Center for Quantitative Economics

Conditioning business and financial cycles on multivariate information

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112/2025

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June 18, 2025

Abstract

We estimate output gaps and financial cycles using a cross-country sample comprising Germany, the United States, and the United Kingdom by extending the approach of Berger, Richter & Wong (2022). Specifically, we apply the trend-cycle decomposition of Beveridge & Nelson (1981) within Bayesian vector autoregression models but select different sets of conditioning variables and shrinkage parameters for output gaps and financial cycles – i. e. credit and property price cycles – in each country. As demonstrated by our cross-country results, this strategy yields more realistic estimates of financial cycle amplitudes while retaining reliable output gap estimates. Our results further indicate that large, positive Beveridge-Nelson-based financial cycles, unlike traditional financial cycles, should not be interpreted as early warning indicators of systemic risk. Instead, they indicate periods of financial overhang that may impose constraints on the broader economy.

Keywords: output gap, financial cycle, Beveridge-Nelson decomposition, Bayesian VAR
JEL Classification: C32, E32, E51

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1 Introduction

The output gap's key role in monitoring the business cycle, thus shaping monetary policy (see e.g. Taylor 1993) and in some cases determining fiscal leeway (as exemplified by the German debt brake) has led to the development of a wide range of estimation approaches. Similarly, growing recognition of the potential impact of financial cycles on the sustainability of output levels has led to increased interest in their estimation and interpretation.

For the output gap, a large number of univariate filtering variants exists (e. g. Hodrick & Prescott 1997, Baxter & King 1999, or Hamilton 2018). However, these methods have been criticized for being inadequate for assessing the relative contributions of transitory and permanent components and their failure to account for the inherently multivariate nature of the business cycle (Quah 1992).

Evans & Reichlin (1994) and Morley & Wong (2020) address these issues by employing the Beveridge & Nelson (1981) (BN) decomposition in a vector autoregression (VAR) model which allows to condition the output gap estimate on multivariate information. As argued by Berger & Ochsner (2022), this approach can be interpreted in the spirit of production function-based frameworks, as the trend component provides a potential output estimate that relies on the dynamics of a broad set of variables rather than the statistical properties of a selected filter applied to GDP. Particularly the incorporation of information regarding the financial sector has drawn growing attention in discussions following the Global Financial Crisis (GFC) – see, among others, Borio et al. (2017), Rünstler & Vlekke (2018), Berger & Dubbert (2022), or Winter et al. (2022).

As stated by Berger, Richter & Wong (2022), the multivariate BN framework is also well-suited for estimating financial cycles. The above-mentioned critiques directed at the univariate estimation of the output gap have increasingly been extended to financial cycle estimation. For instance, Cagliarini et al. (2017) argue that the length of financial cycles primarily reflects the calibration of the filtering method and not necessarily the actual underlying dynamics. Moreover, financial cycle estimates obtained from univariate methods – like the frequently applied Christiano & Fitzgerald (2003) (CF) filter (Drehmann et al. 2012, Stremmel 2015, Oman 2019) – lack a theoretical interpretation of the trend component. By contrast, the BN decomposition provides at least a statistical interpretation. Specifically, the BN-identified trend corresponds to the long-term conditional expectation of the target variable, minus a deterministic drift.

The usage of a VAR model to condition the BN trend on multivariate information offers the additional advantage that not only the output gap but also the financial cycles are derived from a broad set of information reflecting economic developments. As argued by Berger, Richter & Wong (2022), the interaction between business and financial cycles is not unidirectional, and thus financial variables should not be treated as exogenous when incorporated in an output gap estimation model – contrary to, for example, the approach of Borio et al. (2017).

In this paper, we broadly follow the approach of Berger, Richter & Wong (2022) and estimate both business and financial cycles by means of a BN decomposition conditioned on multivariate information. More specifically, we apply the BN decomposition to GDP to retrieve estimates for the output gap, while applying it to total credit and property prices to estimate individual cyclical components for these variables, in line with Berger, Richter & Wong (2022) or Rünstler & Vlekke (2018). This approach has some key advantages: first, it allows for interactions between GDP and financial variables while also incorporating additional conditioning variables which may potentially contain important information beyond that contained in GDP or the financial variables alone. Second, it avoids the need for a priori restrictions on the frequencies of the fluctuations in the target variables. Third, the model enables an assessment of the relative importance of each conditioning variable – and the target variables themselves – for the estimation of the respective cyclical component, as well as for a historical decomposition of the cyclical fluctuations. Although such a decomposition has no causal interpretation, it is interesting with regard to the role of the financial variables for output gap estimation and with respect to the role of output for the estimation of financial cycles.

However, we extend the work of Berger, Richter & Wong (2022) in some crucial ways. First, we use a cross-country sample, including Germany, the United Kingdom, and the United States. While the inclusion of the U.S. allows to compare our results with those of Berger, Richter & Wong (2022) and several other studies, the estimation of output gaps and financial cycles in the other countries sheds additional light on the properties of the BN-obtained cycles in general. Specifically, financial cycles in Germany are known to be rather flat (Rünstler & Vlekke 2018, Schüler et al. 2017, Oman 2019), while financial cycles in the U.K. are known to be relatively closely aligned with those of the U.S. and exhibiting long-term fluctuations with large amplitudes (Drehmann et al. 2012, Rünstler & Vlekke 2018). Second, we restrict our sample to ten variables to limit estimation error, particularly in the case of Germany, for which available time series are shorter due to the reunification. Morley & Wong (2020) show that eight variables are sufficient to estimate the output gap in the U.S. Thus, we proceed in the same way except that we add our financial variables, which are total credit and property prices. Third, we deviate from the idea of a joint model for output gap and financial cycles: According to Morley & Wong (2020), it is crucial to use Bayesian methods to introduce prior shrinkage when estimating the output gap in a VAR. Otherwise, an increasing sample size would mechanically raise the model-implied predictability of output growth, thereby increasing the amplitude of the BN-derived output gap (Evans & Reichlin 1994, Morley & Wong 2020). Berger, Richter & Wong (2022) follow Morley & Wong (2020) and determine the hyperparameter λ, which governs the degree of prior shrinkage by minimizing the one-step ahead root mean squared error (RMSE) of pseudo out-of-sample forecasts of GDP. They then take the financial cycles as by-products of the estimation. In contrast to their approach, we select an own set of conditioning variables for the estimation of our financial cycles, based on their weighted contributions to the standard deviations of credit and property prices. We also determine an own shrinkage parameter λ for this model, which is derived by minimizing the average one-step ahead RMSE of total credit and property prices rather than GDP. Our cross-country analysis reveals that optimizing λ solely based on output forecasts can lead to spurious amplitudes in the financial cycle estimates. For instance, the amplitudes in German financial cycles would be large compared to that of the U.S. in this case, clearly at odds with the literature (e. g. Rünstler & Vlekke 2018) and stylized facts. In contrast, our approach delivers financial cycle estimates with plausible amplitudes without deteriorating the reliability of output gap estimates.

We further clarify the appropriate interpretation of BN-based financial cycles. For example, we find a strong negative correlation of our estimates to cycles derived from the CF filter. More specifically, BN-based financial cycles are typically negative during periods of financial build-ups and positive during downturns. This inversion arises from the behavior of the trend component in the BN decomposition, which is defined as the long-run expectation of the target variable, conditional on the information embedded in the model's conditioning variables.

During financial expansions, the BN trend component tends to overshoot, as persistent growth in financial variables leads to an upward revision in its long-term expectations. Crucially, the model lacks information to anticipate the unsustainability of the boom while it lasts. Once the boom ends due to a shock, the newly incorporated information causes the long-run conditional expectation to collapse. However, credit and property prices typically adjust only sluggishly, leading to what we interpret as "financial overhang" —- i.e., an elevated level of financial variables relative to deteriorated expectations regarding the sustainable long-run level.

The inclusion of conditioning variables beyond those directly tied to the financial sector further allows the BN trends of the financial variables – and thus the BN cycles – to reflect real economic conditions. For example, we observe substantial overhangs in credit and property prices in both Germany and the U.K. following the COVID-19 pandemic. The post-pandemic economic slowdown, combined with high inflation, implies a downward revision in the expected long-run real levels of these financial variables. Consequently, the prevailing levels of credit and property prices in these periods appear unsustainable under current macroeconomic conditions and may impose financial constraints on the broader economy.

The remainder of the paper is structured as follows: Section 2 elaborates on the literature on business and financial cycles and their joint estimation. Section 3 lays out our model and the estimation methodology, including model selection. Section 4 takes a look at our data. Section 5 provides the estimation results. Section 6 concludes.

2 Business & financial cycles – a brief literature review

The surge in research on the real-economy implications of financial developments following the GFC, coupled with the accelerated progress in econometric methodology, has resulted in an extensive and rapidly expanding literature on both business and financial cycles. Given the breadth of concepts, methods, and empirical applications, it has become increasingly difficult to maintain an overview of the field. In the following section, we therefore aim to offer the reader a brief orientation – without any claim to comprehensiveness or full coverage of the existing literature.

2.1 Business cycles

In modern macroeconomics, the business cycle is no longer regarded as a single, self-generating cycle but rather as a complex interplay of overlapping cycles characterized by varying frequencies and determinants such as technological progress, demographic shifts, and financial conditions (Sargent 1987, 282). Despite the inherently multivariate character of the business cycle, the output gap – defined as the cyclical component of GDP – remains the main measure of the current state of the business cycle (see e. g. Morley & Wong 2020).

The output gap is calculated as the difference between realized and trend GDP, where the latter represents an estimate of potential output. Thus, if realized GDP exceeds trend GDP, the output gap is positive, implying that aggregate demand exceeds aggregate supply and inflationary pressure arises. Due to its link to inflation, the output gap plays a vital role in shaping monetary policy (see e. g. Taylor 1993). Furthermore, in countries with fiscal rules, potential output is used to determine the leeway of fiscal policy (Germany with its debt brake is a prominent example).

The U.S. Congressional Budget Office (CBO) and the German Council of Economic Experts (SVR) provide production-function-based output gap estimates that are frequently used as reference values for the respective countries (see e. g. Kamber et al. 2018, Berger & Ochsner 2022). Since these measures are only available with a time lag and rely on specific model assumptions, numerous time-series-based filters have been developed as alternatives. These filters decompose a time series into a trend component, representing an estimate of potential output, and a cyclical component, representing an estimate of the output gap. Common univariate approaches include the Hodrick & Prescott (1997) (HP) filter, the Baxter & King (1999) (BK) filter, and the BN decomposition. However, univariate filters have been criticized for various and well-founded reasons. For instance, Hamilton (2018) recommends avoiding the HP filter, highlighting its tendency to generate spurious cycles, its pronounced end-of-sample bias, and its dependence on an arbitrarily chosen smoothing parameter λ. Schüler (2024), in turn, documents several undesirable properties of Hamilton's proposed alternative – specifically, the use of the eight-quarter-ahead forecast errors from an autoregressive model as the cyclical component of the target variable. According to Schüler, the Hamilton filter can alter the variances of different frequencies, potentially amplifying fluctuations outside the typical range of business cycle dynamics. In addition, the Hamilton filter may also distort the timing relationship between variables, which can result in spurious findings – especially when analyzing co-movements in macroeconomic variables. Quast & Wolters (2022) provide a modified version of the filter that aims to improve coverage of typical business cycle frequencies by using the mean of four- to twelve-quarter-ahead forecast errors.

Beyond the discussion about the relative merits and drawbacks of specific filters, Quah (1992) criticizes univariate approaches more broadly for their inability to identify the underlying drivers of the fluctuations or the relative importance of transitory versus permanent components in GDP. In essence, output gap estimates generated by these filters must be interpreted "off-model" (Morley & Wong 2020).

The strategy proposed by Evans & Reichlin (1994) conceptually addresses these challenges by employing a BN decomposition in which the trend component of a time series is defined as its long-term conditional expectation minus a deterministic drift, which is the expectation of the growth rate. The expectations are taken based on a vector autoregression (VAR) model, meaning they are conditioned on multivariate information. This approach offers three key advantages: first, the BN decomposition allows transitory shocks to have permanent effects on the trend component (Kamber et al. 2018). Second, the use of a multivariate model improves the conceptual foundation of the trend component and thereby the interpretability of the resulting estimates (Morley & Wong 2020). Berger & Ochsner (2022) argue that the VAR-based BN decomposition can be interpreted in spirit of production function approaches. Furthermore, the multivariate conditioning model enables an informational decomposition of the resulting output gap. While this decomposition does not provide a causal interpretation, it reveals which variables contribute relevant information to the output gap estimation (Berger et al. 2023, Berger & Ochsner 2022, Morley & Wong 2020). However, a drawback of the multivariate approach is the proliferation of parameters to be estimated, which increases sampling error. To mitigate this issue, Morley & Wong (2020) introduce prior shrinkage by estimating the model in a Bayesian fashion.[1]

Beyond the debate surrounding the characteristics of the method used, the question of what constitutes a reliable output gap estimate emerges. Since the output gap's policy relevance stems mostly from its relation to inflation, the literature has traditionally focused on its correlation with future inflation rates, which should be positive (see e. g. Jarociński & Lenza 2018). In such a framework, a closed output gap implies a sustainable output level, which is inflation-neutral. However, this inflation-centric perspective has faced criticism, particularly in the aftermath of the GFC, because it neglects the role of financial instabilities in shaping economic dynamics (e.g., Borio 2014 or Borio et al. 2017).

Examining the cyclical dynamics of the financial sector and their potential implications for business cycle fluctuations has therefore attracted growing attention (e.g., Drehmann et al. 2012, Claessens et al. 2012). In this context, estimating business and financial cycles within a unified framework (Rünstler & Vlekke 2018, Berger, Richter & Wong 2022), or at least conditioning output gap estimates on financial variables (Borio et al. 2017), represents an effort to incorporate financial developments and

[1]Prior shrinkage has been proven to be an effective way to address the curse of dimensionality (Bańbura et al. 2010, Giannone et al. 2015).

their possible spillovers into real economic activity.

2.2 Financial cycles

Over the last two decades, the financial dynamics of an economy have been the subject of increased attention in economics. Empirical research, including studies by Aikman et al. (2015), Jordà et al. (2013), and Schularick & Taylor (2012), demonstrate the crucial role of long-term credit fluctuations and the destructive consequences of credit booms and busts on real economic activity. Claessens et al. (2012) find that recessions linked to financial crises, particularly those triggered by house price collapses, are typically longer and more severe than recessions without such crises. Similarly, Jordà et al. (2016) identify recessions following credit booms as particularly costly, with mortgage lending emerging as the primary driver of such booms during the post-World War II period.[2] Adopting a broader historical lens spanning four centuries, Brunnermeier & Schnabel (2015) find that asset price bubbles are usually harmful when financed by credit. Mian et al. (2013) and Mian & Sufi (2014) elucidate the mechanisms through which financial crises can have substantial and lasting effects on the real economy.

The potentially destructive forces of the financial sector, along with its expansion and increasing complexity since the 1970s (Jordà et al. 2016, Schularick & Taylor 2012), have sparked growing interest in the concept of the financial cycle. Pioneered by Borio & Lowe (2002), the financial cycle aims to capture the overall stance of the financial sector. Analogous to business cycle analysis and methodologically closely related to output gap estimation, the financial cycle is typically derived by filtering a financial variable of interest – or an index constructed from multiple variables – thereby obtaining its cyclical component. However, in contrast to the output gap, the financial cycle lacks a well-established theoretical foundation, which has fueled ongoing debate regarding the choice of appropriate target variables.

Borio (2014) provides what is perhaps the most widely accepted definition of the financial cycle, describing it as "[...] self-reinforcing interactions between perceptions of value and risk, attitudes towards risk, and financing constraints, which translate into booms followed by busts." These self-reinforcing dynamics primarily occur between credit and asset prices, as assets serve as collateral for credit. While some studies include equity prices among relevant asset prices (Claessens et al. 2012, Schüler et al. 2017), studies that aim to identify the most significant variables from broader datasets consistently find property prices (Drehmann et al. 2012) or related measures, such as the house price-to-income ratio (Stremmel 2015), to be far more relevant than other asset classes or asset-related variables. Consequently, Borio (2014) suggests that a combination of credit and property prices represents the most parsimonious representation of the financial cycle. Drehmann et al. (2012) use an index that includes the credit-to-GDP ratio, real total credit, and real property prices. They normalize these variables, take the unweighted average, and apply a Christiano & Fitzgerald (2003) (CF) bandpass filter calibrated for medium-term cycles (8-30 years). For the sake of comparison,

[2] Mian & Sufi (2011) provide a detailed account of the effects of mortgage lending in the context of its rapid expansion preceding the Global Financial Crisis in the U.S.

the turning point method is also used in their cross-country analysis, which leads to almost identical results. Peaks in the resulting financial cycles are often observed on the eve of systemic banking crises or, as in the case of Germany in 2000, precede periods of serious financial distress. Therefore, their estimates of the financial cycle can be used as early warning indicators for crises and as measures of systemic risk.

A finding from many studies is that financial cycles tend to have both larger amplitudes and longer durations than business cycles (Borio 2014, Claessens et al. 2012, Drehmann et al. 2012, Oman 2019, Schüler et al. 2017). For example, Schüler et al. (2017) estimate the average length of financial cycles in the G-7 countries to be approximately 15 years, compared to an average business cycle length of nine years. However, significant cross-country differences are observed. The German financial cycle, for example, is characterized by a lower amplitude and shorter duration, a finding corroborated by Drehmann et al. (2012), Rünstler & Vlekke (2018), and Oman (2019). In contrast, Oman (2019) finds very large amplitudes for Greece, Ireland, and Spain. The financial cycles in the U.K. and the U.S. also exhibit relatively large amplitudes and long cycles (Drehmann et al. 2012, Schüler et al. 2017). Examining other large European economies such as France, Italy, and Spain, Rünstler & Vlekke (2018) find a positive correlation between more pronounced financial cycles and higher home ownership rates. This aligns with both theoretical considerations and empirical findings emphasizing the importance of co-movements between credit and property prices in shaping financial developments. However, results vary depending on the methodology and sample used. Cagliarini et al. (2017), for instance, conclude that the evidence for financial cycles to be longer than business cycles remains inconclusive and is at least partially the result of the predefined calibration of the filters used.

2.3 Joint estimation of business and financial cycles

Research on the financial cycle is not an end in itself but derives its relevance from its potential real economy implications. The relationship between financial and economic cycles, particularly their synchronicity, is therefore the focus of much of the literature (Claessens et al. 2012, Drehmann et al. 2012, Oman 2019, Schüler et al. 2017). One strand of literature builds on this analysis by deriving both business and financial cycles from unified models instead of relating individually obtained estimates.

Using such a joint framework, Rünstler & Vlekke (2018) identify a medium-term cycle in GDP that is highly correlated with their estimated credit and property price cycles across all countries except Germany. Borio et al. (2017) argue that a boom in credit and property prices can fuel a boom in real output without generating inflationary pressure. In such a case, it is not a sufficient condition for a sustainable output level to be inflation-neutral, it must also be financially neutral, since in the presence of unsustainable financial build-ups, positive output gaps might arise even in low-inflation environments. Therefore, the authors condition output gap estimates on credit and property prices. However, as Berger, Richter & Wong (2022) point out, this approach assumes that the financial variables are exogenous, even though causality can also run in the opposite direction. For instance, expanding credit volumes may be driven by a real economic boom. Similarly, Cagliarini et al. (2017)

argue that business cycles typically lead the financial cycle, with a reversed lead being more the exception than the rule. Winter et al. (2022) use an unobserved components model to jointly estimate business and financial cycles and analyze their short- and medium-term cyclical oscillations. Consistent with most of the literature, they find the medium-term components to be particularly important for credit and property prices, and also identify a medium-term co-cyclicality between GDP and property prices. An approach that differs more strongly from the rest of the literature has been carried out by Berger, Richter & Wong (2022). Building on Morley & Wong (2020), Berger, Richter & Wong (2022) use a Bayesian VAR-based BN decomposition, extending these authors' work by estimating credit and property price cycles next to the output gap within a unified framework. Thus, their credit and property price cycles are defined as the difference between their respective realizations and trend components, with the latter being conditioned on a broad set of both financial and real economic variables. In doing so, they apply the widely accepted logic for the business cycle – that it is not a single, self-generating cycle, but the result of numerous interacting cycles – to financial cycles, giving particular attention to the interactions with the real economy that are central to its analysis. Interestingly, they find the unconditional correlation between the credit cycle and the output gap to be positive, and therefore argue that an uptick in the financial cycle is not necessarily followed by a subsequent bust in the business cycle.

We broadly adopt the authors' approach and apply it to a cross-country sample of three countries, namely Germany, the U.S. and the U. K, deriving the cycles of credit and property prices from a different variable set than output gap with an individual shrinkage parameter. In the spirit of Morley & Wong (2020), we restrict the size of the respective variable sets to ten variables.

3 Methodology

In this section, we elaborate on our empirical models to retrieve both business and financial cycles. Furthermore, the estimation procedure is outlined. Finally, we discuss our model selection approach, which is employed to determine our final model specifications.

3.1 The model

We begin by laying out the basic model employed to estimate business and financial cycles.[3] For this purpose, we follow the literature stream led by Morley & Wong (2020), Berger et al. (2023) and Berger, Richter & Wong (2022), where the BN decomposition is employed to retrieve trend and cyclical components from a time series of interest. While the majority of this literature focuses on identifying the output gap (see e. g. Berger et al. 2023, Berger, Boll, Morley & Wong 2022, Berger & Ochsner 2022 or Morley & Wong 2020), Berger, Richter & Wong (2022) is a notable exception, identifying both business and financial cycles within a joint framework. Broadly following Berger, Richter & Wong

[3]Our brief elaboration on the model setup follows, for instance, Morley & Wong 2020, Berger, Richter & Wong 2022 or Berger & Dubbert 2022.

(2022), we estimate both the output gap and the financial cycles – that is, the credit and property price cycles – using the BN decomposition.

Within the BN decomposition, the trend of a series x_t is defined as its long-term expectation minus any deterministic drift. More formally,

$$\tau_t = \lim_{h\to\infty} \mathbb{E}[x_{t+h} - h\mu], \tag{1}$$

with h being the forecast horizon and μ being a constant drift term. The corresponding cyclical component follows as the series's deviation from that trend, that is,

$$c_t = x_t - \tau_t. \tag{2}$$

In order to evaluate (1) – and by implication obtaining an estimate of c_t – we follow Evans & Reichlin (1994) and Morley & Wong (2020) in employing a standard VAR(p) model in reduced form to identify the BN trend and cycle using multivariate information:

$$\mathbf{y_t} = \phi_1\mathbf{y_{t-1}} + \phi_2\mathbf{y_{t-2}} + \cdots + \phi_p\mathbf{y_{t-p}} + \mathbf{u_t}, \quad \mathbf{u_t} \sim N(\mathbf{0}, \Sigma), \tag{3}$$

where $\mathbf{y_t}$ is a $M \times 1$ vector of demeaned, stationary variables. Borrowing notation from Berger & Dubbert (2022) and Dubbert & Kempa (2024), the companion form of (3) is

$$\mathbf{Y_t} = \mathbf{F}\mathbf{Y_{t-1}} + \mathbf{H}u_t, \tag{4}$$

where $\mathbf{Y}_t = \{\mathbf{y}'_\mathbf{t}, \mathbf{y}'_\mathbf{t-1}, \ldots, \mathbf{y}'_\mathbf{t-p+1}\}$, $\mathbf{F}$ is the companion matrix and the matrix $\mathbf{H}$ maps the reduced form errors onto the companion form. Collecting the (non-transformed) level variables in $\mathbf{X_t}$, the BN trend and cycle can then be obtained as

$$\tau_t = \mathbf{X_t} + \mathbf{F}(\mathbf{I} - \mathbf{F})^{-1}\mathbf{Y_t}, \tag{5}$$
$$c_t = -\mathbf{F}(\mathbf{I} - \mathbf{F})^{-1}\mathbf{Y_t}. \tag{6}$$

While the vector c_t contains M elements, we are primarily interested in the elements corresponding to the real GDP, credit and property price variables. Thus, c_t contains estimates of our output gap, credit cycle and property price cycle measures.

Finally, as shown by Morley & Wong (2020), c_t can be approximated by

$$c_t \approx \sum_{i=0}^{t-1} \mathbf{\Gamma_{i+1}}\mathbf{H}u_{t-i}, \tag{7}$$

where $\mathbf{\Gamma}_i \equiv \mathbf{F}^i(\mathbf{I} - \mathbf{F})^{-1}$. Thus, the cyclical components in c_t can be interpreted as weighted averages of the forecast errors of the conditioning variables, such that each cyclical component is decomposed into contributions of the conditioning variables, providing a simple way to assess each variable's importance in determining the respective cycle.

3.2 Estimation

In order to retrieve estimates of the cyclical components of the series of interest, in a first step, the slope and variance parameters of equation (3) need to be estimated. Commonly, Bayesian techniques are employed to deal with the potential proliferation of parameters in vector autoregressive models (curse of dimensionality), see, among others, Morley & Wong (2020) or Berger, Richter & Wong (2022). Following the before-mentioned literature, we choose a natural conjugate Normal-Wishart dummy observation prior, which allows a closed-form solution to the estimation problem at hand. For this purpose, consider (3) in extended form, given by

$$\mathbf{y_t} = \begin{bmatrix} \phi_1^{11} & \dots & \phi_1^{1M} & \phi_2^{11} & \dots & \phi_2^{1M} & \dots & \dots & \phi_p^{1M} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \ddots & \vdots \\ \phi_1^{M1} & \dots & \phi_1^{MM} & \phi_2^{M1} & \dots & \phi_2^{MM} & \dots & \dots & \phi_p^{MM} \end{bmatrix} \begin{bmatrix} \mathbf{y}_{t-1} \\ \mathbf{y}_{t-2} \\ \vdots \\ \mathbf{y}_{t-p} \end{bmatrix} + \begin{bmatrix} \mathbf{u}_{1,t} \\ \vdots \\ \mathbf{u}_{M,t} \end{bmatrix}. \tag{8}$$

The prior moments are given by

$$\mathbb{E}\left[\phi_i^{jk}\right] = 0, \tag{9}$$

$$Var\left[\phi_i^{jk}\right] = \begin{cases} \frac{\lambda^2}{i^2}, & j = k \\ \frac{\lambda^2}{i^2}\frac{\sigma_j^2}{\sigma_k^2}, & \text{otherwise.} \end{cases} \tag{10}$$

According to Bańbura et al. (2010), the parameter λ defines the model's "overall shrinkage". Intuitively, λ tending towards zero implies that more weight is put on the prior relative to the data. Thus, since all variables enter the model in a stationary form, the slope parameters will be shrunk towards zero, implying that the variables in $\mathbf{y_t}$ lean more strongly towards being generated by independent white noise processes. Conversely, a higher λ means more weight is put on the data relative to the prior. For increasing values of λ, on the other hand, the slope coefficients' prior variances increase and thus the weight of the prior decreases, implying more weight for the data in terms of informing upon the parameters. Following the above-mentioned literature, λ results from minimizing one-step ahead forecast errors of the respective target variables in a pseudo-out-of-sample forecasting exercise.[4] The prior variance of ϕ_i^{jk} is also influenced by the distance of the respective lag i, where more weight is put on the prior (that is, the respective slope parameter is shrunk more strongly towards zero) for higher lags. Furthermore, the prior variance of ϕ_i^{jk} is reduced for more distant lags such that the respective slope parameter is shrunk more strongly toward zero. Finally, following Morley & Wong

[4]The choice of the target variable depends on the cycles to be retrieved from the model. As outlined further below, we obtain the respective country's output gap from a model where real output growth is the sole target of the above-mentioned forecast exercise. On the other hand, both credit and property price cycles are obtained from a model where both our credit and property price variables serve as targets for the λ optimization problem.

(2020) and Bańbura et al. (2010), the variances σ_j^2 and σ_k^2 are obtained as the residual variances from AR(4) models for the respective variables, estimated with OLS.

3.3 Model selection

In this section, we elaborate on how we select the model specifications for each country. These specifications are chosen mainly along two dimensions: *Parsimony* and *forecast optimization*. Consider parsimony first. According to Morley & Wong (2020), there exists a set of conditioning variables $\mathbf{W_t}$ containing all the relevant information for obtaining the true trends and cycles of the variables stored in $\mathbf{y_t}$, including those of the target variables (given the true parameters of the data-generating process collected in $\mathbf{F}$ in eq. (4)). In an attempt to find $\mathbf{W_t}$, for each country, we complement our target variables with a set of 26 (25 for Germany) conditioning variables. Having estimated the model for the full set of conditioning variables, we then remove the variable with the lowest contribution to the cycle of interest, as measured by the standard deviation of the informational decomposition contributions (see Berger & Ochsner 2022).[5] Reestimating the model without the discarded conditioning variable, we repeat this approach until arriving at a relatively parsimonious model, where $M = 10$. We follow the model size proposed by Morley & Wong (2020), who advocate the use of an eight-variable VAR, and extend it by including our financial variables, namely real total credit and real property prices. This enables us to maintain a parsimonious specification without risking the loss of relevant information that might result from (potentially) replacing two of the seven conditioning variables with financial indicators.[6]

The second dimension governing our model selection approach is forecast optimization. As mentioned above, the shrinkage parameter λ is obtained from minimizing a one-period-ahead forecast error of the target variable(s) in a pseudo-out-of-sample forecasting exercise (see Morley & Wong 2020, Berger, Richter & Wong 2022, Berger et al. 2023).

While our approach to estimating the output gap closely follows the existing literature, we depart from it with respect to the estimation of financial cycles. Specifically, Berger, Richter & Wong (2022) derive their output gap, credit and property price cycles from the same model – comprising 23 variables – with output growth serving as the target variable for the selection of the smoothing parameter λ. In contrast, we estimate two separate models: one for the output gap and another for the financial cycles. This allows us to retain parsimonious, lower-dimensional specifications while still incorporating the most relevant conditioning variables for each target – recognizing that the informational content relevant to business and financial cycles may differ. Moreover, this separation permits the selection of distinct shrinkage parameters (λ) for the two models. This is particularly important given the role of λ in determining the amplitude of the cyclical component in the BN decomposition: since

[5]Note that for the model from which we retrieve the credit and property price cycles, we compute *averages* of these standard deviations.

[6]Note that each additional variable that is added to the model results in $(2M+1)P$ additional parameters to be estimated. While applying Bayesian methods basically enables us to deal with larger models, this approach also has its limits. In particular, an increasing M implies a higher degree of shrinkage, which can result in an artificial amplitude of the respective gap. Thus, limiting the number of variables appears plausible even in case of Bayesian estimation of financial and business cycles.

a lower λ implies stronger shrinkage, the amplitude of the estimated cycle is reduced and a larger share of the variation in the target variable is attributed to its trend (Morley et al. 2023). As a result, optimizing λ based on an output growth target may produce an artificially low amplitude for financial cycles.

This issue is further exacerbated when deviating from our parsimonious specification of ten variables and instead employing a large-scale model that includes all variables relevant to both the output gap and financial cycles. In such cases, the parameter proliferation inherent in high-dimensional VARs intensifies the degree of prior shrinkage, thereby further reducing λ. While Morley & Wong (2020) introduce prior shrinkage in the multivariate model precisely to address this issue – since stronger shrinkage should offset the apparent improvement in the model-implied predictability of the target variables that comes from adding more variables – this approach becomes problematic when extracting multiple cycles from a single model.

To illustrate that this is not merely a theoretical issue, we move ahead to a brief discussion of our results. In the model used to obtain an estimate of the output gap (henceforth the *output gap model*), the estimated λ is higher for Germany and the U.K. compared to the U.S. As a result, the financial cycles derived from this model display an unusually low amplitude in the U.S. relative to the cycles in Germany and the U.K. – a finding clearly at odds with the existing literature and narrative evidence. By contrast, retrieving the financial cycles from a separate model (henceforth the *financial cycle model*), yields a much higher λ for the American financial cycles than for both the U.S. output gap and the German financial cycles, implying a far more realistic amplitude in the U.S. financial cycles.

Our final approach, therefore, involves the estimation of two separate ten-variable models for each country: one for the output gap, with λ optimized solely based on GDP, and one for the financial cycles, with λ optimized based on a weighted average of total credit and property prices.

4 Data

We estimate output gaps and financial cycles for three countries – Germany, the U.K. and the U.S. – as the cyclical components of VAR-based BN decompositions, extending the approach of Berger, Richter & Wong (2022) to a cross-country analysis. For the financial cycle, we select real total credit and real property prices as the variables of interest and decompose both individually, consistent with the literature (Berger, Richter & Wong 2022, Rünstler & Vlekke 2018, Winter et al. 2022). As usual, the output gap is derived from GDP. To condition our estimates, we specify two VAR models for each country, one for the estimation of the two financial cycles and one for the estimation of the output gap. Each model includes credit, property prices, and GDP, along with seven additional conditioning variables selected from a medium-sized pool of 26 candidates (25 for Germany).

Financial cycle variables

To estimate financial cycles, we focus on credit and property prices, which are crucial in determining household net wealth. On the one hand, household net wealth is key to the transmission of financial booms to real economic crises (Jordà et al. 2016, Mian & Sufi 2011, Mian et al. 2013, Mian & Sufi 2014). On the other hand, a large body of literature recommends a combination of credit and property prices (Borio 2014, Borio et al. 2017, Berger, Richter & Wong 2022, Oman 2019, Rünstler & Vlekke 2018, Stremmel 2015, Winter et al. 2022). In contrast to, among others, Drehmann et al. (2012) and Borio (2014), we stick to real total credit and do not additionally include the credit-to-GDP ratio. As Rünstler & Vlekke (2018) point out, the variable is implicitly included in our framework through the inclusion of both credit and GDP.[7]

While our choice of variables is widely undisputed for the U.S. and the U.K., there may be more skepticism in the case of Germany. In international comparison, Germany has a low share of home ownership. Moreover, both periods of financial distress in reunified Germany were unrelated to the domestic housing market (Rünstler & Vlekke 2018).[8] However, for two reasons, we do not choose another approximation for the financial cycle. First, we are interested in the comparison of financial cycles in high amplitude countries like the U.K. and the U.S. and a low amplitude country like Germany in case of the BN decomposition and an output gap conditioned on financials, among other variables. Second, we want to avoid what we call "national overfitting". Financial cycles that are specified to best capture pre-defined, idiosyncratic events like the "Neuer Markt" crash are of little interest to understand the general role of the financial sector for real economic activity. Hence, we include total credit and property prices, deflated with the GDP deflator and expressed in growth rates, as our financial cycle measures.

Data for the financial variables of all three countries is taken from the Bank for International Settlements (BIS).

Conditioning variables

Most of our conditioning variables are consistent across countries. For each country, we include the key macroeconomic aggregates in real terms, important labor market-related variables like the unemployment rate or hours worked, monetary variables like the main policy instrument and a money supply measure, real effective exchange rates, and a consumer confidence index. However, some variables differ. For instance, we use the HWWI energy price index and short-term workers only for Germany, as no equivalents exist for the U.K. and the U.S. Finally, the government budget balance is only included for the U.K. and the U.S., since no quarterly time series spanning the full time horizon is available for the German equivalent. Table 1 gives an overview of the variables and their transformations.

All samples end in 2023:IV, but their starting points differ due to data availability, resulting in varying sample lengths. Specifically, the German sample begins in 1992:III, the U.K. sample in 1983:I,

[7] Note that credit and GDP are included in both the output gap model and the financial cycle model.

[8] The financial distress around the turn of the millennium was caused by a credit boom in the late 1990s and the bust of the Dotcom stock market bubble, commonly referred to as the "New Market" crash in Germany. During the GFC, Germany faced a systemic banking crisis, but this was primarily driven by spillover effects from abroad rather than from domestic financial markets (see e. g. Drehmann et al. 2012).

Germany		United States		United Kingdom	
Real total credit	1	Real total credit	1	Real total credit	1
Real property prices	1	Real property prices	1	Real property prices	1
Real GDP	1	Real GDP	1	Real GDP	1
Real private consumption	1	Real private consumption	1	Real private consumption	1
Real fixed investments	1	Real fixed investments	1	Real fixed investments	1
Real government consumption	1	Real government consumption	1	Real government consumption	1
Real disposable income	1	Real disposable income	1	Real disposable income	1
Hours worked	1	Hours worked	1	Hours worked	1
Real output per hour	1	Real output per hour	1	Real output per hour	1
Consumer price index (CPI)	1	Consumer price index (CPI)	5	Consumer price index (CPI)	1
Population	1	Population	5	Population	5
Building permits	1	Building permits	1	Housing new orders	1
Short-term workers	0	Employment-population ratio	2	Workforce jobs	1
Industrial production	1	Industrial production	1	Industrial production	1
Capacity utilization	0	Capacity utilization	1	Working below capacity	0
FIBOR 3M	2	Federal funds rate	2	Bank of England base rate	2
M3	1	M2	1	Money supply	1
ifo Business expectations	0	Manufacturing new orders	2	Business survey: new order volume	2
Consumer confidence	1	Consumer confidence	1	Consumer confidence	1
Real effective exchange rate	1	Real effective exchange rate	1	Real effective exchange rate	1
World Economic Activity (WEA)*	1	World Economic Activity (WEA)	1	World Economic Activity (WEA)	1
HWWI energy price index	1	Brent oil price	1	Brent oil price	1
Term spread (10Y-3M)	0	Term spread (10Y-3M)	0	Term spread (10Y-3M)	0
Unemployment rate	2	Unemployment rate	0	Unemployment rate	2
Share prices	1	Share prices	1	Share prices	1
Employment	1	Labor force	1	Labor force	1
Real exports	1	Real exports	1	Real exports	1
Real imports	1	Real imports	1	Real imports	1
-		Government budget balance	2	Government budget balance	0

Table 1: Variable sets and transformations for all countries.

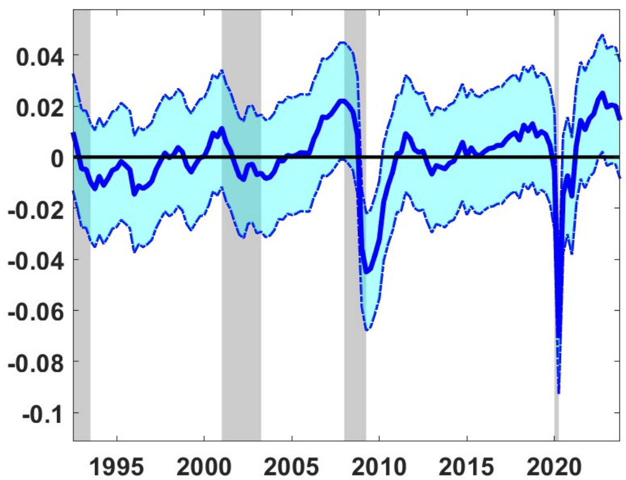
Notes: This table reports the variable sets for all countries along with its transformations. Transformations are: 0: levels; 1: first differences in logs; 2: first differences; 5: second differences in logs. *World Economic Activity is the quarterly mean of the Monthly World Industrial Production Index from Baumeister & Hamilton (2019). Data sources are given in appendix A.

and the U.S. sample in 1970:II. All VAR models are estimated with four lags, which is a standard choice for quarterly data (Morley & Wong 2020).

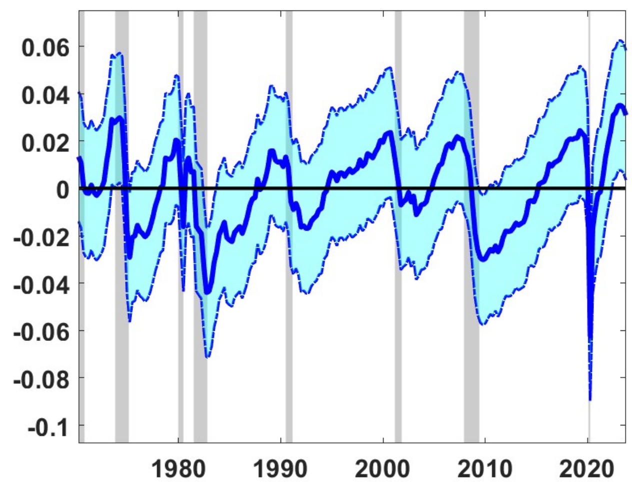
5 Results

We estimate business and financial cycles for three countries using the BN decomposition. To keep the presentation of results concise, we structure the section into two subsections: the first presents our findings on business cycles, the second focuses on financial cycles.

5.1 Output gaps



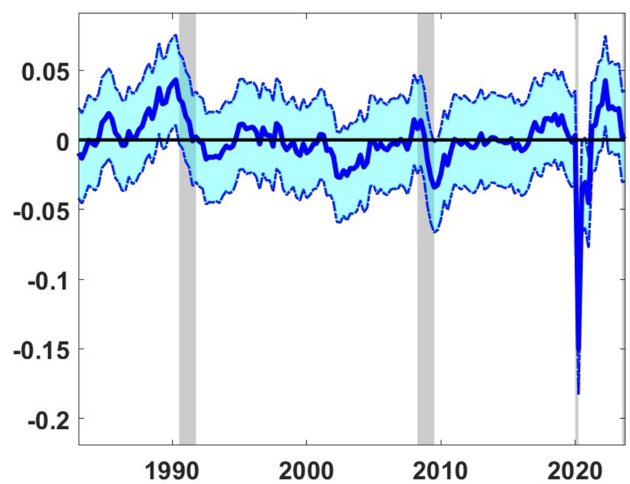
(a) Germany



(b) United States

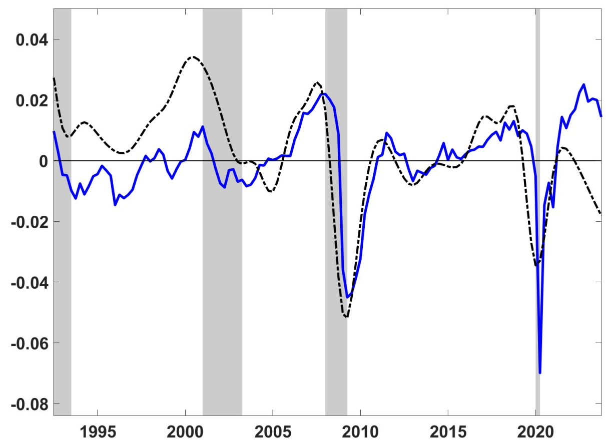
Figure 1: Estimated output gaps from the BVAR.

Units are in percent deviation from trend. Blue shaded areas indicate credible sets. Gray shaded lines indicate recession dates from SVR (Germany), NBER (U.S.), and self-constructed from the narrative record (U.K.).

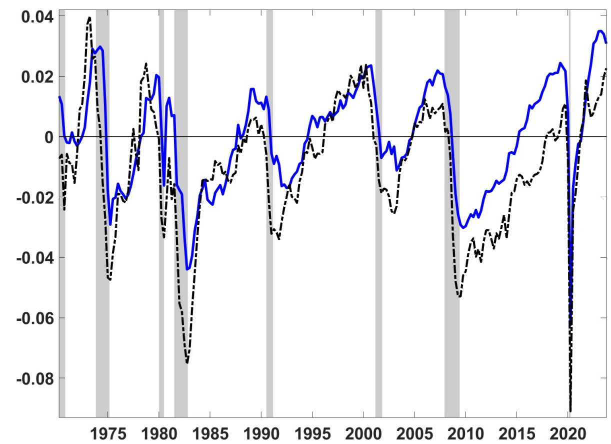


(c) United Kingdom

Figure 1 presents our estimates of the output gap along with the 95% credible sets. The corresponding values of the shrinkage parameter λ are 0.12 for Germany, 0.08 for the U.S., and 0.13 for the U.K.



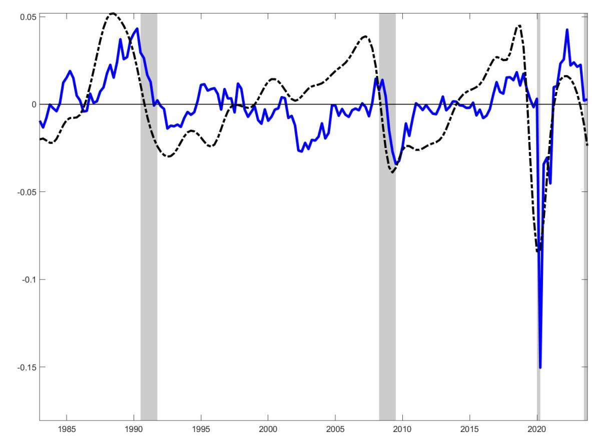
(a) Germany



(b) United States

Figure 2: Comparison with reference output gaps.

Blue lines indicate our estimates. Black lines indicate production function-based output gaps and are taken from the CBO (U.S.), the SVR (Germany), and AMECO (U.K.). SVR and AMECO gaps are only available at annual frequency. We therefore apply cubic spline interpolation to render them comparable to our quarterly estimates.



(c) United Kingdom

We consider our output gap estimates to be reliable across all three countries, as they exhibit pronounced declines at commonly known recession dates and closely align in their qualitative dynamics with production-function based reference estimates from the CBO (U.S.), the SVR (Germany), and AMECO (U.K.), as shown in figure 2.[9]

However, in specific periods, particularly around peaks and troughs, our estimates tend to display lower amplitude. This reflects the tendency of our approach to attribute a greater share of GDP growth fluctuations to potential output—a pattern also observed in Morley & Wong (2020). While this may appear surprising, given that our multivariate BN–based output gap can be interpreted as an empirical approximation to the macroeconomic production function (Berger & Ochsner 2022), the divergence from reference estimates is likely due to the agnostic nature of what constitutes a production factor in our framework.

[9] The reference output gaps for Germany and the U.K. are only available at annual frequency. We therefore apply cubic spline interpolation to render them comparable to our quarterly estimates.

To illustrate the potential divergence between a production factor in a production function and in our approach, consider the COVID-19 recession in the first half of 2020. Our estimated output gap changes in Germany and the U.K. during this period are notably smaller than the observed drop in actual GDP, implying that a considerable portion of the decline is attributed to potential output. Moreover, our potential output estimates for these countries recover more slowly than actual GDP, leading to substantial overheating in the post-pandemic period.[10]

The pandemic induced several unusual supply-side constraints through shortages of specific goods and sector reallocations. For example, the shutdown of oil and gas fields during the initial lockdown period reduced energy supply for years, contributing to sharply rising prices even before the Russian-Ukrainian War. Similar effects were observed for other natural resources as well as for intermediate goods, due to global supply chain disruptions (see, e.g., Bonadio et al. 2021), and even in some consumer product markets, such as vehicles (Bernanke & Blanchard 2023). Although these shocks may not have directly reduced the availability of the primary production factors – capital and labor—they clearly exerted negative and persistent effects on aggregate supply. This observation is related to the rationale for conditioning output gap estimates on financial variables: in crises other than the pandemic, the financial sector could similarly constrain aggregate supply.

However, the pandemic also generated substantial shocks affecting labor supply. Brinca et al. (2021) attribute the majority of the pandemic-induced drop in U.S. employment to labor supply rather than demand factors. Carrillo-Tudela et al. (2023) analyze sectoral labor reallocation in the U.K., which likely entailed significant adjustment costs. In addition, Faberman et al. (2022) provide evidence of a persistent decline in desired working hours in the U.S., lasting through the end of 2021, indicating a sustained reduction in labor supply more than a year after the recession in 2020:II.

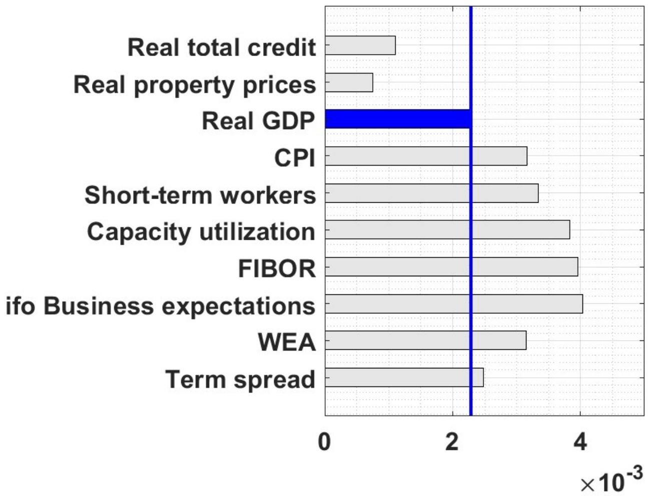
In light of this evidence, we consider a pandemic-induced decline in potential output to be realistic. This is in contrast to Morley et al. (2023), who argue that the sharp rebound in actual GDP implies that the 2020:II dip was largely transitory and should therefore be attributed mostly to the output gap rather than to a decline in potential output.

Informational contributions

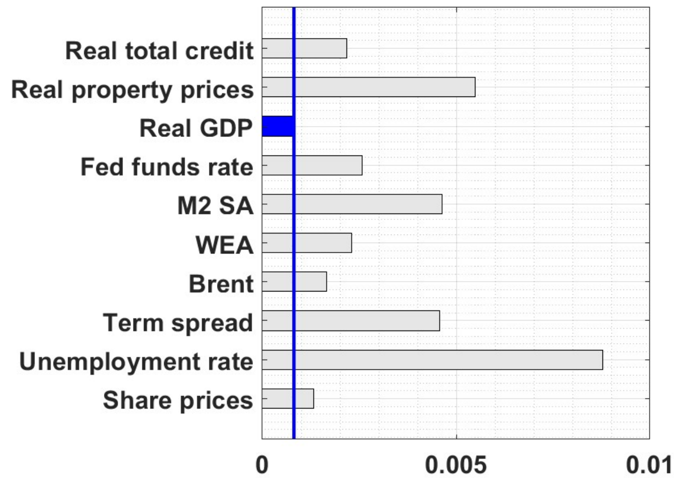
Following Morley & Wong (2020), Berger, Richter & Wong (2022) and Berger & Ochsner (2022), we compute the informational contributions to shed light on the relevance of specific variables for the estimation of the output gap, particularly the relative importance of credit and property prices. Informational contributions quantify how much each variable's forecast errors contribute to the standard deviation of the estimated output gap. Figure 3 displays the results.

Strikingly, GDP exhibits the lowest contribution to its own cyclical component in both the U.S. and the U.K., and is also surpassed by all non-financial variables in Germany. This finding supports the interpretation of the business cycle as the outcome of a broad set of dynamically interacting variables, rather than a single, self-reinforcing cycle. At the same time, it underscores the informational value added by the multivariate approach in capturing the underlying drivers of business cycle fluctuations.

[10]We also find substantial overheating in the U.S., but this is less controversial due to the high growth rates at that time.



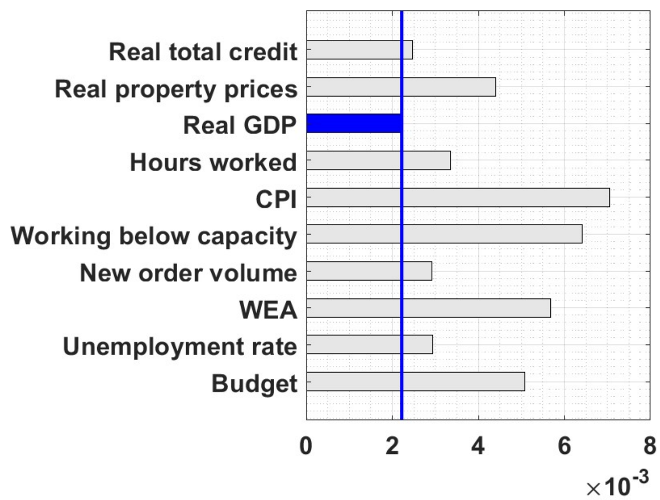
(a) Germany



(b) United States

Figure 3: Informational contributions for output gaps.

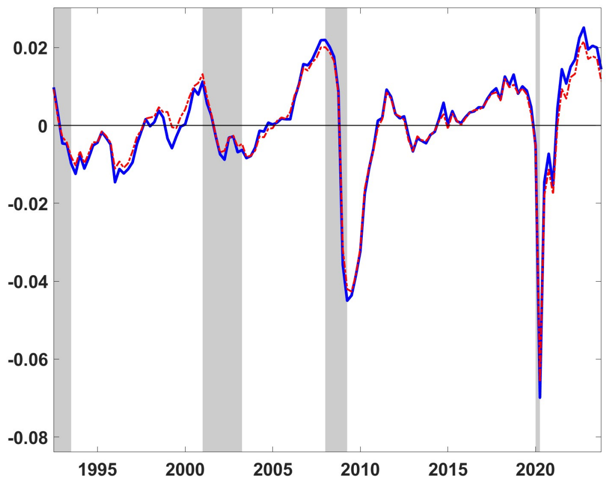
Values indicate each variable's contribution to the standard deviation of the output gap. The displayed variables represent the complete set selected for each country.



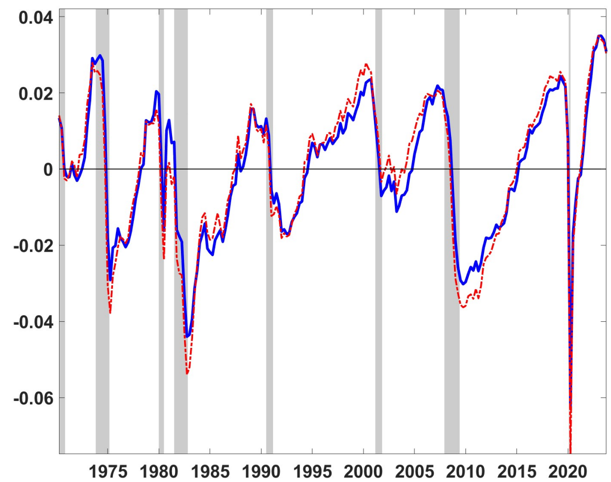
(c) United Kingdom

Turning to the financial variables, we observe notable cross-country differences. In Germany, they play by far the least important role among all variables, in line with the well-documented low movements in Germany's financial cycle(s) (Oman 2019, Rünstler & Vlekke 2018). Accordingly, reestimating the output gap without financial variables yields results that differ from the baseline only within the range of statistical noise, which becomes apparent when looking at figure 4.

By contrast, both credit and property prices exhibit relevant contributions to the output gap estimates in the U.S. and the U.K., with property prices being more important than credit in both countries. In the U.S., property prices rank second among all variables, surpassed only by the unemployment rate. A subsequently conducted historical information decomposition shows that their contributions mostly emerge during the Great Recession and the preceding boom (see also figure 6). While this pattern might initially appear to confirm the informational value of financial variables for



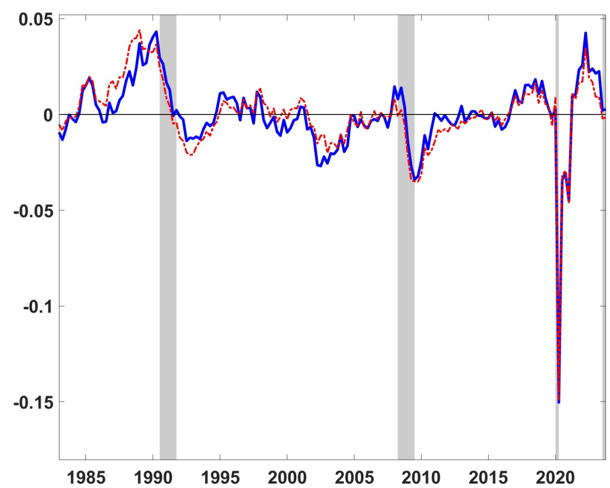
(a) Germany



(b) United States

Figure 4: Comparison of baseline output gaps with output gaps estimated without financials.

Blue lines indicate the baseline estimates based on the full set of selected variables. Red lines show estimates using the same specification but excluding real credit and real property prices.



(c) United Kingdom

output gap estimation – both in signaling a possible overestimation of potential output prior to the Great Recession (Borio et al. 2017, Berger, Richter & Wong 2022) and in capturing its depth and persistence (Borio et al. 2017) – our estimation without credit and property prices does not support this conclusion. Instead, the extent of the pre-crisis overheating remains unchanged. Moreover, excluding financial variables leads to an output gap fluctuating around zero during the 9/11 recession and an even deeper slump during the GFC.[11] The contributions previously attributed to property prices are absorbed by other variables. Specifically, World Economic Activity takes on a larger role during the pre-crisis boom, while the unemployment rate accounts for a greater share during the Great Re-

[11]These differences are driven by an increasing λ, as larger values of λ generally tend to increase the amplitude of the cyclical component in our model.

cession, consistent with the findings of Morley & Wong (2020) (for more details, see figure 15 in the appendix C). However, we note that the substantial contribution of property prices – when included – is consistent with the findings of Winter et al. (2022), who document that GDP and property prices share a medium-term cyclical component in the U.S.

Again looking at figure 4, the differences for the U.K. are also negligible. The reestimated output gap without financial variables closely resembles the baseline estimate, with no economically meaningful deviations. Although the output gap prior to the Great Recession declines slightly, we are cautious in assigning interpretative weight to this isolated result, given the broader pattern of our results.

Country-specific results – Germany

The German variable set favored by our model selection approach features primarily indicators related to either monetary policy and prices as well as industrial activity. The contribution of short-term work – our only selected labor market variable – is largely confined to the pandemic period and its aftermath, when short-term work as a policy instrument was extended to the service sector. While these findings appear plausible given the rigidities of the German labor market and the economy's relatively high industrial share, it is noteworthy that Berger & Ochsner (2022), using a mixed-frequency approach, select a markedly different set of variables yet arrive at broadly similar results. Just as when comparing our baseline output gaps with those estimated without financials (see figure 4), this suggests that very different sets of variables can convey similar informational content.

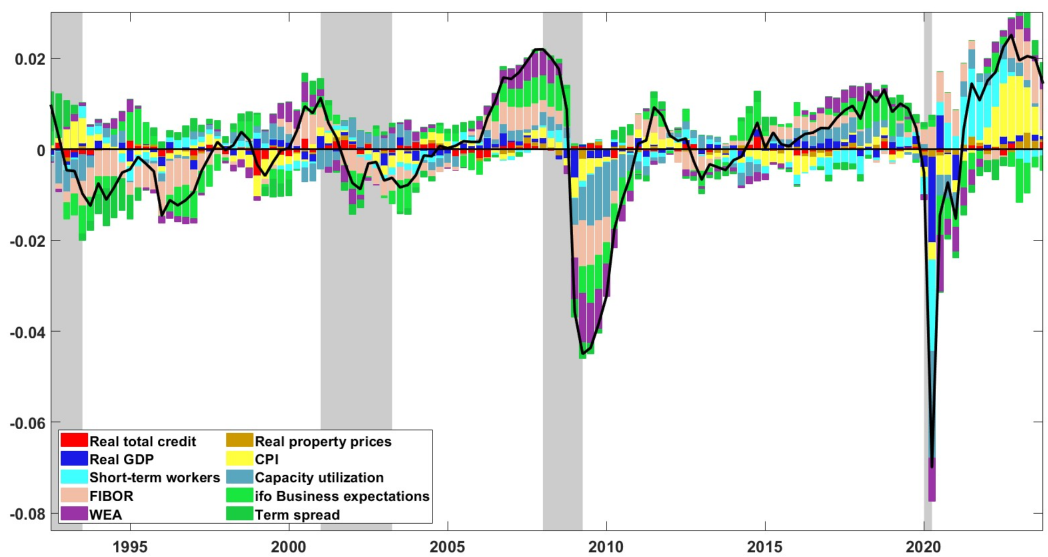


Figure 5: Informational decomposition of the German output gap.

Aside from the post-pandemic overheating discussed above, the most notable deviation from the SVR's output gap estimate arises during the early 2000 slump, where results across studies differ substantially. While the SVR identifies pronounced overheating around the turn of the millennium, followed by an output gap close to zero, Quast & Wolters (2022) report a less amplified boom but a substantially negative output gap thereafter. In yet another study, Berger & Ochsner (2022) find surprisingly persistent overheating until 2005, largely attributed to variables related to external economic relations.

Our informational decomposition reveals that contributions from different variables during this period point in diverging directions. While this decomposition does not permit causal interpretation, we interpret this heterogeneity – when considered alongside the literature – as indicative of the underlying complexity of the early 2000s. Several distinct forces have been investigated as potential drivers for the weak economic performance during this period: negative international spillovers from the U.S. (Eickmeier 2007), a unified Eurozone monetary policy stance that may have been overly contractionary for Germany (Hayo & Hofmann 2006), and a prolonged structural crisis in the German labor market (Rinne & Zimmermann 2013).

Country-specific results – United States

The variable set selected for the United States closely mirrors the structure of a stylized macroeconomic model. It includes monetary policy indicators, the oil price – commonly interpreted as a supply-side shock – the unemployment rate as a key measure of labor market conditions, and property prices, which are particularly important in the U.S. context (Leamer 2007).

However, similar to the German case, we find that the model's results are not particularly sensitive to the inclusion of specific variables, except the unemployment rate, for which an outstanding role is well-documented in the literature (Morley & Wong 2020, Berger et al. 2023).

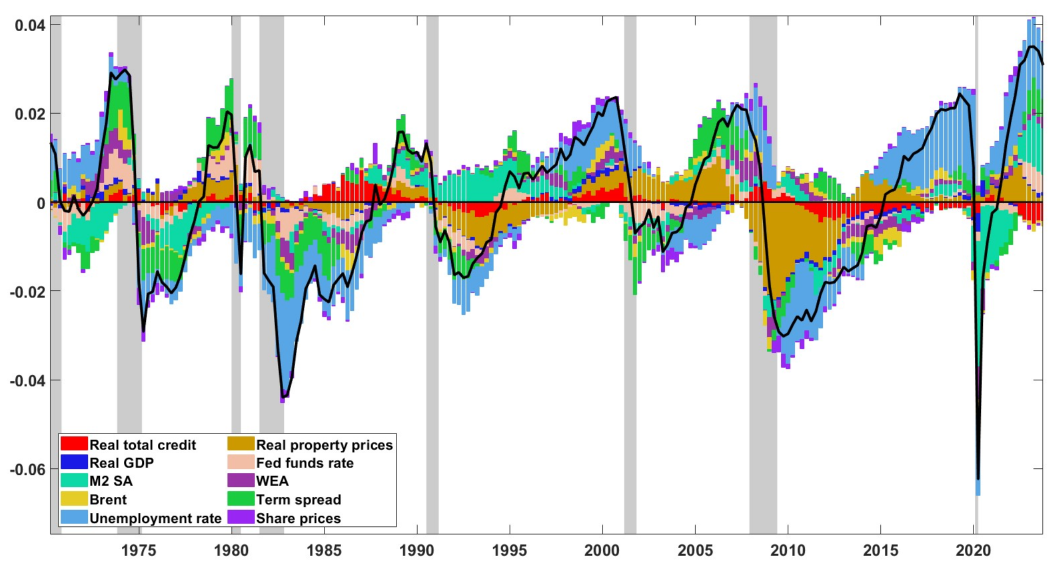


Figure 6: Informational decomposition of the U.S. output gap.

Country-specific results – United Kingdom

Among the three countries, the U.K.'s output gap exhibits the largest positive gaps (approximately 4.3% in 1990:II and 2022:II) and the most negative gap in 2020:II (–15%). However, these extremes are associated with idiosyncratic events, and the output gap generally remains relatively flat in the intervening periods. Although this finding contrasts with the AMECO output gap, which indicates substantial overheating prior to both the GFC and the COVID-19 pandemic, we consider our results plausible. The U.K.'s growth has historically been underpinned by relatively stable expansions in the service sector and labor supply.

As in the German case, the most notable feature of our U.K. output gap estimate emerges during the early 2000s, when we find relatively large negative values, absent in both the AMECO gap and much of the existing literature (Rünstler & Vlekke 2018, Quast & Wolters 2022). Notably, GDP growth during this period was consistently positive, and the output gap estimated by Quast & Wolters (2022) is also positive. In our model, however, the negative values are primarily driven by negative contributions of working below capacity, a measure related to capacity utilization in the industrial sector. Given the rapid expansion of industrial output from 2006 onwards, our estimates may reflect that industrial production could have been operating below its potential earlier in the decade.

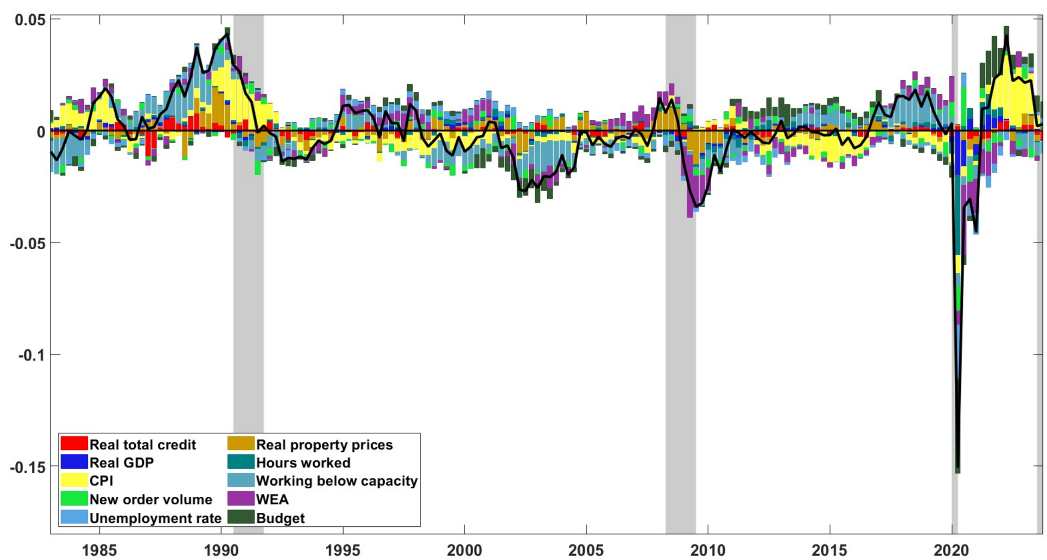


Figure 7: Informational decomposition of the U.K.'s output gap.

5.2 Financial cycles

In order to derive our financial cycle estimates, we use a separate model for each country, in which both the shrinkage parameter (λ) and the set of conditioning variables are selected based on a weighted average of one-step-ahead forecast errors for credit and property prices – rather than for GDP, as in the approach of Berger, Richter & Wong (2022). While this departs from the idea of extracting business and financial cycles from a unified model, it results in more meaningful representations of financial cycles.[12]

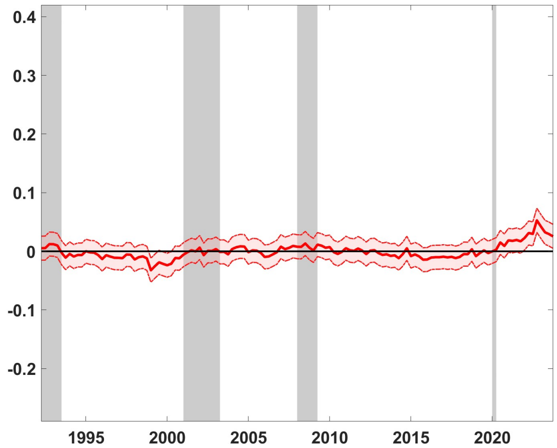
The variables selected for our financial cycle model differ from those used in the output gap model, as does the value of the shrinkage parameter λ – particularly in the case of the U.S., with a value of 0.30. This is substantially higher than the corresponding value in the output gap model ($\lambda = 0.08$) and results in a noticeably greater cycle amplitude.[13] For Germany and the U.K., the differences are more moderate, with $\lambda = 0.13$ and $\lambda = 0.16$, respectively.

Our estimated financial cycles exhibit key characteristics consistent with findings in the existing literature. The German cycles are exceptionally flat, with credit in particular showing a very small amplitude. The property price cycle, by contrast, displays a pronounced peak in the post-pandemic period – a time typically not associated with financial distress, but marked by significant real-economy disruptions in Germany. According to our conditioning model, given the prevailing post-pandemic economic conditions, the observed level of property prices appears substantially higher than what would be expected given the model's information about the overall stance of the German economy.

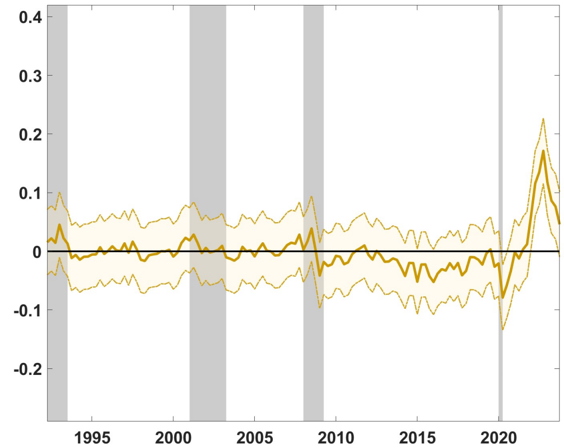
For the U.S., our estimates broadly resemble the qualitative dynamics reported by Berger, Richter & Wong (2022), but differ in amplitude. In particular – and consistent with the results from the unobserved components model of Rünstler & Vlekke (2018) – the peak in property prices during the GFC is substantially larger than all other observed peaks, and also significantly higher than for the estimate of Berger, Richter & Wong (2022).[14] This discrepancy is likely attributable to differences in the selected variable set and the choice of λ, and it underscores the exceptional nature of the U.S. housing bubble preceding the GFC. Similarly, our estimated credit cycle follows a pattern qualitatively similar to that in Berger, Richter & Wong (2022), but exhibits somewhat higher peaks.

Finally, and again consistent with Rünstler & Vlekke (2018), we find that in the U.K., credit and property price cycles follow closely aligned trajectories, with property prices exhibiting somewhat larger peaks. In contrast to the U.S., the GFC-related peak in U.K. property prices is less pronounced and not clearly distinguishable from the peak observed during the late-1980s boom. Similar to the case of Germany, we also observe large positive cyclical components in both financial variables following the COVID-19 pandemic – developments that appear unrelated to financial distress.

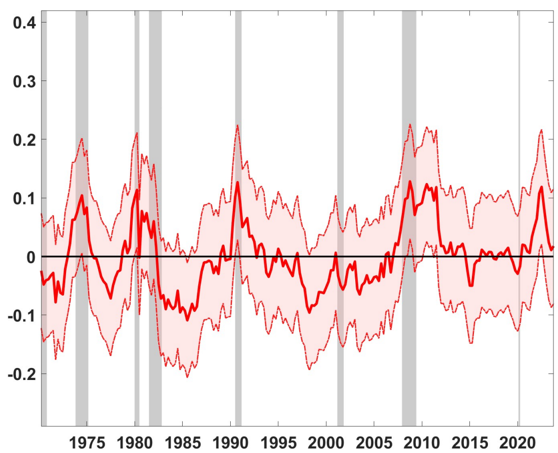
[12]For a more comprehensive justification of our approach, see section 3.3.
[13]We provide the financial cycle estimates implied by our output gap model in appendix D.
[14]Interestingly, the peak is around 0.3 and thus close to the estimate of Rünstler & Vlekke (2018).



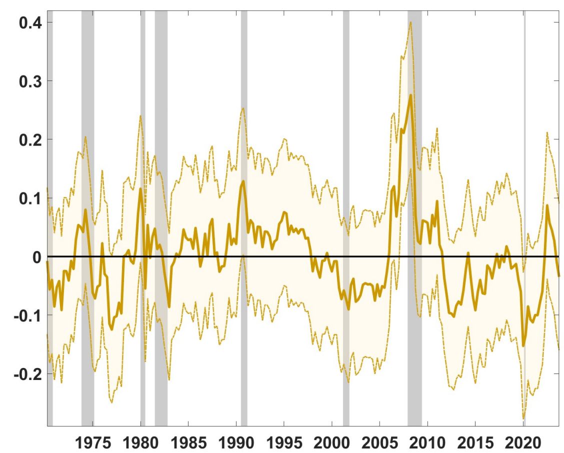
(a) Germany – Credit cycle



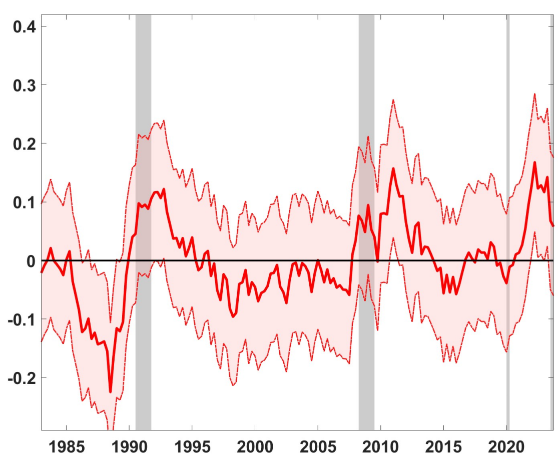
(b) Germany – Property price cycle



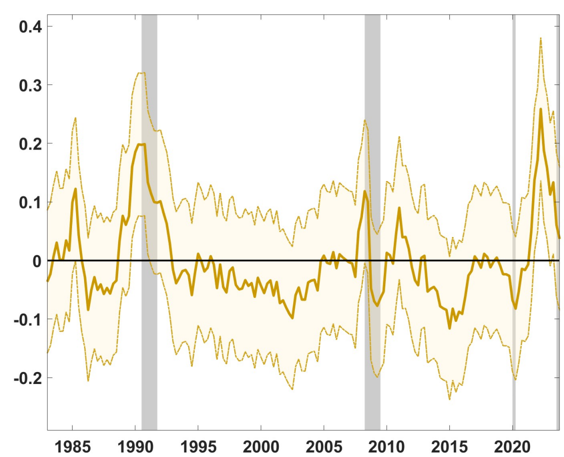
(c) U.S. – Credit cycle



(d) U.S. – Property price cycle

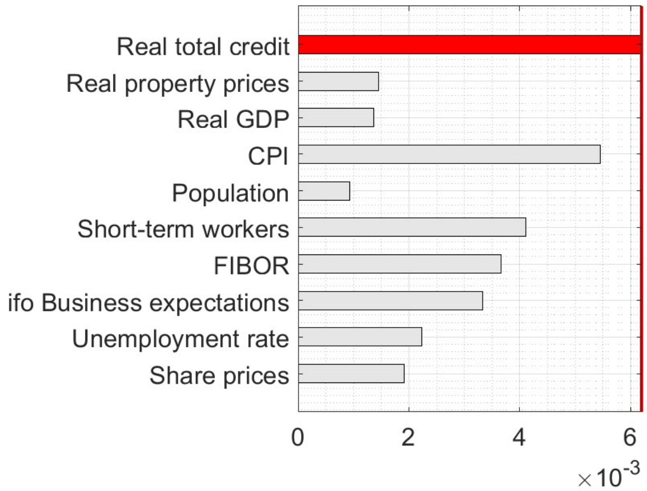


(e) U.K. – Credit cycle

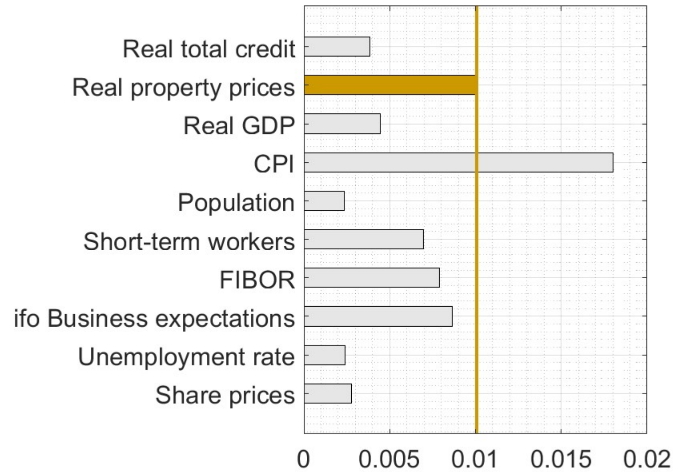


(f) U.K. – Property price cycle

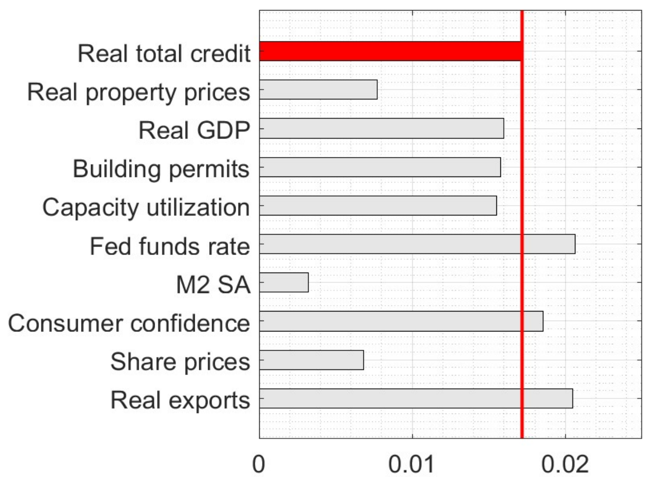
Figure 8: Estimated credit and property price cycles in Germany, the United States and the United Kingdom.



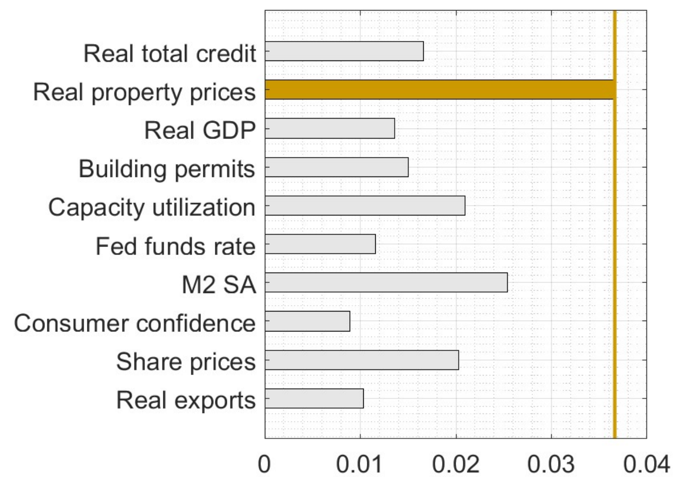
(a) Germany – Credit cycle



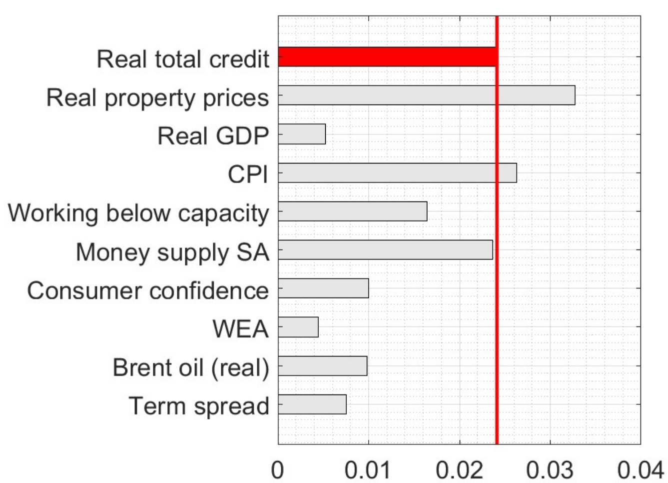
(b) Germany – Property price cycle



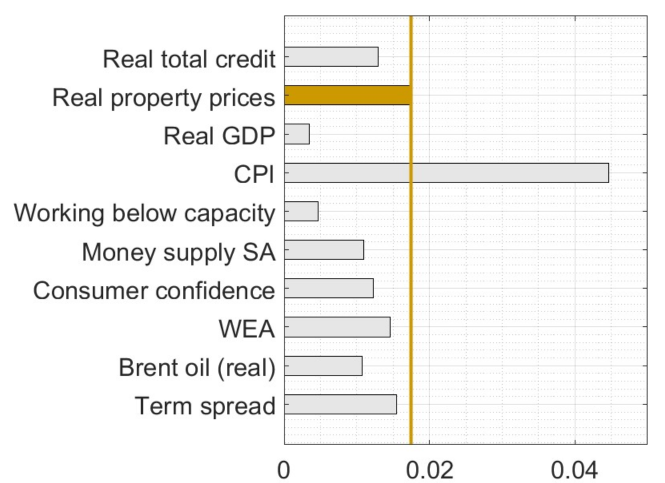
(c) U.S. – Credit cycle



(d) U.S. – Property price cycle



(e) U.K. – Credit cycle



(f) U.K. – Property price cycle

Figure 9: Informational contributions to credit and property price cycles.

Informational contributions

Figure 9 presents the contributions of each variable to the standard deviation of the respective financial cycle. In contrast to the output gap, financial variables account for a significantly larger share of their respective cycle's variation – particularly in the case of property prices – than GDP does for its cycle. Additionally, the CPI, which indirectly affects both financial variables (as they are expressed in real terms), emerges as the most influential variable for property prices and the second-most for credit in both Germany and the U.K.[15]

Further note the dominant contribution of real property prices to their own cyclical component in the U.S., which suggests strong self-reinforcing dynamics in the U.S. housing market.[16] By contrast, credit cycles in the U.S. appear to be influenced by a broader set of variables. In the U.K., property prices contribute substantially to the credit cycle, aligning with the visual similarity observed between the two cyclical components in figure 8.

Interpretation of financial cycles from the BN decomposition

A detailed analysis of our financial cycle estimates raises important questions regarding their interpretation. For instance, we identify the turning point of the U.S. property cycle at the end of 2005, reaching zero in 2006:I – precisely when property prices were at their pre-GFC peak. Thereafter, as property prices began to decline, the cyclical component turned strongly positive. A similar pattern is observed in Germany, where property prices peaked in 2021:IV. In the same quarter, the cyclical component turned positive, followed by a pronounced overshoot despite falling property prices.

These are not isolated anomalies but rather typical patterns in our financial cycle estimates. During periods of strong financial expansion, the cyclical components tend to be negative. Once such growth phases end, the cycles frequently switch to positive values. Moreover, whereas Drehmann et al. (2012) and Borio (2014) find that financial cycles typically peak prior to recessions, our estimates often show peaks occurring during recessions (see figure 8), in line with Berger, Richter & Wong (2022).

To better understand the nature of these cycles, we compare them to financial cycle estimates based on the CF filter. Figure 10 presents the graphical comparison, while table 2 reports the correlations. The CF-based cycles clearly move in opposite directions compared to our estimates, and the correlations are accordingly negative and large.

	Germany	**United States**	**United Kingdom**
Credit	-0.45	-0.63	-0.71
Property prices	-0.59	-0.67	-0.36

Table 2: Correlation with cycles obtained from Christiano-Fitzgerald Filter.

[15]Strictly speaking, we deflate the financial variables using the GDP deflator. However, the CPI and the GDP deflator are highly correlated and carry similar information content.

[16]An example of such dynamics at the micro level is provided by Armona et al. (2019), who find that households do not expect long-term property price growth to be mean-reverting, thus potentially reinforcing existing price trends.

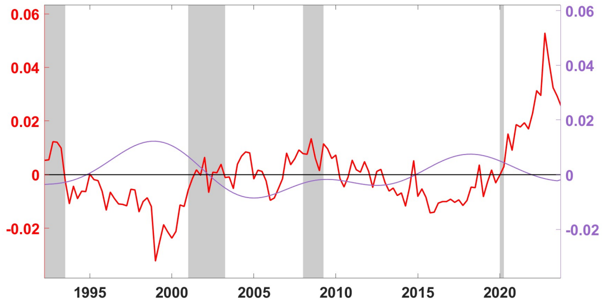
These results suggest that BN-based financial cycles, conditioned on multivariate information, should not be interpreted as indicators of systemic risk in the conventional sense. Instead, we argue that they reflect *financial overhang* – the misalignment between current financial conditions and their evolving long-term expectations given the current economic information. During financial build-ups and economic booms, the trend components of credit and property prices – i.e., their long-term conditional expectations – tend to increase at the same pace or even faster than the observed variables themselves, as their recent history contains little information on the potential limits of the boom.[17] This leads to the counterintuitive feature that negative cyclical values – rather than positive ones – signal increasing systemic risk. When a boom is ended by a shock (such as in case of the US housing bust, which is often attributed to increasing interest rates in 2006, see e. g. Brunnermeier & Schnabel 2015), the trend component adjusts downwards as the included variables, and thus the conditional long-run expectation of the respective target variable, have been shifted by the shock. However, the financial indicators often fail to decline as quickly, due to frictions such as the missing ability of households or firms to reduce their debt or excess market liquidity sustaining elevated property prices.

This interpretation also helps to explain the post-pandemic overshoots in our financial cycles, which are particularly pronounced in Germany and the U.K. and are primarily driven by large forecast errors in inflation – but are not associated with financial distress rooted in the financial system. Since inflation reduced their real values, our model simply suggests that credit and property prices should have declined more sharply than they actually did. In addition, the economic downturns observed in Germany and the U.K. – but not in the U.S. – may have further lowered long-term expectations regarding sustainable levels of debt and property prices under current economic information.

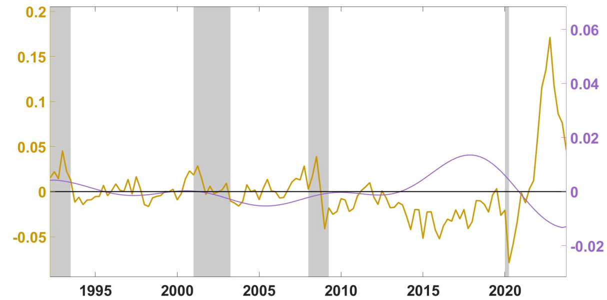
To assess whether BN-based financial cycles are useful for measuring systemic risk, a real-time estimation is required. For the output gap, Berger & Ochsner (2022) and Berger et al. (2023) show that the multivariate BN cycle performs well in real time at least within a mixed-frequency model. However, even if this held for financial cycles, our results would not suggest that BN-based estimates would outperform CF-based cycles in predicting financial crises.

Instead, we view our interpretation of BN-based financial cycles as measures of financial overhang – rather than systemic risk – as a more promising avenue for their usage and future research. For example, Klein (2017) and Bernardini & Peersman (2018) examine the role of credit overhang in amplifying fiscal multipliers, illustrating the broader macroeconomic relevance of financial imbalances beyond the context of systemic crisis prediction.

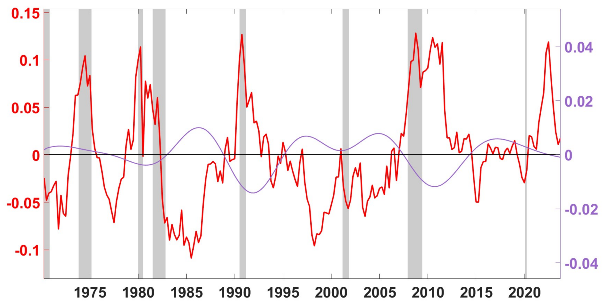
[17] The trend components can be found in appendix B.



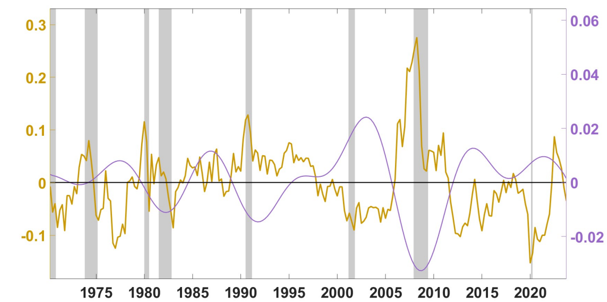
(a) Germany – Credit cycle comparison with CF



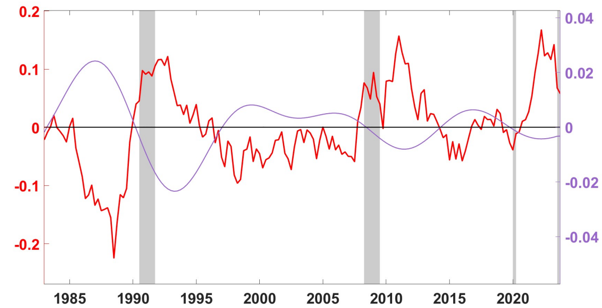
(b) Germany – Property price cycle comparison with CF



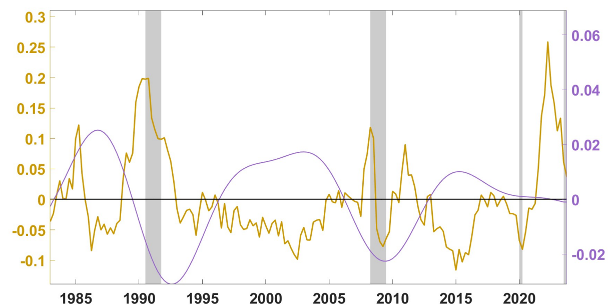
(c) U.S. – Credit cycle comparison with CF



(d) U.S. – Property price cycle comparison with CF



(e) U.K. – Credit cycle comparison with CF



(f) U.K. – Property price cycle comparison with CF

Figure 10: Comparison of our estimates with financial cycles obtained from a Christiano-Fitzgerald filter calibrated for frequencies from 8 to 30 years.

6 Conclusion

We extend the work of Berger, Richter & Wong (2022), who estimate the output gap as well as credit and property price cycles for the U.S. using the Beveridge & Nelson (1981) decomposition, conditioned on a Bayesian VAR, in three key ways – all aimed at producing more realistic financial cycles and offering new insights into their interpretation. First, we employ a cross-country sample including Germany, the U.S., and the U.K., which enables comparative analysis and a better understanding of the characteristics of BN-based financial cycles. Second, we use a smaller sample comprising ten variables in the spirit of Morley & Wong (2020) to limit estimation error and the required degree of prior shrinkage. Third, we do not rely on a single VAR specification for estimating both the output gap and the financial cycles of a country. Our cross-country analysis shows that doing so can lead to artificially low or high financial cycle amplitudes, driven by the degree of prior shrinkage, which plays a crucial role in determining the amplitude of the cyclical components in the BN framework (Morley & Wong 2020). Instead, for each country, we estimate two distinct models, each with its own shrinkage parameter, obtained from minimizing a one-step-ahead loss function of the respective target variables.

Our approach indeed changes the amplitude of financial cycles in the U.S. compared to Berger, Richter & Wong (2022), while retaining their qualitative characteristics: the amplitude of the credit cycle generally increases and the peak in property prices related to the GFC is considerably more pronounced in our work, aligning with the exceptional boom-bust dynamics in the housing market during the 2000s. The relative amplitudes in all countries as well as the periods in which peaks and troughs can be observed also align closely with results of Rünstler & Vlekke (2018), who use a multivariate unobserved components model.

However, the timing of BN-based financial cycles differs notably from that commonly reported in the literature. In particular, we observe large positive cyclical components following a bust, rather than preceding it – and vice versa for negative components. Moreover, we find a strong negative correlation between the BN-based cycles and those obtained using the Christiano & Fitzgerald (2003) filter calibrated to medium-term frequencies. This highlights a key interpretational difference: BN-based financial cycles should be interpreted in reverse relative to cycles filtered using conventional methods. In the BN framework, large positive values in credit or property price cycles indicate that the respective variable is excessively high given current economic conditions – suggesting a credit or property price "overhang." Such an overhang reflects a financial constraint on the economy, stemming from previously accumulated imbalances rather than the build-up of systemic risk. Conversely, negative cyclical components indicate loose financial conditions that potentially result in a bust followed by a period of financial overhang. As such, BN-based financial cycles should be viewed as complementary yardsticks of the financial state of the economy, not as competing measures to financial cycles based on conventional approaches.

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A Data

This section presents data sources. Table 3 includes variables that are obtained from the same sources for multiple countries.

Table 3: Data sources for multiple countries

Variable	**Original definition**
Real total credit	Credit to Private Non-Financial Sector, Provided by All Sectors, Unadjusted For Breaks, Market Value, National Currency. Self-deflated with implicit GDP deflator. Source: Bank for International Settlements (BIS), downloaded from Datastream.
Real property prices	Residential Property Prices, Real, Index, 2010 = 100. Source: BIS, downloaded from Datastream.
Consumer confidence	Consumer Confidence Indicator, Index. Quarterly mean of monthly data. Seasonally adjusted. Source: OECD, downloaded from Datastream.
Real effective exchange rate	Real Narrow Effective Exchange Rate Index, 2020=100. Quarterly mean of monthly data. Source: BIS, downloaded from Datastream.
World Economic Activity	Monthly World Industrial Production Index. Quarterly mean of monthly data. Source: Baumeister & Hamilton (2019).
Share prices	All Shares, Total, Share Prices : All Shares / Broad, Index, 2015=100. Quarterly mean of monthly data. Source: OECD, downloaded from Datastream.
Term spread	10Y government bond yield minus 33 month government bond yield. Own computation.
Brent oil (only for U.S. & U.K.)	Average Brent Oil Price. In current prices, self-deflated with implicit GDP deflator. Quarterly mean of monthly data. Source: The Department of Energy U.K., downloaded from Datastream.

Table 4: Data sources for Germany I

Variable	**Original definition**
Real GDP	Gross Domestic Product. Billion €, in constant prices of 2015. Calendar adjusted, seasonally adjusted. Source: Federal Statistical Office (destatis), downloaded from Datastream.
Real private consumption	Final Consumption Expenditures of Households. Billion €, in constant prices of 2015. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.
Real fixed investments	Real Gross Fixed Capital Formation. Billion €, in constant prices of 2015. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.
Real government consumption	Final Consumption Expenditures of General Government. Billion €, in constant prices of 2015. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.
Real disposable income	Disposable Income. Billion €, in constant prices of 2015. Self-deflated with implicit GDP deflator. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.
Hours worked	Absolute Hours Worked. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.
Real output per hour	Real GDP divided by hours worked. Own computation.
Consumer price index	Consumer Price Index, 2020=100. Quarterly average of monthly data. Source: destatis, downloaded from Datastream.
Population	Absolute Population. Source: destatis, downloaded from Datastream.
Building permits	Absolute Permits of Residential Buildings. Quarterly sum of monthly data. Source: destatis, downloaded from Datastream.
Short-term workers	Absolute Number of Short-Term Workers. Quarterly sum of monthly data. Source: Federal Employment Agency, downloaded from Datastream.
Industrial production	Production in Industry including Construction, 2015=100. Quarterly mean of monthly data. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.

Table 5: Data sources for Germany II

Variable	**Original definition**
Capacity utilization	Capacity Utilization based on Surveys in percentage. Calendar adjusted, seasonally adjusted. Source: ifo Institute Munich, downloaded from Datastream.
FIBOR 3M	Frankfurt Interbank Offered Rate 3 Months. Quarterly mean of monthly data. Source: European Banking Federation, downloaded from Datastream.
M3	German M3 in billion current Euros. Self-deflated with implicit GDP deflator. Quarterly mean of monthly data. Seasonally adjusted. Source: Bundesbank, downloaded from Datastream.
ifo Business expectations	ifo Business Expectations for Industry & Trade Index. Quarterly mean of monthly data. Source: ifo Institute Munich, downloaded from Datastream.
HWWI energy price index	HWWI Commodity Price Index, Energy Raw Materials, Euro Area, Index, 2020 = 100. Source: Bundesbank, downloaded from Datastream.
Unemployment rate	Unemployed Rate of Unemployed Registered, percentage. Quarterly mean of monthly data. Calendar adjusted, seasonally adjusted. Source: Bundesbank, downloaded from Datastream.
Employment	Employed in absolute numbers. Calendar adjusted, seasonally adjusted. Source: Federal Statistical Office.
Real exports	Expenditure Approach, Exports, Goods and Services, Total. Billion €, in constant prices of 2020. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.
Real imports	Expenditure Approach, Imports, Goods and Services, Total. Billion €, in constant prices of 2020. Calendar adjusted, seasonally adjusted. Source: destatis, downloaded from Datastream.

Table 6: Data sources for the United States I

Variable	**Original definition**
Real GDP	Gross Domestic Product. Billion $, in constant prices of 2017. Annualized rate, seasonally adjusted. Source: Bureau of Economic Advisors (BEA), downloaded from Datastream.
Real private consumption	Personal Consumption Expenditures. Billion $, in constant prices of 2017. Annualized rate, seasonally adjusted. Source: BEA, downloaded from Datastream.
Real fixed investments	Gross Private Domestic Investment. Billion $, in constant prices of 2017. Annualized rate, seasonally adjusted. Source: BEA, downloaded from Datastream.
Real government consumption	General Government Final Consumption Expenditure. Billion $, in constant prices of 2017. Annualized rate, seasonally adjusted. Source: BEA, downloaded from Datastream.
Real disposable income	Disposable Personal Income. Billion $, in constant prices of 2017. Annualized rate, seasonally adjusted. Source: BEA, downloaded from Datastream.
Hours worked	Source: Bureau of Labor Statistics, downloaded from FRED.
Real output per hour	Labour Productivity, Output Per Hour of All Persons, Non-Farm Business. Index, 2017=100. Annualized rate, seasonally adjusted. Source: BEA, downloaded from Datastream.
Consumer price index	Consumer Price Index, All Items. Index, 1983=100. Source: OECD, downloaded from Datastream.
Population	Population. In thousands persons. Source: BEA, downloaded from Datastream.
Building permits	Total Building Permits. In thousands. Annualized rate. Quarterly mean of monthly data. Source: Census Bureau, downloaded from Datastream.
Employment-population ratio	Emploment/Population Ratio. In percentage. Quarterly mean of monthly data. Source: Bureau of Labor Statistics, downloaded from FRED.
Industrial production	Total Industrial Production. Index, 2017=100. Seasonally adjusted. Quarterly mean of monthly data. Source: Fed, downloaded from Datastream.
Capacity utilization	Capacity Utilization Rate. In percentage. Seasonally adjusted. Quarterly mean of monthly data. Source: Fed, downloaded from Datastream.

Table 7: Data sources for the United States II

Variable	**Original definition**
Federal funds rate	Federal Funds Rate. In percentage. Quarterly mean of monthly data. Source: Fed, downloaded from Datastream.
M2	Money Supply M2. Billion $, in current prices. Quarterly mean of monthly data. Source: Fed, downloaded from Datastream.
Manufacturing new orders	Business Surveys, Manufacturing, New Orders. Seasonally adjusted. Quarterly mean of monthly data. Institute for Supply Management, downloaded from Datastream.
Unemployment rate	Unemployment Rate. In percentage. Seasonally adjusted. Quarterly mean of monthly data. Source: Bureau of Labor Statistics, downloaded from FRED.
Labor force	Civilian Labor Force. In thousands persons. Seasonally adjusted. Quarterly mean of monthly data. Source: Bureau of Labor Statistics, downloaded from FRED.
Real exports	Exports, Goods and Services. Billion $, in constant prices of 2017. Annualized rate, seasonally adjusted. Source: BEA, downloaded from Datastream.
Real imports	Imports, Goods and Services. Billion $, in constant prices of 2017. Annualized rate, seasonally adjusted. Source: BEA, downloaded from Datastream.

Table 8: Data sources for the United Kingdom I

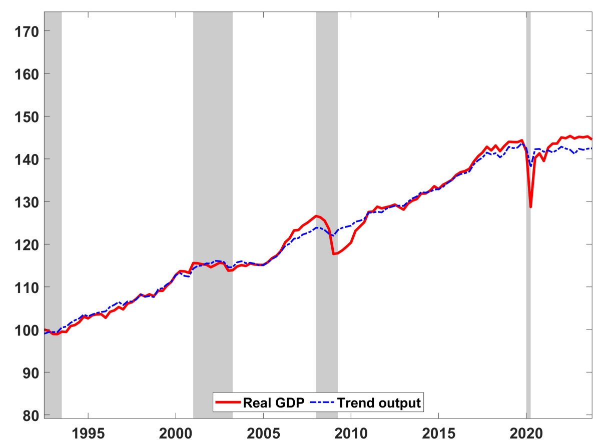
Variable	**Original definition**
Real GDP	Gross Domestic Product. Million £, in constant prices of 2022. Seasonally adjusted. Source: Office for National Statistics (ONS), downloaded from Datastream.
Real private consumption	Final Consumption Expenditure, Households and Non-Profit Institutions. Million £, in constant prices of 2022. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Real fixed investments	Gross Fixed Capital Formation. Million £, in constant prices of 2022. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Real government consumption	General Government: Final Consumption Expenditure. Million £, in constant prices of 2022. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Real disposable income	Million £, in constant prices of 2022. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Hours worked	Labor Force Survey: Total Actual Weekly Hours Worked. Million hours. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Real output per hour	Labor Productivity, Output Per Hour Worked, Whole Economy. Index, 2019=100. Seasonally adjusted. Source: ONS, downloaded from Datastram.
Consumer price index	Consumer Price Index, All Items. Index, 2015=100. Index, 2015=100. Quarterly average of monthly data. Source: OECD, downloaded from Datastream.
Population	Resident Population. In thousands persons. Source: ONS, downloaded from Datastream.
Housing new orders	New Orders, Construction, New Housing. Million £, in constant prices of 2019. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Workforce jobs	Active Population, Aged 15 and Over (Labor Force). In thousands persons. Seasonally adjusted. Source: OECD, downloaded from Datastream.

Table 9: Data sources for the United Kingdom II

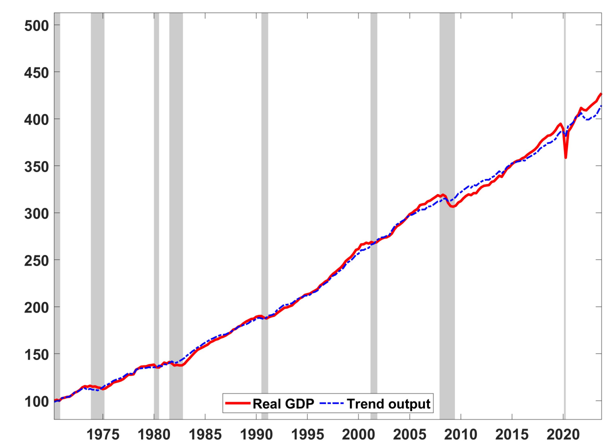
Variable	**Original definition**
Working below capacity	Business Surveys, Industrial Trends, Working Below Capacity. Percentage. Source: Confederation of British Industry (CBI), downloaded from Datastream.
Bank of England base rate	Policy/Bank Rate. Percentage. Quarterly mean of monthly data. Source: Bank of England, downloaded from Datastream.
Money supply	Money Supply, M4. Million £, in current prices. Source: Bank of England, downloaded from Datastream.
Business survey: new order volume	Business Surveys, Industrial Trends, New Order Volume Next 3 Months. Index. Source: CBI, downloaded from Datastream.
Unemployment rate	Claimant Count Rate – All. In percentage. Seasonally adjusted. Quarterly mean of monthly data. Source: ONS, downloaded from Datastream.
Labor force	Workforce Jobs, Total. Thousands persons. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Real exports	Exports, Goods and Services. Million £, in constant prices of 2022. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Real imports	Imports, Goods and Services. Million £, in constant prices of 2022. Seasonally adjusted. Source: ONS, downloaded from Datastream.
Government budget balance	General Government, Total Surplus on Current Budget. Million £, in constant prices of 2022. Source: ONS, downloaded from Datastream.

B Beveridge-Nelson trend components

The following appendix presents the Beveridge-Nelson trend components in levels along the actual time series data of the respective target variable (also included in levels). Note, that while the trend estimates for GDP (figure 11), which are our potential output estimates, are obtained from the output gap model, the trend estimates for total credit (figure 12) and property prices (figure 13) are obtained from the financial cycle model.



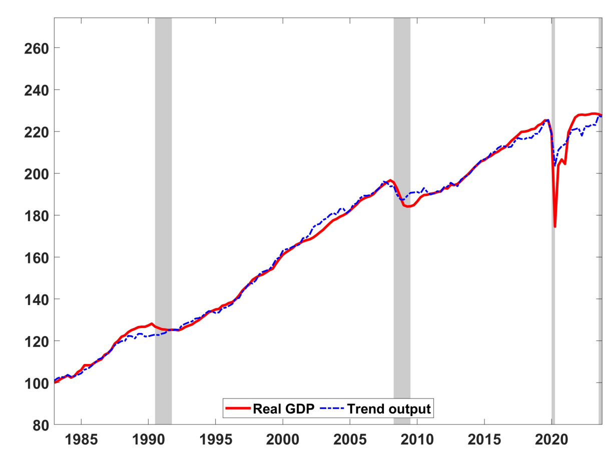
(a) Germany



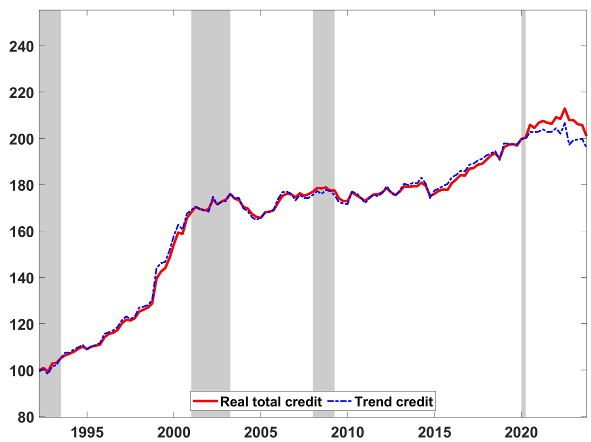
(b) United States

Figure 11: Estimated potential output levels.

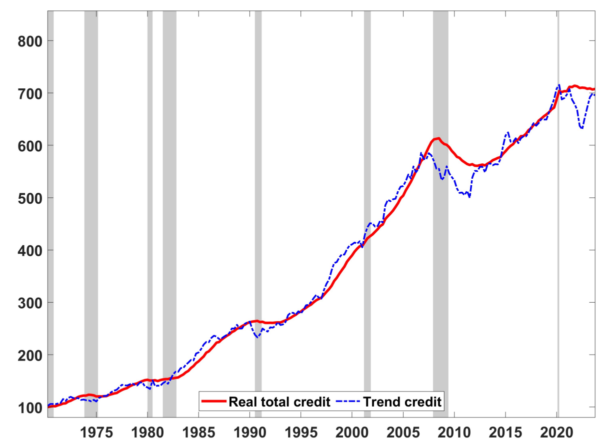
The red line marks the actual time series of GDP, the dashed blue line our potential output estimate in levels, implied by the Beveridge-Nelson decomposition of the variable in growth rates.



(c) United Kingdom



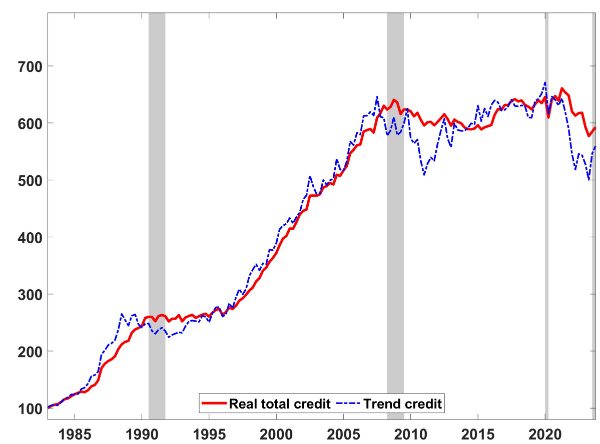
(a) Germany



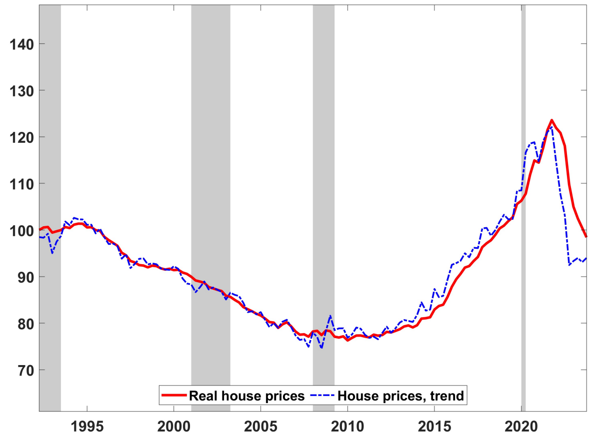
(b) United States

Figure 12: Estimated credit trends.

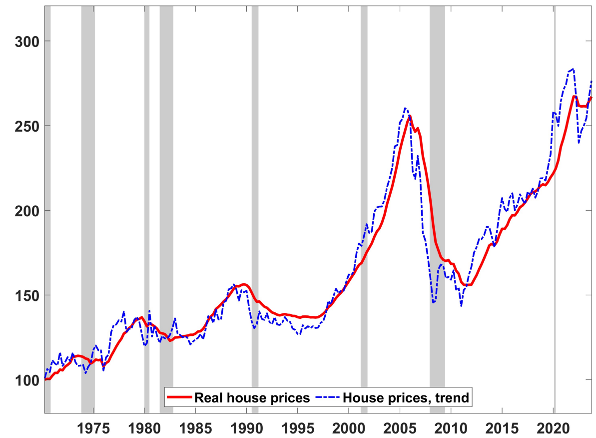
The red line marks the actual time series of total credit, the dashed blue line our trend estimate in levels, implied by the Beveridge-Nelson decomposition of the variable in growth rates.



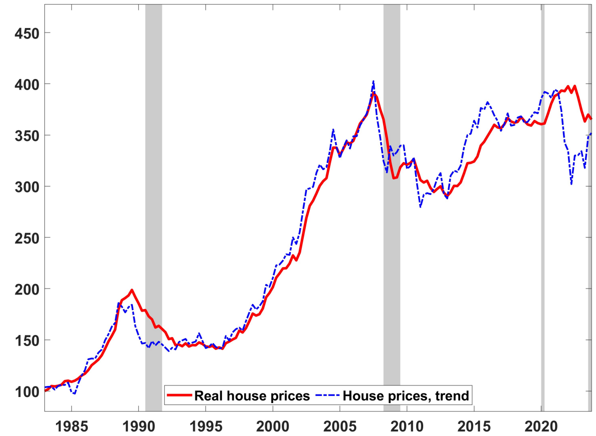
(c) United Kingdom



(a) Germany



(b) United States



(c) United Kingdom

Figure 13: Estimated property price trends.

The red line marks the actual time series of property prices, the dashed blue line our trend estimate in levels, implied by the Beveridge-Nelson decomposition of the variable in growth rates.

C Informational decompositions without financials

This section presents the informational decompositions for the output gaps estimated without real total credit and real property prices.

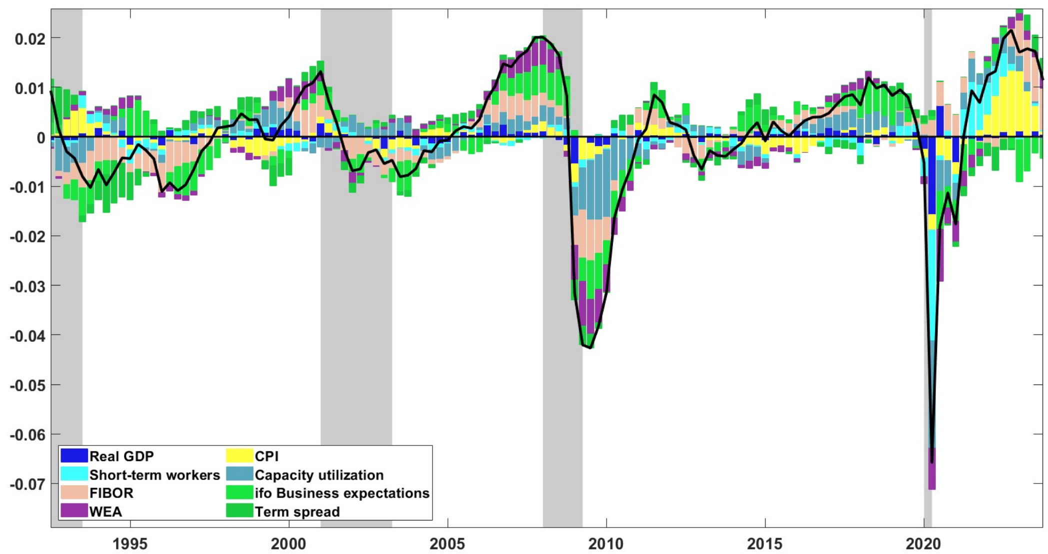


Figure 14: Informational decomposition for the German output gap without financials.

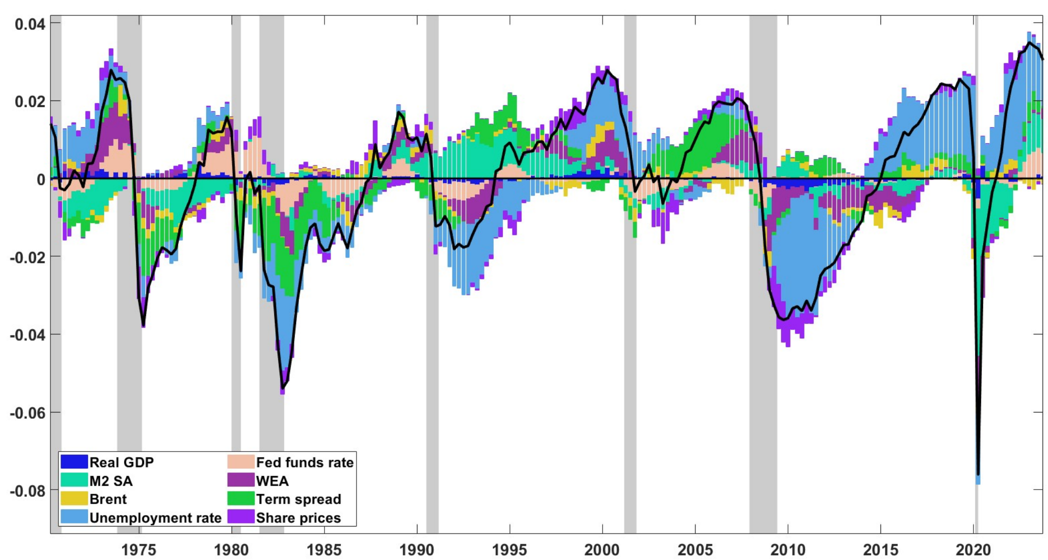


Figure 15: Informational decomposition for the U.S. output gap without financials.

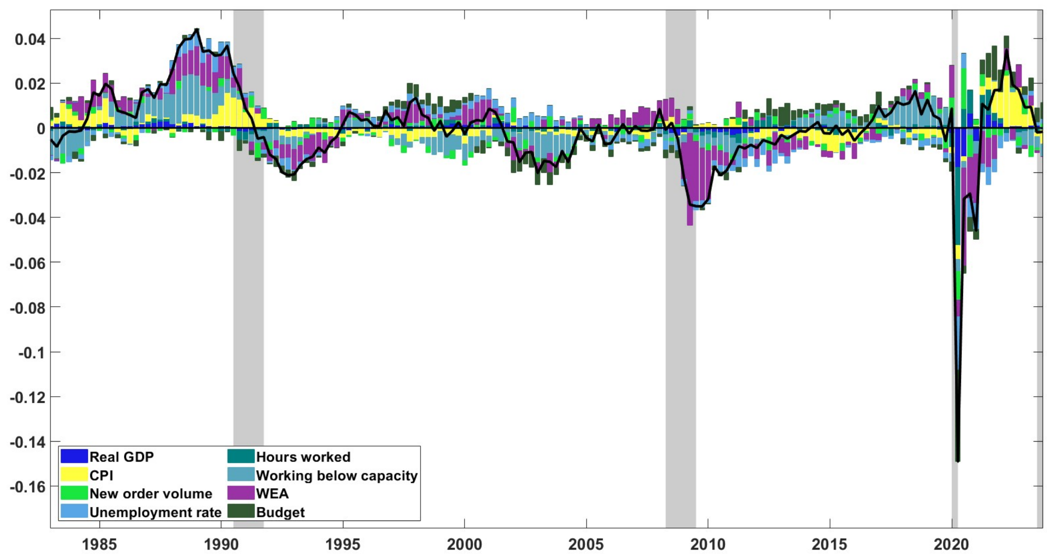
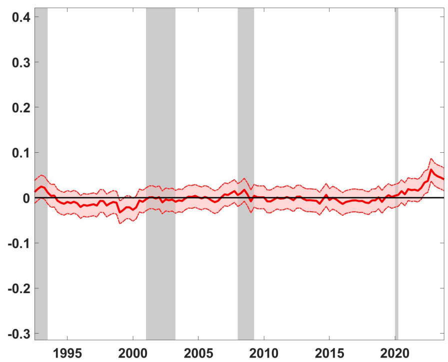


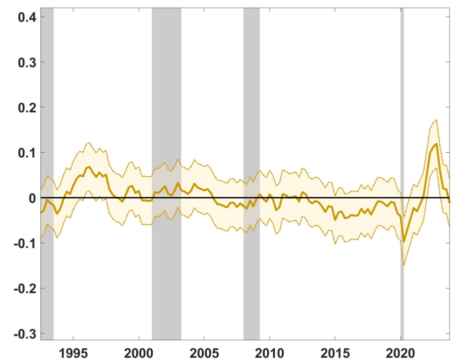
Figure 16: Informational decomposition for the U.K. output gap without financials.

D Financial cycles obtained from the output gap model

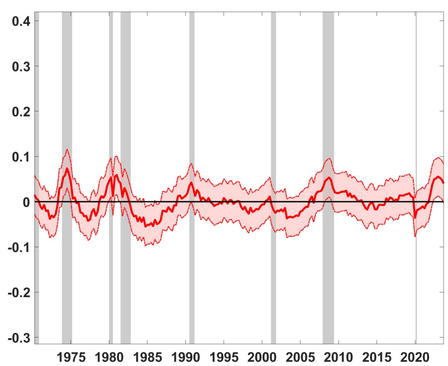
Figure 17 gives the financial cycles obtained from the output gap model.



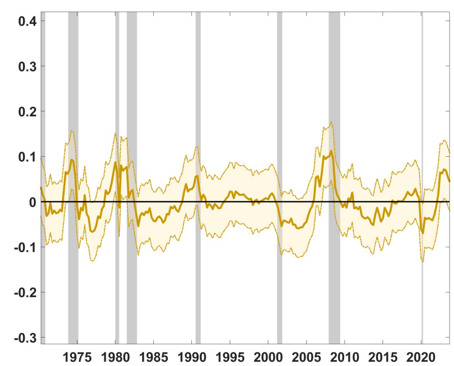
(a) Germany – Credit cycle from output gap model



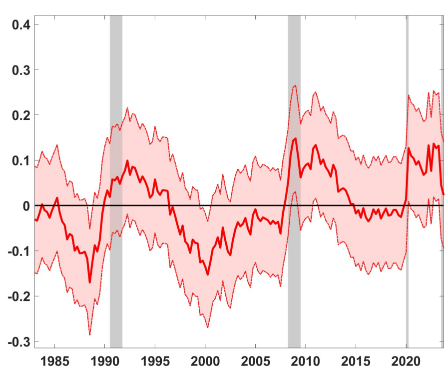
(b) Germany – Property price cycle from output gap model



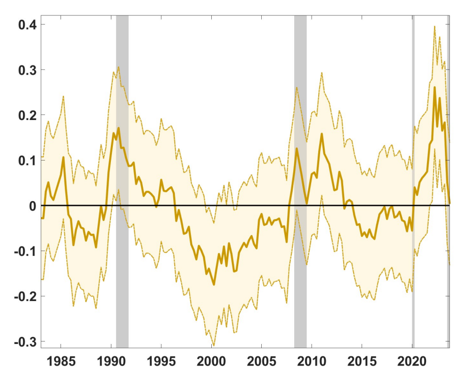
(c) U.S. – Credit cycle from output gap model



(d) U.S. – Property price cycle from output gap model



(e) U.K. – Credit cycle from output gap model



(f) U.K. – Property price cycle from output gap model

Figure 17: Estimated credit and property price cycles in Germany, the United States and the United Kingdom from the output gap model.