period. The term spread is usually highly statistically significant regardless of the sample period, contrasting with the results for money variables. This implies that the term spread contains information beyond that inherent in credit aggregates, whereas this information seems to be incorporated already in monetary aggregates. As with money, we select from Table B1 the two preferred credit growth variables to be included later in the VARs (Table B3 in Appendix B). These are credit to the private non-financial sector (*cr_pr*) and total mortgages of the private non-financial sector (*mo_pr*).[5]

As alternative to credit growth, we also analyse credit impulse variables (ci_t), which might contain useful signals. These are based on the *change* in flow of credit, and defined as follows:

$$ci_t = 100\left(\frac{cr_t - cr_{t-1}}{Y^n_{t-1}} - \frac{cr_{t-4} - cr_{t-5}}{Y^n_{t-5}}\right), \qquad (2)$$

where cr_t is the stock of nominal credit and Y^n refers to nominal GDP. The choice of this variable is motivated by Biggs, Mayer, and Pick (2009) who argue that, to the extent that spending is credit financed, GDP is a function of *new* borrowing, i.e. the flow of credit. If this is true, GDP growth should be related to changes in the flow of credit (or the second derivative of the stock) rather than changes in the stock. The results of the selected credit impulse variables (consistent with the credit growth variables considered above, i.e. *ci_cr_pr* and *ci_mo_pr*) are shown in Table B4 in Appendix B. However, since this theory is subject to some controversy, where the literature has not yet reached a consensus on its appropriateness and validity, we take these results with a pinch of salt.

Finally, all credit standard variables also reveal forecasting properties for GDP growth, in line with the findings by Cunningham (2006), Lown and Morgan (2006) and Kishor and Koenig (2014). Cunningham (2006) has shown that the SLOOS's ability to predict GDP (especially the C&I series) does not extend beyond the simple prediction of one of its components (private investment). In our results, the financial crisis distorted the predictive power of the tightening standards on consumer credit cards, which only have forecasting power when excluding the crisis period. Conversely, and interestingly, the statistical significance of banks' willingness to lend to consumers and tightening standards on consumer loans excluding credit cards in the full sample is driven solely by the crisis period. These results are in line with Cunningham (2006), who finds that survey results directed specifically at consumer lending market conditions never significantly foreshadow changes in personal consumption expenditures. The term spread is generally not significant, again in line with Cunningham's (2006) results, which reveal that the term spread loses predictive power once variables from the SLOOS are included. The best performing credit standard variable that we have chosen to feed into the VARs in the next section. It refers to tightening standards on residential mortgages (*tight*).

[5] Based on economic reasoning, we choose these two variables over break-adjusted real estate loans in bank credit, and break-adjusted bank credit. While the *R*-squared is broadly the same, credit to the private non-financial sector and total mortgages of the private non-financial are broader, enabling us to capture a wider and a more important fraction of the credit segment in the United States.

4. VAR analysis

We now analyse the predictive content of the five monetary and credit variables, which were selected before, with the help of VARs. The variables are: M1 plus sweeps into money market deposit accounts (*m1*), currency in circulation (*cu*), credit to the private non-financial sector (*cr_pr*), total mortgages of the private non-financial sector (*mo_pr*), and tightening standards on residential mortgages (*tight*). We restrict ourselves to a 3-dimensional system in which we add to one of these five variables real GDP and a spread. Our choice of small, parsimonious VARs stems from the fact that it has been found in the literature that these types of models with a limited number of variables perform fairly well in forecasting exercises, especially during periods characterised by structural breaks, which are known to make VARs with a large number of variables fairly sensitive to changes in the specification (see for instance, Clark & McCracken, 2007 and Elbourne & Teulings, 2011). Moreover, by choosing small-scale VARs we avoid losing too many degrees of freedom.

4.1. Benchmark model

The performance of the VAR models will be assessed against a benchmark model. As benchmark, we use a VAR model with GDP growth and the term spread over the period 1985Q1–2014Q4. The selection of the lag order h is based on the Akaike (AIC) and Schwarz (SC) information criteria (see Lütkepohl, 1993), with a maximum of eight lags considered. We then make sure that no residual autocorrelation remains present by conducting VAR residual Portmanteau tests for autocorrelation up to lag h and serial correlation Lagrange-Multiplier tests at lag order h. We end up selecting 2 lags, which are sufficient to ensure white noise residuals. In addition, we have tested two alternative benchmark models, namely a flexible lag and a fixed lag AR model for GDP growth. We find that the predictive power of both models is worse than the main VAR benchmark specification (see Appendix C for more details on the alternative benchmarks).[6] Therefore, we rely on the VAR benchmark in what follows.

4.2. Difference VARs

We focus on VAR models in first differences (except for the spread, credit standards and credit impulse variables) as in the presence of large structural breaks – in our sample represented by the recent financial crisis – such models may be particularly promising because the break has less of a persistent impact than in VARs in levels or in VECMs (see Clements & Hendry, 1998, chs. 6 and 7). Similarly to the single-equation exercise reported in Section 3, we always include a money or credit variable in the VARs, a spread term and real GDP. As regards the spread, we use the term spread in our baseline models, but experiment with alternative spreads in Section 4.2.3.

As with the benchmark, the selection of the lag order is based on the AIC and SC information criteria, with a maximum of eight lags considered. The resulting lag choices of our preferred models are reported in Table B5 in Appendix B. It is evident that in most cases up to 2 lags are enough to ensure white noise residuals. Only credit variables sometimes require richer dynamics.

4.2.1. Recursive out-of-sample forecasts

We *recursively* estimate the different VAR specifications including the best-performing money and credit variables selected via the single-equation exercise in Section 3. The initial sample covers the period 1985Q1–2005Q4, to which we add an additional quarter at a time and recursively conduct out of sample forecasts for up to eight quarters ahead.

The recent financial crisis that started in late 2007 may have led to a structural break in the relationship between money, credit and economic activity. To investigate this empirically, we have conducted Quandt–Andrews breakpoint tests that do not exogenously impose a specific breakpoint in the sample, as well as Chow breakpoint tests to test for a specific break in 2008Q1. While some of the results tentatively confirm the possibility of a structural break around the time of the 2007–09 financial crisis, they are not entirely conclusive as suggested by Table B6 in Appendix B. Going forward, it is also an open question whether an eventual change would be a permanent structural break or whether we might go back to the previous relationships. Given our strong prior, on economic grounds, that a possible break may exist around this time, we investigate whether the forecasting performance of the alternative variables has changed since the financial crisis by distinguishing between two different forecasting samples: one that ends in 2007Q4 (with estimation until 2000Q4), so as to avoid the crisis period and subsequent recovery, and a second sample that includes the full period, ending in 2014Q4 (estimation period until 2005Q4).

Table B7 in Appendix B presents the root mean squared forecast errors (RMSFEs) of the different VAR specifications relative to the benchmark model. The results suggest that money and credit variables contain valuable information for forecasting GDP growth, thus confirming the single equation exercises. Almost all models for the full sample beat the benchmark model

[6] In addition, we compared the forecast errors of our models to the errors obtained by using the median forecasts from the Survey of Professional Forecasters (SPF) up to four quarters ahead. Although we are not able to beat the SPF over these horizons, the forecasting performance of our models is not very different from the SPF. Moreover, the VAR models have the advantage of being timelier, as we are able to produce a 1-step ahead forecast already one month after the end of a quarter, whereas the SPF is released only two weeks after this date.

at all $h = 1–8$ forecasting horizons, as indicated by a relative RMSFE smaller than one. But in most cases, this difference is not statistically significant at conventional levels, based on the Newey–West corrected Diebold–Mariano test statistics (see Diebold, 2012). Nevertheless, some of the models do a good job at longer horizons: notably the two money variables and the model with total mortgages outperform the benchmark in a statistically significant way.

However, excluding the period covering the financial crisis and subsequent recovery changes the results substantially. Information from the pre-crisis sample suggest that before the crisis, the VAR with money or credit variables does not contain additional information content for predicting GDP growth beyond that contained already in the term spread and past GDP growth. This is in line with the findings from the literature that the term spread had been a good predictor of activity in the past but that this link may have become weaker or even disappeared more recently (De Pace & Weber, 2013; Wheelock & Wohar, 2009).[7] Using as a different benchmark a simple autoregressive model of GDP growth (thus leaving out the term spread from the regressions), the VARs with money or credit still beat the benchmark in a statistically significant way (see Appendix C).[8]

Further evidence on how the recent financial crisis has impacted the forecasting performance of our models is provided in Chart B7 in Appendix B, which shows the RMSFEs over time around the crisis period, averaging the forecast errors for up to four quarters, four to eight quarters and all horizons. The chart refers to the VAR with currency, but the results for the models with other money and credit variables are broadly similar. The RMSFE started increasing as the quarter corresponding to the start of the US recession (2007Q4), as defined by the NBER, approached. This is not surprising, as the forecasting performance of all (linear) models deteriorated around that time. As more of the observations from the crisis period were included and as the sharp declines in GDP growth moderated, the accuracy of the model started to improve again, reflected in a gradually declining RMSFE.

4.2.2. Accounting for structural breaks: constant rolling window

Both the recursive forecasting exercises as well as the selection of the variables within the single-equation procedure advise us to be careful when estimating and forecasting over a period which includes the financial turbulences that struck the US economy in late 2007. Giacomini and White (2006) offer a solution to this problem of data heterogeneity and structural shifts, by proposing a rolling-window forecasting scheme to supplement or replace the recursive procedure. They argue that in such environments, the use of an expanding estimation window is not appropriate, as observations from the distant past start losing at some point their predictive relevance. Therefore, they suggest that it is better to base the forecasts on a moving window of the data that discards gradually older observations. Moreover, the results of the Diebold–Mariano tests on the significance of forecast differences should be interpreted with care when nested models are compared. However, Giacomini and White (2006) also show that these tests remain asymptotically valid even for nested models when rolling forecasting procedures are applied. Therefore, we put more weight on the rolling regression approach.

In what follows, we combine a constant estimation window of 64 quarters with our $h = 1, \ldots, 8$ forecast horizons having 49 forecasts each. The full sample ends once again in 2014Q4, while the pre-crisis sample stops in 2007Q4. To be specific, our first estimation sample starts in 1985Q1 and ends in 2000Q4. After having done our up to 8 quarter-ahead forecasts, we proceed to the next estimation sample which runs from 1985Q2 to 2001Q1, and do again the forecasts for up to 8 quarters, and so on and so forth until the last observation where it is possible to forecast eight quarters ahead is reached. The results of these rolling regression exercises in the form of relative RMSFEs are shown in Table B9 in Appendix B.

The five different models all outperform the benchmark model in a statistically significant way in the full sample. Compared to the recursive forecasts (Table B7), and in line with the suggestions by Giacomini and White (2006), the significance of the rolling out-of-sample forecasts is considerably higher.[9] The best models – irrespective of the forecast horizon – are the credit model that refers to total mortgages to the private non-financial sector and the model with currency in circulation. Except for the shortest horizons, there is a statistically significant improvement compared to the VAR benchmark model. As regards currency, there is no need to adjust currency in circulation by foreign holdings as in Aksoy and Piskorski (2005, 2006).

The finding with respect to mortgages (showing up in three variables, mo_pr, ci_mo_pr and tight) may be rationalised by the fact that the housing boom and subsequent bust, and therefore mortgage credit, were at the epicentre of the 2007–09 financial crisis in the United States. Especially the nation-wide collapse in the housing market in the wake of the most recent crisis seems to have signalled the subsequent economic slump quite well. In addition, as Leamer (2007) emphasises, housing activity leads the business cycle in the US more generally. The other variable whose forecast quality improves relative to the pre-crisis period is credit to the private non-financial sector. After having increased substantially until the inception of the crisis at the end of 2007, credit to the private non-financial sector recorded a contraction in absolute terms between 2008 and the first half of 2011. This phenomenon, reductions in aggregate borrowing that took place during the last recession

[7] The loss in the predictive power of the term spread can, for example, be seen in the substantial increase in the RMSFE from the pre-crisis sample to the full sample (RMSFEs in the pre-crisis sample are on average around 54% smaller).

[8] As regards credit impulse variables, the forecasting performance of the model with mortgages performs better than in the pre-crisis sample (see Table B8 in Appendix B), although the RMSFE are not statistically better than the benchmark model.

[9] Although the ratio of the RMSFEs are comparable between the recursive and rolling methods, the fact that the statistical significance increases dramatically is related to the properties of the rolling approach. This technique produces far less volatile out-of-sample forecasts with credit or money variables.

was driven by cutbacks in the provision of credit (Gropp, Krainer, & Laderman, 2014). Only when the banking and financial systems started to show some signs of improvement, did credit supply begin to turn around. This recovery in credit lending, in turn, would stimulate the economy.

Finally, the results are broadly in line with the findings from the recursive forecasts. Another common feature shared with the recursive approach is that in the pre-crisis sample the VAR models with money or credit seem not to have additional information content for predicting GDP growth beyond that contained already in the term spread, with the exception of currency in circulation at longer horizons.[10]

4.2.3. The forecast power of different interest rate spreads

As mentioned before, evidence from the literature suggests that the link between activity and the term spread may have weakened over time (see Wheelock & Wohar, 2009), although there is no consensus as to the causes of this decline.[11] This has led some authors to study the role of other spreads in forecasting real economic activity (see for example, Barnett, 2012; or De Pace & Weber, 2013). Against this background, we investigate whether alternative term and yield spreads improve the forecasting accuracy of our models. For that purpose, we focus on the VAR with currency, which has been found to perform best in many cases. We consider ten alternative spreads, including not only other term spreads but also bond spreads, lending spreads and the external finance premium.

Table B10 in Appendix B shows the RMSFEs of the rolling out-of-sample forecasts. The first takeaway from this table is that, in general and in the full sample, the VAR with currency in circulation is able to consistently outperform the benchmark in a statistically significant way over all horizons, irrespective of the interest rate spread used (the model that employs the bank prime loan rate minus the 3-month Treasury Bill yield – *primebank_3m* – is the only exception). The second key finding is related to the forecasting quality of our VAR with currency and the standard term spread: for the full sample, it is among the best ones for $h = 3–8$. The model with the mortgage term spread (*mortgage_10y*) defined as the rate on 30-year mortgages less the ten-year Treasury yield also does a good job. The predictive role of the mortgage term spread is perhaps not that surprising given the role of the housing cycle in the most recent recession, but also as housing activity tends to lead the overall US business cycle more generally (see Leamer, 2007). For the longest forecast horizons ($h > 3$), the best models are those with the spread between the 3-month commercial paper rate and the 3-month Treasury Bill yield (*efp_financial and efp_nonfinancial*). The benchmark VAR model that only includes GDP growth and the term spread outperforms all other VAR models that additionally include money or credit, with the exception of currency in circulation with the term spread at longer horizons (in line with the results of Table B9).[12] The results for the pre-crisis period point to a rather different picture, highlighting again the role of the term spread for predicting GDP growth.

After having analysed the predictive power of money and credit variables for GDP growth, we also look at the quantitative importance of changes in selected money and credit variables for developments in activity. We do this through the analysis of impulse response functions, which are followed by the variance error decomposition for GDP growth (see Appendix D). The overall conclusion is that impulse response functions and the forecast error variance decomposition analysis are helpful in tracing the effects of a money and credit innovation to GDP growth. Nevertheless, this interpretation should be made with caution as our models have not been selected for structural interpretation but rather for forecasting. A fully-fledged structural analysis would ideally be based on more complex models (Elbourne & Teulings, 2011).

4.2.4. The usefulness of the yield curve slope for economic activity

While the results so far have indicated that the term spread has lost its predictive power for GDP growth, we follow an additional route to explore the usefulness of the term spread by studying the sign of the slope of the yield curve and its link to economic activity. Along the lines of Rudebusch and Williams (2009), we create a dummy variable that takes the value of 1 if the slope of the yield curve is negative and 0 otherwise, and inspect its predictive power for economic activity. We have broadly the same number of periods when the yield curve slope is negative or positive. In contrast to Rudebusch and Williams (2009), who use a simple probit model to study the power of the yield curve to predict recessions, we use the yield curve slope in our VAR framework. Given that we are interested in checking the relative importance of the yield curve slope, in this experiment we also use a simple (fixed lag) AR model for GDP growth as the benchmark model as in Rudebusch and Williams (2009), instead of the VAR with GDP growth and the term spread that we have been using throughout the paper as the main benchmark model. We adopt 5 lags for the new model in order to match the AR benchmark. The results reported below are, however, robust to selecting a different lag structure.

[10] Regarding credit impulse variables, and in line with the recursive approach, the forecasting performance of the model with mortgages performs significantly better than in the pre-crisis sample (see Table B8 in Appendix B). This finding is in line with Biggs et al. (2009) conclusion that the credit impulse measure should be based on the broadest possible credit aggregate to the non-financial private sector.

[11] Wheelock and Wohar (2009) note that the strength of the relationship between the yield curve and economic activity depends on the responsiveness of the monetary authority to output and inflation, and on the extent of inflation persistence.

[12] We also explored the forecasting power of two other VARs that had performed well, notably the VAR with mortgage credit to the non-financial sector (*mo_pr*) or credit standards on mortgages (*tight*) and alternative spreads. These results (available upon request) tentatively suggest that the mortgage spread is somewhat less powerful in models where a mortgage-related variable is already included. Overall, in these VARs, which spread performed best depends strongly on the forecast horizon and the sample.

According to this new VAR model, where the dummy of the yield curve slope is added to GDP growth, we find that the yield curve slope model adds statistically significant forecasting power up to 2 years ahead to a simple AR benchmark model over the full and pre-crisis samples, although this is only valid when resorting to the rolling approach (Table B11 in Appendix B). The difference in the results between the recursive and rolling approach for the full sample is not surprising, given the shortcomings of the recursive approach in the presence of changes in the underlying structure of the economy over time. In fact, when excluding the Great Recession, we obtain qualitatively the same results irrespective of the forecasting method. These findings go in the same direction as those of Rudebusch and Williams (2009), in that the yield curve should be included in the forecasters' information set when trying to predict recessions, or economic growth (in our case).

5. Summary and conclusion

In this paper we have analysed the role of a large set of money and credit variables to forecast real activity in the United States, given the information content of interest rate spreads. Selection of the preferred money and credit variables is done via a single-equation forecasting procedure. The performance of these variables is then assessed within different VAR models, where we distinguish between pre-crisis and post-crisis results.

In the single-equation exercise to pre-select the variables, our preferred variables turn out to be M1 plus sweeps into money market deposit accounts, currency in circulation, credit to the private non-financial sector and total mortgages of the private non-financial sector, as well as tightening standards on residential mortgages. When we assess the performance of the aforementioned five preferred variables with small-scale VAR models, we find that in most cases, and for all forecasting horizons considered (up to 2 years), our models are able to outperform benchmark VARs with GDP growth and together, as well as without, the term spread in rolling forecasting exercises over a sample that includes the most recent crisis period. In the pre-crisis sample, however, the VAR models with money or credit do not seem to have additional information content for predicting GDP growth beyond that contained already in the term spread, with the exception of currency in circulation at longer horizons.

Against this background, our results suggest that the 2007–09 financial crisis has given a role to money and credit variables for predicting GDP growth, a role which may have been played by the term spread before that period. A decisive and open question is whether this change in the relationship between money, credit, the term spread and economic activity has been the result of a permanent structural break or whether we might eventually go back to the previous relationships. However, as a general conclusion, since the small-scale VAR models with the narrow monetary aggregates and with total mortgages to the private non-financial sector deliver good results, it seems wise not to disregard the information inherent in money and credit when forecasting US GDP growth.

Appendix A. Variable definitions

The data are taken form Haver Analytics, Bloomberg, the Center for Financial Stability, the Federal Reserve Board and the Fed St. Louis.

The spreads used in the paper are defined as follows:

(1) Term spreads

- the 10-year Treasury Note yield minus the 3-month Treasury Bill yield;
- the rate on 30-year mortgages minus the 3-month Treasury Bill yield;
- the rate on 30-year mortgages minus the 10-year Treasury Note yield;
- the 10-year Treasury Note yield minus the effective Federal Funds Rate;
- the 3-month Treasury Bill yield minus the effective Federal Funds Rate.

(2) Bond spreads

- the Aaa corporate bond yield minus the 10-year Treasury Note yield;
- the BAA corporate bond yield minus the 10-year Treasury Note yield.

(3) Lending spreads

- the bank prime loan rate minus the 3-month Treasury Bill yield;
- the commercial and industrial (C&I) loan rate minus the 3-month Treasury Bill yield.

(4) External finance premium

- the AA 3-month commercial paper rate (nonfinancial) minus the 3-month Treasury Bill yield;
- the AA 3-month commercial paper rate (financial) minus the 3-month Treasury Bill yield.

Table B1
R-squared from the single-equation approach.

Variable	Horizon							
	1	2	3	4	5	6	7	8
Monetary aggregates								
M1	0.000	0.003	0.009	0.020	0.037	0.059	0.081	0.102
M1 + sweeps	**0.057**	**0.099**	**0.129**	**0.157**	**0.179**	**0.202**	**0.216**	**0.226**
M1 – official currency abroad	0.001	0.007	0.016	0.029	0.045	0.066	0.085	0.103
M1 – currency abroad (Judson)	0.004	0.015	0.029	0.041	0.053	0.070	0.088	0.105
M1 + sweeps – official currency abroad	0.053	0.082	0.099	0.116	0.133	0.155	0.169	0.180
M1 + sweeps – currency abroad (Judson)	0.053	0.086	0.114	0.136	0.153	0.173	0.191	0.204
M2	0.001	0.003	0.008	0.020	0.037	0.060	0.082	0.101
M2 less small time deposits	0.005	0.008	0.015	0.029	0.048	0.073	0.097	0.117
M2-official currency abroad	0.000	0.003	0.009	0.022	0.039	0.063	0.084	0.103
M2 adjusted for FDIC regulation – official currency abroad	0.000	0.003	0.010	0.023	0.042	0.066	0.087	0.106
Savings deposits	0.012	0.018	0.028	0.042	0.060	0.084	0.105	0.124
Small time deposits	0.009	0.007	0.010	0.020	0.036	0.059	0.082	0.103
Total checkable deposits	0.009	0.011	0.017	0.031	0.049	0.074	0.100	0.123
Demand deposits	0.011	0.013	0.017	0.027	0.043	0.064	0.087	0.107
Currency component of M1 + demand deposits	0.000	0.004	0.012	0.028	0.044	0.067	0.088	0.106
Currency	**0.063**	**0.135**	**0.206**	**0.262**	**0.284**	**0.301**	**0.301**	**0.299**
Currency – currency abroad (Judson)	0.028	0.062	0.098	0.128	0.145	0.162	0.172	0.181
Currency – official currency abroad	0.067	0.090	0.113	0.119	0.121	0.127	0.126	0.131
MZM	0.007	0.013	0.017	0.025	0.038	0.059	0.081	0.102
Monetary base	0.014	0.008	0.010	0.021	0.039	0.064	0.090	0.115
Adjusted monetary base	0.013	0.007	0.010	0.021	0.038	0.063	0.090	0.116
St. Louis adjusted monetary base	0.012	0.008	0.009	0.021	0.038	0.062	0.088	0.113
Monetary services index, all assets	0.001	0.002	0.008	0.023	0.042	0.068	0.093	0.114
Monetary services index, M1	0.045	0.081	0.111	0.140	0.161	0.184	0.198	0.209
Monetary services index, M2	0.001	0.006	0.017	0.034	0.053	0.078	0.099	0.117
Monetary services index, M2 less small time deposits	0.007	0.012	0.023	0.038	0.056	0.081	0.103	0.122
Monetary services index, MZM	0.000	0.003	0.011	0.026	0.047	0.074	0.099	0.121
Divisia M3 (Barnett)	0.008	0.013	0.021	0.040	0.063	0.094	0.123	0.144
Divisia M4 (Barnett)	0.001	0.006	0.016	0.039	0.063	0.094	0.121	0.139
Divisia M4 excluding Treasuries (Barnett)	0.023	0.032	0.043	0.068	0.094	0.129	0.159	0.178
Credit aggregates								
Break-adjusted bank credit, all commercial banks	0.065	0.077	0.086	0.109	0.134	0.173	0.204	0.225
Bank credit, all commercial banks	0.028	0.033	0.042	0.064	0.083	0.114	0.133	0.144
Private Depository Institutions: assets: credit market instruments	0.035	0.045	0.051	0.066	0.088	0.113	0.135	0.145
Private domestic nonfinancial sectors: liabs: credit Mkt instruments	**0.055**	**0.069**	**0.082**	**0.100**	**0.118**	**0.143**	**0.164**	**0.176**
Real estate loans in bank credit: all commercial banks	0.022	0.031	0.043	0.060	0.075	0.095	0.112	0.124
Break-adjusted real estate loans in bank credit: all commercial banks	0.055	0.069	0.080	0.098	0.116	0.140	0.162	0.179
Private nonfinancial: liabilities: total mortgages	**0.048**	**0.063**	**0.073**	**0.086**	**0.096**	**0.111**	**0.126**	**0.136**
Credit standards								
Banks tightening C&I loans to large firms	0.261	0.311	0.284	0.231	0.195	0.159	0.142	0.144
Banks tightening C&I loans to small firms	0.277	0.346	0.325	0.269	0.229	0.196	0.179	0.180
Tightening standards for commercial real estate	0.320	0.368	0.370	0.355	0.330	0.294	0.284	0.290
Res mortgages: net share, banks tightening	**0.291**	**0.376**	**0.422**	**0.431**	**0.414**	**0.405**	**0.392**	**0.376**
Banks tightening standards: consumer credit cards	0.045	0.029	0.006	0.001	0.013	0.039	0.070	0.102
Banks tightening stds on consumer loans ex credit cards	0.114	0.089	0.075	0.071	0.077	0.181	0.218	0.210
Banks willingness to lend to consumers	0.181	0.218	0.210	0.195	0.194	0.181	0.177	0.190

Notes: All variables except credit standards are in logarithms and real terms. The selected five variables for the VAR are in bold. Results are based on estimates for the full sample.

As monetary aggregates, we consider:

- The monetary base (non-adjusted and adjusted by the Federal Reserve Board (FRB) or the Federal Reserve Bank of St. Louis).[13]
- The official aggregates MZM, M1 and M2.
- M1 without foreign currency holdings; M1 plus sweeps into money market deposit accounts (with and without foreign currency holdings).[14]
- M2 without foreign currency holdings; M2 less small time deposits (time deposits of less than USD 100,000); M2 adjusted for FDIC regulation; transactions and non-transactions components in M2.

[13] The St. Louis Fed adjusts the monetary base for the effects of changes in statutory reserve requirements on the quantity of base money held by depositories. The FRB also adjusts the base for discontinuities (breaks) associated with regulatory changes in reserve requirements.
[14] Foreign currency holdings are either from the official flow-of-funds statistics (Z.1 release, table L106) or from Judson (2012).

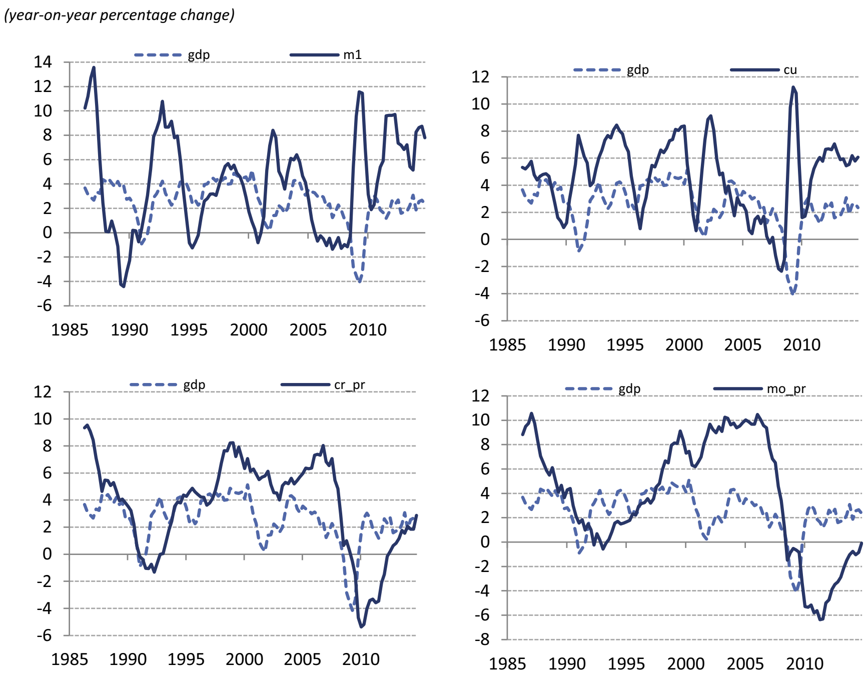
■ Subcategories: currency (with and without foreign currency holdings); savings deposits, including MMDAs; small denomination time deposits; total checkable deposits; demand deposits at commercial banks; currency component of M1 (with and without foreign currency holdings) plus demand deposits.
■ Weighted monetary aggregates: monetary services index (MSI) from the Fed St. Louis (all assets,[15] M1, M2 with and without small time deposits, MZM); Divisia money from W. Barnett (M3, M4 with and without Treasuries).[16]

The credit variables we evaluate are the following:

■ Bank credit of commercial banks (total and break-adjusted).
■ Credit to private Depository Institutions.
■ Credit to the private domestic non-financial sectors.
■ Real estate loans (total and break adjusted).
■ Total mortgages to the private non-financial sector.
■ Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS) on banks' credit conditions: a quarterly survey of major banks in the United States (tightening: C&I loans to large and small firms, commercial real estate, residential mortgages, consumer credit cards and consumer loans excluding credit cards; willingness to lend to consumers).[17]
■ Credit impulse which is based on the change in the flow of credit of different credit aggregates.

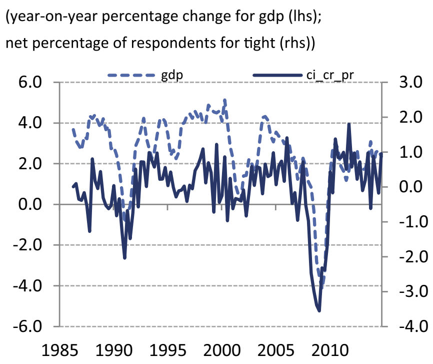
Appendix B. Charts and tables

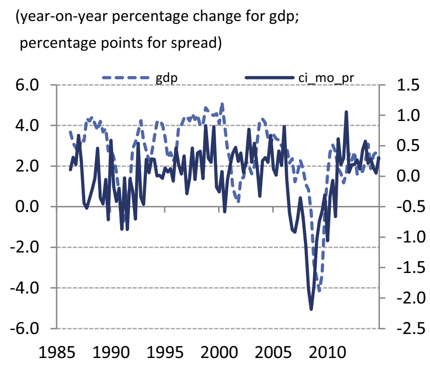
Charts B1 to B4: US GDP, money and credit growth



[15] MSI (all assets) corresponds to the assets in M2 plus institutional money market mutual funds.
[16] See www.centerforfinancialstability.org. Divisia (M3) includes the assets in M2 plus institutional money market funds, large time deposits and repurchase agreements. Divisia (M4) additionally covers commercial paper and Treasury Bills. See Serletis, Istiak, and Gogas (2013) for a comparison among the simple-sum, MSI and CFS Divisia monetary aggregates. An application to the relationship between nominal and real macroeconomic variables is provided by Serletis and Gogas (2014).
[17] The survey (starting in 1967) is currently undertaken at approximately 60 large domestic banks and 24 branches of foreign banks. In aggregate, participating banks account for about 60% of all loans by US banks and about 70% of all US bank business loans (Dufrénot, Klaus, Malik, & Vardoulakis, 2012). For a recent analysis of the (real-time) forecasting properties of banks' willingness to lend for US GDP see Kishor and Koenig (2014).

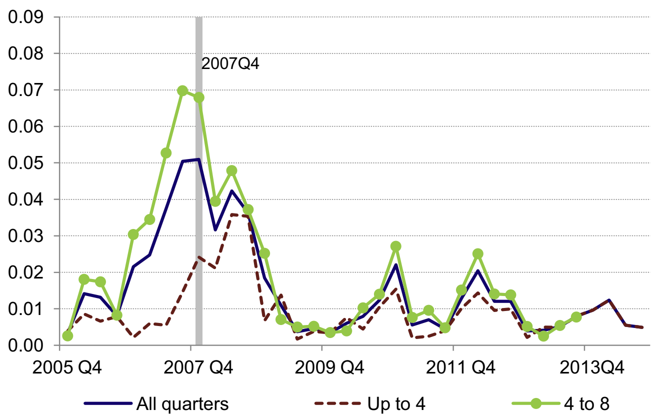
Charts B5 to B6: US GDP, credit standards and term spread





Note: (*gdp*) refers to real GDP, (*m1*) to M1 plus sweeps into money market deposit accounts, (*cu*) to currency in circulation, (*cr_pr*) to credit to the private non-financial sector) and (*mo_pr*) to total mortgages of the private non-financial sector. (*tight*) refers to standards on residential mortgages and (*spread*) refers to the term spread.

Chart B7: Forecasting accuracy over time around the financial crisis (RMSFE)



Notes: RMSFE over time for the VAR with GDP growth, the term spread and currency. Up to 4 (4 to 8) refers to an average RMSFE for horizons 1 to 4 (4 to 8).

Table B2
Money variables: single-equation approach.

	Horizon							
	1	2	3	4	5	6	7	8
Full sample								
Spread	−0.343	−0.316	−0.267	−0.197	−0.121	−0.045	0.021	0.073
	(0.321)	(0.326)	(0.306)	(0.274)	(0.246)	(0.229)	(0.224)	(0.221)
m1	17.887	19.436	19.903	19.737	19.019	18.110	16.834	15.548
	(8.865)**	(9.849)*	(9.987)**	(9.447)**	(8.553)**	(7.653)**	(6.921)**	(6.236)**
R-Squared	0.057	0.099	0.129	0.157	0.179	0.202	0.216	0.226
Spread	−0.174	−0.160	−0.132	−0.075	−0.002	0.075	0.137	0.184
	(0.279)	(0.269)	(0.249)	(0.221)	(0.199)	(0.184)	(0.180)	(0.177)
cu	23.949	28.876	32.250	33.104	31.679	29.693	27.026	24.547
	(13.640)*	(14.672)*	(14.614)**	(13.724)**	(12.585)**	(11.490)**	(10.529)**	(9.521)**
R-Squared	0.063	0.135	0.206	0.262	0.284	0.301	0.301	0.299
Pre-crisis								
Spread	−0.028	0.017	0.040	0.077	0.118	0.164	0.212	0.256
	(0.225)	(0.227)	(0.227)	(0.221)	(0.213)	(0.208)	(0.210)	(0.211)
m1	14.898	14.463	15.023	16.088	16.877	17.340	16.981	15.945
	(7.313)**	(6.545)**	(6.327)**	(6.303)**	(6.214)***	(6.051)***	(5.768)***	(5.323)***
R-Squared	0.076	0.129	0.171	0.219	0.254	0.295	0.326	0.345
Spread	0.149	0.180	0.188	0.212	0.246	0.289	0.334	0.370
	(0.197)	(0.193)	(0.193)	(0.190)	(0.181)	(0.172)*	(0.168)*	(0.165)**
cu	15.119	15.589	18.405	22.214	24.718	26.073	25.619	24.088
	(11.053)	(9.850)	(9.716)*	(10.697)**	(11.569)**	(11.859)**	(11.666)**	(10.822)**
R-Squared	0.055	0.103	0.155	0.225	0.275	0.326	0.357	0.374

Notes: OLS estimates with the Newey–West correction for heteroscedasticity and autocorrelation. The dependent variable is annualised real GDP growth. Standard errors are shown in parentheses.

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Table B3
Credit: single-equation approach.

	Horizon							
	1	2	3	4	5	6	7	8
Full sample								
Spread	0.383	0.412	0.455	0.509	0.556	0.603	0.628	0.630
	(0.202)*	(0.203)**	(0.203)**	(0.200)**	(0.194)***	(0.195)***	(0.205)***	(0.211)***
cr_pr	19.915	18.320	17.658	17.051	16.285	15.677	14.850	13.560
	(6.720)***	(5.821)***	(5.205)***	(4.723)***	(4.257)***	(3.897)***	(3.658)***	(3.598)***
R-Squared	0.055	0.069	0.082	0.100	0.118	0.143	0.164	0.176
Spread	0.225	0.268	0.313	0.365	0.409	0.451	0.476	0.485
	[0.202)	[0.204)	[0.207)	(0.210)*	(0.213)*	(0.218)**	(0.225)**	(0.227)**
mo_pr	11.853	11.147	10.603	9.972	8.980	8.036	7.139	6.097
	(5.007)**	(4.611)**	(4.141)**	(3.747)***	(3.385)***	(3.187)**	(3.123)**	(3.195)*
R-Squared	0.048	0.063	0.073	0.086	0.096	0.111	0.126	0.136
Spread	0.101	0.119	0.149	0.195	0.252	0.309	0.352	0.388
	(0.206)	(0.201)	(0.196)	(0.192)	(0.191)	(0.198)	(0.210)*	(0.219)*
Tight	−0.074	−0.070	−0.066	−0.062	−0.057	−0.052	−0.048	−0.044
	(0.016)***	(0.016)***	(0.015)***	(0.016)***	(0.015)***	(0.014)***	(0.012)***	(0.010)***
R-Squared	0.291	0.376	0.422	0.431	0.414	0.405	0.392	0.376
Pre-crisis								
Spread	0.458	0.474	0.502	0.551	0.595	0.641	0.665	0.662
	(0.225)**	(0.231)**	(0.233)**	(0.229)**	(0.216)***	(0.211)***	(0.214)***	(0.215)***
cr_pr	15.939	13.984	13.270	12.214	10.881	9.897	8.356	5.918
	(11.522)	(10.389)	(9.647)	(8.754)	(7.849)	(7.052)	(6.499)	(6.283)
R-Squared	0.057	0.092	0.117	0.144	0.164	0.194	0.221	0.241

(*continued on next page*)

Table B3 (*continued*)

	Horizon							
	1	2	3	4	5	6	7	8
Spread	0.312	0.342	0.374	0.431	0.485	0.535	0.569	0.581
	(0.191)	(0.201)*	(0.206)*	(0.209)**	(0.208)**	(0.210)**	(0.214)***	(0.213)***
mo_pr	3.822	2.714	2.098	1.491	0.532	−0.678	−2.231	−4.195
	(7.008)	(6.430)	(6.046)	(5.731)	(5.393)	(5.135)	(5.061)	(5.121)
R-Squared	0.031	0.059	0.081	0.111	0.138	0.173	0.207	0.241
Spread	0.159	0.167	0.186	0.218	0.269	0.329	0.389	0.444
	(0.225)	(0.225)	(0.227)	(0.221)	(0.210)	(0.204)	(0.209)*	(0.222)**
Tight	−0.064	−0.049	−0.046	−0.057	−0.063	−0.065	−0.062	−0.055
	(0.019)***	(0.016)***	(0.019)**	(0.025)**	(0.031)**	(0.033)*	(0.032)*	(0.028)**
R-Squared	0.120	0.125	0.152	0.228	0.273	0.310	0.327	0.327

Notes: OLS estimates with the Newey–West correction for heteroscedasticity and autocorrelation. The dependent variable is annualised real GDP growth. Standard errors are shown in parentheses,

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Table B4
Credit impulse variables: single-equation approach.

	Horizon							
	1	2	3	4	5	6	7	8
Full sample								
Spread	0.079	0.128	0.183	0.245	0.300	0.359	0.397	0.420
	(0.176)	(0.175)	(0.176)	(0.182)	(0.190)	(0.199)*	(0.208)*	(0.212)*
ci_cr_pr	1.113	0.876	0.812	0.659	0.560	0.503	0.462	0.431
	(0.404)***	(0.422)**	(0.363)**	(0.322)**	(0.265)**	(0.227)**	(0.198)**	(0.182)**
R-Squared	0.188	0.171	0.181	0.150	0.142	0.153	0.169	0.185
Spread	0.066	0.124	0.180	0.245	0.308	0.370	0.409	0.432
	(0.175)	(0.170)	(0.164)	−0.161	(0.160)*	(0.163)**	(0.169)**	(0.172)**
ci_mo_pr	2.015	1.884	1.851	1.675	1.554	1.465	1.380	1.326
	(0.737)***	(0.738)**	(0.642)***	(0.562)***	(0.465)***	(0.397)***	(0.348)***	(0.311)***
R-Squared	0.208	0.265	0.311	0.307	0.313	0.328	0.344	0.366
Pre-crisis								
Spread	0.260	0.308	0.338	0.404	0.465	0.523	0.565	0.588
	(0.176)	(0.185)*	(0.191)*	(0.193)**	(0.195)**	(0.199)**	(0.204)***	(0.206)***
ci_cr_pr	0.685	0.439	0.539	0.429	0.361	0.333	0.309	0.275
	(0.307)**	(0.299)	(0.270)**	(0.252)*	(0.238)	(0.242)	(0.230)	(0.230)
R-Squared	0.074	0.086	0.132	0.145	0.162	0.193	0.224	0.248
Spread	0.252	0.292	0.320	0.378	0.430	0.484	0.523	0.545
	(0.174)	(0.182)	(0.187)*	(0.182)**	(0.171)**	(0.165)***	(0.162)***	(0.160)***
ci_mo_pr	0.878	0.807	0.961	1.006	1.147	1.199	1.236	1.236
	(0.494)*	(0.381)**	(0.394)**	(0.431)**	(0.442)**	(0.462)**	(0.467)***	(0.464)***
R-Squared	0.059	0.098	0.150	0.190	0.239	0.283	0.327	0.361

Notes: OLS estimates with the Newey–West correction for heteroscedasticity and autocorrelation. The dependent variable is annualised real GDP growth. Standard errors are shown in parentheses.

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Table B5
Lag length selection.

Specification	AIC	SC	Lag excl.	Port	LM	Selection
m1	2	1	2	<3	1	2
cu	2	2	2	<5	1	1,2,4
cr_pr	2	2	2	*	3	1,2,5
mo_pr	5	2	5	<6	1	1,2,3,5
ci_cr_pr	5	2	5w/o3	*	1	1,2,4,5
ci_mo_pr	5	2	5w/o2,3	*	1	1,4,5
Tight	1	1	1	<2	2	1

Notes: AIC (SC): Akaike (Schwarz) information criteria for lag length selection: number refers to chosen lag. Lag excl.: Wald lag exclusion test. Numbers refer to chosen lag. Port: residual Portmanteau test for autocorrelations. LM: residual serial correlation LM test. Selection: final decision on lags. Numbers refer to chosen lag.

* Distorted by crisis.

Table B6
Chow breakpoint and Quandt–Andrews breakpoint tests.

	m1	cu	cr_pr	mo_pr	Tight
Quandt–Andrews					
Date	2008Q3	2008Q1	2009Q2	2001Q1	200Q1
Max LR *F*-statistic	2.05	1.68	1.98	1.45	2.15
Hansen *P*-value	(0.36)	(0.51)	(0.28)	(0.71)	(0.47)
Exp LR *F*-statistic	0.43	0.54	0.42	0.42	0.43
Hansen *P*-value	(0.78)	(0.60)	(0.85)	(0.84)	(0.69)
Ave LR *F*-statistic	0.82	1.06	0.79	0.82	0.78
Hansen *P*-value	(0.64)	(0.37)	(0.73)	(0.68)	(0.61)
Chow Breakpoint test					
Date	2008Q3	2008Q1	2009Q2	2001Q1	200Q1
F-statistic	2.05	1.68	1.98	1.45	2.15
P-value (*F*-test)	(0.06)	(0.10)	(0.04)	(0.17)	(0.08)
Date	2008Q1	2008Q1	2008Q1	2008Q1	2008Q1
F-statistic	1.81	1.68	1.38	1.32	1.15
P-value (*F*-test)	(0.09)	(0.10)	(0.20)	(0.23)	(0.34)

Notes: The null hypothesis of the Quandt–Andrews test: no breakpoints with trimmed data (trimming of 20%). Null hypothesis of the Chow Breakpoint test: no breaks at specified breakpoints. Hansen *P*-values are calculated using Hansen's (1997) method.

Table B7
Relative RMSFE of recursive out-of-sample forecasts for different VARs.

	Forecast horizon							
	1	2	3	4	5	6	7	8
Full sample								
Benchmark model	0.007	0.013	0.018	0.024	0.029	0.034	0.039	0.043
m1	0.95	0.94	0.91*	0.91	0.91	0.92*	0.92*	0.94*
cu	0.91	0.85	0.77*	0.73*	0.73*	0.73**	0.75**	0.79**
cr_pr	1.02	1.01	1.00	0.99	0.98	0.98	0.97	0.98
mo_pr	1.02	0.94	0.89	0.85	0.84	0.82*	0.82*	0.82*
Tight	0.86	0.84	0.79	0.81	0.84	0.88	0.92	0.96
Pre-crisis								
Benchmark model	0.004	0.007	0.010	0.011	0.012	0.013	0.015	0.017
m1	1.00	0.99	0.99	1.00	1.00	0.99	0.97	0.93*
cu	1.00	1.01	1.03	1.04	1.03	1.01	1.00	0.99
cr_pr	1.04	1.03	1.03	1.05	1.06	1.06	1.05	1.04
mo_pr	1.08	1.06	1.05	1.05	1.06	1.06	1.06	1.06
Tight	1.07	1.07	1.10	1.11	1.14	1.11	1.08	1.08

Notes: The 1- to 8-quarter ahead out-of-sample forecasts have been estimated recursively, using 1985Q1 to 2005Q4 as the starting sample (1985Q1 to 2000Q4 for the pre-crisis sample), and then adding one more quarter at a time. The full sample goes up to 2014Q4, whereas the pre-crisis sample stops at 2007Q4. The variable *m1* is M1 plus sweeps into money market deposit accounts, *cu* is currency in circulation, *cr_pr* is credit to the private non-financial sector, *mo_pr* is total mortgages of the private non-financial sector, and *tight* refers to tightening standards on residential mortgages. The reported RMSFE is the ratio between the RMSFE of the several VAR specifications and the one from the benchmark model, implying that values below 1 indicate that the VAR model outperforms the benchmark. The absolute RMSFE for the benchmark model is also reported. Significance levels are based on the Newey–West corrected Diebold–Mariano test statistics (see Diebold, 2012). Using the standard Diebold–Mariano statistic improves somewhat the significance of the results shown in the table (available upon request).

* Denote statistical significance at the 10% level.

** Denote statistical significance at the 5% level.

Table B8
Relative RMSFE of out-of-sample forecasts with credit impulse variables.

	Forecast horizon							
	1	2	3	4	5	6	7	8
Full sample								
Recursive								
Benchmark model	0.007	0.013	0.018	0.024	0.029	0.034	0.039	0.043
ci_cr_pr	0.92	0.99	1.02	1.07	1.09	1.11	1.11	1.11
ci_mo_pr	0.93	0.93	0.92	0.95	0.96	0.97	0.97	0.97
Rolling								
Benchmark model	0.006	0.011	0.016	0.020	0.025	0.028	0.032	0.036
ci_cr_pr	0.91	0.94	0.96	0.99	1.00	1.01	1.02	1.03
ci_mo_pr	0.90	0.88	0.86*	0.87**	0.89**	0.90***	0.91***	0.91***
Pre-crisis								
Recursive								
Benchmark model	0.004	0.007	0.010	0.011	0.012	0.013	0.015	0.017
ci_cr_pr	1.06	0.97	0.94	0.91	0.88	0.90	0.94	0.99
ci_mo_pr	1.05	1.04	1.04	1.04	1.06	1.05	1.04	1.01
Rolling								
Benchmark model	0.004	0.007	0.009	0.010	0.010	0.012	0.013	0.015
ci_cr_pr	1.00	0.99	0.98	0.98	0.97	0.97	0.94**	0.93**
ci_mo_pr	0.97	0.97	0.95	0.95	0.96	0.96	0.97	0.97

Notes: For the recursive approach, the 1- to 8-quarter ahead out-of-sample forecasts use the 1985Q1–2005Q4 as the starting sample (1985Q1–2000Q4 for the pre-crisis sample), and then adding one more quarter at a time. The rolling approach employs a constant number of observations, using 1985Q1–2000Q4 as the starting window, and then rolling the window one quarter at a time. The full sample goes up to 2014Q4, whereas the pre-crisis sample stops at 2007Q4. The variable *ci_cr_pr* is the credit impulse of the credit to the private non-financial sector, and *ci_mo_pr* is the credit impulse of total mortgages of the private non-financial sector. The reported RMSFE is the ratio between the RMSFE of the several VAR specifications and the one from the benchmark model, implying that values below 1 indicate that the VAR model outperforms the benchmark. The absolute RMSFE for the benchmark model is also reported. Significance levels are based on the Newey–West corrected Diebold–Mariano statistic tests (see Diebold, 2012). Using the standard Diebold–Mariano statistic improves somewhat the significance of the results shown in the table (available upon request).

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Table B9
Relative RMSFE of constant rolling out-of-sample forecasts for different VARs.

	Forecast horizon							
	1	2	3	4	5	6	7	8
Full sample								
Benchmark model	0.006	0.011	0.016	0.020	0.025	0.028	0.032	0.036
m1	0.99	0.97	0.95	0.96	0.97	0.97	0.98	0.99
cu	0.93	0.86	0.80**	0.76**	0.76**	0.75**	0.76***	0.79***
cr_pr	0.99	0.92	0.89*	0.87**	0.87***	0.87***	0.87***	0.89***
mo_pr	0.98	0.85*	0.81**	0.78***	0.78***	0.78***	0.79***	0.81***
Tight	0.89	0.87	0.85*	0.84**	0.86**	0.87**	0.88***	0.90***
Pre-crisis								
Benchmark model	0.004	0.007	0.009	0.010	0.010	0.012	0.013	0.015
m1	1.01	0.99	0.99	1.00	1.01	1.00	0.99	0.97
cu	1.00	1.01	0.95	0.93*	0.89**	0.86*	0.86*	0.86*
cr_pr	0.99	1.01	0.99	1.01	1.03	1.03	1.02	1.02
mo_pr	0.90	0.94	0.96	0.96	0.96	0.94	0.94	0.93
Tight	1.08	1.05	1.09	1.09	1.09	1.08	1.04	1.02

Notes: The 1- to 8-quarter ahead out-of-sample forecasts have been estimated with a constant number of observations, using 1985Q1–2000Q4 as the starting window, and then rolling the window one quarter at a time. The full sample goes up to 2014Q4, whereas the pre-crisis sample stops in 2007Q4. The variable *m1* is M1 plus sweeps into money market deposit accounts, *cu* is currency in circulation, *cr_pr* is credit to the private non-financial sector, *mo_pr* is total mortgages of the private non-financial sector, and *tight* refers to tightening standards on residential mortgages. The reported RMSFE is the ratio between the RMSFE of the several VAR specifications and the one from the benchmark model, implying that values below 1 indicate that the VAR model outperforms the benchmark. The absolute RMSFE for the benchmark model is also reported. Significance levels are based on the Newey–West corrected Diebold–Mariano statistic tests. Using the standard Diebold–Mariano statistic improves somewhat the significance of the results shown in the table (available upon request).

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Table B10
Relative RMSFE of rolling out-of-sample forecasts for VARs with alternative spreads.

	Forecast horizon							
	1	2	3	4	5	6	7	8
VAR with currency – full sample								
Benchmark model	0.006	0.011	0.016	0.020	0.025	0.028	0.032	0.036
Term spread	0.93	0.86	0.80**	0.76**	0.76**	0.75**	0.76***	0.79***
mortgage_3 m	0.92	0.88	0.82*	0.78**	0.79**	0.80**	0.82**	0.84***
mortgage_10y	0.88	0.85	0.81*	0.80**	0.80**	0.81**	0.83**	0.85**
Aaacorp_10y	0.86*	0.87*	0.84*	0.83**	0.82**	0.83**	0.83**	0.85**
Baacorp_10y	0.82	0.80**	0.76**	0.76***	0.77**	0.79**	0.81**	0.83***
10y_fundsrate	0.90	0.86	0.80**	0.77**	0.77**	0.78**	0.79***	0.82***
3 m_fundsrate	0.91	0.86*	0.81**	0.80**	0.79**	0.80**	0.81***	0.84***
primebank_3 m	1.01	1.04	1.04	1.04	1.05	1.06	1.07	1.08
c&i_3 m	0.93	0.89	0.85*	0.84*	0.83**	0.83**	0.84**	0.85**
efp_financial	0.82	0.78*	0.72**	0.71**	0.68***	0.69***	0.71***	0.74***
efp_nonfinancial	0.83	0.81*	0.76**	0.74**	0.71***	0.72***	0.73***	0.75***
VAR with currency – Pre-crisis sample								
Benchmark model	0.004	0.007	0.009	0.010	0.010	0.012	0.013	0.015
term spread	1.00	1.01	0.95	0.93*	0.89**	0.86*	0.86*	0.86*
mortgage_3 m	0.98	1.01	0.97	0.96	0.95	0.94	0.95	0.95
mortgage_10y	1.03	1.00	1.01	1.00	0.97	0.95	0.94	0.93
Aaacorp_10y	0.99	1.00	1.03	1.07	1.06	1.05	1.04	1.03
Baacorp_10y	0.93	0.93	0.97	1.03	1.02	1.02	1.02	1.01
10y_fundsrate	1.02	1.01	0.95	0.94*	0.91**	0.89	0.89	0.89
3 m_fundsrate	1.05	1.07	1.08	1.10	1.09	1.08	1.08	1.07
primebank_3 m	1.05	1.11	1.15	1.20	1.23	1.26	1.29	1.28
c&i_3 m	1.02	1.03	1.05	1.06	1.04	1.03	1.03	1.02
efp_financial	0.97	1.05	1.08	1.13	1.09	1.10	1.07	1.05
efp_nonfinancial	0.98	1.06	1.09	1.14	1.10	1.10	1.10	1.09

Notes: The 1- to 8-quarter ahead out-of-sample forecasts have been estimated recursively, using 1985Q2–2005Q4 as the starting sample (1985Q1–2000Q4 for the pre-crisis sample), and then adding one more quarter at a time. The full sample goes up to 2014Q4, whereas the pre-crisis sample stops at 2007Q4. The variable *term spread* is the 10-year Treasury Note yield minus the 3-month Treasury Bill yield (our benchmark), *mortgage_3m* and *mortgage_10y* are respectively the 30-year mortgage rate minus the 3-month Treasury Bill or minus the 10-year Treasury Note yield, *Aaacorp_10y* and *Baacorp_10y* are the Aaa or the Baa corporate bond yield minus the 10-year Treasury Note yield, *10y_fundsrate* and *3m_fundsrate* are the 10-year Treasury Note yield or the 3-month Treasury Bill yield minus the effective Federal Funds Rate, *primebank_3m* and *c&i_3m* are the bank prime loan rate or the commercial and industrial (C&I) loan rate minus the 3-month Treasury Bill yield, *efp_financial* and *efp_nonfinancial* are the AA 3-month commercial paper rate (respectively, financial and nonfinancial) minus the 3-month Treasury Bill yield. The reported RMSFE is the ratio between the RMSFE of the several VAR with currency in circulation and alternative spreads and the one from the benchmark model, implying that values below 1 indicate that the VAR model outperforms the benchmark. The absolute RMSFE for the benchmark model is also reported. Significance levels are based on the Newey–West corrected Diebold–Mariano statistic tests (see Diebold, 2012).

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Table B11
Relative RMSFE of out-of-sample forecasts with the yield curve slope model.

	Forecast horizon							
	1	2	3	4	5	6	7	8
Recursive								
Full sample	0.91	0.95	0.98	1.01	0.98	0.98	0.98	1.00
Pre-crisis	0.78***	0.81**	0.85*	0.87**	0.8***	0.77***	0.81**	0.84**
Rolling								
Full sample	0.85***	0.88**	0.93*	0.97	0.94**	0.94**	0.96*	0.99
Pre-crisis	0.81***	0.83**	0.89**	0.94	0.90***	0.88***	0.89***	0.92***

Notes: The reported RMSFE is the ratio between the RMSFE of a VAR specification with GDP growth and the yield curve slope dummy and the one from an AR benchmark model for GDP growth, implying that values below 1 indicate that the VAR model outperforms the benchmark. Significance levels are based on the Newey–West corrected Diebold–Mariano statistic tests (see Diebold, 2012).

* Denote statistical significance at the 10% level.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 1% level.

Appendix C. Alternative benchmarks

As first alternative benchmark model, we use a simple autoregressive model for year-on-year GDP growth over the period 1985Q1–2014Q4. First, following a general-to-specific approach, the model is estimated with eight lags and insignificant coefficients are successively eliminated. We end up with the following benchmark specification, where y_t is the log level of GDP and Δ is the difference operator[18]:

$$(2)\Delta_4 y_t = \underset{(2.13)}{0.0028} + \underset{(19.96)}{1.18}\,\Delta_4 y_{t-1} - \underset{(-5.59)}{0.46}\,\Delta_4 y_{t-3} + \underset{(2.84)}{0.17}\Delta_4 y_{t-5}$$

t-statistics in parenthesis; adjusted R^2: 0.85; Portmanteau $\chi^2(6) = 5.94$ (0.114); normality $\chi^2(2) = 12.78$ (0.002); serial correlation $\chi^2(5) = 0.107$ (0.743).

Overall, the diagnostic statistics do not suggest evidence of model misspecification. In particular, there is no evidence of residual autocorrelation, according to the Ljung Box test of autocorrelation for the first 6 lags (Portmanteau). Although the Jarque–Bera test of normality based on skewness and kurtosis of the residuals suggest some evidence of kurtosis, this result could be due to the inclusion of the 2007–09 financial crisis. As we are mainly interested in forecasting, this result does not pose a major problem. As regards serial correlation, the Lagrange Multiplier test fails to reject the null hypothesis of no serial correlation for the first five lags.

The second autoregressive benchmark model assumes instead a fixed number of lags (5 lags):

$$(2)\Delta_4 y_t = \underset{(2.09)}{0.0027} + \underset{(12.54)}{1.17}\,\Delta_4 y_{t-1} - \underset{(-0.23)}{0.03}\,\Delta_4 y_{t-2} - \underset{(-1.80)}{0.26}\,\Delta_4 y_{t-3} - \underset{(-2.00)}{0.30}\,\Delta_4 y_{t-4} + \underset{(3.26)}{0.31}\Delta_4 y_{t-5}$$

t-statistics in parenthesis; adjusted R^2: 0.86; Portmanteau $\chi^2(6) = 1.83$ (0.176); normality $\chi^2(2) = 12.67$ (0.002); serial correlation $\chi^2(5) = 0.88$ (0.346).

Table C1 shows that the RMSFE of the alternative benchmarks presented above are considerably larger than those from a VAR with GDP growth and the term spread (used as the benchmark in the main text). On average, the RMSFE are around 7–8% larger for the autoregressive benchmarks. The difference increases significantly when only the pre-crisis period is taken into account.

Table C1
Relative RMSFE of out-of-sample forecasts.

Full sample			
		% Worsening	
Horizons	Benchmark VAR	Refined AR	AR – 5 lags
1	0.007	15.0	12.9
2	0.013	9.9	9.1
3	0.018	7.0	6.1
4	0.024	2.6	2.3
5	0.029	6.4	5.7
6	0.034	7.2	6.7
7	0.039	7.5	6.7
8	0.043	6.4	5.7
Pre-crisis sample			
		% Worsening	
Horizons	Benchmark VAR	Refined AR	AR – 5 lags
1	0.004	33.7	36.2
2	0.007	24.5	28.1
3	0.010	17.9	22.6
4	0.011	11.1	17.4
5	0.012	17.8	24.1
6	0.013	20.3	26.3
7	0.015	17.4	22.8
8	0.017	11.6	16.6

Notes: The *Benchmark VAR* includes GDP growth and the term spread (displaying the absolute RMSFE from recursive out-of-sample forecasts), while the *Refined AR* is an autoregressive process of GDP growth with lags 1, 3 and 5, and the *AR – 5 lags* is also an autoregressive process of GDP growth but with 5 lags. The two last columns on the right show the % worsening of the RMSFE from the *Benchmark VAR* over the full and pre-crisis samples.

[18] In the pre-crisis model, there are minor differences with lag 5 only marginally significant.

Appendix D. Impulse responses and variance decomposition

After having analysed in the main text the predictive power of money and credit variables for GDP growth in the United States, in this section, we look at the quantitative importance of money and credit variables for developments in activity by analysing typical impulse response functions of 3 selected VARs, followed by the variance error decomposition for GDP growth. The criterion for selecting these three models relies on choosing those that performed best in Table B9 in Appendix B, while at the same time trying to capture the 3 different dimensions, i.e. money, credit and credit standards. The chosen models are those that employ currency in circulation (*cu*), mortgage credit to the non-financial sector (*mo_pr*) and credit standards on mortgages (*tight*).

For the identification of the VAR we apply a Cholesky decomposition of the following contemporaneous ordering of the variables: GDP growth before the term spread, and with the money or credit variable as the last one, as is usually done in the literature (see for instance, Lown & Morgan, 2006). In Chart D1 we show selected impulse responses of GDP growth (with standard error bands) over 12 quarters, following a shock to either the credit or money variable and to the term spread for each of the three models.

First, the left-hand panel shows the response of output growth to a one-standard deviation shock to *cu* (amounting roughly to a 0.7% quarterly increase in currency in circulation), which turns statistically significant after roughly 1 year. This expansion of money leads to a statistically significant increase in GDP growth of just below 0.2% after five quarters, remaining statistically significantly above zero for three more quarters. As we have seen before, GDP growth does not respond in a statistically significant manner to shocks to the term spread if money is included in the model. Second, the middle panel shows innovations in *mo_pr* (corresponding to a 0.6% quarterly increase in mortgage lending) which decrease over time, although remaining significantly above zero for three years. A positive credit shock stimulates GDP, as expected, with the expansion in economic activity being statistically different from zero after three quarters (and up to 6 quarters). In this specification, GDP also appears not to react significantly to a term spread shock. Finally, the right-hand panel shows selected impulse responses based on a shock to credit standards (*tight*), with the one-standard deviation innovation amounting to roughly a 7% net tightening lasting about two years. Following this shock, output growth declines immediately, remaining significantly below zero for the duration of the shock, in line with the findings in Lown and Morgan (2006), while a positive term spread shock, reflecting a lower short-term interest rate, boosts permanently GDP growth.

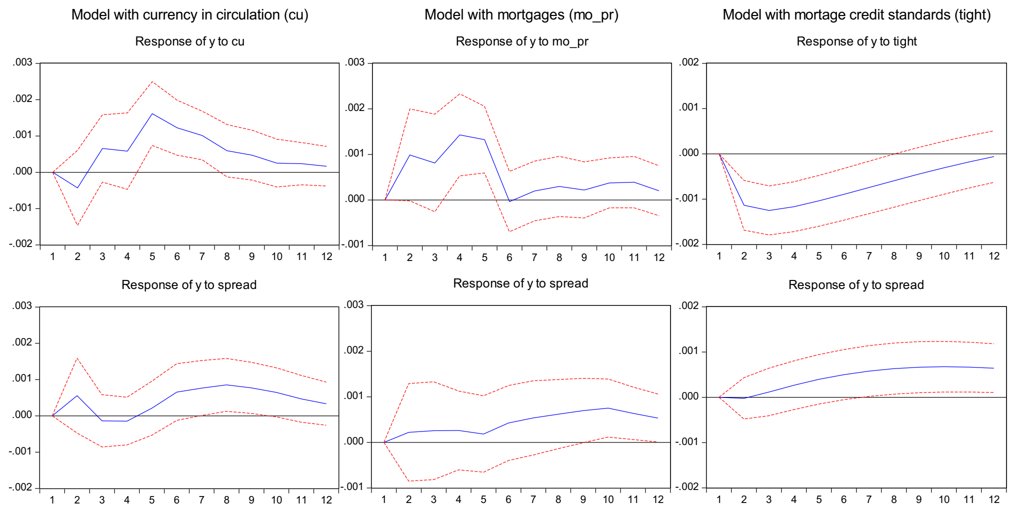
As a robustness check, we find that the results above remain broadly unchanged when altering the ordering of the VAR and also when restricting the estimation of the VAR to the pre-crisis sample.

Table D1
Variance decomposition of GDP growth for selected VARs.

Full sample				Pre-crisis sample			
Model with *cu*				Model with *cu*			
Horizon	GDP growth	Spread	cu	Horizon	GDP growth	Spread	cu
1	100.0	0.0	0.0	1	100.0	0.0	0.0
4	96.7	1.3	2.0	4	96.9	2.4	0.7
8	79.8	5.1	15.1	8	89.8	5.1	5.1
12	76.9	7.8	15.3	12	87.9	6.6	5.5
Model with *mo_pr*				Model with *mo_pr*			
Horizon	GDP growth	Spread	mo_pr	Horizon	GDP growth	Spread	mo_pr
1	100.0	0.0	0.0	1	100.0	0.0	0.0
4	91.9	0.5	7.6	4	93.2	2.4	4.5
8	86.2	2.8	10.9	8	89.9	4.6	5.5
12	82.4	6.4	11.2	12	88.8	5.7	5.4
Model with *tight*				Model with *tight*			
Horizon	GDP growth	Spread	Tight	Horizon	GDP growth	Spread	Tight
1	100.0	0.0	0.0	1	100.0	0.0	0.0
4	88.8	0.2	11.1	4	98.1	0.5	1.4
8	81.3	2.5	16.2	8	96.6	1.7	1.7
12	77.8	5.9	16.3	12	95.6	2.4	2.1

Notes: The table shows the percentage contribution of each shock to the forecast error variance of GDP growth at different horizons, conditional on data for both the full sample (1985Q1–2014Q4) and the pre-crisis sample (1985Q1–2007Q4).

Chart D1: Impulse responses to Cholesky one S.D. innovations ± 2 S.E



Notes: Impulse responses for GDP growth (*y*) following innovations in the term spread, the growth of currency in circulation (*cu*; first panel), growth of mortgage credit (*mo_pr*; middle panel) and credit standards on mortgages (*tight*; right panel) over 12 quarters. Cholesky decomposition applied to the VAR, with GDP growth ordered first and with the money or credit variable ordered last. The solid blue line refers to the point estimates, with the associated ± 2 standard error bands shown by the dashed red line.

While impulse response functions are helpful in tracing the effects of a money or credit shock to GDP growth, an investigation of the forecast error variance decomposition complements this analysis, as it provides information about the relative contribution of each innovation to the variance of the error made in forecasting h-step ahead GDP growth. In this context, Table D1 shows whether unexpected swings in the money and credit variables have accounted for a large share of the overall variability in GDP growth over the full sample (1985Q1–2014Q4) and the pre-crisis sample (1985Q1–2007Q4) for different time horizons, and using the same three above-mentioned VAR specifications. Overall, the importance of innovations in growth of currency in circulation, mortgage credit growth and credit standards on mortgages in explaining the error variance of GDP growth increases over the forecast horizon. Interestingly, innovations in the credit and money variables are significantly more important in explaining the variance of GDP growth when including the crisis period. However, and not surprisingly due to our focus on forecasting, they still remain relatively small. Focusing on the full sample, innovations in currency in circulation account for around 15% of the error variance in GDP growth after two years; the second VAR shows mortgage credit growth accounting for roughly 11%; and the last specification indicates that credit standards on mortgages explain a little more than 16% in the error variance of output growth. The shocks to the term spread account for a much smaller share of the errors in GDP growth across the three models.

When interpreting the results from the impulse response analysis and the variance decomposition, one needs to bear in mind that our models have not been selected for structural interpretation but rather for forecasting, and the "selection of an empirical model by its forecast performance may be a good way to select a forecasting model, but it is not so to select a model for evaluating economic theory or a policy model" (see e.g. Clements & Hendry, 1998). The choice of limiting ourselves to small parsimonious VAR models stems from the findings in the literature that these types of models perform fairly well in forecasting exercises, while for structural analysis more complex models may be more appropriate (see for instance Elbourne & Teulings, 2011).

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