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## Atypical Behavior of Money and Credit: Evidence From Conditional Forecasts

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# Atypical Behavior of Credit: Evidence From a Monetary VAR

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## Abstract

Credit boom detection methodologies (such as threshold method) lack robustness as they are based on univariate analysis and do not account for endogenous interactions between credit, asset prices and real activity. I propose a quantitative indicator to detect atypical behavior of credit from a monetary VAR. The indicator robustly detects episodes of financial distress as well as credit booms in Euro Area, Japan and the U.S. The analysis proves useful in real time.

JEL classification codes: C11; C13; C53; E51; E58

Keywords: Credit; Bayesian VAR; Conditional Forecasts

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# 1 Introduction

Credit booms are costly. After a credit boom, recessions and financial crises are more painful than otherwise (Taylor (2012)). Timely identification of credit cycles as well as understanding their causes is crucial for developing appropriate policy responses. In exceptional times, when risk is mispriced (see e.g. Ioannidou et al. (2008)), quantity information on balance sheets of financial intermediaries can be particularly useful for understanding the behavior of the financial sector.

Recent work of Shin and coauthors (see e.g. Adrian and Shin (2008), Adrian, Estrella and Shin (2010)) analyzes balance-sheets of market-based financial intermediaries (brokers and dealers) prior to the Great Recession 2007-2008. They find that exceptional balance sheet growth prior to the Great recession was accentuated by low monetary policy rates in the U.S. Shin and Shin (2011) analyze the liability side of commercial banks balance sheets and show that growth of non-core bank liabilities (wholesale funding) is a good indicator of systemic risk and lending booms.

Warning indicators literature finds that many of the bank balance sheet variables lack predictive power in forecasting episodes of financial distress and are at most contemporaneous to financial distress events (see e.g. Bongini et al. (2002)). A notable exception is credit-to-GDP ratio, which was shown to have predictive power for banking crises and to be particularly useful for identifying credit booms (Borio and Lowe (2002), Drehmann et al. (2010), Mendoza and Terrones (2008)).

The identification of credit boom episodes in this literature is often based on threshold methodology (see Gourinchas et al. (2001)). According to this methodology, credit variable (often, credit-to-GDP ratio) is decomposed into trend and cyclical component with some filter (Hodrick-Prescott or its versions), and then large deviations from trend (those surpassing a certain threshold) are considered as excessive credit and are therefore indications of a credit boom. Mendoza and Terrones (2008) show that this methodology may be quite sensitive to the smoothness of the trend and therefore deliver controversial results. Furthermore, credit-to-GDP ratio by construction signals a credit "boom" in situations when GDP is falling, whereas credit is relatively stable or is falling at a slower pace than GDP. These episodes do not constitute a credit boom and have to be deleted manually. Finally, threshold methodology is univariate and cannot account for endogenous interactions between credit, real economy, asset prices, and policy. I will address these drawbacks and propose an indicator to detect atypical behavior of credit from a multivariate system - a monetary vector autoregression (VAR).

Monetary VARs are often used at the European Central Bank (ECB) to conduct monetary analysis in the context of its "monetary pillar". The primary purpose of monetary analysis was in understand-

ing implications of monetary developments for price stability. This approach was often criticized (e.g. Woodford (2008)). However, as the crisis of 2007-2008 unfolded, the neglect of information contained in money and credit aggregates was seen as a mistake (see DellAriccia et al. (2012)). Monetary analysis was brought into discussion again, but now the focus was different - financial (rather than price) stability. This idea was summarized by Gali (2010): "...Paradoxically, the financial crisis may end up vindicating the monetary pillar and restoring its weight in monetary policy analysis. But the resulting pillar is likely to be a highly reconstructed version of the original one, with a strong emphasis on financial stability issues..."

Following these ideas, this paper proposes a quantitative indicator to identify atypical behavior of credit from a monetary VAR. The analysis is conducted for the U.S., Euro Area, and Japan. The rest of the paper is organized as follows. Section 2 presents the approach, the data and justifies the choice of econometric methodology. Section 3 discusses the results for revised and real-time data exercises, while section 4 examines the robustness of main findings. Section 5 concludes and outlines directions for future research.

## **2 Methodology and Data**

Credit booms are usually defined as episodes of particularly rapid growth of credit to the private sector (Gourinchas et al. (2001)). To identify these episodes, time series of credit (real or nominal credit variables, credit-to-GDP ratios) are decomposed into trend and cyclical component with some filtering technique (Hodrick-Prescott filter or extended Hodrick-Prescott filter), and a threshold determines when a deviation from trend can be regarded as too large. Consequently, the detection of a credit boom might depend on the smoothness of the trend (see Mendoza and Terrones (2008)) and on the choice of a particular variable, which is detrended. In contrast to this approach, I apply a different operational definition of credit booms seeing them as departures from fundamentals rather than from their own trend, while business cycle variables are seen as fundamentals for credit. When credit growth, justified by fundamentals (the current state of the business cycle), is substantially lower than the actual credit growth, this is a signal of a credit boom in the economy (and vice versa for a credit bust).

Some versions of the threshold method also account for business cycle fundamentals by looking

at credit-to-GDP ratios rather than pure credit variables to determine the phases of the credit cycle. Despite being an intuitive normalization, credit-to-GDP ratio eliminates valuable information contained in levels of both variables and therefore might produce misleading results. For instance, this indicator wrongly signals a credit boom, when the growth of the ratio is caused by the fall in GDP rather than growth in credit (see DellAriccia et al. (2012)); such episodes have to be manually eliminated. I connect the values of credit to business cycle fundamentals by constructing conditional forecasts of credit, without building ratios to GDP.

Another important drawback of the threshold methodology is its univariate approach, which ignores endogenous interactions between variables. Credit booms, however, are general equilibrium phenomena, therefore it appears reasonable to detect them from multivariate systems rather than single time series<sup>1</sup>. This point is also stressed by Borio and Lowe (2002): "...it is the combination of events that matters for detecting problems in financial stability: it is not just credit growth, or an asset price boom, the interactions between credit, asset prices and real economy should not be ignored..." I therefore use a multivariate model - a vector autoregression - as a credit boom detection tool.

On methodological grounds, my benchmark model is close to the one of Giannone et al. (2009), who use Bayesian vector autoregression (BVAR) methodology to study monetary developments in the Euro Area<sup>2</sup>. I estimate monetary VARs for the U.S., Euro Area and Japan based on the monthly data series presented in Table 1.

Data sources include FRED Database, database of Robert J. Shiller (U.S. stock prices), ECB-

Table 1: Data and Data Transformations in the Baseline Monetary VAR: US / Euro Area / Japan

Variable	Transformation
Industrial Production (IP) Index/ IP Index / IP Index	Log-Level
Consumer Price Index (CPI)/HICP / CPI	Log-Level
Federal Funds Rate (FFR)/EONIA / Discount Rate	Level
Stock Prices (S&P 500)/EUROSTOXX /MSCI	Log-Level
M1/M1/M1	Log-Level
M2/M3/M2	Log-Level
Total Loans and Leases/Total Loans (all maturities)/Domestic Credit	Log-Level

<sup>1</sup>Gourinchas et al. (2001) also point this out in their study.

<sup>2</sup>Giannone et al. (2009), however, do not construct indicators of atypical behavior.

EACBN database, Bank of Japan, and in the case of real-time data for the U.S. the database of the Federal Reserve Bank of Philadelphia.

These variables are typically used in monetary VARs (see Giannone et al. (2009), Banbura et al. (2008)) and capture the factors relevant for the purposes of this study: the real economy, asset prices, and monetary variables (credit and money aggregates). Industrial production captures business cycle activity and will be used as conditioning variable for credit later on; consumer price index captures the price level. Federal Funds Rate, EONIA and discount rate represent respective short-term interest rates. S &P 500, EUROSTOXX and MSCI Japan <sup>3</sup> capture stock prices developments. Monetary block of the VAR consists of narrow and broad money aggregates as well as credit aggregate. Definitions of broad money differ across countries; therefore M2 is used in case of the U.S. and Japan, whereas M3 - in case of Euro Area for comparability. Total loans represent bank credit to non-financial institutions (firms and households) the variable of interest to detect a credit boom. All data series are seasonally adjusted. Each region is estimated separately. The sample size is 1959/1-2010/12 for the U.S., 1970/1-2009/4 for Japan and 1994/1 - 2009/12 for Euro Area. I estimate the VAR in (log)-levels rather than differences in order not to lose information contained in levels of variables. As noted by Giannone et al. (2009), the assessment of level-relationships is particularly important in monetary analysis <sup>4</sup>.

The estimation approach is Bayesian rather than classical ("frequentist"), as Bayesian methodology contains a useful tool - prior shrinkage - to deal with overfitting when estimating densely parameterized systems. This is an important advantage since the detection of credit booms (busts) is based on out-of-sample conditional forecasts.

The benchmark model is a linear BVAR, which is estimated in a rolling window approach and used to generate conditional forecasts for credit. The idea is to use this relatively simple model as a benchmark for "normal times" and inspect deviations from this benchmark.<sup>5</sup> In particular, I use the

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<sup>3</sup>The coverage of MSCI is very similar to S&P and EUROSTOXX, for the U.S. MSCI and S&P 500 are almost identical.

<sup>4</sup>An alternative approach would be to estimate a BVAR in differences as proposed by Villani (2008). However, the forecasting properties of such models often depend on the assumptions about the steady state of a VAR (see Jarocinski and Smets 2008).

<sup>5</sup>Alternatively to a rolling window, one could proceed with a time-varying parameters approach (such as random walk) directly. This, however, would only allow inspecting atypical behavior at the end of the sample, whereas the goal of this study is to detect and compare episodes of atypical behavior across time.

prior of Sims and Zha (1998) which is imposed on the structural VAR of the form:

$$\sum_{l=0}^p y_{t-l} A_l = d + \epsilon_t, t = 1..T, \quad (1)$$

where  $T$  is the sample size,  $y_t$  is the vector of observations,  $A_l$  is the coefficient matrix of the  $l$ th lag,  $p$  is the maximum lag,  $d$  is a vector of constants, and  $\epsilon_t$  is a vector of i.i.d. structural Gaussian shocks with:

$$E(\epsilon_t^T \epsilon_t | y_{t-s}, s > 0) = I$$

$$E(\epsilon_t | y_{t-s}, s > 0) = 0, \forall t.$$

The maximum lag order is 13 months, which is typically used in the literature for monthly data.

Working with multivariate methodology brings many advantages over univariate approaches (simultaneity and endogeneity of variables are accounted for by construction), but there are also costs. As already noted above, VARs are densely parameterized and generally prone to overfitting, i.e. good in-sample and poor out-of-sample forecasting performance. In Bayesian estimation, the prior determines the degree of shrinkage, therefore the choice of prior hyperparameters becomes crucial for the forecasting performance of the model. The trade-off here is as follows. When the prior is too loose (i.e. very uninformative), the model generates dispersed forecasts due to high estimation uncertainty. When the prior is too tight, estimated coefficients will be very close to prior values, which is likely to lead to poor forecasts as well. Therefore the goal is to choose the "right" amount of shrinkage when one sets the hyperparameters of the prior (see Giannone et al. (2011) for more discussion of this argument). Here I follow one of the approaches in the BVAR literature and obtain the values of prior hyperparameters via maximization of marginal likelihood over the training sample. In the case of U.S. the training sample contains 1959/1 - 1973/12, in the case of Japan - 1970/1 - 1975/12<sup>6</sup>, whereas for Euro Area due to lack of data for the training sample I resort to values reported in Jarocinski and Mackowiak (2011) who also maximize marginal likelihood of a Euro Area BVAR under the same prior of Sims and Zha (1998). The values of prior hyperparameters are presented in Table 2.

In Table 2,  $\mu_1$  measures overall tightness,  $\mu_2$  determines relative tightness of autoregressive coefficients, while  $\mu_3$  determines relative tightness of the constants.  $\mu_4$  is the lag decay parameter,  $\mu_5$  and  $\mu_6$  stand for "one-unit-root" and "no-cointegration" priors respectively (see Sims and Zha (1998)).

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<sup>6</sup>Marginal likelihood is computed as in Chib (1995), optimization is performed via grid search.

Table 2: Prior Hyperparameter Values for US and Euro Area (Sims and Zha (1998) prior)

Country	$\mu_1$	$\mu_2$	$\mu_3$	$\mu_4$	$\mu_5$	$\mu_6$
US	0.6	0.1	0.1	1	5	5
Euro Area	0.1	1	2	1	1	1
Japan	0.8	0.1	0.2	1	2	2

In the baseline exercise under revised data, conditional forecasts are produced for the horizon of 4 years. Forecast densities are simulated with the Gibbs sampler of Waggoner and Zha (1999) imposing hard conditions<sup>7</sup>. In what follows point forecasts refer to the mean of the distribution, forecast bands correspond to the 16-th and 84-th percentiles and pointwise contain 68 % of probability mass. The VAR is estimated in a rolling window approach, the size of rolling window is 15 years (180 months). Importantly, although we estimate an identified VAR under Cholesky identification, the ordering of variables does not affect the distribution of conditional forecasts and therefore is of no relevance for the results. A formal proof of this result is presented in Waggoner and Zha (1999) (see Proposition 1).

After estimating the BVAR up to some point within the sample, I construct conditional out-of-sample forecasts of credit (conditioned variables are future values of the business cycle proxied by industrial production) and compare the forecasts with the observed values. Suppose, for instance, the conditional forecast of credit is substantially lower than its actual (observed) value. It means that the amount of credit which is consistent with the current state of the business cycle (as captured by our model forecast) is smaller than what we observe in reality. Conditional on our model, this deviation indicates that there is more credit in the economy than justified by the fundamental variable (business cycle) - a possible indication of a credit boom.

A quantitative deviation criterion captures these ideas as follows. If the actual value of the variable goes out of the probability bands, it is regarded as a substantial deviation. If the actual value stays within the bands, it is not regarded as a deviation. At each period of time the criterion contains information from several estimated rolling windows. They are averaged (forecast pooling), and forecasts at longer horizons are discounted. Discounting is introduced to account for worsening of forecasting

<sup>7</sup>Importantly, conditioning algorithm of Waggoner and Zha (1999) preserves endogeneity.

performance of the model at longer horizons.<sup>8</sup> Formally, the criterion can be expressed as follows:

$$crit_t = \frac{\sum_{h=1}^H \beta^h (y_{t,h}^{act} - y_{t,h}^b)}{H}, \quad (2)$$

where  $H$  - is the maximum forecast horizon,  $h$  is the index for the respective estimation window ( $h = 1$  corresponds to the latest available value for this point in time  $t$ ,  $h = H$  corresponds to the value from the earliest estimation window for this point in time).  $y_{t,h}^{act}$  is the actual value of the variable at time  $t$  and estimation window  $h$  and  $y_{t,h}^b$  is the value of probability band, which was crossed by the actual value at this point in time and this estimation window<sup>9</sup>. The interpretation of the criterion values is straightforward. A positive (negative) value corresponds to the credit boom (crunch), whereas zero stands for no-deviations case. In the next section I apply this methodology to detect atypical behavior credit in the U.S., Euro Area, and Japan.

### 3 Results and Discussion

#### 3.1. Revised Data Analysis

The criterion described in previous section is first applied to the U.S. data on total loans and leases (Figure 1). Solid line represents the values of the criterion in the respective month, while dashed lines depict means of the criterion over the entire sample (this helps distinguishing large deviations from smaller ones). The largest downward deviations are associated with episodes of financial distress or banking crises: 1989-1991 - consequences of the Savings and Loan Crisis which started in 1984, 1992-1993 - severe recession accompanied by a credit crunch. Somewhat smaller downward deviation is detected around 2000 - 2001 - the dotcom bubble episode accompanied by a moderate contraction in credit. These deviations correspond to periods of financial distress and are detected contemporaneously. Interestingly, these findings are consistent with the results of Bordo et al. (2000), who use quantitative and qualitative criteria and also characterize these periods as "moderate" financial distress.<sup>10</sup>

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<sup>8</sup>In particular,  $\beta$  is set to 0.97 in all baseline computations. However, any value between 0.90 and 1 delivers very similar results.

<sup>9</sup>Due to high computational costs (associated especially with Gibbs sampling algorithm) rolling windows have a step of one year.

<sup>10</sup>The episode of the dotcom bubble is certainly not in the sample of Bordo et al. (2000). Financial distress of the other episodes is labeled by Bordo et al. (2000) "moderate" as their sample period also contains the Great Depression.

[insert Figure 1]

Upward credit deviations were detected in two cases: a smaller deviation around 1996 and a very large and persistent deviation in 2003-2007 - the credit boom prior to the Great Recession. Again, in the case of 1996 deviation, the result is consistent with findings of Bordo et al. (2000), who describe this episode as moderate financial expansion due to the booming of the stock market and increased borrowing by households and firms. The criterion captured these developments as well. Importantly, the criterion identified the most recent credit boom several years prior to the outbreak of the Great Recession in 2007-2008; it was a warning in advance<sup>11</sup>.

The analysis for Euro Area is limited to the Great Recession episode due to data availability. The findings are similar to the case of the U.S.: a persistent and substantial upward deviation i.e. credit boom is detected in 2004-2007 (Figure 2). Again, this warning came in advance.

[insert Figure 2]

In the case of Japan (Figure 3) downward deviations in the credit indicator also correspond to the episodes of financial distress or crises: 1989-1991 - burst of the asset price bubble accompanied by a substantial credit contraction, 1996 - credit crunch (see Ishikawa and Tsutsui (2005)), 1997-1998 - Asian crisis. As for the upward deviations, the largest is observed in 1986-1989 - credit boom preceding the asset price collapse in 1990. Smaller and much less persistent upward deviations are detected in 1995 as well as in 2000-2001, both episodes occur in the expansionary or peak phase of the Japanese business cycle (see McAdam (2007) for the business cycle dates in Japan).

[insert Figure 3]

Another important question besides timely identification of credit booms is the question about their nature. Here I consider one of the hypotheses referring to the building of credit booms in a low interest rate environment. There are several theoretical explanations for this effect. For instance, "search for yield" hypothesis (see Borio and Zhu (2008)) suggests that bank managers may engage in excessive lending activities to achieve nominal revenue targets, which do not change despite low interest rates. Another explanation refers to "income and valuation effects" (Adrian and Shin (2009),

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<sup>11</sup>Our findings are different from Mendoza and Terrones (2008), who identify a credit boom in 1999 and do not identify excessive credit growth prior to the Great Recession, even though their sample ends in 2006.

Adrian, Moench and Shin (2010)): under low interest rates borrowing constraints of the banks become laxer. Therefore banks are able to borrow more (e.g. on the interbank market), which eventually translates into excessive lending activities.

The necessary condition for the above hypotheses to be at work is abnormally low short-term interest rate. Indeed, in the business cycle conditioning exercise I find downward deviation of policy interest rates around the credit boom episode in the 2000s for the U.S. (Figure 4). As shown on Figure 4, in early 2000s the interest rate stayed at too low values from November 2001 to August 2004. Noteworthy, Taylor (2007) also showed that the Federal Funds rate deviated from the Taylor rule downwards in 2002 Q2 - 2006 Q2. Can credit boom be explained by the atypically low interest rates?

[insert Figure 4]

To test it, I perform a conditioning exercise with the monetary policy rate (the Federal Funds rate in the U.S., EONIA in the Euro Area, and discount rate for Japan) instead of the business cycle variable. Now conditional forecasts of credit can be seen as amounts of credit consistent with the stance of monetary policy (rather than business cycle, as was done before). The results show that, indeed, the size of upward deviations prior to the crisis 2007 is substantially reduced in this case. Figure 5 illustrates this finding for the U.S. credit variable. On the left panel of Figure 5, where the forecasts are conditioned on the business cycle we see that the model systematically underestimates the actual credit growth rates. The only change on the right panel is that the conditioning variable is the Federal Funds rate; the model is estimated over the same rolling window as on the left panel. However, now the gap between conditional forecasts and observed values decreases substantially so that in many periods actual values fall within the forecast bands. It is certainly also reflected in the values of the criterion, which are substantially reduced now.<sup>12</sup>

[insert Figure 5]

Results for Euro Area credit boom in early 2000s are qualitatively very similar and therefore omitted here. As for Japan, conditioning on the short-term rate does not help explaining the credit

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<sup>12</sup>Importantly, the values of downward deviations (not shown), which were associated with banking crises and credit crunch in the 1980s and early 1990s, were not affected by the change of the conditioning variable by much.

boom in 1986-1989, as Figure 6 illustrates. That credit boom must have had a different nature, not associated with low monetary policy rates.

[insert Figure 6]

One should not, however, overestimate the role of monetary policy in the credit boom episodes of early 2000s in the U.S. and Euro Area. As Figure 7 illustrates, low monetary policy rates deliver only a partial explanation of the credit boom, as atypical behavior of credit cannot be eliminated completely, as the criterion still remains positive even under the interest rate conditioning. There exist additional factors driving excessive lending behavior and excessive risk taking of commercial banks during credit booms (e.g. moral hazard or inappropriate micro- and macroprudential regulation). Testing these factors, however, requires a structural model and goes beyond the scope of this paper.

[insert Figure 7]

### 3.2. Real-Time Exercise (U.S.)

Previous section of the paper demonstrated that credit booms and busts are detectable with revised data. When conditioning on the future path of the business cycle variable (the IP), we used future values of the revised IP series. Furthermore, the data for the remaining variables in the VAR also contained revisions. However, actual decision making occurs in real time, when data (if available at all) contain errors which can only be corrected later. Therefore now I turn to an exercise with real-time data to see if atypical behavior of credit can be revealed under these conditions. The analysis of this section is performed for the U.S. economy.

I use real-time data set of the Federal Reserve Bank of Philadelphia for the U.S. (see Appendix for description of data series). Four variables in the baseline monetary VAR are subject to revisions: IP, CPI, M1, and M2. To understand the magnitude of the revisions, I calculated growth rates for these variables based on revised data from the FRED database as well as based on the respective vintages from the real time data set. Figure 8 illustrates the size of misperceptions, which are measured as the difference between the real-time growth rate and revised growth rate. As we can see, the biggest revisions occur in the IP series<sup>13</sup>, whereas the revisions in monetary aggregates and especially the CPI

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<sup>13</sup>This fact is not surprising. Problems with correctly estimating the output gap in real time are well-known in the literature (see Orphanides and Wieland (2012) for a recent discussion).

are rather small. These large revisions in the IP series might considerably affect our results as business cycle variable is used for in-sample estimation of the BVAR as well as (pseudo) out-of sample forecasting exercise, where it is used as conditioning variable.

[insert Figure 8]

To study atypical behavior of credit in real-time a (pseudo) nowcasting exercise is conducted. I use the data which are the latest available at a certain point in time, then step one year back and estimate the VAR with this data. Then I perform the conditional forecast exercise (nowcast) for the last year of available data and compute the deviation criterion as in formula (2). Due to lack of comparable real-time data I have to start the analysis in 1994 (see Appendix for details on data availability).

Figure 9 plots the criterion values for loans in real time. Similar to the analysis with revised data, downward episode around 2001 is detected, so are upward episodes in 1996 and in early 2000s (credit boom prior to the Great Recession). Even though the signals now appear somewhat noisier than under revised data, the direction and timing of deviations are the same as in the revised data analysis and therefore robust.

[insert Figure 9]

### 3.3. Atypical Behavior of Money

Using a monetary VAR, it is straightforward to study atypical behavior of money; this question has also become a subject of academic discussion in the aftermath of the Great Recession. One of the reasons is empirical: prior to the crisis of 2007-2008 large swings in broad money growth were observed in many advanced economies, including the U.S. and Euro Area (Figure 10). In particular, period of accelerating growth rates prior to the crisis was followed by an abrupt and remarkable fall in growth rates, as the crisis unfolded. This latter fall in money growth was so substantial that it called analogies to downward dynamics observed during the Great Depression <sup>14</sup>. Furthermore, several recent contributions investigate the role of monetary aggregates as uncertainty indicator (see e.g. Cronin et al. (2011)). Finally, on theoretical grounds, the research of De Santis (2012) shows that there exists a stable relation between broad money and asset prices. Therefore atypical movements

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<sup>14</sup>Giannone et al. (2010) conduct a detailed comparison of these two episodes and show that the fall of money growth in 1930s was much more severe and was accompanied by a fundamentally different monetary policy response.

in money might reflect the stage of the financial cycle. Little is known about empirical properties of money as financial instability indicator. An important question is, whether monetary aggregates can provide additional useful information to the one already contained in credit aggregates. I inspect this question in what follows.

[insert Figure 10]

I apply the criterion from formula (2) to broad money aggregates of the U.S., Euro Area, and Japan (see Figures 11, 12 and 13 respectively). The first remarkable finding is the absence of atypical downward behavior of monetary aggregates at the outset of the Great Recession in 2007-2008 in both the U.S. and Euro Area. This finding first appears surprising given the magnitude of the fall of money growth rates (Figure 10). However, as the criterion illustrates, this downward movement is a reflection of the business cycle (recession) in both the U.S. and Euro Area and is quite well forecasted by the model. It was the upward pre-crisis development (2003-2007) in money growth that was atypical, not its downturn afterwards.

[insert Figures 11, 12 and 13]

The second finding is that atypical behavior of broad money occurs largely in the same episodes as atypical behavior of credit. It applies to both upward and downward deviations in all three regions analyzed.<sup>15</sup> Both money and credit aggregates indicate an excessive growth in 2002(4)-2006(7), prior to the Great Recession. There are only some minor differences in the timing: the money boom in the U.S. started and ended about one year earlier than the respective credit boom. The timings of money and credit booms largely coincide in Japan and Euro Area. To sum up, the revised data analysis shows that atypical behavior of monetary aggregates mostly resembles the one of credit.

The results for real time are depicted on Figure 14 (U.S. case). There are many similarities with the revised data analysis (Figure 11). There is again a downward anomaly around 1994 associated with the consequences of the severe recession and credit crunch in the 1990s. The prolonged episode of excessive money growth prior to the Great Recession is also present here. However, the timing is rather different: the boom starts already in 2002 (and not in 2004). Furthermore, there is a sizable

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<sup>15</sup>In the case of the U.S. monetary aggregate does not exhibit atypical behavior around the dotcom bubble episode in 2001 and in the moderate expansion in 1996-1997, whereas credit does.

downward deviation in 2004, which sends a wrong signal. To sum up, the performance of money based indicator deteriorates in real time substantially.

[insert Figure 14]

## 4 Robustness

Findings are conditional on the baseline model and the assumptions of the forecasting exercise. Therefore, in this section I test how sensitive the results are to the main assumptions. Baseline VAR specification contains only few aggregated variables, and one has to inspect if the results change when additional variables are included. In the case of U.S. I perform baseline forecasting exercise (revised data) on the 18 variables monetary VAR (see Table 3 for description of variables). In this exercise I condition on the unemployment rate and industrial production - variables capturing the business cycle. Atypical behavior is revealed in the same episodes as before (see Figure 15 for an illustration for M2 money aggregate), i.e. the results are not driven by the omitted variable bias.

[insert Figure 15]

I further test the robustness with respect to the values of prior hyperparameters. As expected, imposing looser priors leads to a substantial worsening of the overall forecasting performance of the model (the amount of shrinkage is further from optimum), i.e. there are now generally more deviation episodes than under a tighter prior. However, the deviations detected with tighter priors remain the largest in size under loose priors.

Finally, I test the robustness of all specifications with respect to the size of rolling window (10 years, 20 years, 25 years). It did not significantly affect the results.

## 5 Conclusions and Further Work

This paper develops a criterion to detect episodes of atypical behavior of credit and tests it for the U.S., Euro Area, and Japan. In contrast to the threshold methodology, the approach is multivariate and explicitly takes endogenous interactions of variables into account. It allows detecting credit booms without resorting to detrending procedures and credit-to-GDP ratios, which might deliver misleading

Table 3: Data and Data Transformations in the Extended Monetary VAR (U.S.)

Variable	Transformation
Industrial Production	Log-Level
Consumer Price Index (CPI)	Log-Level
Unemployment Rate	Level
Producer Price Index (PPI)	Log-Level
Federal Funds Rate (FFR)	Level
Oil Price	Log-Level
Stock Prices (S & P 500 composite)	Log-Level
1 Year Bond Rate	Level
3 Years Bond Rate	Level
5 Years Bond Rate	Level
10 Years Bond Rate	Level
M1	Log-Level
MZM	Log-Level
M2	Log-Level
Commercial and Industrial Loans (C & I)	Log-Level
Real Estate Loans	Log-Level
Consumer Loans	Log-Level
Prime Loan Rate	Level

results and lack robustness. The proposed approach identifies credit booms as departures from fundamentals.

The analysis under revised data shows that downward credit deviations are associated with periods of financial distress and/or banking crises. Upward deviations are associated with episodes of credit booms, notably, credit boom prior to the Greta Recession in the U.S. and Euro Area as well as credit boom preceding the burst of the asset price bubble in Japan in 1986 -1989. Interestingly, credit boom episode in early 2000s can be to some extent explained by abnormally low policy rates in the U.S. and Euro Area. This finding gives some support to the hypothesis of excessive lending of banks in a low interest rate environment. Short interest rates alone cannot, however, eliminate excessive

atypical behavior of credit completely, which indicates that other factors explaining this phenomenon are still to be explored. The analysis proves robust also in real time, as the example of the U.S. shows.

Money booms are often reflections of credit booms. These findings hold for all regions and are quite robust. In real time, however, the performance of money-based indicator deteriorates substantially: signals become noisier and might even point in the wrong direction.

There are still many open questions to be answered in future work. First, more has to be learned about the nature of credit deviations from its fundamentals. Low monetary policy rates seem to deliver only a partial explanation. Second, it is still unclear, how policy should respond to credit booms once they are detected. An open question remains, whether monetary policy can reduce unsustainable credit growth by tightening interest rates and whether this task should be better delegated to macroprudential policy instead. A structural model would be better suited to address these questions. Finally, it is certainly desirable to test the proposed criterion for other countries, especially emerging market economies, which have experienced several credit boom episodes in the 1980s and 1990s. I leave these questions for future work.

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## 6 Figures

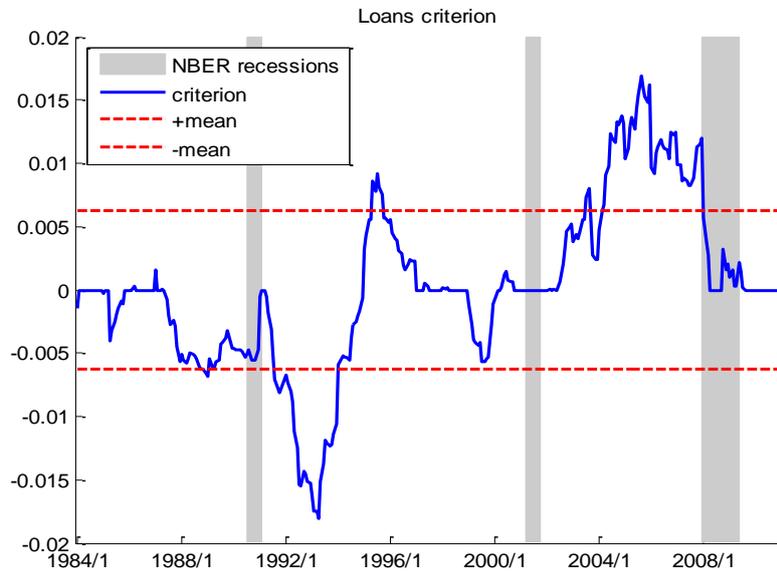
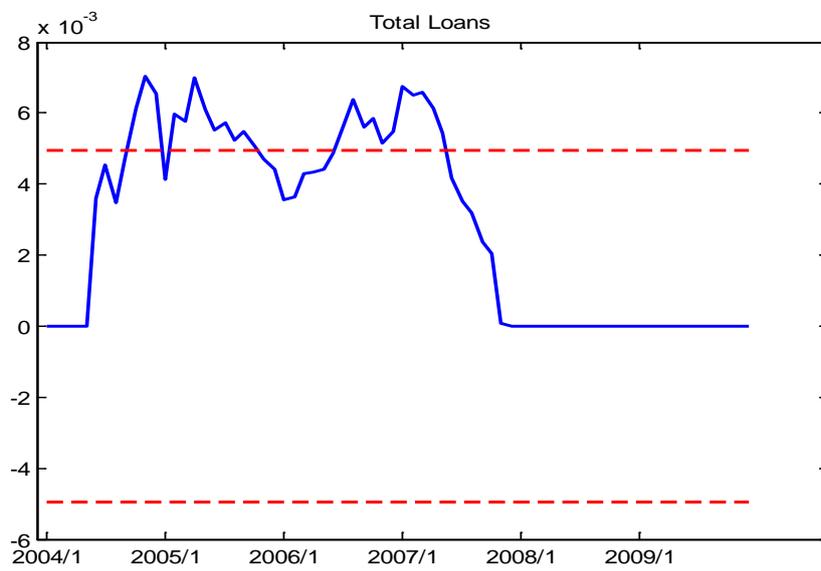


Figure 1: Criterion Values for Total Loans and Leases (U.S.).



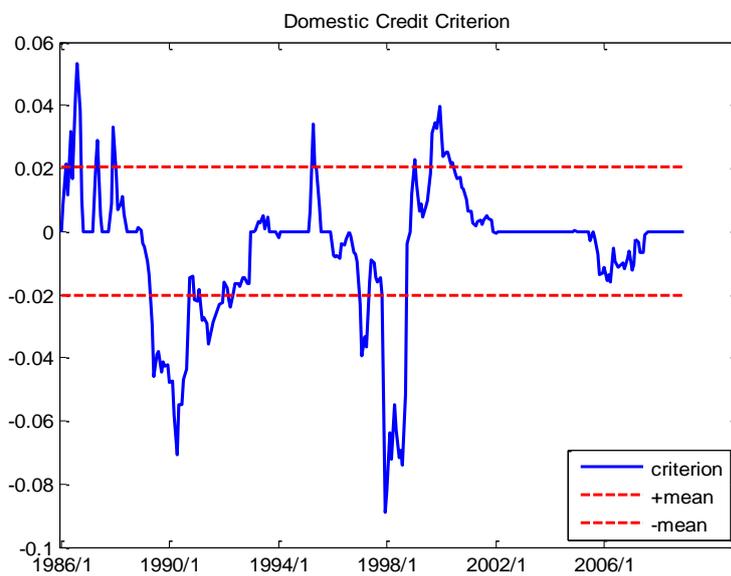


Figure 3: Criterion Values for Domestic Credit (Japan).

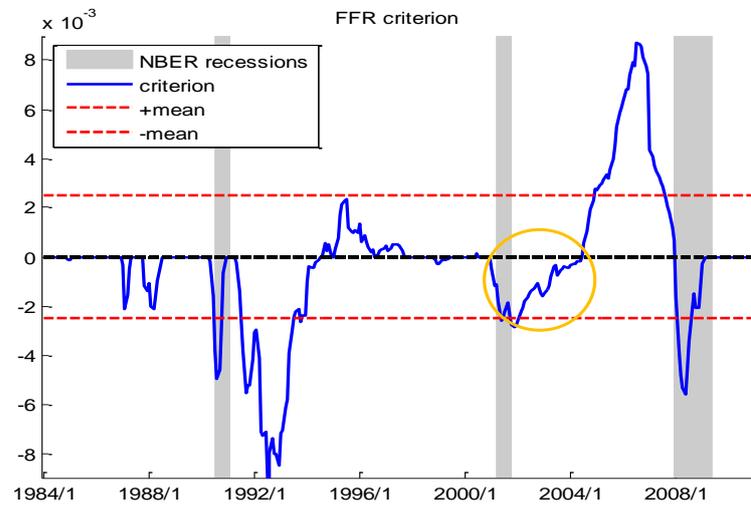


Figure 4: Criterion Values for the Federal Funds Rate (U.S.).

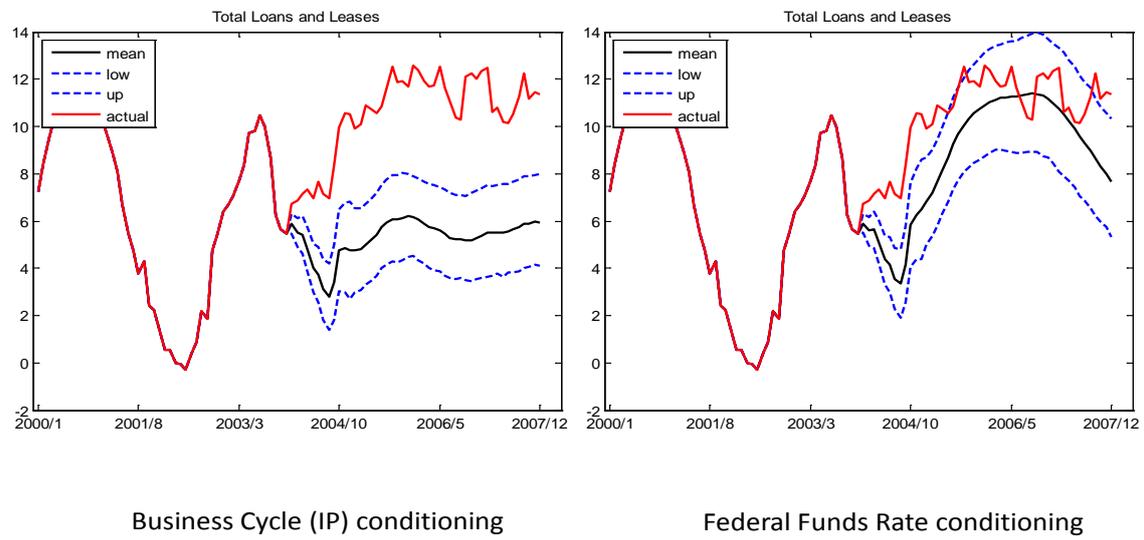


Figure 5: Credit Forecasts in the US: Conditioned on the IP (left panel) and on the FFR (right panel)

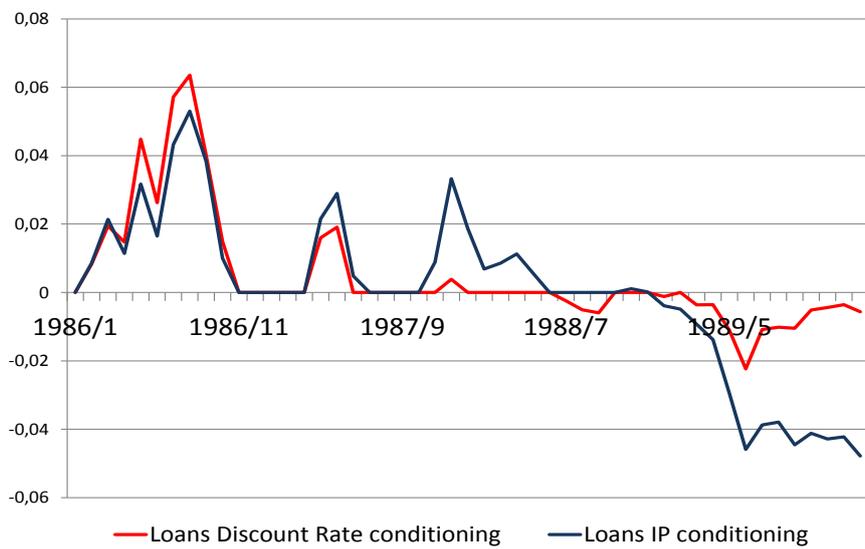


Figure 6: Criterion for Domestic Credit in Japan in the 1986-89 Boom Episode: IP Conditioning vs. Short-Term Rate Conditioning

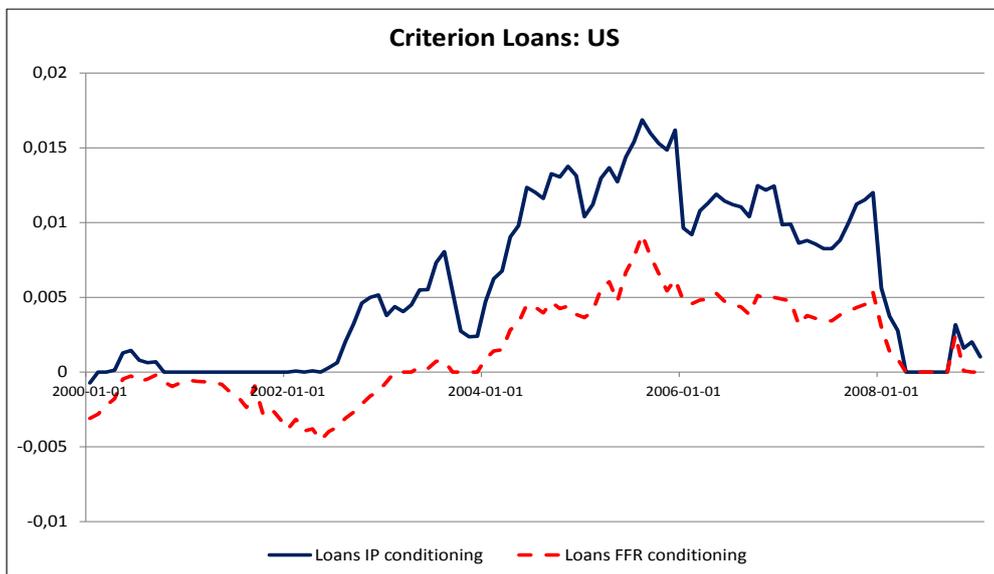


Figure 7: Criterion for U.S. Loans in the 2004-2008 Boom Episode: IP Conditioning vs. Short-Term Rate Conditioning

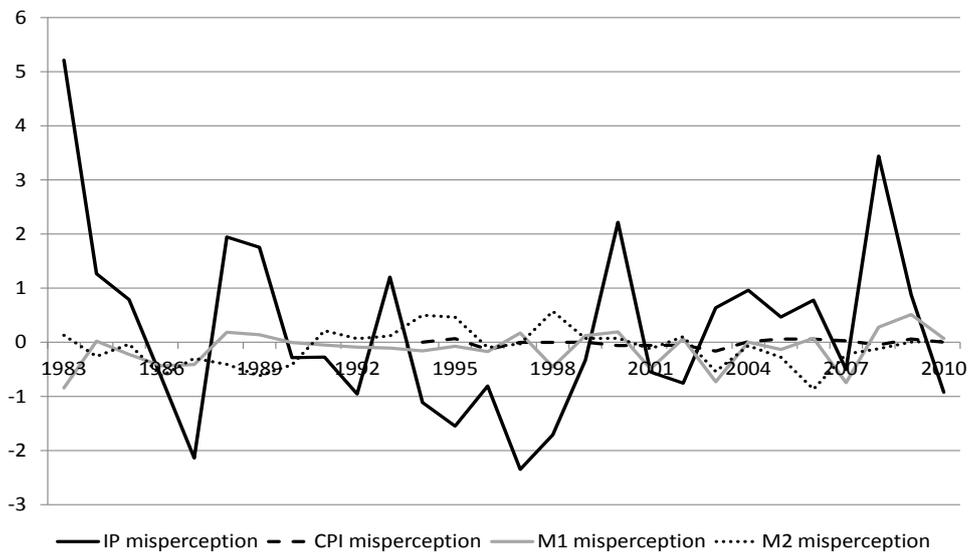


Figure 8: Real-Time Misperceptions in Growth Rates of IP, CPI, M1, and M2 in the U.S.

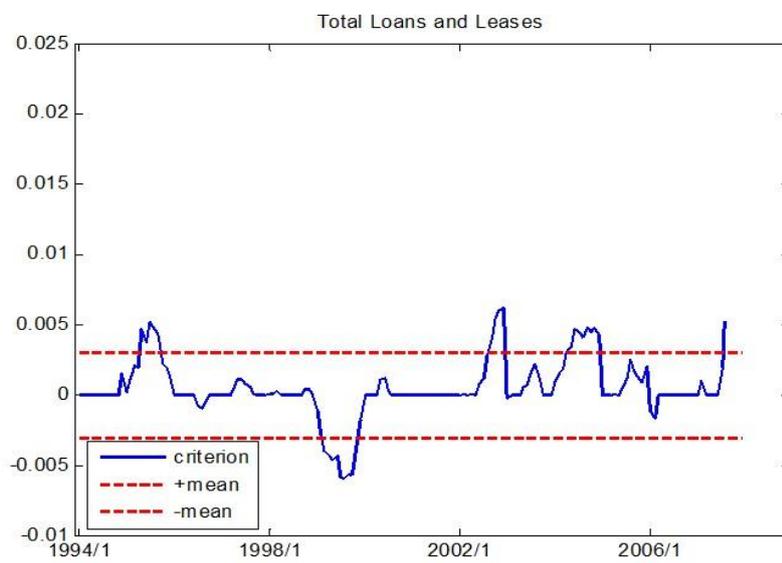


Figure 9: Criterion Values Under IP Conditioning for Loans (US): Real-Time Analysis

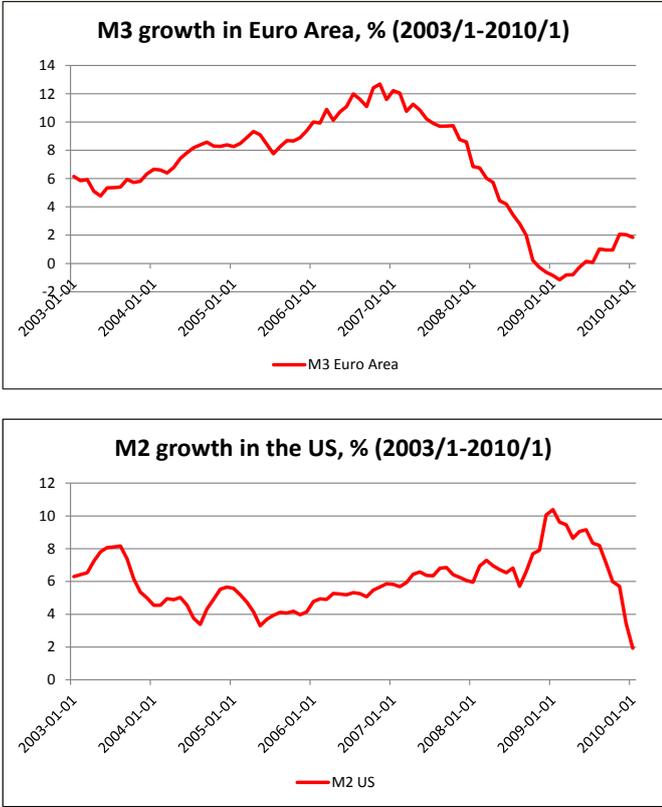


Figure 10: Growth of Broad Money in Euro Area and in the US in 2003-2010, in percent

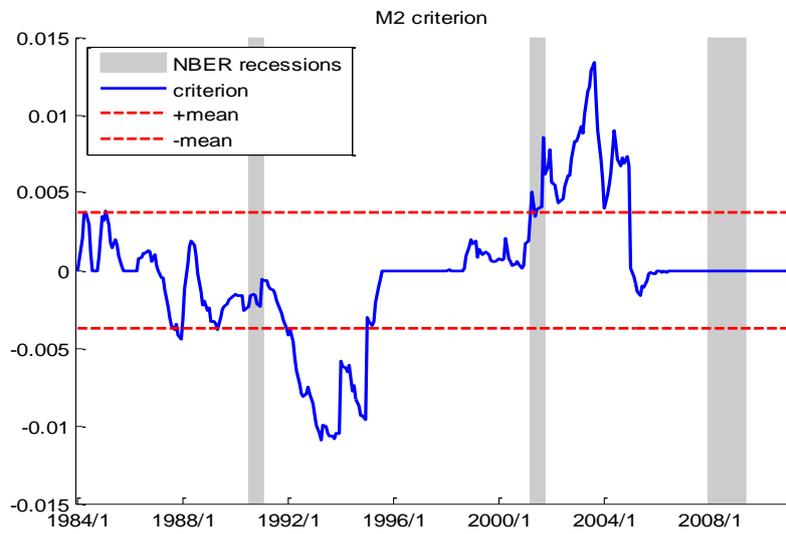


Figure 11: Criterion Values for M2 (US)

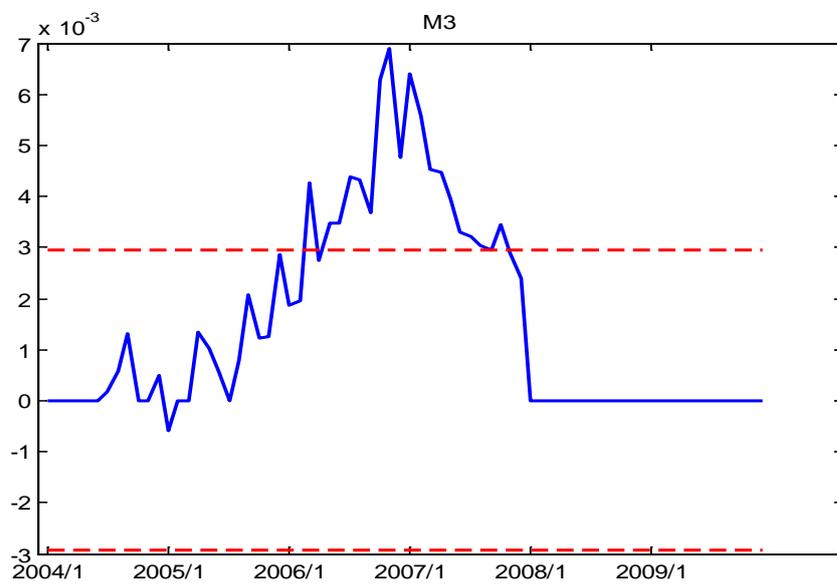


Figure 12: Criterion Values for M3 (Euro Area)

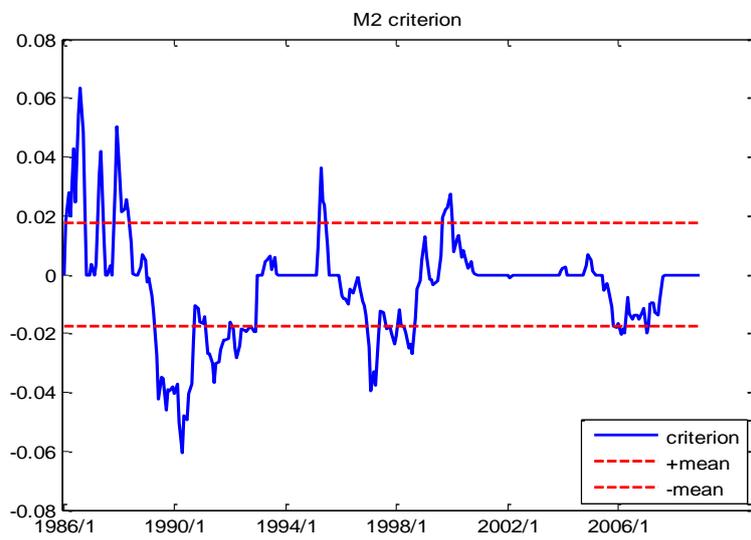


Figure 13: Criterion Values for M2 (Japan)

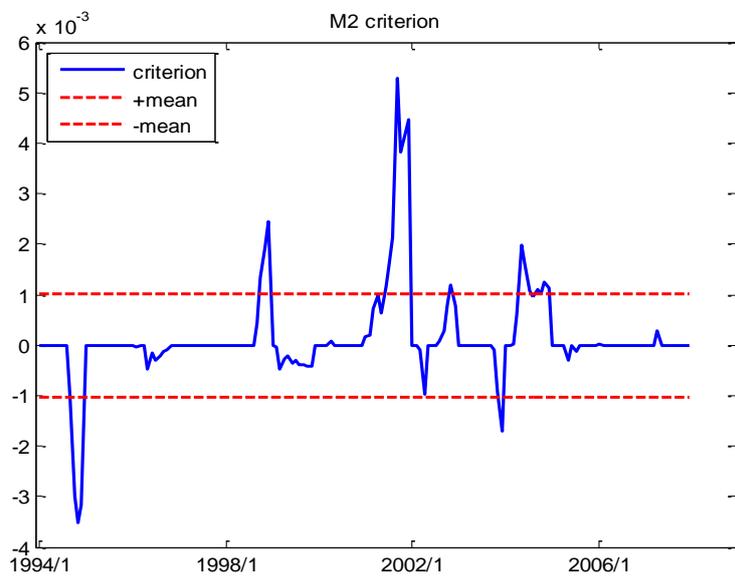


Figure 14: Criterion Values Under IP Conditioning for M2 (US): Real-Time Analysis

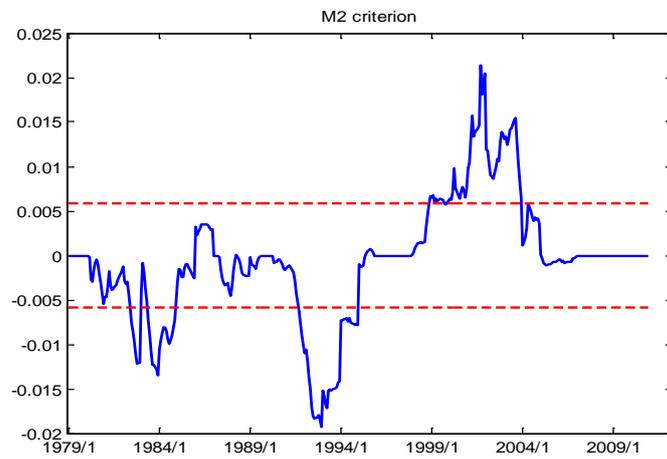


Figure 15: Criterion Values for M2 in the Extended Monetary VAR (US)

## 7 Appendix

In the exercise with real-time data we rely on the dataset of the Federal Reserve Bank of Philadelphia.

Out of 7 variables in the baseline VAR, there are four, which are subject to regular revisions:

- Industrial Production Index: monthly observations from the real-time data set of the Philadelphia Fed. To estimate a 15 year rolling window ending in (for instance) December 1983, we have to rely on the monthly vintage of January 1984;
- M1 and M2 aggregates: monthly observations from the real-time data set of the Philadelphia Fed. To estimate a 15 year rolling window ending in (for instance) December 1983, we have to rely on the monthly vintage of second quarter 1984 (February), as M1 and M2 vintages are available at quarterly frequency.
- Consumer Price Index: monthly observations from the real-time data set of the Philadelphia Fed. Vintages are available at quarterly frequency starting from Q3 1994.

Federal Funds effective rate, S &P 500 index and loans are not revised.