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Abstract

Accurate real-time macroeconomic data are essential for policy-making and economic nowcasting. In this paper, I introduce a real-time database for German regional economic accounts (READ-GER). The database contains real-time information for nine macroeconomic aggregates and the 16 German states. I conduct both a revision analysis and a nowcasting experiment. Whereas the first estimates show no systematic revision errors by pooling the states together, this procedure suppresses the revision characteristics of single states. For half of the 16 German states I find that the first estimates are no optimal predictions, thus, leaving room for improvements in the future. The real-time nowcasts for real gross domestic product growth based on a mixed-frequency Vector Autoregression are very accurate, beat several benchmark models and are as precise or better as the first official estimates. More regional data would help to further increase the model's nowcast performance and thus its properties for the first estimates from regional accounts.

JEL-Codes: C320, C530, C820, E010, E320, R110.

Keywords: regional economic nowcasting, revision analysis, mixed-frequency Vector Autoregression, real-time regional accounts.

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1 Introduction

Real-time data are probably the most important prerequisite for economic nowcasting experiments. They are used to judge the models' performance in a realistic environment that an applied forecaster faces. Recently, the interest in sub-national or regional nowcasting applications is rising. Unfortunately, geographically-disaggregated real-time information on, for example, macroeconomic aggregates is missing, whereas this is fairly standard for national-level variables. Germany is no exception from this observation.

In this paper, I introduce a real-time regional accounts database for the 16 German states (READ-GER) that can be accessed at `https://www.robertlehmann.net/data`. The annual database covers nine macroeconomic aggregates for the period from 1991 to 2021 and currently 19 vintages starting with the publication in 2003. Among the macroeconomic aggregates READ-GER contains, for example, real gross domestic product, total domestic employment, and gross wages and salaries. I use parts of the real-time data for both a detailed regional revision analysis and a nowcasting experiment.

Revisions to macroeconomic aggregates are, in general, not avoidable due to late data deliveries or a redefinition of methodological principles. If first estimates of macroeconomic aggregates reflect the 'true' state of the economy well, then decision-makers can build their policies (for example, optimal interest rates) on well grounded information sets. Thus, well-behaved and irrelevant revisions are virtually harmless. Croushore (2011) surveys the US literature, finding that revisions shape policy decisions. As shown by Orphanides (2001), optimal Taylor-Rule-implied interest rates vary with different vintages of macroeconomic data. The study of Aruoba (2008) diagnoses revisions to US national accounts to be biased and predictable. The same holds true for Germany as shown by Strohsal and Wolf (2022).[1] In my paper, I broaden the picture for Germany and analyze the properties of revisions to state-level growth of real gross domestic product, real gross value added manufacturing and total employment based on the vintages in READ-GER. Especially the revisions to real gross domestic product growth once caused a very intensive debate in the largest German state, North Rhine-Westphalia. The West German Broadcasting Cologne (WDR) titled on April 5, 2018: the "Fairy tale of former zero growth" (own translation).[2] The first estimate for North Rhine-Westphalia's economic growth was 0,0%, making it a defining topic in the election campaign at that time. The final value amounts to 1,1%, which is far from a stagnation. In my paper, I extend the descriptive analysis by Döhrn (2021) and apply Minzer-Zarnowitz-type of regressions as in Strohsal and Wolf (2022) to test whether state-by-state revisions are unbiased, efficient and unpredictable. It turns out that the first estimates in regional accounts are no optimal predictions for half of the states, leaving room for future improvements.

[1] In case of Norway, Helliesen *et al.* (2022) state that growth rates of real national accounts figures—with the exception of gross fixed capital formation—are unbiased, efficient and accurate.

[2] The German speaking blog can be found under the following permanent link: `https://blog.wdr.de/landtagsblog/das-maerchen-vom-null-wachstum`.

Nowcasting in real-time can reveal results or model rankings that clearly differ from final vintage exercises. Bokun *et al.* (2023) conclude for the US states that the judgment on the suitability of state-level forecasting models should be based on real-time exercises rather than revised data. The international literature on regional economic forecasting has grown in recent years (see Chernis *et al.*, 2020; Koop *et al.*, 2020; Gil *et al.*, 2019).[3] Contributions for Germany all have in common that they are based on the respective final vintage of regional accounts data and executed either for single states or aggregates (see Kuck and Schweikert, 2021; Claudio *et al.*, 2020; Lehmann and Wohlrabe, 2017; Henzel *et al.*, 2015; Lehmann and Wohlrabe, 2015; Kholodilin *et al.*, 2008). I contribute to this literature by employing the real-time information from READ-GER in the mixed-frequency Vector Autoregression environment from Lehmann and Wikman (2023). Their model, based on the contribution from Koop *et al.* (2020), is able to connect the annual regional accounts information with quarterly national and regional information to calculate quarterly state-level gross domestic product data that are currently not available from official statistics. Given this connection, the model can formulate annual, state-level nowcasts within a year. These nowcasts for real gross domestic product growth turn out to be very accurate and they significantly outperform various benchmark models. Furthermore, the real-time nowcast errors are on average smaller or as precise as the revision errors from official statistics, making the mixed-frequency approach an attractive tool in applied work. Moreover, the model comes with the nice bi-product of quarterly real gross domestic product estimates for all German states.

The paper is organized as follows. Section 2 introduces the institutional setting for regional accounts in Germany. The structure of the database READ-GER is described in Section 3. The results from the revisions analysis and the nowcasting experiment are presented in Section 4 and Section 5, respectively. The last section concludes.

2 Institutional Setting

In Germany, data from regional accounts are calculated and provided by the Working Group Regional Accounts (`https://www.statistikportal.de/de/vgrdl`). This working group was formed in 1954 and consists of the states' Statistical Offices, the Federal Statistical Office, and the Association of German Cities; the group is headed by the Statistical Office Baden-Wuerttemberg. The term 'regional' comprises the three levels of the NUTS-classification for homogeneous economic units in Europe. Macroeconomic data are provided by the working group for the 16 German states (NUTS-1), the 38 governorates (NUTS-2), and the 400 districts (NUTS-3). The range of available macroeconomic aggregates varies across the three layers with more data published at the top level.

[3] Lehmann and Wohlrabe (2014) survey contributions prior to the year 2015.

The working group mainly has eight products in his publication portfolio. These products vary by the macroeconomic aggregates included, the publication delay, and the regional layer (see Table 1). Regional accounts in Germany only include annual information; Lehmann and Wikman (2023) calculate quarterly gross domestic product (GDP) estimates for all 16 German states simultaneously. The eight products are labeled with unique identifiers that represent a series-volume-combination. Here, the series (S) marks the regional layer, with S1 identifying the state- and S2 identifying both the governorate- and district-level. The volumes (V) define the different macroeconomic aggregates included.[4] In the following, I will only concentrate on the state-level and leave lower regional layers aside. Usually, the year t starts with the release of the first two products of the working group at the end of March, after German GDP for year $t-1$ has been released (see Figure 1). This is why both products are subject to a publication delay of three months. The first product, *S1V1*, comprises the complete production side of GDP up to year $t-1$. Next to GDP, S1V1 includes total employment, the number of total hours worked, and gross value added (GVA) for several industries. Both, GDP and GVA, are published in nominal and real terms.

The second product, *S1V2*, collects the payments of the labor market with both employee compensations and gross wages and salaries (GWS). All wages are again published with some industrial granularity. In June, *S1V4* and *S1V5* are released. S1V4 includes the capital side of the economy up to year $t-3$ with gross fixed assets (equipment, buildings etc.) and the capital stock. S1V5 instead includes the components of both the expenditure and the income approach of GDP. However, the publication lags are not identical across all components. Whereas private consumption expenditures or savings are available up to $t-2$, other components either have higher publication lags (government consumption up to $t-3$) or are not calculated at all (exports, imports, inventories). In September, a state-level GDP estimate for the first half-year of year t is published, but will not be revised afterwards. Thus, this estimate is not comparable to the official annual values. The last state-level product of the working group, *S1V3*, is released in November of a given year. This product includes gross fixed capital formation (GFCF) up to year $t-2$ both in nominal and real terms.

The way how the group works and how it is organized is worth mentioning.[5] Each component of GDP is coordinated and calculated by one state member of the working group. For example, the Statistical Office Bavaria calculates annual GDP for all 16 German states simultaneously for the first two calculation rounds. The sum of state aggregates are consistent to the German values, which is achieved by fixing the top aggregate. This means that, for example, German GDP is not calculated by summing up the state values. Instead, it is fixed by the Federal Statistical Office and state-level GDP is achieved by breaking down the German aggregate. This breakdown is either done bottom-up or top-down. The bottom-

[4]I translated the abbreviations on my own. Originally, the series' label is R (in German: *Reihe*) and the volumes' label is B (in German: *Band*).

[5]A more detailed methodological description of the working group can be found here: `https://www.statistikportal.de/de/vgrdl/methoden-und-informationen`.

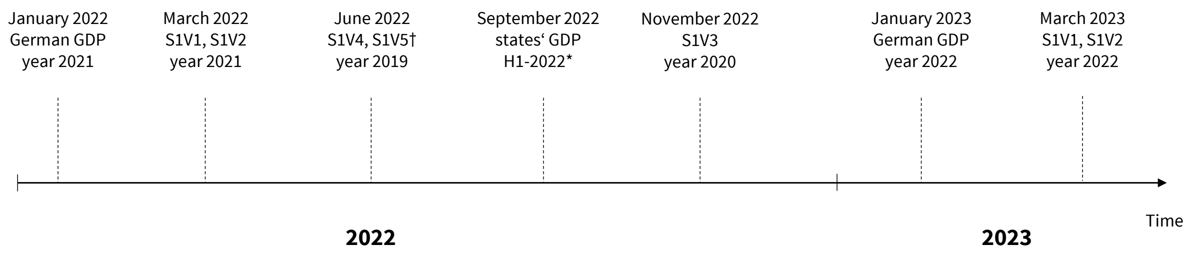
up approach is characterized by summing up state-specific industrial GVA together with net taxes to achieve GDP. The delta of the sum in state-level GDP and the fixed German benchmark is allocated according to the states' weights in economic activities. Instead, the top-down approach makes usage of key regional economic indicators to break down German GDP. All aggregates in German regional accounts are consistent with the latest European System on National Accounts.

Table 1: Product Portfolio of the Working Group Regional Accounts

Product	**Layer**	**Aggregates**	**Delay**
S1V1	states	gross domestic product, gross value added (total & industries), employment (total & industries), hours worked (total & industries), inhabitants	3 months
S1V2	states	employee compensations (total & industries), gross wages and salaries (total & industries), domestic workers (total & industries)	3 months
S1V3	states	gross fixed capital formation (total, equipment, buildings, other, industries)	23 months
S1V4	states	gross fixed assets (total, equipment, buildings, other, industries), capital stock (total & industries)	30 months
S1V5	states	gross domestic product: expenditure (e.g., private consumption), production (e.g., gross wages and salaries), and income (e.g., gross national income) approach, savings etc.	6 months†
S2V1	districts	gross domestic product, gross value added (total & industries), employment (total & industries), hours worked (total & industries), inhabitants	19 months
S2V2	districts	employee compensations (total & industries), gross wages and salaries (total & industries), domestic workers (total & industries)	19 months
S2V3	districts	net national income, disposable income	21 months

Notes: The products have unique identifier with a series-volume-combination. The series (S) labels either state- (S1) or district-level (S2) publications. The volumes (V) capture different macroeconomic aggregates. Publication delays always represent the number of months after which the last available year is published. The macroeconomic aggregates included in S1V5 are subject to different publication delays (†), however, the volume is always published six months after the respective year ends.

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



Notes: The expenditure components of state-level GDP, published in S1V5, are subject to different publication lags (†). State GDP values for the first half-year (H1) are not revised afterwards (∗) and are thus not comparable with annual values. *Sources:* Federal Statistical Office, Working Group Regional Accounts.

3 Structure of the Database

The new database provides real-time information on state-level macroeconomic aggregates extracted from the group's products introduced in the previous section. I call it Real-time READ-GER: Regional Economic Accounts Database for Germany. The database can be accessed at `https://www.robertlehmann.net/data` and it will be updated with new releases after they become available. Currently, READ-GER is Excel-based only.

READ-GER contains real-time information on single macroeconomic aggregates, that is, the values are tracked over time in several vintages. I do not extract all macroeconomic aggregates, but rather the most important ones both from a public and an academic point of view. The first vintage usually starts with the publication in 2003, thus, it comprises the years running from 1991 to 2002. Currently, the latest vintage is the one published in March 2022 with the aggregates running from 1991 to 2021. READ-GER only contains the raw data. So it is up to the user to apply meaningful transformations.

The vintages are organized in sheets representing single aggregate-state-combinations that are labeled as, for example, *V1–1*. The identifier prior to the hyphen, V1, is the running number for the variables and the number following the hyphen represents the German state. Thus, on each sheet the user can track one single economic aggregate for one single German state over time and vintage. Overall, READ-GER contains the following information:

- **aggregates:** V1 – real gross domestic product (2003), V2 – nominal gross domestic product (2003), V3 – total domestic employment (2003), V4 – total hours worked (2005), V5 – number of inhabitants (2003), V6 – number of domestic workers (2003), V7 – gross wages and salaries (2003), V8 – real gross value added (2013), V9 – nominal gross value added (2013);

- **states:** 1 – Baden-Wuerttemberg, 2 – Bavaria, 3 – Berlin, 4 – Brandenburg, 5 – Bremen, 6 – Hamburg, 7 – Hesse, 8 – Mecklenburg-West Pomerania, 9 – Lower Saxony, 10 – North Rhine- Westphalia, 11 – Rhineland-Palatinate, 12 – Saarland, 13 – Saxony, 14 – Saxony-Anhalt, 15 – Schleswig-Holstein, 16 – Thuringia;

- **industries:** a – agriculture, forestry and fishing, b – producing industry (excl. construction), c – manufacturing, d – construction, e – trade, transportation and storage, accommodation, information and communication, f – financial and insurance services, real estate activities, business services, g – public services, education, health activities, arts and entertainment, other services, activities of households.

The current version of the database comprises nine aggregates for the 16 German states. Those aggregates that can be divided into industries, READ-GER offers seven categories. The figures in brackets after each aggregate mark the year of the first vintage. Especially the number of vintages for gross value added is much smaller compared to the other aggregates. The main reason is the change in classification standards after which industries are no longer comparable to those prior of 2013. To guide the user through the database, I give another three examples for the unique identifier. V2–3 is the sheet that comprises nominal gross domestic product for Brandenburg with vintages running from 2003 to 2021. Total hours worked for Lower Saxony with vintages from 2005 to 2021 is labeled as V4–9. Real gross value added in manufacturing for Saxony can be found in sheet V8c–13.

Figure 2 presents a snapshot from READ-GER for real gross domestic product for Hamburg (V1–6). The upper left corner always names the German state. Column A shows the years. The vintages start with column B. Cell B12 marks the first raw data. The upper part of the sheet contains important information on the vintages. Row 1 presents the publication dates. Row 3 labels the variable in the specific sheet (here: GDP, real). The basis on which the data depend can be found in row 4. For real GDP, row 4 contains the price basis. Until 2004, real GDP in Germany was based on a constant price basis. The current accounting standards express price-adjusted GDP in previous year prices. Row 5 names the unit on which the data depend. For real GDP, this is an index with changing base year. For total employment, the unit is 1,000 persons instead. The frequency is shown in row 6, which is annual (A) for all aggregates. As the German values serve as the benchmark, row 7 names the calculation base. For example, the March 2005 vintage is based on information from August 2004 and February 2005. Row 8 contains the original source from the working group (e.g., S1V1). Finally, row 9 and row 10 express the classification standards on which the current vintage is based on. 'WZ-Code' represents the current Classification of Economic Activities and row 10 the underlying SNA standard.

Over the years, the working group faced some severe issues, for example, by switching to the new industrial classification. These issues lead sometimes to missing past values in the time series that were resolved with new vintages. So missing values in READ-GER is an expression of non-available data. I collected the data from old annual publications that are, to the best of my knowledge, not available via permanent link by the working group. I hope that both the public and the academic community find these database interesting for own (research) activities. In the following, I analyze some revision properties of selected economic aggregates and apply a real-time forecasting experiment for state-level real GDP growth that is new in the academic literature for Germany.

Figure 2: Snapshot of READ-GER

	A	B	C	D	E	F	G	H	I	J
1	Hamburg	April 2003	April 2004	March 2005	August 2006	March 2007	March 2008	March 2009	March 2010	March 2011
2										
3	Variable	GDP, real	GDP, real	GDP, real	GDP, real	GDP, real	GDP, real	GDP, real	GDP, real	GDP, real
4	Price basis	constant	constant	constant	previous year	previous year	previous year	previous year	previous year	previous year
5	Base year	1995 = 100	1995 = 100	1995 = 100	2000 = 100	2000 = 100	2000 = 100	2000 = 100	2000 = 100	2000 = 100
6	Frequency	A	A	A	A	A	A	A	A	A
7	Calculation base	08-2002 / 02-2003	08-2003 / 02-2004	08-2004 / 02-2005	08-2005 / 02-2006	08-2006 / 02-2007	08-2007 / 02-2008	08-2008 / 02-2009	08-2009 / 02-2010	08-2010 / 02-2011
8	Source	S1V1	S1V1	S1V1	S1V1	S1V1	S1V1	S1V1	S1V1	S1V1
9	WZ-Code	2003	2003	2003	2003	2003	2003	2003	2003	2003
10	SNA standard	ESA 1995	ESA 1995	ESA 1995	ESA 1995	ESA 1995	ESA 1995	ESA 1995	ESA 1995	ESA 1995
11	Contents									
12	1991	96.8	96.8	96.8	88.6	88.6	88.6	88.6	88.6	88.6
13	1992	98.1	98.1	98.1	89.4	89.4	89.4	89.4	89.4	89.4
14	1993	98.0	98.0	98.0	89.8	89.8	89.8	89.8	89.8	89.8
15	1994	98.9	98.9	98.9	90.8	90.8	90.8	90.8	90.8	90.8
16	1995	100.0	100.0	100.0	91.9	91.9	91.9	91.9	91.9	91.9
17	1996	101.1	101.1	101.1	93.1	93.1	93.1	93.1	93.1	93.1
18	1997	103.1	103.1	103.1	94.7	94.7	94.7	94.7	94.7	94.7
19	1998	105.2	105.2	105.2	95.4	95.4	95.4	95.4	95.4	95.4
20	1999	106.7	106.5	106.5	96.2	96.2	96.2	96.2	96.2	96.2
21	2000	109.3	109.5	110.4	100.0	100.0	100.0	100.0	100.0	100.0
22	2001	110.2	111.5	113.1	105.5	104.1	104.1	104.1	104.1	104.1
23	2002	110.7	112.1	114.9	104.6	104.3	104.3	104.3	104.3	104.3
24	2003		111.6	114.1	100.3	102.4	101.2	101.2	101.2	101.2
25	2004			115.8	101.0	103.9	101.7	101.7	101.7	101.7
26	2005				102.2	105.0	103.3	102.7	102.3	102.3
27	2006					108.3	106.3	104.5	104.0	104.4
28	2007						109.3	106.3	105.2	105.9

4 Revision Properties of Regional Accounts Data

A prerequisite for meaningful policy decisions is the precise measurement of the current economic stance. Therefore, the first published values should come as close as possible to the final or true values. In the following, I want to study the behavior of revisions to regional accounts in Germany. READ-GER makes such an exercise possible. I start by briefly describing the revision process to regional accounts in Germany. A discussion on how I assess the properties of revisions follows. Finally, I present the accuracy of three macroeconomic aggregates, namely, real GDP, real GVA manufacturing, and total employment.

Revision practice. According to the quality reports of the working group, revisions to regional accounts can be divided into *ongoing revisions* and *general revisions*.[6] Both forms of revisions vary significantly in their impact for regional accounts. Whereas ongoing revisions are characterized by the successive integration of new data that become available with different time lags, general revisions are mainly intended to introduce new concepts to the accounting system such as revised methods, definitions, or classifications. Ongoing revisions can take place by each vintage published up to a year after which the values are called 'final'. General revisions take place periodically, usually each five years. In my case, the general revisions of the years 2011, 2014 and 2019 are relevant.

Strohsal and Wolf (2022, p. 1253) describe revisions in a very interesting way: "Therefore, benchmark (general) revisions can be interpreted as a redefinition of the truth, while ongoing revisions are an attempt to get closer to a given definition of the truth." Given this description, it is crucial to differentiate between both forms of revisions. If we want to assess the accuracy of the working group's estimates, we need to distinguish between both forms in general and only evaluate ongoing revisions. However, given the data situation, this is not possible at all. Nevertheless, the working group publishes revision reports that describe the general revisions' influence on the most important macroeconomic aggregates over time.[7] I can use these to assess the impacts of general revisions in a realistic way and I let flow in these information in the interpretation of my results.

The working group generally differentiates between two estimates and a final value. A first estimate for year t usually becomes available in March of year $t+1$, which is called 'first update' (in German: *1. Fortschreibung*). In March of year $t+2$ the 'second update' for year t (in German: *2. Fortschreibung*) is released together with the first update for $t+1$. The final value (in German: *Originaerberechnung*) for year t is published in March of year $t+3$, where all relevant statistics can be accessed by the working group.

Assessment of revisions. In the following, I assess the accuracy of the first update with respect to the final values of the working group. In other words, I investigate the nowcasting properties of the working group's first estimates. Let $y^{i,s}_{t|t+1}$ denote the first update of a specific variable for year t and German state s which has usually been released in March of year $t+1$. According to this definition, $y^{f,s}_{t|t+3}$ is the final value that becomes available in March of year $t+3$. The final revision investigated here, $r^{f,s}_{t|t+3}$, is than defined as

$$r^{f,s}_{t|t+3} = y^{f,s}_{t|t+3} - y^{i,s}_{t|t+1}\,. \tag{1}$$

[6] The current, German-speaking version of the quality report can be accessed here: `https://www.statistikportal.de/sites/default/files/2022-09/vgrdl_Qualitaetsbericht_2022.pdf`.

[7] The revision reports for each general revision can be accessed here: `https://www.statistikportal.de/de/vgrdl/methoden-und-informationen#revisionen`.

As example, let us take the year 2015. The first update for the year 2015 becomes available in March 2016: $y^{i,s}_{2015|2016}$. The final values are released in March 2018, $y^{f,s}_{2015|2018}$, leading to the investigated final revision $r^{f,s}_{2015|2018} = y^{f,s}_{2015|2018} - y^{i,s}_{2015|2016}$. For real GDP and total employment, I analyze the revision properties for the first estimates between 2009 and 2019. As with the general revision in 2011 a new classification of economic activities was introduced to regional accounts, the analysis for real GVA manufacturing only comprises the years 2012 to 2019. As the current vintage of READ-GER is March 2022, the last year with both a first update and a final value is 2019. Please note that the revision results have to be interpreted cautiously according to the number of observations and the period under investigation.

To assess the revision properties, I follow Lehmann and Wollmershäuser (2020) and Strohsal and Wolf (2022). According to the latter, revisions should fulfill three important properties. First, they should be unbiased in the sense: $\mathrm{E}\left(r^{f,s}_{t|t+3}\right) = 0$. Second, the revisions should not vary much, thus, they should exhibit a small variance: $\mathrm{Var}\left(r^{f,s}_{t|t+3}\right)$ is small. Third, dependent on the information set available at the first update, $I^{i,s}_{t|t+1}$, the revisions should be unpredictable, $\mathrm{E}\left(r^{f,s}_{t|t+3}|I^{i,s}_{t|t+3}\right) = 0$, that is, the available information are not able to explain the revisions. In other words, if the first update of the working group is an optimal forecast of the true value, revisions are unpredictable. I operationalize the testing of the revision properties by running the following Minzer-Zarnowitz-type regressions,

$$y^{f,s}_{t|t+3} = \alpha^{f,s} + \beta^{f,s} y^{i,s}_{t|t+1} + \varepsilon^{f,s}_{t|t+3}\,. \tag{2}$$

Based on this equation, one can investigate the data structure in several ways. I can either exploit the time series dimension only and run this regression for each state separately. Or I make usage of the panel dimension and explore different forms of variation. The latter has the advantage to model dependencies across states but comes with the price of getting average effects in the data only. Therefore, I exploit the whole set of variation by first applying panel techniques to the data. And second, I run these regressions on each German state separately. Thus, the two coefficients of the model, $\alpha^{f,s}$ and $\beta^{f,s}$, are estimated in different ways; the error term is expressed by $\varepsilon_{t|t+3}$. The usual way to start is to pool the data by treating each state equally. The resulting coefficients are $\alpha^{f,\text{pool}}$ and $\beta^{f,\text{pool}}$. I estimate the pooled model by OLS and account for both serial and cross-sectional correlation in the error term. It is reasonable to assume that both forms of correlations are present. Serial correlation arises from the fact that revisions influence the level of the series and not its transformations. As I will investigate growth rates, the revisions to previous years' levels will automatically lead to revisions of growth rates for the current year because of base effects. Cross-sectional correlation might arise from the calculation process itself. As argued in Section 2, the top-level or German aggregate is always fixed and serves as the benchmark. If, therefore, the average of a state-level aggregate does not match the German value, the difference is allocated across the states according to their economic weights.

The pooled estimation comes with the assumption of treating the states equally and leaving state-specific peculiarities unconsidered. I break with this assumption and introduce state-specific fixed-effects to the regression, therefore controlling for unobserved heterogeneity across the states within the revision process. The resulting coefficients are $\alpha^{f,\text{fix}}$ and $\beta^{f,\text{fix}}$. The inference of these coefficients is also based on controlling for serial and cross-sectional correlation in the error term. Finally, I estimate the Minzer-Zarnowitz regression for each state separately, controlling for heteroscedasticity and serial correlation in the error term. The coefficients are state-specific and denoted as $\alpha^{f,s}$ and $\beta^{f,s}$.

Unbiasedness can be investigated across the regressions by testing whether $\alpha = 0$. If up- and downward revisions equalize, no systematic bias in any direction exists. Efficiency of the first update can be investigated across the regressions by testing whether $\beta = 1$. With the joint hypothesis, $\alpha = 0$ and $\beta = 1$, I test whether the first update is an optimal forecast for the final value, thus, the revisions are purely random. If this joint hypothesis is rejected, it can be argued that the revisions are predictable. To judge whether the variance of revisions is small, a reference is needed. The natural reference is the variation of the final values. As variances are rather hard to interpret, I switch to the standard deviations (SD) in revisions and final values. The ratio between both figures, $\text{SD}\left(r^{f,s}_{t|t+3}\right) / \text{SD}\left(y^{f,s}_{t|t+3}\right)$, called Noise-to-Signal-Ratio (NTS), is used to judge whether the revisions' variation is small. A value less than one indicates that revisions vary less than the series. The larger the NTS gets, the more relevant are the revisions in economic terms.

I select the following three macroeconomic aggregates—transformed into annual growth rates before—for which I investigate the revision properties: real gross domestic product, real gross value added in manufacturing, and total employment. The choice of real GDP growth is obvious as it is the most important number for economic prosperity. The manufacturing industry is very important for the German business model and it underlies significant business cycle dynamics. As the German states show a large heterogeneity in their industrial mix, this investigation might also give some hints on what drives GDP revisions. Furthermore, regional GDP is calculated from the production side approach, thus, large industrial revisions directly map into GDP. The last aggregate represents the labor market. Interestingly, labor market figures (e.g., total employment and total hours worked) are not calculated by the Working Group Regional Accounts itself but rather by another committee: the Working Group Employment Accounts (`https://www.statistikportal.de/de/etr/der-ak-etr`). Both working groups base their calculations on different data inputs, that is, revisions in employment figures might not necessarily be reflected in macroeconomic aggregates (Döhrn, 2021). However, the Working Group Regional Accounts use the labor market variables as references to calculate, for example, labor productivity measured as GDP per employee or as input to calculate employees' compensations.

Before turning to the revision properties, it is worthwhile to study the working group's statements on the impact of general revisions. The general revision of 2011 with first estimates published in 2012 is mainly characterized by the change in the Classification of Economic Activities. The new classification comes with a considerable change in the composition of industries. This is the main reason why I start evaluating real GVA in manufacturing with the year 2012, as industries are not comparable to former vintages. According to the working group, the general revision of 2011 mainly affected the level of nominal GDP for the years 2008 to 2010 and real GDP growth for the years 2009 and 2010. However, the group also states that these two years were subject to ongoing revisions, but it gives no concrete statements on the strength of both effects. The general revision of 2014 with first estimates published in 2015 is mainly characterized by the implementation of the 2010 European System of National Accounts (ESA). Most important is the general treatment of research and development (R&D) expenditures. Before the general revision, R&D expenditures were mainly treated as intermediates. With the implementation, R&D expenditures are classified as fixed investment. Again, the general revision mainly affected the level of (nominal) GDP but leave the business cycle dynamics rather intact. However, the working group states that the values of 2012 and 2013 are affected by both influences, but the report gives no information of the relative strength between both effects. The last general revision of 2019 brought no conceptual changes. If I interpret the working group's report correctly, the changes in the values for 2017 and 2018 are mainly driven by ongoing revisions. The latest general revision also brought some changes to total employment, which has not been affected by the previous two revision rounds. However, as stated by the Working Group Employment Accounts, the employment dynamics are almost left untouched, so I expect that the majority of changes in the growth rates for the years 2017 and 2018 are due to ongoing revisions.[8]

To summarize the potential influences of general revisions, I guess that they are not the driving force behind my results. The years in my sample that could possibly be affected by both types of revisions are: 2009, 2010, 2012, 2013, 2017, and 2018. All other years are not affected as their evaluation period does not overlap with a general revision (for example, the final revision for 2015 comes with the 2018 vintage of regional accounts). Furthermore, given the statements of both working groups, the effect of general revisions for the years 2017 and 2018 are also of minor importance and mainly driven by ongoing revisions. For the other four years, it is not possible—with the exception of total employment—to assess the relative strength between ongoing and benchmark revisions. This should be kept in mind, together with the limited number of observations.

[8] The statement on the changes to employment figures can be found here: `https://www.statistikportal.de/de/etr/generalrevision-2019`.

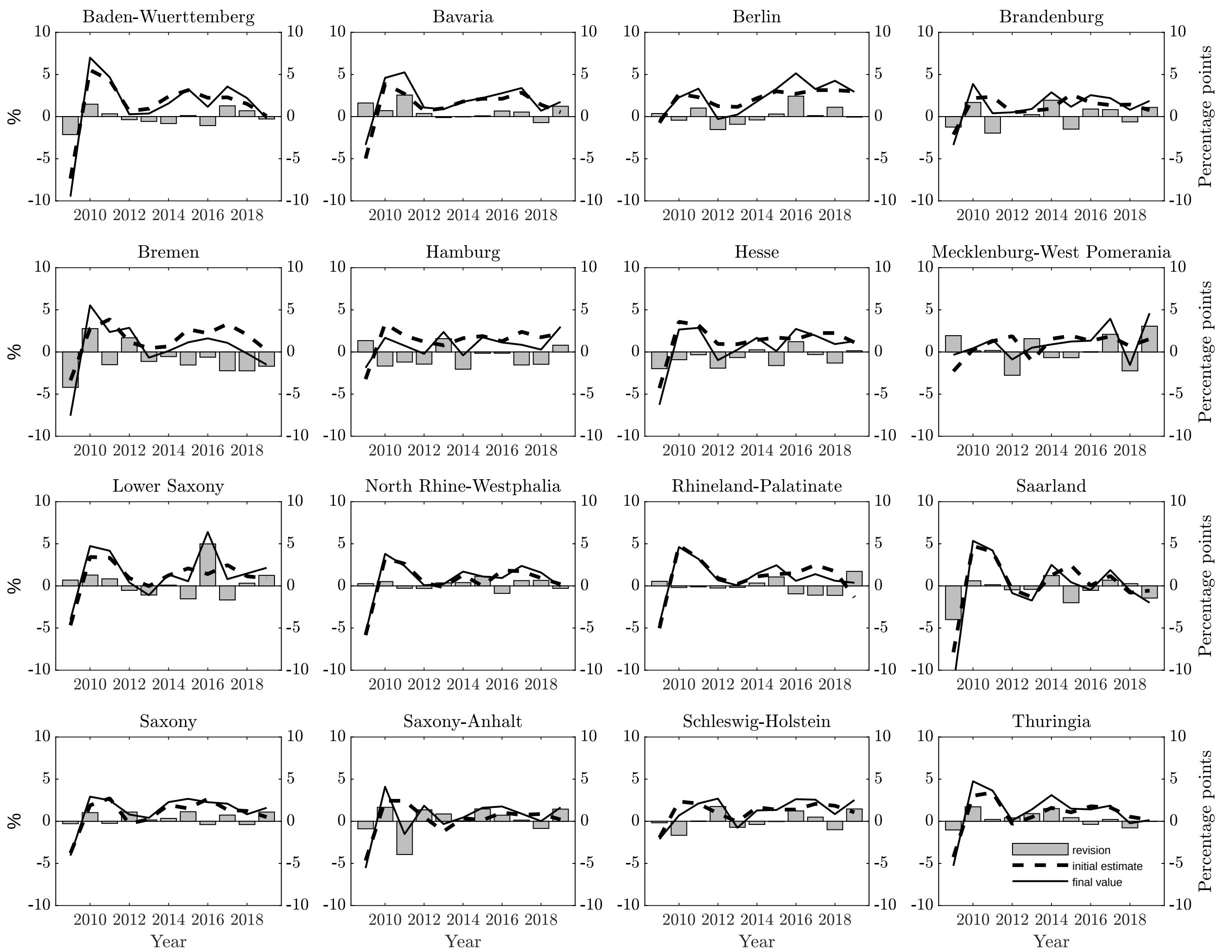
For each of the three macroeconomic aggregate, I discuss six precision measures. These are: the mean revision (MR), the minimal and maximal revision (MIN and MAX), the standard deviation in revisions (SD), the NTS, and the mean absolute revision (MAR) in order to prevent that positive and negative values cancel each other out. Additionally, I show the estimation outcomes from the Minzer-Zarnowitz regressions (henceforth: MZ-regression), together with the p-values from the tests on unbiasedness, efficiency, and predictability.

Real gross domestic product. I start by a visual inspection of the first estimates and the final values of real GDP growth per German state. The dashed lines in Figure 3 represent the initial estimates of the working group, $y^{i,s}_{t|t+1}$. The solid black lines are the final values, $y^{f,s}_{t|t+3}$. The corresponding revisions, $r^{f,s}_{t|t+3}$, are the differences between both lines and held in grey bars. Overall, the span and variation in revisions is quite heterogeneous across the states. There is a tendency towards optimism in first GDP estimates for Bremen, Hamburg, and Hesse. The first estimates for North Rhine-Westphalia, Saxony, Saxony-Anhalt, and Thuringia seem to be too pessimistic. Brandenburg and Mecklenburg-West Pomerania show first estimates that rather alternate. The amount of extreme values is quite small, given the states' revision properties. I would classify 7 observations as extreme values: Bavaria 2011, Berlin 2016, Bremen 2009, Mecklenburg-West Pomerania 2019, Lower Saxony 2016, Saarland 2009, and Saxony-Anhalt 2011. According to my calculation of revisions, only the Bremen and Saarland values for 2009 might possibly be severely biased due to the influence of general revisions. However, no information on the relative strength between ongoing and benchmark revisions is publicly available. The huge revision for Lower Saxony in 2016 is mainly driven by the largest German car producer and I will elaborate on this issue in the next section on revisions in industrial gross value added. For the other extreme values, I cannot find—to the best of my knowledge—any explanation on the statistical offices' homepages. Thus, I treat these values similar to the other ongoing revisions.

The precision measures for real GDP growth and the corresponding output from the MZ-regressions are shown in Table 2 and Table 3. The mean revision of real GDP growth estimates vary remarkably across the 16 German states, with an average overestimation of the final values for Bremen (-1.02 percentage points) and an average underestimation for Bavaria (0.63 percentage points). This heterogeneity is also reflected in the revisions' variation. The standard deviations lie between 0.58 percentage points (North Rhine-Westphalia) and 1.90 percentage points (Bremen). However, the revisions are smaller compared to the variation in final values. For all states, the NTS is smaller than one, with Baden-Wuerttemberg (0.24) at the lower tail and Mecklenburg-West Pomerania (0.86) at the upper tail of the distribution. Nevertheless, the variation in NTS might be interpreted as an expression that for some states the revisions are economically relevant. And this is especially true for specific years. I observe minimal revisions between -4.20 percentage points (Bremen) and -0.39 percentage points (Saxony). The maximal revisions lie between 1.13 percentage points (North Rhine-

Westphalia) and 4.99 percentage points (Lower Saxony). To get an expression of the values behind these percentage points, I refer Lower Saxony's maximal error to its real GDP in 2021 which amounts approximately to 281 billion euro. A five percentage points revision error would, c.p., lead to an overestimation of GDP by approximately 14 billion euro. Such dimensions seem very relevant for public finances or the German debt brake.

Figure 3: First Estimates, Final Values and Revisions of Real GDP Growth



Notes: The figure compares the initial estimates of real GDP growth (dashed lines) with the final values (solid lines) for each German state. The revisions (in percentage points) are the difference between both values and displayed on the right vertical.

Table 2: Precision of First Estimates for Real GDP Growth

State	MR (in p.p.)	MIN (in p.p.)	MAX (in p.p.)	SD (in p.p.)	NTS	MAR (in p.p.)
Baden-Wuerttemberg	-0.12	-2.14	1.47	1.06	0.24	0.83
Bavaria	0.63	-0.71	2.56	0.91	0.34	0.79
Berlin	0.18	-1.54	2.42	1.07	0.53	0.79
Brandenburg	0.13	-1.96	1.94	1.31	0.76	1.09
Bremen	-1.02	-4.20	2.77	1.90	0.51	1.83
Hamburg	-0.54	-2.04	1.58	1.30	0.64	1.22
Hesse	-0.67	-1.98	1.22	1.00	0.34	0.97
Mecklenburg-West Pomerania	0.24	-2.77	3.06	1.82	0.86	1.39
Lower Saxony	0.43	-1.67	4.99	1.84	0.56	1.30
North Rhine-Westphalia	0.20	-0.89	1.13	0.58	0.25	0.52
Rhineland-Palatinate	-0.02	-1.12	1.73	0.89	0.35	0.69
Saarland	-0.53	-4.00	1.23	1.48	0.34	1.07
Saxony	0.39	-0.39	1.14	0.65	0.30	0.63
Saxony-Anhalt	0.19	-3.94	1.66	1.64	0.66	1.22
Schleswig-Holstein	0.09	-1.66	1.76	1.06	0.54	0.81
Thuringia	0.29	-1.03	1.72	0.86	0.31	0.69

Notes: The table shows state-specific descriptive statistics (in percentage points, p.p.) for real gross domestic product growth revisions. The descriptive statistics comprise the mean revision (MR), the minimal (MIN) and maximal (MAX) revision, the standard deviation (SD) in revisions, the Noise-to-Signal Ratio (NTS) as the ratio between the standard deviation in revisions and the standard deviation of the variable's latest vintage, and the mean absolute revision (MAR). The period comprises the years from 2009 to 2019.

Taken all 16 German states together in the panel setup, the first estimates of real GDP growth are unbiased, efficient, and the revisions are not predictable (see Table 3). This is per se good news and goes into the direction of Strohsal and Wolf (2022) as the states are coordinated on the German value. However, the panel estimates suppress the heterogeneities across states. The state-specific MZ-regressions hint instead on the fact that the revisions for 9 out of 16 states are predictable, that is, the first estimate is not an optimal forecast for the final value. The predictability is either driven by an over- or underestimation (Bavaria, Bremen, Mecklenburg-West Pomerania, Saxony), inefficiency (Hamburg, Thuringia) or both characteristics simultaneously (Baden-Wuerttemberg, Hesse, Saarland). For the other seven states I detect no systematic distortions, thus, they can be described as optimal forecasts for the period under investigation. The nine states together represent more than 45% of German GDP. The three states for which all three characteristics are not met represent approximately one-fourth of the German economic activity. My results, however, should be interpreted as first hints towards the question on optimal estimates as the analysis is based on 11 observations. Nevertheless, the results either call for potential improvements in German GDP growth estimates, for an improvement of calculation methods for the first update of state-level GDP, or a better data input. As GDP is calculated as the sum of industrial GVA, I dig deeper into this process in the following.

Table 3: MZ-Regression Results for Real GDP Growth

State	α	$\alpha = \mathbf{0}$	β	$\beta = \mathbf{1}$	$\alpha = \mathbf{0}$, $\beta = \mathbf{1}$	$\mathbf{R^2_{adj.}}$
Baden-Wuerttemberg	-0.46	**0.05**	1.24	**0.00**	**0.00**	0.97
Bavaria	0.74	**0.02**	0.92	0.38	**0.04**	0.83
Berlin	-0.42	0.60	1.28	0.37	0.43	0.65
Brandenburg	0.07	0.88	1.05	0.91	0.90	0.46
Bremen	-1.59	**0.01**	1.39	0.20	**0.03**	0.69
Hamburg	0.10	0.66	0.54	**0.00**	**0.00**	0.36
Hesse	-0.91	**0.00**	1.18	**0.01**	**0.00**	0.86
Mecklenburg-West Pomerania	0.62	**0.03**	0.54	0.15	**0.02**	0.06
Lower Saxony	0.43	0.35	0.99	0.94	0.63	0.54
North Rhine-Westphalia	0.22	0.14	0.97	0.52	0.22	0.94
Rhineland-Palatinate	0.15	0.57	0.84	0.12	0.28	0.87
Saarland	-0.61	**0.08**	1.31	**0.00**	**0.01**	0.94
Saxony	0.37	**0.05**	1.02	0.88	**0.01**	0.88
Saxony-Anhalt	0.20	0.58	0.96	0.89	0.83	0.51
Schleswig-Holstein	0.19	0.58	0.92	0.62	0.80	0.48
Thuringia	0.09	0.69	1.24	**0.01**	**0.03**	0.92
Panel: pooled	-0.08	0.49	1.07	0.22	0.44	0.75
Panel: fixed-effects	-0.09	0.21	1.08	0.15	0.32	0.77

Notes: The table shows the estimation output from the Mincer-Zarnowitz regressions (MZ-regressions) for real gross domestic product growth either for each German state separately or in a panel setup (pooled, fixed-effects). The corresponding coefficient estimates, α and β, are shown together with the p-values from the single and joint hypotheses tests. A p-value that is at least smaller than 10% is hold in boldface. The parameter inference of the state-specific estimates is based on standard errors consistent to heteroskedasticity and autocorrelation. In the panel setup it is additionally controlled for cross-sectional correlation across state revisions. The period comprises the years 2009 to 2019 (no. of state-specific observations: 11, no. of observations in the panel: 176).

Real gross value added manufacturing. The manufacturing industry plays a crucial role for Germany's economic development as its business model is mainly based on investment good production and exports. Manufacturing's share in total German nominal GVA was about 20% in 2021; the corresponding figure for the EU27 is more than 16%. Germany is highly industrialized, but the importance of manufacturing varies significantly across the states. In 2021, Berlin shows the lowest share of manufacturing in total GVA with 6% and Baden-Wuerttemberg the highest with 30%. So the first estimate of manufacturing GVA might be one crucial factor for the first update of GDP growth estimates.

The revisions for GVA in manufacturing are in general larger compared to those for real GDP growth as the mean absolute revisions clearly show (see the Supplementary Material for the concrete numbers). The mean absolute revisions range from 1.18 percentage points for Baden-Wuerttemberg up to 6.42 percentage points for Lower Saxony. The latter is mainly driven by the extreme correction in 2016, which—according to Döhrn (2021)—can be attributed to a sharp drop in intermediate consumption of the largest German car producer that is operating in the city of Wolfsburg. For sure, the variation in GVA manufacturing is much higher compared to GDP, which is one reason that explains parts of the larger revisions.

However, this is not the only source of explanation. The NTS is larger or equal to one for 6 out of the 16 German states, thus, the variation in revisions is quite large and economically meaningful. The mean revisions also do not cancel out to zero on average for most of the states. They range from an average overestimation of -1.24 percentage points in Bremen to a large average underestimation of 3.58 percentage points in Schleswig-Holstein. The latter state is also an interesting case as all first updates in the years 2012 to 2019 underestimate the final value; both the minimal and the maximal revision is positive. Over the years, one can also observe severe revisions. For Bremen, the minimal revision is -10.07 percentage points and the maximal revision for Schleswig-Holstein amounts to 9.89 percentage points, despite the already mentioned extreme revision for Lower Saxony (22.39 p.p.). Therefore it comes with no surprise that the revisions' volatility is quite heterogeneous across the states.

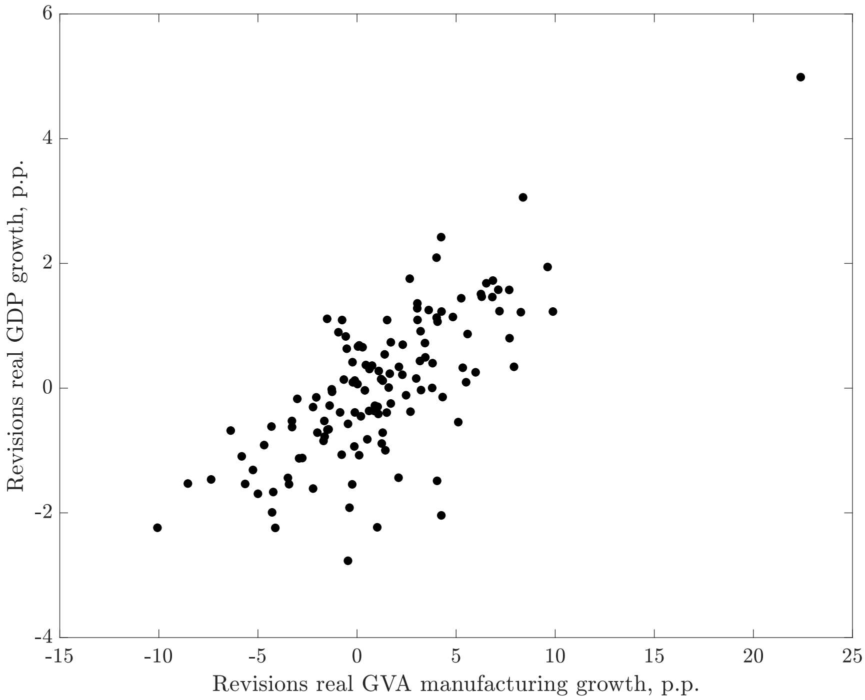
According to the panel-based MZ-regressions, the first estimates are no optimal predictions for the final values (see the Supplementary Material). On average, the first updates for GVA growth in manufacturing lie significantly below the final estimates. Furthermore the first updates are not efficient and the revisions are predictable according to my criteria. However, this cannot translated to each of the German states. For 6 out of 16 German states significant improvements of the first estimates seem possible. However, the number of observations further shrinks compared to GDP, which has to be taken into account. Based on the methodological guide of the working group, I suggest that mainly three reasons are crucial for the revisions in manufacturing.[9] First, the data availability is worse compared to the situation at the national level. For example, industrial production is not publicly available for most of the states and turnover might not be a good indicator to estimate gross value added. Second, the working group has almost no early information on intermediate consumption, which can severely bias the transition from production to gross value added. Finally, it is a rather hard task to distribute total economic activity of a multi-state company to the specific local entity. If these first estimates do not coincide with the final report of a group, large revisions are the ultimate consequence.

Regional gross domestic product is calculated as the sum of industrial GVA. Thus, one can ask whether and how much do industrial revisions shape the revisions in GDP. A strong correlation between revisions for GVA manufacturing and GDP exists as Figure 4 shows. Despite the heterogeneity in the importance of manufacturing across the states, the slope of a simple regression is 0.21 and highly significant. This means that a revision in GVA manufacturing of 1 percentage points leads, on average, to a revision in real GDP of 0.21 percentage points. Both revision series correlate by 0.74. The significant connection between both variables is also not driven by the outlier for Lower Saxony. Without this outlier, the slope between the revisions of GDP and GVA manufacturing still amounts to 0.20. In future research activities it might be fruitful to explore how much the revisions in service activities

[9] The detailed methodological guide can be found here: `https://www.statistikportal.de/de/vgrdl/methoden-und-informationen`.

shape the revisions in GDP as the data availability for the regional service industries is even worse compared to manufacturing. Here, one can only rely on employment figures subject to social security that might not be good proxies for all service activities (for example, financial services or education). A first impression can be gained by taking a closer look at the largest industry: public services. The public services' share in total 2021 GVA ranges from 18% (Baden-Wuerttemberg) to almost 34% (Berlin). Despite the fact that the revisions for public services are much smaller (mean absolute revision over all states: 0.81 percentage points) than those for manufacturing (mean absolute revision over all states: 3.21 percentage points), the slope between public services' revisions and those for GDP amounts to 0.27. However, both revisions only correlate by 0.22. To fully understand the whole calculation process and the reasons behind the revisions, it seems very fruitful to deeply explore the production side approach of GDP estimation.

Figure 4: Revisions in GVA Manufacturing and GDP Growth



Notes: The figure compares the revisions (in percentage points, p.p.) for real gross value added (GVA) growth in manufacturing with revisions in real gross domestic product (GDP) growth for all 16 German states and the years 2012 to 2019.

Total employment. The revisions for total employment growth are rather small in magnitude compared to both GDP and GVA in manufacturing (see, again, the Supplementary Material for more details). The mean absolute revisions range from 0.11 for Hesse to 0.35 percentage points for Mecklenburg-West Pomerania. All NTS are smaller than one. However, for some states the NTS seem to be economically relevant, for example, for Saxony-Anhalt (0.73). For most of the states, positive and negative revisions amount to almost zero, but the span between the minimal and the maximal revision are quite large. I again observe for Mecklenburg-West Pomerania the largest minimal revision with -0.62 percentage points. The maximal revision was produced for Bremen with 0.91 percentage points.

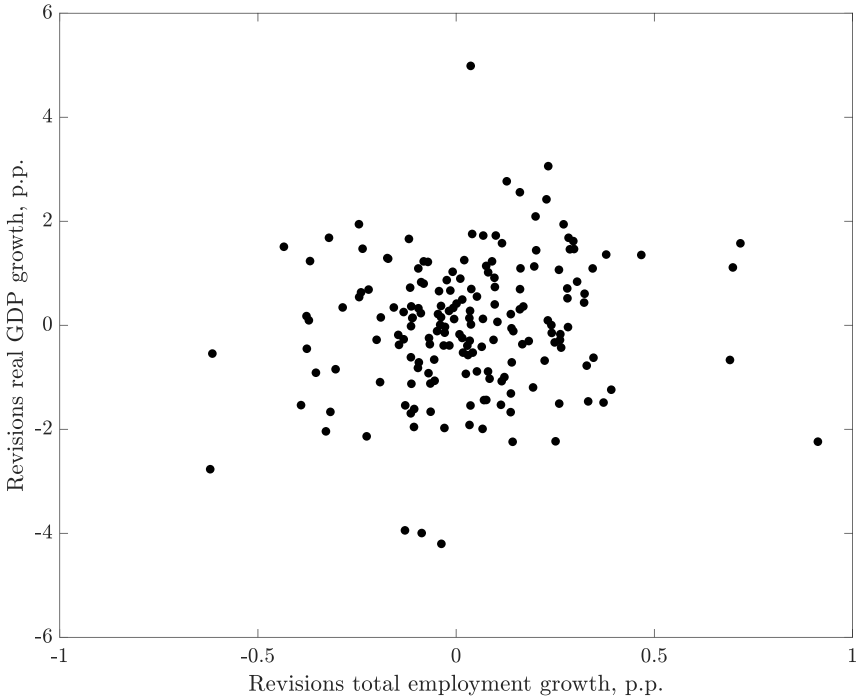
The pooled MZ-regressions show no special abnormalities. However, if I explicitly control for state fixed-effects, that is, unobserved state revision characteristics, the first employment growth estimates are no optimal forecasts. This result is mainly driven by the systematic underestimation of the final values. The state-specific estimates suggest potential accuracy improvements for 7 out of 16 German states. In 2021, these seven states were responsible for almost 70% of all employed persons in Germany. Strohsal and Wolf (2022) detect that quarterly employment figures for Germany are biased, inefficient and not optimal. As the state-level employment figures are also coordinated on the German value, it seems reasonable to hypothesize that the German revisions spill over to the state-level estimates. If this is true, one has to recommend that the estimation process has to be adjusted. The German value should not be fixed by the Federal Statistical Office, but rather be the sum of state-level estimates. This might significantly reduce the revision errors for both the state and the national figures. Future research activities might concentrate on such important questions.

Additional explanations for the previous results might be found in the methodological guide of the Working Group Employment Accounts.[10] According to this guide, the calculation of employed persons is carried out for 88 industries and the persons' occupation. Whereas the number of workers are based on the figures from the Federal Employment Agency, regional information on, for example, self-employed persons is rather hard to acquire. Here, information from secondary sources are incorporated, thus, the data availability might be the main reason for the detected revisions.

Finally, I compare the revisions for total employment growth with the revisions for real GDP growth (see Figure 5). Both revisions do not seem to be connected. The corresponding correlation coefficient between the two series is 0.13. This finding gives rise to the hypothesis that the first estimates of both employment development and real GDP growth are not connected at all. Döhrn (2021) emphasizes that the large revisions in real GDP growth mainly drive the huge revisions in labor productivity as the revisions in employment growth are rather small. He suggests to connect both accounts with each other to rationalize estimates for economic activity (either GDP or industrial GVA). His main argument is that in a competitive economy firms in a specific industry should show similar productivity developments, thus, large annual differences in state-specific labor productivity growth need to be explained in more detail. My results point in the same direction, that is, employment accounts should at least be used to cross validate estimations for industrial gross value added.

[10]The methodological guide of the Working Group Employment Accounts can be found here: `https://www.statistikportal.de/de/etr/definitionen-und-methoden#methoden`.

Figure 5: Revisions in Total Employment and GDP Growth



Notes: The figure compares the revisions (in percentage points, p.p.) for total employment growth with real gross domestic product (GDP) growth revisions for all 16 German states and the years 2009 to 2019.

5 Regional GDP Nowcasting in Real-time

Next to a revision analysis, READ-GER allows to carry out a regional nowcasting exercise in real-time. More precisely, I apply the methodology by Lehmann and Wikman (2023) and compare my real GDP growth nowcasts to both the initial and the final values of the Working Group Regional Accounts. Whereas the first comparison can be seen as an expression how good the model might work in applied nowcasting, the second comparison can be interpreted on whether the model is able to reduce revision errors. I first briefly describe the nowcasting model. Second, I introduce the main steps undertaken in the real-time setup. Finally, I discuss the overall performance together with a comparison to the working group's revisions.

Model setup and estimation. The model I build my nowcasts on was developed by Koop *et al.* (2020) for the United Kingdom and transferred to the German states by Lehmann and Wikman (2023). Its main purpose is to calculate unobserved quarterly growth rates of regional accounts variables, to be more precise, real GDP growth. However, given its structure, it can also be used to generate quarterly nowcasts for annual changes. The model is a Vector Autoregressive process with mixed-frequencies (MF-VAR) in state space form. It links observed quarterly German GDP growth with unobserved quarterly state-level GDP growth and additional exogenous predictors. The VAR has the following form,

$$y_\tau = \Phi_0 + \sum_{i=1}^{p} \Phi_i y_{\tau-i} + u_\tau\,, \quad u_\tau \overset{iid}{\sim} N(0, \Sigma_\tau)\,, \tag{3}$$

where y_τ is the vector of quarterly GDP growth.[11] The lag length is chosen to be $p = 7$ quarters. The system is informed by further restrictions. First, I have to ensure that state-level quarterly GDP growth equals the official annual values from the working group. Following Mariano and Murasawa (2003, 2010), Mitchell *et al.* (2005) and Schorfheide and Song (2015), the official annual growth rate for each German state s, $y_\tau^{s,A}$, is only observed in the fourth quarter of a given year and equals the weighted sum of contemporaneous and lagged values of quarterly state-level GDP growth, y_τ^s:

$$y_\tau^{s,A} = \frac{1}{4}y_\tau^s + \frac{1}{2}y_{\tau-1}^s + \frac{3}{4}y_{\tau-2}^s + y_{\tau-3}^s + \frac{3}{4}y_{\tau-4}^s + \frac{1}{2}y_{\tau-5}^s + \frac{1}{4}y_{\tau-6}^s\,. \tag{4}$$

Given this relationship, the system is informed by three measurement equations. Therefore, the second restriction links the annual growth rates, y_τ^A, to the unobserved quarterly rates in the following way:

$$y_\tau^A = M_\tau^A \Lambda^A z_\tau\,, \tag{5}$$

with z_τ as the vector of unobserved state-level quarterly GDP growth. The matrix Λ^A contains the weights from Equation (4). The matrix M_τ^A controls the point in time when the annual aggregation constraint has to hold, thus, $M_\tau^A = 1$ if $\tau = 4$ and $M_\tau^A = 0$ otherwise. This matrix takes an important role for nowcasting annual GDP growth and missing observations at the end of the sample, which will be discussed in the following section.

The third restriction expresses the properties for German quarterly GDP growth, y_τ^{GER}. The structure of this restriction is much easier compared to the states' form as German GDP growth is always observed. The second measurement equation reads as follows:

$$y_\tau^{GER} = M_\tau^{GER} \Lambda^{GER} y_\tau\,. \tag{6}$$

Here, Λ^{GER} only grabs the German values from the vector y_τ. The matrix M_τ^{GER} is constructed according to M_τ^A. It takes a value of one if the value is observed and zero otherwise. In our case, German GDP growth is always observed and determines the nowcasting dates.

With the previous two measurement equations, I model the temporal nature of the data. I furthermore need to ensure that the weighted state-level GDP growth has to equal the official German value. This ensures consistency between regional and national accounts data. For this purpose, I add the fourth restriction to the system and inform it with the following cross-section restriction:

[11] The vector y_τ actually also includes the exogenous predictors. However, to ensure readability, I only discuss the relationship across GDP figures.

$$y_\tau^{GER} = \frac{1}{S}\sum_{s=1}^{S} y_\tau^s + \eta_\tau\,, \quad \eta_\tau \sim N(0, \sigma_{cs}^2)\,. \tag{7}$$

The model is based on log-differenced data for which Koop *et al.* (2020) show that national GDP growth can be expressed as the simple average of regional GDP growth. I follow them in my application.

Next to German GDP growth, the MF-VAR is informed by further macroeconomic and regional variables. For the national variables, I follow Koop *et al.* (2020) as well as Reif (2022) and add four macroeconomic variables measured at the German level: the seasonally-adjusted consumer price index (CPI), the bank rate (yields on debt securities), the exchange rate (real effective exchange rate against 51 trading partners), and the oil price. As the data situation at the German state level is quite unsatisfactory, the choice of regional indicators that are available for all states simultaneously and as long time series is very limited. I therefore rely on the number of unemployed people and a survey-based indicator, the ifo Business Climate Industry and Trade. The latter counts as one of the most important business cycle indicators for Germany and its regional counterparts were certified to have good forecasting properties (see, Lehmann, 2023, for a literature survey). More regional indicators, such as industrial production, would be preferable. However, they are not available at all.

Instead of applying MCMC sampling, the inference here is based on Variational Bayes (VB) methods as introduced by Gefang *et al.* (2020). For the German case, Lehmann and Wikman (2023) have shown that in-sample estimates either based on MCMC or VB methods produce highly correlated outcomes. VB methods are much more efficient and less time-consuming than MCMC sampling. The main drawback is their approximate nature of the posterior density. However, given their efficiency and the fact that the in-sample estimates are close to each other, I decided to apply them here. The missing quarterly state-level observations are filled in with the Kalman filter.

Nowcasting exercise. In my nowcasting application, I strictly follow the publication scheme in Figure 1. Annual state-level GDP growth for year t is normally released at the end of March in $t+1$. Quarterly German GDP is released in revised form approximately 55 days after the end of each quarter. Therefore, we can formulate four nowcasts for annual state-level GDP growth within year t, based on different quarterly information sets. We calculate the nowcasts by explicitly using the ragged-edge nature of the data and adjust the matrices M_t^A and M_t^{GER} from Equations (5) and (6) accordingly. For each quarter in year t for which German GDP growth is released, we calculate state-level growth rates out-of-sample and use these together with the in-sample estimates from year $t-1$ and the aggregation condition in Equation (4) to generate annual state-level GDP growth. The four information sets are:

1. I_1: German GDP growth for quarter one (y_1^{GER}) and annual state-level GDP growth for year $t-1$ available;

2. I_2: y_1^{GER}, y_2^{GER} and annual state-level GDP growth for year $t-1$ available;

3. I_3: y_1^{GER}, y_2^{GER}, y_3^{GER} and annual state-level GDP growth for year $t-1$ available;

4. I_4: all four quarters for German GDP growth and annual state-level GDP growth for year $t-1$ available.

The period runs from 2012 to 2021 and the nowcasts are produced each quarter. Thus, we end up with 40 nowcasts in total, 10 predictions per quarter, or 4 nowcasts per year. We start in the first quarter of 2012. At this point, German GDP growth is available for the first quarter of 2012 and annual state-level GDP growth for the year 2011. We estimate the model, formulate a nowcast for 2012 and recursively move forward by one quarter. In the next quarter, the data set is enlarged by German GDP growth for the second quarter of 2012 and the model is re-estimated. This procedure is done until the end of the sample. The state-level regressors—survey information and the number of unemployed persons—are always available for the quarter at hand as they exhibit no or a smaller publication lag than German GDP growth. The real-time data for German GDP growth and the CPI are extracted from the Bundesbank's real-time database. To the best of our knowledge, the exchange rate, the oil price, and the regional unemployment figures are not available in real-time, thus, we take the latest vintage of data. The bank rate is not revised and the revisions' in survey data are only due to the seasonal adjustment procedure, thus, I also treat their latest vintage as real-time data.

The accuracy of the nowcasts are judged by the root mean squared forecast error (RMSFE) either compared to the initial ($y_{t|t+1}^{i,s}$) or the final release ($y_{t|t+3}^{f,s}$) of regional accounts data; the Supplementary Material contains mean absolute forecast errors (MAFE). The comparison to the initial estimates are important for applied forecasting work as a forecaster usually wants to come as close as possible to the first release, given the data available to that point in time. The comparison to the final value can be interpreted in the same way as the revision errors by the working group. I can judge whether the MF-VAR produces larger, smaller or equal revision errors. To judge how large or small the RMSFEs are, I calculate the Noise-to-Signal Ratio (NTS) that expresses the RMSFE in terms of the standard deviation of the underlying series that we want to nowcast. In our case, this is annual state-level GDP growth.

The nowcasting results of my MF-VAR are compared to four benchmarks: the Random-Walk (RW, last known value represents the nowcast), the in-sample mean (ISM, the average growth rate up to year $t-1$ represents the nowcast), an uninformative VAR(1) model, and an uninformative AR(1). All benchmark models are also estimated with real-time data. To decide whether the forecast errors of the MF-VAR are significantly different from the AR(1) benchmark, we apply the test for equal predictive ability by Diebold and Mariano (1995), modified via the small sample correction by Harvey *et al.* (1997).

Performance for first updates. Table 4 presents the RMSFEs for the four information sets within a year (Q1 to Q4) and the benchmark models. Overall, the MF-VAR delivers very encouraging results for applied regional economic nowcasting in Germany. Especially with the release of information for the second quarter in a given year, the nowcast accuracy sharply increases compared to the benchmark models. On average, the RMSFEs of the MF-VAR are already 40% lower in Q2 of year t compared to both the in-sample mean and the AR(1) benchmark; the average gain over the Random-Walk is 55% and 60% over the uninformative VAR(1). The corresponding average RMSFE amounts to 1.48 percentage points. According to the Diebold-Mariano test, all nowcast errors in quarter two—with the exception of the Saarland—are significantly lower than those of the autoregressive model.

Table 4: RMSFEs for Annual State-Level GDP Growth Nowcasts, Initial Release

State	MF-VAR-SV				RW	ISM	VAR1	AR1
	Q1	Q2	Q3	Q4				
Baden-Wuerttemberg	3.33	**1.81**	**1.27**	**1.04**	3.62	2.49	4.95	2.68
Bavaria	3.15	**1.51**	**1.21**	**0.97**	3.40	2.47	2.91	2.68
Berlin	2.84	**1.53**	**1.38**	**1.35**	2.96	2.14	4.50	2.66
Brandenburg	1.78	**0.76**	**0.73**	**0.90**	2.00	2.57	3.10	1.77
Bremen	3.70	**2.08**	**1.60**	**1.41**	4.07	2.82	4.39	2.93
Hamburg	3.33	**1.75**	**1.32**	**1.04**	3.59	**2.34**	4.52	2.54
Hesse	3.22	**1.53**	**1.13**	**0.93**	3.59	2.32	3.38	2.53
Mecklenburg-West Pomerania	2.44	**1.17**	**0.98**	**0.99**	2.56	2.23	2.60	2.26
Lower Saxony	2.52	**0.95**	**0.72**	**0.72**	3.01	2.10	2.88	2.07
North Rhine-Westphalia	2.57	**1.14**	**0.80**	**0.58**	2.81	1.88	3.22	1.92
Rhineland-Palatinate	4.52	**3.10**	**2.68**	**2.31**	4.77	3.43	2.92	3.62
Saarland	3.37	1.94	**1.54**	**1.45**	3.79	2.66	5.07	2.44
Saxony	2.90	**1.36**	**1.00**	**0.70**	2.98	2.89	3.39	2.63
Saxony-Anhalt	2.36	**0.92**	**0.71**	**0.76**	2.51	2.67	2.85	2.05
Schleswig-Holstein	2.30	**0.92**	**0.49**	**0.44**	2.39	1.58	2.63	1.79
Thuringia	2.66	**1.27**	**0.78**	**0.55**	2.92	3.28	2.71	2.38

Notes: The table shows the root mean squared forecast errors (RMSFE) in percentage points for the four quarterly information sets within a year (Q1 to Q4) and the four benchmark models. The benchmarks are: the Random-Walk (RW), the in-sample mean (ISM), a Vector Autoregressive model of first order (VAR1), and an autoregressive process of first order (AR1). A model's RMSFE hold in boldface indicates significant smaller forecast errors than the AR1 at least to the 10% level. The nowcasting period comprises the years 2012 to 2021. The nowcasts are compared to the first release of real state-level GDP growth.

It is not surprising that the increase in nowcast accuracy occurs from the first quarter of year t to the second quarter. The RMSFEs in Q1 are smaller than those of the Random-Walk what might be expected by looking at the aggregation condition in Equation (4). If we conduct a forecasting experiment in Q4 of $t-1$ with no annual information for the given year and a forecast error of zero, the aggregation condition would collapse into the Random-Walk. In our case, we enrich these information set with German GDP growth for Q1 of year t, thus, we add only on quarter and move the aggregation condition in Equation (4) forward. This information, on average, is only slightly accuracy-increasing (approximately 8 percentage points over the Random-Walk). However, this changes with the second quarter.

By moving the nowcast experiment forward within the year, the nowcast accuracy further increases. All nowcast errors from the MV-VAR are significantly smaller according to the Diebold-Mariano test. In Q4, the average gain of the MF-VAR is 60% over both the AR(1) and the in-sample mean, 70% over the VAR(1) that models state interdependencies, and 69% over the Random-Walk. Also the size of the errors in Q4 is very encouraging for applied state-level nowcasting. The average RMSFE in Q4 is 1.01 percentage points with 10 states for which we observe lower RMSFEs. For Rhineland-Palatinate, the Saarland, and Bremen, however, the RMSFEs are higher compared to all other states. I suggest that structural characteristics in the regional industrial mix drive these nowcast errors. The result for Rhineland-Palatinate can be explained by an extra boom in the aftermath of the first Corona-year. In 2021, the economic activity in Rhineland-Palatinate was mainly stimulated by the development of the COVID-19-vaccine by Biontech, whose headquarter is located in the state's capital Mainz. All models cannot anticipate this special effect. In general, the MF-VAR is able to catch these developments if further regional indicators, such as industrial production, would be available. However, German GDP growth, the unemployment rate and the survey indicators are in this special case not enough to detect such a large increase. If I exclude the year 2021 from the RMSFE calculation, the error for Rhineland-Palatinate drops to 0.77 percentage points.

Next to the discussion on the absolute size of the errors, I need to discuss their properties relative to the underlying dynamics of the series to nowcast. I do so by calculating the NTS that is the ratio between the RMSFEs and the standard deviation in annual state-level real GDP growth. Table 5 reveals that the nowcasts from the MF-VAR can be interpreted as valuable signals, also for the states with the slightly higher RMSFEs. With the availability of information for Q2 of year t, the NTS drops significantly below one. By moving forward to the fourth quarter, the NTS further decrease and range between 0.23 (Schleswig-Holstein) and 0.69 (Rhineland-Palatinate). In the end, the NTS for the MF-VAR simply state that the RMSFEs vary much less compared to the underlying series that we want to nowcast. This is also good news for applied economic nowcasting at the German state level, especially as all benchmarks—again with some few exceptions—produce RMSFEs that are much higher than the variation in the series. Based on our results, the MF-VAR already delivers accurate nowcasts in late summer.

Table 5: Noise-to-Signal Ratios for Annual State-Level GDP Growth Nowcasts, Initial Release

State	**MF-VAR-SV**				**RW**	**ISM**	**VAR1**	**AR1**
	Q1	**Q2**	**Q3**	**Q4**				
Baden-Wuerttemberg	1.29	0.70	0.49	0.40	1.40	0.96	1.91	1.04
Bavaria	1.43	0.68	0.55	0.44	1.54	1.12	1.32	1.21
Berlin	1.06	0.57	0.52	0.50	1.11	0.80	1.68	0.99
Brandenburg	0.98	0.42	0.40	0.49	1.09	1.41	1.70	0.97
Bremen	1.71	0.96	0.74	0.65	1.88	1.30	2.02	1.35
Hamburg	1.17	0.61	0.46	0.36	1.26	0.82	1.58	0.89
Hesse	1.43	0.68	0.51	0.42	1.60	1.03	1.51	1.13
Mecklenburg-West Pomerania	0.93	0.45	0.37	0.38	0.98	0.85	0.99	0.86
Lower Saxony	0.91	0.34	0.26	0.26	1.09	0.76	1.04	0.75
North Rhine-Westphalia	1.25	0.56	0.39	0.28	1.37	0.92	1.57	0.94
Rhinland-Palatinate	1.34	0.92	0.79	0.69	1.41	1.02	0.86	1.07
Saarland	1.25	0.72	0.57	0.54	1.40	0.99	1.88	0.91
Saxony	1.38	0.65	0.48	0.33	1.42	1.38	1.62	1.25
Saxony-Anhalt	1.29	0.51	0.39	0.42	1.38	1.46	1.56	1.12
Schleswig-Holstein	1.23	0.49	0.26	0.23	1.28	0.85	1.41	0.96
Thuringia	1.27	0.61	0.37	0.26	1.40	1.57	1.30	1.14

Notes: The table shows the Noise-to-Signal Ratios (NTS) for the four quarterly information sets within a year (Q1 to Q4) and the four benchmark models. The NTS is defined as the ratio between the root mean squared forecast error and the standard deviation of annual real GDP growth. The benchmarks are: the Random-Walk (RW), the in-sample mean (ISM), a Vector Autoregressive model of first order (VAR1), and an autoregressive process of first order (AR1). The nowcasting period comprises the years 2012 to 2021. The nowcasts are compared to the first release of real state-level GDP growth.

Performance for final values. In the following I examine how much informational content the real-time nowcasts have for the final values. Table 6 present the RMSFEs based on the latest vintage. The general results from the comparison to the initial values are untouched as I only changed the benchmark to which all nowcasts are referred to. Furthermore, the nowcast accuracy for the final values decreases, which is no surprise as newly published information over the years cannot be accessed in real-time. Two exceptions exist: Bremen and Hesse. For these two states, the RMSFEs become smaller. They decrease from 1.41 to 1.26 percentage points (Bremen) and from 0.93 to 0.86 percentage points (Hesse), respectively. The RMSFEs in the fourth quarter range from 0.66 percentage points (North Rhine-Westphalia) to 2.31 percentage points (again, Rhineland-Palatinate). This is a similar range as for the initial values. However, the average RMSFE increases from 1.01 percentage points to 1.38 percentage points. Nevertheless, this is still a very good performance. I interpret this finding in a way that the MF-VAR produces accurate real-time nowcasts for the final values and seems to anticipate revisions to the data. This statement can be investigated by comparing my real-time nowcasts with the initial estimates of the working group. In other words, I compare the nowcast errors for the final values with the revision errors from the previous section.

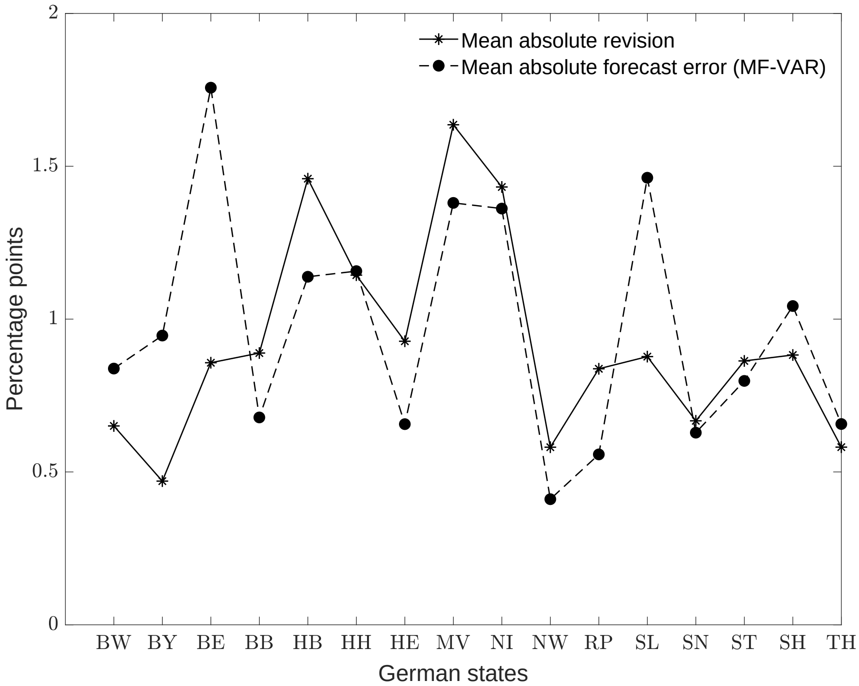
Table 6: RMSFEs for Annual State-Level GDP Growth Nowcasts, Final Release

State	**MF-VAR-SV**				**RW**	**ISM**	**VAR1**	**AR1**
	Q1	**Q2**	**Q3**	**Q4**				
Baden-Wuerttemberg	3.38	**1.90**	**1.35**	**1.10**	3.66	2.51	5.03	2.69
Bavaria	3.09	**1.62**	**1.32**	**1.08**	3.30	2.18	2.87	2.61
Berlin	3.20	2.14	2.06	2.04	3.30	2.80	5.25	3.18
Brandenburg	1.88	1.05	1.05	1.21	2.11	2.46	3.56	1.96
Bremen	3.48	**1.95**	**1.46**	**1.26**	3.82	**2.10**	3.60	2.09
Hamburg	3.69	**2.31**	**1.98**	**1.70**	3.92	**2.77**	4.58	2.91
Hesse	3.26	**1.65**	**1.19**	**0.86**	3.65	**2.20**	3.31	2.35
Mecklenburg-West Pomerania	3.29	2.42	2.20	2.04	3.37	2.90	3.25	3.11
Lower Saxony	2.93	1.89	1.86	1.91	3.40	2.67	3.51	2.74
North Rhine-Westphalia	2.62	**1.19**	**0.83**	**0.66**	2.89	1.98	3.60	2.08
Rhineland-Palatinate	4.50	**3.10**	**2.68**	**2.31**	4.72	**3.29**	2.97	3.53
Saarland	3.68	2.38	1.99	1.92	4.17	2.96	5.51	2.66
Saxony	2.83	**1.35**	**1.03**	**0.82**	2.93	2.65	3.64	2.62
Saxony-Anhalt	2.35	**1.04**	**0.94**	**0.97**	2.48	2.38	2.78	2.09
Schleswig-Holstein	2.39	**1.29**	**1.13**	**1.19**	2.46	1.81	2.43	2.06
Thuringia	2.76	1.52	**1.13**	**0.98**	3.04	3.18	3.06	2.53

Notes: The table shows the root mean squared forecast errors (RMSFE) in percentage points for the four quarterly information sets within a year (Q1 to Q4) and the four benchmark models. The benchmarks are: the Random-Walk (RW), the in-sample mean (ISM), a Vector Autoregressive model of first order (VAR1), and an autoregressive process of first order (AR1). A model's RMSFE hold in boldface indicates significant smaller forecast errors than the AR1 at least to the 10% level. The nowcasting period comprises the years 2012 to 2021. The nowcasts are compared to the final release of real state-level GDP growth.

The revisions currently end with the year 2019, thus, the period under investigation changes in the following and runs from 2012 to 2019. Furthermore, I now compare the mean absolute revision (MAR) with the mean absolute forecast error (MAFE). The main reason is that the Working Group Regional Accounts usually comments on absolute rather than squared terms, thus, my results are comparable to official statements and delimitations. Figure 6 shows the values for the MAR and the MAFE across the 16 German states and Figure 7 its corresponding differences. For 9 of the 16 German states, the MF-VAR produces smaller nowcast errors compared to the revisions. Nevertheless, the MF-VAR's performance is much worse for Berlin and the Saarland compared to the official estimates; the differences are 0.90 and 0.59 percentage points, respectively. There seems to be also some room for improvement for Baden-Wuerttemberg and Bavaria.

Figure 6: Comparison between Nowcast and Revision Errors for Annual Real GDP Growth

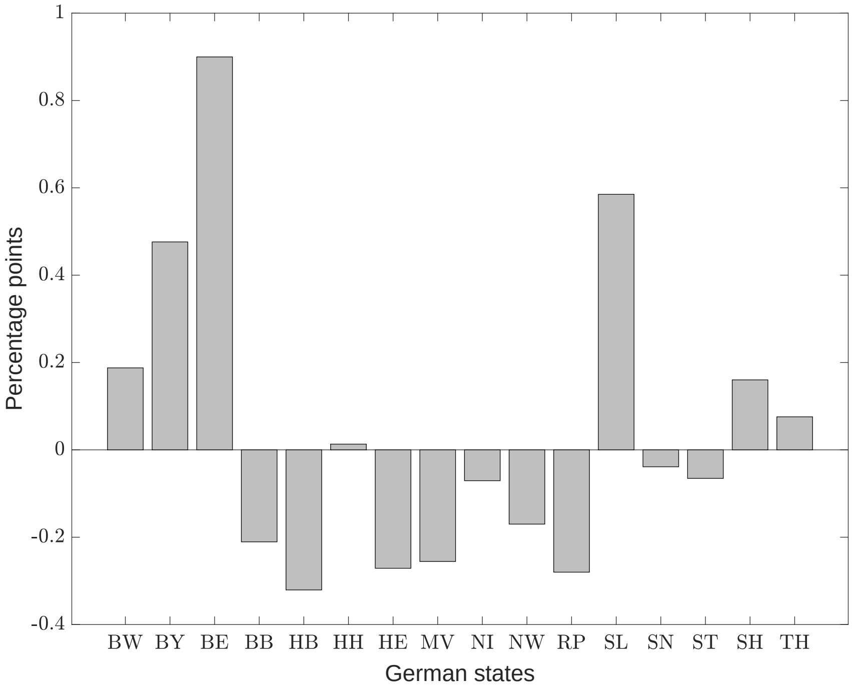


Notes: The solid line shows the mean absolute revision in annual real GDP growth based on READ-GER. The dashed line represents the mean absolute forecast errors from the mixed-frequency Vector Autoregression (MF-VAR) for annualized real GDP growth. The real-time errors are calculated with respect to the final values. All nowcasts were generated in the fourth quarter of a given year. The nowcasting period ranges from 2012 to 2019. The abbreviations for the German states are the following: BW: Baden-Wuerttemberg, BY: Bavaria, BE: Berlin, BB: Brandenburg, HB: Bremen, HH: Hamburg, HE: Hesse, MV: Mecklenburg-West Pomerania, NI: Lower Saxony, NW: North Rhine-Westphalia, RP: Rhineland-Palatinate, SL: Saarland, SN: Saxony, ST: Saxony-Anhalt, SH: Schleswig-Holstein, TH: Thuringia.

By grouping all states together, the mean absolute revision amounts to 0.92 percentage points and the mean absolute forecast error of the MF-VAR to 0.97 percentage points. This corresponds to a ratio between the MAFE and the MAR of 1.05. However, by leaving the values of Berlin and the Saarland aside, the MAR is 0.93 and the MAFE 0.88 percentage points. This corresponds to a ratio of 0.94. If it is possible to better model Berlin and the Saarland, for example by adding more regional information, the MF-VAR introduced by Lehmann and Wikman (2023) and applied here might be able to produce real-time nowcasts that, on average, incorporate smaller revisions than official estimates. Last but not least, the MF-VAR comes with the useful bi-product of quarterly state-level GDP estimates.

The good nowcast accuracy of the MF-VAR encourages future investigations. As the accurate nowcasts are solely based on German GDP growth, state-level survey information and unemployment rates, I hypothesize that this accuracy can be further increased with a better regional database. Given the high degree of industrialization in Germany, comparable time series for industrial production across all states would clearly be a benefit for the model and thus the nowcasts. This might be one reason why the RMSFE based on the initial estimates for Bremen is a bit higher compared to the other states. Bremen's industrial dynamics are strongly shaped by one large car manufacturer, thus, the model without industrial production, but with survey information and unemployment rates only, might not fully grab these state-level idiosyncratics. The same holds true for service-oriented states such as Berlin. With long time series on either service turnover or the volume of work, the model might better grab state-level particularities such as the development of the COVID-19-vaccine by Biontech in 2021 that pushed annual GDP growth in Rhineland-Palatinate.

Figure 7: Differences between Real GDP Growth Nowcast and Revision Errors



Notes: The bars represent the differences between the mean absolute forecast errors and the mean absolute revisions for annual real GDP growth. The real-time errors are calculated with respect to the final values. All nowcasts were generated in the fourth quarter of a given year. The nowcasting period ranges from 2012 to 2019. The abbreviations for the German states are the following: BW: Baden-Wuerttemberg, BY: Bavaria, BE: Berlin, BB: Brandenburg, HB: Bremen, HH: Hamburg, HE: Hesse, MV: Mecklenburg-West Pomerania, NI: Lower Saxony, NW: North Rhine-Westphalia, RP: Rhineland-Palatinate, SL: Saarland, SN: Saxony, ST: Saxony-Anhalt, SH: Schleswig-Holstein, TH: Thuringia.

6 Conclusion

The German state level currently lacks the availability of real-time regional accounts data, thus, the public and scientific community cannot assess its quality or apply them in adequate real-time nowcasting exercises. This paper fills this gap and introduces the Real-time READ-GER: Regional Economic Accounts Database for Germany. It offers nine macroeconomic aggregates for all 16 German states in real-time with vintages running from 2002 to 2021 and is publicly accessible from the author's homepage. Based on these data, I execute both a revision analysis and a real-time nowcasting experiment.

The revision analysis is executed for three macroeconomic aggregates: real gross domestic product, real gross value added manufacturing, and total employment. For all states together, the first estimates of real gross domestic product growth show no systematic bias. However, this angle suppresses differences across the regional entities. The annual first estimates are no optimal nowcasts in case of nine out of 16 German states, which leaves room for improvement. For gross value added in manufacturing, the revisions are much larger in magnitude and economically relevant. The first estimates are no optimal predictions in case of six German states. The revisions for employment growth are much smaller compared to gross domestic product and gross value added growth, however, the first estimates are not optimal for seven out of the 16 German states. Thus, improvements are possible for all three macroeconomic aggregates.

The real-time nowcasting exercise based on a Vector Autoregression with mixed-frequencies reveals two main findings. First, the model produces very accurate nowcasts for annual state-level GDP growth and significantly outperforms a bunch of benchmarks. Second, the MF-VARs real-time nowcast errors are on average smaller or even as good as the first official estimates. As the MF-VAR incorporates only a small number of regional indicators and is mainly informed by German GDP growth, these results are promising as long as more regional data become available. As a nice bi-product, quarterly state-level GDP growth rates can be estimated that are not officially published yet.

Given the revisions and the nowcasting results, the policy recommendations from the current paper mainly focus on the official data collection and calculation process. I suppose that two reasons are responsible for the emerging revisions. First, the data availability at the German state level is unsatisfactory. Second, the calculation process of regional accounts might be improved, despite its complexity. The data availability at the state level should indeed be enhanced. For example, the most important monthly business cycle indicator, industrial production, is currently only publicly available for a handful of states. Other indicators are missing entirely. There should be enough budget to increase the regional statistical offices' financial resources. Furthermore, maybe the calculation process of regional accounts is not optimal and can be broadened. Currently, the German values are fixed and if the state sum does not equal this benchmark, the resulting difference is distributed across the German states. Despite the fact that this would initiate a large institutional reform, it might be fruitful for some macroeconomic aggregates—in terms of revisions—that German National Accounts are the sum of the states' values instead of fixing the German figures. I am aware that the calculations of regional accounts is a complex procedure and that my recommendations do not cover this entire process. However, it would be very interesting to see how precise such as procedure is. One could start by evaluating the internal first estimates of the working group before they are benchmarked to the German value. Maybe this has been done before, but I am not aware of any study on this subject as these data are not publicly available. It might also be fruitful to include new model classes such as the MF-VAR introduced here for the production of estimates that stand as guidance or plausibility checks beside the official calculations.

Finally, the MF-VAR seems to have much potential as it produces very accurate nowcasts. Currently, it only incorporates regional survey information and unemployment figures. Furthermore, it is mainly informed by quarterly German GDP growth. If the effort is undertaken to collect hard regional indicators such as industrial production or turnover in the service sector from non-electronic sources, I suppose that the good nowcast accuracy can further be increased.

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READ-GER: Introducing German Real-time Regional Accounts Data for Revision Analysis and Nowcasting*

– Supplementary Material –

Robert Lehmann

Abstract

This is the supplementary material to the article by Lehmann (2023). It contains the detailed revision results for both real gross value added growth in manufacturing and total employment growth. Furthermore, the material presents additional nowcasting results such as the mean absolute forecast errors.

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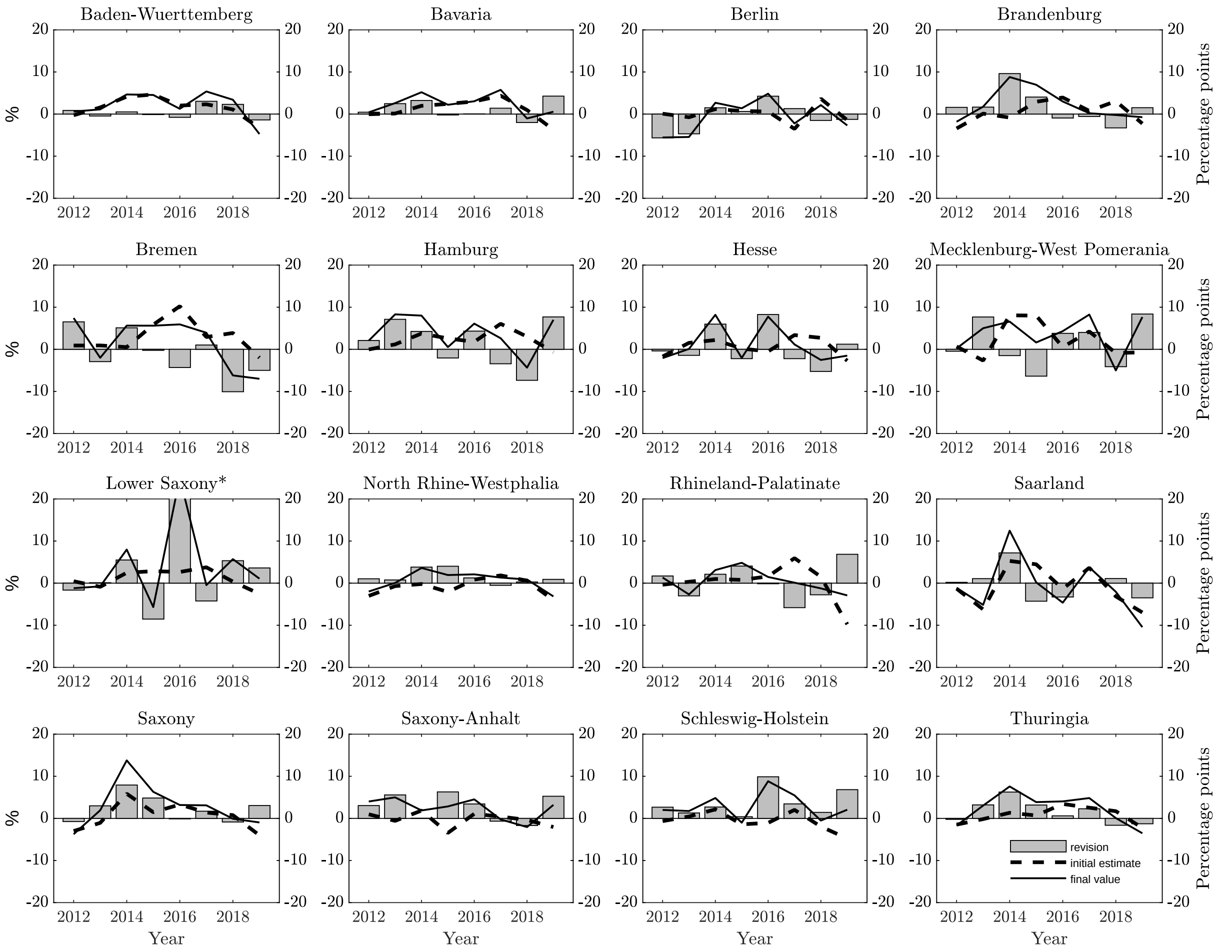
A. Revision Results Gross Value Added Manufacturing

The following section contains the revisions results for gross value added (GVA) growth in manufacturing. I start by showing the first estimates (dashed lines) together with the final values (solid lines) and the corresponding revisions (grey bars) in Figure A1.

Figure A1: First Estimates, Final Values and Revisions of Real GVA Growth in Manufacturing



Notes: The figure compares the initial estimates of real gross value added (GVA) growth in manufacturing (dashed lines) with the final values (solid lines) for each German state. The revisions (in percentage points) are the difference between both values and displayed on the right vertical. To ensure readability, the vertical axes are capped at 20%, that is, the outlier for Lower Saxony (25%) is not fully displayed (*).

The precision measures for real GVA growth revisions in manufacturing are captured by Table A2. It contains the mean revisions (MR), the minimal and maximal revisions (MIN and MAX), the revisions' standard deviations (SD), the Noise-to-Signal Ratio (NTS) as the ratio between the standard deviation in revisions and the standard deviation of the variable's latest vintage, and the mean absolute revisions (MAR).

Table A1: Precision of First Estimates for Real GVA Growth in Manufacturing

State	**MR (in p.p.)**	**MIN (in p.p.)**	**MAX (in p.p.)**	**SD (in p.p.)**	**NTS**	**MAR (in p.p.)**
Baden-Wuerttemberg	0.50	-1.38	3.04	1.53	0.45	1.18
Bavaria	1.21	-2.00	4.26	2.05	0.82	1.76
Berlin	-0.68	-5.65	4.24	3.30	0.80	2.60
Brandenburg	1.70	-3.28	9.62	3.87	1.08	2.90
Bremen	-1.24	-10.07	6.52	5.49	0.95	4.40
Hamburg	1.58	-7.36	7.70	5.36	1.00	4.79
Hesse	0.50	-5.25	8.27	4.52	1.05	3.37
Mecklenburg-West Pomerania	1.43	-6.37	8.38	5.39	1.14	4.54
Lower Saxony	2.82	-8.54	22.39	9.28	0.96	6.42
North Rhine-Westphalia	1.44	-0.52	4.02	1.62	0.66	1.57
Rhineland-Palatinate	0.38	-5.82	6.86	4.15	1.47	3.31
Saarland	-0.17	-4.29	7.19	3.69	0.53	2.59
Saxony	2.35	-0.85	7.92	3.04	0.55	2.78
Saxony-Anhalt	2.66	-1.69	6.29	3.07	1.81	3.25
Schleswig-Holstein	3.58	0.40	9.89	3.21	0.91	3.58
Thuringia	1.55	-1.63	6.25	2.68	0.71	2.33

Notes: The table shows state-specific descriptive statistics (in percentage points) for real gross value added growth revisions in manufacturing. The descriptive statistics comprise the mean revision (MR), the minimal (MIN) and maximal (MAX) revision, the standard deviation (SD) in revisions, the Noise-to-Signal Ratio (NTS) as the ratio between the standard deviation in revisions and the standard deviation of the variable's latest vintage, and the mean absolute revision (MAR). The period comprises the years from 2012 to 2019.

The results from the Minzer-Zarnowitz regressions (MZ-regressions) for revisions of real GVA growth in manufacturing are displayed in Table A2. The upper part of the table shows the state-specific regressions and the lower part both panel regression outcomes (pooled estimates or time invariant state fixed-effects).

Table A2: MZ-Regression Results for Real GVA Manufacturing Growth

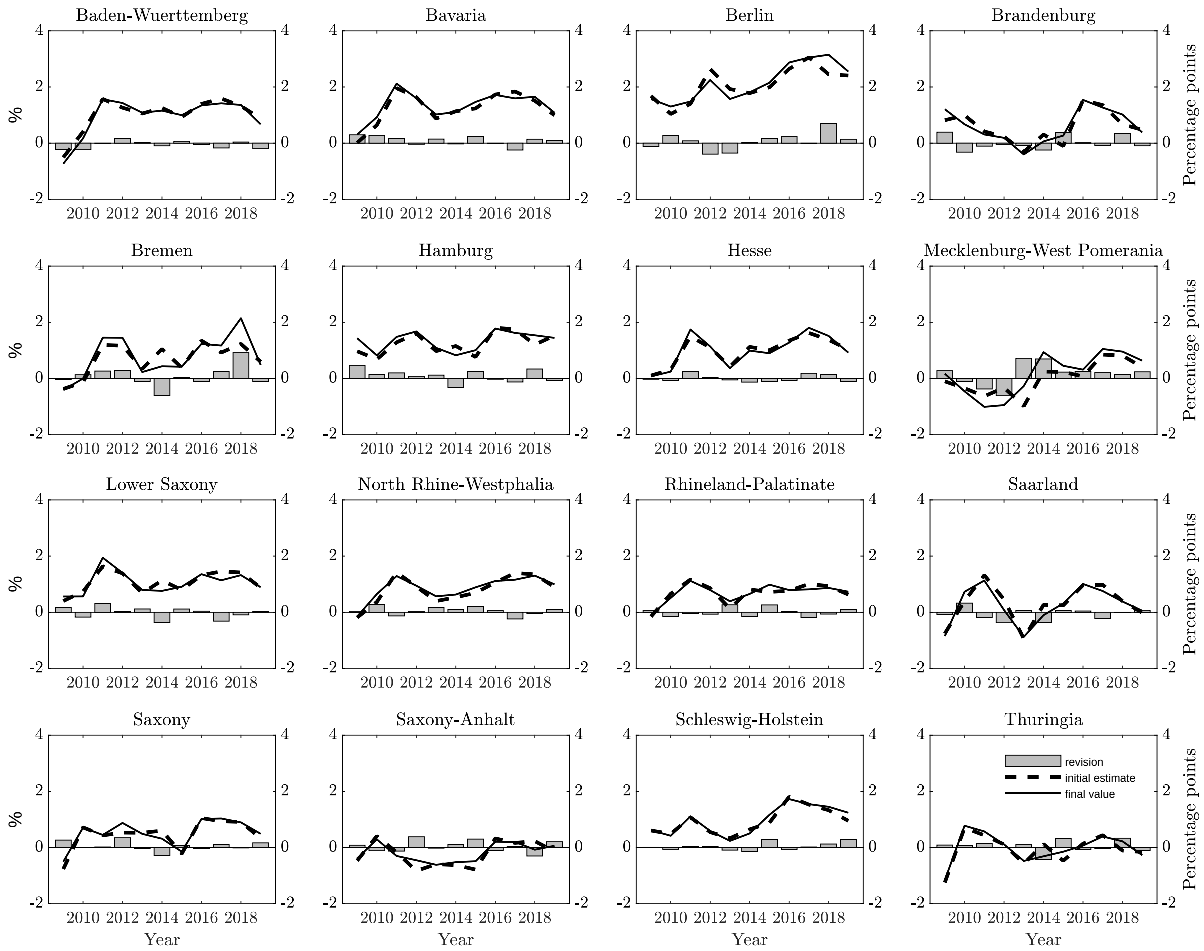
State	α	$\alpha = \mathbf{0}$	β	$\beta = \mathbf{1}$	$\alpha = \mathbf{0}$, $\beta = \mathbf{1}$	$\mathbf{R^2_{adj.}}$
Baden-Wuerttemberg	0.25	0.65	1.16	0.40	0.60	0.77
Bavaria	1.65	**0.03**	0.61	0.10	**0.06**	0.31
Berlin	-0.68	0.66	1.00	0.99	0.90	0.17
Brandenburg	1.99	0.28	0.46	0.17	0.27	0.00
Bremen	-0.17	0.95	0.63	0.30	0.14	0.03
Hamburg	4.92	**0.01**	-0.51	**0.01**	**0.01**	0.00
Hesse	0.89	0.53	0.39	0.35	0.55	0.00
Mecklenburg-West Pomerania	3.09	**0.07**	0.23	**0.05**	**0.10**	0.00
Lower Saxony	2.85	0.15	0.97	0.87	0.32	0.00
North Rhine-Westphalia	1.26	0.13	0.78	0.40	0.19	0.43
Rhineland-Palatinate	0.47	0.66	0.25	**0.00**	**0.00**	0.03
Saarland	-0.01	0.99	1.23	0.31	0.37	0.69
Saxony	2.10	**0.06**	1.42	0.31	0.15	0.70
Saxony-Anhalt	2.38	**0.06**	-0.06	**0.00**	**0.00**	0.00
Schleswig-Holstein	3.28	**0.01**	0.55	**0.09**	**0.02**	0.00
Thuringia	1.29	0.30	1.35	0.31	0.35	0.43
Panel: pooled	1.45	**0.06**	0.68	**0.07**	**0.01**	0.19
Panel: fixed-effects	1.45	**0.05**	0.68	**0.02**	**0.01**	0.19

Notes: The table shows the estimation output from the Mincer-Zarnowitz regressions (MZ-regressions) for real gross value added growth in manufacturing either for each German state separately or in a panel setup (pooled, fixed-effects). The corresponding coefficient estimates, α and β, are shown together with the p-values from the single and joint hypotheses tests. A p-value that is at least smaller than 10% is hold in boldface. The parameter inference of the state-specific estimates is based on standard errors consistent to heteroskedasticity and autocorrelation. In the panel setup it is additionally controlled for cross-sectional correlation across state revisions. The period comprises the years 2012 to 2019 (no. of state-specific observations: 8, no. of observations in the panel: 128).

B. Revision Results Total Employment

As for gross value added manufacturing, I start by showing the first estimates (dashed lines) together with the final values (solid lines) and the corresponding revisions (grey bars) for total employment growth in Figure B1.

Figure B1: First Estimates, Final Values and Revisions of Total Employment Growth



Notes: The figure compares the initial estimates of total employment growth (dashed lines) with the final values (solid lines) for each German state. The revisions (in percentage points) are the difference between both values and displayed on the right vertical.

The precision measures for total employment growth revisions are captured by Table B1. I again present the mean revisions (MR), the minimal and maximal revisions (MIN and MAX), the revisions' standard deviations (SD), the Noise-to-Signal Ratio as ratio between the standard deviation in revisions and the standard deviation of the variable's latest vintage, and the mean absolute revision (MAR).

Table B1: Precision of First Estimates for Total Employment Growth

State	**MR (in p.p.)**	**MIN (in p.p.)**	**MAX (in p.p.)**	**SD (in p.p.)**	**NTS**	**MAR (in p.p.)**
Baden-Wuerttemberg	-0.06	-0.24	0.17	0.13	0.20	0.12
Bavaria	0.09	-0.24	0.30	0.16	0.37	0.15
Berlin	0.07	-0.39	0.70	0.30	0.41	0.22
Brandenburg	0.01	-0.32	0.39	0.25	0.44	0.19
Bremen	0.08	-0.61	0.91	0.38	0.46	0.26
Hamburg	0.09	-0.33	0.47	0.22	0.54	0.19
Hesse	0.00	-0.13	0.25	0.13	0.26	0.11
Mecklenburg-West Pomerania	0.15	-0.62	0.72	0.40	0.46	0.35
Lower Saxony	-0.02	-0.37	0.31	0.21	0.58	0.16
North Rhine-Westphalia	0.05	-0.24	0.28	0.15	0.31	0.13
Rhineland-Palatinate	0.00	-0.19	0.26	0.16	0.46	0.13
Saarland	-0.06	-0.38	0.32	0.21	0.36	0.17
Saxony	0.05	-0.29	0.34	0.17	0.36	0.12
Saxony-Anhalt	0.04	-0.30	0.38	0.20	0.73	0.16
Schleswig-Holstein	0.04	-0.14	0.29	0.14	0.31	0.11
Thuringia	0.03	-0.43	0.33	0.21	0.51	0.15

Notes: The table shows state-specific descriptive statistics (in percentage points) for total employment growth revisions. The descriptive statistics comprise the mean revision (MR), the minimal (MIN) and maximal (MAX) revision, the standard deviation (SD) in revisions, the Noise-to-Signal Ratio (NTS) as the ratio between the standard deviation in revisions and the standard deviation of the variable's latest vintage, and the mean absolute revision (MAR). The period comprises the years from 2009 to 2019.

Finally, Table B2 presents the Minzer-Zarnowitz regressions (MZ-regressions) for total employment growth revisions. Again, the upper part shows the state-specific estimates and the lower part the results from both panel regressions (pooled or time invariant state fixed-effects).

Table B2: MZ-Regression Results for Total Employment Growth

State	α	$\alpha = \mathbf{0}$	β	$\beta = \mathbf{1}$	$\alpha = \mathbf{0}$, $\beta = \mathbf{1}$	$\mathbf{R^2_{adj.}}$
Baden-Wuerttemberg	-0.18	**0.00**	1.11	**0.02**	**0.01**	0.97
Bavaria	0.31	**0.00**	0.82	**0.01**	**0.00**	0.93
Berlin	0.10	0.60	0.99	0.89	0.65	0.77
Brandenburg	0.04	0.72	0.96	0.67	0.91	0.81
Bremen	-0.02	0.80	1.14	0.44	0.73	0.74
Hamburg	0.43	**0.01**	0.72	**0.01**	**0.02**	0.63
Hesse	-0.14	**0.04**	1.14	**0.06**	**0.10**	0.96
Mecklenburg-West Pomerania	0.14	0.33	1.10	0.68	0.13	0.69
Lower Saxony	0.06	0.72	0.92	0.71	0.93	0.74
North Rhine-Westphalia	0.21	**0.04**	0.80	**0.07**	**0.10**	0.92
Rhineland-Palatinate	0.15	0.17	0.79	**0.09**	0.18	0.82
Saarland	-0.04	0.43	0.93	0.13	0.30	0.90
Saxony	0.12	**0.03**	0.86	**0.00**	**0.00**	0.89
Saxony-Anhalt	-0.04	0.21	0.67	**0.00**	**0.00**	0.82
Schleswig-Holstein	-0.00	0.98	1.04	0.66	0.59	0.91
Thuringia	0.03	0.58	0.91	0.31	0.30	0.84
Panel: pooled	0.05	0.12	0.98	0.51	0.27	0.92
Panel: fixed-effects	0.07	**0.02**	0.95	0.19	**0.05**	0.92

Notes: The table shows the estimation output from the Mincer-Zarnowitz regressions (MZ-regressions) for total employment growth either for each German state separately or in a panel setup (pooled, fixed-effects). The corresponding coefficient estimates, α and β, are shown together with the p-values from the single and joint hypotheses tests. A p-value that is at least smaller than 10% is hold in boldface. The parameter inference of the state-specific estimates is based on standard errors consistent to heteroskedasticity and autocorrelation. In the panel setup it is additionally controlled for cross-sectional correlation across state revisions. The period comprises the years 2009 to 2019 (no. of state-specific observations: 11, no. of observations in the panel: 176).

C. Additional Nowcasting Results

The following Table C1 presents the Noise-to-Signal Ratios (NTS) based on the root mean squared forecasts errors for the final values of annual real gross domestic product growth.

Table C1: Noise-to-Signal Ratios for Annual State-Level GDP Growth Nowcasts, Final Release

State	**MF-VAR-SV**				**RW**	**ISM**	**VAR1**	**AR1**
	Q1	**Q2**	**Q3**	**Q4**				
Baden-Wuerttemberg	1.31	0.73	0.52	0.42	1.41	0.97	1.94	1.04
Bavaria	1.40	0.73	0.60	0.49	1.49	0.98	1.30	1.18
Berlin	1.20	0.80	0.77	0.76	1.23	1.05	1.96	1.19
Brandenburg	1.03	0.58	0.57	0.67	1.16	1.35	1.95	1.08
Bremen	1.60	0.90	0.67	0.58	1.76	0.97	1.66	0.96
Hamburg	1.29	0.81	0.69	0.60	1.37	0.97	1.61	1.02
Hesse	1.45	0.74	0.53	0.38	1.63	0.98	1.47	1.05
Mecklenburg-West Pomerania	1.25	0.92	0.84	0.78	1.29	1.11	1.24	1.19
Lower Saxony	1.06	0.69	0.67	0.69	1.23	0.97	1.27	0.99
North Rhine-Westphalia	1.28	0.58	0.41	0.32	1.41	0.97	1.76	1.02
Rhinland-Palatinate	1.33	0.92	0.79	0.69	1.40	0.98	0.88	1.05
Saarland	1.36	0.88	0.74	0.71	1.54	1.10	2.04	0.99
Saxony	1.35	0.64	0.49	0.39	1.40	1.26	1.74	1.25
Saxony-Anhalt	1.29	0.57	0.52	0.53	1.36	1.31	1.53	1.15
Schleswig-Holstein	1.28	0.69	0.61	0.64	1.32	0.97	1.30	1.10
Thuringia	1.32	0.73	0.54	0.47	1.46	1.52	1.46	1.21

Notes: The table shows the Noise-to-Signal Ratios (NTS) for the four quarterly information sets within a year (Q1 to Q4) and the four benchmark models. The NTS is defined as the ratio between the root mean squared forecast error and the standard deviation of annual real GDP growth. The benchmarks are: the Random-Walk (RW), the in-sample mean (ISM), a Vector Autoregressive model of first order (VAR1), and an autoregressive process of first order (AR1). The nowcasting period comprises the years 2012 to 2021. The nowcasts are compared to the final values of real state-level GDP growth.

As the Working Group Regional Accounts only publishes revision errors in absolute terms (mean absolute revision, MAR), I decided to publish also the mean absolute forecast errors (MAFE) in addition to the root mean squared forecasts errors in the main paper. This ensures the comparability between my nowcast errors and the group's revisions. Tables C2 and C3 present the corresponding errors for the first and the final values, respectively.

Table C2: MAFEs for Annual State-Level GDP Growth Nowcasts, Initial Release

State	MF-VAR-SV				RW	ISM	VAR1	AR1
	Q1	Q2	Q3	Q4				
Baden-Wuerttemberg	2.19	1.36	1.01	0.87	2.39	1.62	4.21	2.16
Bavaria	1.94	1.12	0.92	0.75	2.09	1.44	2.48	1.86
Berlin	1.71	1.27	1.27	1.18	1.68	1.80	3.91	1.98
Brandenburg	1.25	0.54	0.52	0.61	1.40	2.15	2.69	1.23
Bremen	2.41	1.44	1.10	1.05	2.73	1.82	3.52	2.26
Hamburg	1.98	1.19	0.94	0.78	2.09	1.28	3.36	1.86
Hesse	1.82	0.96	0.80	0.68	2.06	1.34	2.84	1.96
Mecklenburg-West Pomerania	1.87	1.08	0.84	0.81	1.93	1.56	2.24	1.76
Lower Saxony	1.68	0.79	0.48	0.56	2.13	1.18	2.41	1.57
North Rhine-Westphalia	1.76	0.93	0.64	0.45	2.03	1.22	2.52	1.35
Rhineland-Palatinate	2.43	1.58	1.26	1.21	2.64	2.07	2.44	2.48
Saarland	2.53	1.62	1.19	1.27	2.91	1.82	4.25	1.64
Saxony	1.91	1.05	0.79	0.53	2.09	2.13	2.66	1.81
Saxony-Anhalt	1.56	0.76	0.58	0.60	1.74	2.21	2.22	1.42
Schleswig-Holstein	1.39	0.66	0.43	0.38	1.58	1.04	2.13	1.47
Thuringia	1.74	0.95	0.60	0.45	1.99	2.72	2.18	1.65

Notes: The table shows the mean absolute forecast errors (MAFE) in percentage points for the four quarterly information sets within a year (Q1 to Q4) and the four benchmark models. The benchmarks are: the Random-Walk (RW), the in-sample mean (ISM), a Vector Autoregressive model of first order (VAR1), and an autoregressive process of first order (AR1). The nowcasting period comprises the years 2012 to 2021. The nowcasts are compared to the first release of real state-level GDP growth.

Table C3: MAFEs for Annual State-Level GDP Growth Nowcasts, Final Release

State	MF-VAR-SV				RW	ISM	VAR1	AR1
	Q1	Q2	Q3	Q4				
Baden-Wuerttemberg	2.27	1.51	1.17	0.96	2.48	1.72	4.43	2.16
Bavaria	2.12	1.37	1.22	0.99	2.17	1.38	2.40	2.06
Berlin	2.42	1.94	1.86	1.70	2.44	2.44	4.55	2.69
Brandenburg	1.40	0.74	0.78	0.90	1.49	1.96	2.91	1.36
Bremen	2.33	1.53	1.22	1.04	2.68	1.68	2.91	1.73
Hamburg	2.55	1.86	1.61	1.30	2.58	1.85	3.20	2.17
Hesse	2.08	1.26	1.01	0.71	2.50	1.52	2.84	1.81
Mecklenburg-West Pomerania	2.87	1.97	1.67	1.58	3.00	2.41	2.42	2.71
Lower Saxony	2.41	1.62	1.40	1.49	2.82	1.87	2.85	2.07
North Rhine-Westphalia	1.75	0.94	0.65	0.55	2.01	1.39	2.94	1.61
Rhineland-Palatinate	2.44	1.62	1.36	1.27	2.69	1.97	2.54	2.23
Saarland	3.14	2.23	1.78	1.76	3.48	2.35	4.45	2.06
Saxony	1.79	1.09	0.88	0.57	1.92	1.84	2.83	1.81
Saxony-Anhalt	1.61	0.93	0.84	0.81	1.67	1.73	2.10	1.58
Schleswig-Holstein	1.79	1.23	1.02	0.99	1.92	1.51	2.03	1.82
Thuringia	2.05	1.30	0.93	0.76	2.27	2.58	2.12	1.94

Notes: The table shows the mean absolute forecast errors (MAFE) in percentage points for the four quarterly information sets within a year (Q1 to Q4) and the four benchmark models. The benchmarks are: the Random-Walk (RW), the in-sample mean (ISM), a Vector Autoregressive model of first order (VAR1), and an autoregressive process of first order (AR1). The nowcasting period comprises the years 2012 to 2021. The nowcasts are compared to the final values of real state-level GDP growth.