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Regional Economic Forecasting: State-of-the-Art Methodology and Future Challenge

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Abstract

Over the last decade, the topic of regional economic forecasting has become increasingly prevalent in academic literature. The most striking problem in this context is data availability at a regional level. However, considerable methodological improvements have been made to address this problem. This paper summarizes a multitude of articles from academic journals and describes state-of-the-art techniques in regional economic forecasting. After identifying current practices, the article closes with a roadmap for possible future research activities.

JEL-Code: E270, E370.

Keywords: regional economic forecasting, regional gross-domestic product, regional labour markets.

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1. Scope and aim of this article

Data unavailability, low data publication frequency and substantial data revisions are the most striking problems facing regional economic forecasting. These barriers can prevent academics from conducting more intensive studies of regional economic forecasting compared to that of national aggregates. However, there is a fast-growing body of literature that is tackling these issues by, for example, applying new methodologies especially developed for regional purposes.

The scope of this brief survey article is to present state-of-the-art methodology in regional economic forecasting. It concentrates on two specific macroeconomic aggregates: (i) total output such as gross-domestic product (GDP) or gross-value added (GVA) and (ii) labour market variables like total employment or the unemployment rate. It is important to note that forecasting literature on other regional variables like revenues or housing prices already exists; so this article does not focus on these issues, but provides relevant references to the corresponding literature instead. After presenting the findings of existing studies, we outline key areas for future research in the field of regional economic forecasting.

2. State-of-the-art in regional economic forecasting

In order to summarise existing literature on this topic, the articles in question must be classified. In addition to the regional and the target variable that each study focuses on, Table 1 presents five main features of such articles. Firstly, we name the data frequency that the forecasting exercise is based on. Secondly, we identify the methodology that is used in each study. Thirdly, to understand the purpose of the forecast, we indicate the forecasting horizon. Fourthly, we give a statement on the forecasting performance of the methods applied in each single study. Finally, we identify potential areas for future research, whenever they are named in the specific study. These five specifics constitute the scope and aim of this article. All of the studies in Table 1 are ordered anti-chronologically. The results from Table 1 can be summarised as follows:

1. Most of the studies focus on regional labour market forecasting. Studies for gross domestic product (GDP) or gross value-added (GVA) tend to be scarce. However, thanks to new methodological approaches (e.g. spatial panel data models), the strand of literature focusing on GDP or GVA developed rapidly in the 2010s.
2. The *Data frequency* column reveals that no monthly output variables have been used as a target variable. This might be due to the fact that industrial production, for example, which is often used at a national level, is not available at a monthly frequency for regional units. For labour market analyses, monthly indicators are even available in very small regions. From a time series perspective, this is a huge advantage in comparison to output variables.
3. The labour studies show a higher regional disaggregation than the studies with output variables. Whereas many labour market studies focus on smaller regions below the state level, nearly all output studies are conducted for rather large regional entities like states. One prominent exception is the study by Baltagi et al. (2014), which uses data from the NUTS-2 level.
4. To mitigate the problem of a data scarce environment, spatial panel data models are becoming increasingly common practice in regional forecasting. Many authors explicitly mention the necessity of spatial effects to capture, for example, regional spillovers (Baltagi et al., 2014). In this context, the study by Mayor and Patuelli (2012) is worth mentioning. They explicitly examine the trade-off between the cross section and time dimension. The main message from their exercise is that time series models work better than spatial models when the time dimension is higher than the

cross section. In cases where the two dimensions nearly equal each other, spatial models outperform more sophisticated time series models. Additionally, Rapach and Strauss (2012) emphasise the outstanding role of labour market data in studying such methodological differences. In this way, future regional economic forecasting literature may be able to improve forecasting performance by simply applying models that are designed for different cross section and time dimension setups.

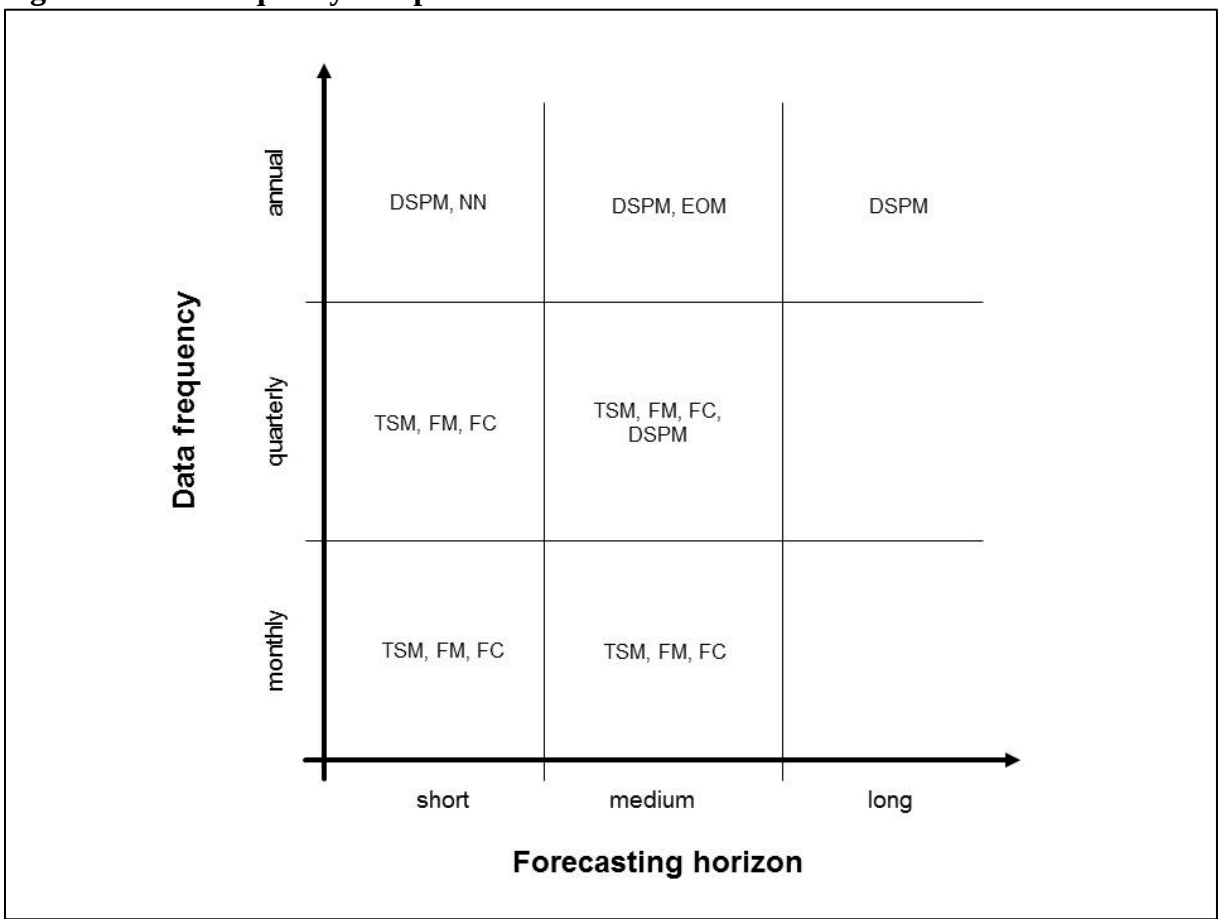
5. Factor models and forecast combinations tend to be scarce in literature on this topic. However, since data sets have become even larger in the recent past, existing studies clearly state the benefits of large data set methods for regional economic forecasting.
6. Nearly all studies apply parametric methods by postulating a linear relationship between the target variable and the independent variables. This has, among others, been criticized by Patuelli et al. (2008) or Blien and Tassinopoulos (2001) since academic literature on the topic has not yet reached a consensus on regional economic interdependencies or linkages. The studies mention that non-linear models clearly show forecast improvements and are a good competitor to standard techniques. Additionally, only a handful of papers apply structural models. Most of the existing literature prevents the application of structural models due to data scarcity.
7. Most of the studies compare their methodology with benchmark models such as the univariate autoregressive process by using standard accuracy measures (e.g., root mean squared forecast errors). However, only a handful of articles offer statements about the statistical significance of forecast error differences (e.g., Lehmann and Wohlrabe, 2015, 2014 or Kopoin et al., 2013).
8. All of the papers present point forecasts. Up to this date and to the best of our knowledge, no studies featuring density or interval forecasts at a regional level exist. Additionally, most of the papers evaluate one single point forecast of a different method with the ex post realization of the specific variable. The paper by Mayor et al. (2007) is one exception: this study provides different scenarios and discusses the role of a scenario analysis for regional economic forecasting.
9. Most of the studies focus on either the short term (one year ahead) or calculate medium term (up to three years ahead) forecasts. However, there are studies that produce forecasts ranging from five (Kholodilin et al., 2008) up to fifteen (Girardin and Kholodilin, 2011) or even twenty years (Polasek et al., 2007).[1]
10. The bulk of studies concerning labour market variables are conducted for the U.S. The opposite holds for studies with output target variables. Here, to the best of our knowledge, most of the existing literature focuses on Germany or Europe.

Academic improvements in regional forecasting, however, do not tell us anything about their practical relevance. Since regional economic forecasting has become increasingly attractive within the last ten years, it has also gained practical relevance over this time period. The following examples are aimed at emphasising the role of regional economic forecasting in practice. The Ifo Institute, Dresden Branch (Ifo), as well as the Halle Institute for Economic Research (IWH), provide regional economic forecasts for Germany. As mentioned by Blien and Tassinopoulos (2001), the Institute for Employment Research (IAB) provides regional labour market forecasts for the Federal Employment Agency in Germany. The Simon Center for Regional Economic Forecasting prepares forecasts for the metropolitan St. Louis area and

[1] To clarify our wording, we have to define the different forecasting ranges used. These definitions should not be mixed up with the wording in standard macroeconomics. In our setup, the short term comprises of all studies with a forecast horizon up to one year. Additionally, short term forecasts should not be mixed up with Nowcasts, which focus on an “ultra” short forecast horizon (e.g., the current and following quarter). Medium term forecasts are produced for horizons of up to three years. All papers that concentrate on forecasts with a horizon longer than three years are classified as long term.

the State of Missouri. The Economic Forecasting Project by the Old Dominion University and the REMI (Regional Economic Models, Inc.) are other prominent representatives.
To develop a roadmap for the practical use of these forecasts, we draw attention to Figure 1 which builds upon our literature review. In future research it can be rearranged or complemented.

Figure 1: Data frequency and preferable methods



Note: DSPM…dynamic spatial panel data models, EOM…entropy-optimizing method, FC…forecast combination, FM…factor models, NN…neural network models, TSM…time series models.

Figure 1 clearly demonstrates that a practical forecast based on annual data should incorporate spatial effects, or make use of more uncommon methods like neural networks. Turning to the other extreme, monthly data, time series models or methods based on large data sets can improve forecasting accuracy. The same holds for quarterly data. However, forecasting accuracy with spatial effects and monthly data has not been tested yet. Additionally, studies with monthly or quarterly data do not evaluate their models for longer horizons. Since most of the studies focus on point forecasts, literature on different scenario analyses is scarce. Based on this state-of-the-art discussion, we now turn to the agenda for future research.

3. A roadmap for future research

This short discussion of state-of-the-art methodology has shown that regional economic forecasting is a constantly evolving field in academic literature and has grown increasingly attractive within the last decade. This is not surprising since regional policy-makers have to rely on unbiased regional economic forecasts. However, there is still a great deal of room left for improvement. In this section, we discuss potential topics that should be addressed in future

research activities. As in the section before, we summarise possible research activities as follows:

- Dynamic spatial panel data models should be applied to quarterly instead of annual GDP data in order to capture business cycle effects more accurately. From our point of view, this can only be done by using quarterly information. Since quarterly information is almost not available for regional GDP, future research could apply disaggregation methods as in Wenzel and Wolf (2013). Additionally, the studies by Lehmann and Wohlrabe (2015, 2014) use quarterly information that is provided by other researchers. The methods for disaggregation are used by the European Commission and can be easily applied to regional data.
- Sticking again to the discussion of spatial effects, we have no clear evidence of the forecasting accuracy of these models for GDP or GVA in smaller regions like cities, rural districts or counties. To date, we have only evidence for states (see, for example, Kholodilin et al., 2008). For Germany, there are GDP data available on an annual basis for all free cities and counties. Such research activities can further develop the discussion started by Mayor and Patuelli (2012), which mentions the trade-off between the cross section and time dimension.
- To date, there is only little evidence of how regional forecast errors are distributed over the business cycle. Future research should concentrate on the question of how well the methods are suited to forecasting different phases of the business cycle. The great economic downturn of the years 2008/2009 in particular yield criticism on standard methods at the national level. However, detecting turning points is a major task not only for regional economic forecasts, but also for their national counterparts.
- Another methodological application is the consideration of indicators from different regional entities. At a regional level, we could ask whether we can generate more accurate forecasts if we incorporate information from the national or even international level. Different trade patterns or high heterogeneity in regional economic structures in particular justify such an analysis.
- As put forward by Blien and Tassinopoulos (2001), it is absolutely necessary to better understand economic linkages at a regional level in greater detail, and to use this knowledge to create unbiased forecasts. In a better data environment, this could easily be achieved by using structural models. Since it is nearly impossible to generate these data, especially for macroeconomic aggregates like GDP or consumption, techniques such as the ENTROP method or non-linear models should be studied more intensively and compared to standard methods.
- Following on from the previous point, we consider whether linear models are preferable to their non-linear counterparts. The existing studies only evaluate non-linear techniques for specific years and regions. Future research activities should evaluate this question over time and for different regional entities.
- From a general point of view, no “meta-study” exists that compares different forecasting methods. All of the existing studies compare accuracy to that of standard benchmark models. However, the methods coexist with each other and we have found no evidence of which works best for different situations (business cycle phases, trade-off between time and cross section dimension etc.). The study by West and Fullerton (1996) states that different regions are more predictable than others. Yet what are the reasons for these differences?
- In addition to the previous point, future research should analyse regional economic forecasting for another set of countries. The studies mentioned in this paper only focus on eight different countries. Most of the literature, in turn, analyses either Germany or

the US. Whenever there is a need for forecasts by a huge amount of different country-specific policy-makers, future research should replicate papers for different countries.

- The studies by Lehmann and Wohlrabe (2015, 2014) show that large data set methods such as forecast combinations are able to produce more accurate forecasts in comparison to standard univariate models. However, another way of dealing with large data sets are Bayesian Vector Autoregressions (BVAR). To the best of our knowledge, this approach has only been adopted by Puri and Soydemir (2000) or Dua and Miller (1996).
- We further emphasise the application of methods that are intensively discussed at the national level like, for example, methods based on mixed frequencies (e.g., MIDAS or bridge equations), boosting algorithms or time-varying parameters (TVP).
- The real time aspect of economic forecasting is neglected by almost all studies. It is not only that the papers do not explicitly account for publication lags (pseudo real time analysis), revisions of regional economic variables are only studied by Coomes (1992). However, this paper only focuses on regional labour market figures. As is clearly mentioned by Coomes (1992), revisions at the regional level have a higher magnitude than at the national level. This could cause significant forecast errors.
- A potential research area is the aggregation of different forecasts. One issue raised in Lehmann and Wohlrabe (2014) is whether the aggregation of sectoral forecasts leads to lower forecast errors compared to a direct forecast of the aggregate (e.g., sectoral GVA vs. total GVA) at the regional level. Such an analysis can easily be conducted for labour market variables, where nearly all of the data are available. This research question can also be combined with a discussion of spatial effects.
- Another avenue of research is to ask whether the aggregation of regional economic forecasts leads to lower forecasting errors of the national aggregate. As an example we use the economic development of Germany. Germany consists of 16 different states. The question is: what is the most accurate way to forecast total German GDP? There are two possibilities: (i) a direct forecast of German GDP, or (ii), a prediction based on an aggregation of forecasts for each of the 16 single states. The second approach may lead to lower forecasts errors since it accounts for region-specific developments.
- In the end, we stick to the purpose of regional economic forecasting. Most of the studies focus on point forecasts. However, regional policy-makers are potentially interested in density (or interval) forecasts, or a scenario analysis, rather than in standard point estimates. Future research should discuss how all of the methods available are able to address this question.

Huge advances have been made in regional economic forecasting over the last decade, as shown by this discussion of state-of-the-art methodology. However, there is still a great deal of room left for future research on this topic and we emphasise the need to devote more attention to several of the points already raised in academic literature and listed above.

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Table 1: Overview of regional forecasting studies

Study	Region	Target variable	Data frequency	Methodology	Forecast horizon	Forecast performance	Future Research
Lehmann and Wohlrabe (2015)	GER: two states (NUTS-1, Saxony and Baden-Württemberg) and Eastern Germany	GDP, total	quarterly	time series models, forecast combination, factor models	point forecasts with horizon one up to four quarters ahead	forecast combination with best results in comparison to standard univariate benchmark model	to use time series models, yearly data are disaggregated to quarterly information large data set methods
Baltagi et al. (2014)	Europe: 255 NUTS-2 regions	GVA per worker, total	annual	dynamic spatial panel data models	point forecasts with horizon one and two years ahead	better ex post performance in comparison to standard spatial and non-spatial estimators	spatial models absolutely necessary to capture regional spillovers
Lehmann and Wohlrabe (2014)	GER: one state (NUTS-1, Saxony)	GVA, total and sectoral	quarterly	time series models, forecast combination, factor models	point forecasts with horizon one up to four quarters ahead	forecast combination with best results in comparison to standard univariate benchmark model sectoral disaggregated forecasts better in the short run	to use time series models, yearly data are disaggregated to quarterly information **sectoral** disaggregation large data set methods
Kopoin et al. (2013)	CAN: two provinces (Quebec and Ontario)	GDP, total	quarterly	factor models	point forecasts with horizon one up to twelve quarters ahead	international and national indicator have predictive information in the short run (one year ahead); afterwards only regional information matter	international, national and regional information for the exercise large data set methods

Wenzel (2013)	GER: all German states (NUTS-1)	GDP, total	annual	panel data models	point forecasts with horizon one and two years ahead	regional business survey data produce lower forecasts errors for one year ahead forecasts	--
Wenzel and Wolf (2013)	GER: four German states (NUTS-1, Bremen, Hamburg, Lower Saxony and Schleswig-Holstein	GDP, total	quarterly	time series models	point forecasts with horizon one up to three quarters ahead	business survey data outperform univariate benchmark model	to use time series models, yearly data are disaggregated to quarterly information
Mayor and Patuelli (2012)	CH: all Swiss cantons (NUTS-3); ESP: all provinces (NUTS-3)	unemployment rate	CH: monthly; ESP: quarterly	spatial panel data models and SVAR	point forecasts with horizon one up to twenty-four months ahead (Switzerland) or one up to eight quarters ahead (Spain)	performance of each method depends highly on the data frequency; SVAR better in Switzerland; spatial models with more accuracy in Spain	data frequency very important for the usage of methods future literature should focus on the trade-off between the cross-section and time dimension, especially for long term forecasts
Rapach and Strauss (2012)	USA: all federal states	employment, total	quarterly	time series models, forecast combination, factor models	point forecasts with horizon two and four quarters ahead	all model classes better than the univariate benchmark model combination strategies work well for all states, especially in recessions	labor market data perfectly suited to study the different methodological approaches (time series vs. panel data) generalization of the results
Girardin and Kholodilin (2011)	CHN: all provinces	GDP, total	annual	spatial panel data models	point forecasts with horizon one up to fifteen years ahead	higher forecast accuracy with spatial effects (in	only few studies which focus on GDP and spatial

						comparison to a standard univariate benchmark model and standard panel data models) for very long horizons, a large improvement with spatial effects is observable	effects especially for long term forecasts, spatial effects should be included
Schanne et al. (2010)	GER: all labor market regions	unemployment	monthly	univariate spatial GVAR	point forecasts with horizon one up to twelve months ahead	GVAR performs better than the univariate benchmark model spatial effects show a large improvement for longer horizons	results highly depend on the model specification and the specific region
Kholodilin et al. (2008)	GER: all German states (NUTS-1)	GDP, total	annual	dynamic spatial panel data models	point forecasts with horizon one up to five years ahead	higher forecast accuracy with spatial models in comparison to standard panel models (again: large improvement in the long run)	--
Patuelli et al. (2008)	GER: all labor market regions	employment, total	annual	neural network models, genetic algorithms	point forecast for one single year	neural network models with good performance, better in comparison to a random walk	introduction of non-linear models
Dreger and Kholodilin (2007)	GER: one state (NUTS-1, Berlin)	GDP, total	quarterly	static factor models	point forecasts with horizon one up to eight quarters ahead	significant in-sample improvement	--
Longhi and Nijkamp (2007)	GER: labor market regions in Western	employment, total	annual	static non-spatial and spatial panel data	point forecasts for three single years	forecast improvement in	results highly depend on the

	Germany			models		comparison to a naïve benchmark model	model specification and the specific region
Patuelli et al. (2007)	GER: all districts (NUTS-3)	employment, total	annual	neural network models, Friedman statistic	point forecasts for three single years	neural network models are able to forecast the ranking of regional units	introduction of non-linear models
Polasek et al. (2007)	AUS: regions	GDP and employment, total	annual	dynamic spatial panel data models	point forecasts up to twenty years ahead	no evidence on performance	--
Mayor et al. (2007)	ESP: one autonomous community (Asturias, NUTS-2)	employment, total and sectoral	quarterly	dynamic Shift-share-techniques in combination with time series models	point forecasts one-step ahead for three different years	dynamic models with the best forecasting performance	discussion on forecasting and scenario analyses comparison of shift-share techniques with standard methods
Longhi et al. (2005)	GER: all labor market regions in Western Germany	employment, total	annual	artificial neural network models, panel data models, forecast combinations	point forecast for one single year	artificial neural network model with best performance in comparison to a naïve no-change forecast	introduction of non-linear models test on whether the performance holds over time
Rapach and Strauss (2005)	USA: one federal state (Missouri)	employment, total	monthly	time series models, combination, factor models	point forecasts for three, six, twelve and twenty-four months ahead	forecast combination methods outperform the standard univariate benchmark model	--
Bandholz and Funke (2003)	GER: one state (NUTS-1, Hamburg)	GDP, total	quarterly	leading indicator based on a dynamic factor model	--	business cycle dating and development of regional leading indicator	usage of leading indicators to date regional business cycle important for forecasters to

							predict turning points
Megna and Xu (2003)	USA: one federal state (New York)	coincident index	monthly	leading indicator based on a dynamic factor model	point forecasts with horizon up to twelve months	leading indicator is able to predict regional recessions	--
Blien and Tassinopoulos (2001)	GER: all districts (NUTS-3) in Western Germany	employment, total	annual	entropy-optimizing procedure (ENTROP)	point forecast for the year 1999 (2 years ahead)	ENTROP method shows improvements over standard methods	method is able to reproduce regional linkages and causations forecasts are used by the Federal Employment Agency in Germany
Puri and Soydemir (2000)	USA: counties in Southern California	employment, industrial	quarterly	time series models	point forecasts with horizon up to four quarters ahead	BVAR best model; other time series models outperform the naïve benchmark	--
Shoesmith (2000)	USA: all federal states	employment, non-agricultural	monthly	time series models with composite leading indicators	point forecasts for one, three, six, nine and twelve months ahead	national indicator with higher forecast accuracy than the regional indicator	--
Trívez and Mur (1999)	ESP: one autonomous community (Aragón, NUTS-2)	employment, sectoral	quarterly	time series models	point forecasts for the four quarters of one specific year	transfer functions outperform the ARIMA benchmark	--
Miller (1998)	USA: one federal state (Idaho) and related sub-regions	employment, total	monthly	time series models	point forecasts for the twelve months of one specific year	state-level forecasts produce lower forecast errors than sub-state-level forecasts	--
Dua and Miller (1996)	USA: one federal state (Connecticut)	employment (coincident index), non-farm employment, unemployment rate	monthly	time series models based on leading indicator	point forecasts for one up to six months ahead (three different time	BVAR dominates simple VAR model, both outperform the	--

					periods)	univariate benchmark	
West and Fullerton (1996)	USA: metropolitan areas in federal state (Florida)	employment, total	quarterly	time series and structural models,	point forecasts for horizon one up to ten quarters ahead	structural models not worse than time series models; both outperform the historical average as benchmark	meta study to discuss the accuracy of different methods
Holmes and Shamsuddin (1993)	CAN: one province (British Columbia)	employment, industrial	monthly	time series models with leading indicators based on different methods	point forecasts with horizon one up to twelve months ahead	models with leading indicator outperform ARIMA benchmark	--
Coomes (1992)	USA: one federal state (Virginia) and one statistical area (Louisville)	job estimates, sectoral	monthly	Kalman filtering	--	practical relevance to incorporate revisions into economic forecasts	studying revisions at the regional level
LeSage (1990)	USA: metropolitan areas in federal state (Ohio)	employment, total	monthly	time series models	Point forecasts with horizon of one up to twelve months ahead	error correction models with best performance	error correction models especially useful to model long run relationships and short term fluctuations
Weller (1989)	USA: one metropolitan statistical area (Erie)	employment, total	monthly	time series models	point forecasts with horizon one up to twelve months ahead; calculated for two specific years	univariate benchmark is outperformed	data unavailability prevents the estimation of regional structural models
Weller and Kurre (1989)	USA: one metropolitan statistical area (Erie)	employment, total and sectoral	monthly	time series models and shift-share techniques	point forecasts for each of the twelve months of 1984	incorporation of shift-share techniques leads to lower forecast errors	--
Glennon et al. (1987)	USA: one statistical area (Louisville)	employment, sectoral	quarterly	time series and structural models	no clear description	univariate models with best performance in	structural models at the regional level can be used

						comparison to structural models	for scenario analyses
Weller and Kurre (1987)	USA: one metropolitan statistical area (Erie)	employment, total	quarterly	time series models	point forecasts with horizon one up to four quarters ahead	transfer functions improve regional forecast	--
Thirlwall (1975)	UK: government office regions (NUTS-1)	unemployment rate, vacancies	quarterly	time series models	point forecasts for the year 1973	--	--

Note: AUS…Austria, CAN…Canada, CH…Switzerland, CHN…China, ESP…Spain, GER…Germany, GDP…gross-domestic product, GVA…gross-value added, UK…United Kingdom, USA…United States of America.

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