ELENA AFANASYEVA

Atypical Behavior of Credit: Evidence from a Monetary VAR

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Institute for Monetary and Financial Stability
Goethe University Frankfurt
House of Finance
Grüneburgplatz 1
D-60323 Frankfurt am Main
www.imfs-frankfurt.de | info@imfs-frankfurt.de

Atypical Behavior of Credit: Evidence from a Monetary VAR

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Elena Afanasyeva *

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Abstract

Credit boom detection methodologies (such as threshold method) lack robustness as they are based on univariate detrending analysis and resort to ratios of credit to real activity. I propose a quantitative indicator to detect atypical behavior of credit from a multivariate system - a monetary VAR. This methodology explicitly accounts for endogenous interactions between credit, asset prices and real activity and detects atypical credit expansions and contractions in the Euro Area, Japan and the U.S. robustly and timely. The analysis also proves useful in real time.

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

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*Goethe University Frankfurt, House of Finance, Grueneburgplatz 1, PF H31, 60323 Frankfurt am Main. E-mail address: eafanasyeva@wiwi.uni-frankfurt.de. I thank Pooyan Amir Ahmadi, Alex Bick, Matthias Burgert, Steffen Elstner, Jie Fu, Klodiana Istrefi, Michele Lenza, Oscar Jorda, Akira Kohsaka, Sigrid Roehrs, Volker Wieland, Maik Wolters, the participants of Money and Macro Brown Bag seminar at Goethe University, GSEFM Summer Institute 2012, VfS 2012, 7th Ifo Wokrshop "Macroeconomy and Business Cycles", and 75th IAES Conference for very helpful comments and discussions. All remaining errors are mine.

1 Introduction

Credit provision is one of the key determinants of economic growth and prosperity. Credit is needed for implementing new investment projects and thereby is also often fostering technological progress, as it provides financial resources to the sectors of the economy where they can be most efficiently used. Credit allows households to smooth consumption over the life cycle, thereby increasing their welfare. Increased access to credit often goes hand-in-hand with financial deepening in developing and emerging markets.

However, all of these benefits materialize only in sustainable credit expansions. Unsustainable credit expansions or ”bad” credit booms, on the contrary, end up in adverse economic outcomes accompanied by asset price bubbles, deterioration of lending standards, overleveraging, and often a bust ending in a severe recession or a financial crisis. Indeed, there is ample empirical evidence showing the link between rapid credit expansions and the occurrence of banking crises (Borio and Lowe, 2002; Bongini et al., 2002). Certainly, not all credit booms end up in severe crises: Mendoza and Terrones (2008) show that only a third of credit booms in advanced economies were associated with crisis episodes. Nevertheless, most of the credit booms are costly. After a credit boom, also normal recessions (not just financial or banking crises) are more painful than otherwise (Taylor, 2012). Even if a severe crisis does not occur, credit booms leave large sectors of the economy overleveraged, financial intermediation becomes impaired. Therefore credit booms are good predictors of creditless recoveries (see Dell'Ariccia et al., 2012). Timely and correct identification of credit cycles as well as understanding of their causes are crucial for developing appropriate policy responses to mitigate the costs of unsustainable credit expansions.

The identification of credit booms in the literature is often based on the threshold methodology (see Gourinchas et al., 2001), which defines credit booms as episodes of particularly rapid credit growth. According to this approach, credit variable (typically, credit-to-GDP ratio) is decomposed into trend and cyclical component with a filter (such as Hodrick-Prescott filter 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. This approach, however, has drawbacks, which may lead to erroneous credit boom identification.

First of all, the detection of the boom depends on the smoothness of the trend: the closer the trend follows actual data, the smaller the deviations from the trend and the less booms can be detected. A change in trend smoothness parameter leads to substantial differences in timing and duration of a credit boom (see Mendoza and Terrones, 2008). Furthermore, it is a priori not clear whether the traditionally chosen smoothness parameters of the HP-filter that are tailored at business cycle frequency are also appropriate for detecting phases of financial cycles, since the duration of a financial cycle is shown to be substantially longer than the one of the business cycle (15-20 years vs. 8 years). Second, although being an intuitive normalization, credit-to-GDP ratio (which is most widely used in threshold analysis) can send wrong signals by construction: this ratio increases and suggests a credit ”boom” interpretation in situations when GDP is falling, whereas credit is relatively stable or is falling at a slower pace than GDP. For instance, many of these spurious ”booms” occur in recessions. These episodes have to be cross-checked and excluded manually. Finally, threshold methodology is univariate in its nature and cannot account for endogenous interactions between credit, real economy, asset prices, and monetary policy[1]. As credit booms are general equilibrium phenomena, it appears reasonable to detect them from a multivariate perspective (see Gourinchas et al., 2001). This paper proposes an indicator to detect atypical behavior of credit from a multivariate system - a monetary vector autoregression (VAR).

As will be shown later, multivariate approach makes credit boom detection more robust; the detection also becomes independent of the detrending technique and the trend smoothing parameter. Furthermore, it gives credit boom (or bust) episodes an intuitive interpretation. As noted earlier, credit booms go wrong when they are unsustainable, i.e. credit growth is much more ahead of the income generation process in the economy. Therefore, eventually, this credit cannot be repaid, causing a wave of delinquencies and impairing balance sheets of financial intermediaries. Actually, the idea of relating credit flows to real activity in identifying financial imbalances also lies at the root of financial instability hypothesis by Minsky (1986), who stresses the importance of financial versus real factors linked in firms' balance sheets. According to Minsky (1986), there is an important assymetry here: loans are granted on the basis of expected profits, while loans are repaid out of realized profits. In good times, lending institutions tend to reduce their safety margins, and the economy moves towards a more fragile structure, as outstanding debt cannot eventually be repaid out of realized profits. To capture and identify this dynamic disproportion between credit growth and real activity quantitatively, I resort to conditional forecasts from a VAR and view credit booms as departures from business cycle

[1]Borio and Lowe (2002) also stress the importance of considering multiple time series to detect episodes of financial instability: in particular, they detrend credit-to-GDP ratio and additional variables, e.g. housing prices. My study complements this line of research by explicitly emphasizing the role of endogenous interactions between variables of interest instead of detrending them separately.

fundamentals. In particular, when credit growth, justified by the current state of the business cycle (and captured by the conditional forecast), is substantially lower than the actual credit growth observed in the economy, this is a signal of a credit boom (vice versa for a credit bust). This approach therefore allows to detect unsustainable credit expansions without resorting to static credit-to-GDP ratios and takes endogenous dynamic interactions between relevant variables into account.

On this basis I construct a quantitative criterion and apply it to a set of advanced economies: the U.S., the Euro Area and Japan for the sample ending in 2009-2010, i.e. the build-up and the unwinding of financial vulnerabilities associated with the Great Recession and financial crisis of 2008 can be studied. The chosen countries are advanced economies with different financial systems and different exposure to financial distress events, which makes them an interesting test for the methodology. The rest of the paper is organized as follows. Section 2 presents the approach in more detail, describes the data sets and justifies the choice of econometric methodology. Section 3 discusses the results for revised and real-time data exercises. These two exercises can be also called ”ex post” and ”ex ante” respectively. In the case of revised data the goal is to test the methodology under ”ideal conditions” (revised data do not contain real-time errors) and thereby to create a benchmark for more policy-relevant, real-time analysis. In the ”ex ante” exercise only the vintages of data are used as they would be available for a policy maker at this point in time. Section 4 examines the robustness of main findings, while section 5 concludes and outlines directions for further work.

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) for an illustration) and on the choise 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 signals a credit boom, when the growth of the ratio is due to the fall in GDP rather than to the rapid 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 or other real activity measures.

Another potential weakness 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[2]. 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, the benchmark model is close to the one of Giannone, Lenza and Reichlin (2012), who use a monetary Bayesian vector autoregression (BVAR) methodology to study monetary developments in the Euro Area[3]. 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 to understand 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..." This paper employs

[2]Gourinchas et al. (2001) also point this out in their study.

[3]Giannone, Lenza and Reichlin (2012), however, do not construct indicators of atypical behavior.

monetay VAR to detect episodes of financial instability.

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

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

prices), ECB-EABCN 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, Lenza and Reichlin, 2012; Banbura et al., 2008) and contain 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[4] capture stock price 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, Lenza and Reichlin

[4]The coverage of MSCI is very similar to S&P and EUROSTOXX, for the U.S. MSCI and S&P 500 are almost identical.

(2012), the assessment of level-relationships is particularly important in monetary analysis [5].

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 (see Canova, 2006). 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 typical interactions of variables and to inspect deviations from this benchmark, thereby detecting atypical developments.[6] In particular, I use the prior of Sims and Zha (1998) which is imposed on the structural VAR[7] of the form:

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

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[8], d is a vector of constants, and ϵ_t is a vector of i.i.d. structural Gaussian shocks with:

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

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.

[5] An alternative approach would be to estimate a BVAR in diffrerences as proposed by Villani (2009). However, the forecasting properties of such models often depend on the assumptions about the steady state of a VAR (see Jarocinski and Smets, 2008).

[6] Alternatively to a rolling window, one could proceed with a time-varying parameters approach (e.g. under random walk assumption) directly. This, however, would only allow to inspect atypical behavior at the end of the sample, whereas the rolling window approach allows to detect and compare episodes of atypical behavior across time.

[7] 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).

[8] Following Giannone, Lenza and Reichlin (2012), I set the maximum lag order to 13 months. This lag structure of approximately one year is typically used in the literature for monthly data. The rate of decay for the lag order weights is determined by the prior.

As already noted above, VARs are densely parameterized systems that are 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, Lenza and Primiceri (2012) and Canova (2006) 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[9], 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 Appendix A1.

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[10]. 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.

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 the model forecast) is smaller than what is observed in reality. Conditional on the 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

[9]Marginal likelihood is computed as in Chib (1995), optimization is performed via grid search.

[10]The conditioning algorithm of of Waggoner and Zha (1999) was chosen as it preserves endogeneity.

within the bands, it is not regarded as a deviation. At each period of time the criterion utilizes forecast information from several estimated rolling windows. They are averaged (forecast pooling), and forecasts from earlier rolling windows are discounted.[11] The forecasts from earlier rolling windows are utilized in the criterion since they reflect the forecasting ability of the model at longer horizons (longer than one year) and there is no prior reason to favor short-term forecasts to long-term forecasts in the case of credit.[12] Formally, the criterion can be expressed as follows:

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

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[13]. The interpretation of the criterion values is straightforward. A positive (negative) value corresponds to the credit boom (bust), whereas zero stands for no-deviations case. In the next section I apply this methodology to detect atypical behavior of 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. Large downward deviations correspond

[11] In particular, β is set to 0.97 in all baseline computations. However, any value between 0.90 and 1 (i.e. no discounting) delivers very similar results.

[12] The literature has found evidence in favor of long-run relations envolving credit in the multivariate systems (see Hofmann, 2001). However, there appears to be no consensus on the forecasting horizon, at which credit is forecasted best.

[13] Due to high computational costs (associated especially with Gibbs sampling algorithm) rolling windows have a step of one year.

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.[14] Somewhat smaller downward deviation is detected around 2000 - 2001, i.e. the years of the dotcom-bubble burst. This episode reflects a rather small downward deviation in credit, which is also consistent with the evidence that the dotcom bubble appears to have been rather equity-financed than credit-financed.

[insert Figure 1]

Upward credit deviations were detected in two cases: a smaller deviation around 1996 and a substantial 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 captures these developments as well. Importantly, the criterion identifies the most recent credit boom several years prior to the outbreak of the Great Recession in 2007-2008. Notably, here my 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. I discuss possible reasons for these differences below.

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 comes 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. Later in 1996-1998, Japan has expereinced a systemic banking crisis followed by a credit crunch, which is also detected by the criterion[15]. As for the upward devi-

[14] Financial distress in these episodes is labeled by Bordo et al. (2000) ”moderate” as their sample period also contains the Great Depression of 1930s, which serves as a benchmark for severe financial distress.

[15] The wave of bankruptsies among financial institutions in Japan has already started in the middle of 1995, when several credit cooperatives and a regional bank were closed. In 1997 several large profile financial institutions (e.g. Hokkaido Takushoku Bank) went bancrupt (see Kanaya and Woo (2000) for a detailed overview of those events).

ations, 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.

[insert Figure 3]

The credit boom detection literature has stressed the nexus between credit booms and asset price booms. Borio and Lowe (2002) find that swings in asset prices (especially housing prices) tend to go hand in hand with the cycles of credit expansion. Figures 4-6 plot the criterion for asset price indices used in the baseline VAR (MSCI, Eurostoxx and S&P respectively). Indeed, many of the credit boom episodes overlap with atypical upward behavior of asset price indices: Japanese credit and asset price boom in late 1980s (see Figure 4), smaller Japanese expansionary episodes in 1995 and 2001; Euro Area credit boom prior to the Great Recession (Figure 5). For the U.S., however, only two of credit expansions (in 1996 and in 2004-2007) are associated with rather moderate upward atypical behavior in S&P index (see Figure 6). The largest boom in asset price index, however, occurred in 1999-2000, which was subsequently followed by a large bust in 2001 (the burst of the dotcom bubble). This episode is, however, not associated with substantial deviations in credit: dotcom-bubble was largely equity-financed. A weaker nexus between asset price boom and credit boom of the 2004-2007 in the U.S. is understandable as well, since the asset price measure does not relate to housing prices.[16]

This example shows that atypical credit expansions are indeed often associated with asset price booms. However, the types of assets linked to credit cycles may differ across countries and time.

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. The ”search for yield” hypothesis (see Borio and Zhu, 2008) suggests that bank managers may engage in excessive lending and risk-taking activities to achieve nominal revenue targets. Another explanation refers to ”income and valuation effects” (see Adrian and Shin, 2010; Adrian, Moench and Shin, 2010).

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 7). As shown on Figure

[16] Housing price indices for the U.S. are available only for a part of the sample and at quarterly frequency from the BIS property price database.

7, in early 2000s the interest rate stay at too low values from November 2001 to August 2004. Noteworthy, Taylor (2007) also shows 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 7]

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 current stance of monetary policy (rather than with the 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 8 illustrates this finding for the U.S. credit variable. On the left panel of Figure 8, where the forecasts are conditioned on the business cycle, the model systematically underestimates the actual credit growth rates at all forecast horizons. 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.[17]

[insert Figure 8]

Results for Euro Area credit boom in early 2000s are qualitatively similar. As for Japan, conditioning on the short-term rate does not help explaining the credit boom in 1986-1989, as Figure 9 illustrates.

[insert Figure 9]

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 10 illustrates, low monetary policy rates deliver

[17] 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 from the IP index to the Federal Funds rate by much.

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 10]

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

Previous section of the paper demonstrated that credit booms and busts are detectable under the "ideal conditions" of revised data. When conditioning on the future path of the business cycle variable (the IP), I used future values of the revised IP series. Furthermore, the data for all the other 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 (for reasons of data availability).

I use real-time data set of the Federal Reserve Bank of Philadelphia for the U.S. (see Appendix A2 for description of data series). Four variables in the baseline monetary VAR are subject to revisions: industrial production, concumer prices (CPI), M1 and M2 monetary aggregates. To understand the magnitude of the revisions, I compute 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 11 illustrates the size of real-time 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[18], whereas the revisions in monetary aggregates and especially the CPI are rather small. These large revisions in the IP series might considerably affect the results as business cycle variable influences in-sample estimation of the BVAR as well as (pseudo) out-of sample forecasting exercise, where it is used as conditioning variable.

[insert Figure 11]

[18]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 (2013) for a recent discussion).

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 A2 for details on data availability).

Figure 12 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 episode in 1996 and 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 12]

3.3. Comparison with Univariate Detrending Methodologies

In this section I compare my results with those, obtained using univariate detrending methodologies. I will illustrate the main differences on the example of the U.S., although the same logic carries over to Japan and Euro Area. The main findings are summarized in Table 2, which lists the episodes and the direction and strength (size) of deviations in the credit variable.

First, I compare the results with univariate detrending of the credit variable (nominal credit, for comparability with the VAR[19]), where the trend is determined over the entire sample (second row in Table 2).[20]. The most striking differences appear in 1991-1994, where a moderate boom is detected instead of the bust (credit crunch), and in 2004-2007, where no substantial deviations can be detected. Credit boom preceding the Great Recession is detected in 2008-2009, i.e. after the onset of the recession. The reason for these outcomes is very likely the use of the entire sample for trend computation. For instance, in the boom episode of 2004-2007, credit is constantly growing in line with the strong upward trend, therefore the deviations from trend appear small in those years. Consequently, univariate methodology does not detect a boom. Only in recession, already in 2008-2009, when the trend reverts and starts declining (accounting for lower credit growth in the following years), the upward deviations from trend become evident. Therefore this credit boom is detected later.[21] Based on this evidence, rolling window approach appears to be more favorable.

[19]Detrending of real credit yields nearly identical results to detrending of nominal credit for the U.S.

[20]A similar approach was used by Mendoza and Terrones (2008)

[21]This goes in line with the findings of Mendoza and Terrones (2008), who do not detect a credit boom in the U.S. on the sample ending in 2006.

Table 2: Credit Boom Detection in the U.S.: Comparison of Methodologies

Methodology	1987-1989	1991-1994	1996	2004-2007	2008-2009
Monetary VAR	moderate bust	big bust	moderate boom	big boom	-
Detrending of nominal credit (entire sample)	-	moderate boom	moderate boom	-	big boom
Detrending of nominal credit normalized with IP (entire sample)	moderate boom	moderate boom	moderate boom	-	big boom
Detrending of nominal credit normalized with IP (rolling sample)	moderate bust	boom followed by bust	moderate boom	moderate boom	big boom

Second, univariate threshold methodologies are usually applied for credit variables normalized to real activity (e.g. credit-to-GDP ratios). As I use monthly data, I rescale credit by the industrial production index instead of GDP, which only becomes available at quarterly frequency. I apply detrending to this variable, first determining the trend over the entire sample (third row in Table 2). The use of the normalized credit variable complicates the detection of credit booms further, as the ratio mistakenly signals a credit boom during recessions, e.g. in 1991-1994, when a credit crunch actually occured. As industrial production drops faster than the credit variable, credit normalized by real activity increases, therefore generating a positive deviation from trend. The boom of 2004-2007 is again detected later due to two factors: detrending over the entire sample and rapid increase of credit to real activity ratio in the Great Recession.

Finally, I perform rolling window detrending of credit normalized by real activity (see the last row of Table 2).[22] This approach yields the results that are much closer to the VAR approach: the

[22]This approach is quite close to the one of Borio and Lowe (2002). Borio and Lowe (2002), however, use annual data for credit-to-GDP ratios and compute cumulative deviations from trend. In line with the cumulative approach, I regard the

direction of the deviations is now mostly the same, although there are some differences in timing. In particular, in the most recent boom episode prior to the Great Recession, univariate detecting is somewhat delayed: the credit boom around the Great Recession still has its peak in 2008-2009, whereas upward deviations in 2004-2007 are rather small.[23]

Summing up, univariate detrending may generate misleading results, when the trend is determined over the entire sample and when ratios of credit to real activity are used. In this case, even under rolling window approach, the peak of the credit boom may be delayed to recession years, when real activity drops rapidly. Under these circumstances, the multivariate approach accounting for business cycle fundamentals without forming the ratios, appears to perform better.

3.4. 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 13). 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 [24]. Furthermore, several recent contributions investigate the role of monetary aggregates as uncertainty indicator (see e.g. Cronin and Kennedy, 2007). 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 in money might reflect the stage of the financial cycle. Little is known about empirical properties of money as financial instability indicator. The 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.

deviations as substantial, when they occur several periods in a row.

[23] I also examined rolling detrending of non-normalized credit variables (nominal and real credit). The results around the Great Recession episode become more similar to those from the VAR, but the results in earlier episodes differ and become sensitive to trend smoothing parameter.

[24] Giannone, Lenza, Pill and Reichlin (2011) 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.

[insert Figure 13]

I apply the criterion from formula (2) to broad money aggregates of the U.S., Euro Area, and Japan (see Figures 14, 15 and 16 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 13). 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 is the upward pre-crisis development (2003-2007) in money growth that is atypical, not its downturn afterwards.

[insert Figures 14, 15 and 16]

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.[25] 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 data are depicted on Figure 17 (U.S. case). There are many similarities with the revised data analysis (Figure 14). There is again a downward deviation 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 downward deviation in 2004, which sends a wrong signal. To sum up, the performance of money based indicator deteriorates in real time quite substantially.

[insert Figure 17]

[25] 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.

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 extended monetary VAR (see Table 3 for description of variables).

In this exercise I again condition on industrial production business cycle fundamental.[26] The

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

[26]The results, however, are very similar when I condition on both business cycle indicators - industrial production and unemployment rate - simultaneously.

first goal of this exercise is to check whether the addition of further variables alters the quality and timing of atypical behavior for the variables, which are common in baseline and extended VAR. This is generally not the case (see Figure 18 for an illustration for M2 money aggregate), i.e. the results in the baseline do not seem to be driven by the omitted variable bias, when the set of variables is extended and includes time series typically used in large monetary BVARs (see Banbura et al., 2009).

[insert Figure 18]

Furthermore, the extended VAR allows studying atypical behavior of various categories of credit in more detail. Here I include real estate loans, commercial and industrial loans and consumer loans, which taken together account for about 90 % of total loans and leases in the U.S. in 1960-2010 (see Appendix A3 for the definitions of these loan categories). The criterion values for real estate loans are depicted on Figure 19. The main findings are in line with those of the aggregate credit measure, e.g. there is a bust in lending in early 1990s and build-up of excessive credit prior to the Great Recession. There is, however, one important difference - a substantial bust (the biggest in the entire sample) in real estate lending during and after the Great Recession of 2008. This example shows that it is also useful to apply the criterion to disaggregated credit measures to obtain additional information that would be hidden in the aggregate picture.

Indeed, when looking at the aggregate credit measure (see Figure 1), this credit contraction at the end of sample is not observed, because other credit components (C&I loans and consumer loans) do not exhibit such an abrupt fall as real estate lending and more so they even grow (see Figure 20). Growth of C&I loans in recession years 2008-2009 and afterwards has been subject of concern for regulatory authorities (see Duke, 2012). The drop in real estate lending is likely to have contributed to the growth of other lending activities, especially C&I lending, as banks are willing to generate loan volume without resorting to real estate lending. Duke (2012) mentions that aggressive competition for C&I loans has started after the Great Recession and that it might potentially lead to deterioration of lending standards and excessive unsustainable lending in this sector. The criterion supports this hypothesis revealing substantial upward deviations in C&I lending in 2008-2010. The other deviations in C&I criterion are plausible as well, mainly supporting the conclusions of aggregate credit measure analysis. The credit crunch in early 1990s and credit expansion in 1996 are revealed again. There is an additional bust episode after the burst of the dotcom bubble and recession in 2001, which is reasonable, as corporate lending was perceived riskier after the burst of the bubble and banks decreased this type of lending activities for some time (this situation is similar to the bust in real estate lending after the Great Recession described above).

Consumer lending criterion [27] delivers results that are somewhat similar to C&I criterion, detecting credit crunch in early 1990s and moderate expansion in 1996 as well as substantial expansion in the years after the Great Recession. However, there are also substantial bust episodes around 1999 and 2005. These results should be interpreted with caution: in contrast to C&I loans, industrial production may not be the appropriate fundamental for consumer credit. [28]

All in all, the analysis of the extended model shows that disaggregated credit measures support the main findings of the analysis with the aggregate measure and also deliver additional valuable information. One has, however, to be cautious when choosing fundamentals for different types of credit: although being applicable to the aggregate credit measures, the same fundamentals may become inappropriate for certain types of credit activities.

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 away 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.

Many studies operate with real credit measures to detect credit booms: Mendoza and Terrones (2008) use real credit per capita as benchmark measure of credit, while Gourinchas et al. (2001) use credit-to-GDP ratio. Furthermore, Mendoza and Terrones (2008) argue that credit boom detection methodologies should be robust to the credit measure used. Therefore I conduct the baseline exercise for the U.S. using real credit per capita as credit measure. Overall the results remain qualitatively similar to the benchmark case. All the big deviation episodes (such as credit bust in early 1990s, expansion in 1996 and credit boom prior to the Great Recession) are still robustly detected. Only the moderate contractionary episode around 2000 appears less important under the real measure.[29]

Finally, I test the robustness of all specifications with respect to the size of rolling window (10

[27] These results are available upon request.

[28] It might appear somewhat surprising that no credit crunch is detected in both C&I and consumer loans in the years of the Great Recession. The data suggest, however, that there was none. This is also in line with empirical evidence reported in Chari et al. (2008), who show that a credit crunch in these types of loans appears to be one of the myths of the Great Recession.

[29] These results are available upon request.

years, 20 years, 25 years). The size of the rolling window does 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. The proposed approach identifies credit booms as departures from fundamentals and allows detecting credit booms without resorting to univariate detrending procedures and credit-to-GDP ratios, thereby avoiding the problem of spurious credit boom identification.

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 Great 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.

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. Third, it would be interesting to test the proposed criterion for other countries, especially emerging market economies, which have experienced several credit boom episodes in the 1980s and 1990s. Finally, even though the analysis proves quite robust in real time, it is nevertheless desirable to make it even less prone to misperceptions contained in real-time data. I leave these questions for future work.

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6 Figures

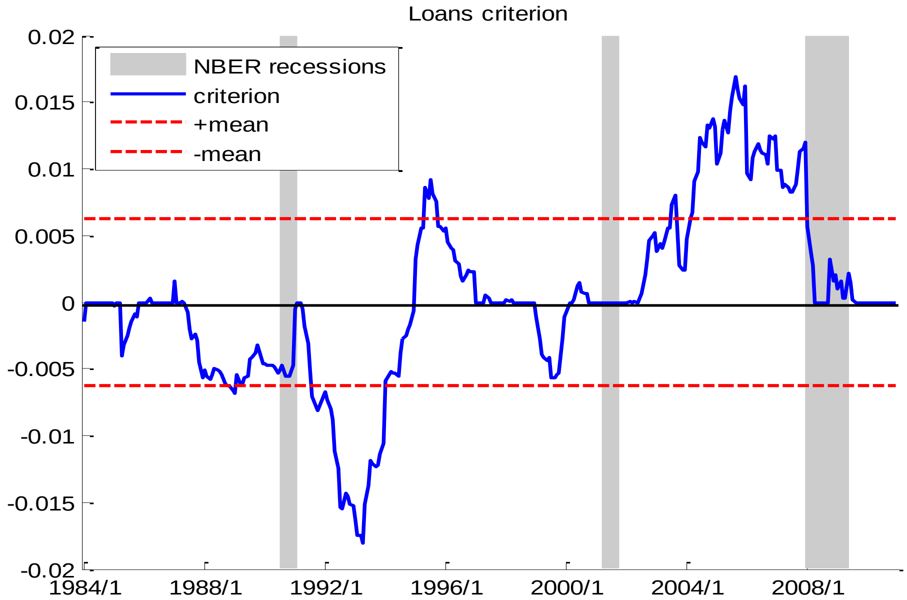


Figure 1: Criterion Values for Total Loans and Leases (U.S.).: positive values indicate atypical credit expansions, negative values indicate atypical credit contractions.

1987-1989 - credit bust following Savings and Loans crisis, 1991-1994 - credit crunch; 1996 - ”moderate financial expansion” (in terminology of Bordo et al. 2000), 2004-2007 - credit boom prior to the Great Recession.

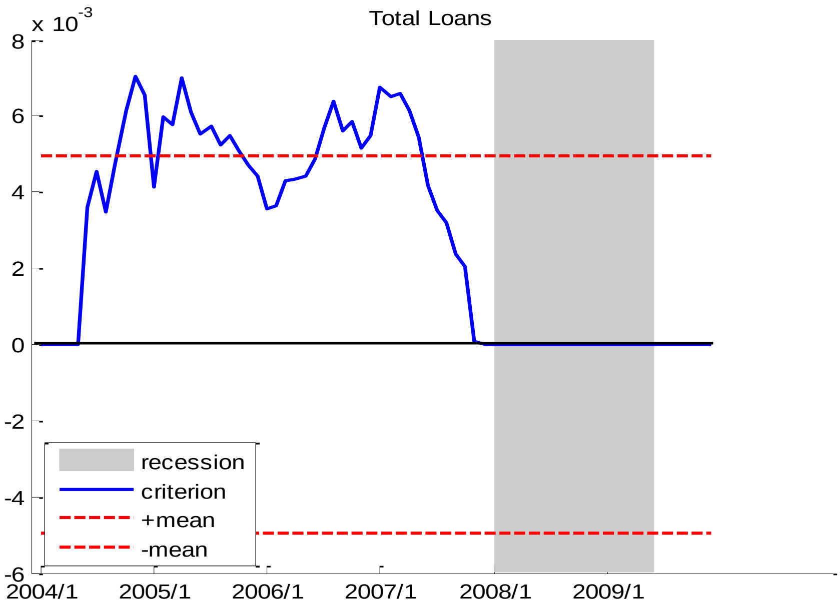


Figure 2: Criterion Values for Total Loans and Leases (Euro Area): positive values indicate atypical credit expansions, negative values indicate atypical credit contractions.

The duration of the recession is set according to the dates of the Euro Area Business Cycle Dating Committee.

2004-2008 - credit boom prior to the Great Recession.

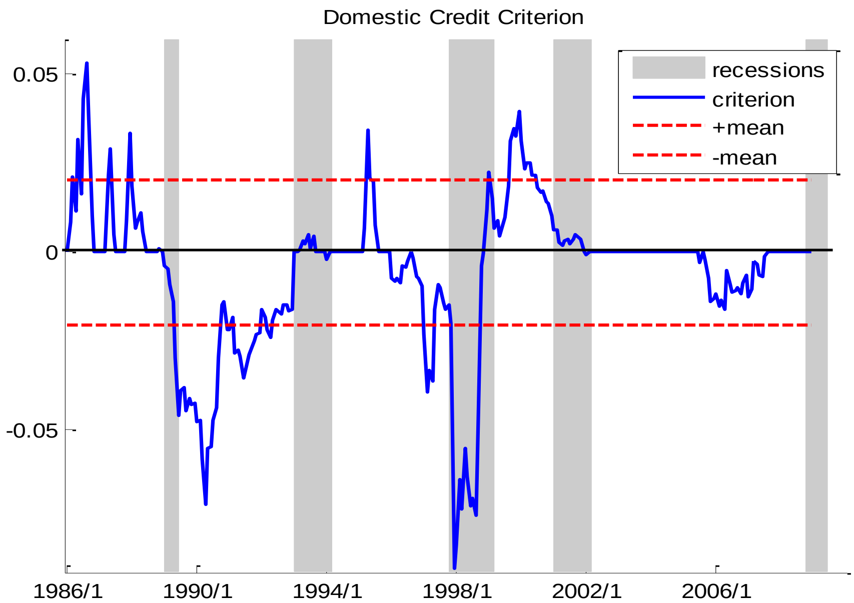


Figure 3: Criterion Values for Domestic Credit (Japan): positive values indicate atypical credit expansions, negative values indicate atypical credit contractions.

The duration of the recessions is set according to the dates reported by McAdam (2007) and Altug and Bildirici (2010), who use Markov switching methodology to detect business cycle turning points in Japan.

1986-1989 - credit boom; 1990-1994 - credit bust associated with the burst of the asset price bubble; 1995 - moderate financial expansion; 1996 -1998 - systemic banking crisis and credit crunch; 2000 - moderate financial expansion.

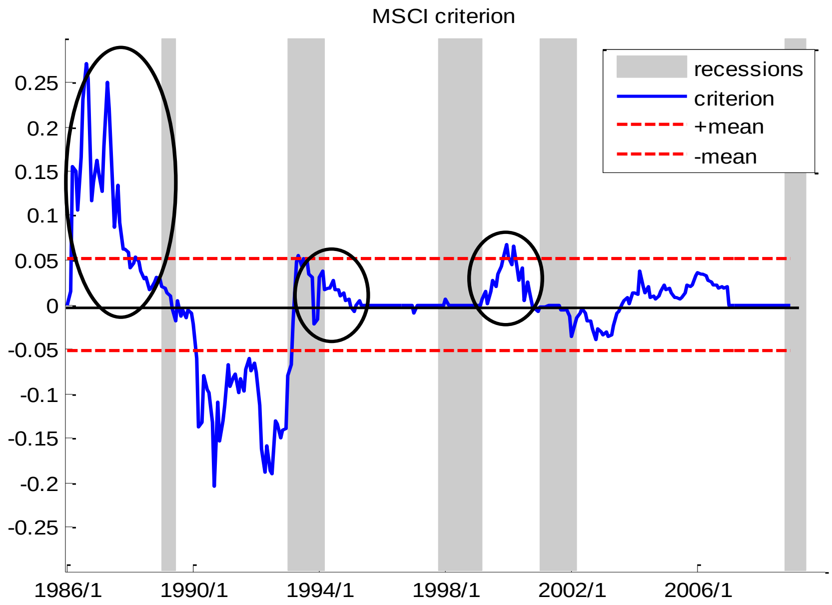


Figure 4: Criterion Values for MSCI (Japan): positive values indicate atypical expansions, negative values indicate atypical contractions.

The circled episodes overlap with atypical credit expansions.

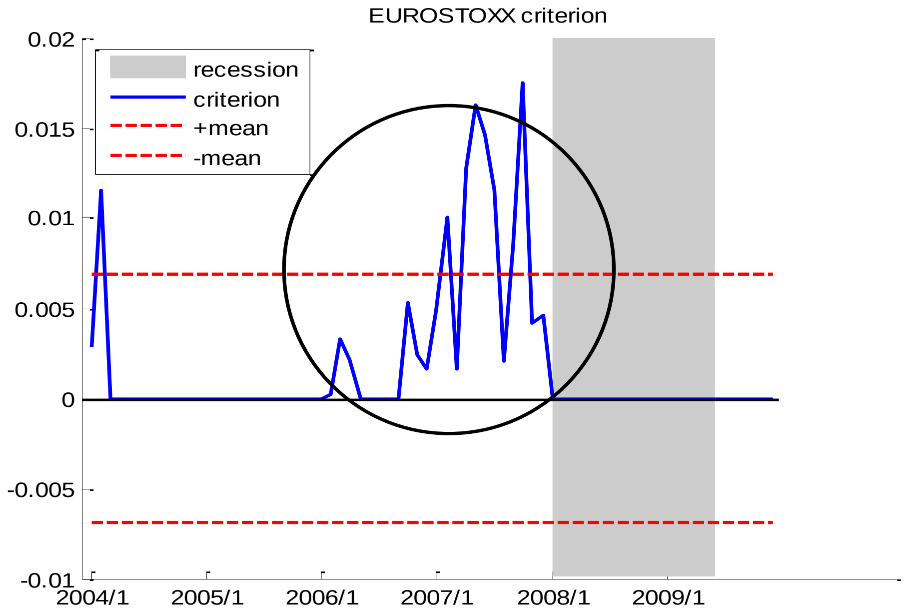


Figure 5: Criterion Values for Eurostoxx (Euro Area): positive values indicate atypical expansions, negative values indicate atypical contractions.

The circled episode overlaps with atypical credit expansion.

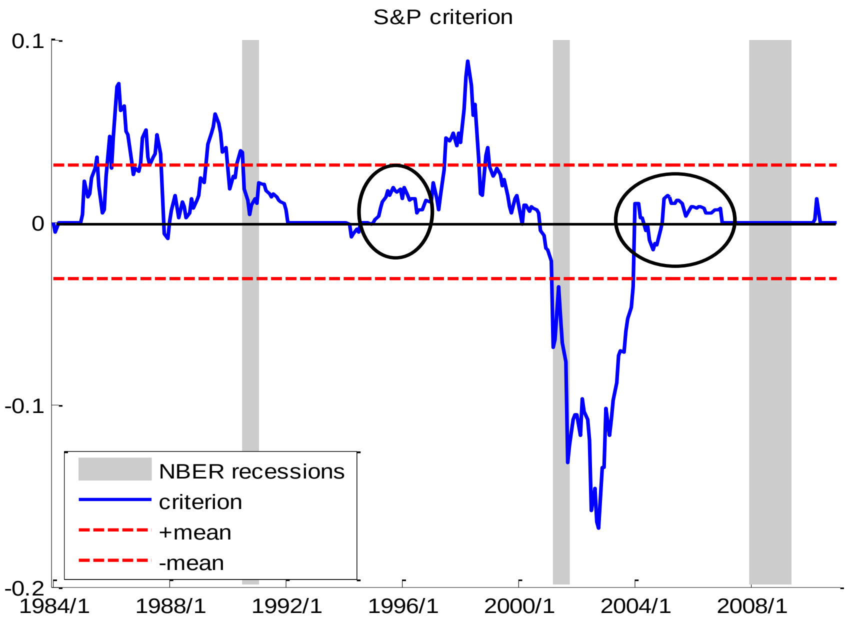


Figure 6: Criterion Values for S&P 500 (U.S.): positive values indicate atypical expansions, negative values indicate atypical contractions.

The circled episodes overlap with atypical credit expansions.

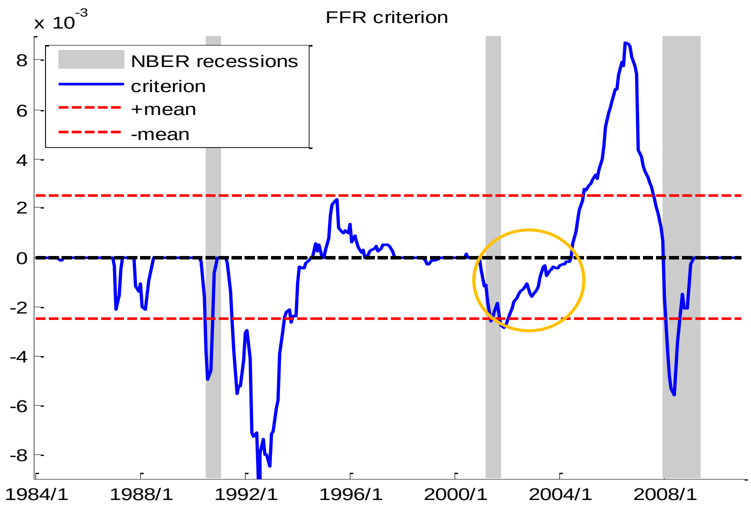
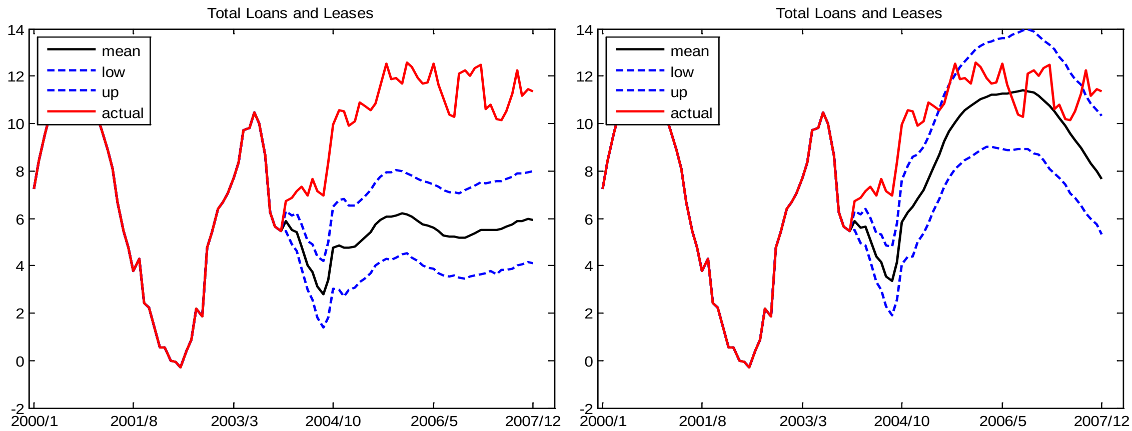


Figure 7: Criterion Values for the Federal Funds Rate (U.S.).

Circled episode indicates the period of atypically low policy rate preceding the credit boom of 2004-2007.



Business Cycle (IP) conditioning

Federal Funds Rate conditioning

Figure 8: Credit Forecasts for 2004-2007 in the US: Conditioned on the industrial production (left panel) and on the Federal Funds Rate (right panel)

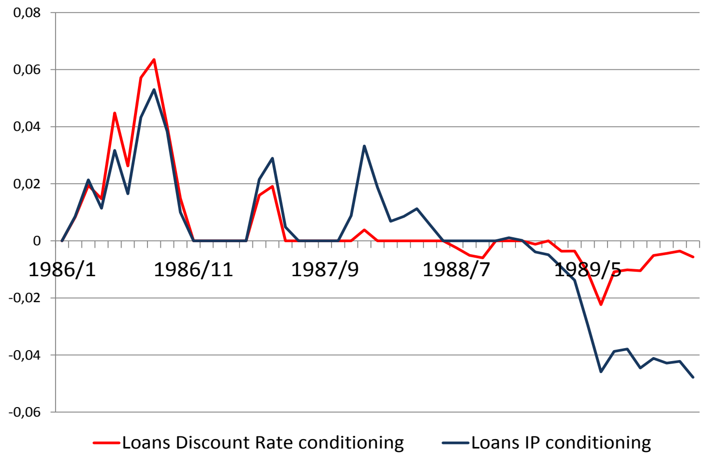


Figure 9: Criterion for Domestic Credit in Japan in the 1986-1989 Boom Episode: IP Conditioning vs. Short-Term Rate Conditioning

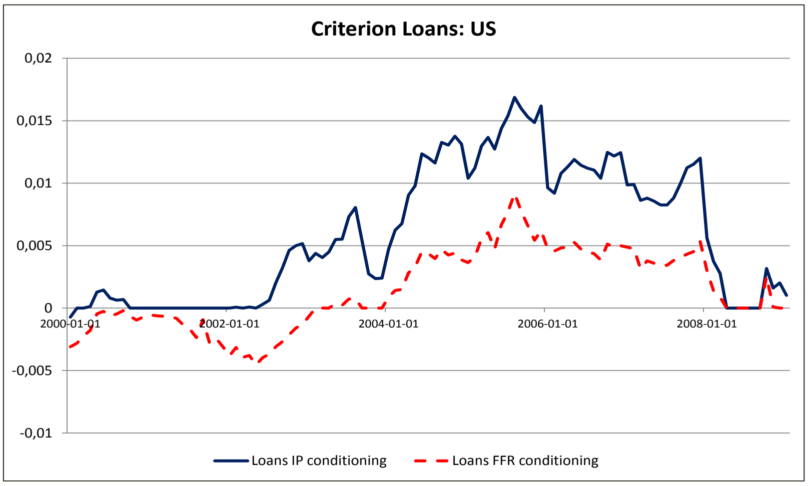


Figure 10: Criterion for U.S. Loans in the 2004-2007 Boom Episode: IP Conditioning vs. Short-Term Rate Conditioning

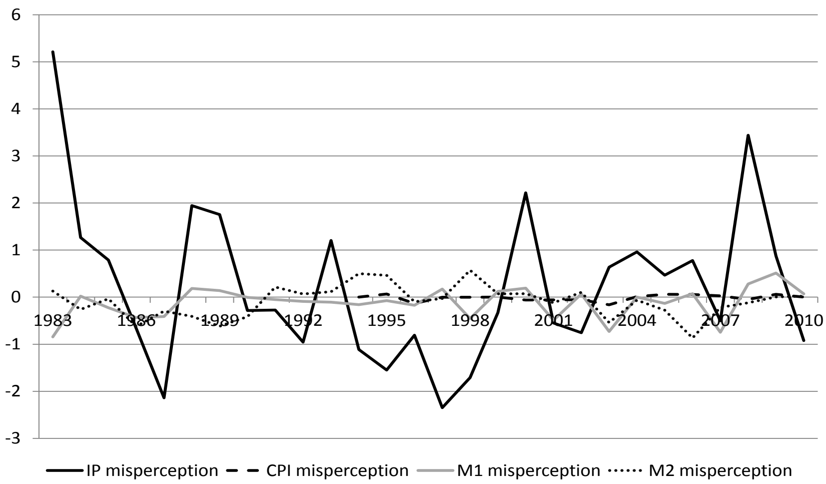


Figure 11: Real-Time Misperceptions in Growth Rates of industrial production (IP) index, consumer price index (CPI), narrow money (M1), and broad money (M2) in the U.S.

Misperception is defined as a difference between the real-time growth rate and revised growth rate.

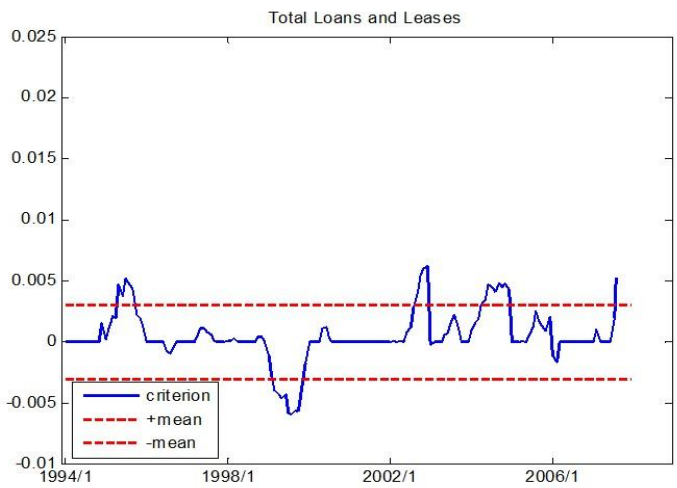


Figure 12: Criterion Values Under IP Conditioning for Loans (US): Real-Time Analysis.

Positive values indicate atypical credit expansions, negative values indicate atypical credit contractions.

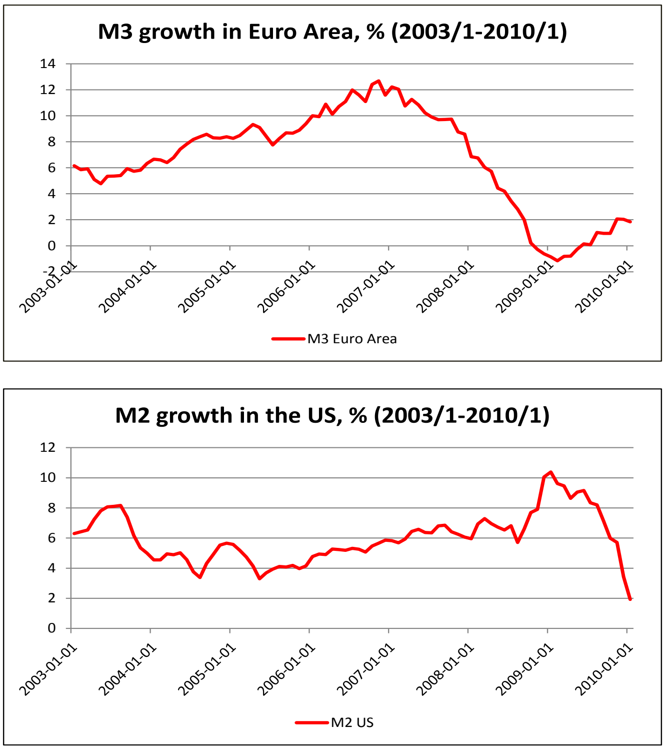


Figure 13: Growth of Broad Money in Euro Area and in the US in 2003-2010, in percent

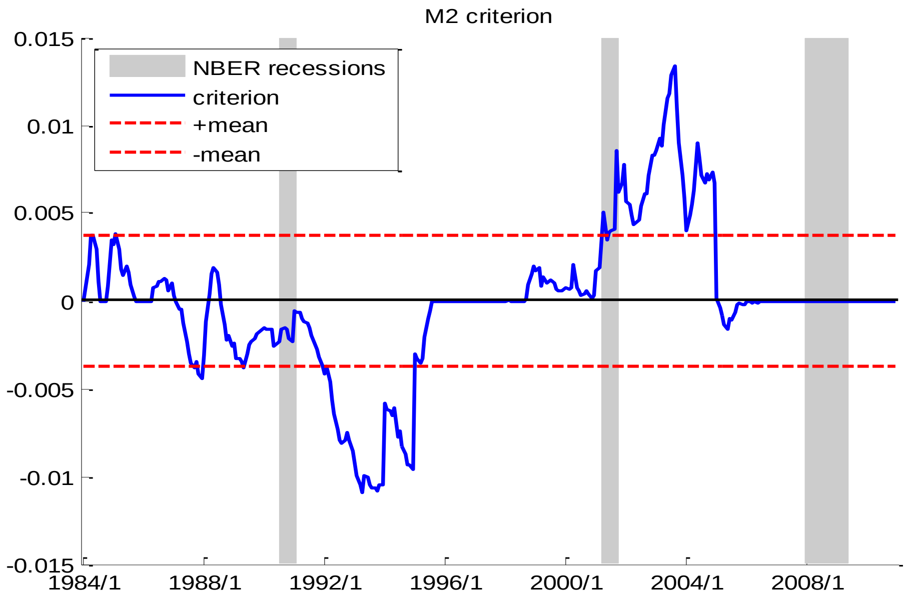


Figure 14: Criterion Values for M2 (US): positive values indicate atypical money expansions, negative values indicate atypical money contractions.

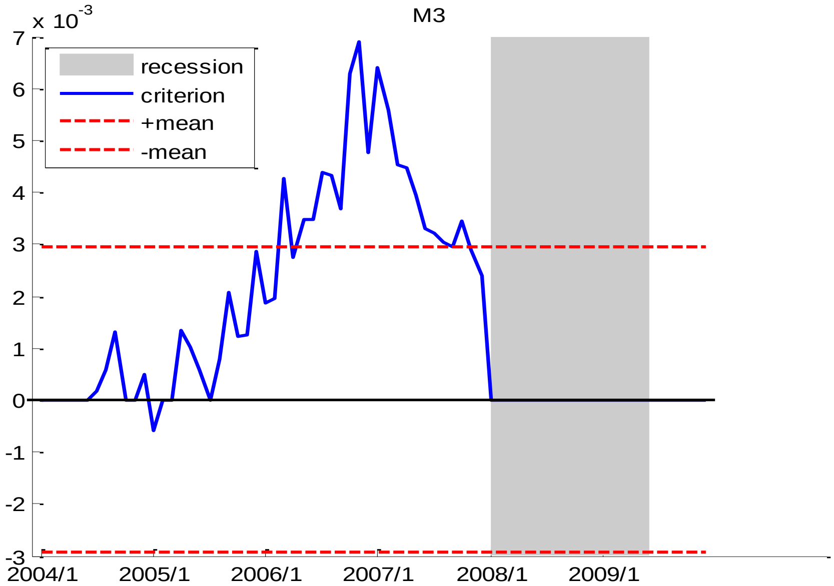


Figure 15: Criterion Values for M3 (Euro Area): positive values indicate atypical money expansions, negative values indicate atypical money contractions.

The duration of the recession is set according to the dates of the Euro Area Business Cycle Dating Committee.

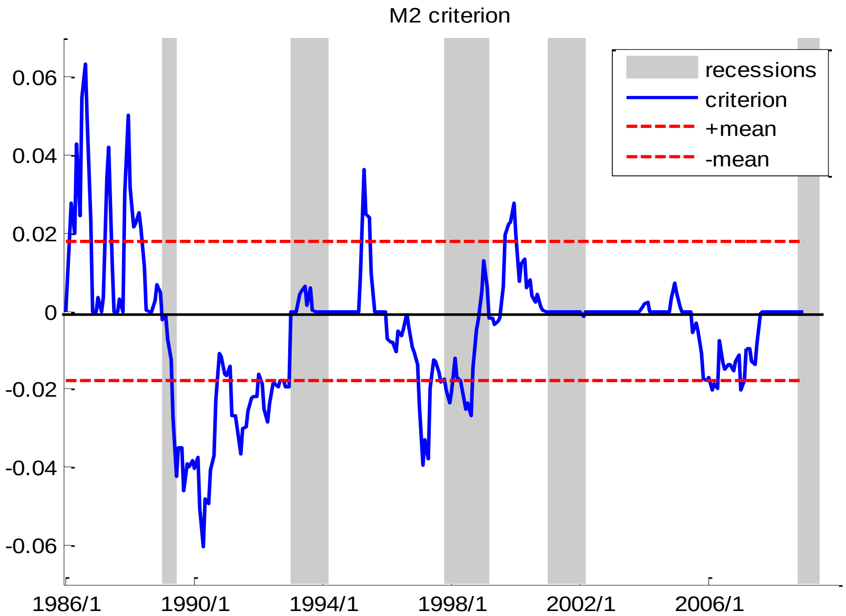


Figure 16: Criterion Values for M2 (Japan): positive values indicate atypical money expansions, negative values indicate atypical money contractions.

The duration of the recessions is set according to the dates reported by McAdam (2007) and Altug and Bildirici (2010), who use Markov switching methodology to detect business cycle turning points in Japan.

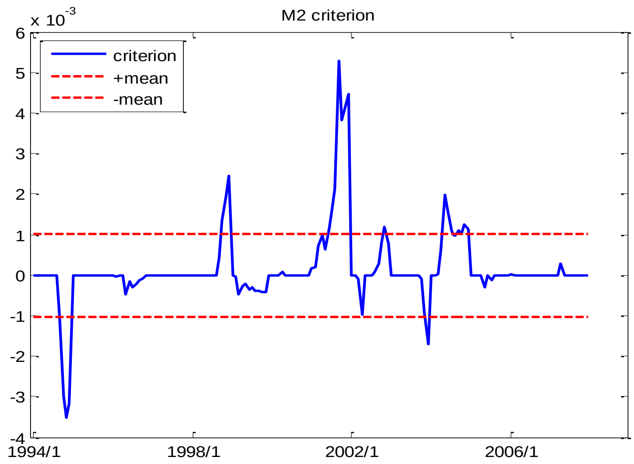


Figure 17: Criterion Values Under IP Conditioning for M2 (US), Real-Time Analysis: positive values indicate atypical money expansions, negative values indicate atypical money contractions.

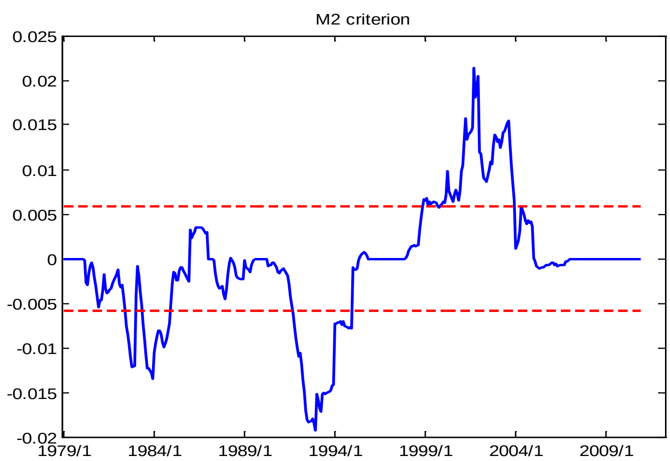


Figure 18: Criterion Values for M2 in the Extended Monetary VAR (US): positive values indicate atypical money expansions, negative values indicate atypical money contractions.

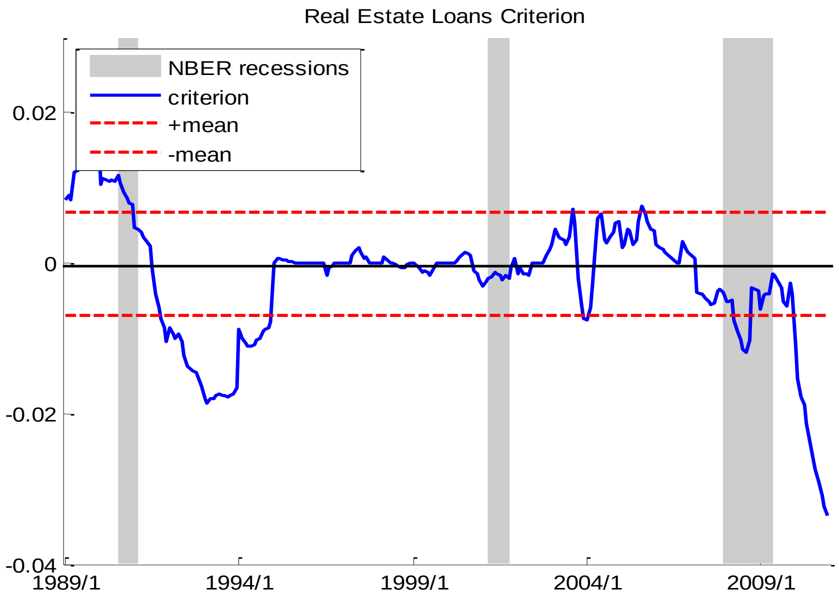


Figure 19: Criterion Values for Real Estate Loans in the Extended Monetary VAR (US): positive values indicate atypical expansions, negative values indicate atypical contractions.

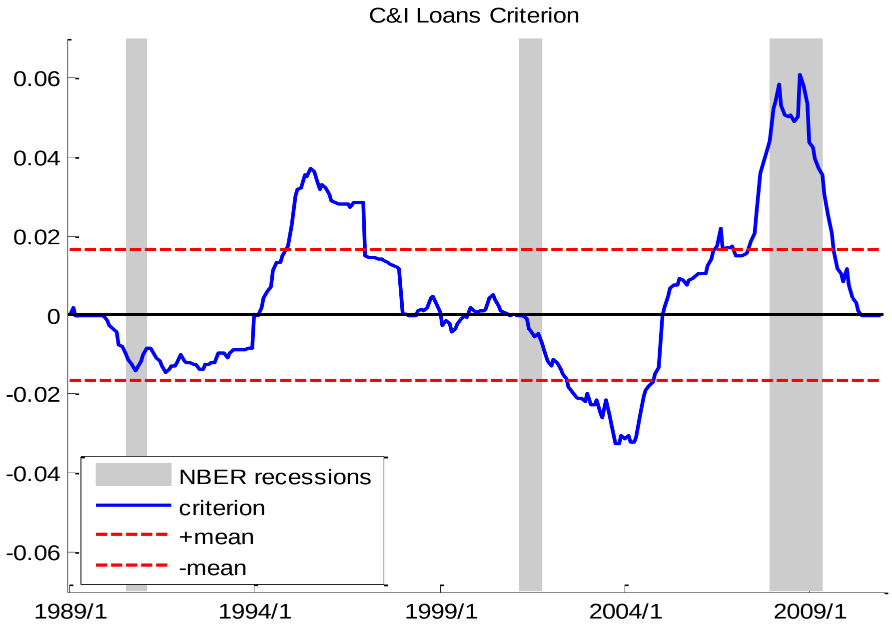


Figure 20: Criterion Values for Commercial and Industrial Loans in the Extended Monetary VAR (US): positive values indicate atypical expansions, negative values indicate atypical contractions.

Appendix

A1. Selection of Prior Hyperparameters

Prior Hyperparameter Values for U.S., Euro Area and Japan (Sims and Zha (1998) prior)

Country	μ_1	μ_2	μ_3	μ_4	μ_5	μ_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 Table above, μ_1 measures overall tightness, μ_2 determines relative tightness of autoregressive coefficients, while μ_3 determines relative tightness of the constants. μ_4 is the lag decay parameter, μ_5 and μ_6 stand for ”one-unit-root” and ”no-cointergration” priors respectively (see Sims and Zha (1998)).

A2. Real-Time Data Set

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.

A3. Loan Categories in the Extended VAR

- **Real estate loans** include all loans backed by commercial or residential real estate.
- **Consumer loans** cover most short- and intermediate-term credit extended to individuals. They include revolving credit (credit card and credit balances outstanding on unsecured revolving lines of credit) and nonrevolving credit (secured and unsecured credit for automobiles, mobile homes, trailers, durable goods, vacations and other purposes). Consumer credit excludes loans secured by real estate (mortgage loans, home equity loans and home equity lines of credit); the latter are covered by the category ”Real Estate Loans”.
- **Commercial and industrial (C&I) lending** includes loans to corporations, commercial enterprises or joint ventures that are not maintained in real estate or consumer installment loan portfolios. C&I loans are typically made in the form of a seasonal or working-capital loan, term business loan or loan to an individual for a business purpose.

Source: Federal Reserve Bank of Philadelphia.

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