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REGIONALIZING NATIONAL-LEVEL GROWTH PROJECTIONS IN THE VISEGRAD COUNTRIES – THE ISSUE OF EX-POST RESCALING

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Biographical Notes

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Abstract

Regional economic inequalities in the countries of the Visegrad Group appear to be persistent in the long run, and many empirical studies suggest that their further increase is expected, at least in the medium run. Our study provides empirical results with a methodological focus concerning the long-term prediction of regional economic growth in the Visegrad countries. Our method delivers sub-national gross domestic product projections in a spatial downscaling approach according to which a selected national-level predicted growth path is downscaled to the regional level. In order to keep the regional results consistent with the national-level prediction, an ex-post proportional rescaling is needed which assures that the regional GDP values sum up to the projected national-level aggregate. This article examines the issues emerging from the practice of ex-post rescaling and uses out-of-sample tests on historical data sets to analyse the consequences of various methodological options. Taking into account the pros and cons, our study argues for the usefulness of ex-post rescaling in the case of the regional GDP downscaling in the Visegrad countries.

Keywords: Regionalization, projections, predictive capacity, gross domestic product, Visegrad countries.
JEL Classification: C53, O11, O47, R11.

1. Introduction

In the Central and Eastern European countries economic convergence has been at the forefront of socio-economic research since the systemic change, reflecting the societies' expectations regarding catching-up with Western Europe (Lux, 2017; Cristescu, 2018). Although national economies are constantly closing the development gap regarding gross domestic product (GDP) per capita, there is an ongoing regional and social polarization in these countries (Benedek and Kocziszky, 2015; Görmar et al., 2019). For this reason, the expected future long-run evolution of the economic development paths of these countries worth a detailed investigation in a regional disaggregation (Lengyel and Kotosz, 2018).

Regional economic inequalities in the Visegrad countries (Czechia, Hungary, Poland and Slovakia) appear to be persistent in the long run, and several empirical studies have expected their further increase at least in the medium run (Egri and Tánczos, 2018). Our study provides empirical analyses with a methodological focus concerning the long-term prediction of regional economic growth in the Visegrad countries. The core interest of our study is not specifically the issue of regional convergence within the Visegrad countries, but, in close relation to it, the interregional distribution of regional gross value added, measured by the GDP estimated at the NUTS 3 level.

Long-term economic predictions are widespread in the field of integrated assessment modelling (IAM) that consider the interactions of climate effects, economic variables and energy use (Wang et al., 2017), while projections with a narrower economic focus are also published by major international organizations (OECD, European Commission, International Institute for Applied Systems Analysis - IIASA). As IAMs primarily capture global changes, they are often elaborated at the global or macro-regional spatial scale, typically distinguishing between not more than 10 to 20 world regions. Therefore, there is a need to assess the projected phenomena at a finer spatial resolution: spatial downscaling is a process where information at a larger spatial scale is translated to smaller scales while maintaining consistency with the original dataset (van Vuuren, Smith and Riahi, 2010). The same considerations motivated Batista e Silva et al. (2016) to apply the regional downscaling on the national-level economic projections of the European Commission. The authors also argue for a procedure under which the projected GDP for each NUTS 2 region is rescaled in order to match the country totals from the reference projections. Some issues emerge in connection with this procedure which will be in the focus of this article.

There are several available methodological options to downscale national growth projections to the regional level (Zsibók, 2018). We opted to use extrapolations reflecting a ‘business-as-usual’ framework. From a theoretical point of view, the extrapolative approach may capture the path-dependent nature of regional economic growth (Dyba et al., 2018). However, the traditional concept of path dependency is not entirely suitable to describe the evolution of regional growth paths within the Visegrad countries, since various country-level effects determine the growth prospects of the individual regions (Lengyel and Kotosz, 2018).

Our methodological approach will not definitely lead to precise GDP forecasts (hence, we better use the expressions ‘predictions’, ‘projections’ or ‘conditional scenarios’), rather, it allows us to see future trends that could be derived if past trends are assumed to continue. The advantage of the extrapolative method lies in its transparency and simplicity. Although a practice with more sophisticated theoretical underpinnings would allow elaborating more sound predictions, we think that our simplistic approach may provide instructive lessons about the working of regional economies in the Visegrad countries. In order to achieve this, we use accuracy tests for our predictions with out-of-sample testing. This means that we split our historical time series into two parts, a ‘learning period’ and a ‘test period’, then compare the calculated GDP values with the actual values observed in the test period. The results of the out-of-sample tests inform about the usefulness of the different extrapolative prediction methods. However, their interpretation should take into account the fact that the test period is relatively short.

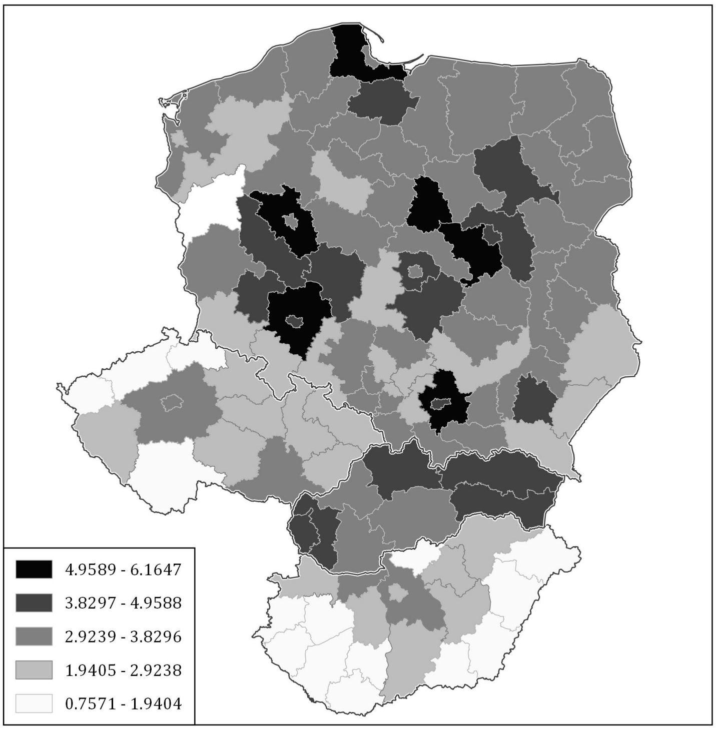
The aim of this article is twofold: first, it intends to assess in detail the consequences of the ex-post proportional rescaling during the spatial downscaling from a methodological point of view. Second, it intends to broaden the territorial coverage of the above-mentioned accuracy tests regarding the extrapolative prediction methodologies compared to previous researches based on Hungarian data (Zsibók, 2019).

2. Data and Methodology

The centre of interest in this research is the prediction of regional-level GDP based on an exogenous national-level projection and historical regional-level time series in the Visegrad countries. The relevant level of spatial disaggregation is the NUTS 3 level, since the NUTS 2 level seems not to capture the regional level economic processes properly (Lengyel and Kotosz, 2018), at the same time, the data availability also supports the NUTS 3 level analysis. In order to achieve the above-mentioned goal, we collected historical NUTS 3 level GDP data from the EuroStat database for the period spanning from 2000 to 2017. In the case of Poland, the statistical codings of the regions were revised (revision of the NUTS 2016 nomenclature, effective from 2018), hence we have comparable data only until 2015. GDP data measured at current market prices were recalculated based on the GDP deflator published by the EuroStat, i.e. they are presented at constant, 2005 prices.

In this paper we investigate the regional inequalities in the countries of the Visegrad group one-by-one, and do not use cross-country comparisons, therefore we won't calculate comparable GDP values at PPP, instead, we evaluate the regional-level economic growth paths in national currencies. The NUTS-3 level average GDP growth rates are depicted on Chart 1.

Chart 1. Average GDP growth rates in the base period in the Visegrad countries at constant, 2005 prices, %



Source: Author's elaboration based on Eurostat data

GDP per capita can be decomposed into two main factors, labour productivity and employment, which are the two main determinants of regional competitiveness (Gardiner, Martin and Tyler, 2004; Zdražil and Applová, 2016). Employment changes can be further decomposed to the changes in the employment rate and the share of the working-age population within the total population, as well as the hours worked, as described by the growth accounting literature (Kónya, 2018). It is useful to analyse the regional processes in a decomposed form since this informs us about the importance of the contribution of the different components to regional growth. Our previous research found that the projections led to very similar results both when they were elaborated through the projection of the employment, demographic indicators and productivity separately, and when they were calculated in an aggregate form (Zsibók, 2019). For this reason, at this stage of the research, we focus on the aggregate GDP, without decomposition.

2.1. Long-term national-level projections

Following the logic of spatial downscaling, we first select solid national-level, long-term GDP projections for the Visegrad countries, then combine them with historical, regional-level data describing the interregional distribution of GDP. Among the available national-level, long-term GDP projections, we prefer the European Commission's Ageing Report (EC, 2018). The main reasons for choosing this projection is that the results and the documentation of the underlying methodology are readily available, and the outputs fall in the middle range of other relevant projections (such as Riahi et al., 2017, and OECD, 2020).

At the national level, the EC's projections are calculated on the basis of a production function approach, and they assume a catching-up process for those countries where the GDP per capita is lower than the EU average, including the four Visegrad countries. The projected national-level growth rates apparently do not comply with the observed growth paths of the countries in the corresponding period. The main reason behind this is that the projected growth rates refer to the growth of the potential GDP, not the actual GDP. The output gap is the deviation of the actual GDP from the potential GDP in the percentage of the potential GDP. For long-term projections, we might assume that the output gap will close on the medium term, that is, projected growth rates will reflect the potential growth rates after around 2025, until then, they gradually converge towards it. This estimation is in line with that of the European Commission (EC, 2018) that assumes that the output gap closes within 3 years, and the OECD's Long-term Baseline Projections that expect it to close until around 2030. We think that the timeframe of the EC's reference projections is too long (ending in 2070, see Table 1), therefore we present our own results only until 2060.

Table 1. Projected long-term potential output growth rates in the Visegrad Group (percentage)

	Czechia	Hungary	Poland	Slovakia
2020	1.89	1.87	2.62	2.76
2025	1.56	2.40	2.15	2.93
2030	1.82	2.13	1.94	2.84
2035	1.43	1.62	1.54	2.18
2040	1.15	1.24	1.20	1.76
2045	1.08	1.29	0.88	1.21
2050	1.05	1.47	0.74	1.19
2055	1.21	1.34	0.77	1.15
2060	1.49	1.26	0.96	1.25
2065	1.58	1.39	1.01	1.41
2070	1.41	1.35	0.98	1.49

Source: authors' elaboration based on EC (2018)

2.2. Regional downscaling with extrapolations

In the second step of our empirical work, we use extrapolative techniques to regionalize the national-level projections. In this process, we follow the methodological considerations of Batista e Silva et al. (2016) in a modified form and analyse different combinations of the past regional growth rates and the projected national-level growth rates. The authors point out that "a calculation rule for a disaggregation embodies necessarily one or more assumptions regarding the regional distribution of a given national total figure" (p.11).

The variants of trend extrapolations are calculated according to the following equation:

$$g_{i,t+n}^{Y} = w_{NAT,t+n} * g_{NAT,t+n}^{Y} + w_{reg,t+n} * g_{i,tB}^{Y}, \tag{1}$$

where superscript Y denotes GDP, hence, $g_{i,t+n}^{Y}$ is the growth rate of GDP in region i through period $t+n$, $g_{i,tB}^{Y}$ is the average past growth rate in the base period (t_B lasts from 2000 to 2017), $g_{NAT,t+n}^{Y}$ is the projected national level GDP growth rate through period $t+n$, $w_{NAT,t+n}$ and $w_{reg,t+n}$ are the time-varying weights assigned to the projected national growth rate and the past regional average growth rates in period $t+n$, respectively, with $w_{reg,t+n} = 1 - w_{NAT,t+n}$. We start our extrapolations from the year 2020 on a yearly interval.

Generally, the regional downscaling method prescribes a proportional ex-post rescaling which ensures that the sum of the projected regional GDP volumes equals the national-level projected GDP aggregate. The following equation delivers the rescaled NUTS 3 level values:

$$Y_{i,t+n} = Y_{NAT,t+n} \cdot \frac{Y'_{i,t+n}}{\sum_{i=1}^{r} Y'_{i,t+n}}, \tag{2}$$

where $Y_{i,t+n}$ is the projected GDP of the i^{th} region after rescaling in period t+n, $Y_{NAT,t+n}$ is the projected national GDP in period t+n, $Y'_{i,t+n}$ is region i's projected GDP in period t+n before rescaling, $\sum_{i=1}^{r} Y'_{i,t+n}$ is the sum of regional GDP values in period t+n before rescaling, r is the number of regions, t=2015 is the base year (because Poland's time series ends in this period) and n, running from 1 to 41, is the number of years in the projection horizon (from 2020 to 2060).

The following issues might be considered in connection with the procedure of ex-post proportional rescaling:

- Without ex-post rescaling, the top-down nature of our projections would be given up, because the regional growth paths would evolve on their own.
- Batista e Silva et al. (2016) highlight that beyond the required compatibility between aggregate and disaggregate projections, there are other aspects to consider with respect to the practice of ex-post rescaling. Rescaling imposes national constraints on the regional growth paths. This means that regional processes are bound to the national trends to some extent, and the effects of the different assumptions (calculation rules) are limited to within-country variations, therefore, it is implicitly assumed that the interregional distribution of the GDP does not have any impact on the national growth prospects. That's why top-down regional forecasting methods are called 'distributive' or 'competitive' vis-á-vis bottom-up methods which take a 'generative' approach (Cappello, Caragliu and Fratesi, 2017). However, this assumption might be uncertain, since a couple of studies revealed the impact of interregional disparities on national economic growth (see for example Garretsen et al., 2013; Gardiner et al. 2013).
- Our opinion is that due to the fact that long-run projections incorporate a large uncertainty, and even more so at lower degrees of spatial disaggregation, this practice may carry some kind of guarantee; namely, it may assure that projected regional processes will not decouple too much from the national trends. This practice prevents us from predicting counterintuitive outcomes when the regional GDP values are aggregated.
- Ex-post proportional rescaling helps us in overcoming the problems with the output gap, since the historical time series reflect actual GDP, while the projected growth rates refer to potential GDP. In this procedure, actual GDP values are applied to calculate the interregional distribution of the GDP, and after the rescaling, the structure and the variance of the interregional disparities remains the same.

- Batista e Silva et al. (2016) suggest considering also the alternative which relaxes the national constraints while maintains compliance with EU-level projected volumes, that is, shifting the constraints from the national level to the EU-level. In the case of our research, this option would mean rescaling regional GDP values so that they sum up to the Visegrad Group aggregate GDP, instead of national aggregates. Batista e Silva et al. (2016) find this procedure useful in order to test different convergence hypotheses, such as conditional convergence schemes, where other growth factors and determinants are considered. The imposed national constraints assume that the reallocation of the production (and the underlying production factors) takes place within the borders, and no international reallocation is assumed. The international reallocation of the production factors is addressed only by the reference projections at country level. Our opinion is that this problem is more relevant when the regional downscaling is elaborated at the European level, since the movement of production factors is more intensive between the individual Visegrad countries and the rest of the EU, compared to the internal migration or capital reallocation within the Visegrad Group macro-region (Kancs, 2011; Horridge and Rokicki, 2018). The ex-post rescaling at the Visegrad Group supranational level would assume fully flexible internal migration and capital flows within the macro-region, which is not the case.

The results of our empirical analysis in the rest of this paper will shed more light upon these issues.

2.3. Predictive accuracy

We check the predictive capacity of our projection methods with out-of-sample tests using historical data[1]. In this test, we divide our historical time series into a 'learning' or 'training' period and a 'test' period. Our historical database covers 18 years. Therefore, the learning period lasts from 2000 to 2012, and a test period from 2013 to 2017 in this case. This choice was affected by the nature of the GDP dynamics in this period, namely, the apparent impact of the global financial crisis.

We used standard statistical loss functions to check the predictive capacity of the projection methods. For choosing the preferred error statistics, we compare results of the measures that use either absolute deviations or relative (percentage) errors. In the first class of accuracy measures, the mean absolute error, MSE (mean squared error), and RMSE (root mean squared error) are often used. With

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[1] Zsibók (2019) introduces the methodological issues of out-of-sample testing in more detail.

respect to the nature of our data, we encounter the problem of comparability between regions when using these measures, since they cannot account for the scale of the given territorial unit, i.e. the same prediction error counts more in a smaller region and less in a bigger region. For this reason, we prefer using relative accuracy measures, specifically, MAPE (mean absolute percentage error) and AMAPE (adjusted, or symmetric, mean absolute percentage error). While in absolute numbers, the largest prediction error is measured in the largest (capital) regions, in relative terms, the percentage error is the smallest there among the regions. MAPE seems to be a reasonable choice, however, it has certain shortcomings (Makridakis, 1993; Goodwin and Lawton, 1999), notably that it is not a symmetric measure: equal errors above the actual value result in a greater absolute percentage error than those below the actual value. For this reason, we take the adjusted MAPE as decisive when studying prediction errors, and report only this statistic.

We test the predictive capacity of our projections with the following statistical loss function:

$$AMAPE = \frac{100}{m}\sum\frac{|\hat{Y}_{t+m}-Y_{t+m}|}{\left|\frac{\hat{Y}_{t+m}+Y_{t+m}}{2}\right|}, \quad (3)$$

where t is the year of the last historical data taken as known (year 2012), m, running from 1 to 5 (between 2013 and 2017) is the number of the years during the test period, the variable with a hat denotes the predicted value of the given variable in period $t + m$. Unfortunately, none of these measures informs us about whether the inaccuracy occurs in the form of over- or underpredicted values in the forecast.

3. Results

3.1. The synchronization of the regional growth processes

The first question to think about is that what would be a reasonable weight assigned to the projected national trend vis-á-vis the regional weights in Eq. (1). A principal component analysis can give us some good indications about it, following for example Beck, Hubrich and Marcellino (2006) and Stock and Watson (2002). Similarly to a dynamic factor model, we extract one or more principal components from the historical regional-level GDP series and regard them as country-level common factors (Owyang, Rapach and Wall, 2009): each of these common factors (estimated by the principal components) is associated with a set of factor loadings that indicate the extent to which each region's economy is related to the national trend. Our decision about the number of the extracted principal components is determined, first, by the eigenvalues which should be higher than 1, and second, by the cumulative variance explained by the principal components. Our results show important differences between the countries of the Visegrad Group. In the case of Czechia, Poland and Slovakia, one principal component was extracted in each of them, while in Hungary, we extracted three principal components (Table 2).

Table 2. Extracted principal components of the regional GDP time series in the Visegrad countries

	Components	Eigenvalues	% of variance explained	Cumulative %
Czechia (14 regions)	1	13.26	94.73	94.73
Hungary (20 counties)	1	13.82	69.11	69.11
	2	3.18	15.89	85.00
	3	1.71	8.57	93.57
Poland (72 subregions)	1	70.12	97.39	97.39
Slovakia (8 regions)	1	7.83	97.83	97.83

Source: Authors' elaboration

Generally, the results of the principal component analysis show that the regional GDP time series closely follow the national tendencies, especially in Slovakia and Poland, where one principal component explains more than 97 percent of the total variance. In Czechia, the regional trends are also closely connected to each other, one principal component is enough to explain 94.7 percent of the total variance of the regional GDP time series. Hungary is an outlier in this respect, since there are three principal components with eigenvalues above 1, of which the first one explains only 69.1 percent of the total variance, while the first three principal components together explain not more than 93.6 percent. This indicates a lower degree of regional economic cohesion in Hungary.

Now, we look at the component loadings associated with each region[2]. In Czechia, there is only one outlier region with a component loading of 0.861 (Karlovarský Region), while other regions have values between 0.944 (Ústecký Region) and 0.994 (Pardubický Region). In Poland, the lowest component loading was measured in Legnicko-Głogowski (0.924), and the rest of the regions have component loadings between 0.939 (Sosnowiecki) and 0.998 (City of Łódź). In Slovakia, the component loadings vary in a narrow range between 0.982 (Region of Banská Bystrica) and 0.996 (Region of Žilina), reflecting really synchronized trends. In contrast, component loadings are quite diverse in Hungary, varying between -0.086 (Nógrád) and 0.973 (Csongrád) with respect to the first principal component, -0.680 (Tolna) and 0.965 (Nógrád) for the second principal component and -

[2] The presentation of detalied results are available at the Authors.

0.436 (Zala) and 0.518 (Békés) for the third principal component. The average of the individual regional component loadings with respect to the first principal component is 0.79 which reflects a moderately high importance of the common national trend in determining regional GDP series. We will take these results into consideration when we design the weighting scheme of our regional GDP projections (described in Eq. (1)).

3.2. Our weight structure

As mentioned before, the weighting system applied by Batista e Silva et al. (2016) in their trend scenario is time-varying, under which they assign a weight (w_{reg}) of 1.00 to the past regional growth rates in the first part of their projection period (until 2020), implying that the projected national trend does not play a role, at all. Then, the value of the weight indicator gradually decreases to 0.75 between 2020-25, 0.50 between 2025-30, 0.25 between 2030-35, after which only the projected national growth rate is applied in the calculation of expected regional growth rates. In this paper, we intend to analyze this trend approach in more detail, considering several other possibilities.

First, our focus is on the out-of-sample accuracy of the different assumptions behind our projection method, and the regional GDP projections will be prepared later. Basically, the calculation of the 'business-as-usual' projections depends on two parameters: the first one reflects the alternatives determining whether the weights of the past regional growth rates and the projected national growth rates ($w_{reg,t+m} = 1 - w_{NAT,t+m}$) are constant throughout the projection horizon or they are time-varying. In the latter case, this parameter determines that how fast do the regional growth rates converge towards the projected national growth rates. The second parameter determines the weights assigned to the national projected growth rate in the first period of the projection ($t + m = t + 1 = 2013$ in our out-of-sample tests). The specific formula for calculating the time-varying weighting scheme is

$$w_{NAT,t+m+1} = w_{NAT,t+m} + \gamma, \quad (4)$$

where γ is the parameter which determines the speed of the convergence of the regional growth rates towards the national growth rate (see Zsibók, 2019 for more details). For example, Batista e Silva et al. (2016) used a weighting system in which $w_{NAT,t+m} = 0$ and $\gamma = 0.25$ on 5-year intervals, and the weight of the national growth rate is maximized at 1.

A large variety of weighting schemes derive from Eqs. (1) and (4):

1) "Latest differences" scheme: The simplest weighting scheme is the one that assumes that the interregional distribution of the GDP remains constant in the future, reflecting the state of the last known period (2012). This assumption is described by the parameter values $\gamma = 0.00$ and

$w_{NAT,t+m}$ = $w_{NAT,t+1}$ = 1. This option allows no interregional convergence or divergence, it freezes the cross-sectional variance of the regional GDP at its initial value, and regional growth paths follow the evolution of the national growth path. For this reason, this could be regarded as a benchmark case.

2) "Historical differences" scheme: It would also be straightforward to consider not only the state in the last known period, but to calculate the average interregional distribution of the GDP in the whole base period (2000-12) for a richer information base. This option freezes the cross-sectional variance of the regional GDP not at its 2012 value, but at its average value measured between 2000 and 2012. In practice, the share of the regions within the national GDP is calculated, averaged over the base period, and this average share is applied for all periods of the projection horizon. This assumption follows the common wisdom that the average historical cross-sectional distribution might be suitable to describe the prevailing interregional processes.

3) "Regional divergence" scheme: The other extreme of the weighting scheme is the one that considers only the past regional growth rates and projects them throughout the entire projection horizon. This version can be described by the parameter values γ = 0.00 and $w_{NAT,t+m}$ = $w_{NAT,t+1}$ = 0. Following the fact that the interregional variance of the GDP has been growing in all Visegrad countries during the base period, this projection method predicts continuously growing regional inequalities.

4) "Differing constant weights" scheme: The common attribute of the above extrapolation variants is that they use constant weights for the national and regional growth rate, either $w_{NAT,t+m}$ = 1 or 0. Besides these two extreme cases, we consider other possibilities from 0.1, 0.2, …to 0.9. Based on the results of the principal component analysis, we would expect that the prediction errors (the AMAPE values) will be lower for higher relative weights of the national growth rate.

5) "Differing time-varying weights" scheme: Finally, the range of the varieties can be extended further if we depart from the time-invariant weights and assume that during the first part of the projection horizon, the past regional growth rates are more important in determining the predicted regional growth prospects, and later, the common national growth rate gains more and more importance. This approach reflects the intuition that in shorter time horizons, the past growth performances are indicative of the future prospects, but in longer time horizons, it is more certain if regional growth rates are approximated by the predicted national average (see Batista e Silva et al., 2016). The convergence of the regional weights from their historical

level towards the projected national growth rate is described by the γ parameter. We experiment with several different values of this parameter, namely, γ = 0.00, 0.01, 0.0125, 0.025, 0.05, 0.1, 0.125, 0.2 and 0.25. We repeat here that γ = 0.00 means that the weights are time-invariant.

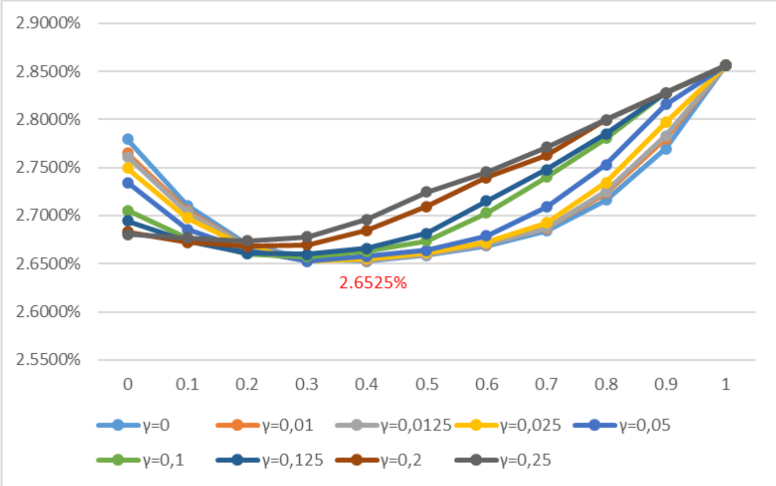
Table 3. Selected cases for evaluation

Scheme	$w_{NAT,t+m}$	γ	Description
"Latest differences"	1	0	extrapolates the last known interregional distribution; regions follow the common national growth rate
"Historical differences"	1	0	adjusted to extrapolate average historical interregional distribution; regions follow the common national growth rate
"Regional divergence "	0	0	extrapolates past regional growth rates
"Differing constant weights"	>0 and <1	0	adjusts the national growth rate with the past regional growth rates in each region
"Differing time-varying weights"	>0 and <1	>0	projected regional growth rates converge towards the national growth rate

In sum, we have 9 different γ parameters and 11 different weights for $w_{NAT,t+1}$, implying 99 different combinations, constrained by the condition $w_{NAT,t+m} \leq 1$. The most important limitation of our out-of-sample tests is that the test period contains only five years (three in Poland), therefore, the interpretation of the results is more certain on the medium run than on the long run.

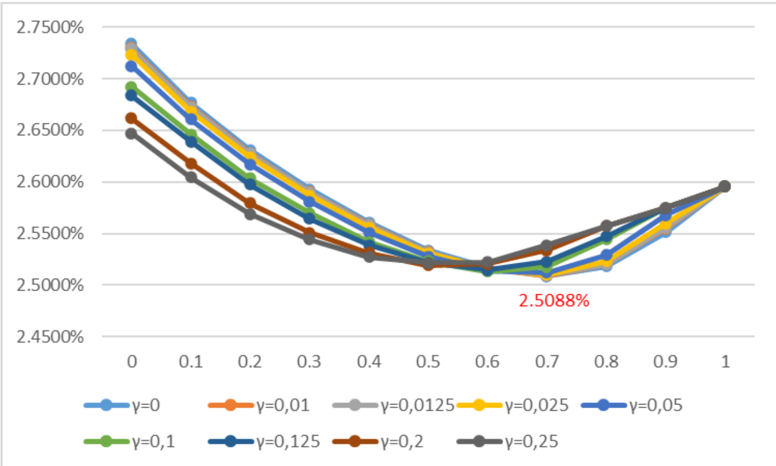
Note that these possibilities do not count with decreasing regional inequalities during the projection horizon. This assumption is based on the results of previous studies as Smetkowski (2013), Kuc (2017) or Lengyel and Kotosz (2018). Indeed, the prevailing process of regional concentration cannot continue beyond all limits in the future. We expect that in the short to medium run, regional inequalities will continue to grow, but with a slowing pace. On the long run, they might stabilize at a somewhat higher level than nowadays. We do not expect that regional inequalities will sink below the average level measured in the period between 2000 and 2017. It would be possible, but a strong regional policy commitment would be needed to reach a higher spatial balance, which would be likely to manifest only after 2040 or 2050.

Chart 2. Average prediction errors (AMAPE) under different weighting schemes, Czechia



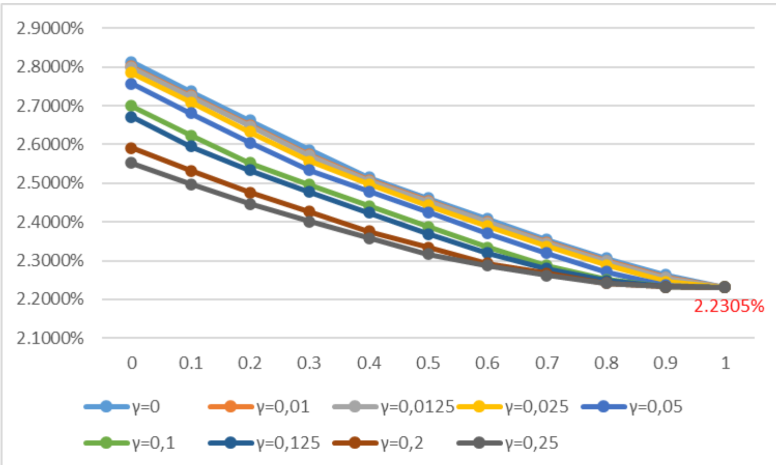
Source: Authors' elaboration

Chart 3. Average prediction errors (AMAPE) under different weighting schemes, Poland



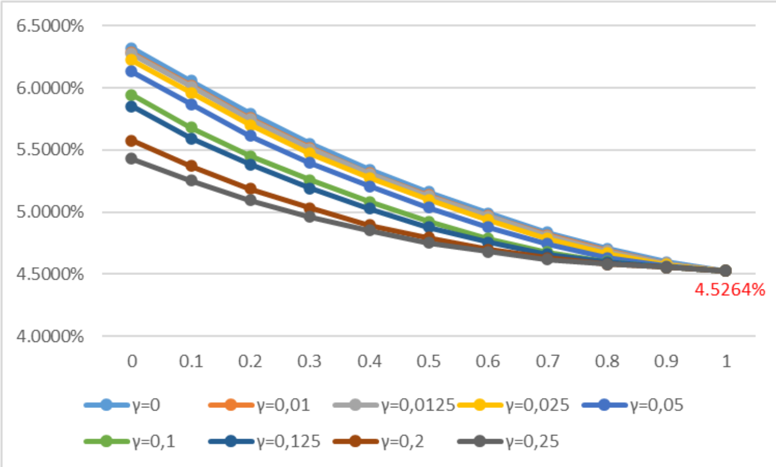
Source: Authors' elaboration

Chart 4. Average prediction errors (AMAPE) under different weighting schemes, Slovakia



Source: Authors' elaboration

Chart 5. Average prediction errors (AMAPE) under different weighting schemes, Hungary



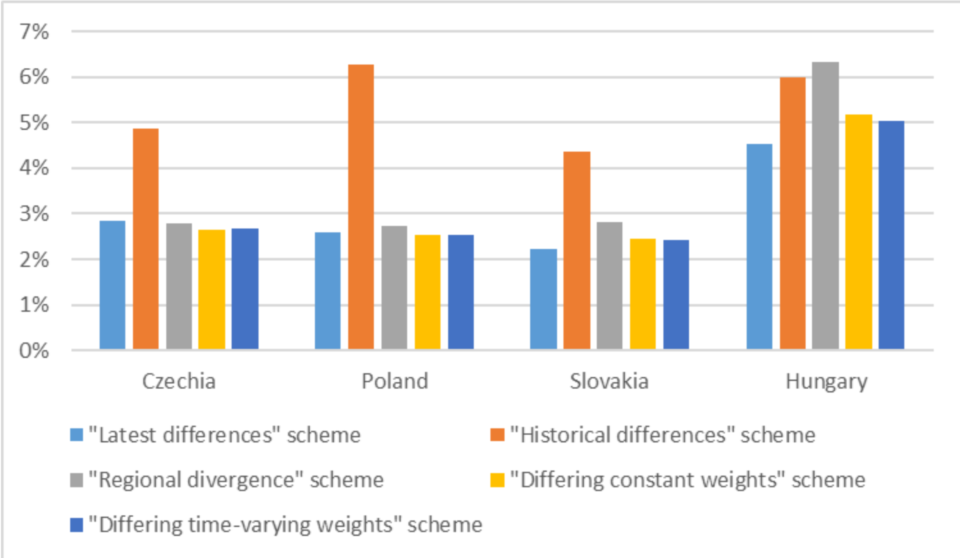
Source: Authors' elaboration

Charts 2 to 5 show the graphs of the out-of-sample tests based on the AMAPE values (the detailed tables can be found in the Appendix). The lowest average prediction errors are highlighted with red numbers. The results partly confirm our expectations. Hungary seems to be an outlier again, since its average prediction errors are higher than those measured in the other Visegrad countries. The lowest prediction errors were measured in Slovakia, and they are slightly higher in Poland and Czechia.

The case of Czechia suggests that the most accurate regional-level GDP predictions can be reached by using constant weights (γ=0.0), where the projected national-level growth rate is weighted 40%, and the past regional-level GDP growth rates are weighted 60% in each period throughout the projection horizon. This scheme would result a 2.65 percent prediction error. Similar results can be observed in the Polish case, as the most accurate predictions were obtained with time-invariant weights (γ=0.0), where the predicted national-level growth rate is weighted 70% and the past regional-level growth rates are weighted 30% throughout the whole projection horizon. This weighting scheme resulted in a 2.51 percent prediction error averaged over the regions.

The out-of-sample tests on the Hungarian data recommend to use only the national-level growth rate in the process of the prediction ($w_{NAT,t+m}$ = 1), while with every other $w_{NAT,t+1}$ weights, the highest convergence parameter (γ=0.25) proved to be the best. However, even the most accurate predictions have relatively large average error values, around 4.53 percent. Slovakia displays a similar pattern in the structure of the prediction errors as Hungary, because the out-of-sample tests prescribe using only the national-level projected growth rate ($w_{NAT,t+m}$ = 1), and with every other $w_{NAT,t+1}$ weights, γ=0.25 delivered the lowest errors. The most accurate predictions were obtained in Slovakia, resulting an average AMAPE of 2.23 percent.

Chart 6. Average prediction errors in the Visegrad countries according to five different extrapolation schemes (AMAPE values)



Source: Authors' elaboration

Note: "Differing constant weights" scheme was illustrated with parameter values $w_{NAT,t+1}$=0.5 and γ=0.0, and "Differing time-varying weights" scheme was illustrated with parameter values $w_{NAT,t+1}$=0.5 and γ=0.05 for all Visegrad countries.

Comparing the predictive performance of the five different extrapolation schemes, we find quite similar patterns across the countries, especially in Czechia, Poland, and Slovakia (Chart 6). Our most important, general result is that the past historical distribution (the average shares of the regional GDP values within the total national GDP over the base period) is not useful in extrapolating regional GDP paths ("Historical differences" scheme). In contrast, the results are much better if we use the interregional distribution of the last year of the learning period ("Latest differences" scheme). Indeed, this method came up as the most accurate in Slovakia and in Hungary. Apart from "Historical differences" scheme, the method using only the past regional GDP growth rates ("Regional divergence" scheme) performed relatively poorly in most of the countries, especially in Hungary. Another important lesson from the out-of-sample tests is that the use of the convergence parameter (γ) did not really improve the accuracy in the test period. However, we think that this result is specific to the relatively short length of the test period, anyway, "Differing constant weights" scheme delivered quite good results with respect to prediction accuracy, therefore we do not recommend abandoning its use during the long-run projections.

3.3. Long-run predictions

In this step of our work, we need to decide on the best extrapolation method in the four countries of the Visegrad Group, based on the results of the out-of-sample accuracy tests. We do not recommend using exactly those parameters which were prescribed by the out-of-sample tests on the historical, 5-year period, but consider them as benchmark. We think that the assumption of some kind of convergence between the long-run regional growth rates ($\gamma > 0$) is helpful in handling the uncertainty of the far future, and it may express some kind of path dependence (Dyba et al, 2018; Lengyel and Kotosz, 2018), under which past growth performance does play a role, but with a gradually decreasing importance. If we intend to leave enough room for the convergence process, it is recommended to use a relatively smaller weight for the national growth rate at the beginning of the projection horizon and/or a relatively smaller convergence parameter. Nevertheless, it is straightforward to assume that, as a result of the convergence, the weight of the national growth rate reaches 1 at some part of the projection horizon. As mentioned before, full convergence of the regional growth rates is not a valid assumption in practice, but the use of the same regional growth rates is recommended due to the uncertainty of the regional processes in the far future. For this reason, we estimate regional growth rates with the common, projected national growth rate after 2040, stating that we cannot foresee whether a region's growth rate will be below or above the national average in 20 years from now on. At this stage of our research we follow "Differing time-varying weights" scheme, and prepare the projections with identical parameters for each country, namely, $w_{NAT,t+1} = 0.75$ and $\gamma = 0.01$, since these parameters are fairly between those obtained in the out-of-sample tests.

Turning to the issue of ex-post proportional rescaling, first, we notice that this procedure is not needed if the extrapolations are calculated on the basis of equal regional growth rates that follow the national projections, because they lead to the same results (under "Latest differences" and "Historical differences" schemes). In other cases, if we compare the results of the projections with and without the ex-post proportional rescaling, the direction of the differences is varying in the involved countries. It might be explained by the different regional settings (one or more core cities), the interregional flow of resources within the countries as well as the agglomeration effects. According to the results of the out-of-sample accuracy tests, the prediction errors increased in each case when the out-of-sample predictions were made without the ex-post rescaling. The deterioration of the accuracy was the highest in Slovakia and in Hungary. "Regional divergence" and "Differing constant weights" schemes provided greater deterioration than "Differing time-varying weights" scheme in each country. These results strongly support the use of an ex-post proportional rescaling (Table 4).

Table 4. Average prediction errors according to five different extrapolation schemes and the application of rescaling (AMAPE values)

Scheme	Rescaled values	Czechia	Poland	Slovakia	Hungary
"Latest differences"	yes	2.86%	2.60%	2.23%	4.53%
	no	2.86%	2.60%	2.23%	4.53%
"Historical differences"	yes	4.88%	6.26%	4.35%	5.99%
	no	4.88%	6.26%	4.35%	5.99%
"Regional divergence"	yes	2.78%	2.73%	2.81%	6.32%
	no	3.15%	3.33%	5.70%	8.54%
"Differing constant weights"	yes	2.69%	2.68%	2.67%	5.85%
	no	3.14%	3.30%	5.20%	7.48%
"Differing time-varying weights"	*yes*	*2.66%*	*2.53%*	*2.42%*	*5.04%*
	no	*2.79%*	*2.69%*	*3.32%*	*5.70%*

Source: Authors' elaboration

Ex-post proportional rescaling might give counterintuitive results, when there are large differences between the growth rates of the individual regions, especially under "Regional divergence" scheme. It may occur that even when a poorer region has a slightly positive GDP growth rate before the rescaling, its GDP turns into a decreasing trend after the ex-post rescaling.

We also note that it is not enough to project the GDP values on the basis of the regional growth rates first, and then, in a final step, to rescale them, since this procedure would lead to counterintuitive results (extremely high GDP values in more developed regions or extremely low values in poorer regions). Instead, the rescaling must be calculated in an iterative manner in each period of the projection horizon.

4. Conclusion

Our article investigated the performance of the extrapolative regional downscaling methods with respect to the GDP in the Visegrad Group countries. One important aim of our research was to broaden the geographical coverage of a previous research conducted in Hungary with the same extrapolative methodology. This comparative approach indeed proved to be useful, since the most important findings were reaffirmed on the Visegrad countries' data, while new, richer insights were obtained by revealing some apparent differences.

Our present research reaffirmed that the average historical interregional distribution of the GDP is not a good indicator for the predictions. At the same time, the simple use of past regional growth rates causes too much interregional variance, either with or without the ex-post proportional rescaling. Therefore, a combination of past regional growth rates and the projected national growth rate should be used for the most accurate extrapolations.

The results of the analysis of the Visegrad Group showed that Hungary is an outlier in several aspects: first, the synchronization of the regional GDP trends is the lowest among the Visegrad countries as reflected by the principal component analysis. Second, the interregional variance of the GDP is relatively high, and, as a consequence, the extrapolative predictions are definitely less accurate: while the average accuracy of the predictions are between 2 and 3 percent in Czechia, Poland and Slovakia, that of Hungary is around 5 percent in average.

With respect to the issue of ex-post proportional rescaling, our research provided some deeper insights, of which the most important is that it is recommended to follow this procedure. The only problem with this exercise is theoretical, that is, it assumes that the interregional distribution of the GDP does not have any impact on the national growth potential. However, our purely statistical methodology cannot handle this, therefore we recommend extending it with more sophisticated approaches, such as a system dynamics framework.

Future researches might consider analyzing regional GDP trends in a decomposed way, differentiating between productivity and employment impacts. Although we did not intend to articulate policy recommendations, it is clear from our results that committed regional policy efforts are needed in the Visegrad countries to curb the trend of continuously increasing spatial inequalities and polarization.

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Appendix

Table A1. Average prediction errors (AMAPE) under different weighting schemes, Czechia, %

$w_{NAT,t+1}$	γ=0	γ=0.01	γ=0.0125	γ=0.025	γ=0.05	γ=0.1	γ=0.125	γ=0.2	γ=0.25
0.0	2.7791	2.7649	2.7613	2.7494	2.7344	2.7052	2.6946	2.6830	2.6806
0.1	2.7106	2.7053	2.7040	2.6973	2.6854	2.6764	2.6738	2.6720	2.6768
0.2	2.6708	2.6686	2.6684	2.6671	2.6645	2.6602	2.6610	2.6680	2.6737
0.3	2.6553	2.6543	2.6540	2.6529	2.6527	2.6574	2.6597	2.6698	2.6781
0.4	**2.6525**	2.6536	2.6539	2.6552	2.6578	2.6631	2.6659	2.6845	2.6961
0.5	2.6587	2.6598	2.6600	2.6614	2.6640	2.6738	2.6817	2.7096	2.7246
0.6	2.6688	2.6702	2.6705	2.6723	2.6789	2.7028	2.7153	2.7397	2.7450
0.7	2.6842	2.6868	2.6874	2.6923	2.7090	2.7401	2.7476	2.7629	2.7713
0.8	2.7161	2.7233	2.7251	2.7341	2.7528	2.7804	2.7849	2.7995	2.7995
0.9	2.7695	2.7801	2.7828	2.7969	2.8155	2.8276	2.8276	2.8276	2.8276
1.0	2.8562	2.8562	2.8562	2.8562	2.8562	2.8562	2.8562	2.8562	2.8562

Note: The number with grey background represents the lowest AMAPE value.

Table A2. Average prediction errors (AMAPE) under different weighting schemes, Hungary, %

$w_{NAT,t+1}$	γ=0	γ=0.01	γ=0.0125	γ=0.025	γ=0.05	γ=0.1	γ=0.125	γ=0.2	γ=0.25
0.0	6.3197	6.2819	6.2724	6.2253	6.1312	5.9438	5.8506	5.5766	5.4285
0.1	6.0557	6.0181	6.0087	5.9618	5.8683	5.6820	5.5931	5.3715	5.2557
0.2	5.7930	5.7556	5.7467	5.7022	5.6134	5.4524	5.3817	5.1852	5.0950
0.3	5.5506	5.5187	5.5108	5.4709	5.3943	5.2586	5.1926	5.0322	4.9626
0.4	5.3416	5.3133	5.3067	5.2736	5.2083	5.0846	5.0282	4.8958	4.8534
0.5	5.1622	5.1367	5.1303	5.0984	5.0385	4.9257	4.8764	4.7925	4.7537
0.6	4.9926	4.9700	4.9643	4.9361	4.8798	4.7873	4.7556	4.6961	4.6806
0.7	4.8341	4.8137	4.8089	4.7847	4.7426	4.6761	4.6587	4.6310	4.6202
0.8	4.7048	4.6902	4.6866	4.6684	4.6327	4.6006	4.5962	4.5830	4.5830
0.9	4.5987	4.5874	4.5848	4.5751	4.5635	4.5547	4.5547	4.5547	4.5547
1.0	4.5264	4.5264	4.5264	4.5264	4.5264	4.5264	4.5264	4.5264	**4.5264**

Note: The number with grey background represents the lowest AMAPE value.

Table A3. Average prediction errors (AMAPE) under different weighting schemes, Poland, %

$w_{NAT,t+1}$	γ=0	γ=0.01	γ=0.0125	γ=0.025	γ=0.05	γ=0.1	γ=0.125	γ=0.2	γ=0.25
0.0	2.7341	2.7298	2.7287	2.7232	2.7123	2.6925	2.6835	2.6614	2.6470
0.1	2.6767	2.6732	2.6723	2.6681	2.6608	2.6462	2.6390	2.6181	2.6047
0.2	2.6312	2.6283	2.6275	2.6240	2.6170	2.6037	2.5974	2.5794	2.5688
0.3	2.5930	2.5906	2.5899	2.5869	2.5809	2.5698	2.5646	2.5506	2.5443
0.4	2.5611	2.5590	2.5585	2.5559	2.5508	2.5420	2.5386	2.5310	2.5275
0.5	2.5338	2.5323	2.5320	2.5306	2.5279	2.5233	2.5218	2.5192	2.5219
0.6	2.5168	2.5163	2.5162	2.5155	2.5142	2.5133	2.5145	2.5208	2.5223
0.7	**2.5088**	2.5094	2.5095	2.5102	2.5123	2.5180	2.5225	2.5336	2.5387
0.8	2.5184	2.5200	2.5205	2.5231	2.5295	2.5444	2.5474	2.5574	2.5574
0.9	2.5515	2.5548	2.5556	2.5598	2.5681	2.5751	2.5751	2.5751	2.5751
1.0	2.5955	2.5955	2.5955	2.5955	2.5955	2.5955	2.5955	2.5955	2.5955

Note: The number with grey background represents the lowest AMAPE value.

Table A4. Average prediction errors (AMAPE) under different weighting schemes, Slovakia, %

$w_{NAT,t+1}$	γ=0	γ=0.01	γ=0.0125	γ=0.025	γ=0.05	γ=0.1	γ=0.125	γ=0.2	γ=0.25
0.0	2.8126	2.8013	2.7985	2.7844	2.7561	2.6995	2.6712	2.5908	2.5517
0.1	2.7370	2.7257	2.7229	2.7087	2.6804	2.6237	2.5952	2.5326	2.4973
0.2	2.6612	2.6498	2.6470	2.6328	2.6044	2.5523	2.5328	2.4759	2.4469
0.3	2.5851	2.5737	2.5708	2.5566	2.5329	2.4956	2.4772	2.4260	2.4010
0.4	2.5151	2.5078	2.5060	2.4968	2.4785	2.4417	2.4234	2.3760	2.3589
0.5	2.4612	2.4539	2.4521	2.4429	2.4245	2.3878	2.3694	2.3338	2.3166
0.6	2.4072	2.3999	2.3980	2.3889	2.3705	2.3337	2.3192	2.2924	2.2870
0.7	2.3539	2.3469	2.3452	2.3364	2.3188	2.2876	2.2799	2.2667	2.2614
0.8	2.3064	2.2994	2.2976	2.2888	2.2713	2.2518	2.2491	2.2421	2.2421
0.9	2.2633	2.2564	2.2547	2.2461	2.2368	2.2322	2.2322	2.2322	2.2322
1.0	2.2305	2.2305	2.2305	2.2305	2.2305	2.2305	2.2305	2.2305	**2.2305**

Note: The number with grey background represents the lowest AMAPE value.