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Can Forecast Errors Predict Financial Crises? Exploring the Properties of a New Multivariate Credit Gap

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Can Forecast Errors Predict Financial Crises? Exploring the Properties of a New Multivariate Credit Gap ☆

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Abstract

Yes, they can. I propose a new method to detect credit booms and busts from multivariate systems – monetary Bayesian vector autoregressions. When observed credit is systematically higher than credit forecasts justified by real economic activity variables, a positive credit gap emerges. The methodology is tested for 31 advanced and emerging market economies. The resulting credit gaps fit historical evidence well and detect turning points earlier, outperforming the credit-to-GDP gaps in signaling financial crises, especially at longer horizons. The results survive in real time and can shed light on the drivers of credit booms.

Keywords: Credit Boom, Credit Gap, Bayesian VAR, Conditional Forecasts, Early Warning, Financial Crises
JEL classification: C11, C13, C53, E51, E58

1. Introduction

Robust and adequate identification of credit cycles is a challenging and important task. Unsustainable credit expansions can end up in adverse economic outcomes. Schularick and Taylor (2012) among others demonstrate that systemic financial crises are essentially credit booms gone bust. Even when credit booms do not end in financial crises, they are still costly. Jorda et al. (2013) show that after a credit boom, recessions are more painful, even if a financial or banking crisis does not occur. Credit booms leave large sectors of the economy overleveraged, which impairs financial intermediation during the subsequent recovery. Therefore credit booms can be good predictors of creditless recoveries (Dell'Ariccia et al., 2012). Given the link between credit booms and financial crises, measures of excessive credit are

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used as guidelines for tightening the macroprudential tools.[1] Accordingly, the measures of excessive credit need to be adequate and robust.

I propose a new methodology to detect credit booms and busts from Bayesian vector autoregression (VAR) forecast errors. To that end, I employ a different operational definition of credit booms, viewing them as departures from the fundamentally-justified levels rather than deviations from a univariate trend, such as Hodrick-Prescott (HP) trend. When the actual level of credit is systematically higher (lower) than the level of credit justified by the fundamentals, this indicates a credit boom (bust) in the economy. Similarly to the intuition behind the credit-to-GDP ratios, I use real economic activity variables as the fundamentals for credit and operationalize this idea by constructing (pseudo) out-of-sample forecasts for credit, which are conditioned on the path of real economic activity four years ahead. To perform these forecasting exercises, I estimate medium-scale monetary Bayesian vector autoregressions (BVARs), thereby employing a fully multivariate approach.

The new method is applied to 31 advanced and emerging market economies and the results are compared with those of credit-to-GDP gaps – an established and well-performing benchmark tested on large panels of countries (Mendoza and Terrones (2008), Gourinchas et al. (2001), and Drehmann et al. (2010)). The resulting BVAR-based credit gaps are consistent with historical evidence across the panel of countries. Elevated credit gaps precede crises, turn negative at or shortly after a crisis onset, and stay in the negative territory for the post-crisis bust period, in line with various crisis chronologies and economic history studies. The BVAR-based credit gaps robustly outperform credit-to-GDP gaps as crisis predictors, especially at longer horizons of 3- to 4 years ahead. The reason is that BVAR-based gaps detect turning points earlier. First, in credit-to-GDP ratios, the link with the real activity is by construction largely *static*, confined to the ratio within one period, which alters the dynamics of the credit-to-GDP time series and shifts the identified peak of the financial cycle a year or two forward. By contrast, the VAR machinery and the conditioning on the path of real activity when forming credit forecasts retain a *dynamic* link between these variables, taking the lead-lag relationships into account. Second, because of time variation in parameters, the implied trend in the BVAR methodology is much more flexible than a nearly linear Hodrick-Prescott trend of credit-to-GDP ratios. Hence, turning points leading to both booms and busts are often identified faster with a BVAR, and this feature survives in real time.

This paper primarily speaks to the literature that identifies and studies credit cycles. The prevalent filtering method – univariate detrending of credit-to-GDP ratios with the HP filter – quite successfully points to systemic crises in large panels but also has drawbacks. For instance, Hamilton (2018) discusses how the filter itself can induce inconsistent dynamics. Edge and Meisenzahl (2011) show how end-point characteristics of the HP filter impair the reliability of gap estimates in real-time, when it comes to the detrending of credit-to-GDP ratios. In my approach, I propose an

[1] In fact, the Macro Variables Task Force of the Basel Committee has proposed measures of excessive credit growth (in particular, deviations of the credit-to-GDP ratio from its trend) as a reference point to determine the need to tighten bank capital requirements.

alternative way of multivariate filtering, departing from the HP filter (similarly to Hamiltons proposal) and yet retaining the useful linkage of credit with economic fundamentals, when identifying credit cycles (similar to the underlying idea of credit-to-GDP ratio detrending). The combination of these features improves early warning properties and eliminates spurious credit cycle peaks after crises, also in real-time conditions.[2]

In contrast to univariate detrending methods, the BVAR-based approach in addition allows to shed some light on the nature of credit booms. For instance, several studies emphasize the role of short-term rates in the build-up of credit booms. In particular, "too low for too long" rates (Taylor, 2007) may stimulate risk-taking behavior (Borio and Zhu, 2012; Adrian and Shin, 2010). I show that the credit boom in the U.S. and the euro area countries in the years before to the Great Recession can be, to a large extent (though not completely), explained by the path of the monetary policy rates.

Finally, this paper also contributes to the ongoing debate of, which financial indicators are more informative about the build up of systemic financial vulnerabilities ahead of crises. There is literature on the link of asset prices swings to crises (Borio and Lowe (2002), Shiller (2008), and references therein) as well as on the role of broad money growth in comparison with credit growth (Schularick and Taylor, 2012). I compute the gaps for asset prices and broad money using the BVAR-based methodology. Running an early-warning horse race exercise between these gaps and BVAR-based credit gaps, I find that credit gaps tend to dominate as early warning indicators at all horizons. The reason is that broad money gaps - when elevated - often tend to reflect monetary policy actions, such as quantitative easing policies among others, which leads to sizeable and prolonged positive gaps *after* the crisis onset. For asset price gaps, the rate of false positives is substantially higher than that of BVAR-based credit gaps because of much higher volatility of the former.

The rest of the paper is organized as follows. Section 2 presents the approach to credit boom identification in more detail, describes the data and justifies the choice of the econometric methodology. Section 3 discusses the historical plausibility of results and runs a horse-race exercise of BVAR-based credit gaps against credit-to-GDP gaps to compare their crisis prediction qualities. Section 4 illustrates the performance of the gaps in real time, while Section 5 studies the role of short-term interest rates during credit booms. Section 6 discusses the properties of asset price gaps and money gaps. Section 7 illustrates the robustness of the methodology to the battery of extensive robustness checks, and Section 8 provides concluding remarks and outlines directions for further work.

2. Approach, Methodology, and Data

Credit booms are usually defined as episodes of particularly rapid growth of credit to the private sector relative to the growth of the real economy. To identify such episodes, actual developments in the credit-to-GDP ratio are typically

[2] There are more departures from HP filtering in the literature, when it comes to measuring excess credit. Jorda et al. (2013) resort to growth rates, for example.

compared with the long-run smooth trend computed with the HP filter, for instance. In contrast with the detrending approach, I apply a different operational definition of credit booms, viewing them as departures from fundamentally justified levels. Similarly to the credit-to-GDP gap, I employ real economic activity variables as fundamentals for credit. When actual credit growth is persistently higher than the credit growth supported by the fundamentals, the economy is in a credit boom (and vice versa for a credit bust). The intuition is straightforward: When the economy is not generating enough income relative to the rapid growth of debt, those debts eventually become harder to repay or less sustainable.[3]

The second feature of my approach is that it is multivariate and accounts for endogenous interactions between credit and the other variables in the economy that would be relevant for the credit cycle. Given that credit booms are general equilibrium phenomena, it appears desirable to detect them from multivariate systems rather than single time series. 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..." A further advantage of a multivariate approach is in overcoming the endogeneity and simultaneity biases, which might distort the results of univariate regressions. Therefore I use a monetary VAR as a credit boom detection tool. This approach allows for linking the values of credit to the fundamentals without resorting to direct normalization of credit by real activity measures, such as credit-to-GDP ratios. In particular, based on the VAR estimation, I construct pseudo out-of-sample forecasts for credit, which are conditioned on real activity. These forecasts represent the fundamentally justified levels of credit and serve as a comparison benchmark for the actual credit values. In what follows, I discuss the operationalization of this approach in more detail.

On methodological grounds, the benchmark model is a medium-sized monetary VAR, which is estimated at a monthly frequency for the set of advances and emerging market economies. The variables in the system are typically used in monetary VARs (Giannone et al. (2019), and Banbura et al. (2010)) and contain: real economic activity (represented by industrial production, unemployment rate, or other business cycle indicators depending on the country), broad consumer price indexes, monetary policy rates (or other short-term rates and spreads, depending on the country), asset prices (broad stock market indexes), and monetary variables (credit and narrow and broad money aggregates). For small open economies in the sample, the set of variables typically contains either nominal exchange rates relative to the USD or the broad real exchange rate. The primary source for the credit variable is the International Financial Statistics (IFS) database, which provides data on bank claims on domestic private sector (firms and households) at a

[3]The financial instability hypothesis of Minsky (1986) also provides motivation for real activity variables as the choice of fundamentals for credit. According to Minsky, there is a remarkable asymmetry in the loan creation process: While loans are granted based on expected profits (or expected real economic activity), loans are eventually paid out of the realized profits (or realized real economic activity). Once the profit expectations are elevated, the economy goes into a financially unstable, fragile state since the realized profits are not sufficient to pay out the debts. As a result, an unsustainable credit boom occurs.

monthly frequency (IFS line 32d). In many cases, however, these data are subject to large structural breaks due to definition changes following the transition of the country to new accounting standards, for example. In those cases, the broad measures of credit to the nonfinancial sector provided by the Bank for International Settlements (BIS) are used instead. The full set of time series, their transformations, and data sources are given in Appendix A. Overall, all the data series are chosen to reflect the same economic concepts across countries as close as possible and to ensure a sample that is long enough to render VAR estimation and forecasting exercises feasible. A separate VAR is estimated for each country.

Since I base the detection of credit booms (busts) on pseudo out-of-sample conditional forecasts, the forecasting performance of the VAR is a crucial component of the detection technology. The trade off here is as follows. If the forecasting performance is generally very poor, a lot of deviations from normality would be detected and only some portion of them would reflect credit booms or busts, the rest being just poor forecasting. At the same time, if the forecasting performance of the system is reasonably good, the idea is that a VAR would capture typical interactions between the variables on a certain sample and then project them into the conditional forecast. In this case, the deviation of the forecast from the observed variable would also reflect a deviation from this typical variable co-movement captured by the VAR – a credit boom or a credit bust. In practice, the deviation of conditional forecast from observed levels could generally reflect both sides of this trade off: inability to forecast and deviation from a typical behavior. In order to mitigate the problems associated with poor forecasting performance, the estimation approach is Bayesian rather than classical ("frequentist"). Bayesian methodology contains a useful tool – prior shrinkage – to deal with overfitting in estimation of densely parameterized systems, such as VARs. The use of priors makes the forecasting performance of Bayesian VARs (BVARs) more efficient. In particular, I estimate the VAR in log-levels rather than differences in order to avoid losing information contained in levels of variables. As noted by Giannone et al. (2019), the assessment of level-relationships is particularly important in monetary analysis.[4]

The benchmark model is a linear BVAR. The system is estimated with the prior distribution of Sims and Zha (1998), which is imposed on a structural VAR 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 lth lag, p is the maximum lag, d is a vector of constants, and ϵ_t is a vector of i.i.d. structural Gaussian shocks with:

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

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

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

Although I estimate an identified VAR under the Cholesky identification, the ordering of variables does not affect the distribution of conditional forecasts and therefore is irrelevant for what follows. A formal proof of this result is presented in Waggoner and Zha (1999) (see Proposition 1). The maximum lag order is set to 13 months. This lag structure of approximately one year is standard in the literature for monthly data (Giannone et al. (2019), and Banbura et al. (2010)). 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 – that is, good in-sample fit but poor out-of-sample forecasting performance. In Bayesian estimation, the prior determines the degree of shrinkage. Therefore the choice of prior hyperparameters is quite important for the forecasting performance of the model. The trade off here is as follows. When the prior is too loose (that is, very uninformative), the model generates dispersed forecasts because of high estimation uncertainty. When the prior is too tight, the estimated coefficients will be very close to the values determined by the prior, 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 (Giannone, Lenza, and Primiceri (2015) 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 by maximizing the marginal likelihood over the training sample.[5]

In the forecasting exercise, forecast densities are simulated with the Gibbs sampler of Waggoner and Zha (1999) imposing hard conditions – that is, the forecasts are conditioned on the exact path of the real activity variable rather than its possible ranges.[6] The VAR is estimated in a rolling window approach, where the size of the rolling window is between 9 and 15 years.[7] The rolling window allows one to study the atypical deviations throughout the sample as well as to capture time variation in parameters in an efficient way.[8] Time variation in parameters, in turn, has direct implications for *trend flexibility* and inter alia allows one to better capture phenomena like financial deepening when compared with constant-parameter models.

The forecasting exercise for each rolling window proceeds as follows. After estimating the BVAR up to $t-4$ years within the sample, I construct out-of-sample forecasts of credit that are conditional on a path of future values of the real economic activity variables. To be precise, these forecasts should be considered pseudo out-of-sample, since I condition on the known future values of the business cycle variable. I further compare these forecasts with the observed values of credit. Suppose, for instance, the actual (observed) value of credit is substantially higher than its conditional forecast. Conditional on the model specification, this deviation indicates that there is more credit in the

[5] The marginal likelihood is computed as in Chib (1995), and optimization is performed via a grid search. For countries, where data samples are shorter, I adopt the values from the original paper of Sims and Zha (1998) and conduct a sensitivity analysis with respect to the hyperparameters.

[6] For each rolling window 60000 draws are produced, the first 15000 of them are discarded as burn-in.

[7] The choice of the rolling window size effectively determines the flexibility or smoothness of the 'trend' and is determined based on data availability for a particular country rather than optimized. Optimizing the length of the rolling window for each country (similar to choosing an optimal smoothing parameter for the HP filter) may improve early warning properties of BVAR-based gaps further.

[8] Bauwens et al. (2015) show that rolling-window models often forecast better than full-fledged time-varying parameter models.

economy than justified by the fundamental variable – a possible indication of a credit boom. More formally, I compute the following deviation, or a *forecast error*:

$$dev_{t,h} = y^{act}_{t,h} - y^{m}_{t,h},$$

where index t refers to a particular point in time and index h refers to the respective estimation window ($h = 1$ corresponds to the most recent forecast for this point in time t, $h = H$ corresponds to the forecast from the earliest estimation window for this point in time), and $y^{m}_{t,h}$ is the point forecast.[9] Note that the deviation defined above is sign-preserving: it is positive for potential boom episodes and negative for potential bust episodes.[10]

The baseline forecasting horizon is set to four years, and the estimation proceeds in rolling windows. Accordingly, at each point in time there are several forecasts and therefore several deviations available from different rolling windows. The most recent rolling window would yield a short-term forecast and a respective deviation, while the most distant rolling window would yield a longer horizon forecast and a respective deviation for this particular point in time. It would be hard to motivate the choice of one particular forecast horizon that would be relevant to detect credit booms. Furthermore, choosing only one forecast horizon, for instance, the one with the smallest prediction error, could potentially bias the results. Therefore I use the forecasts and the deviations from all forecasting horizons and pool (average) them as follows:

$$gap_t = \frac{\sum_{h=1}^{H} dev_{t,h}}{H}, \tag{2}$$

where H - is the maximum forecast horizon, h is the index for the respective estimation window.

In the next section, I apply the methodology to a set of 31 advanced and emerging market economies in order to evaluate the quality of the resulting credit gap measure.

3. Historical Plausibility and Crisis Prediction

Credit gaps are latent variables. There are no actual data to compare them against in order to assess their quality. However, a comparison against historical evidence is possible and useful. Similarly to the output gaps, one could expect a credit gap to build up and stay positive during a boom phase, for example, preceding a crisis, and then to turn at crisis onset and stay negative during a credit bust or credit crunch, for example, following a crisis.

Figures 1 – through 4 show the BVAR credit gaps for 31 advanced and emerging market economies plotted along with the vertical bars that signify the onset of systemic banking crises, financial crises or events relevant for macroprudential policy. The timing of these events is taken from the following chronologies: Laeven and Valencia

[9] I use the mean as the point estimate in the baseline specifications. Median point estimate delivers similar results.

[10] An earlier version of this credit gap considers deviations being significant once they surpass a threshold - the upward (downward) band around the point forecast for the boom (bust) (see Afanasyeva (2013) for more details). This feature often helps reduce the noise in the resulting credit gap series by removing smaller, less profound episodes. At the same time, however, imposing thresholds can worsen early warning quality for some countries, as smaller upward deviations at the onset of the credit boom are zeroed out.

(2013) (LV henceforth), Schularick and Taylor (2012) (ST henceforth), Baron et al. (2018) (BVX henceforth), and Lo Duca et al. (2017) (LD henceforth).[11]

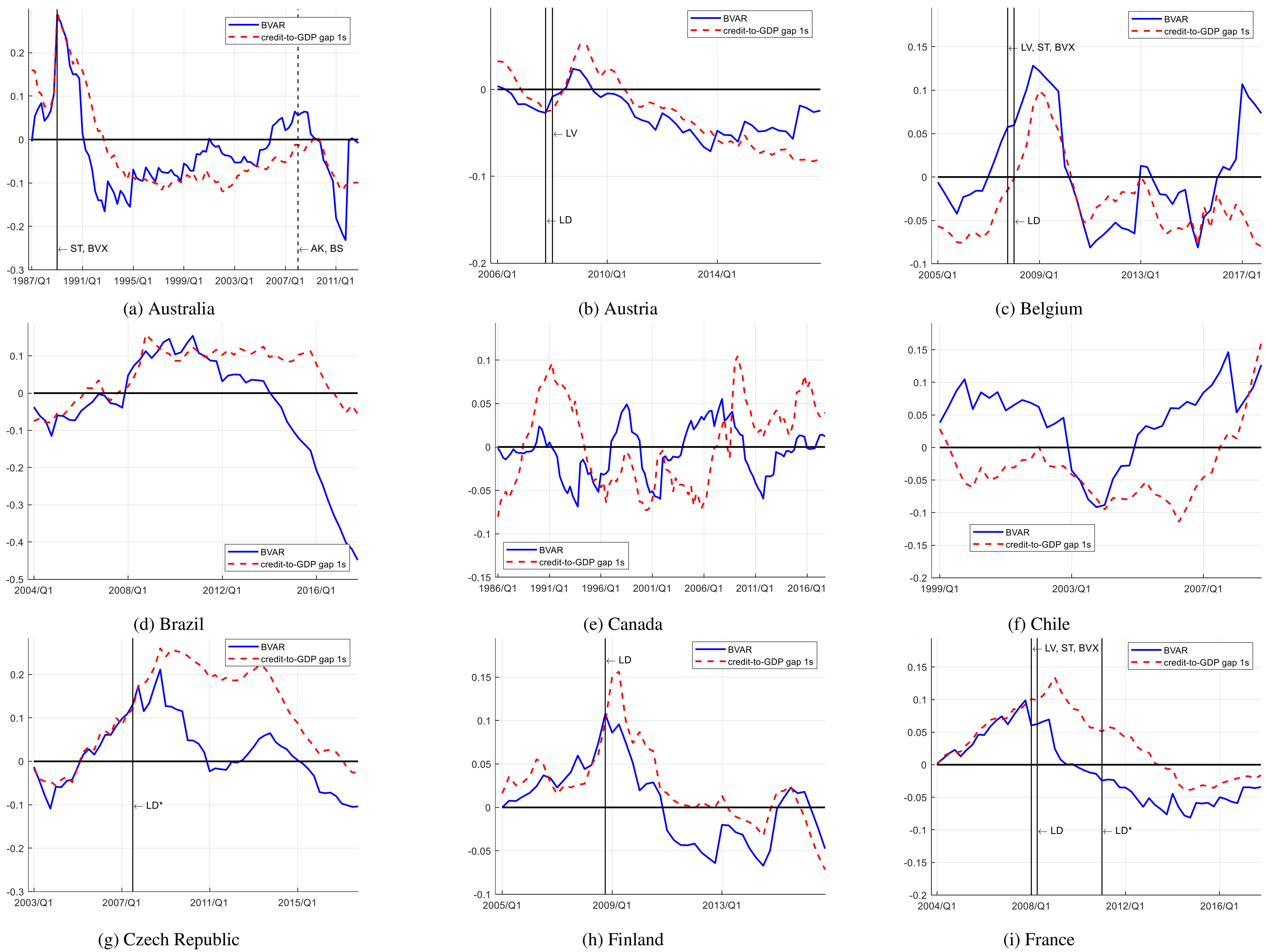
As figures 1 – through 4 illustrate, the resulting BVAR-based credit gaps are largely consistent with historical evidence for the respective countries. Major crises, such as the Global Financial Crisis in the U.S. and Europe (Aliber and Kindelberger (2015)), the Heisei bubble burst of the late 1980s in Japan (Shiratsuka (2005)), the Savings and Loan Crisis in the U.S. (Elliott, Feldberg, and Lehnert (2013)), the Asian financial crisis of 1998 in South Korea and Malaysia (Aliber and Kindelberger (2015)), were preceded by credit expansions and overheating, and it is indeed reflected in persistent and sizeable positive values of the corresponding gap measures. At the crisis onset date or shortly thereafter, the credit gaps tend to decline precipitously, marking the post-crisis credit bust period. These busts and credit crunches are also well documented in the literature. To give one illustrative example, in the U.S., the BVAR credit gap adequately reflects credit crunches, such as the one in the aftermath of the 1974 banking crisis, the S&L crisis and the GLobal Financial Crisis (Bordo and Haubrich (2010)) as well as the prolonged credit crunch of the early 1990s (Bernanke and Lown (1991)). Interestingly, the BVAR credit gaps also reflect somewhat less prominent episodes in the financial cycle – episodes not uniformly identified as crises preceded by major credit booms by the chronologies. For instance, in the case of Japan, a minor short-lived boom episode in 2001 emerges a period when Bank of Japans QE policies were announced and had a profound effect on bank lending (Bowman et al. (2015)). The reason is that, in contrast to filters with a built-in length of a cycle (such as HP filter or bandpass filter), this approach does not a priori exclude cycles of a certain length. Hence, these less prominent episodes are not necessarily interpretable as noise, but reflect the ability of the BVAR gap to capture both larger and smaller waves of the financial cycle.

In order to quantify these qualitative observations and in order to put the results in context, I conduct a horse-race exercise to compare early warning properties of the BVAR credit gap with the established, well-performing benchmark on large panels of countries – the credit-to-GDP gap (see Drehmann et al. (2010), for example). The latter version of the credit gap is obtained by detrending the logarithm of the credit-to-GDP ratio with the HP filter that extracts lower-frequency movements (by applying the smoothing parameter of 400.000). I compare BVAR gaps with both one- and two-sided versions of the credit-to-GDP gaps. While the information set of the one-sided version is comparable with the one of the BVAR gap (also a one-sided measure), two-sided credit-to-GDP gaps are often used and examined, as they encompass more information.

To visualize the cyclical differences between the measures, I first construct the Burns-Mitchell diagrams for the BVAR gaps and credit-to-GDP gaps around systemic crises (figures 5 and 6).[12] To plot a Burns-Mitchell diagram,

[11] I focus on financial crises and exclude sovereign debt crises, where they fall into the span of the sample, as the underlying credit series do not contain government debt and are hence not capable to reflect the relevant sovereign debt dynamics by construction.

[12] A full set of country-specific graphs comparing BVAR credit gaps with two-sided credit-to-GDP gaps is presented in Appendix B.



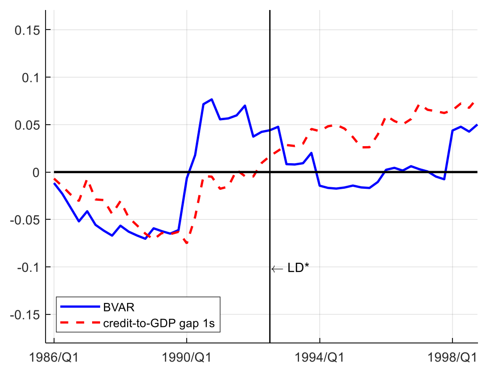
(a) Australia (b) Austria (c) Belgium

(d) Brazil (e) Canada (f) Chile

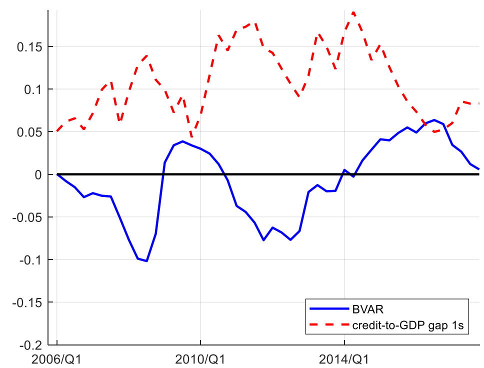
(g) Czech Republic (h) Finland (i) France

Figure 1: BVAR and One-Sided Credit-to-GDP Gaps across Countries: Australia - France

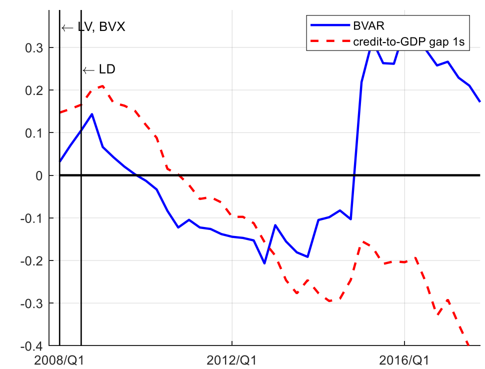
Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis). For Australia, AZ stands for Aliber and Kindleberger (2015) and BS stands for Brunnermeier and Schnabel (2016).



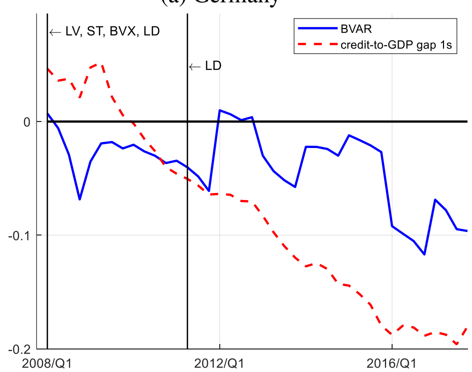
(a) Germany



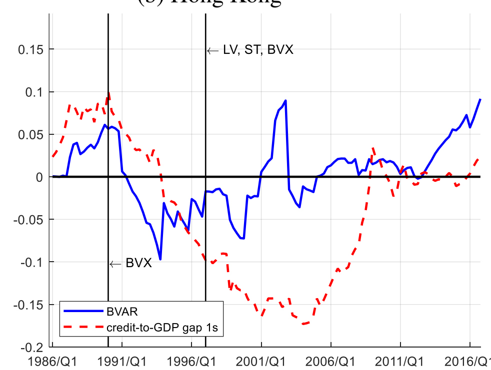
(b) Hong Kong



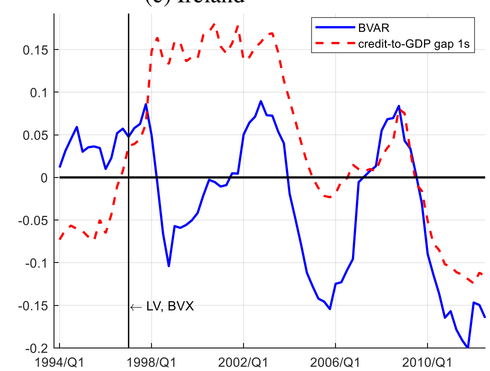
(c) Ireland



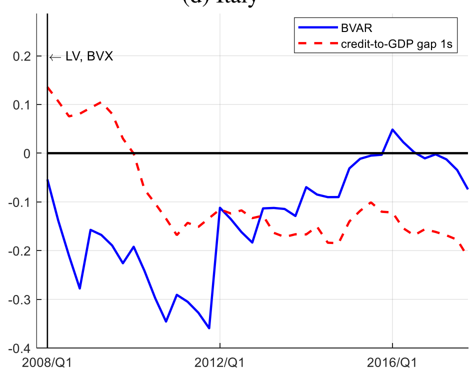
(d) Italy



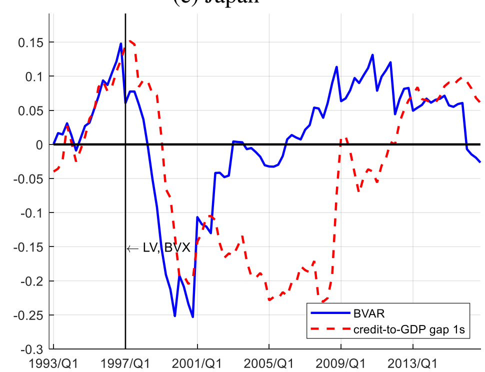
(e) Japan



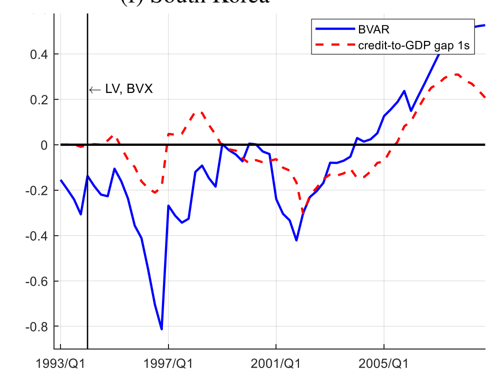
(f) South Korea



(g) Luxembourg



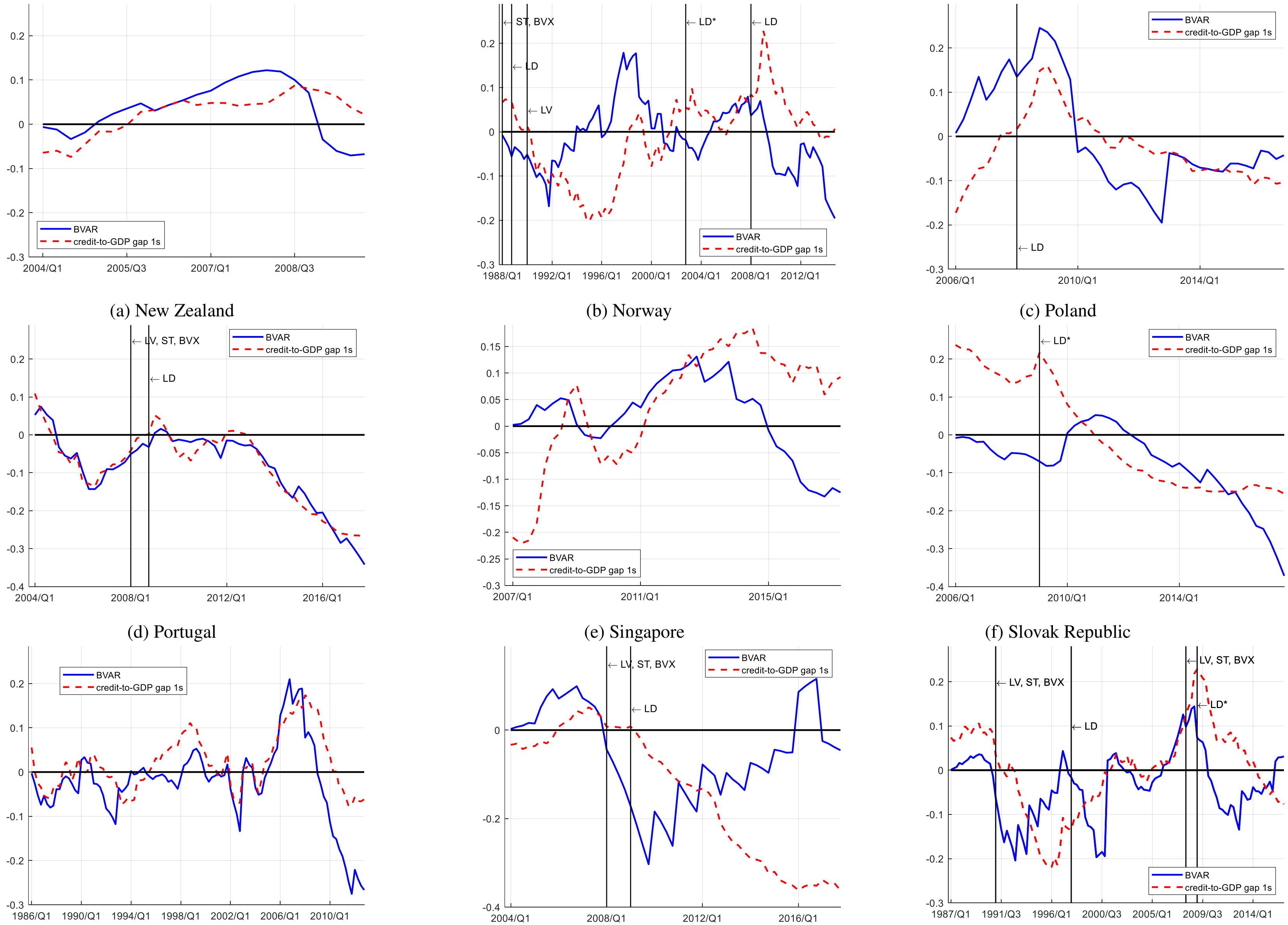
(h) Malaysia



(i) Mexico

Figure 2: BVAR and One-Sided Credit-to-GDP Gaps across Countries: Germany - Mexico

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, $*$ indicates a residual event (rather than a systemic crisis).



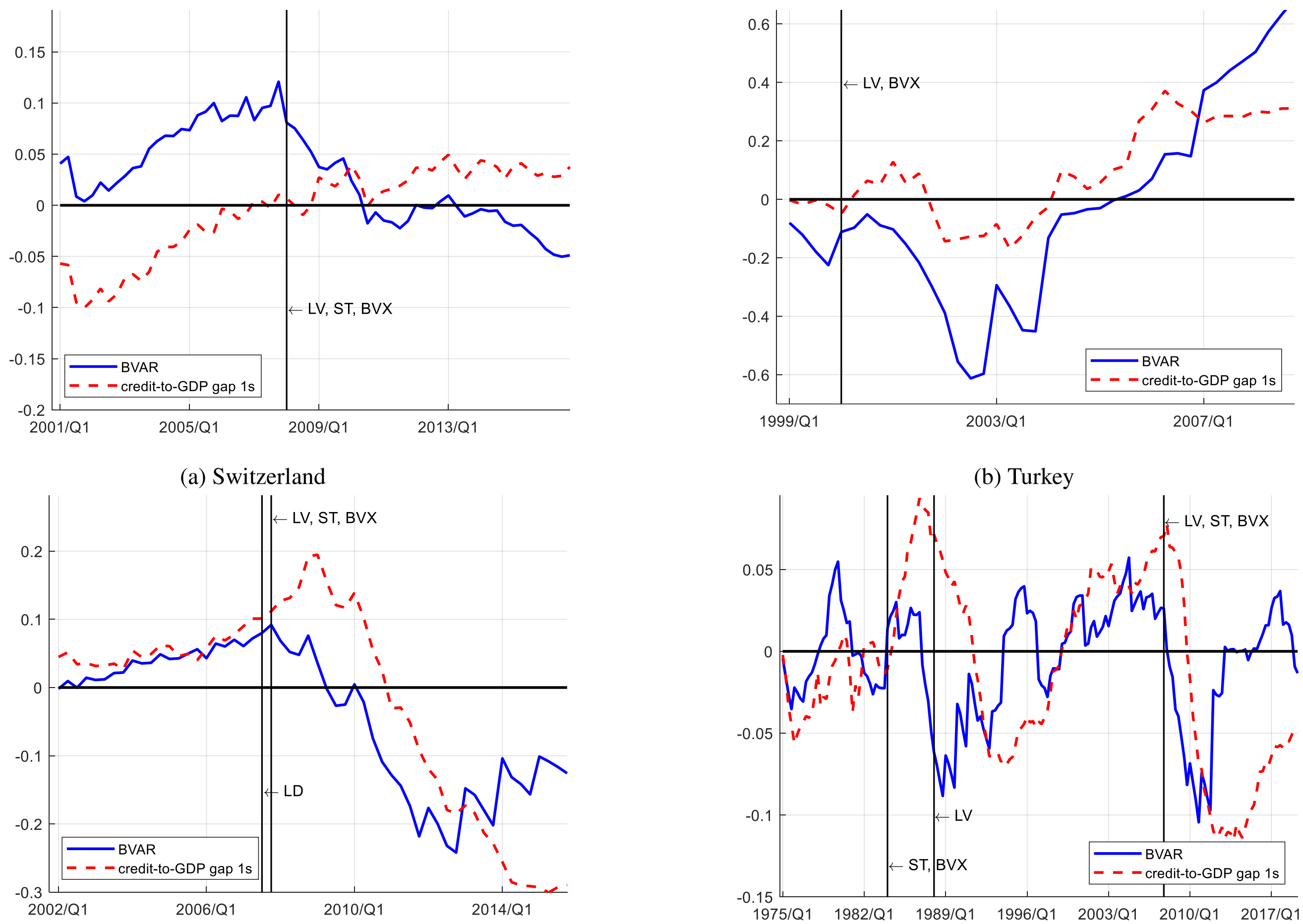
(a) New Zealand (b) Norway (c) Poland

(d) Portugal (e) Singapore (f) Slovak Republic

(g) South Africa (h) Spain (i) Sweden

Figure 3: BVAR and One-Sided Credit-to-GDP Gaps across Countries: New Zealand - Sweden

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis).



(a) Switzerland

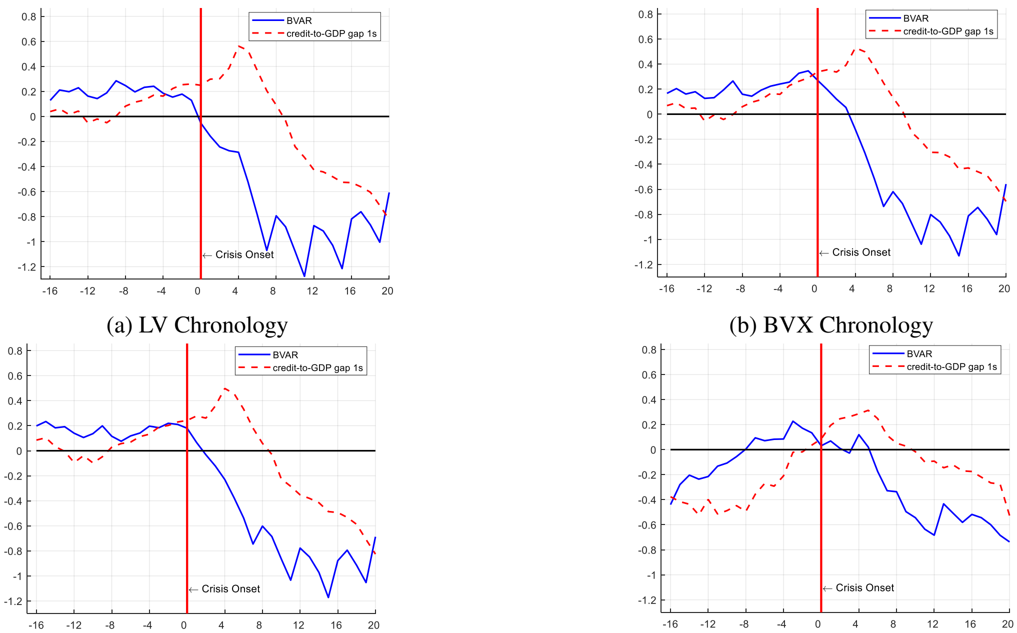
(b) Turkey

(c) United Kingdom

(d) United States of America

Figure 4: BVAR and One-Sided Credit-to-GDP Gaps across Countries: Switzerland - USA

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, $*$ indicates a residual event (rather than a systemic crisis).



(a) LV Chronology

(b) BVX Chronology

(c) ST Chronology

(d) LD Chronology

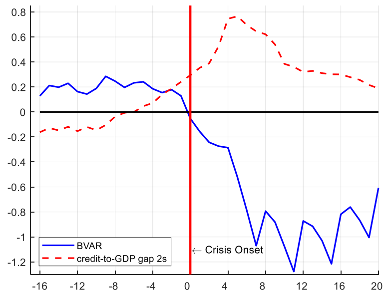
Figure 5: Average Burns-Mitchell Diagrams Around Crises: BVAR Credit Gap and One-Sided Credit-to-GDP Gap.

Notes: Time on the horizontal axes is in quarters. Credit gaps are expressed in fractions of their respective peak values during the credit cycle surrounding the crisis. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017).

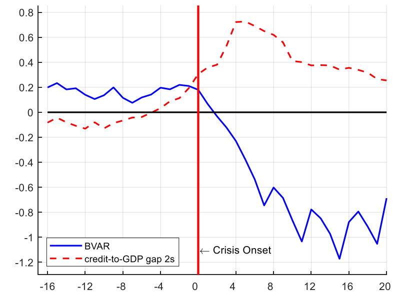
I normalize the time series by its peak value around the critical event as timed by the crisis chronology. I employ all four chronologies in order to use maximal cross-country information (a larger number of crisis episodes) and for robustness, as crisis timings can vary considerably. For instance, the onset of the savings and loan crisis is dated with a difference of four years in various chronologies, and there are more analogous examples in the sample of countries. Furthermore, there is considerable disagreement among chronologies as to whether or not a crisis even occurred (see Appendix D). The reasons are different qualifying criteria across chronologies. Typically, the choice is based on a set of qualitative (narrative, subjective) and/or quantitative indicators. Baron et al. (2018) point out that chronologies placing considerable weight on subjective information may suffer from look-back bias. I therefore also include the BVX crisis chronology, which primarily relies on bank equity returns data in identifying the onset of a crisis. In addition, the LD chronology differs from the other three (LV, ST and BVX), as it provides dates for systemic crises as well as residual events – episodes that do not meet the criteria of systemic crises and yet are relevant for macroprudential or other regulatory policies.

The Burns-Mitchell diagrams in figures 5 and 6 display typical, averaged credit cycles across the set of countries that have crisis observations according to the corresponding chronology.[13]

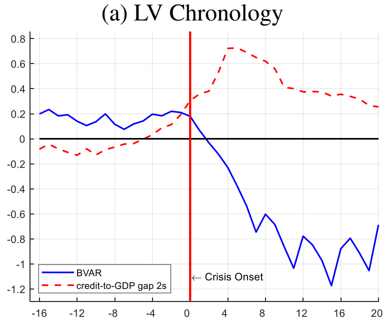
[13] In these exercises, I exclude crisis episodes, which are not preceded by at least four years of credit gap estimates in order to have an equal number of credit gap observations across episodes at the relevant horizons: zero to four years ahead. This selection gives a fair chance to predictive



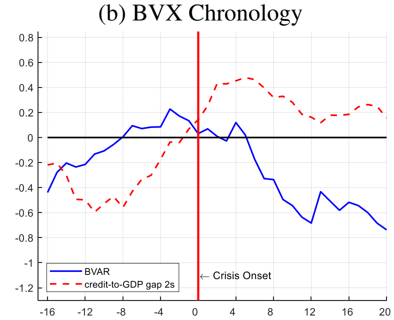
(a) LV Chronology



(b) BVX Chronology



(c) ST Chronology



(d) LD Chronology

Figure 6: Average Burns-Mitchell Diagrams Around Crises: BVAR Credit Gap and Two-Sided Credit-to-GDP Gap.

Notes: Time on the horizontal axes is in quarters. Credit gaps are expressed in fractions of their respective peak values during the credit cycle surrounding the crisis. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017).

The diagrams illustrate substantial differences across the methodologies. First, BVAR credit gaps are persistently positive four years prior to the crisis event for most chronologies. One-sided credit-to-GDP gaps become positive about two years before the crisis, whereas two-sided credit-to-GDP gaps mostly stay in the negative territory and turn positive a year before the crisis. These findings suggest that BVAR credit gaps detect booms earlier and can have good early warning qualities. Second, there are substantial differences between BVAR gaps and credit-to-GDP gaps in the post-crisis quarters as well. While BVAR gaps turn negative and decline precipitously at the onset of the crisis or shortly thereafter, credit-to-GDP gaps have a *delayed peaking* feature and typically turn negative about two years after the onset of the crisis for one-sided credit-to-GDP gaps and substantially later for two-sided credit-to-GDP gaps. This feature again stresses a better ability of the BVAR gap to detect a turning point, now from positive into negative territory. The policy implications of these differences can be quite profound. Should macroprudential policy react to such a false positive signal by either raising the capital requirements or not releasing them in time, the action can have profound negative effects on both lending and the real economy (see Edge and Meisenzahl (2011) for numerical examples). Finally, the BVAR gaps rebound back into positive territory faster than credit-to-GDP gaps that tend to stay negative there for many years after a crisis (see Australia in figure 1a, as an example).

abilities of credit gaps across these horizons for a panel of countries. The corresponding list of countries and episodes is presented in Appendix D.

There are primarily two reasons why BVAR gaps detect turning points earlier and are substantially less prone to *delayed peaking*. The first reason is the link between credit and the real economic activity fundamental: it is rather *static* for credit-to-GDP gaps and much more *dynamic* for BVAR gaps. Credit-to-GDP gaps are based on a ratio – a time series that gives rise to its own dynamics with peaks in the post-crisis quarters. The reason is that GDP tends to fall faster than credit during crises (Krishnamurthy and Li (2020) illustrate this stylized fact across 41 financial crises), which raises the ratio in those years substantially, thereby shifting the implied peak of the financial cycle several years into the future. By contrast, the BVAR credit gap links credit to real activity variables via conditional forecasts in a multivariate system, accounting for lead-lag relationships between credit and real activity. The second reason is the degree of trend flexibility. Due to time variation in parameters from rolling window estimation, the trend implied by the BVAR gaps is quite flexible and responsive to new observations. By contrast, for credit-to-GDP gaps, a high smoothing parameter implies a nearly linear, inflexible HP trend. When faced with the artificial peak generated by the normalization to GDP, this trend does not adjust upwards, thus generating a persistent series of positive credit gaps after a crisis. The rigidity of the trend also explains why credit-to-GDP gaps stay in the negative after the crisis for many years. All these features become even more pronounced for two-sided credit-to-GDP gaps, as this method yields an additional reason for trend rigidity. During a prolonged credit expansion, the two-sided trend is likely to absorb a lot of the accelerating dynamics, so that the resulting cyclical component is either mildly positive or even negative.

The previous qualitative discussion suggests that BVAR-based gaps can have good early warning properties and perhaps even outperform their credit-to-GDP counterparts. Note that both methods are supplied with the same credit measures on the same time span to ensure comparability of results. In order to formally test the significance of these observed differences, I run pooled logit regressions for BVAR credit gaps and both versions of credit-to-GDP gaps, for each of the crisis chronologies separately. The goal is to test whether credit gaps can predict the onset of the crisis up to four years in advance and how well they can predict it. To evaluate the latter part of the question, I compute the area under the receiver operating characteristic (ROC) curve. This curve plots a true positive rate against a false positive rate. A value of 0.5 would indicate diagnostic properties of a fair coin: it would correctly predict a crisis in 50 percent of cases, and the corresponding ROC curve would be a diagonal line. In other words, the further away from 0.50 the ROC value, the better the diagnostic qualities.

Table 1 illustrates the results for the relevant countries and a full sample. The pooled logit coefficients for BVAR credit gaps are highly statistically significant at all horizons, regardless of chronology, while ROC values fluctuate around 0.70. One-sided credit-to-GDP gaps are equally good as contemporaneous predictors of crises (although their ROC values are a bit higher at this horizon), signal crises comparably well (albeit with a somewhat lower ROC value) one to two years ahead, and are substantially worse than BVAR gaps at longer horizons of three to four years. For these longer horizons, the ROC values are larger by even more than for 1-2 years ahead, so that we can reject the Null of equal diagnostic performance between BVAR gaps and credit-to-GDP gaps at high statistical levels. Two-sided credit-to-GDP gaps are marginally competitive with BVAR gaps only contemporaneously. At all other horizons, statistical significance of the corresponding coefficients fades away, ROC values decrease, and the p-values rejecting the Null of equal diagnostic performance between BVAR gaps and credit-to-GDP gaps are mostly lower than 0.01.

Table 1: Crisis Predictability Results across Various Chronologies, Full Sample

LV Chronology (981 observation, 12 crisis episodes)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	8.72***	0.63	8.29***	0.70	0.43	6.18***	0.67	0.75
1 year ahead	12.73***	0.69	7.42**	0.68	0.84	4.25	0.62	0.18
2 years ahead	12.17***	0.70	6.55**	0.68	0.16	2.23	0.57	0.00
3 years ahead	11.78**	0.69	5.85*	0.65	0.02	0.70	0.53	0.00
4 years ahead	11.78***	0.70	6.07**	0.65	0.02	0.04	0.51	0.00

BVX Chronology (1037 observations, 12 crisis episodes)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	12.14***	0.71	9.78***	0.73	0.83	6.88***	0.68	0.00
1 year ahead	13.03***	0.74	7.64***	0.71	0.12	3.27	0.58	0.00
2 years ahead	12.11***	0.73	7.03***	0.69	0.03	1.15	0.52	0.00
3 years ahead	11.52***	0.72	6.22***	0.67	0.00	-0.24	0.51	0.00
4 years ahead	11.37***	0.72	6.41***	0.67	0.00	-0.82	0.52	0.00

ST Chronology (866 observations, 10 crisis episodes)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	12.01***	0.69	9.57***	0.70	0.90	7.72***	0.70	0.96
1 year ahead	12.15***	0.73	7.91***	0.70	0.36	4.59**	0.59	0.01
2 years ahead	11.40***	0.72	7.53***	0.69	0.22	2.75	0.54	0.00
3 years ahead	11.12**	0.71	6.79***	0.67	0.07	1.78	0.53	0.00
4 years ahead	11.42**	0.71	7.18***	0.68	0.10	1.36	0.52	0.00

LD Chronology (860 observations, 14 crises and residual events)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	5.64**	0.63	6.71***	0.71	0.34	4.61***	0.60	0.83
1 year ahead	7.15***	0.67	5.55***	0.68	0.79	1.98	0.54	0.02
2 years ahead	7.93***	0.69	4.52**	0.65	0.20	-0.16	0.52	0.00
3 years ahead	7.92***	0.69	4.07	0.63	0.01	-1.51	0.56	0.00
4 years ahead	7.64***	0.68	3.61	0.62	0.00	-2.31	0.59	0.00

Notes: Standard errors of pooled logit regression coefficients are clustered at crisis episodes. ***, **, * stand for 1%, 5%, and 10% statistical significance levels, respectively. ROC p values reflect, at which level of statistical significance the Null of equal ROC between BVAR credit gap and the corresponding credit-to-GDP gap can be rejected.

The previous results may deliver conservative estimates on the differences between BVAR gaps and credit-to-GDP gaps. First, there are episodes within those full samples that count as a false positive for the BVAR gaps and boost the diagnostic qualities of credit-to-GDP gaps. Consider the example of Australia (figure 1a). All four chronologies account for only one crisis for this country – the one in the late 1980s. In particular, there is no crisis in 2008. At the same time, Aliber and Kindelberger (2015) as well as Brunnermeier and Schnabel (2011) describe the early 2000s in Australia as an example of a credit boom that was eventually landed successfully due to timely interventions of monetary and macroprudential policies. The BVAR-based credit gap detects this credit boom in a timely manner, whereas one-sided credit-to-GDP gap stays in the negative territory. The previous pooled logit regression assigns this episode as a false positive for the BVAR gap, lowering its ROC, and as a success for the credit-to-GDP gap. Second, many country samples end in 2018 and 2019, whereas not all crises chronologies are updated that far into the future. Hence, BVAR credit gaps, which tend to rebound faster after the Global Financial Crisis, might receive even more potentially inadequate false positives for these years as well.

In order to clean the exercise from these potential biases, I next concentrate on systemic crises only and run the pooled logit regressions on 10-year windows around the systemic crises rather than the full samples as before. The question now is, conditional on the presence of a systemic crisis, how do early warning qualities of credit gaps compare. The results are presented in table 2. The differences between BVAR-based gaps and credit-to-GDP gaps are even starker, as expected. One-sided credit-to-GDP gaps are still significant crisis predictors at horizons zero to two years, yet the corresponding ROC numbers are substantially lower relative to BVAR gaps. We can largely reject the Null of equal predictive qualities of BVAR gaps and one-sided credit-to-GDP gaps for horizons one to four years ahead. As for two-sided credit-to-GDP gaps, they remain good contemporaneous predictors and emerge as (marginally) significant predictors 4 years ahead, albeit with a *negative* sign. In other words, negative two-sided credit-to-GDP gaps can be statistically significant predictors of a vulnerability build-up in the medium term.

A few countries were not prominently featured in the previous regressions. The first group are the countries, where the crisis onset falls within the first few quarters of available gap estimates, such as Italy, Luxembourg, or Ireland, for example (figures 2d, 2g, and 2c). These countries do not have a sufficient number of pre-crisis credit gap observations to participate in the early warning comparison exercise. The post-crisis behavior of BVAR gaps in these cases does not differ from the one of the other countries where the build up phase is also available. BVAR credit gaps go into negative territory at the onset date and rebound faster than their credit-to-GDP gap counterparts. Second, there is a subset of countries where the chronologies do not assign any crises episodes, such as South Africa (figure 3g, Chile (figure 1f), Singapore (figure 3e), or Canada (figure 1e). In these cases, whenever both methods identify a credit expansion, for example, credit expansions in the early 2000s, BVAR-based credit gaps tend to identify it earlier. These observations further support the conclusion that BVAR-based gaps can detect turning points faster.

Overall, the proposed BVAR credit gap methodology delivers reasonable results for both advanced and emerging market economies, even though in the latter case, data constraints are often binding.[14] That said, there are several

[14]For instance, industrial production time series for South Africa had to be substituted by a survey-based measure on business cycle.

Table 2: Crisis Predictability Results across Various Chronologies, 10-Year Windows around the Crises

LV Chronology (658 observation, 12 crisis episodes)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	8.75***	0.63	6.33**	0.64	0.93	3.97*	0.62	0.90
1 year ahead	13.61***	0.69	5.21	0.63	0.06	1.74	0.56	0.02
2 years ahead	13.55***	0.71	4.03	0.60	0.00	-0.71	0.50	0.00
3 years ahead	13.65***	0.71	2.98	0.57	0.00	-2.85	0.55	0.00
4 years ahead	14.24***	0.72	3.09	0.57	0.00	-4.09	0.58	0.00

BVX Chronology (658 observations, 12 crisis episodes)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	10.94***	0.70	7.62***	0.66	0.43	4.38***	0.63	0.49
1 year ahead	12.57***	0.74	4.96**	0.63	0.00	0.48	0.52	0.00
2 years ahead	12.26***	0.74	4.02	0.61	0.00	-2.10	0.55	0.00
3 years ahead	12.20***	0.73	2.79	0.57	0.00	-4.17	0.59	0.00
4 years ahead	12.63***	0.74	2.79	0.57	0.00	-5.45*	0.62	0.00

ST Chronology (589 observations, 10 crisis episodes)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	10.43***	0.67	7.17***	0.62	0.55	5.17***	0.63	0.79
1 year ahead	10.57**	0.71	4.82**	0.62	0.00	1.56	0.53	0.00
2 years ahead	9.95**	0.70	4.03	0.60	0.00	-0.79	0.52	0.00
3 years ahead	9.84**	0.69	2.88	0.57	0.00	-2.29	0.55	0.00
4 years ahead	10.38**	0.70	3.02	0.67	0.00	-3.21	0.57	0.00

LD Chronology (688 observations, 14 crises and residual events)

Horizon	BVAR credit gap		Credit-to-GDP gap (one-sided)			Credit-to-GDP gap (two-sided)		
	Coeff.	ROC	Coeff.	ROC	ROC p-val.	Coeff.	ROC	ROC p-val.
contemporaneously	4.33*	0.60	5.82***	0.66	0.44	3.21*	0.56	0.79
1 year ahead	5.80**	0.64	4.33**	0.63	0.83	0.36	0.50	0.02
2 years ahead	6.50***	0.66	2.98	0.60	0.05	-2.14	0.58	0.01
3 years ahead	6.45***	0.66	2.29	0.57	0.00	-4.03	0.62	0.22
4 years ahead	6.08***	0.65	1.57	0.55	0.00	-5.48*	0.66	0.78

Notes: Standard errors of pooled logit regression coefficients are clustered at crisis episodes. ***, **, * stand for 1%, 5%, and 10% statistical significance levels, respectively. ROC p values reflect, at which level of statistical significance the Null of equal ROC between BVAR credit gap and the corresponding credit-to-GDP gap can be rejected.

unsatisfactory country-specific results, such as those for Austria (figure 1b), Portugal (figure 3d) or Turkey (figure 4b), where BVAR-based gaps do not adequately reflect the build-up of financial vulnerabilities in the run-up to the crises. Interestingly, in these cases, BVAR credit gaps and credit-to-GDP gaps are quite correlated – that is, both approaches do not work well. One reason of these failures could be that the chosen data series (the credit series, most importantly) do not fully reflect the dynamics of the credit cycle in this particular economy.[15] Perhaps, a more detailed look at the decomposition of credit aggregates by lender and borrower could yield better answers.

4. Credit Gap Performance in Real Time

The previous section computed the gaps under the 'ideal conditions' of ex-post revised data. Another test of the credit gap methodology is its reliability in real time – when actual decision making occurs. Two concerns arise in real time: end-point filtering problems and the use of the real-time data vintages per se. I address both these dimensions in turn and illustrate them for the U.S. economy as a representative example.[16]

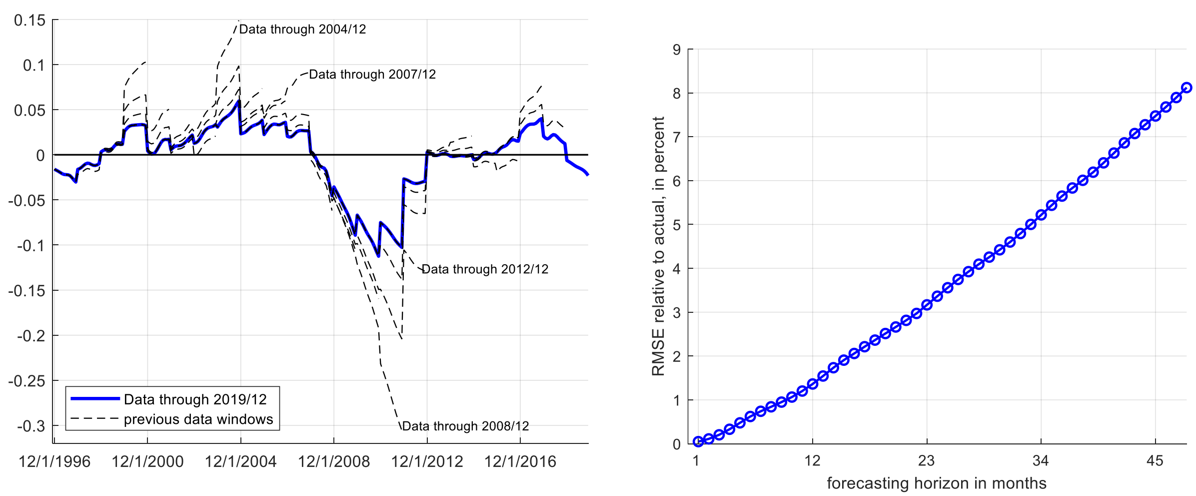


Figure 7: Quasi Real-Time Exercise for the U.S.: Credit Gaps (in Percentage Points) from Various Estimation Windows (left) and the Corresponding Average Root Mean Squared Errors of Conditional Credit Forecast by Horizon (right).

First, consider a revised data vintage as of March 2020, but instead of aggregating all the information in the credit gap as of March 2020, let the computation pause each year in March. The resulting quasi real-time credit gaps are shown in figure 7. In this exercise, as the data stem from the same vintage (hence the quasi reference), the end-point

[15]For some of the emerging markets, the sovereign debt often triggers crises. Government debt is excluded from the credit aggregates studied in this paper.

[16]U.S. example is chosen because of its longer sample and a larger number of real-time vintages available for the time series of the BVAR.

qualities of the filter come to light. On the one hand, the real-time version of the credit gap still correctly reflects the signs and overall dynamics of the full-sample time series. The only change in sign occurs around 2015, when the credit gap is nearly zero and the real-time versions are either slightly above or below zero. By comparison, Edge and Meisenzahl (2011) find that real-time credit-to-GDP gaps change signs 27 percent of the time. Also, the ability to swiftly capture turning points is preserved for real-time BVAR gaps. For instance, while the estimate from the window ending in December 2007 shows a positive gap, the next computed estimate already displays a deep credit bust following the onset of the Great Recession.

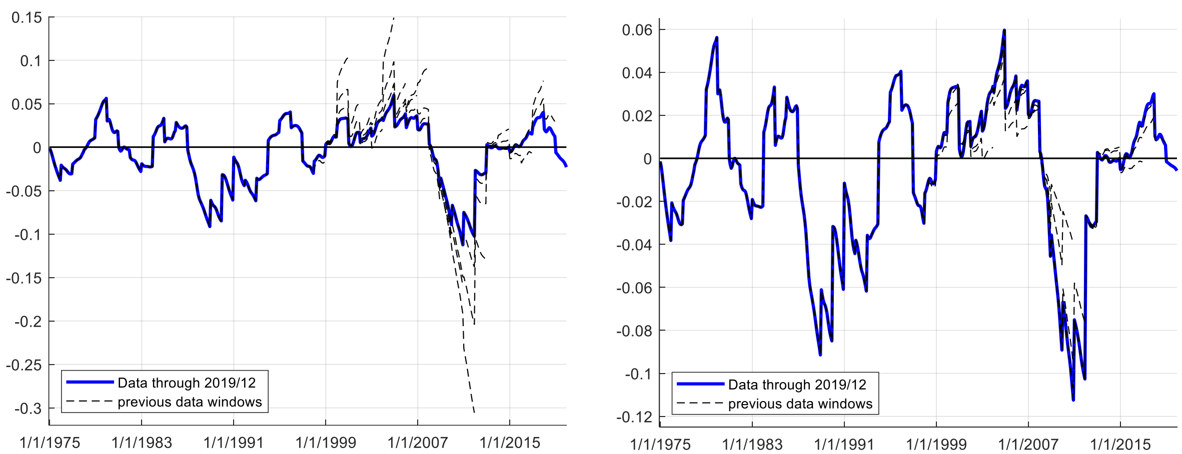


Figure 8: Quasi Real-Time Exercise: U.S. Credit Gaps from Various Estimation Windows with Baseline (left) and Adjusted Weights (right).
Notes: Time on the horizontal axes is in months. Credit gaps are expressed in percentage points.

On the other hand, the end-point problem of the filter manifests itself in the overshooting feature: The last 12-15 months of the respective estimation window, although retaining the correct sign, tend to overestimate the magnitude of the gap in absolute terms. This feature is especially prominent at the points in time where the gap increases or decreases at a high rate, such as, for instance, at the height of the credit boom preceding the Great Recession or at the time of a rapid reversal following the onset of the Global Financial Crisis (figure 7). The reason for such overshooting is that, at the end of the respective data window, forecasts at longer horizons receive disproportionately higher weights, as only those forecasts are available and tend to be the least accurate. Figure 7 illustrates the average root-mean-squared errors of conditional credit forecasts by horizon: from 1 to 48 months. These errors display a clear *upward-sloping* profile. Within a full sample (as of March 2020, for instance), these forecasts would be pooled with shorter-term forecasts from the next estimation windows and smoothed out due to averaging at each point in time with equal weights (as in

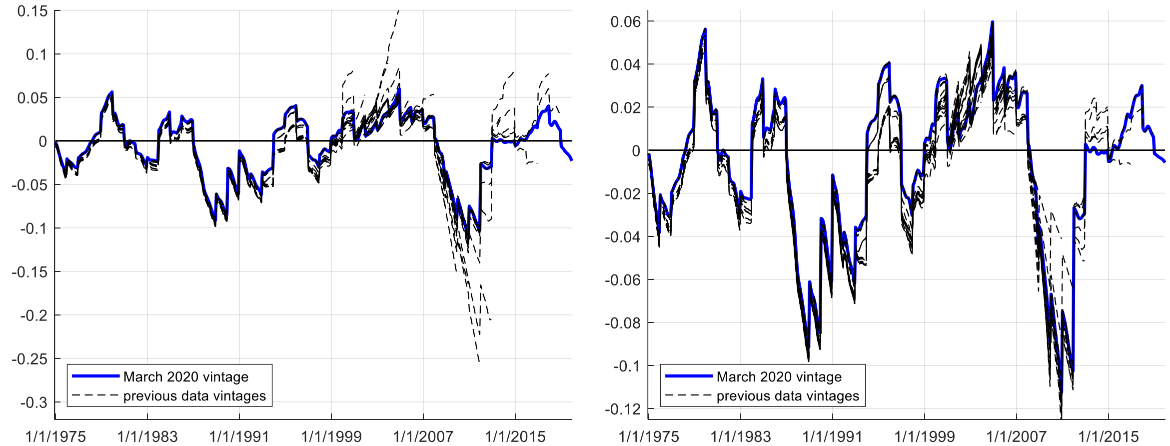


Figure 9: Real-Time Exercise: U.S. Credit Gaps from Various Estimation Windows with Baseline (left) and Adjusted Weights (right).
Notes: Time on the horizontal axes is in months. Credit gaps are expressed in percentage points.

equation (2)). In real time, the very last forecast 48 months ahead, would receive a weight of one (as opposed to 1/n, with n being the number of forecasts available in full sample), since it is the only forecast available.

These observations suggest a way to mitigate the overshooting property – by reducing the disproportionately high weights of longer-term forecasts at the end of the sample. One simple weight adjustment rule illustrated in figure 8 reduces the weights of longer-horizon forecast errors at the end of the sample, so that they are equal to their within-sample arithmetic average counterparts – (1/n). For instance, if the actual weight at the end of the sample is x, it is multiplied by the factor $1/(nx)$.[17] This rule reduces the overshooting considerably, bringing the real-time vintages of credit gap very close to the full-sample revised version (right panel of Figure 8).

Finally, I add the second real-time data aspect to the exercise. Each estimation window is now based on the respective real-time data vintage – the time series as they are available at that particular point in time (see Appendix C for details on the data sources, the corresponding time series revisions, and timing of data vintages). The results with baseline, or full-sample, and adjusted weighting are in figure 9. Baseline weighting results closely resemble their quasi real-time counterparts from the previous exercise (figure 8, left panel). Hence, the primary quantitative source of real-time discrepancies of the gap estimate stems from the end-point properties of the filter rather than the use of the actual real-time data vintages. Also in this case, adjusted weighting scheme mitigates the overshooting feature to a similar degree as in the quasi real-time exercise (figure 10). Average deviations of real-time gaps from the full-sample

[17] Alternatively, a rule that makes the weights an inverse function of RMSEs at the corresponding horizon could be constructed.

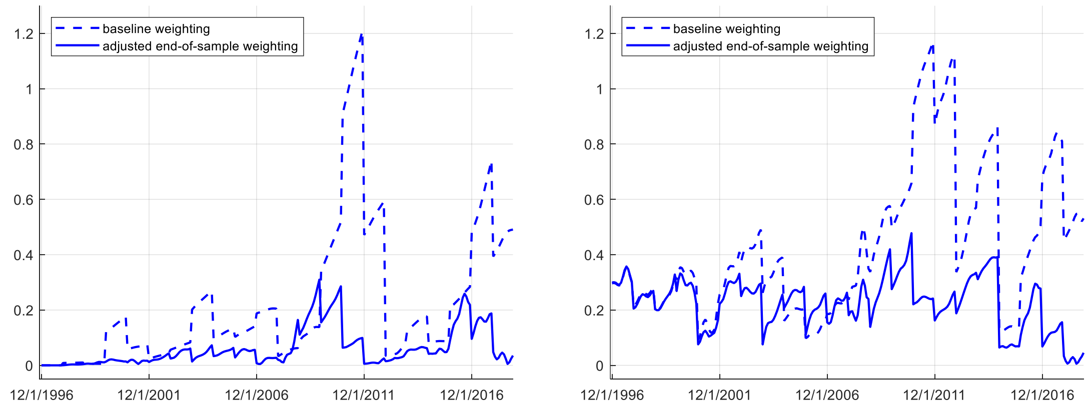


Figure 10: Average Absolute Deviations of Quasi Real-Time Credit Gaps (left) and Real-Time Credit Gaps (right) from their Respective Full-Sample Counterparts, as a Fraction of the Full-Sample Credit Gap Standard Deviation. Time on the horizontal axes is in months.

counterparts are about three to four times smaller with weight adjustment and measure *at most* 31 percent of the credit gap standard deviation for the quasi real-time version and 43 percent for the real-time version, respectively. Putting these numbers in perspective, Edge and Meisenzahl (2011) show that credit-to-GDP gap revisions in real time have a typical size of about one standard deviation of the gap and have a maximum value of slightly above two standard deviations.

5. Credit Booms and Short-Term Interest Rates

Another important question besides timely identification of credit booms is the question about their nature. The advantage of the VAR core of my methodology is that such questions can be studied. Here I illustrate it for the example of the role of short-term interest rates during the build-up of a credit boom. One of the hypotheses refers to the origin of credit booms in a low interest rate environment. There are several theoretical explanations for this effect: the "search for yield" theory by (Borio and Zhu, 2012) among others, and "income and valuation effects" by (Adrian and Shin, 2010; Adrian et al., 2010). There is also quite a bit of empirical evidence examining these hypotheses in applications to various countries in the years before the Global Financial Crisis.[18]

To study the role of short-term interest rates for credit booms, I perform a forecast exercise for credit where I condition on the path of the monetary policy rate (the federal funds rate in the U.S.) instead of the real economic

[18] For instance, Jimenez et al. (2014) and Ioannidou et al. (2015) study the channel using loan-level data. At the macro level, Buch et al. (2014) and Afanasyeva and Guentner (2020) study the question using the FAVAR approach.

activity. Now conditional forecasts of credit can be seen as amounts of credit consistent with the current stance of monetary policy rather than with the real economic activity, as was done before. The results show that, indeed, the size of the credit gaps before the crisis is substantially reduced. Figure 11 illustrates this finding for the U.S. credit variable. In the left panel of figure 11, where the forecasts are conditional on industrial production, the model systematically under-predicts the actual growth rates of credit at all forecast horizons. Accordingly, credit gaps are positive, and a credit boom is detected in these years. The only change in the right panel is that the forecasts are conditional on the federal funds rate path, while the same VAR model is estimated over the same rolling window as in the left panel. Now the gap between the conditional forecasts and the observed credit values decreases substantially. The mean forecasts even resemble the shape of the actual credit growth much closer, and the bands reflecting the estimation uncertainty now include the actual credit growth starting from 2005.

Results for many of the euro area economies are qualitatively similar for this episode the credit boom preceding the Global Financial Crisis. Conditioning on the short-term interest rates reduces the values of the credit gap or, in other words, it explains away some portions of this particular credit boom.

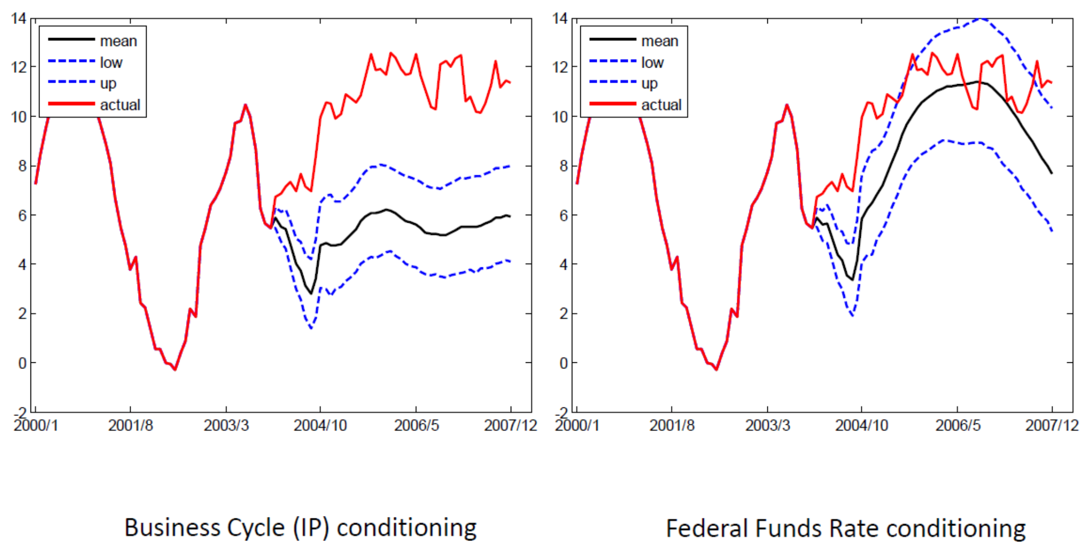


Figure 11: Credit Forecasts for 2004-2007 in the U.S.: conditioned on industrial production (left panel) and on the Federal Funds Rate (right panel). Notes: Forecast bands correspond to the 16-th and 84-th percentiles and pointwise contain 68% of the probability mass. Forecasts of log-levels are converted to year-on-year growth rates.

These findings suggest that monetary policy rates could have played a nontrivial role in the build-up of the credit boom before the Great Recession, feeding risk-taking motives of financial intermediaries. One should not, however, overestimate these results. As figure 11 illustrates, monetary policy rates cannot explain the credit boom of 2003 to 2007 completely as the gap between observed credit and its conditional forecast still remains positive, especially in the early phase of this credit boom. There are additional factors driving excessive lending behavior and excessive

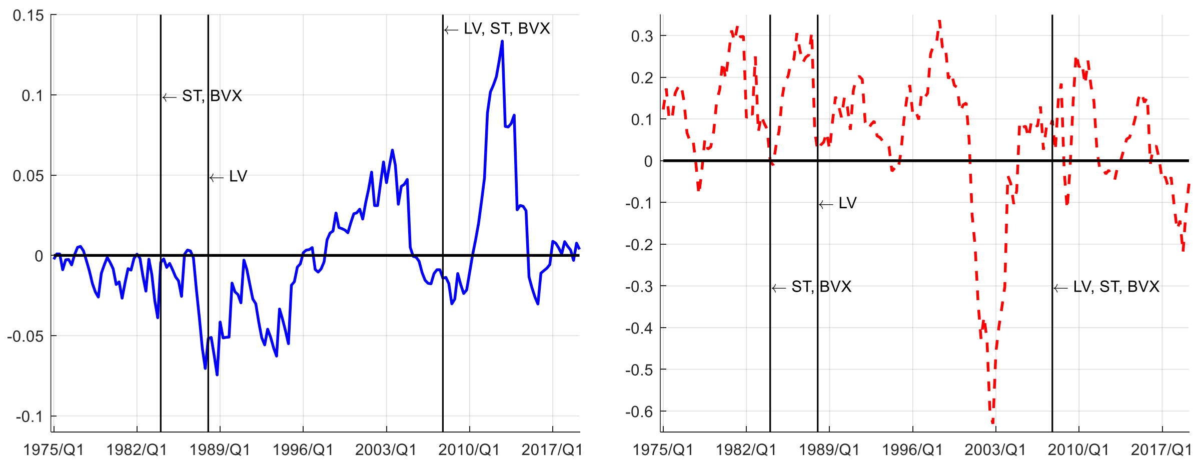


Figure 12: Gaps for M2 Monetary Aggregate (left) and Asset Prices (right) in the U.S.
Notes: LV refers to the chronology of Laeven and Valencia (2013); BVX refers to the chronology of Baron et al. (2018); ST refers to the chronology by Schularick and Taylor (2012). Gaps are expressed in percentage points. Time on the horizontal axes is in quarters.

risk taking of financial intermediaries during credit booms. For instance, the stance and implementation of regulatory policies, market sentiment, and overheated macroeconomic conditions during credit booms could be additional driving forces. Evaluating the contribution and relative importance of these factors is an important question for future work.[19]

6. Money and Asset Price Gaps

Broad monetary aggregates and asset prices have been linked to the emergence of financial imbalances in the academic literature and policy discussions. I apply the BVAR methodology to construct the corresponding gaps and compare their properties with those of credit gaps. [20]

The role of money as an early warning indicator for financial imbalances has become a subject of academic discussion in the aftermath of the Great Recession. One of the reasons is empirical. Before the crisis of 2007-2008, large swings in broad money growth were observed in many advanced economies, including the U.S. and the euro area. In particular, a period of accelerating growth rates before the crisis was followed by an abrupt and remarkable

[19]In fact, some of the ongoing recent work on this question includes Krishnamurthy and Li (2020), Gorton and Ordonez (2020) and Afanasyeva et al. (2020).

[20]Recall that real economic activity is the only variable in the BVAR that is being conditioned on in the forecasting exercises. Hence, money and asset price gaps are the byproducts of the credit gap computation and can be calculated the same way as credit gaps.

fall in growth rates, as the crisis unfolded.[21] Several studies investigate the link of money and credit dynamics to crises and asset price booms. For instance, Schularick and Taylor (2012) contrast the credit view with the money view, studying trends in a long historical data set. The credit boom detection literature has also stressed the nexus between credit booms and asset prices movement. Borio and Lowe (2002) find that swings in asset prices tend to go hand in hand with the credit cycle.

I compute the gaps for broad money and asset prices for the same set of countries as before in order to test whether these gaps have better early warning qualities than credit gaps and what kind of episodes these gaps reflect. While detailed graphical results for each country are presented in Appendix E, consider an illustrative and representative example of the U.S. in figure 12.

Although a prolonged period of positive money gaps precedes the Global Financial Crisis (figure 12, left panel), money gaps are mildly negative before the savings and loan crisis regardless of the chronology considered. Furthermore, the largest spike in broad money gap dynamics occurs shortly after the Global Financial crisis between 2010 through the beginning of 2014 – the years, when QE 1, 2, and 3 were launched. More generally, I find similar tendencies for other countries. First, there are often substantial, persistent positive money gaps preceding the Global Financial Crisis, but not necessarily before the other crises in the sample (see, for example, Sweden (figure E.3i) and Norway (figure E.3b) in Appendix E). Second, in contrast with credit gaps that plummet into negative territory with the crisis onset, money gaps typically stay positive for several quarters after the crisis onset, reflecting in many cases consequences of post-crisis monetary easing policies. These features may diminish early warning qualities of broad money in a horse race against credit gaps.

Asset price gaps (figure 12, right panel) are larger in size than money gaps and are more volatile. At the onset date of both systemic crises in the U.S., these gaps tend to decline precipitously. The largest boom-bust dynamics is, however, observed around the dot-com bubble episode. Although the gap swings up slightly before the Global Financial Crisis, it rebounds quite quickly shortly thereafter. Again, these tendencies are representative for many countries in the sample. Periods of positive asset price gaps precede many major crises episodes (such as the Global Financial Crisis or the Heisei bubble episode in Japan in the late 1980s, to name a few prominent examples), they are generally volatile, spiking shortly thereafter. This feature could increase the false positive rate, when it comes to the early warning qualities of asset price gaps relative to credit gaps.

To formalize the early warning horse race between BVAR credit gaps and their respective money and asset counterparts, I compare the results from the corresponding pooled logit regressions (table 3). In these regressions, I consider

[21] This latter fall in money growth was so substantial that it revolved analogies to the downward dynamics observed during the Great Depression. Giannone, Lenza, Pill, and Reichlin (2011) conduct a detailed comparison of these two episodes.

each gap as an early warning indicator in isolation.[22]

Table 3: Crisis Predictability Results across Various Chronologies and BVAR Gaps, Full Sample

	LV Chronology (981 observation, 12 crises)						BVX Chronology (1037 observations, 12 crises)					
Horizon	Credit gap		Money gap		Asset pr. gap		Credit gap		Money gap		Asset pr. gap	
	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC
contemp.	8.72^{***}	0.63	3.60	0.60	-0.78	0.60	12.14^{***}	0.71	3.70	0.63	-0.91^{*}	0.61
1Y ahead	12.73^{***}	0.69	4.54	0.60	0.79	0.55	13.03^{***}	0.74	4.29	0.63	0.54	0.54
2Y ahead	12.17^{***}	0.70	3.83	0.61	1.15	0.58	12.11^{***}	0.73	3.62	0.61	0.90	0.58
3Y ahead	11.78^{**}	0.69	2.88	0.59	1.13	0.58	11.52^{***}	0.72	2.76	0.60	1.00	0.58
4Y ahead	11.78^{***}	0.70	2.05	0.57	0.62	0.53	11.37^{***}	0.72	1.86	0.57	0.62	0.55

	ST Chronology (866 observations, 10 crises)						LD Chronology (860 observations, 14 crises)					
Horizon	Credit gap		Money gap		Asset pr. gap		Credit gap		Money gap		Asset pr. gap	
	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC	Coeff.	ROC
contemp.	12.01^{***}	0.69	4.28	0.64	-0.35	0.55	5.64^{**}	0.63	6.44^{**}	0.73	-0.65^{**}	0.60
1Y ahead	12.15^{***}	0.73	4.12	0.61	1.26	0.60	7.15^{***}	0.67	9.13^{**}	0.78	0.68	0.55
2Y ahead	11.40^{***}	0.72	3.26	0.59	1.69^{*}	0.65	7.93^{***}	0.69	11.36^{**}	0.80	1.16	0.59
3Y ahead	11.12^{**}	0.71	2.02	0.57	1.59^{*}	0.64	7.92^{***}	0.69	12.11^{**}	0.80	1.64^{**}	0.63
4Y ahead	11.42^{**}	0.71	0.97	0.55	0.92	0.59	7.64^{***}	0.68	11.27^{**}	0.78	1.75^{**}	0.64

Notes: Standard errors of pooled logit regression coefficients are clustered at crisis episodes. ***, **, * stand for 1%, 5%, and 10% statistical significance levels, respectively.

Across the majority of chronologies (LV, ST, and BVX), the coefficients for money gaps are insignificant, and the ROC numbers for money gaps are smaller than those of credit gaps at all horizons. The LD chronology is a notable exception, where broad money gaps are not only significant along with credit gaps, but are actually somewhat better in their early warning qualities. The reason for this result stems from the country sample composition for this chronology. The sample primarily consists of European countries with observations surrounding the Global Financial Crisis. As discussed before, increases in broad money gaps have been quite substantial and synchronous across the countries for this particular credit boom.

Asset price gaps signal the onset of the crises contemporaneously, as they rapidly decrease at this date: The pooled logit coefficients are marginally significant but negative. At longer horizons, due to a higher rate of false positives, the significance goes away and the ROC numbers are always smaller when compared with credit gaps. For the LD chronology sample, which is largely centered around the Global Financial Crisis, there is some (albeit not very strong) significance of asset price gaps as predictors at horizons of three and four years before to the crisis. Also in this case,

[22]The results convey the same message, when all three gaps are included into one pooled regression simultaneously – that is, the gap with the best early warning qualities still prevails in this setting, leaving the other competitors insignificant and their contribution to the increase in ROC mostly marginal.

however, credit gaps dominate in terms of statistical significance and the ROC values.

These results indicate that, *on average*, BVAR credit gaps provide a middle ground between asset price gaps that are more volatile and hence often prone to false positives and the credit-to-GDP gaps that target credit cycles at a lower frequency. Broad money gaps are useful predictors for a subset of episodes. That said, the ranking of early warning indicators may differ for a particular country taken individually (see, for example the performance of asset price gaps for Sweden (figure E.3i) in Appendix E) and may depend on a type of asset price considered.

7. Robustness Exercises

All findings presented previously are conditional on the baseline model specification and the assumptions of the forecasting exercise. A first robustness check regards the credit measure in the system. I replace the broad total nonfinancial credit measure from the flow of funds by the total loans and leases measure in the baseline VAR system and rerun the whole exercise. The latter measure is available at a monthly frequency and is narrower, as it includes credit to the nonfinancial sector on *bank* balance sheets only. The results presented in figure F.1 are quite intuitive. Major boom-bust episodes around the systemic banking crises are still reflected in for the alternative measure, although the bank-based credit gap predicts the savings and loan crisis, which primarily affected bank balance sheets, even earlier. Also, as to be exepcted, bank credit measure dips substantially more in 1975 to1979 – the years of a credit crunch following the banking crisis of 1974. A broader measure from the flow of funds reflects this bust too, but the downturn is smaller (in absolute terms) quantitatively. A final noteworthy difference is the dot-com episode, where the bank-based measure fluctuates around zero, reflecting the well-known fact that this particular boom episode was not funded by bank credit (Aliber and Kindelberger (2015) among others).

Several studies use real credit measures in order to detect credit booms. For instance, Mendoza and Terrones (2008) use real credit per capita as a benchmark measure of credit. Overall the results for the real per capita credit measure are quite similar to the nominal credit measure (figure F.2), although the credit boom preceding the Great Recession is somewhat more protracted for the real per capita credit version.

I next inspect the robustness with respect to the variables included in the baseline model specification. There could be potential considerations of omitted variable bias or, on the contrary, the presence of some variable, such as asset prices, driving the major results. To test these hypotheses more thoroughly, I consider both a smaller system (consisting of industrial production, short-term interest rate, broad measure of money (M2) and credit) and a larger system (table F.2 for description of 16 variables included in it). Table F.3 sheds light on the forecasting qualities of the systems across rolling windows. We know from the VAR forecasting literature (see, for instance, Banbura, Giannone, and Reichlin (2010)) that the forecasting performance of BVARs can be improved once additional variables are included – that is, in medium and large systems (once proper prior shrinkage is applied). Indeed, in many rolling windows and on average across all windows (although by a narrow margin), the larger BVAR system delivers smaller forecast errors.

The inspection of the resulting credit gaps (figure F.3 in Appendix F) reveals, however, that the timing of the identified events across three systems is nearly identical. The addition of new variables does improve the forecasting accuracy of the system in the early 1990s (the credit crunch period) and the early 2000s (the credit boom period) consistently with the forecast errors in table F.3. Quantitative differences in the gap estimates are, however, small. The only exception is the episode at the start of the sample for the largest VAR system in 1989. In smaller systems, both the reduced and the baseline VAR, the gap is mildly negative, whereas for the larger system it is mildly positive.

In a similar vein, replacing the monetary policy rate by the shadow rate estimate of Wu and Xia (2016) during the zero lower bound period as well as including commodity prices do not affect the results substantially. I also included the national Freddie Mac housing price index for the U.S. BVAR and performed the forecasting exercises conditioning on it (rather than on real activity variables). In this case, the credit boom before the Great Recession is first detected about a year before the crisis onset, when the trend in housing prices starts to reverse itself. This exercise again underscores the importance of the variable that is conditioned on. As housing prices themselves were the major driving force of the credit boom in the early 2000s, conditioning credit forecasts on them helps explain this boom rather than identify it in time.[23]

Continuing on the choice of the fundamental variable, I consider alternatives for real activity variables. For some of the advanced economies, including the U.S., baseline monthly VARs employ industrial production as real activity variable. Arguably, broader measures, such as GDP, could be a more appropriate choice. Therefore I compute credit gaps using monthly measures of real GDP constructed by Mark Watson instead of industrial production. The results are quite similar to the baseline. Major episodes are identified at the same time; minor episodes, such as a small upward deviation in 2016-2017 in the U.S., become less pronounced. The results do not change substantially also when credit forecasts are conditional on both the unemployment rate and the industrial production index in the larger system.

Finally, the robustness with respect to the size of the rolling window, the forecasting horizon, and the prior tightness is examined. Varying the size of the rolling window for the U.S. between 10 and 20 years does not affect the results significantly. Applying a forecast horizon of one year produces credit gaps that identify only a subset of episodes. Large credit booms are still detected but the signal becomes noisier and less persistent. For instance, there are interrupted upward deviations in the 2003 to 2007 episode. There is a benefit in accounting for the forecasts at longer horizons, given that large credit booms build up gradually and are quite persistent phenomena. In the baseline specification, prior hyperparameters, including the overall prior tightness, are set based on marginal likelihood maximization. In the robustness exercise, I relax the tightness of the prior to test to what degree the prior is driving the results (figure F.4). Although the relaxation of prior tightness somewhat increases the errors in several episodes somewhat (as is to be

[23]To conserve space, these and some other results in this section are omitted and available upon request.

expected, since prior shrinkage is no longer 'optimal' and overfitting becomes more prominent), the overall contours of the credit gap dynamics still remain similar (the correlation between the two credit gaps is 0.89). The episodes identified as busts typically run even deeper with a looser prior, the timing and size of the booms are quite close, although a looser prior magnifies the credit expansion of the late 1990s somewhat. These observations suggest that the baseline 'optimized prior helps identifying the episodes more precisely but is not solely driving the major results.

8. Concluding Remarks

This paper develops a new methodology to identify credit booms and busts from BVAR forecast errors and tests the approach for 31 advanced and emerging market economies. Qualitatively, the results are intuitive and fit historical evidence well. Quantitatively, the new approach can detect turning points earlier, which implies better early warning properties of these gaps ahead of crises or policy-relevant events. The VAR core of the methodology also allows to test hypotheses about the nature of the particular credit boom episode, such as the role of monetary policy rates, for example.

There are several open questions for future work. First, more has to be learned about the nature of credit booms, the reasons for credit deviations from various fundamentals. The semi-structural exercise in this paper suggests that a monetary policy stance accounts for part of the explanation only, when it comes to the credit boom preceding the Global Financial Crisis. The credit gap approach in this paper does not make fully structural identifying assumptions, by letting reduced-form evidence speak. A formal identification and joint structural modelling of the productive capacity of the economy along with the fundamentally sustainable level of credit could be a next fruitful step. Second, while this paper focuses on the totality of nonfinancial credit to the private sector, a more detailed look into the decomposition of credit can be a useful extension. In the context of some emerging markets and perhaps also advanced economies, accounting for the dynamics of government debt in the computation of credit gaps may lead to a fuller representation of financial vulnerabilities and credit cycle. Finally, the credit aggregates considered in this paper largely leave out the financial intermediation through the shadow banking system – yet another important dimension of credit cycle that needs to be properly accounted for going forward.

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Appendix A. Data

Table A.1: Data and Transformations Used in the Baseline Monetary VAR Models and Credit-to-GDP Gaps across Countries.

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	Australia			
	Monetary VAR: 1978M2 - 2012M12			
1	Unemployment Rate	FRED	Level	yes
2	Consumer Price Index	IFS	Log-Level[a]	yes
3	Central Bank Policy Rate	BIS	Level	no
4	MSCI Australia, National Currency	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency	FRED	Log-Level	yes
6	M3 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Deposit Money Banks, Claims on Private Sector, National Currency	IFS	Log-Level	yes
	Credit-to-GDP Gap: 1978Q2 - 2012Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes
	Austria			
	Monetary VAR: 1997M10 - 2017M12			
1	Industrial Production Index	FRED	Log-Level	yes
2	Consumer Price Index	FRED	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	MSCI Austria, National Currency[d]	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency[d]	Oesterreichische Nationalbank	Log-Level	yes
6	M2 Monetary Aggregate, National Currency[d]	Oesterreichische Nationalbank	Log-Level	yes
7	Total Credit to Private Non-Financial Sector by Domestic Banks, National Currency[d]	Oesterreichische Nationalbank	Log-Level	yes
	Credit-to-GDP Gap: 1997Q4 - 2017Q4			
8	GDP, Current Prices, National Currency[d]	IFS	Level[c]	yes
	Belgium			
	Monetary VAR: 1996M12 - 2017M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	MSCI Belgium, National Currency[d]	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency[d]	National Bank of Belgium	Log-Level	yes
6	M2 Monetary Aggregate, National Currency[d]	National Bank of Belgium	Log-Level	yes

Continued on next page

Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
7	Total Credit to Private Non-Financial Sector by Domestic Banks Adjusted for Breaks, National Currency[d]	FRED	Log-Level[aa]	yes
	Credit-to-GDP Gap: 1996Q4 - 2017Q4			
8	GDP, Current Prices, National Currency[d]	FRED	Level[c]	yes

Brazil

	Monetary VAR: 1995M1 - 2017M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Central Bank Policy Rate	BIS	Level	no
4	Yahoo IBOVESPA	Yahoo Finance	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log-Level	no
6	M3 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Total Credit to Private Non-Financial Sector by Domestic Banks Adjusted for Breaks, National Currency	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1996Q1 - 2017Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes

Canada

	Monetary VAR: 1970M1 - 2017M12			
1	Industrial Production Index	FRED	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Central Bank Policy Rate	BIS	Level	no
4	MSCI Canada, National Currency	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency	FRED	Log-Level	yes
6	M3 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Total Credit to Private Non-Financial Sector by Domestic Banks Adjusted for Breaks, National Currency	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1970Q1 - 2017Q4			
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes

Chile

	Monetary VAR: 1987M12 - 2008M12			
1	Unemployment Rate (population aged 15 years and older)	IFS	Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Exchange Rate relative to the USD	FRED	Log-Level	no
4	MSCI Chile, National Currency	MSCI	Log-Level	no

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
5	M1 Monetary Aggregate, National Currency	FRED	Log-Level	yes
6	M3 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Deposit Money Banks: Claims on the Private Sector, National Currency	IFS	Log-Level	yes
	Credit-to-GDP Gap: 1996Q1 - 2008Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes

Czech Republic

Monetary VAR: 1994M6 - 2017M12

No.	Series Name	Retrieved from	Transformation	Seasonal Adjustment
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Commercial Bank Lending Rate over Deposit Rate Spread	IFS	Level	no
4	Share Price Index	Bloomberg	Log-Level	no
5	M1 Monetary Aggregate, National Currency	FRED	Log-Level	yes
6	M3 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Total Credit to Private Non-Financial Sector by Domestic Banks Adjusted for Breaks, National Currency	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1995Q1 - 2017Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes

Finland

Monetary VAR: 1996M1 - 2016M12

No.	Series Name	Retrieved from	Transformation	Seasonal Adjustment
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Money Market Rate	IFS	Level	no
4	Industrial Share Price Index[d]	IFS	Log-Level	no
5	Finnish Contribution to the M1 Monetary Aggregate, National Currency[d]	Bank of Finland	Log-Level	yes
6	Finnish Contribution to the M2 Monetary Aggregate, National Currency[d]	Bank of Finland	Log-Level	yes
7	Credit to Private Non-Financial Sector by Domestic Banks Adjusted for Breaks, National Currency[d]	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1996Q1 - 2016Q4			
8	GDP, Current Prices, National Currency[d]	IFS	Level[c]	yes

France

Monetary VAR: 1993M4 - 2017M12

No.	Series Name	Retrieved from	Transformation	Seasonal Adjustment
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
3	Central Bank Discount Rate	FRBOG/IF	Level	no
4	MSCI France, National Currency[d]	MSCI	Log-Level	no
5	French Contribution to the M1 Monetary Aggregate, National Currency[d]	Banque de France	Log-Level	yes
6	French Contribution to the M3 Monetary Aggregate, National Currency[d]	Banque de France	Log-Level	yes
7	Credit to Private Non-Financial Sector by Domestic Banks Adjusted for Breaks, National Currency[d]	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1993Q2 - 2017Q4			
8	GDP, Current Prices, National Currency (converted from USD to EUR)	IFS	Level[c]	yes

Germany

Monetary VAR: 1970M1 - 1998M12

No.	Series Name	Retrieved from	Transformation	Seasonal Adjustment
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Discount Rate	FRBOG/IF	Level	no
4	MSCI Germany	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency	IFS	Log-Level	yes
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Banking Institutions Claims on Private Sector, National Currency	IFS	Log-Level	yes
	Credit-to-GDP Gap: 1979Q1 - 1998Q4			
8	GDP, Current Prices, National Currency (converted to DM from EUR)	FRED	Level[c]	yes

Hong Kong

Monetary VAR: 1997M1 - 2017M12

No.	Series Name	Retrieved from	Transformation	Seasonal Adjustment
1	Unemployment Rate	IFS	Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Discount Rate	IFS	Level	no
4	Hang Seng Index	Yahoo Finance	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log-Level	no
6	M2 Monetary Aggregate, National Currency	Hong Kong Census and Statistics Department	Log-Level	yes
7	Total Credit to Private Nonfinancial Sector, Adjusted for Breaks, National Currency	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1997Q2 - 2017Q4			
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	Ireland			
	Monetary VAR: 1991M1 - 2017M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	Yahoo ISEQ[d]	Yahoo Finance	Log-Level	no
5	Contribution to M1 Monetary Aggrgeate, National Currency[d]	Central Statistics Office: Ireland	Log-Level	yes
6	Contribution to M3 Monetary Aggregate, National Currency[d]	Central Statistics Office: Ireland	Log-Level	yes
7	Total Credit to Private Nonfinancial Sector, Adjusted for Breaks, National Currency[d]	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1991Q1 - 2017Q4			
8	GDP, Current Prices, National Currency[d]	IFS	Level[c]	yes
	Italy			
	Monetary VAR: 1999M1 - 2017M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	FTSE MIB Index[d]	Bloomberg	Log-Level	no
5	Italian Contribution to M1 Monetary Aggrgeate, National Currency[d]	Bank of Italy	Log-Level	yes
6	Italian Contribution to M3 Monetary Aggregate, National Currency[d]	Bank of Italy	Log-Level	yes
7	Total Credit to Private Nonfinancial Sector, Adjusted for Breaks, National Currency[d]	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1999Q1 - 2017Q4			
8	GDP, Current Prices, National Currency[d]	IFS	Level[c]	yes
	Japan			
	Monetary VAR: 1970M1 - 2016M12			
1	Industrial Production Index	FRED	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Discount Rate	FRED	Level	no
4	MSCI Japan, National Currency	MSCI	Log-Level	no
5	M1 Monetary Aggrgeate, National Currency	IFS	Log-Level	yes
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Total Credit to Private Nonfinancial Sector, Adjusted for Breaks, National Currency	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1970Q1 - 2016Q4			

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes
	Korea			
	Monetary VAR: 1978M1 - 2012M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Discount Rate	IFS	Level	no
4	MSCI Korea, National Currency	MSCI	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log-Level	no
6	M2 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Deposit Money Banks, Claims on Private Sector, National Currency	IFS	Log-Level	yes
	Credit-to-GDP Gap: 1978Q1 - 2012Q3			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes
	Luxembourg			
	Monetary VAR: 1999M1 - 2017M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	Luxembourg Stock Exchange Index[d]	Bloomberg	Log-Level	no
5	M1 Contribution, National Currency[d]	Banque Centrale du Luxembourg	Log-Level	yes
6	M2 Contribution, National Currency[d]	Banque Centrale du Luxembourg	Log-Level	yes
7	Total Credit to Private Nonfinancial Sector, Adjusted for Breaks, National Currency[d]	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1999Q1 - 2017Q4			
8	GDP, Current Prices, National Currency[d]	IFS	Level[c]	yes
	Malaysia			
	Monetary VAR: 1981M1 - 2016M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Base Lending Rate over 3-Month Time Deposit Rate	IFS	Level	no
4	MSCI Malaysia, National Currency	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency	IFS	Log-Level	yes
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Credit to Private Nonfinancial Sector by Domestic Banks, Adjusted for Breaks, National Currency	FRED	Log-Level[a]	yes

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
		Credit-to-GDP Gap: 1991Q1 - 2016Q4		
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes
		Mexico		
		Monetary VAR: 1978M1 - 2008M12		
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Central Bank Policy Rate	BIS	Level	no
4	Total Share Price Index for Mexico	FRED	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log-Level	no
6	M3 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Deposit Money Banks, Claims on Private Sector, National Currency	IFS	Log-Level	yes
		Credit-to-GDP Gap: 1993Q1 - 2008Q4		
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes
		New Zealand		
		Monetary VAR: 1988M9 - 2010M12		
1	Unemployment (in thsd. persons)	FRED	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Central Bank Policy Rate	BIS	Level	no
4	MSCI New Zealand, National Currency	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency	FRED	Log-Level	yes
6	M3 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Deposit Money Banks, Claims on Private Sector, National Currency	IFS	Log-Level	yes
		Credit-to-GDP Gap: 1989Q1 - 2010Q4		
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes
		Norway		
		Monetary VAR: 1979M1 - 2014M12		
1	Industrial Production Index	FRED	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	MSCI Norway, National Currency	MSCI	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log-Level	no
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Total Credit to Private Nonfinancial Corporations, Adjusted for Breaks, National Currency	BIS	Log-Level[a]	yes
		Credit-to-GDP Gap: 1979Q1 - 2014Q4		
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	Poland			
	Monetary VAR: 1997M1 - 2016M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	WIG Index	Bloomberg	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log-Level	no
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Total Credit to Private Nonfinancial Corporations, Adjusted for Breaks, National Currency	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap: 1997Q1 - 2016Q4			
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes
	Portugal			
	Monetary VAR: 1995M1 - 2017M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	PSI20 Index[d]	Bloomberg	Log-Level	no
5	M1 Portuguese Contribution, National Currency[d]	Bank of Portugal	Log-Level	yes
6	M2 Portuguese Contribution, National Currency[d]	Bank of Portugal	Log-Level	yes
7	Total Credit to Private Nonfinancial Corporations, Adjusted for Breaks, National Currency[d]	FRED	Log-Level[a]	yes
	Credit-to-GDP Gap:1995Q1 - 2017Q4			
8	GDP, Current Prices, National Currency[d]	IFS	Level[c]	yes
	Singapore			
	Monetary VAR: 1991M1 - 2017M12			
1	Manufacturing Production Index	IFS	Log-Level*	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Deposit Rate	IFS	Level	no
4	MSCI Singapore, National Currency	MSCI	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log-Level	no
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Deposit Money Banks, Claims on Private Sector, National Currency	IFS	Log-Level	yes
	Credit-to-GDP Gap: 1991Q1 - 2017Q2			
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	Slovak Republic			
	Monetary VAR: 1997M11 - 2017M12			
1	Registered Unemployment Rate	FRED	Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	3-Month Interbank Rate	FRED	Level	no
4	SKSM Index	Bloomberg	Log-Level	no
5	M1 Monetary Aggregate, National Currency	Slovak National Bank	Log-Level	yes
6	M3 Monetary Aggregate, National Currency	Slovak National Bank	Log-Level	yes
7	Loans to Households and Non-Profit Organizations, National Currency	Slovak National Bank	Log-Level	yes
	Credit-to-GDP Gap: 1997Q4 - 2017Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes
	South Africa			
	Monetary VAR: 1974M6 - 2012M12			
1	Business Confidence Index	FRED	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Discount Rate	FRED	Level	no
4	Share Price Index: Industry and Commerce	IFS	Log-Level	no
5	Exchange Rate relative to the USD	FRED	Log- Level	no
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Total Credit to Private Non-Financial Sector Adjusted for Breaks, National Currency	BIS	Log-Level[a]	yes
	Credit-to-GDP Gap: 1974Q3 - 2012Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes
	Spain			
	Monetary VAR:1993M1 - 2017M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Short-Term Interbank Rate	FRED	Level	no
4	MSCI Spain, National Currency[d]	MSCI	Log-Level	no
5	Long-Term Government Bond Yield	FRED	Level	no
6	M2 Monetary Aggregate, Spain Contribution National Currency[d]	Central Bank of Spain	Log-Level	yes
7	Total Credit to Private Non-Financial Sector Adjusted for Breaks, National Currency[d]	BIS	Log-Level[a]	yes
	Credit-to-GDP Gap: 1995Q1 - 2017Q4			
8	GDP, Current Prices, National Currency[d]	FRED	Level[c]	yes

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	Sweden			
	Monetary VAR:1971M1 - 2016M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Central Bank Policy Rate	BIS	Level	no
4	MSCI Sweden, National Currency	MSCI	Log-Level	no
5	Exchange Rate relative to the USD	IFS	Log-Level	no
6	M3 Index	FRED	Log-Level	yes
7	Total Credit to Private Non-Financial Sector Adjusted for Breaks, National Currency	BIS	Log-Level[a]	yes
	Credit-to-GDP Gap: 1980Q1 - 2016Q4			
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	Switzerland			
	Monetary VAR: 1985M1 - 2016M12			
1	Registered Unemployment Rate	FRED	Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Central Bank Policy Rate	BIS	Level	no
4	MSCI Switzerland, National Currency	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency	IFS	Log-Level	yes
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Deposit Money Banks: Claims on Private Sector, National Currency	IFS	Log-Level[a]	yes
	Credit-to-GDP Gap: 1985Q1 - 2016Q4			
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	Turkey			
	Monetary VAR: 1988M1 - 2008M12			
1	Industrial Production Index	IFS	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Discount Rate	FRED	Level	no
4	MSCI Turke, National Currency	MSCI	Log-Level	no
5	Exchange Rate against the USD	FRED	Log-Level	no
6	M2 Monetary Aggregate, National Currency	IFS	Log-Level	yes
7	Deposit Money Banks: Claims on Private Sector, National Currency	IFS	Log-Level[a]	yes
	Credit-to-GDP Gap: 1998Q1 - 2008Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes

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Table A.1 – *Continued from previous page*

No.	Series Name	Retrieved from	Transformation[a]	Seasonal Adjustment[b]
	United Kingdom			
	Monetary VAR: 1987M1 - 2016M12			
1	Industrial Production Index	FRED	Log-Level	yes
2	Consumer Price Index	IFS	Log-Level	yes
3	Central Bank Policy Rate	BIS	Level	no
4	MSCI UK, National Currency	MSCI	Log-Level	no
5	M1 Monetary Aggregate, National Currency	FRED	Log-Level	yes
6	M2 Monetary Aggregat, National Currencye	FRED	Log-Level	yes
7	Deposit Money Banks: Claims on Private Sector, National Currency	IFS	Log-Level[a]	yes
	Credit-to-GDP Gap: 1987Q1 - 2016Q4			
8	GDP, Current Prices, National Currency	IFS	Level[c]	yes
	United States of America			
	Monetary VAR: 1959M1 - 2018M12			
1	Industrial Production Index	FRED	Log-Level	yes
2	Consumer Price Index for All Urban Consumers: All Items	FRED	Log-Level	yes
3	Effective Federal Funds Rate	FRED	Level	no
4	S&P 500	R. Shiller Data Base	Log-Level	no
5	M1 Monetary Aggregate, National Currency	FRED	Log-Level	yes
6	M2 Monetary Aggregate, National Currency	FRED	Log-Level	yes
7	Total Credit to the Nonfinancial Sector, National Currency	Flow of Funds	Log-Level[a]	yes
	Credit-to-GDP Gap: 1959Q1 - 2018Q4			
8	GDP, Current Prices, National Currency	FRED	Level[c]	yes

[a]If marked, the time series is originally available at quarterly frequency and is interpolated to monthly frequency with cubic splines.
[b]If the corresponding macroeconomic time series is not seasonally adjusted in the original source, I remove seasonality with the X12 procedure of the Census Bureau. Financial time series are not seasonally adjusted.
[c]To construct the credit-to-GDP gaps, I form the credit-to-GDP ratio using the same credit measure as in monetary BVAR. This ratio is then logged and HP-filtered with a smoothing parameter $\lambda = 400000$.
[d]National currency refers to the euro for these countries.

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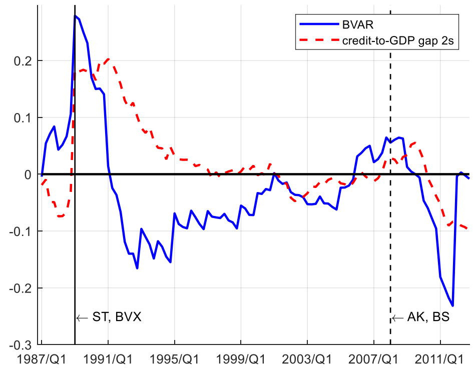
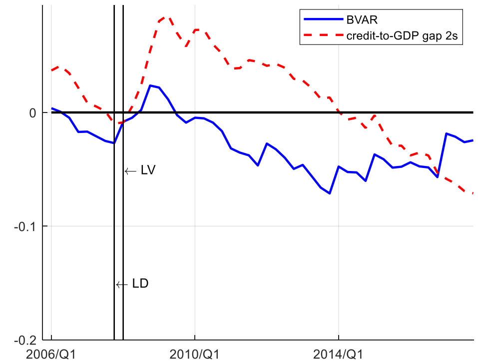
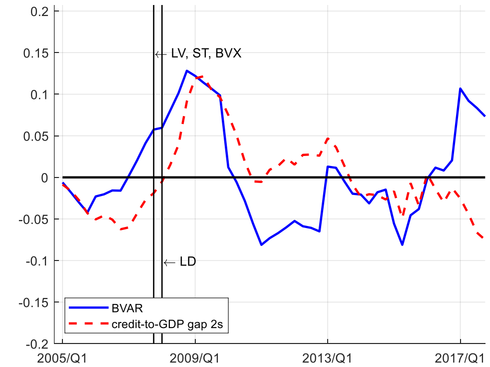
Appendix B. BVAR Credit Gaps and Two-Sided Credit-to-GDP Gaps



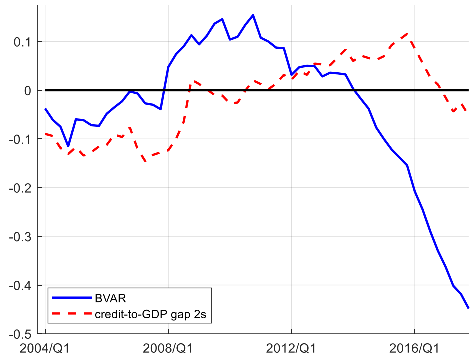
(a) Australia



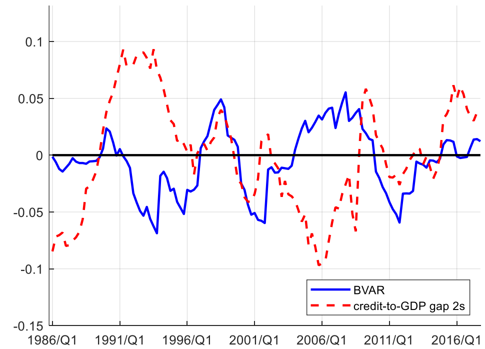
(b) Austria



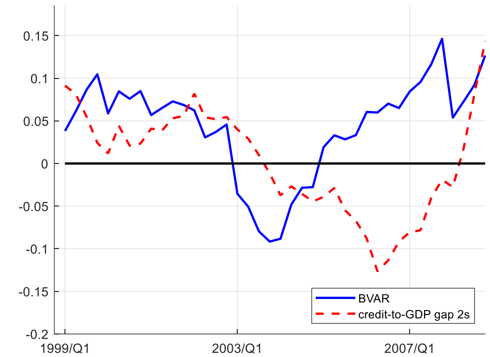
(c) Belgium



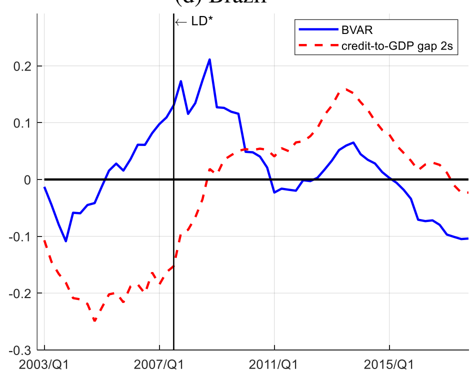
(d) Brazil



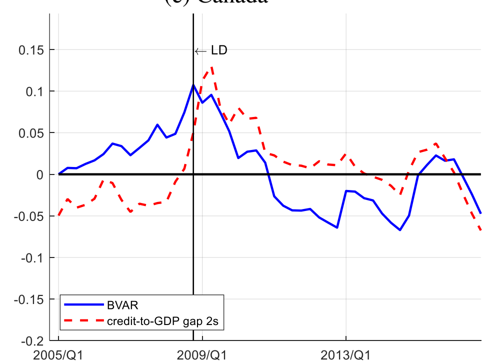
(e) Canada



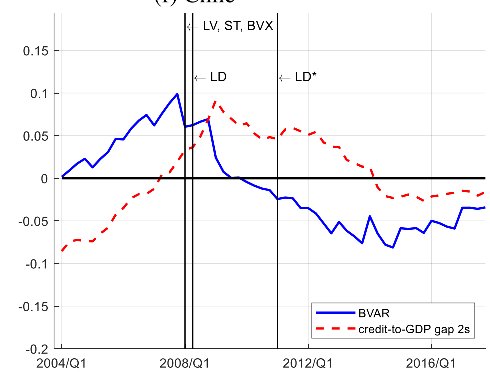
(f) Chile



(g) Czech Republic



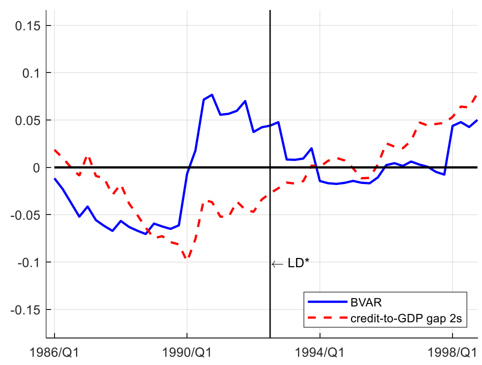
(h) Finland



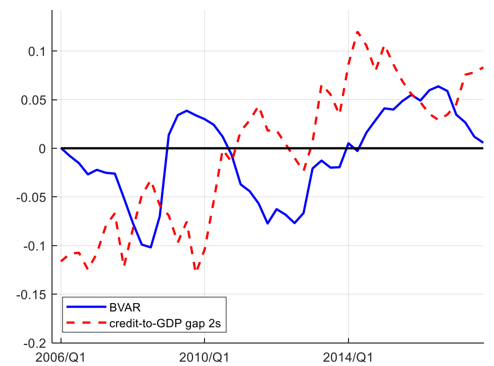
(i) France

Figure B.1: BVAR and Two-Sided Credit-to-GDP Gaps across Countries: Australia - France

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis). For Australia, AZ stands for Aliber and Kindleberger (2015) and BS stands for Brunnermeier and Schnabel (2016).



(a) Germany



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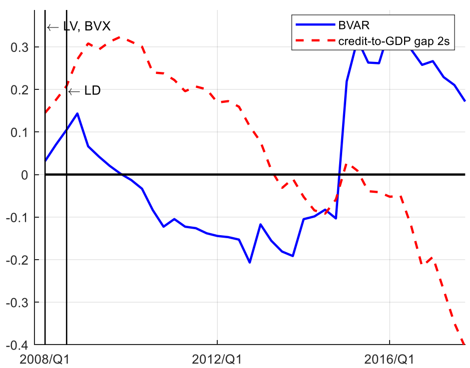
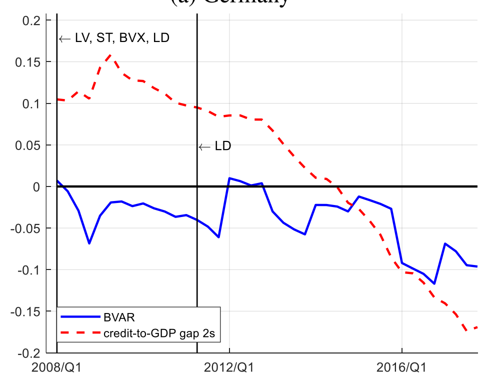


(c) Ireland



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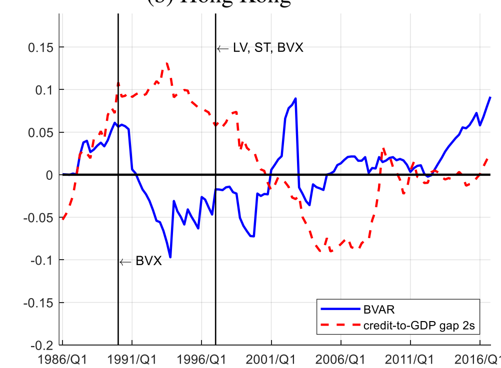
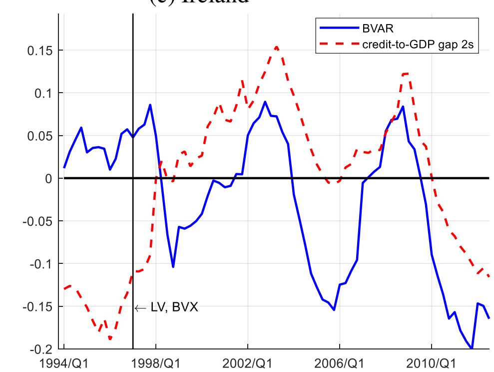
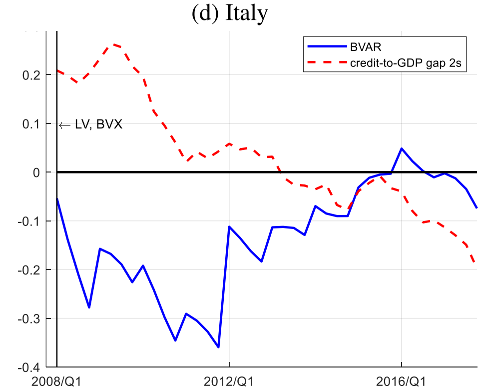


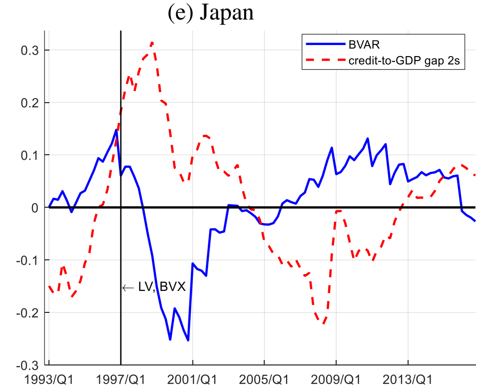
(e) Japan



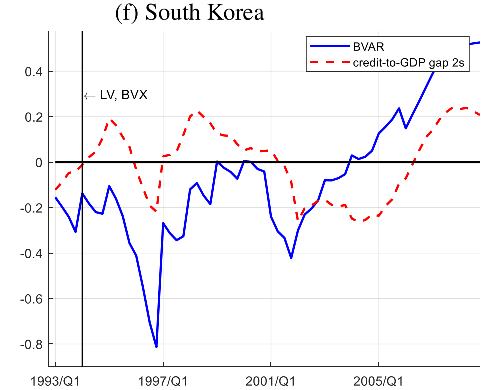
(f) South Korea



(g) Luxembourg



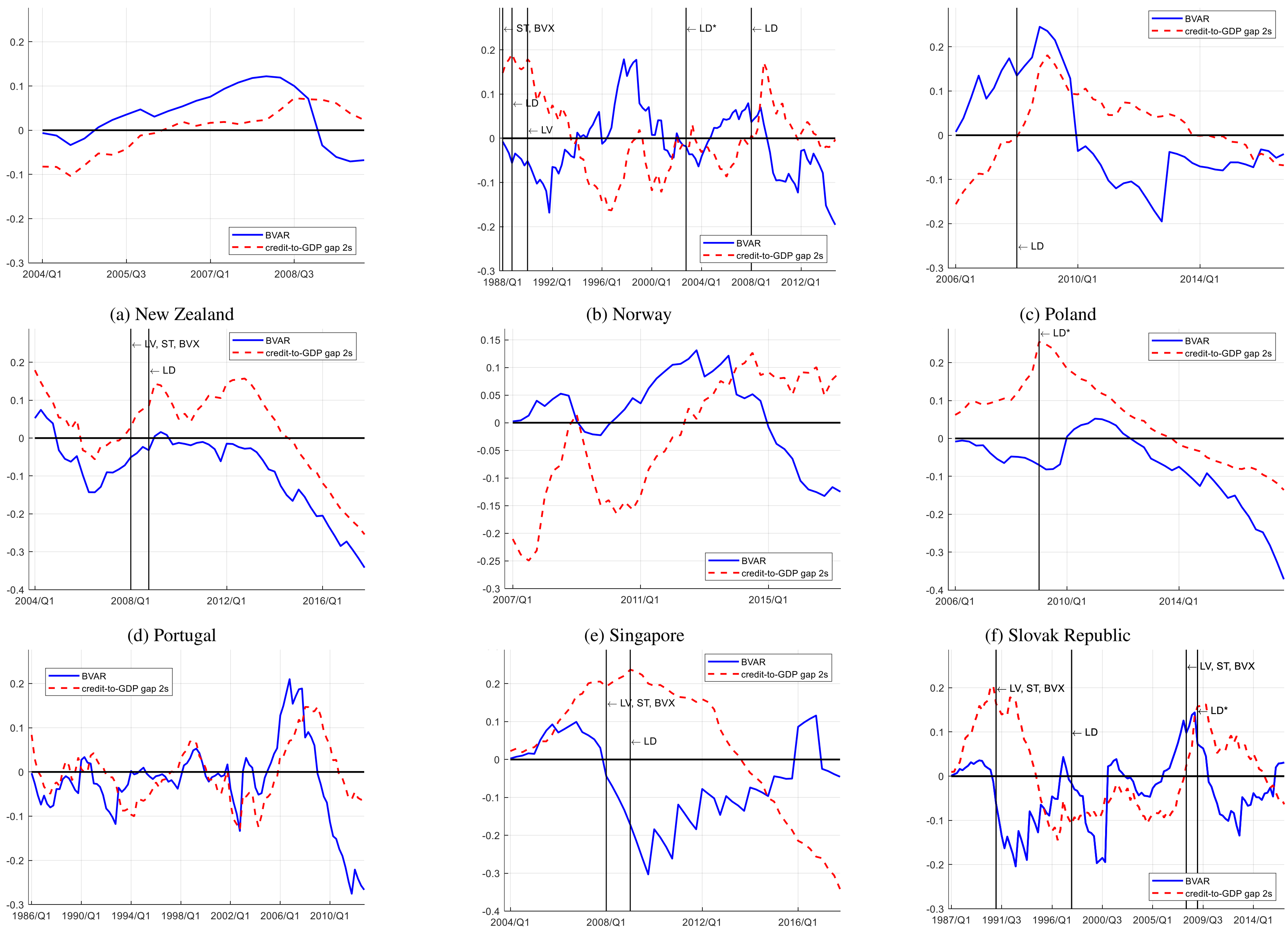
(h) Malaysia



(i) Mexico

Figure B.2: BVAR and Two-Sided Credit-to-GDP Gaps across Countries: Germany - Mexico

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis).



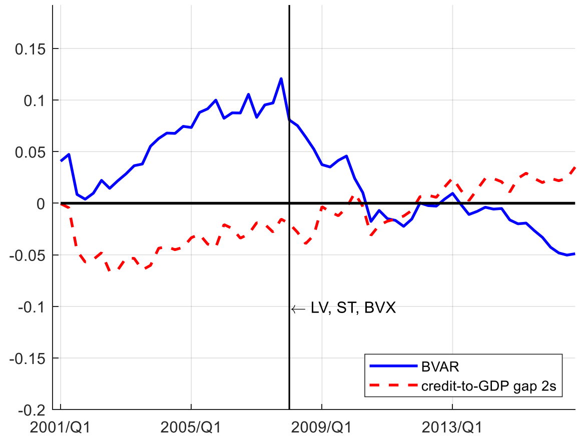
(a) New Zealand (b) Norway (c) Poland

(d) Portugal (e) Singapore (f) Slovak Republic

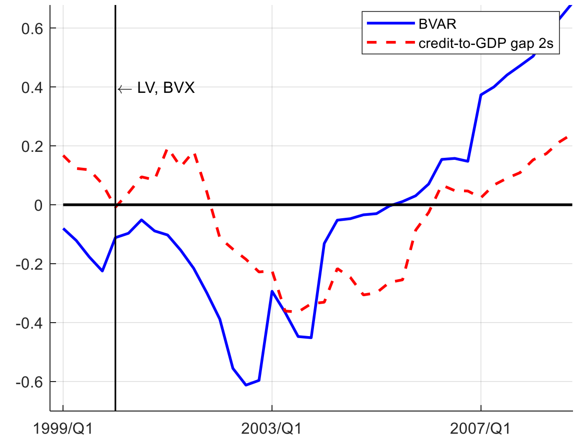
(g) South Africa (h) Spain (i) Sweden

Figure B.3: BVAR and Two-Sided Credit-to-GDP Gaps across Countries: New Zealand - Sweden

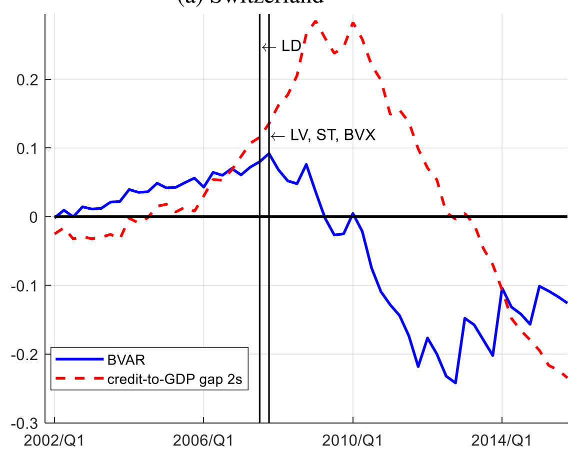
Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, $*$ indicates a residual event (rather than a systemic crisis).



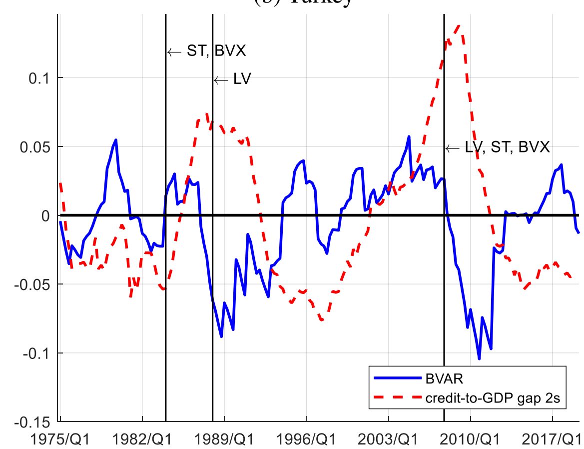
(a) Switzerland



(b) Turkey



(c) United Kingdom



(d) United States of America

Figure B.4: BVAR and One-Sided Credit-to-GDP Gaps across Countries: Switzerland - USA

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis).

Appendix C. Real-Time Data Set and Timing: U.S. Example

In the baseline VAR, industrial production (IP), consumer price index (CPI), both monetary aggregates as well as the total nonfinancial credit aggregate are subject to revisions in real time. The revisions are displayed in Figures C.1 - C.5. I use the Archival Federal Reserve Economic Data (ALFRED) database to retrieve the real-time vintages for IP, CPI, M1 and M2. ALFRED also provides a more recent portion of vintages of the total nonfinancial credit series produced by the Flow of Funds. These vintages start in 2014. In addition, I use internal databases of the Federal Reserve Board to retrieve vintages of the credit variable starting from 1996. The Federal Funds Rate and the stock market prices are not revised.

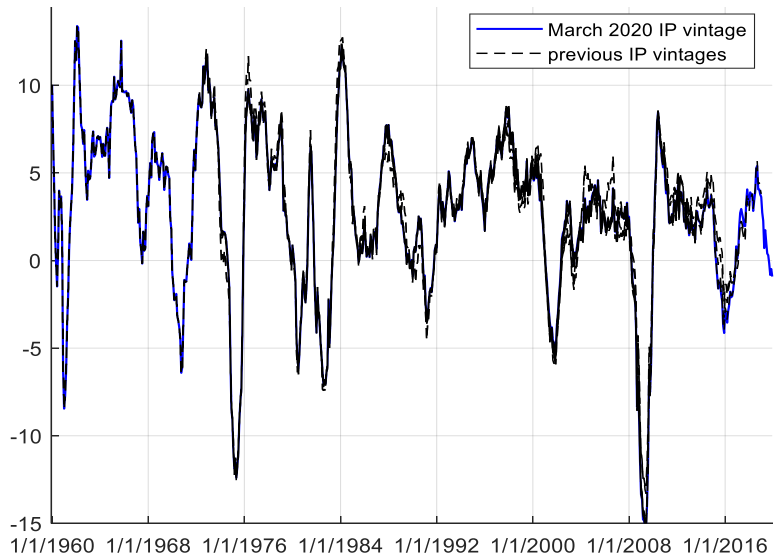


Figure C.1: Year-on-Year Growth (Percent) of the Industrial Production Index across Various Data Vintages.

Quantitatively, the revisions are most sizeable for real activity variables and for the Flow of Funds credit aggregate. The revisions stem from updates in aggregate calculations as well as definitional changes. For the Flow of Funds credit aggregates, definitional changes can lead to quite sizeable revisions in some quarters, for instance, when the coverage of financial institutions expands. Flow of Funds publishes many of the changes in definitions and computational methodology of their aggregate variables here: `https://www.federalreserve.gov/apps/fof/FOFHighlight.aspx`.

As for the timing, Flow of Funds credit aggregates are released at quarterly frequency and with a delay of about one quarter. For instance, the vintage covering the data through the fourth quarter of a respective year, is typically released in the second week of March of the next year. All other variables in the VAR are updated sooner and often at higher frequency than the credit variable. In choosing the corresponding real-time vintage of those variables, I pick the vintage released closest to the corresponding date of the Flow of Funds release. That way, all variables at a certain point in time would adequately reflect the (policy makers) information set at that time.

Figure C.2: Year-on-Year Growth (Percent) of the Consumer Price Index across Various Data Vintages.

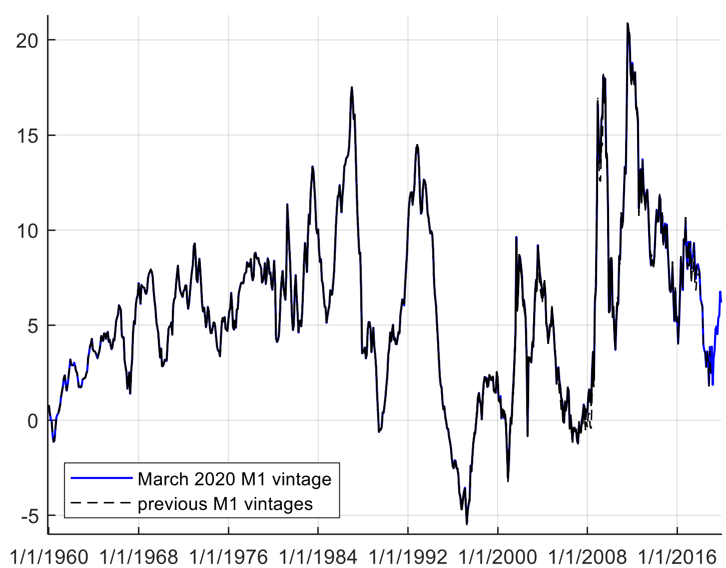


Figure C.3: Year-on-Year Growth (Percent) of the M1 Monetary Aggregate across Various Data Vintages.

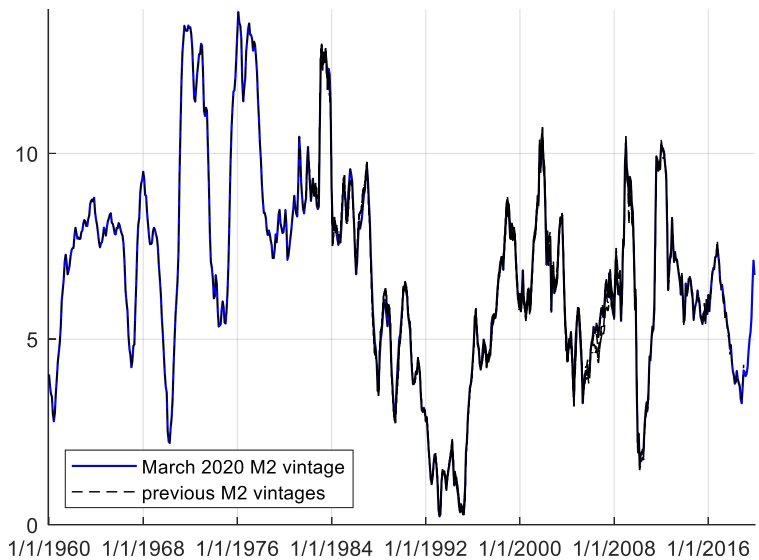


Figure C.4: Year-on-Year Growth of the M2 Monetary Aggregate across Various Data Vintages.

Notes: Time is in months. Growth rates are in percent.

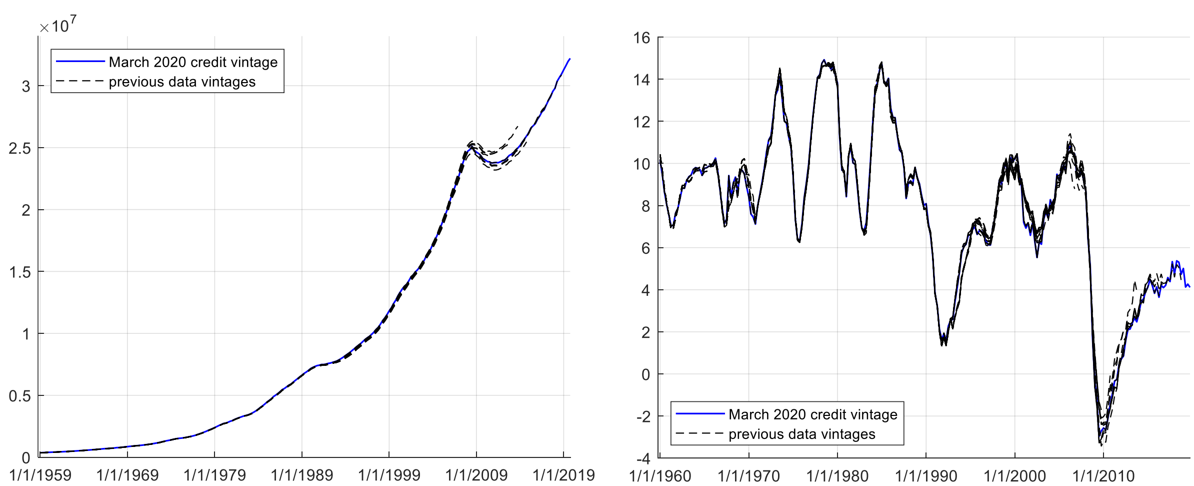


Figure C.5: Levels and Year-on-Year Growth Rates of the Total Nonfinancial Credit across Various Data Vintages.

Notes: Time is in months. Credit volume is expressed in levels (Billions of USD) in the left panel and in year-on-year growth rates in percent in the right panel.

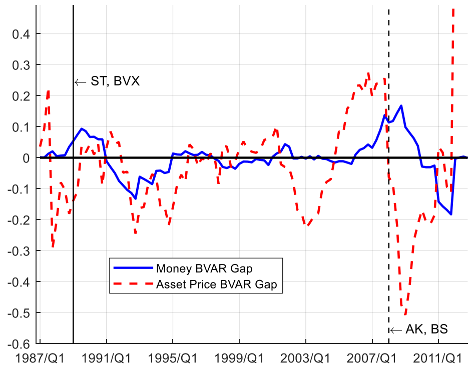
Appendix D. Countries in Burns-Mitchell Diagrams and Pooled Logit Regressions by Chronology

The countries below have crises within their samples timed according to the corresponding chronology and have at least four years of computed credit gaps preceding the crisis onset. The resulting selection is illustarted in the table below.

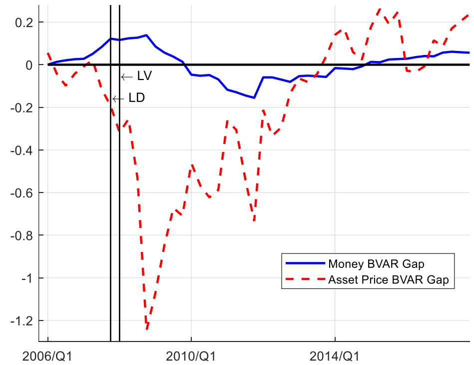
Country	LV Chronology	BVX Chronology	ST Chronology	LD Chronology
Austria	x			x
Australia		x	x	
Belgium	x	x	x	x
Czech Republic				x
Finland				x
France	x	x	x	x
Germany				x
Japan	x	xx	x	
Malaysia	x	x		
Norway				xx
Poland				x
Portugal	x	x	x	x
Slovak Republic				x
South Korea	x	x		
Spain	x	x	x	x
Sweden	xx	xx	xx	xx
Switzerland	x	x	x	
UK	x	x	x	x
USA	xx	xx	xx	

Notes: LV refers to Laeven and Valencia (2013), BVX refers to Baron et al. (2018), ST refers to Schularick and Taylor (2012), and LD refers to Lo Duca et al. (2017). ’x’ indicates a crisis episode, ’xx’ indicates two separate crisis episodes that satisfy the selection criteria.

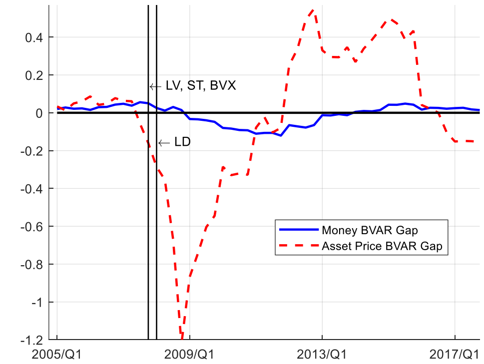
Appendix E. BVAR-Based Gaps for Broad Money and Asset Prices



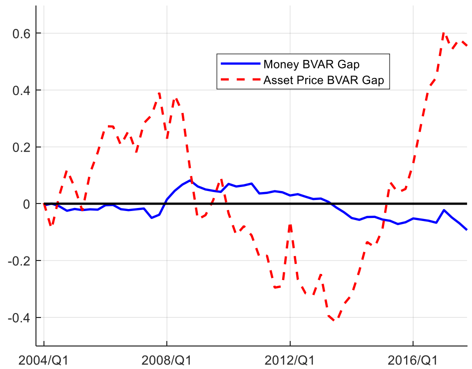
(a) Australia



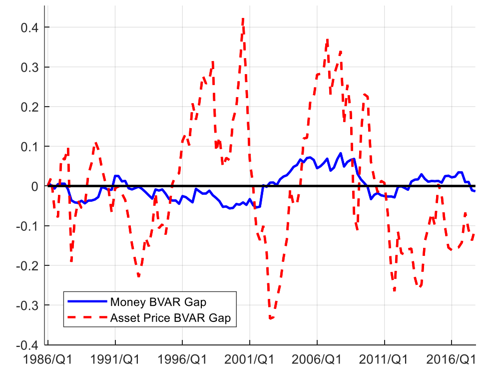
(b) Austria



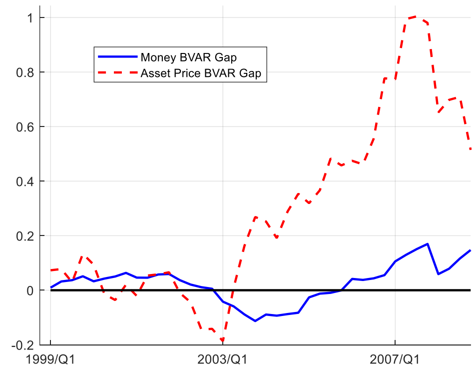
(c) Belgium



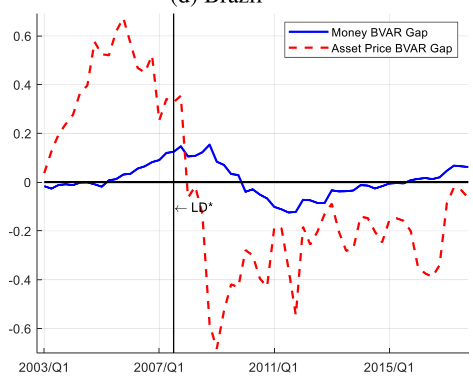
(d) Brazil



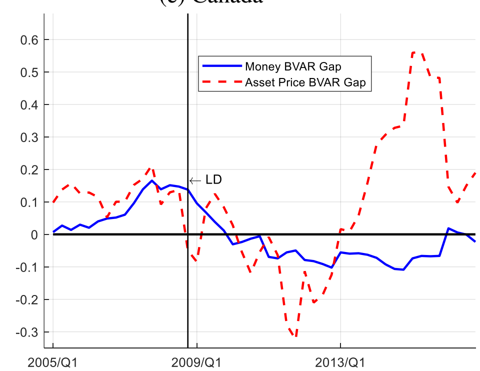
(e) Canada



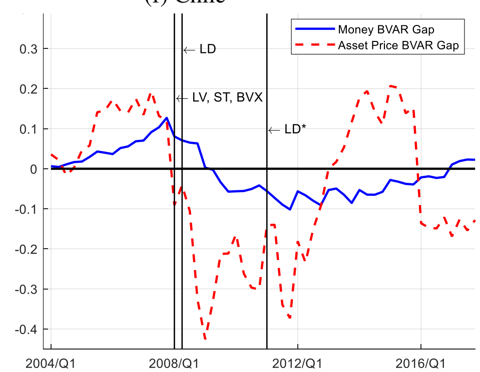
(f) Chile



(g) Czech Republic



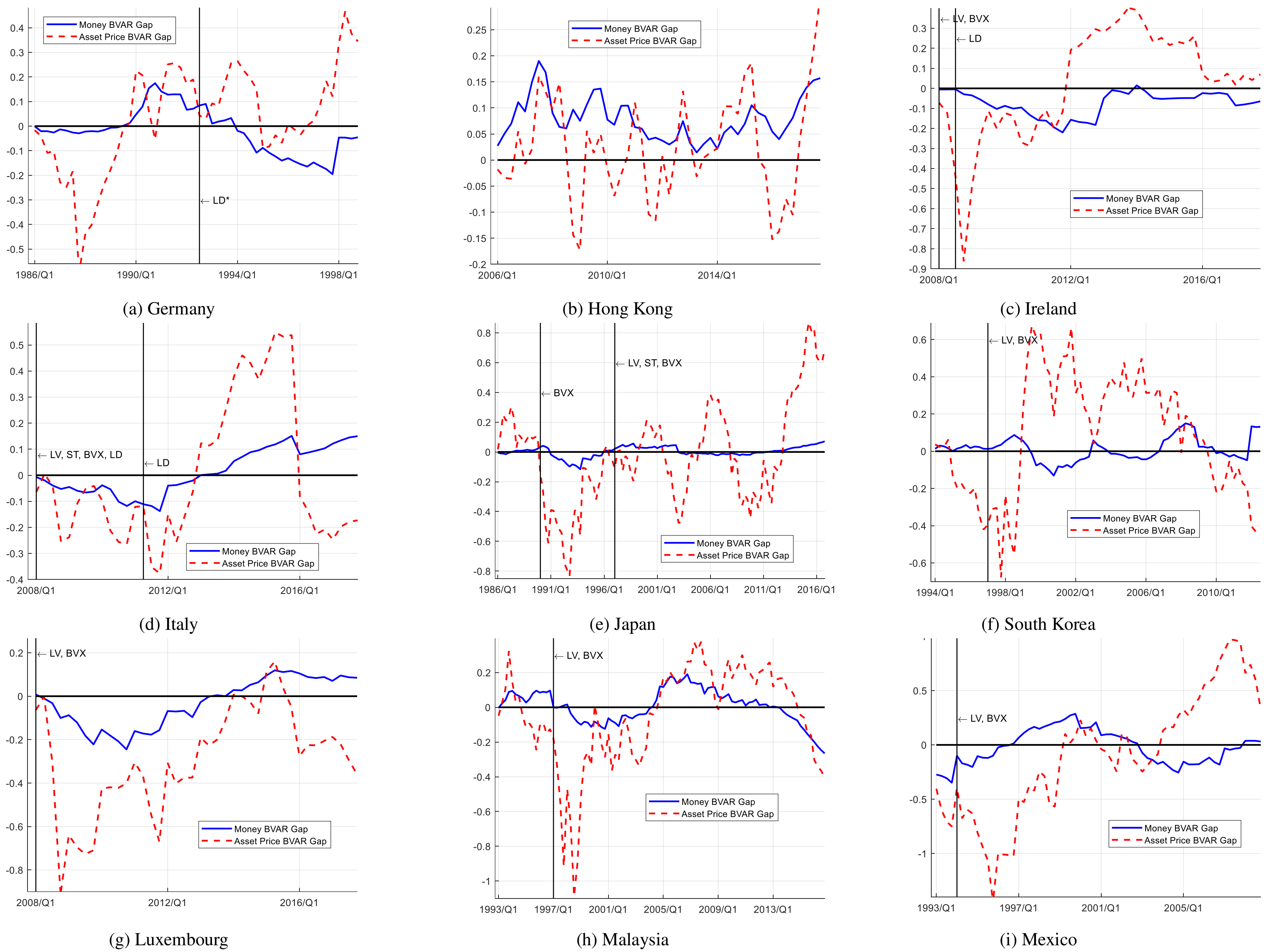
(h) Finland



(i) France

Figure E.1: BVAR Gaps for Broad Money and Asset Prices across Countries: Australia - France

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis). For Australia, AZ stands for Aliber and Kindleberger (2015) and BS stands for Brunnermeier and Schnabel (2016).



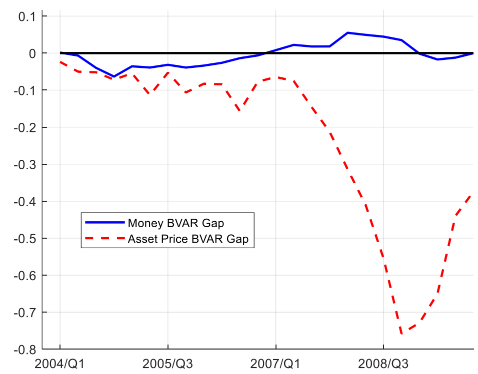
(a) Germany (b) Hong Kong (c) Ireland

(d) Italy (e) Japan (f) South Korea

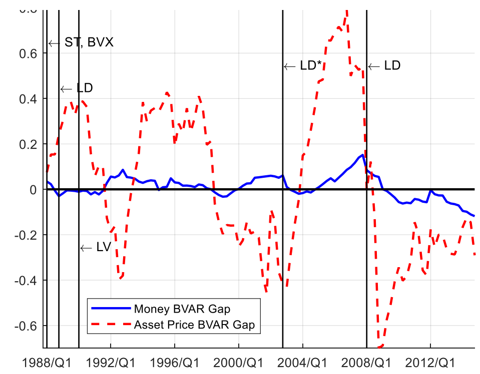
(g) Luxembourg (h) Malaysia (i) Mexico

Figure E.2: BVAR Gaps for Broad Money and Asset Prices across Countries: Germany - Mexico

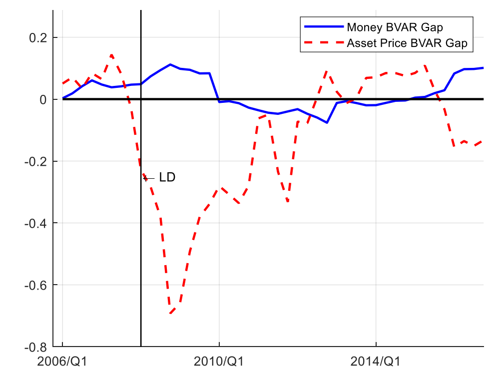
Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, $*$ indicates a residual event (rather than a systemic crisis).



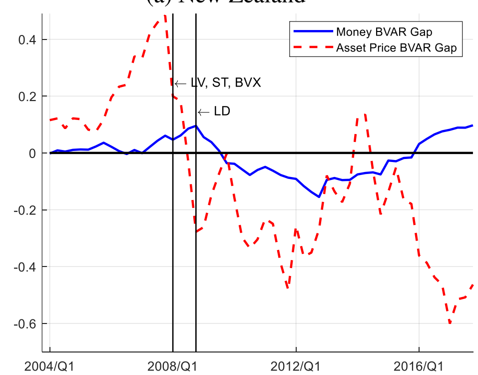
(a) New Zealand



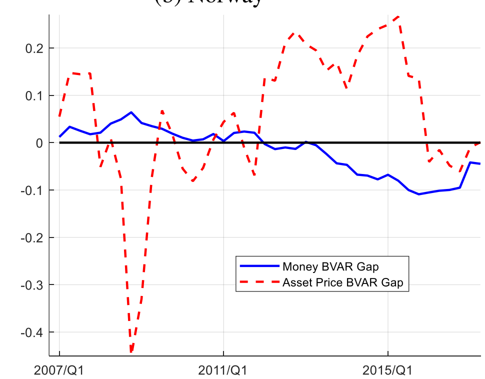
(b) Norway



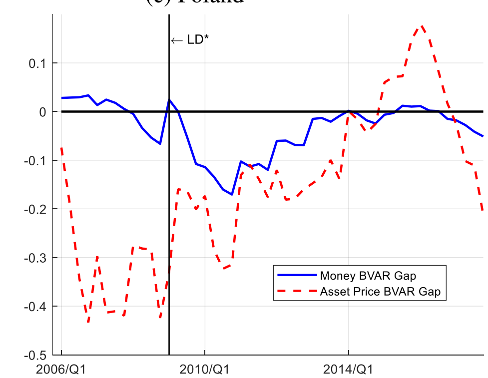
(c) Poland



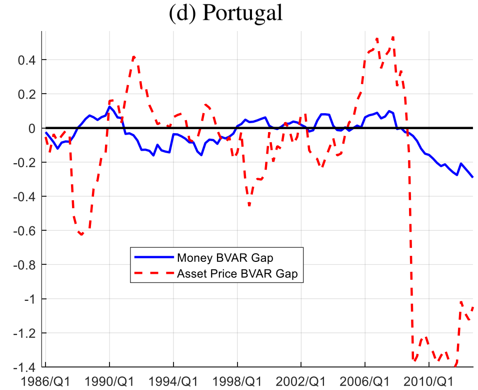
(d) Portugal



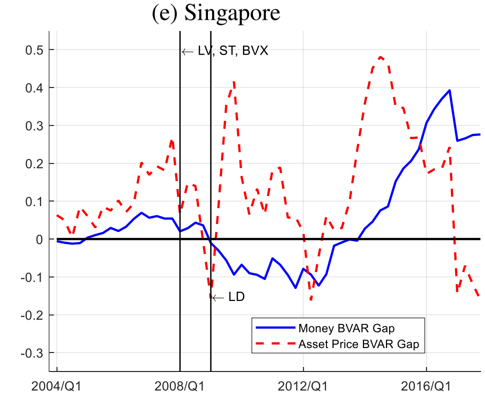
(e) Singapore



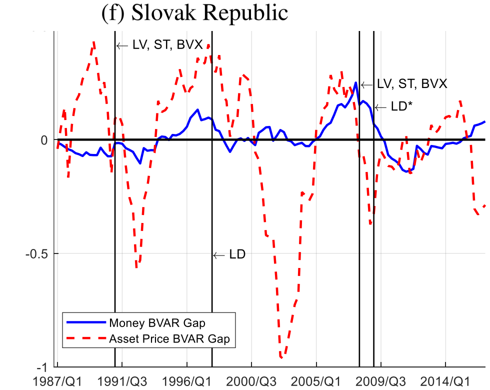
(f) Slovak Republic



(g) South Africa



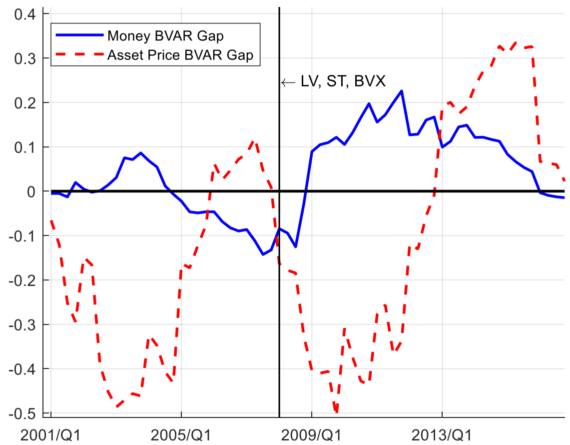
(h) Spain



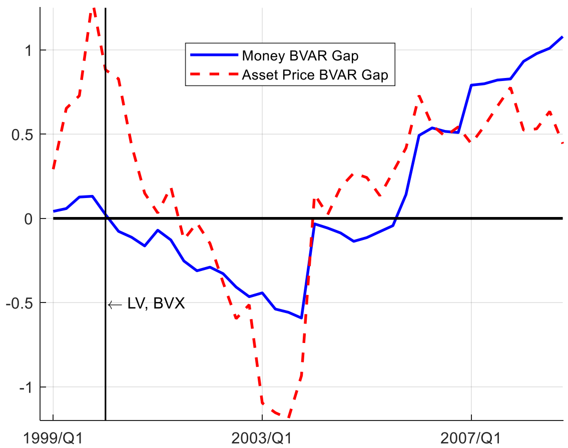
(i) Sweden

Figure E.3: BVAR Gaps for Broad Money and Asset Prices across Countries: New Zealand - Sweden

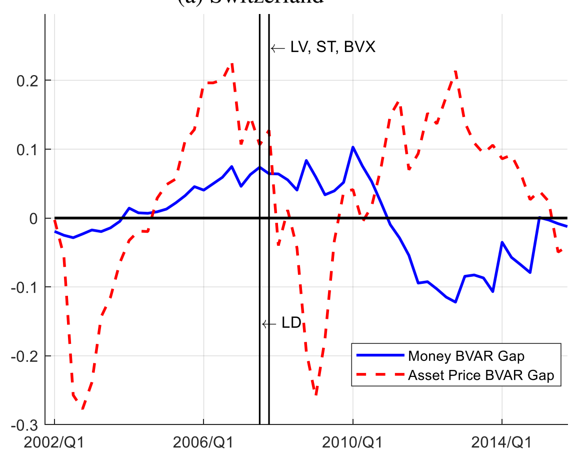
Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis).



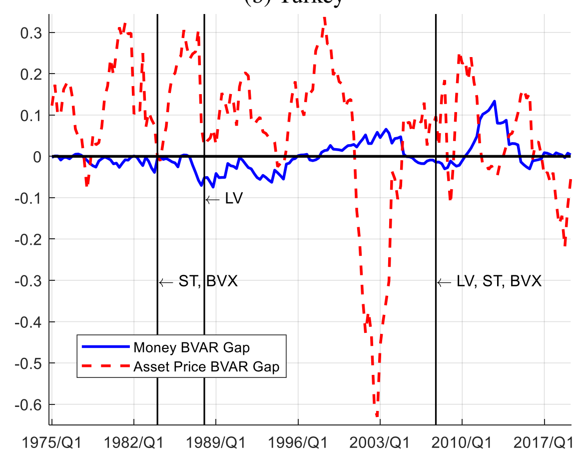
(a) Switzerland



(b) Turkey



(c) United Kingdom



(d) United States of America

Figure E.4: BVAR Gaps for Broad Money and Asset Prices across Countries: Switzerland - USA

Notes: Time on the horizontal axis is in quarters. Credit gaps are expressed in percentage points. Vertical lines signify the onset of crises according to the following chronologies: ST - Schularick and Taylor (2012), BVX - Baron et al. (2019), LV - Laeven and Valencia (2013), LD - Lo Duca et al. (2017). In case of LD chronology, ∗ indicates a residual event (rather than a systemic crisis).

Appendix F. Robustness Results

Table F.2: 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
Prime Loan Rate	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
Total Loans and Leases	Log-Level

Notes: All data series are retrieved from the FRED.

Table F.3: Root Mean Squared Errors (RMSE)[a] of Forecasts in Total Loans and Leases (U.S.)

	1988[b] (1989-1992)[c]	1989 (1990-1993)	1990 (1991-1994)	1991 (1993-1995)	1992 (1993-1996)
4VAR	3.93	11.13	8.96	**2.39**	**8.38**
7VAR	**3.13**	**10.69**	11.00	3.60	10.91
16VAR	3.78	11.26	**7.37**	2.50	9.64
	1993 (1994-1997)	1994 (1995-1998)	1995 (1996-1999)	1996 (1997-2000)	1997 (1998-2001)
4VAR	6.18	3.13	2.94	**1.35**	**2.13**
7VAR	4.81	1.58	4.86	1.52	2.25
16VAR	**4.80**	**1.44**	**1.97**	1.37	4.34
	1998 (1999-2002)	1999 (2000-2003)	2000 (2001-2004)	2001 (2002-2005)	2002 (2003-2006)
4VAR	3.01	**2.01**	4.18	11.64	5.55
7VAR	3.11	2.73	5.41	**9.66**	5.74
16VAR	**2.34**	3.81	**3.25**	11.35	**3.49**
	2003 (2004-2007)	2004 (2005-2008)	2005 (2006-2009)	2006 (2007-2010)	all windows (average)
4VAR	12.50	6.34	3.16	**1.87**	5.30
7VAR	12.93	4.22	2.83	4.17	5.53
16VAR	**9.79**	**2.64**	**1.26**	2.58	**4.68**

[a] Reported RMSEs are somputed with respect to the forecast mean across all horizons, i.e. $RMSE = \sqrt{\frac{\sum_{t=1}^{H}(y_t - \hat{y}_t)^2}{H}}$, where H is the forecast horizon and $\hat{y}_t$ is the forecast mean. Replacing the mean by the median does not change the results substantially. The smallest RMSEs are in bold.

[b] The year denotes the last year in the 15 year estimation rolling window.

[c] The year span denotes the forecasting period of the particular rolling window.

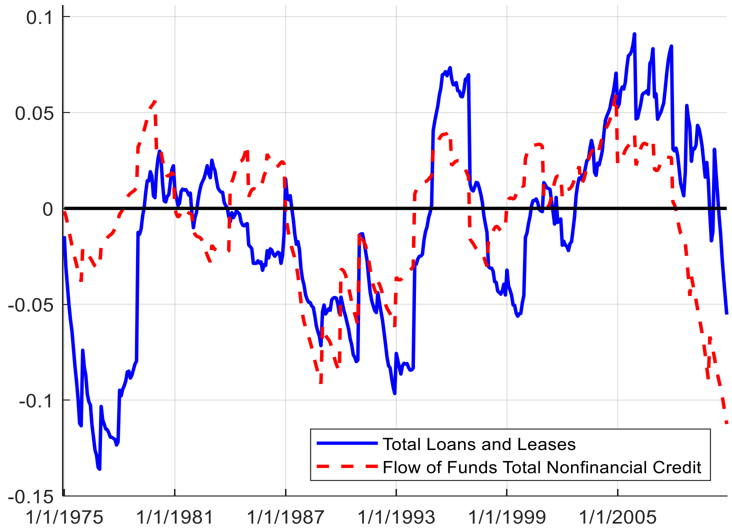


Figure F.1: Credit Gap Values for Total Loans and Leases (U.S.) and the Baseline Flow of Funds Total Nonfinancial Credit Meassure.

Notes: Positive values indicate atypical credit expansions. Negative values indicate atypical credit contractions. Time is in months, credit gap is expressed in percentage points.

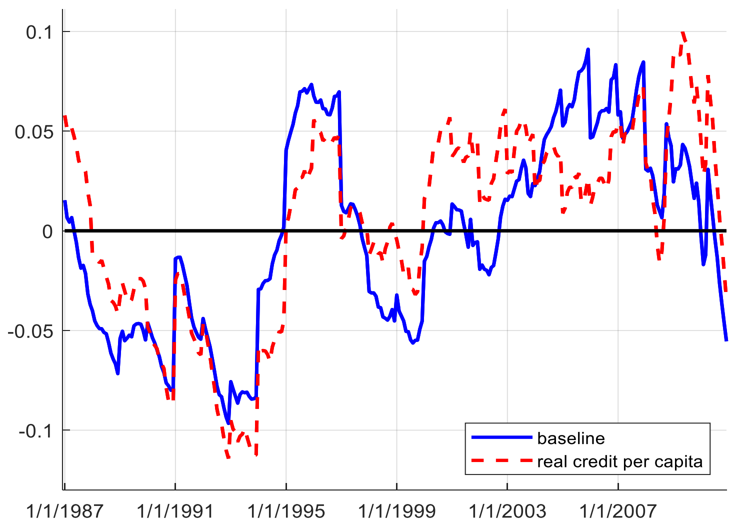


Figure F.2: Credit Gap Values for Total Loans and Leases (U.S.) for Baseline Specification and for an Alternative Specification with Real Total Loans and Leases Per Capita as Credit Measure.
Notes: Positive values indicate atypical credit expansions. Negative values indicate atypical credit contractions. Time is in months, credit gap is expressed in percentage points.

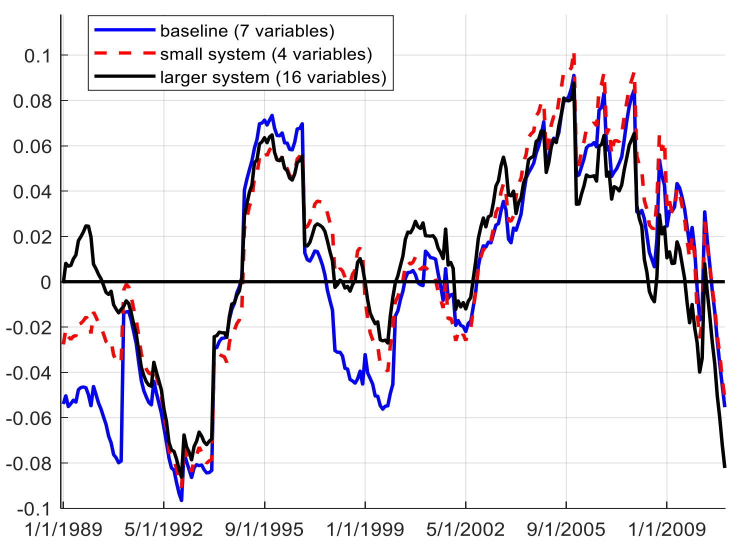


Figure F.3: Credit Gap Values for Total Loans and Leases (U.S.) with for the Baseline, Smaller and Larger VAR Systems.
Notes: Positive values indicate atypical credit expansions. Negative values indicate atypical credit contractions. Time is in months, credit gap is expressed in percentage points.

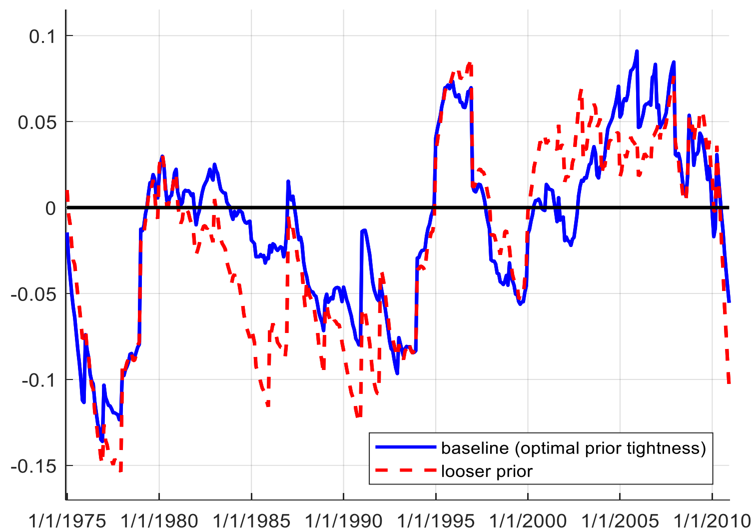


Figure F.4: Credit Gap Values for Total Loans and Leases (U.S.) for Baseline (Optimized) Prior Hyperparameters and for a Looser Prior.
Notes: Positive values indicate atypical credit expansions. Negative values indicate atypical credit contractions. Time is in months, credit gap is expressed in percentage points.