ifo WORKING PAPERS

370
2022

April 2022

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ifo INSTITUTE
Leibniz Institute for Economic Research
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Imprint:

ifo Working Papers
Publisher and distributor: ifo Institute – Leibniz Institute for Economic Research at the University of Munich
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An electronic version of the paper may be downloaded from the ifo website:
www.ifo.de

ifo Working Paper No. 370

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Abstract

To date, only annual information on economic activity is published for the 16 German states. In this paper, we calculate quarterly regional GDP estimates for the period between 1995 to 2020, thereby improving the regional database in Germany. The new data set will regularly be updated when quarterly economic growth for Germany becomes available. We use the new data for an in-depth business cycle analysis and find large heterogeneities in the duration and amplitudes of state-specific business cycles as well as in the degrees of cyclical concordance.

JEL code: C32; C53; E32; R11
Keywords: Regional economic activity; mixed-frequency vectorautoregression; regional business cycles; concordance; Bayesian methods

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* We wish to thank Stefan Sauer for providing us the regional survey data. The data will regularly be updated and published on the author's private homepage at https://www.robertlehmann.net/data.

1. Introduction

The sharp decline in economic activity due to the Corona-pandemic led one aspect appear crystal clear: policymaker are in need of timely available information on the economic stance to formulate appropriate policy instruments. Whereas data availability is quite satisfactory at the national level, the regional database is lacking important macroeconomic information. It is therefore hard to assess regional economic conditions in a timely manner.

Macroeconomic aggregates such as gross domestic product (GDP) are released on a quarterly basis at the national level and become available shortly after the respective quarter ends. For most advanced economies, no quarterly regional GDP exists at all. One exemplary exception is the US, where quarterly state GDP data are released approximately four months after the end of the quarter. For large European economies such as Germany, only annual information on state-specific GDP growth are available. In our paper, we fill this gap and provide quarterly GDP estimates for each of the 16 German states, together with an in-depth business cycle analysis.

In Germany, annual GDP data at the state level (NUTS-1 in the Nomenclature of Territorial Units for Statistics) are calculated by a specific working group and are released approximately one quarter after the specific year ends. So assessments on the regional economic stance on an annual basis can only be formulated with a substantial delay; more timely or even real-time assessments are, however, impossible with these data. Koop *et al.* (2020c) developed an econometric framework and published quarterly GDP data for the UK regions since 1970. In their conclusion they state (Koop *et al.*, 2020c, p. 195): "We hope that the methodology we proporse will be useful in applications beyond the UK that seeks to improve the regional database." We do so for the German case as it is an economically interesting one. First, the German states are characterized by quite heterogeneous economic structures. On the one hand, Germany consists on highly industrialized states mainly in the south of the German territory. On the other hand, strongly service-oriented states exist that, for example, focus on tourism activities or communication technologies. Second, a lot of structural change is going on across the states. For example, regions such as the Ruhr area have to develop new economic ideas as rather old technologies or industrial clusters are no longer supported. On the opposite, large and economic prospering regions exist that host headquarters of large German firms. And third, structural characteristics such as demographic indicators vary tremendously across the German states. This leads to large productivity disparities within Germany that might get even more pronounced in the future.

With our paper, we enrich the regional database in Germany and contribute to the literature on regional business cycles. We provide quarterly real GDP estimates for each of the 16 German states and the period from 1995 to 2020 based on the methodology by Koop *et al.* (2020c). They formulated a mixed-frequency vectorautoregressive model with stochastic volatility in the error term (MF-VAR-SV). In a state space representation, quarterly and unobserved regional GDP growth is linked to official annual information together with additional macroeconomic indicators and regional information. As macroeconomic indicators we add—next to quarterly German GDP—consumer price inflation, the bank rate, the exchange rate, and the oil price. To date, no comprehensive and long time series on regional indicators are available in Germany. Therefore, we had to explore other sources of regional information and use the regional business survey results of the German ifo Institute. Furthermore, the MF-VAR-SV is specified in a way that it ensures the quarterly state-specific estimates to fulfill two essential criteria. First, the quarterly estimates have to meet the annual values of regional GDP (temporal constraint). Second, the sum of quarterly state GDP has to add up to the official quarterly German value which is published by the Federal Statistical Office (cross-sectional restriction). The MF-VAR-SV is estimated with Bayesian Markov Chain Monte Carlo (MCMC) algorithms. These data are then used for an in-depth business cycle analysis that reveals quite large heterogeneities across the German states. On a regular basis—namely the publication of quarterly German GDP—the regional data will be updated and made available online to the general public.[1]

Our paper complements the existing literature on the provision of regional data. Cuevas *et al.* (2015) introduce a time series approach together with standards in national accounting to estimate quarterly GDP for the Spanish regions. Their methodology ensures that temporal and cross-sectional constraints are met, thereby taking into account the issues that arise from chain-linking. In the same vein are the UK applications by Koop *et al.* (2020b,c). They bring together vectorautoregressions with mixed-frequencies and national accounting standards. The frequency mismatch between annual and quarterly data is modeled in a state space representation by simultaneously guaranteeing that temporal and cross-sectional aggregates have to be met. Baumeister *et al.* (2022) go one step further in terms of frequency. Based on rather unconventional data such as electricity consumption, they develop a weekly indicator to track state-level economic activity in the US. Their chosen methodology is a dynamic factor model with mixed-frequencies to bring together weekly, monthly, and quarterly observations. Bokun *et al.* (2020) instead compiled a real-time dataset for the US states and use this for regional and national forecasting purposes. As the data situation at the regional level in Germany is definitely expandable, we provide one piece of the puzzle—namely quarterly real GDP—to stimulate further research for the German case in this area.

Our data also enrich the possibilities for regional forecasting analyses, especially for Germany. The regional now- and forecasting literature has developed fast in recent years and the issue becomes more interesting to the public and academic community.[2] Newer articles either exploit a factor model structure on the data (Chernis *et al.*, 2020; Gil *et al.*, 2019) or apply vector autoregressions with mixed-frequencies (Koop *et al.*, 2020a,c). The regional forecasting literature for Germany has also developed in the last decade. Earlier articles ei-

[1]The data can be accessed at the author's private homepage: `https://www.robertlehmann.net/data`.
[2]Lehmann and Wohlrabe (2014) provide an early survey on the articles published until the mid 2010s.

ther rely on panel data models for annual information due to missing quarterly observations (Kholodilin *et al.*, 2008) or on simple time series and indicator approaches applied to semi-official quarterly estimates for a small subset of German states (Henzel *et al.*, 2015; Lehmann and Wohlrabe, 2015). Newer articles apply more sophisticated approaches such as boosting (Lehmann and Wohlrabe, 2017), use mixed-frequency approaches such as MIDAS (Claudio *et al.*, 2020) and compare the latter to dynamic factor models (Kuck and Schweikert, 2021). All these articles have in common that they either focus on one single state, state aggregate (for example, Eastern Germany) or on a small subset of regional entities. Our estimates make it possible to study the performance for all 16 states simultaneously.

The paper is organized as follows. Section 2 introduces the GDP publication scheme in Germany together with a timeline of national and regional accounts. In Section 3 we present the MF-VAR-SV as well as the applied data. The quarterly regional GDP estimates together with a business cycle analysis and a short discussion are presented in Section 4. Section 5 concludes.

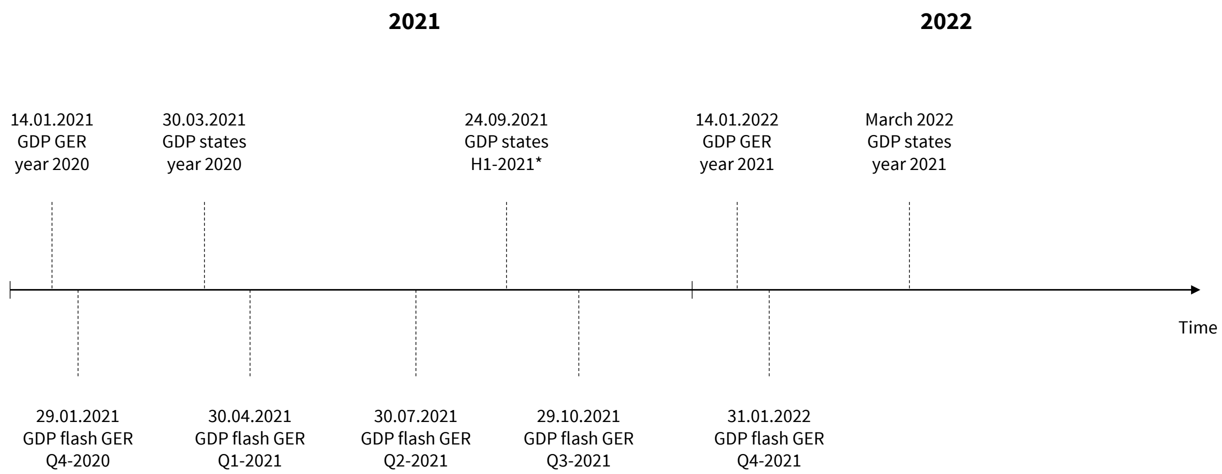
2. Background: GDP Publication Scheme

In Germany, regional national accounts data are provided by the Working Group Regional Accounts (`https://www.statistikportal.de/de/vgrdl`). This Working Group consists of the 16 Statistical Offices of the German states, the Federal Statistical Office, and the Association of German Cities; the lead management of the Working Group has the Statistical Office Baden-Wuerttemberg. In the following, we focus on the 16 German states which corresponds to the official NUTS-1-level to classify homogeneous economic units in Europe; the German districts are classified as NUTS-3 (see Table A1 in Appendix A for an overview).

The regional data include more or less the complete production, expenditure and income approach of state GDP together with selected aggregates at the district-level. Each component is coordinated and calculated by a single German state separately. The consistency with the German values is achieved by fixing the top aggregate, meaning that, for example, German GDP is not calculated as the sum of all state values. State GDPs are, on the opposite, calculated by breaking down the German value. This is either done by a bottom-up approach or by a top-down method. The first approach is characterized by a proportional allocation to the state aggregates of the delta between the state sum of GDP and the fixed German benchmark. The second method is characterized by an application of regional key indicators to break down German GDP to the regional unities. All data calculations are based on the current European System on National Accounts to ensure comparability within Germany and across Europe.

Figure 1 shows the publication timeline of national and regional accounts in Germany for the year 2021 and the first quarter of 2022. Compared to Germany, the publication of state-level GDP mainly has two disadvantages. First, only annual values are available (for example, the values for 2020 were published at March 30, 2021). For Germany, quarterly GDP flash estimates are published roughly 30 days after the end of a specific quarter (for example, the value for the third quarter of 2020 was published at October 29, 2021).[3] This first disadvantage prevents users from formulating statements on the current economic situation at the state-level. Second, values for the past year become available at the end of March of the current year, whereas the Federal Statistical Office publishes a first estimate for the German aggregate already in mid-January (for example, the 2021 value was published at January 14, 2022). Both the previously described coordination process along the calculation process of state values and a longer publication delay of regional key statistics seem to be the main reasons for this discrepancy.

Figure 1: Publication Timeline of National and Regional Accounts in Germany



Notes: The abbreviation GER stands for Germany that is classified as NUTS-0. The NUTS-1-level in Germany is represented by the 16 states. Quarters and half-years are abbreviated by Q and H, respectively. The half-year values for state-specific GDP are not revised afterwards (∗). *Sources:* Federal Statistical Office, Working Group Regional Accounts.

Today, only a very few regional statistical offices publish quarterly GDP figures to which we can compare our estimates to. For example, Baden-Wuerttemberg and Rheinland-Pfalz regularly update quarterly GDP figures on their homepages. In addition, the Halle Institute for Economic Research publishes a non-official quarterly GDP series for Eastern Germany and the ifo Institute Munich calculated quarterly GDP estimates for Sachsen. However, these examples have in common that they either base their estimates on univariate approaches or publish a quarterly series for one single state. Our approach, on the opposite, has a multivariate structure and produces consistent estimates for all 16 German states simultaneously. The following paragraph describes this multivariate approach and the data we apply.

[3]Is has to be noted that the Working Group Regional Accounts publishes GDP growth rates for the first half of a specific year at the end of September. However, these values are not revised afterwards and are therefore not comparable with upcoming publications of annual values.

3. Methodology

3.1. A Model with Mixed-Frequencies

The circumstance that we can rely on data with different frequencies and publication schemes only, calls for an empirical model that can handle these features of the data. A very popular approach is the Vectorautoregressive model with mixed-frequencies (MF-VAR). We follow the article by Koop *et al.* (2020c) that brought forward this type of model to estimate or interpolate GDP for the various regions of the United Kingdom. The main idea is to link low frequency variables to observables measured at a higher frequency, given that there is an existing relationship between both groups. In vein of Mariano and Murasawa (2010) and Schorfheide and Song (2015), the model is set out in state space form. The state equations are given by a standard VAR at the quarterly frequency and the measurement equations ensure that the accounting rules are met. Put differently, the estimated states—in our case quarterly GDP at the regional level—need to sum up to the German value and they have to add up to the observed annual values of regional GDP. Finally, the Kalman Filter is applied to fill in missing values.

Notation. We now set up the MF-VAR by strictly following Koop *et al.* (2020c). Thererfore, we use the following notational conventions:

a) $t = 1, \ldots, T$: time dimension denoting quarters

b) $r = 1, \ldots, R$: cross-section dimension defining the $R = 16$ German states

c) Y_t^{GER}: level of German GDP in quarter t

d) $y_t^{GER} = \log(Y_t^{GER}) - \log(Y_{t-1}^{GER})$: quarterly German GDP growth

e) Y_t^r: GDP level of region r in quarter t, **not observed**

f) $Y_t^{r,A} = Y_t^r + Y_{t-1}^r + Y_{t-2}^r + Y_{t-3}^r$: annual GDP of region r, only observed in the fourth quarter of each year

g) $y_t^{r,A} = \log(Y_t^{r,A}) - \log(Y_{t-4}^{r,A})$: annual GDP growth of region r, **observed** but only in the fourth quarter of each year

h) $y_t^A = \left(y_t^{1,A} \ldots y_t^{16,A}\right)'$: vector of observed annual GDP growth for all German regions

i) $y_t^r = \log(Y_t^r) - \log(Y_{t-1}^r)$: quarterly regional GDP growth, **to be estimated**

j) $y_t^Q = (y_t^1 \ldots y_t^{16})'$: vector of unobserved quarterly GDP growth for all German regions

State space form. The vector of unobserved quarterly GDP growth for all German states, y_t^Q, together with quarterly German GDP growth, y_t^{GER}, and augmented by additional exogenous predictors is modeled by a VAR.[4] The total vector of German and regional GDP, $y_t = \left(y_t^{GER}, y_t^{Q'}\right)'$, with a dimension of $n = R + 1$ is assumed to evolve as:

$$y_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i y_{t-i} + u_t\,, \quad u_t \overset{iid}{\sim} N(0, \Sigma_t)\,. \tag{1}$$

This state equation assumes some intertemporal interconnections between regional GDP and implies that quarterly German GDP growth has valuable information for the economic development of each German state and vice versa. u_t denotes the Gaussian error term with the variance-covariance-matrix Σ_t, on which we elaborate at the end of this section.

Next to the state equation in (1), we need to impose further restrictions on the system—so called measurement equations—that have to be met when estimating the unobserved quarterly growth rates for the German regions, y_t^Q. First, we are in need of a temporal constraint that links the observed annual values of regional GDP in f) and g) to the unobserved quarterly values in e) and i). And second, we have to ensure that the (weighted) sum of quarterly regional GDP meets the German value. In the following, we describe both restrictions and how we augment our system by those.

According to Mariano and Murasawa (2003, 2010), Mitchell *et al.* (2005) and Schorfheide and Song (2015) the annual growth rate of regional GDP, $y_t^{r,A}$, can be expressed as a weighted sum of the contemporaneous and lagged values of the unobserved quarterly growth rates y_t^r:

$$y_t^{r,A} = \frac{1}{4}y_t^r + \frac{1}{2}y_{t-1}^r + \frac{3}{4}y_{t-2}^r + y_{t-3}^r + \frac{3}{4}y_{t-4}^r + \frac{1}{2}y_{t-5}^r + \frac{1}{4}y_{t-6}^r\,.$$

Obviously, the first two quarters in the given year as well as the last quarter of the previous year get the highest weight for the annual growth rate. Given this linear relationship, we can define the first measurement equation for the German regions in style of Koop *et al.* (2020c):

$$y_t^A = M_t^A \Lambda^A z_t\,, \tag{2}$$

where $z_t = \left(y_t' \dots y_{t-6}'\right)'$. The matrix Λ^A contains the weights of the previously introduced temporal constraint for the annual values. With the matrix M_t^A we can control regional observables and unobservables. As $y_t^{r,A}$ is only available in the fourth quarter of each year, $M_t^A = 1$ if $t = 4$ and $M_t^A = 0$ otherwise. As emphasized by Koop *et al.* (2020c), M_t^A has an important role for real-time now- and forecasting purposes as well as to model the missing observations at the end of the data set.

[4]Following Koop *et al.* (2020c), we also add several German and regional predictors to the model. For a better readability, we skip the exogenous variables from the notation and only show the relationships across GDP figures.

The next measurement equation deals with the data structure for Germany. As we observe quarterly German GDP growth, the structure is much simpler. The link between annual and quarterly growth for Germany is modeled by:

$$y_t^{GER} = M_t^{GER} \Lambda^{GER} y_t \,. \tag{3}$$

The matrix Λ^{GER} now only grabs the German values of GDP out of y_t for each quarter t. M_t^{GER} is constructed as M_t^A, with $M_t^{GER} = 1$ if the value is currently observed or $M_t^{GER} = 0$ if publication delays exist.

Both measurement equations (2) and (3) impose the temporal nature of the data. In addition, as we model regional activity, the estimated latent states have to add up to the German value so that the system is consistent with national and regional accounts. Thus, we add the following cross-sectional restriction as a third measurement equation to the system:

$$y_t^{GER} = \frac{1}{R} \sum_{r=1}^{R} y_t^r + \eta_t \,, \quad \eta_t \sim N(0, \sigma_{cs}^2) \,. \tag{4}$$

As we transform the data in log-differences, Koop *et al.* (2020c) show that this first order approximation holds and German GDP growth, y_t^{GER}, can be expressed as a simple average of the regional growth rates, y_t^r. However, this relationship is not perfect so that the error term η_t captures this approximation. The stochastic nature of this relationship also captures an accounting feature of the system. In Germany, price-adjustment is based on the usage of previous year prices and no longer on fixed prices of a given year as it was the standard until 2005. Due to the chain-linking nature of the data, the sum of price-adjusted volumes does not result in correct values of higher aggregates such as GDP (see, for example, IMF, 2018). This issue is called additive inconsistency. Thus, the sum of price-adjusted regional GDP does not equal price-adjusted German GDP. This inconsistency, together with the first order approximation, is also grabbed by the cross-sectional error η_t.

Stochastic volatility. The last step we need to undertake is to set a definition on how the variance-covariance-matrix of the VAR, Σ_t, looks like. The recent literature on the dynamics of the German business cycle is strongly in favor of changes in the volatility and thus allowing for a heteroscedastic error structure (see Reif, 2022). We follow Koop *et al.* (2020c) and apply the stochastic volatility specification of Cogley and Sargent (2005) and Carriero *et al.* (2016):

$$\Sigma_t^{-1} = \mathbf{L}'\mathbf{D}_t^{-1}\mathbf{L} \,, \quad \text{with} \quad \mathbf{L} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{1,1} & 1 & \cdots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{n,1} & \cdots & a_{n,n-1} & 1 \end{bmatrix}_{n \times n} \tag{5}$$

and $\mathbf{D}_t = \text{diag}[\exp(h_{1,t}) \dots \exp(h_{n,t})]^{-1}$. It grabs the log-volatilities $\mathbf{h}_t = (h_{1,t} \dots h_{n,t})'$ that follow a Random Walk specification:

$$\mathbf{h}_t = \mathbf{h}_{t-1} + \nu_t \,, \quad \nu_t \sim N(0, \Sigma_h) \,, \tag{6}$$

with $\Sigma_h = \text{diag}(\omega^2_{h_1} \dots \omega^2_{h_n})$. The stochastic volatility specification together with the complete state space model is labeled as MF-VAR-SV. In the following, we discuss the priors set to estimate the model.

3.2. Prior Setting

The MF-VAR-SV is clearly over-parameterized. Even without exogenous variables, the number of endogenous variables is $n = R+1 = 17$, so 16 latent variables have to be estimated based on a few annual observations only. On top, we have to estimate the volatilities. We achieve the attenuation of the parameter problem by efficiently shrinking the priors to zero and follow Koop *et al.* (2020c) in this respect. They apply the Dirichlet-Laplace hierarchical prior that induces a theoretical-optimal shrinkage (see Bhattacharya *et al.*, 2015).

VAR parameter. Our VAR from Equation (1) can be expressed as a multivariate regression problem with the coefficient k-dimensional vector $\beta = \text{vec}([\Phi_0 \Phi_1 \dots \Phi_p]')$ to be estimated. With $\beta = (\beta_1 \dots \beta_k)'$, the prior for each coefficient is (Bhattacharya *et al.*, 2015):

$$\beta_j \sim N(0, \psi_j^\beta \vartheta_{j,\beta}^2 \tau_\beta^2) \,, \tag{7}$$

$$\psi_j^\beta \sim \text{Exp}\left(\frac{1}{2}\right) \,, \tag{8}$$

$$\vartheta_{j,\beta} \sim \text{Dir}\left(\alpha_\beta, \dots, \alpha_\beta\right) \,, \tag{9}$$

$$\tau_\beta \sim \text{G}\left(k\alpha_\beta, \frac{1}{2}\right) \,. \tag{10}$$

The unknown variance parameters of the coefficients have to be estimated and are automatically chosen by the algorithm. Thus, the algorithm decides how much shrinkage on the parameters is allowed. If the variance is close to zero, it is likely that the coefficient β_j is set to zero. The Dirichlet-Laplace prior is a global-local prior with only one hyperparamter α_β. One part of the coefficient variance is global (τ_β), meaning that this term applies similarly to all coefficients. Another part is local (ψ_j^β), meaning that it applies individually to each coefficient β_j. The last term, $\vartheta_{j,\beta}$, leads the Dirichlet-Laplace prior to produce a posterior that optimally contracts to its true value (see Bhattacharya *et al.*, 2015).

Stochastic volatility. For the parameters that control the error covariances in the $\mathbf{L}$ matrix, $\mathbf{a} = (a_{1,1} \ldots a_{n,n-1})'$, we also apply a Dirichlet-Laplace prior in a similar fashion to the VAR coefficients. The terms are $\psi_i^a, \vartheta_{i,a}$ and τ_a, with one hyperparameter α_a. For the ω_{h_j}, we assume: $\omega_{h_j}^2 \sim \text{IG}(\nu_{h_j}, S_{h_j})$.

Cross-section restriction. It appears—due to the approximate nature of Equation (4) and the accounting standards—that the sum of regional GDP growth does not have to equal German GDP growth. For this cross-sectional error we assumed: $\eta_t \sim N(0, \sigma_{cs}^2)$. The variance term is modeled in such a way that the prior mean is close to zero, using the following tight prior: $\sigma_{cs}^2 \sim \text{IG}(1000, 0.001)$.

3.3. Posterior Simulation

Hyperparameter choices. We follow Koop *et al.* (2020c) and set the following hyperparameters. For the Dirichlet-Laplace prior, we choose similar hyperparameter for both the coefficients and the stochastic volatility: $\alpha_\beta = \alpha_a = 0.5$. To draw the initial conditions of the stochastic volatilities, $\mathbf{h}_0$, we follow Chan and Eisenstat (2018) and set: $\mathbf{a}_h = \mathbf{0}$, $\mathbf{V}_h = 10$, $\nu_i = \nu_{h_j} = 5$, and $S_i = S_{h_j} = 0.01$.

Start values and algorithm. As the starting values for the Dirichlet-Laplace prior we set: $\psi_j^\beta = \vartheta_{j,\beta} = \tau_\beta = \psi_i^a = \vartheta_{i,a} = \tau_a = 0.1$. For the cross-section restriction, we initialize the error with: $\eta_0 = 0.0001$. Our MCMC algorithm is similar to Koop *et al.* (2020c) with a total of 20,000 draws, whereas the first 10,000 draws are discarded.

3.4. National and Regional Data

Gross domestic product. We rely on the latest vintage of national and regional accounts data. Quarterly price-, seasonal- and calendar-adjusted German GDP, Y_t^{GER}, is consistently available from the Federal Statistical Office for the period 1991 to 2021. For the same period, the Working Group Regional Accounts publishes annual chain-linked indices (2015 = 100) for real GDP at the regional level, $Y_t^{r,A}$. These regional figures are consistent with currently valid national accounting standards, coordinated on the annual German value and for a consistent delimitation of the German states after reunification. Germany consists of $R = 16$ NUTS-1 regions for which we estimate quarterly GDP growth rates, y_t^Q. As we transform our data in log-differences, we can rely on annual regional GDP growth ($y_t^{r,A}$) from 1992 to 2021. The quarterly German GDP growth figures therefore start in the first quarter of 1992 ($t_0 = $ 1992-Q1).

Macroeconomic and regional indicators. It seems reasonable to augment the MF-VAR by additional macroeconomic and regional variables that might explain quarterly growth at the state level. In line with Koop *et al.* (2020c); Reif (2022); Schorfheide and Song (2015) we select the following four macroeconomic variables, measured at the German level: the seasonal-adjusted consumer price index, the bank rate, the exchange rate, and the oil price (see Appendix B for more details on the additional indicators). With the exception of the bank rate that enters the model in quarterly first differences, all other macroeconomic series are transformed in quarterly log-differences.

We tried to follow Cuevas *et al.* (2015) and add a number of very important regional indicators to our model. However, consistent long time series for the German states are not easy to find from official sources. Either changes in statistical standards (for example, new industrial classifications) prevent the timely comparability of economic indicators, the time series is too short for our purposes (for example, total employment) or economic time series are not publicly available for all states (for example, industrial production). The only exception is the number of unemployed people that is available from the Federal Employment Agency on a monthly basis starting in December 1991. For our purpose, the unemployment figures also enter the model in log-differences after the monthly values were averaged to meet the quarterly frequency.

Unemployment as one single indicator at the regional level alone might not be sufficient enough due to several other influences. Next to business cycle fluctuations, the number of unemployed people is also driven by large labor market reforms (see, for an evaluation of the Hartz-reforms, Hochmuth *et al.*, 2021), policy instruments such as short-time work (see Balleer *et al.*, 2016), or a shrinking labor force due to demographic changes. Thus, we want to add indicators that closer track aggregate economic fluctuations. We do so by relying on qualitative survey information that are found to track and forecast economic activity quite well (see, for example, Angelini *et al.*, 2011; Basselier *et al.*, 2018). In Germany, the ifo Institute is the largest survey provider with the ifo Business Climate as its most famous survey-based indicator. Next to the forecasting power of the ifo Business Climate (see Lehmann and Reif, 2021), the survey has proved to have high forecasting power in several dimensions (see, for a recent literature survey, Lehmann, 2020). So it does for the German states, for which the ifo Institute provides a large subset of its indicators. We apply the ifo Business Climate Industry and Trade for each of the German states or state aggregates which are available on a monthly basis since January 1991.[5] The seasonally-adjusted survey indicators enter the model in quarterly first differences after they have been averaged.

[5]Industry and Trade is the aggregation of manufacturing, construction, retail sales, and wholesale trade. Unfortunately, the survey indicators for the service sector are only available since January 2005 and thus not suited for our purposes. Due to representation issues, business climates are not available for all 16 German states separately. However, the ifo Institute provides state aggregates. In the end we come up with 10 regional ifo Business Climates Industry and Trade.

The regional indicators enter the model equation-wise as exogenous regressors, thus, the indicator for region r only explains movements in state-specific GDP growth. So in the end we deal with a 21 dimensional MF-VAR-SV where two exogenous indicators additionally explain economic activity for each state. According to Koop *et al.* (2020c) we also specify the VAR with a leg length of $p = 7$, which meets the intertemporal restriction of Mariano and Murasawa (2003).

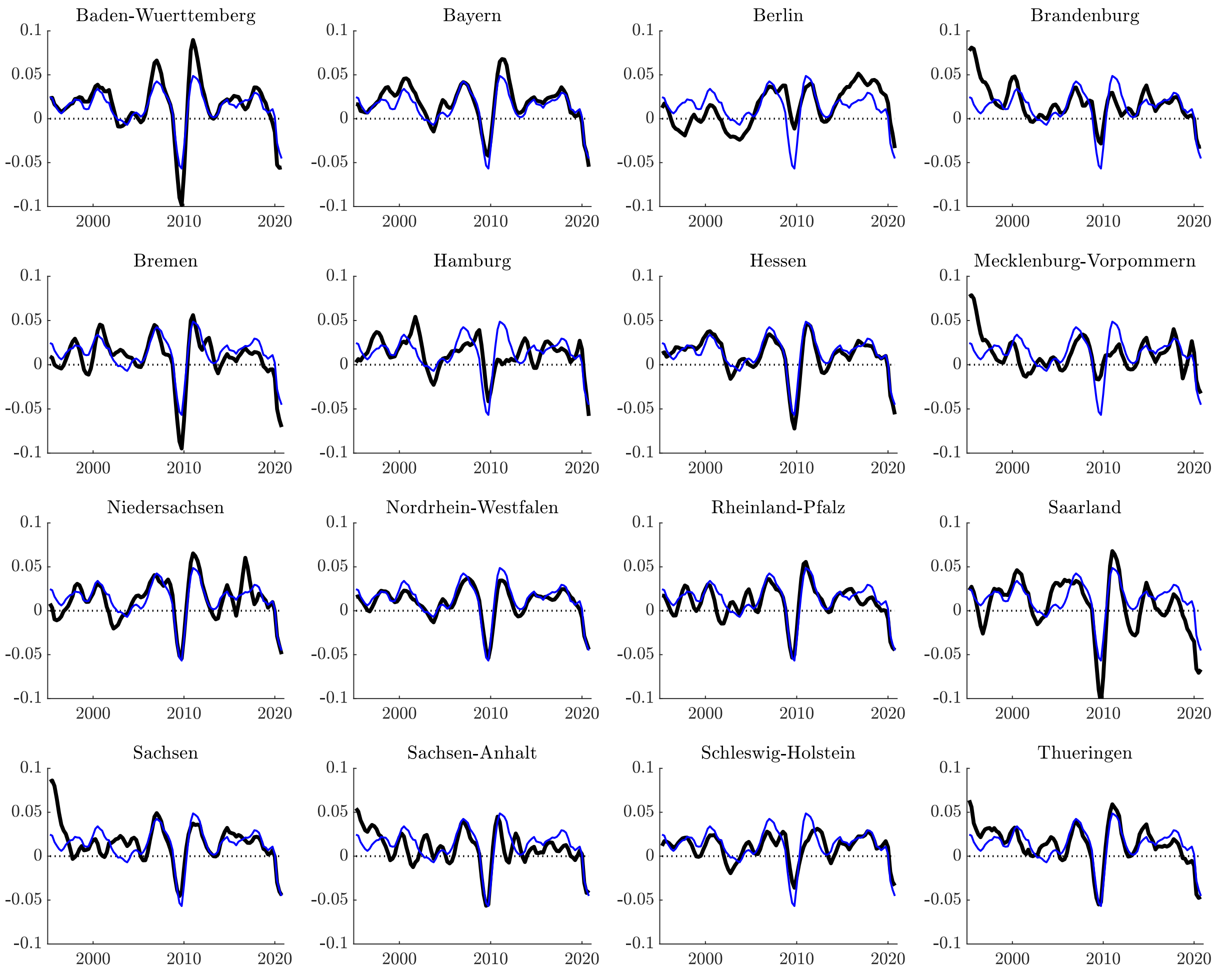
4. Quarterly Regional GDP

In this section, we present time series of GDP estimates for all 16 German states from 1995 to 2020 together with a comparison to the official data for Germany. Based on these estimates we apply standard business cycle dating algorithms and compare the cyclical behavior of economic activity across the German states.

4.1. Time Series from 1995 to 2020

Figure 2 shows the quarterly and annualized quarter-on-quarter GDP growth rates for all 16 German states (black line) together with the official date for Germany. The series are running from the second quarter 1995 to the fourth quarter of 2020. Obviously, we observe a large heterogeneity across the states as well as different growth patterns compared to Germany. The annualized growth rates for Germany seem to be mainly characterized by very large and economic relevant (in terms of share in German GDP) states such as Baden-Wuerttemberg, Bayern, and Nordrhein-Westfalen; these three states together held a share of more then 54% in German GDP as of 2020. The correlation coefficients in Table 1 underpin this observation (Baden-Wuerttemberg: 0.97, Bayern: 0.94, Nordrhein-Westfalen: 0.96). The state Hessen also shows a large homogeneity with the development of German economic activity; both annualized growth rates correlate by 0.95. The lowest correlation and thus the largest heterogeneity in economic growth compared to Germany is observed for Mecklenburg-Vorpommern (0.52) and the two city-states Berlin (0.55) and Hamburg (0.59). Whereas Mecklenburg-Vorpommern is mainly characterized by a large amount of touristic activity due to its location at the baltic sea, Berlin and Hamburg are the two states with the highest share of service activities in its total gross value added; on the opposite, the lowest shares of manufacturing in overall economic activity can be observed for these three states. The service sector of Berlin can mainly be described by the location of large parts of the federal government (for example, ministries), headquarters of large firms, a strong information and communication industry (for example, large, international publisher), and the occurrence of interest groups and political parties. Hamburg instead has a large share in transportation and logistic activities, which is not surprising as the largest German seaport is located there. On top, Hamburg also has a large information and communication industry with, for example, the production of Germany's most important newscast: the *Tagesschau*. Next to Baden-Wuerttemberg, Bremen and Saarland show the largest variation in annualized growth; the respective standard deviations are 2.6% and 3.2% (Germany: 2.0%). The lowest variation in annualized growth can be observed for Schleswig-Holstein (1.5%).

Figure 2: Annualized Growth Rates for all German States Compared to Germany



Notes: The black lines show the annualized growth rates for each state. The blue lines represent the changes for Germany.

A special focus should be put on the Eastern German states (Brandenburg, Mecklenburg-Vorpommern, Sachsen, Sachsen-Anhalt, and Thueringen). After reunification, Eastern Germany faced a fast and strong catch-up process to the Western German states until 1995 (Ragnitz, 2019), which can also be seen in Figure 2 by the large annualized growth rates at the beginning of the sample. Since 1996, convergence in terms of GDP per capita more or less stopped (1996: 60.5% of Western German GDP per capita; 2020: 70.5% of the Western German value). The large catch-up at the beginning of the 1990's is be the main reason why the correlation coefficients—except for Thueringen—are smaller compared to Western German states. If we look at the data after 2000, the correlations increase but are still smaller in comparison to Western Germany. This might be an expression that Eastern German Business Cycles are nowadays more synchronized to Western German ones, which is one the main results by Gießler *et al.* (2021). In the following, we will investigate this issue by implementing a business cycle dating algorithm.

Table 1: Correlation of the State-specific Annualized Rates with Germany

State	**Corr**	**State**	**Corr**
Baden-Wuerttemberg	0.97	Niedersachsen	0.87
Bayern	0.94	Nordrhein-Westfalen	0.96
Berlin	0.55	Rheinland-Pfalz	0.88
Brandenburg	0.62	Saarland	0.87
Bremen	0.89	Sachsen	0.69
Hamburg	0.59	Sachsen-Anhalt	0.71
Hessen	0.95	Schleswig-Holstein	0.82
Mecklenburg-Vorpommern	0.52	Thueringen	0.85

Notes: The correlations are calculated for the total sample ranging from 1995 to 2020.

4.2. Business Cycle Dating

The annualized growth rates revealed a large heterogeneity in economic activity across the German states. Large differences in the variation of annualized growth have been observed, calling for a deeper investigation of the state-specific business cycles. We implement the well-known and accepted algorithm for monthly data by Bry and Boschan (1971), that has been extend to quarterly data by Harding and Pagan (2002). We choose this non-parametric dating algorithm as it is simple and easy to replicate for readers due to its high transparency. Harding and Pagan (2003) also show that non-parametric approaches are very robust compared to parametric ones by, for example, adding new observations.

The Bry-Boschan-algorithm (henceforth: BBQ-algorithm for quarterly data) models the development of economic activity in terms of so called classical business cycles. Here, business cycle fluctuations are identified in the levels of the data, thus, a business cycle is defined as the movement around an unknown trend. The growth cycle instead models business cycle fluctuations as the (percentage) deviation of the current economic activity from this unknown trend. Whereas the latter approach is in need to specify a trend before the dating can start, the former approach can easily be applied to the level series. We follow Bry and Boschan (1971) and Harding and Pagan (2002) and use the quarterly levels of our estimated series. This done by setting the first quarter of 1995 to 100 and multiplying this start value with our quarterly states until the end of our sample.

With the BBQ-algorithm, we divide the business cycle into two phases—upswing and downswing—that follow each other based on predefined criteria. Upswings (downswings) are characterized by time periods with increasing (decreasing) economic activity. Both phases are connected by peaks and troughs, whereas the peak (trough) is the point in time where an upswing (downswing) ends. A complete cycle is the time period in which each phase has been passed once. In practice, the BBQ-algorithm identifies the peaks and troughs in the time series, allowing for dating the complete cycle.

According to Harding and Pagan (2002), a dating algorithm has to fulfill three requirements. First, the approach needs to identify at least a minimum number of peaks and troughs. Second, peaks and troughs have to differ from each other and should vary over time. Third, the identified phases must satisfy some standard or minimum requirements for a cycle. A peak P_t (trough T_t) at quarter t occurs if the level of economic activity, y, is k periods lower (higher) before and after this point in time:

$$P_t = (y_{t-k}, \ldots, y_{t-1}) < y_t > (y_{t+1}, \ldots, y_{t+k}) \ ,$$
$$T_t = (y_{t-k}, \ldots, y_{t-1}) > y_t < (y_{t+1}, \ldots, y_{t+k}) \ .$$

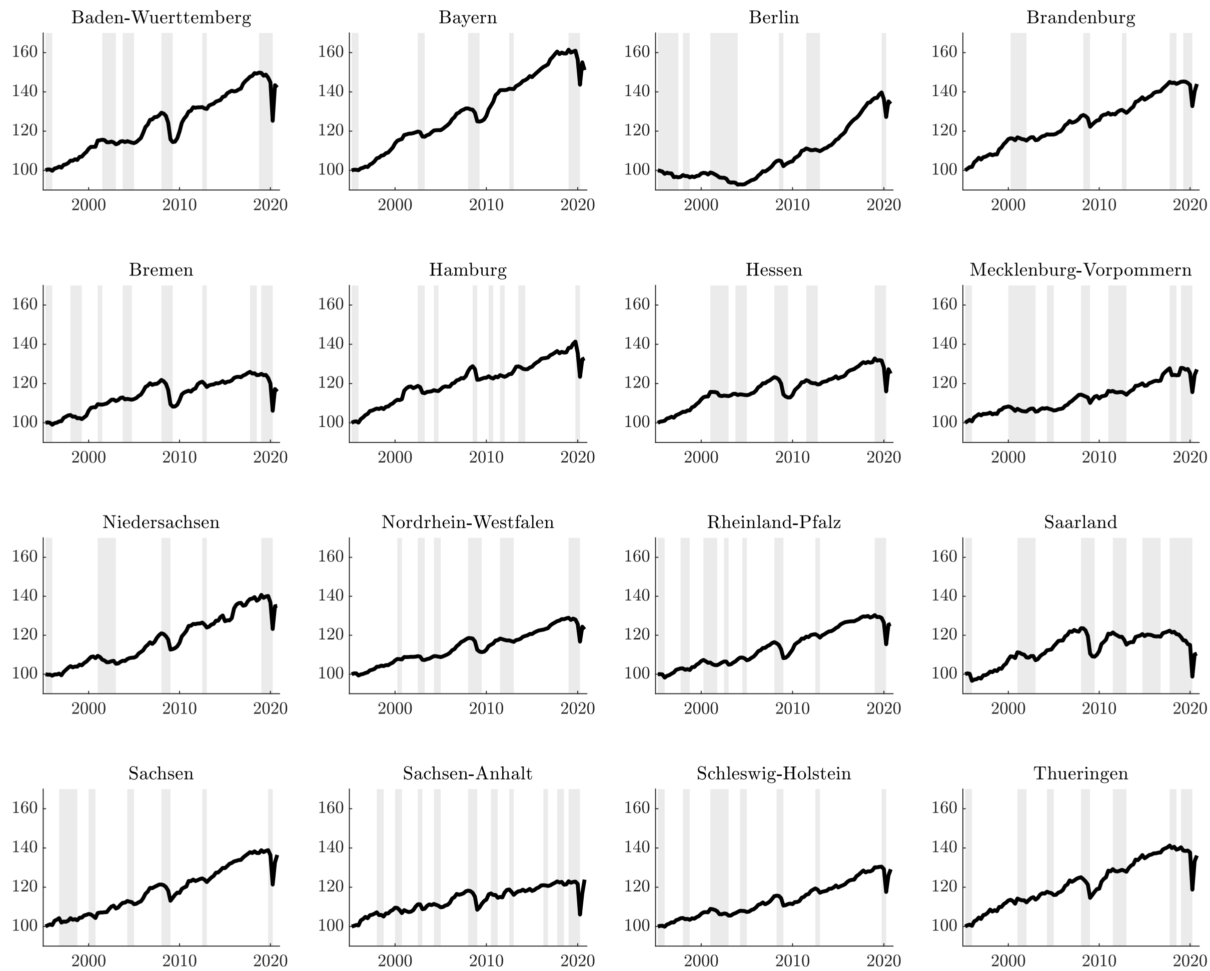
For our state-specific business cycle dating we apply rather standard values from the literature on the US and on Germany (Harding and Pagan, 2002, 2003; Schirwitz, 2009). The time span that defines peaks an troughs is set to $k = 2$ quarter. Additionally, upswings and downswings have at least to last two quarter and a complete cycle comprises at least five consecutive quarter.

Based on these rules, Figure 3 shows the dated business cycle phases for each German state together with the levels of the estimated quarterly series. The shaded areas indicate the downswing phases for each state; upswings are indicated by non-shaded areas. The figure reveals two major results. First, severe differences in the trends across the states exist. Whereas economic strong states such as Baden-Wuerttemberg and Bayern exhibit a quite stable trend, economic more weak states either show a much slower trend development or—in case of the Saarland—the trend is even flat. Second, the number, the duration and the amplitudes of the business cycles vary significantly across the 16 states. For example, the cycles of Niedersachsen and Bayern are quite smooth with very few downswing phases. On the opposite, the Saarland and Sachsen-Anhalt either show very long or numerous downswings.

Table 2 summarizes the average duration and amplitude of the state-specific up- and downswing phases. As suggested, the Saarland exhibits the longest average duration in downswing phases with 7.6 quarters. The shortest downswings reveals Hamburg (2.3 quarters). This heterogeneity can also be found for the upswing phases. The longest average upswing phases are found for Bayern (20.5 quarters), Niedersachsen (19.5 quarters), and Brandenburg (15.3 quarters). These phases are almost three times higher compared to Sachsen-Anhalt, for which an upswing only lasts 6.6 quarters on average. The states Bremen, Mecklenburg-Vorpommern, and Rheinland-Pfalz immediately follow with rather short upswing phases of a bit more than 10 quarters.

The state-specific business cycles also significantly differ in their amplitudes, which are defined as the percentage change in the levels between a peak and a trough. The Saarland, Baden-Wuerttemberg and Niedersachsen show the deepest downswings with an average change of -8.8%, -6.8%, and -6.6%, respectively. For Brandenburg, Nordrhein-Westfalen and Schleswig-Holstein, the recessions are only half as deep as for the three previous mentioned states (-3.3%, -3.4%, and -3.6%). Contrary, the strongest upswings are found for Bayern (13.9%), Niedersachsen (12.0%), and Baden-Wuerttemberg (11.3%). Interestingly, the Saarland with the deepest recessions also exhibits relatively large upswings with 9.3%. The smallest upswing phases are experienced by Sachsen-Anhalt (4.1%), Nordrhein-Westfalen (5.6%), and Mecklenburg-Vorpommern (6.0%).

Figure 3: Phases of Economic Contraction for all German States



Notes: The black lines show the quarterly GDP levels for each state, with the first quarter of 1995 normalized to 100. The grey-shaded areas represent downswing phases according to the BBQ-algorithm; the opposite holds true for upswings.

These observed heterogeneities in the business cycles finally raise the question, how the state-specific phases overlap. We measure this by the concordance index (CI) of Harding and Pagan (2002). The CI can be interpreted as a measure for how large the co-movement between two business cycles is. It is defined as the ratio when both economies are in the same business cycle phase compared to the total number of observations:

$$\mathrm{CI}_{i,j} = \frac{1}{T} \sum_{t=1}^{T} \left[U_{i,t} U_{j,t} + (1 - U_{i,t})(1 - U_{j,t}) \right] .$$

If state i is facing an upswing at time t, it applies that $U_{i,t} = 1$. The same holds true for the second state j. A downswing is therefore assigned a value of zero and vice versa. For the CI holds: $\mathrm{CI}_{i,j} \in [0, 1]$. A value of one is observed if both business cycles overlap perfectly and all up- and downswings as well as peaks and troughs are identical. The opposite holds true for a value of zero. This means that if state i is in an upswing phase, state j shows a downswing and vice versa.

Table 2: Durations and Amplitudes of the State-specific Business Cycles

State	**Duration (# quarters)**		**Amplitude (in %)**	
	Down	**Up**	**Down**	**Up**
Baden-Wuerttemberg	4.8	14.6	-6.8	11.3
Bayern	3.8	20.5	-4.8	13.9
Berlin	5.0	13.2	-4.2	9.8
Brandenburg	3.8	15.3	-3.3	7.5
Bremen	3.7	10.1	-5.0	6.0
Hamburg	2.3	11.6	-3.6	6.6
Hessen	5.8	12.0	-5.3	6.7
Mecklenburg-Vorpommern	5.8	10.3	-3.7	6.0
Niedersachsen	4.8	19.5	-6.6	12.0
Nordrhein-Westfalen	4.2	11.0	-3.4	5.6
Rheinland-Pfalz	3.6	10.3	-3.9	6.2
Saarland	7.6	11.8	-8.8	9.3
Sachsen	3.7	14.4	-4.4	8.3
Sachsen-Anhalt	3.0	6.6	-3.8	4.1
Schleswig-Holstein	3.5	12.7	-3.6	6.3
Thueringen	4.2	12.0	-5.2	8.0

Notes: An upswing (Up) is the time period between one trough and the following peak. The opposite holds true for a downswing (Down). The duration measures the average number of quarters that up- and downswings last. The amplitude measures the average percentage change in GDP in up- or downswing phases.

Table 3 summarizes the CI for each state pair as well as a comparison to Germany. The strongest overlap in business cycles are observed for the pairs Bayern and Niedersachsen (92.2%), Baden-Wuerttemberg and Niedersachsen (91.3%), and Mecklenburg-Vorpommern and Thueringen (90.3%). The concordance between Bayern and Baden-Wuerttemberg is also very high (89.3%) which is not surprising as both states share a common border. The lowest concordance can be found between the Saarland and Sachsen (53.4%), Berlin and Sachsen-Anhalt (58.3%), and the Saarland and Hamburg (63.1%). It would be interesting to see if these patterns are also reflected in interregional connections across the states. Such analyses can be carried out with the regional input-output tables by Krebs (2020), but we leave this for future research activities.

Table 3: Concordance of Regional Business Cycles

	BW	BY	BE	BB	HB	HH	HE	MV	NI	NW	RP	SL	SN	ST	SH	TH	DE
BW	–	89.3	71.8	75.7	82.5	76.7	87.4	81.6	91.3	81.6	83.5	76.7	72.8	74.8	87.4	83.5	91.3
BY		–	72.8	80.6	83.5	83.5	78.6	76.7	92.2	86.4	86.4	75.7	75.7	77.7	82.5	82.5	96.1
BE			–	67.0	68.0	71.8	72.8	70.9	78.6	67.0	72.8	68.0	68.0	58.3	82.5	72.8	70.9
BB				–	79.6	69.9	76.7	80.6	84.5	78.6	82.5	71.8	77.7	79.6	78.6	84.5	80.6
HB					–	70.9	75.7	75.7	81.6	73.8	83.5	70.9	74.8	78.6	81.6	85.4	85.4
HH						–	71.8	69.9	77.7	77.7	73.8	63.1	70.9	68.9	79.6	75.7	85.4
HE							–	82.5	84.5	88.3	76.7	77.7	69.9	71.8	80.6	84.5	80.6
MV								–	84.5	80.6	82.5	79.6	68.0	77.7	80.6	90.3	80.6
NI									–	78.6	88.3	81.6	71.8	73.8	90.3	86.4	92.2
NW										–	80.6	71.8	79.6	81.6	74.8	82.5	86.4
RP											–	69.9	81.6	81.6	88.3	82.5	88.3
SL												–	53.4	65.0	71.8	81.6	73.8
SN													–	82.5	79.6	71.8	79.6
ST														–	75.7	75.7	81.6
SH															–	82.5	86.4
TH																–	86.4
DE																	–

Notes: BW: Baden-Wuerttemberg, BY: Bayern, BE: Berlin, BB: Brandenburg, HB: Bremen, HH: Hamburg, HE: Hessen, MV: Mecklenburg-Vorpommern, NI: Niedersachsen, NW: Nordrhein-Westfalen, RP: Rheinland-Pfalz, SL: Saarland, SN: Sachsen, ST: Sachsen-Anhalt, SH: Schleswig-Holstein, TH: Thueringen, DE: Germany.

The largest overlap to the German business cylce is observed for Bayern (96.1%), Niedersachsen (92.2%), and Baden-Wuerttemberg (91.3%). Especially for Bayern and Baden-Wuerttemberg, the result is not surprising as both contribute to German GDP by 18% and 15%, respectively. With 9% share in German GDP, Niedersachsen is also quite important. The lowest concordance to the German business cycle shows Sachsen (79.6%), the Saarland (73.8%), and Berlin (70.9%). Especially the latter is characterized by a large amount of public service activities for which might assume that they follow other regularities than standard business cycle fluctuations with different degrees in capacity utilization. In the end, we find large heterogeneities in business cycle fluctuations across the German states. Future research might go in the direction of asking which underlying forces lead to these overall results.

4.3. Comparison to other Estimates

As stated in Section 2, some official and non-official GDP estimates for the German states exist. The Statistical Office in Baden-Wuerttemberg publishes a long time series of quarterly real GDP. The ifo Institute has worked on quarterly real GDP for Sachsen-Anhalt until 2017. Nierhaus (2007) calculated quarterly estimates for Sachsen that have regularly been published at the ifo Institute's homepage until 2020.[6] Figure 4 compares our annualized estimates (black and solid lines) to the results of the three other sources (red and dotted lines). Overall, our estimates fit the other data very well. Especially the concurrence with the official estimates by the Statistical Office Baden-Wuerttemberg makes us think that our estimates are not severely biased.

Some differences at the end of the sample for Sachsen-Anhalt occur. But this is not a methodological issue but rather a timing one. Our estimation sample runs until 2020 and is based on the latest vintage of data. Their estimates are based on data until 2018, so no revisions in the official annual data that occurred later on are mirrored in their estimates. In the end, we are quite confident that our estimates are close to potential official data.

[6] The data for Baden-Wuerttemberg can be accessed here: `https://www.statistik-bw.de/GesamtwBranchen/KonjunktPreise/BIP_Q.jsp`. The documents for Sachsen-Anhalt are available here: `https://www.ifo.de/publikationen/2017/monographie-autorenschaft/die-gesamtwirtschaftliche-lage-im-2-quartal-2017`. The last data for Sachsen can be found at: `https://www.ifo.de/publikationen/2020/aufsatz-zeitschrift/vierteljaehrliche-vgr-fuer-sachsen-ergebnisse-fuer-das`.

Figure 4: Comparison of the Estimates to other Sources

Notes: The black lines show our estimated annualized growth rates. The red dotted lines represent the rates from other sources.

5. Conclusion

Regional macroeconomic aggregates such as GDP are only available at an annual frequency for most countries. This circumstance prevents, for example, policymaker from assessing the current state of the regional economy in a timely manner. This paper uses a modern time series framework to estimate regional quarterly real GDP based on nationwide developments and an under-explored source of regional information.

We apply this time series framework to the case of Germany. The German states are characterized by a large heterogeneity in their industrial mix, making them especially interesting for a business cycle analysis. Such an analysis revealed large differences in the state-specific duration and amplitudes of upswing and downswing phases. Downswing phases last, on average, between a span of 2.3 to 7.6 quarter; the span for upswings ranges from 6.6 quarter to 20.5 quarter. The average loss in economic activity in a downswing ranges from -8.8% to -3.3%. For upswings, the average increase of GDP lies between 4.1% to 13.9%. In addition, we find a large heterogeneity in the degrees of business cycle concordance across states as well as compared to Germany. We hope that new research ideas will be developed based on our data and that the general public finds them interesting enough.

The next step is to build up a comprehensive regional dataset for Germany and enrich our estimates with these indicators. Another step is to apply a rather structural analysis and to test how exogenous shocks hit state-specific economic activity. We also think of enlarging the econometric model by disaggregating GDP growth into its supply-side sub-components together with standards in national accounting. Finally, our data can be used for applied forecasting purposes by each interested external user.

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A. Economic Units in Germany

Table A1: Overview of the German NUTS-regions

Level	**Region(s)**
NUTS-0	Germany
NUTS-1	16 states Baden-Württemberg, Bayern, Berlin, Brandenburg, Bremen, Hamburg, Hessen, Mecklenburg-Vorpommern, Niedersachsen, Nordrhein-Westfalen, Rheinland-Pfalz, Saarland, Sachsen, Sachsen-Anhalt, Schleswig-Holstein, Thüringen *Translation* Baden-Württemberg, Bavaria, Berlin, Brandenburg, Bremen, Hamburg, Hesse, Mecklenburg-West Pomerania, Lower Saxony, North Rhine-Westphalia, Rhineland-Palatinate, Saarland, Saxony, Saxony-Anhalt, Schleswig-Holstein, Thuringia
NUTS-2	38 regions
NUTS-3	401 districts

Source: European Union (2016).

B. Details on the Applied Indicators

Table B1: Details on the Macroeconomic and Regional Indicators

Variable	**Description**	**Source**
	Macroeconomic Indicators	
Consumer price	Total average price index of all goods and services consumed by German households, monthly, seasonally adjusted, log-differences, source code: `BBDP1.M.DE.Y.VPI.C.A00000.I15.A`.	Deutsche Bundesbank
Bank rate	Yields on debt securities outstanding, listed federal securities, mean residual maturity of more than 9 and up to 10 years, monthly, first differences, source code: `BBSIS.M.I.UMU.RD.EUR.S1311.B.A604.R0910.R.A.A`)	Deutsche Bundesbank
Exchange rate	Nominal effective exchange rate against 51 economies, deflated by relative consumer prices, monthly, log-differences, source link: `https://www.bis.org/statistics/eer.htm?m=6_381_676`	Bank for International Settlements
Oil price	Brent Europe Spot Price in USD, monthly, log-differences, accessed via Macrobond, code: `uscaes0302`	Energy Information Administration
	Regional Indicators	
Unemployment	Number of unemployed persons, 16 German states separately, monthly, seasonally adjusted, log-differences, source link: `https://statistik.arbeitsagentur.de/DE/Navigation/Grundlagen/Methodik-Qualitaet/Saisonbereinigung/Saisonbereinigung-Nav.html`	Federal Employment Agency
ifo Business Climate	Geometric average of the assessment of business situation and business expectations, industry and trade, monthly, seasonally adjusted, first differences. **Question:** 'We assess our current business situation as [...]' **Answer:** (+) good, (=) satisfactory, or (–) bad. **Question:** 'In the next 6 months, our business situation will be [...]' **Answer:** (+) rather favorable, (=) rather stay the same, or (–) rather unfavorable. **State availability (6):** Baden-Württemberg, Bayern, Hessen, Niedersachsen, Nordrhein-Westfalen, Sachsen. **State aggregates (4):** Middle Germany (Sachsen-Anhalt, Thüringen), Northern Germany (Bremen, Hamburg, Schleswig-Holstein), North-East-Germany (Berlin, Brandenburg, Mecklenburg-Vorpommern), Rheinland-Pfalz & Saarland.	ifo Institute