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FBK-IRVAPP Working Paper No. 2021-02

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FBK-IRVAPP Working Paper No. 2021-02

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Forecasting Regional GDPs: a Comparison with Spatial Dynamic Panel Data Models

Anna Gloria Billé, Alessio Tomelleri and Francesco Ravazzolo

Abstract

The monitoring of the regional (provincial) economic situation is of particular importance due to the high level of heterogeneity and interdependences among different territories. Although econometric models allow for spatial and serial correlation of various kinds, the limited availability of territorial data restricts the set of relevant predictors at a more disaggregated level, especially for GDPs. Combining data from different sources at NUTS-3 level, this paper evaluates the predictive performance of a spatial dynamic panel data model with individual fixed effects and some relevant exogenous regressors, by using data on total GVA for 103 Italian provinces over the period 2000-2016. A comparison with nested panel sub-specifications as well as pure temporal autoregressive specifications has also been included. The main finding is that the spatial dynamic specification increases forecast accuracy more than its competitors throughout the out-of-sample, recognizing an important role played by both space and time. However, when temporal cointegration is detected, the random walk specification is still to be preferred in some cases even in the presence of short panels.

Key words: Prediction, Spatial Correlation, Panel Data, Regional GVA forecasting.

Acknowledgments: This paper started as Tomelleri's doctoral thesis chapter. We would like to thank all the thesis reviewers for their careful and insightful comments on our paper and, indeed, on the whole development of this work itself. All remain errors are ours.

1 Introduction

Forecasting economic growth among and within countries is a major macroeconomic concern both for researchers and policy institutions. Since regional disparities in economic performance can be found for most of the economies, the prediction of future behaviour of the single regions within the national context is gaining increasing attention (OECD, 2018). Regional and provincial forecasting is, however, limited by the scarcity of disaggregated data collected for sufficiently long panels over time and across spatial units. In addition, the number of regions/provinces to forecast is generally much higher than the number of available time periods. Due to the short length, each time series taken by itself often provides insufficient sample information to precisely estimate province-specific parameters. At the same time, regions are open, small and highly interconnected economies, implying a high degree of interaction among neighbouring territories. Ignoring the underlying spatial process might result in biased estimation coefficients and, therefore, in sub-optimal forecasts. To this purpose, the use of spatial dynamic models allows for simultaneous spatial dependence together with dynamic interaction.

This paper aims to take advantage of the comprehensive set of valid tools, and empirical evidence in spatial econometrics, discussed in the next section, to perform gross value added (GVA) forecast among Italian provinces. More precisely, we use a spatial dynamic panel data model (SDPD) specification proposed by Baltagi et al. (2014) and its subspecifications, adopting the bias-corrected QML approach described by Yu et al. (2008) and treating the space-time lagged dependent variables as potential regressors. The paper combines data from different sources at the NUTS-3 level and evaluates the predictive performance of a spatial dynamic panel data model with individual time fixed effects and some relevant exogenous regressors. To improve the GVA forecast, we also show how important is the introduction of a space-time lag treated as exogenous regressor. To conclude, we improved the GVA forecasts for all Italian provinces simultaneously.

The data on total GVA for 103 Italian provinces over the period 2000-2016 has been enriched with information related to business demography, employees, foreign trade, and overnight stays by sector and province. This is undoubtedly a strength of this work, as the availability of relevant predictors at the NUTS-3 level is often limited to a small set of short and sometimes unbalanced panels. To the extent of our knowledge, there is no contribution in terms of spatial modelling estimation and forecasting at NUTS-3 level for regional GDPs. Moreover, the Italian case seems particularly interesting from an economic point of view as the Italian economy has never fully recovered from the 2008 financial crisis and the subsequent debt crisis. Even compared to other advanced economies, it is the worst performer (see, OECD 2021).

The general contribution consists of comparing the forecasting performances of a SDPD model with other panel specification and some benchmark univariate models at a high level of disaggregation (NUTS-3). Results show that models that take into account spatial dynamic autocorrelation tend to perform better in terms of forecasting accuracy in some cases. They are also, on average, more reliable than other nested panel sub-specifications as well as pure temporal autoregressive specifications. Accounting for lagged spatial dependence reduces RMSE considerably. However, when temporal cointegration is detected, the random walk specification is still to be preferred in some cases, even in the presence of short panels. From an economic point of view, this may be due to the low growth rate shown by most of the provinces in the period of analysis. On the other hand, an important finding is that the SDPD model performs better when the panel is short, while the AR needs a much longer time series to perform slightly better. This result is very important because it shed some light in the empirical application of an SDPD model, highlighting its superior performances in panel data that are usually characterised by not too long time windows. This coincides with the empirical setting of regional GDP/GVA forecasting.

The paper distinguishes itself from the earlier studies in three major aspects. First, it compares a wide range of spatial/non-spatial models estimating GVA forecasts at a high level of disaggregation (NUTS-3). The difficulty in building a panel setting at this level of disaggregation is evident and well expressed in most of the empirical papers and examples in the literature (Arkadievich Kholodilin et al., 2008; Baltagi, 2008; Baltagi et al., 2012; Lehmann and Wohlrabe, 2014). Despite the little evidence of economic output forecasting at this level of disaggregation already with non-spatial panel data (Lehmann and Wohlrabe, 2014), there are some contributions mainly focusing on labour market aspects such as un/employment rate, see Mayor and Patuelli (2012), Rapach and Strauss (2012), among others. When it comes to GDP forecasting with spatial models, Arkadievich Kholodilin et al. (2008) and Girardin and Kholodilin (2011) provide evidence for Germany and China relying on pooled panels with spatial effects without, however, considering economic determinants of GDP and with a lower level of disaggregation (state/regional level). In our setting, biases resulting from aggregation over more disaggregated data may be reduced or eliminated.

Second, among the comparison of the spatial model, it introduces a spatiotemporal lag to consider spillover effects that may not occur instantaneously and show how spatial effects improves the forecast. Forecasting studies using spatial panel data models are rare and those involving forecasting with a dynamic component are almost absent from the literature (Baltagi et al., 2014; Servén and Abate, 2020). Third, it derives interesting policy recommendation about considering spatial spillovers and, in this setting, the role of small firms and foreign trade in driving the economic output of Italian provinces.

The paper is organised as follows. Section 2 gives some background about the reference literature, section 3 describes the dataset and its different sources, while section 5 outline the model. Section 5 describes its empirical application, presents and discussed the result. Section 6 draws the conclusion and outlines key issues for future research.

2 Spatial forecasting literature at regional level

The forecasting literature is rich in time series applications but less rich in panel data applications, especially at the regional level. The use of panel data allows to better control for heterogeneity across individuals, firms and territories at different administrative levels. Economists have used panel data to forecast gasoline consumption across OECD countries (Baltagi and Griffin, 1997), pooling dynamic panel-data models to forecast gdp growth rates (Hoogstrate et al., 2000), forecast economic outputs with country-specific models (Marcellino et al., 2003), forecast combination methods for output growth (Stock and Watson, 2004), forecast economic and financial variables across a large number of countries (Pesaran et al., 2009), to mention a few at the national level.

When it comes to the regional sub-national level (NUTS >1), the biggest challenge is data availability. Finding relevant predictors at a higher level of disaggregation is not an easy task to perform, especially for high-frequency data. This is particularly the case when the dependent variable refers to the economic aggregate such as gross domestic product (GDP) or gross value added (GVA), and to labour market variables like total employment or unemployment rate (Lehmann and Wohlrabe, 2014). In addition, increasing the frequency of the data restricts the already limited number of relevant predictors at regional level.

Recent economic contributions at the national level underline the importance of taking into account both temporal and spatial dependence. For instance, Servén and Abate (2020) used a spatial dynamic panel model to shed some light on the determinants of countries' exposure to global shocks. Mitze et al. (2016) investigated the nature and magnitude of technology- and trade-related research and development (R&D) spillovers within sectoral productivity patterns among 13 major OECD countries in the period 1988-2006. At the regional level, Benos et al. (2015) incorporated geographical, economic and technological effects using different weighting matrices to test for the existence and magnitude of interregional externalities, whereas Fidrmuc and Degler (2021) extend their analysis on inter-regional consumption risk sharing in Russia comparing spatial and non-spatial specifications, underling the importance of controlling for the strongly connected regional economies within the country.

Over the last decade, given the increasing availability of regional economic data, the topic of regional economic forecasting has also become increasingly widespread in academic literature. For instance, Baltagi and Li (2004) and Baltagi and Li (2006) showed the forecast superiority of spatial panel data models in predicting demand equation for cigarettes and liquor across the US. Estimating models at a higher level of disaggregation has fostered the need to implement specifications to consider the interdependence between different territories. In this way, many authors accounted for spatial effects to capture regional spillovers either when dealing with GVA, see Baltagi et al. (2014) and Girardin and Kholodilin (2011) or by investigating labour market performance, see Cueto et al. (2015), Vega and Elhorst (2016), Watson and Deller (2017), Kosfeld and Dreger (2019), Longhi and Nijkamp (2007), Fingleton et al. (2015), Fingleton (2019), Mayor and Patuelli (2012), among others.

While many studies focus on regions and other administrative entities below the national level, most of the empirical literature on GDP/GVA regional forecasting is conducted at the national level. Exceptions are the studies of Arkadievich Kholodilin et al. (2008), Girardin and Kholodilin (2011) and Baltagi et al. (2014), whose works are at the NUTS-2 (regional/subnational) level. Arkadievich Kholodilin et al. (2008) considered a SDPD model to forecast the annual growth rate of real GDP of 16 German Länder (states), finding that SEM and SLM produce lower RMSE especially at longer horizons. Using a panel of 31 Chinese regions, Girardin and Kholodilin (2011) implemented multi-step forecasts of the annual real gross regional product (GRP) growth rates. In the spirit of Arellano and Bond (1991) and Mutl (2006), Baltagi et al. (2014) show how the

GMM estimator applied to a SDPD model with spatially correlated disturbances improves the forecast performance by a big margin: the gain in forecasting accuracy is higher when accounting for both heterogeneity and endogeneity in the 255 NUTS-2 European regions of the model. In addition, these studies produce forecasts ranging from five (Arkadievich Kholodilin et al., 2008) up to fifteen (Girardin and Kholodilin, 2011) years ahead, where most of the regional forecasting papers focus on either the short term (one year ahead) or the medium term (up to three years ahead).

In this paper we focus on a higher level of disaggregation, capturing economic interdependencies among small territories (NUTS-3 provinces) and exploiting heterogeneity at a more disaggregated level. Our paper contributes to the literature of GDP forecasting in this direction.

3 Data

Given the scarcity of panel data at the NUTS-3 level, this papers uses information from different sources. The dependent variable is the gross value added (GVA) at the provincial level that represents the net result of output at basic prices less intermediate consumption valued at purchasers' prices and measured in accordance with the European System of Accounts (ESA) 2010. We chose GVA because it has the comparative advantage of being a direct outcome of variation in factors that determine regional competitiveness. Moreover, it can be decomposed by sectors of the regional (provincial) economy. Our measure of GVA comes from the National and Regional Accounts provided by the Italian National Institute of Statistics (ISTAT). We divide each province-specific GVA by the amount of workforce employed in the province in order to control for the size of the local labour force.

The data covers the period from 2000 to 2016 and, to obtain a balanced panel, we exclude provinces created after 2000.[1] This does not bias our estimates since the dependent variable is related to the GVA per worker. Worth mentioning is the fact that Istat data is published three times a year. In December of year t, the data of year $t-2$ is available, even if provisional. The whole series is re-elaborated in each edition so that different editions of the regional economic accounts may lead to different values. We pre-

[1] New provinces become effective in some Italian regions between 2004 and 2009: the province of Barletta-Andria-Trani in 2004, four new provinces in Sardinia in 2005 and Fermo e Monza-Brianza 2009.

ferred to download the entire series and drop 2017 since it is provisional. The delay and uncertainty surrounding these estimates at the provincial level also give rise to the need to better explore the interdependencies between territorial economic performances.

We compute the log of the GVA per worker for the 103 provinces[2] and we obtain the number of registered and active firms as well as the relative number of employees from the Infocamere Database of the Chambers of Commerce. Import and export come from ISTAT as well as the overnight stay data. The number of total active enterprises per province has been divided by the relative number of employees. In this way, we can control for changes occurred both within business demography and the labour force. The resulting ratio is coherent with the denominator in the dependent variable, but it is not easy to interpret. It basically reports the number of enterprises per worker: it would have been easier to interpret the number of workers over enterprises. However, at the econometric level, the results do not change since, taking the logarithm, the ratio or its inverse only changes the sign of the coefficient but not the order of magnitude. This only needs to be considered when interpreting the results.

We take account of the provincial structure of enterprises by dividing the number of active firms by the number of employees according to three class-size k: 1-9, 10-49 and more than 49 employees[3]. Official statistics assign enterprises with fewer than 10 employees to micro enterprises, small enterprises (10 to 49 employees), medium-sized enterprises (50 to 249 employees). Large enterprises employ 250 persons or more. Given the impossibility of distinguishing for the last category, for simplicity, we shift the entire classification downwards so that enterprises with less than 10 employees are assigned to small enterprises; medium-sized enterprises are those with 10 to 49 employees and so on. We would have liked to look at the sub-categories of the latter and be able to differentiate among large companies, but a change in the categories made by Infocamere in 2008 made this not possible. The series was changed in the middle of the panel, not distinguishing enterprises with more than 49 employees. Nonetheless, it constitutes the smaller group within the three categories, as shown in Table 1.

Italy has an export-oriented economy and is the 9th largest exporter and 11th largest importer worldwide, with trade making up nearly 59.5% of its GDP (World Bank, 2018).

[2]There is no chance to obtain real GVA at the provincial level. We obtain the deflator as the ratio of nominal and real GVA at the regional level and then assign it to the provinces within each region. The results do not change estimated coefficients and the forecasts that much and are available upon request.

[3]This is in line with Eurostat (Structural business statistics (SBS) size class).

In an open economy like this, the development of provincial foreign trade significantly impacts economic growth. The foreign trade variables control for the total value of goods flowing in and out of the territories. It would have been better to use input-output matrices at the provincial level to account for inter-provincial exchanges. Unfortunately, only a few provincial statistical offices produce this type of data, and they are not enough to be able to determine data for the other territories.

With 63.2 million tourists per year (2018),[4] Italy is the fifth most visited country in international tourism arrivals. We chose to control for overnight stays instead of arrivals since the former takes account of the nights spent in a tourist location. Foreign trade variables, as well as the GVA, are expressed in thousands of Euro, while overnight stays represent the total amount of tourist presences in each province at time t. A summary of the variables is shown in Table 1.

4 Model and forecasting procedure

In this section, we compare different model specifications for forecasting the growth rates of GVA for 103 Italian provinces (NUTS-3 level). Among them, the first-order spatial dynamic panel data (SDPD) model, allowing for spatial, time and space-time lags of the dependent variable, is a good candidate to predict regional GVA (Baltagi et al., 2014). The SDPD model is specified as follows

$$\begin{aligned} &y_{n,t} = \rho W_n y_{n,t} + \phi y_{n,t-1} + \gamma W_n y_{n,t-1} + X_{n,t}\beta + \alpha_n + \delta_t \iota_n + \epsilon_{n,t} \quad t = 1, ..., T \\ &\epsilon_{n,t} \sim N(0, \sigma^2 I_n) \end{aligned} \tag{1}$$

where $y_{n,t}$ is the dependent variable vector of provinces at time t, $X_{n,t}$ is a $n \times k$ matrix of exogenous variables at time t with β the vector of parameters, $W_n y_{n,t-1}$ is an n-dimensional vector of spatiotemporal lagged variables with coefficient γ, ϕ is the temporal autoregressive coefficient, ρ is the spatial (simultaneous) autoregressive coefficient, while α_n and δ_t represent individual territorial and time fixed effects, respectively. Finally, $\epsilon_{n,t}$ contain independent, normally distributed error terms with zero mean and constant variances σ^2_ϵ. W_n is assumed to be a time-invariant $n \times n$ spatial weights matrix of known constants with zero diagonal elements and weights defined according to the k-nearest neighbour (k-nn) criterion. The weights matrix is then row-normalized such that

[4]International Tourism Highlights, 2019 Edition.

$\sum_j w_{ij} = 1 \quad \forall i$. Starting from the structural model in equation (1), we specify the following reduced form due to the simultaneity of the previous model specification

$$y_{n,t} = (I - \rho W_n)^{-1} \left[\phi y_{n,t-1} + \gamma W_n y_{n,t-1} + X_{n,t}\beta + \alpha_n + \delta_t \iota_n + \epsilon_{n,t} \right] \tag{2}$$

assuming that $A_\rho = (I - \rho W_n)^{-1}$ exist and it is unique. The invertibility of the matrix A_ρ can be ensured by the following Lemma (Kelejian and Prucha, 2010)

Lemma 1 *Let $\overline{\tau}$ denotes the spectral radius of the square n-dimensional W_n matrix, i.e.: $\overline{\tau}_{W_n} = max\{|\omega_1|, ..., |\omega_n|\}$, where $\omega_1, ..., \omega_n$ are the eigenvalues of W_n, respectively. Then, $A_\rho := (I - \rho W_n)$ is nonsingular for all values of ρ in the interval $(-1/\overline{\tau}, 1/\overline{\tau})$.*

and the following two assumptions are necessary conditions for estimation

Assumption 1 *The elements of $X_{n,t}$ are uniformly bounded constants in n and t, $X_{n,t}$ has a full column rank, and $lim_{T\to\infty} \sum_t \left(X'_{n,t} X_{n,t}\right) / nT$ exists and it is nonsingular.*

Assumption 2 *Matrices W_n and A_ρ^{-1} are uniformly bounded in both row and column sum norms.*

The predicted coefficients refer to the SDPD model in equation (2). In the analysis, the model is estimated for both a full-sample and an in-sample period. The in-sample period has an initial length of $(t_0, T-t)$ and is then evaluated on the remaining $[(t+1), T]$ years. Estimation of the model through the out-of-sample period(s) has been done using an "expanding window" with a one-period horizon ($h = 1$), where the forecast for observation $t + 1$ is based on the data in the interval (t_0, t). More specifically, we start to estimate our model for the period 2000-2008, and we make a one-year out-of-sample forecast for 2009. Then, we estimate the model for the period 2000-2009 and the forecast for 2010; we continue with this procedure up to 2016.

The goal is to generate a point forecast of the dependent variable for each year of the out-of-sample. Starting from equation (2), the point forecasts is obtained using the following expression:

$$\hat{y}_{n,t+1} = (I - \hat{\rho} W_n)^{-1} \left[\hat{\phi} y_{n,t} + \hat{\gamma} W_n y_{n,t-1} + X_{n,t}\hat{\beta} + \hat{\alpha}_n + \hat{\delta}_t \iota_n \right]. \tag{3}$$

While the forecasting procedure has been made by using some algebra, the estimation procedure was implemented through the **spml** package in R. We compare the forecast accuracy of the SDPD model shown in equation (3), with three sub-specifications: (i) a spatial panel data (SPD) model by letting $\phi = \gamma = 0$, (ii) a dynamic panel data (DPD) model by letting $\rho = \gamma = 0$ and (iii) a simple panel data (PD) model by letting $\rho = \phi = \gamma = 0$. We also compare these point forecasts with a univariate province-specific autoregressive (AR) and random-walk (RW) model, assuming growth equal to the average and zero growth, respectively.

We evaluate the forecast accuracy by computing the root mean squared error (RMSE) from the forecast errors e_t by province i and year t:

$$(i) \quad RMSE_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_{it} - \hat{y}_{it})^2} \quad \forall i, \qquad (ii) \quad RMSE_t = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{it} - \hat{y}_{it})^2} \quad \forall t \tag{4}$$

In the first case, we obtain a measure of forecast accuracy for each provincial series, i.e. a temporal provincial-specific RMSE, while the second is a measure of forecast performance for each year of the expanding window, i.e. cross-sectional year-specific RMSE. In other words, the former is an RMSE at every single province on the total years of the forecast, while the latter is an RMSE at every single year on the total cross-sectional data. In this way, it is possible to understand if the yearly cross-sectional forecast error is driven by the behaviour of certain provinces for which the model fails to perform so well.

In addition, we also propose a weighted version of the above RMSEs by considering both the number of inhabitants and the GVA per province and year. The above RMSE are then modified as follows

$$(i) \quad WRMSE_i = \sqrt{\sum_{t=1}^{T}\frac{I_{it}(y_{it} - \hat{y}_{it})^2}{\sum_t I_{it}}} \quad \forall i, \qquad (ii) \quad WRMSE_t = \sqrt{\sum_{i=1}^{n}\frac{I_{it}(y_{it} - \hat{y}_{it})^2}{\sum_i I_{it}}} \quad \forall t \tag{5}$$

where $\frac{I_{it}}{\sum_t I_{it}}$ and $\frac{I_{it}}{\sum_i I_{it}}$ are the specific weights, and I_{it} can be eighter the number of inhabitants or the GVA in province i and year t. Results on RMSEs and WRMSEs are reported in Section 5.1.

Finally, we checked for the presence of outliers for each year of the expanding window, as shown in Figure 3, with observations that increase by 103 province-specific residuals from 2009 to 2016. The dashed red line represents the $\pm$ 2.57 limits for the standardized residuals and corresponds to $\alpha = 0.01$.

5 Empirical Application on Regional GDPs

The analysis focuses on testing the forecast accuracy of our SDPD model specification in predicting GVA per worker at the provincial level. In this setting, the relative economic performance in neighbouring provinces is allowed to influence the economic output of a specific territory: this is captured by the spatial (simultaneous) autoregressive coefficient ρ. Additionally, spillover effects could last more than one period and the space-time coefficient γ takes account for them, as described in equation (1).

In the empirical setting, we consider a log-log model by taking the logarithm of both the dependent variable and the logarithm of our covariates. We chose the logarithmic transformation because this combination maintains the symmetry of the individual variables and improves the forecast. Thus, the empirical model becomes:

$$\begin{aligned}
ln\left(\frac{GVA_{i,t}}{worker_{i,t}}\right) = \phi ln\left(\frac{GVA_{i,t-1}}{worker_{i,t-1}}\right) + \rho\sum_{j=1}^{n} w_{ij}\left(\frac{GVA_{j,t}}{worker_{j,t}}\right) + \\
+ \gamma\sum_{j=1}^{n} w_{ij} ln\left(\frac{GVA_{j,t-1}}{worker_{j,t-1}}\right) + \beta_{1k} ln\left(\frac{firms_{it,k}}{worker_{it,k}}\right) + \beta_2 lnIMP_{it} + \\
+ \beta_3 lnEXP_{it} + \beta_4 lnOVER_{it} + \beta_5 ln\left(\frac{firms}{worker}\right)_{it,k=2} \times lnEXP_{it} + \\
+ \beta_6 ln\left(\frac{firms}{worker}\right)_{it,k=2} \times lnIMP_{it} + \beta_7 lnIMP_{it} \times lnEXP_{it} + \delta_t \iota_n + \epsilon_{i,t} \\
i = 1, ..., n; \quad t = 1, ..., T; \quad k = 1, ..., 3
\end{aligned} \tag{6}$$

As reported in section 3, the total number GVA of each province has been divided by the total number of employees. This helps to control for the relative size of each local economy and can also be seen as a measure of labour productivity for each province i at time t.

From a preliminary analysis, we found the model to be spatially cointegrated. We tested stationarity for each of the 103 provinces using an Augmented Dickey-Fuller and a Kwiatkowski-Phillips-Schmidt-Shin test, looking for constant and linear trends. Results show that, for every test, at least 70% of the single provincial time series were not stationary. We then decided to take the first differences of the model in equation 6. By doing this, the individual fixed effects cancel each other out while the temporal fixed effects remain in first differences. The first differences of the time fixed-effects instead help account for changes in the business cycle, such as the entry into the Euro area and the great recession. We obtained time fixed-effects for the forecast equation by subtracting the vector of fitted values coming from the structural model in equation 1, by those obtained by the reduced form in equation 2. The result is a vector of province-specific time fixed effects.

Dealing with the forecast at the national level allows having a wide range of valuable predictors: industrial production and sales, wages, prices (consumer, producer), monetary aggregates, interest rates, stock prices. This is not the case when working at the regional/county level of disaggregation as the data constraint increases. From the narrow set of indicators available at the provincial level, we selected the best predictors also according to the literature on spatial/non-spatial forecasting at the regional level. The final set of variables encompasses business demography, employment, trade and tourism.

Business demography plays a crucial role in GDP growth (Van Stel et al., 2005) and business statistics are ancillary to both the estimate of GDP and the identification of each sector's contribution to the economy (Ahmad, 2008). Employment dynamics among firms its partially constraint by business demography, but it is also a relevant predictor of the economic output. In this way, we take account of the provincial structure of enterprises by dividing the number of active firms by the number of employees according to three class-size. The variable $\frac{firms_{it,k}}{worker_{it,k}}$ can be seen as an indicator of average firm size per employee, as described in Section 3.

EXP_{it} and IMP_{it} are province-specific foreign trade variables representing the total volume of export and import at the provincial level. This is meant to capture economic interdependences with foreign countries/territories. $OVER_{it}$ control for the total number of overnight stays in each province. The relevance of the tourist sector and foreign trade for Italy has been described in section 3. Foreign trade variables, as well as the GVA, are expressed in thousands of Euro, while overnight stays represent the total amount of tourist presences in each province at time t.

Unfortunately, there is no chance to obtain real GVA at the provincial level (NUTS 3). We obtain the GVA deflator as the ratio between nominal and real GVA at the regional level (NUTS 2) and then assign it to the provinces within each region. The results do not change significantly, neither in terms of estimated coefficients nor in terms of forecasts. Since the inflation rate has not significantly increased in the country, especially after 2008, and since after the first difference, the GVAs were trend-stationary, we rely on the nominal GVA for all the analysis in this paper. For the sake of simplicity, and since the focus of the paper is about comparing the predictive performance of the SDPD model, we did not compare models on the "estimated" real GVA.

We then verified whether the selected variables and their interactions were significant not only in the estimation over the entire length of the panel but also in the individual years of the expanding window. The result of this selection includes the interaction between firms over the employee of medium-sized enterprises with both import and export, plus the interaction between import and export. Those variables are included in the model above, which configures the reference model for which we subsequently test the forecast performance.

5.1 Results

In this section, we mainly provide the results of our model comparison also in terms of forecast performance. We first estimate our benchmark model (2) and its competitors for the entire period 2000-2016 and report the coefficient in Table 2. We also report the estimated coefficients of our benchmark model (SDPD), expanding the in-sample period of one year at a time through the expanding window, Table 3.

The simultaneous spatial autoregressive coefficient ρ is highly significant in both the full sample model (statistically significant at 0.1% for both the SDPD and SPD model) and in the expanding window (statistically significant at 0.1% in all the years of the expanding window), confirming the presence of spatial spillovers among provincial log(GVAs). The coefficient representing the spatio-temporal γ is significant at 5% but only in the full sample size case and in the last year of the expanding window, i.e. 2015. The plot of standardized residuals resulting from the expanding window estimation procedure from 2009 to 2016 (2016 represents the full sample) shows the potential presence of outliers at $\alpha = 0.05$ for the SDPD model. There are some outliers that appear immediately in 2009, while fewer appear in the subsequent years. This might be related to the financial crisis in 2008-2009.

The estimated coefficient of the variable $\frac{firms_{it,k}}{worker_{it,k}}$ is only significant for small enterprises, but this is the case for all the sub-specifications in the full sample and all the years of the in-sample estimation. This correlation is very informative about the negative relation between the relative size of small companies and economic growth. Since the ratio increases only if the denominator decreases or the numerator increases, and since the variable is constrained to the category 1-9 employees, the negative coefficient tells us an interesting story: if the share of small business becomes, on average smaller, GVA per worker decreases. This is also supported by the fact that small enterprises are less likely to invest in some crucial determinants of GVA growth, such as human capital and innovation, than larger enterprises.

A similar story occurs for medium-sized enterprises (10-49 employees), but the coefficient turns not to be significant once we introduce the interaction with export, and this is the case also in the in-sample estimation. Economically speaking, this is a sign that when medium-sized enterprises tend to be export-oriented, the dynamics expressed for small firms are no longer significant. Reasonably, the propensity to export has such a positive effect on GVA that it cancels out the negative dynamics produced by the greater fragmentation within medium-sized enterprises.

The share of large firms is economically associated with economic growth, higher demand for goods and services from abroad (especially for an economy like Italy that is short of raw materials) and high export rates (export-oriented economy), but as soon as it is divided by the number of employees, its coefficient lost statistical significance. Here we probably pay the cost of having merged the categories of medium-sized and large companies, which are known to have slightly different business dynamics. In fact, due to technicalities in the data structure, it was impossible to classify the enterprises differently[5].

Both the import and export variable are significant in almost all years of the expanding window. This confirms the importance of foreign trade for the growth of Italian provinces. Moreover, the interaction of import end export at the provincial level could be seen as an important factor related to the openness of territory: it has a positive effect on economic growth both in the full sample SDPD model and in all the years of the in-sample estimation, underlying its importance for the local economies.

Forecasting performances of the model in equation 6 are compared to the three sub-specifications and to the AR and RW models by computing both RMSEs (equation (4)) and population weighted RMSEs (equation (5)). Moreover, as described in section 4, the RMSEs are calculated in two ways: by using (i) a temporal provincial-specific $RMSE_i$ (see Figures 1 and 2) and (ii) a cross-sectional year-specific $RMSE_t$ (see Table 4). In this way, it is possible to understand if the yearly cross-sectional forecast error is driven by the behaviour of certain provinces for which the model fails to perform so well, while weighting for the population helps us to consider the relative dimension of a provincial

[5]The size classes of firms with more than 49 employees has changed several times between 2000 and 2016, see section 3.

economy within the national context.

Table 4 reports the ratio between cross-sectional year-specific RMSEs for each model specification over the cross-sectional year-specific RMSE of the RW specification, both in terms of the standard and the weighted version, i.e. $RMSE_t$ and $WRMSE_t$, respectively. Weighting for province-specific populations increases the RMSEs, as we weigh more errors for larger provinces. Nevertheless, it does not change the results compared to the reference model, i.e. the results are similar to those computed without the population weights. The average performance of the SDPD model confirms its superiority over the AR model. Among the other specifications, not considering the spatial components leads to a less accurate point forecast. The dynamic panel (DPD) and standard panel data (PD) models perform worse than using the AR model. Within the spatial models, the SPDP model performs slightly better than the SPD model in some years, but the difference is relatively small. Finally, when temporal cointegration is detected, the random walk specification is still to be preferred in some cases, even in the presence of short panels. From an economic point of view, this may be due to the low growth rate shown by most of the provinces in the period of analysis. For the sake of clarity, this part of the analysis is discussed in detail at the end of this section.

Figure 1 compares forecast accuracy from another perspective, showing the differences between the forecast errors of the SDPD and the AR model at the provincial level for each year. Forecast errors are expressed in absolute value and turn out to be negative when SDPD performs better and vice versa. These differences are attributed to a chromatic scale for each province on the Italian map: a darker colour indicates where the SDPD performs better than its competitor. As shown in Figure 1, the SDPD model performs undoubtedly better when the panel is short, while the AR needs a much longer time series to perform slightly better. Looking at the magnitude of the errors, one can see that when the SDPD model performs better, the differences from the AR are substantial, while when it is the AR that performs better (the last two years of the out-of-sample), the differences with the SDPD are minimal.

In Figure 2 we compare the temporal provincial-specific RMSEs (on the left), i.e. $RMSE_i$ of equation (4), with their weighted versions (on the right), i.e. $WRMSE_i$ of equation (5), between the SDPD model and the AR model. The regional distributions are shown in terms of differences between the RMSEs of the two model specifications. On the left, the Figure highlights the provinces where the SDPD performs better (associated with negative values), and the ones where it performs worse (associated with positive values). It seems that in the majority of the provinces where the spatial effects improve on average, the forecast performances are in the south and the central–north part of Italy. With the same scale of the distribution, the weighting version on the right–hand side shows the same conclusion in terms of the spatial distribution, although the population weights reduce the variability and the RMSE differences. This result offers empirical evidence on how the dynamic spatial model is preferable in panel data usually characterized by not too long windows. Not surprisingly, the empirical setting in which we want to predict regional GDP/GVA is exactly this.

So far, we have demonstrated the superiority of the SDPD model over its competitors. However, it is necessary to say a few words about the low RMSE shown by the RW model. Intuitively, in years of negative or close to zero growth, the random walk is the model to be preferred. Indeed, in a context of low variability, there might be cointegration between the provincial time series, making the RW model more capable of capturing the evolution of the business cycle. Therefore, it is interesting to investigate which years and, in particular, for which provinces this was the case. We use the differences of the forecast errors in absolute values between the SDPD and the RW models, i.e. $|e_{SDPD}|-|e_{RW}|$, so that in cases of negative values, the SDPD model is to be preferred and vice versa. A first selection criterion was to pick up the provinces according to their growth rate in the out-of-sample period.

The sample has then been divided into two groups according to the temporal (8-years) positive and negative average growth rates. The result is reported in Figure 4. The red line indicates the provinces with a temporal negative average growth rate, while the blue line the positive ones. A zero line marks the threshold under which the SDPD model performs better (i.e. negative values). As we can observe, the RW model generally performs better when there is negative growth or close to zero (red line)[6]. As for the SDPD (blue line), the group of temporal positive average growth rate shows only 4 years over 8 of better performance, leading to the explanation that financial crisis and sovereign debt crisis have probably decreased increased the SDPD forecast errors in specific years.

To further detail the previous issue, we also split the provinces based on the annual growth rates rather than the 8-years average growth rates. In other words, the time-

[6]Interesting to note that the majority of territories that belong to the red line group are all geographically located in the central and southern areas of the country, see Table 5.

averaged growth rate (year by year) of each group of provinces changes according to the group's composition [7]. Figure 5 shows that the forecast performance of the SDPD model is undoubtedly related to the yearly growth of the single territory since the blue line is constantly below the zero line. It seems that when there is positive growth, the SDPD model performs better than RW and vice versa. Intuitively, regardless of the sign, the RW performs better only when there is zero or close to zero growth. With the first grouping criterion, we find that the mean of the positive growth group is equal to 0.075, 1.74 times higher than the mean of the second one in absolute value (the mean of the negative growth group is equal to -0.043). The same occurs with the second criterion: the average growth of the provinces in the first group (positive growth group) is on average 1.2 times higher than that of the provinces with negative growth (and even 1.5 if we exclude 2009 and 2012, ascribable to financial crisis and sovereign debt crisis).

In conclusion, in the case of positive growth at the provincial level, the spillover effect between territories (from year to year) is higher than in the case of negative growth. Therefore, when the spatial spillover effect is high, the SDPD model correctly captures it. On the other hand, negative or close to 0 growth among territories require an RW specification which assumes zero variability in the mean part of the equation. If we look at Table 5, we also see that most of the provinces with positive growth are concentrated in the north part of Italy, where provincial economies are generally larger, more internationalised and interconnected as well as robust to shocks of the economy. This intuition is very interesting but goes beyond the scope of this paper. In this way, we leave this question open for future research.

6 Conclusion

In this paper, we compare the forecasting performances of an SDPD model on the GVA of 103 Italian provinces. We consider different sub-optimal SDPD specifications and a standard set of univariate province-specific autoregressive (AR) and random-walk model (RW), assuming respectively growth equal to the average and zero growth.

We show that the SDPD model performs better, on average, than its competitors and

[7] To take into account the change in the composition of the two samples, descriptive Tables 5 and 6 are shown in the appendix. They describe the composition of the two groups by geographical area and by listing all the provinces selected in the group with positive growth (conversely, those that do not appear fall into the other group).

than the simple univariate time series. However, when temporal cointegration is detected, the random walk specification is still to be preferred in some cases, even in the presence of short panels. From an economic point of view, this may be related to the low growth rate shown by most of the provinces in the period of analysis.

We find that especially when the panel is short, accounting for spatial dependence undoubtedly increases forecasting accuracy in terms of RMSE to any other sub-optimal SDPD specifications and to the AR. The gain in forecasting accuracy comparing the SDPD and the AR model is, on average, 11 per cent. It becomes even higher when comparing the SDPD model to model specifications not accounting for spatial dependences. A more accurate view is given by plotting province-specific forecast errors in each of the out-of-sample years: although the model fails to be the most accurate one in the last years, it performs better when the panel is short. On the contrary, the AR needs a much longer time series to perform slightly better. This result is very important because it sheds some light on the empirical application of an SDPD model, highlighting its better performances in panel data that are usually characterised by not too long time windows. Not surprisingly, the empirical setting of regional GDP/GVA forecasting is exactly this.

We also show the relevance of foreign trade on the economic performance of the Italian province, denoting its positive influence on economic growth. This also helps to deal with the Italian business demography, which is catheterised by small and medium-size enterprises. Generally speaking, small firms are less prone to invest in human capital and are, on average, less innovative than large firms. This could negatively affect economic growth, and it is shown in the paper. However, once the export variable interacts with small-medium firms, this negative effect turns to be not significant, suggesting how the propensity to export can mitigate the negative dynamics produced by the higher fragmentation within small-sized enterprises.

A more elaborate approach is to explore the influence of sector-specific spatial dynamics on economic growth, where spatial dependence occurs among the economic sectors of the various territories. This would also push the forecast at an even higher level of disaggregation, however, is left for future research.

In conclusion, it would be important for local policymakers to understand the crucial role of regional forecasting for policymaking: being able to identify the crucial determinant of economic growth today means to pave the ground, if not ensure, future growth.

Acknowledgments

This paper started as Tomelleri's doctoral thesis chapter. We would like to thank all the thesis reviewers for their careful and insightful comments on our paper and, indeed, on the whole development of this work itself. All remain errors are ours.

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Tables

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	$n \times T$
firms1	6.06E+04	1.18E+05	4331	2.28E+06	1751
firms2	2.28E+03	4.93E+03	85	1.17E+05	1751
firms3	2.79E+02	6.91E+02	5	1.69E+04	1751
ln(GVA/worker)	3.963	0.14	3.526	4.363	1751
ln(realGVA/worker)*	4.069	0.129	3.749	4.421	1751
firm/employees1	0.653	0.199	0.452	2.825	1751
firm/employees2	0.046	0.004	0.033	0.056	1751
firm/employees3	0.006	0.002	0.001	0.013	1751
import_prov1	3.05E+03	7.07E+03	2.05E+01	7.81E+04	1751
export_prov1	3.21E+03	4.82E+03	8.545	4.45E+04	1751
overnights	3.53E+06	5.34E+06	6.49E+04	3.50E+07	1751

Note: The table presents summary statistics for the 103 provinces of the panel 2009-2016 resulting from different data sources (ISTAT, Infocamere, Coeweb). Firms are divided into three categories according to the firm size: 0-9, 10-49 and more than 49 employees. Aggregate output and variables concerning foreign trade are expressed in thousands of Euro.

*realGVA refers to the one obtained using the deflator at the regional level.

Table 2: Estimates SDPD model and its sub-specifications (full sample sizes)

Coefficients	SDPD	SPD	DPD	PD
ρ	0.3051	0.3067		
	(0.0426)	(0.0427)		
γ	0.1315			
	(0.0621)			
ϕ	- 0.1746		- 0.1676	
	(0.0249)		(0.0251)	
$ln(firms/empl)1$	- 0.0246	- 0.0257	- 0.0269	- 0.0282
	(0.0095)	(0.0107)	(0.0108)	(0.011)
$ln(firms/empl)2$	- 0.0992	- 0.0660	- 0.0478	- 0.0475
	(0.0653)	(0.0674)	(0.0683)	(0.0692)
$ln(firms/empl)3$	0.0011	0.0014	0.0014	0.0015
	(0.0015)	(0.0015)	(0.0015)	(0.0016)
$ln(import)$	0.0016	0.0072	0.0050	0.0049
	(0.0138)	(0.0141)	(0.0143)	(0.0145)
$ln(export)$	- 0.0410	- 0.0062	- 0.0014	- 0.0014
	(0.015)	(0.0127)	(0.0129)	(0.0131)
$ln(overnights)$	0.0039	0.0041	0.0051	0.0052
	(0.0049)	(0.005)	(0.0051)	
$ln(firms2 * exp)$	0.5166	- 0.0631	- 0.0135	- 0.0093
	(0.2785)	(0.3033)	(0.3075)	(0.3117)
$ln(firms2 * imp)$	- 0.3297	0.9021	0.9847	0.9863
	(0.3044)	(1.143)	(1.159)	(1.1745)
$ln(imp * exp)$	0.0028	0.1689	0.0709	0.0652
	(0.0006)	(0.2715)	(0.2753)	(0.279)
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				

Note: The table presents the coefficients resulting from the spatial dynamic panel data (SDPD) model and its sub-specifications: spatial panel data (SPD) model, dynamic panel data (DPD) model and standard panel data (PD) model. Estimated standard errors are in parentheses.

Table 3: Estimates of the SDPD model (expanding window in-samples)

Coefficients	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
ρ	0.306	0.387	0.413	0.410	0.398	0.387	0.361	0.319
	(0.060)	(0.052)	(0.048)	(0.046)	(0.045)	(0.043)	(0.043)	(0.043)
γ	0.081	0.107	0.091	0.101	0.069	0.058	0.069	0.176
	(0.093)	(0.089)	(0.075)	(0.068)	(0.068)	(0.066)	(0.067)	(0.064)
ϕ	- 0.029	- 0.031	- 0.099	- 0.075	- 0.076	- 0.093	- 0.098	- 0.194
	(0.039)	(0.036)	(0.033)	(0.031)	(0.03)	(0.029)	(0.029)	(0.027)
$ln(firms_1/workers_1)$	- 0.016	- 0.017	- 0.021	- 0.021	- 0.022	- 0.022	- 0.022	- 0.024
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.01)
$ln(firms/empl)2$	- 0.039	- 0.060	- 0.097	- 0.095	- 0.093	- 0.089	- 0.085	- 0.087
	(0.063)	(0.064)	(0.062)	(0.061)	(0.062)	(0.062)	(0.065)	(0.067)
$ln(firms/empl)3$	0.001	0.002	0.002	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$ln(import)$	- 0.047	- 0.065	- 0.034	- 0.030	- 0.025	- 0.020	0.002	0.005
	(0.021)	(0.021)	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
$ln(export)$	0.047	0.032	0.005	- 0.004	- 0.014	- 0.015	- 0.037	- 0.044
	(0.022)	(0.021)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
$ln(overnights)$	- 0.000	- 0.002	0.000	0.000	0.001	0.003	0.003	0.003
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$ln(firms2 * imp)$	1.038	1.186	0.596	0.459	0.267	0.193	- 0.307	- 0.420
	(0.431)	(0.436)	(0.341)	(0.32)	(0.319)	(0.31)	(0.322)	(0.325)
$ln(firms2 * exp)$	- 0.982	- 1.073	- 0.364	- 0.187	- 0.019	0.029	0.479	0.578
	(0.418)	(0.419)	(0.306)	(0.287)	(0.286)	(0.277)	(0.288)	(0.291)
$ln(imp * exp)$	0.001	0.003	0.002	0.002	0.002	0.002	0.002	0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

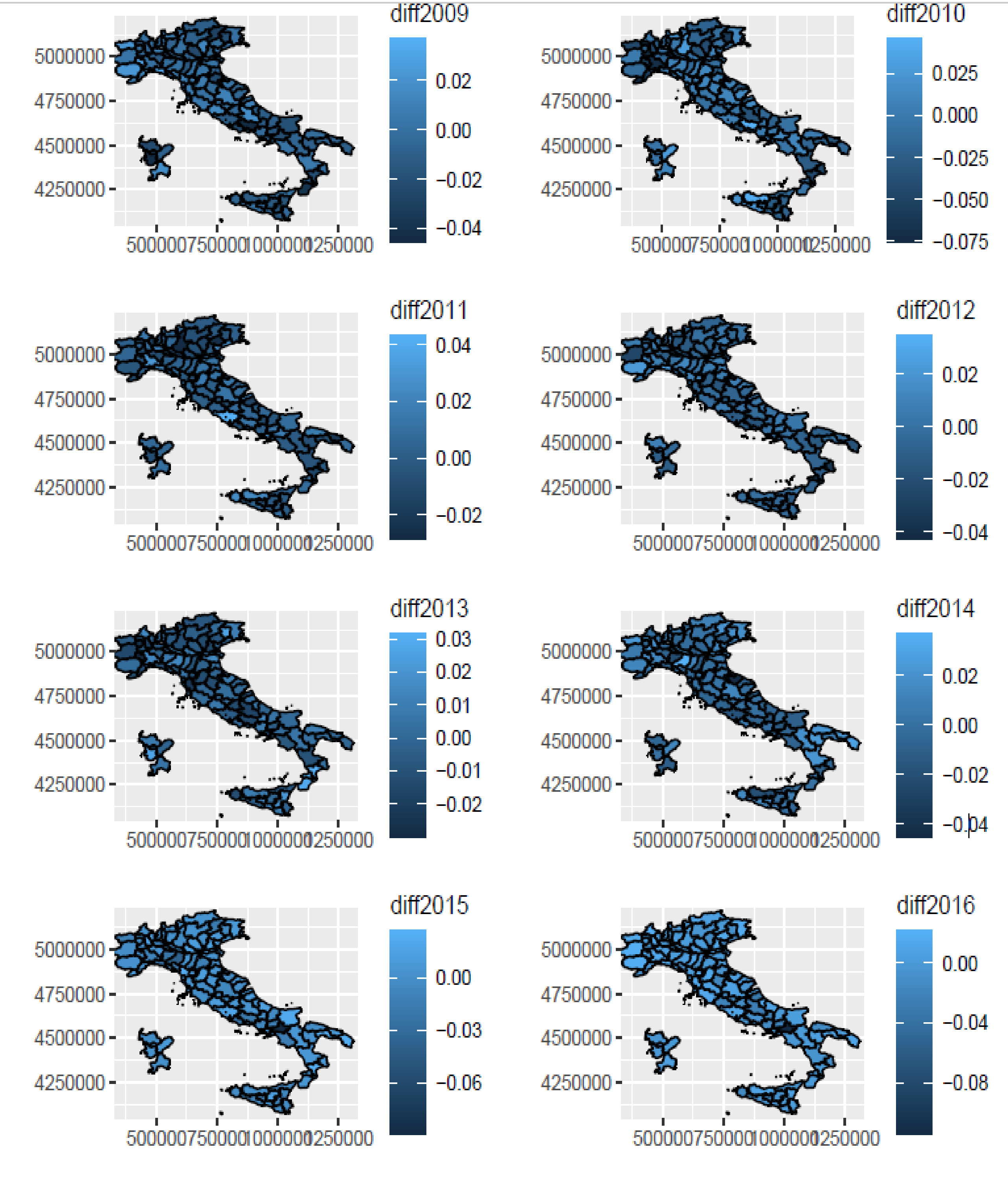
Table 4: Forecasting accuracy

Model	2009	2010	2011	2012	2013	2014	2015	2016	Mean
					RMSE in ratio to the RW model				
SDPD	1.55	0.75	1.13	1.31	0.93	1.09	0.95	1.13	1.10
SPD	1.57	0.75	1.13	1.32	0.93	1.08	0.96	1.09	1.10
DPD	1.36	2.16	1.17	0.97	1.76	1.39	2.14	2.05	1.63
PD	1.36	2.16	1.18	0.98	1.77	1.39	2.14	2.05	1.64
AR	1.70	1.22	0.94	1.46	0.90	1.05	1.16	1.30	1.22
RW	*0.03*	*0.03*	*0.02*	*0.02*	*0.03*	*0.03*	*0.03*	*0.02*	*0.03*
					Weighted RMSE in ratio to the RW model				
SDPD	1.56	0.75	1.13	1.31	0.93	1.09	0.95	1.13	1.10
SPD	1.57	0.74	1.12	1.32	0.93	1.08	0.96	1.09	1.10
DPD	1.36	2.16	1.17	0.97	1.76	1.39	2.14	2.06	1.64
PD	1.36	2.16	1.18	0.97	1.77	1.39	2.14	2.06	1.64
AR	1.70	1.22	0.94	1.46	0.90	1.05	1.15	1.31	1.22
RW	*0.11*	*0.10*	*0.07*	*0.09*	*0.10*	*0.11*	*0.11*	*0.07*	*0.10*

Note: Cross-sectional temporal-specific RMSEs without (Panel A) and with (Panel B) population weights, i.e. $RMSE_t$ and $WRMSE_t$, of the spatial dynamic panel data (SDPD) model, the spatial panel data (SPD) model, the dynamic panel data (DPD) and the panel data (PD) model. $n = 103$ provinces and $T = 2009, ..., 2016$ years. For ease of comparison, values are in ratio to the RW model.

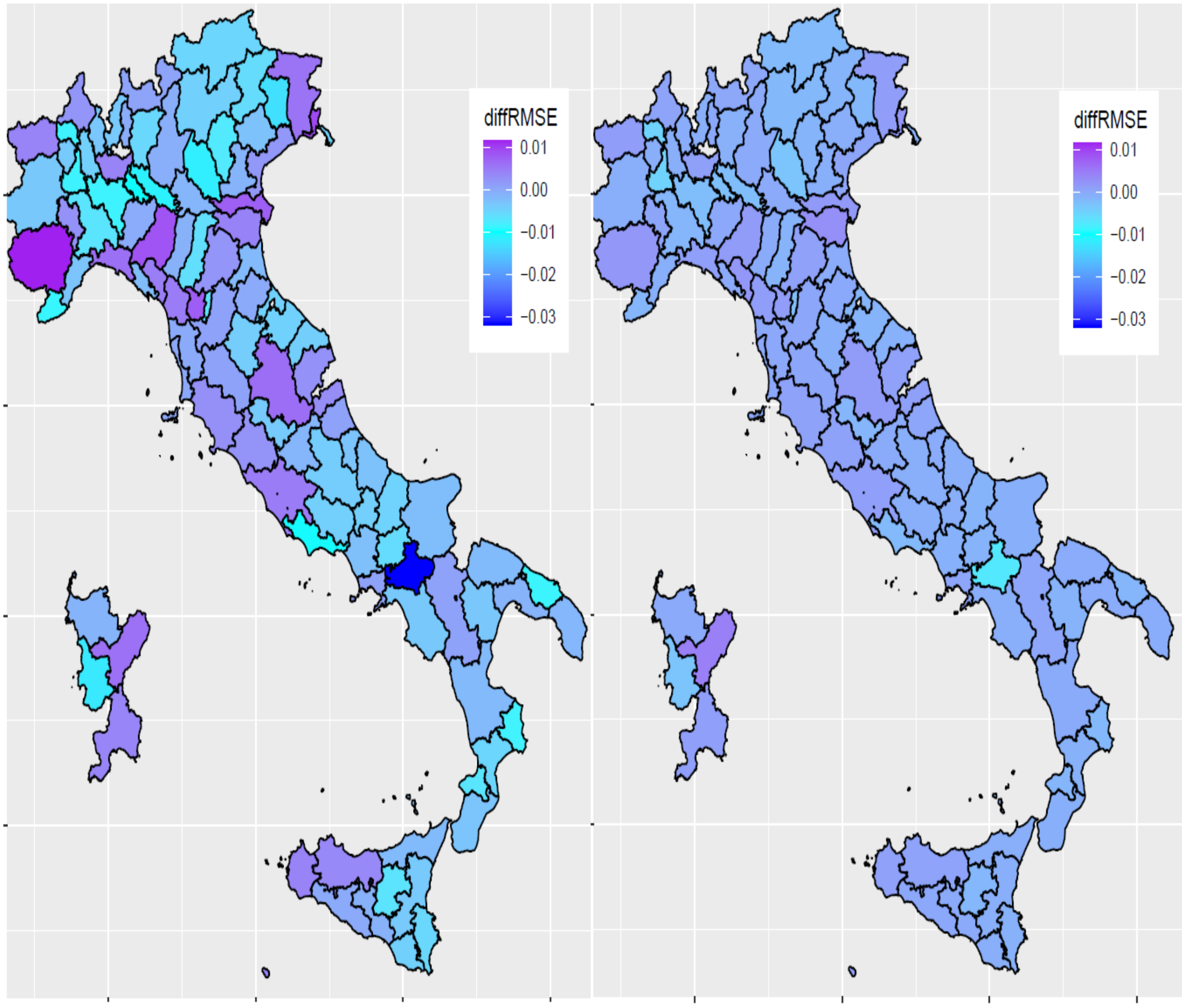
Figures

Figure 1: Differences in forecast errors between SDPD and AR model by year (2009-2016)



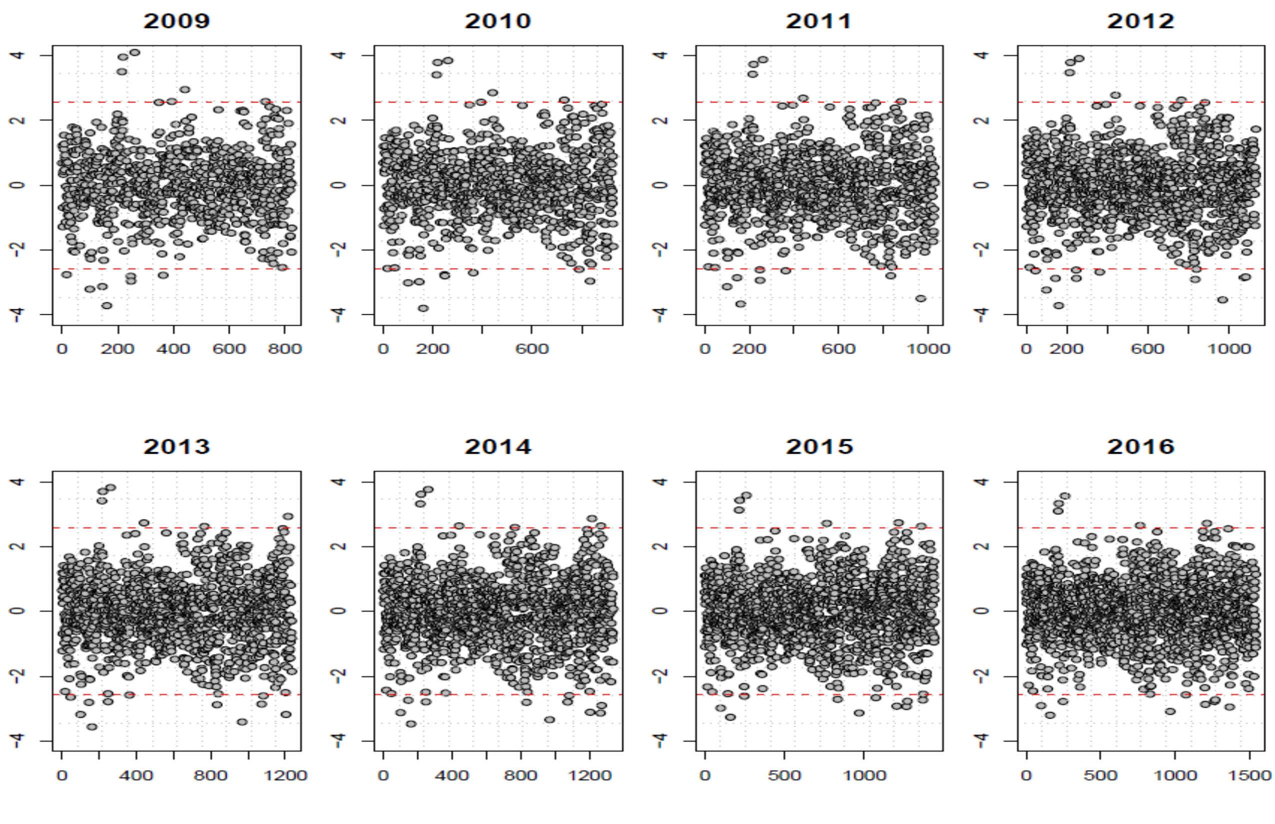
Note: The figure shows differences at the provincial level between the SDPD and the AR model in terms of forecast errors for each year. Forecast errors are expressed in absolute value. Differences are attributed to a chromatic scale on the Italian map that reports with a darker colour the provinces where the SDPD performs better than the AR.

Figure 2: Difference in the means (left-hand side) and weighted means (right-hand side) of forecast errors between SDPD and AR model (2009-2016)



Note: The figure differences at the provincial level between the SDPD and the AR model in terms of temporal (on the left) and weighted temporal (on the right) provincial-specific RMSE, i.e. $RMSE_i$ and $WRMSE_i$. Each RMSE considers the total years of the forecast. Differences are attributed to a chromatic scale on the Italian map that reports with a darker blue colour the provinces where the SDPD performs better than the AR.

Figure 3: Standardized residuals to control for potential outliers

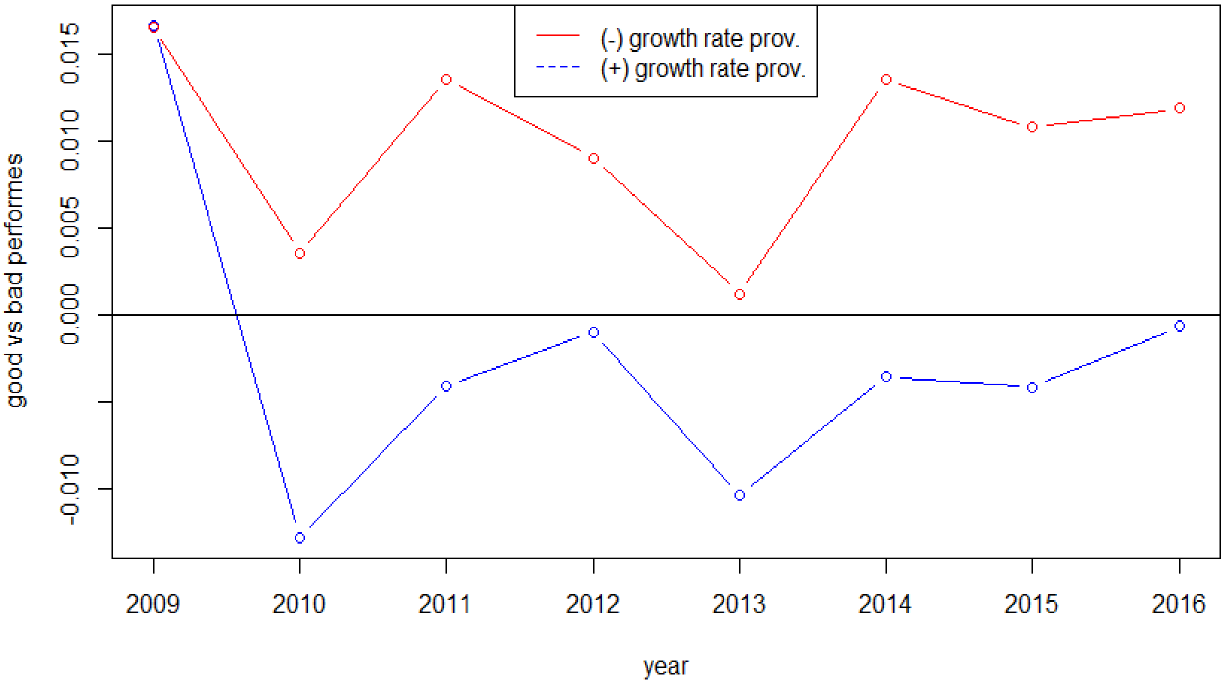


Note: The limits are ± 2.57, which corresponds to 0.01 alpha.

Figure 4: Differences in forecast errors between SDPD and RW model grouping on average growth rate (2009-2016)

Note: The 23 provinces with negative growth rates (red line) over the period are Savona, Pescara, Isernia, Campobasso, Benevento, Napoli, Avellino, Matera, Cosenza, Crotone, Reggio Calabria, Trapani, Palermo, Messina, Agrigento, Caltanissetta, Enna, Catania, Ragusa, Oristano, Terni, Ascoli Piceno, Rieti. Apart from Savona, they are all geographically located in the central and southern areas of the country.

Figure 5: Differences in forecast errors between SDPD and RW model grouping on yearly growth rate (2009-2016)



Note: Grouping by positive annual growth excluding 3 year-specific outliers: Verona in 2011, Catanzaro in 2014 and Lucca in 2015. Grouping by negative annual growth without an outlier Bari in 2009.

Appendix

Table 5: Distribution of the group's provinces with positive annual growth by geographical area

	2009	2010	2011	2012	2013	2014	2015	2016
Nord West	12,5%	29,9%	23,5%	10,3%	29,3%	27,5%	23,5%	25,3%
Nord East	12,5%	23,9%	28,4%	17,2%	39,0%	30,4%	28,4%	27,8%
South	25,0%	17,9%	22,2%	34,5%	14,6%	14,5%	22,2%	16,5%
Islands	25,0%	7,5%	6,2%	17,2%	7,3%	5,8%	8,6%	8,9%
Central Italy	25,0%	20,9%	19,8%	20,7%	9,8%	21,7%	17,3%	21,5%
	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%

Figure 6: Provinces included in the group with yearly positive growth rate (2009-2016)

2009	2010	2011	2012	2013	2014	2015	2016
Lodi	Torino	Torino	Valle d'Aos	Torino	Biella	Torino	Torino
Teramo	Vercelli	Vercelli	La Spezia	Vercelli	Novara	Vercelli	Biella
Catanzaro	Biella	Biella	Varese	Verbano-Cu	Cuneo	Biella	Verbano-Cu
Enna	Verbano-Cu	Verbano-Cu	L'Aquila	Novara	Asti	Novara	Novara
Ragusa	Novara	Cuneo	Pescara	Cuneo	Alessandria	Cuneo	Cuneo
Verona	Cuneo	Asti	Caserta	Asti	Valle d'Aos	Asti	Asti
Massa-Carr	Asti	Valle d'Aos	Benevento	Alessandria	Imperia	Alessandria	Alessandria
Lucca	Alessandria	Imperia	Salerno	Lecco	Genova	Savona	Imperia
	Valle d'Aos	Savona	Taranto	Pavia	La Spezia	Genova	Savona
	La Spezia	La Spezia	Lecce	Lodi	Varese	La Spezia	Genova
	Varese	Como	Foggia	Cremona	Como	Varese	La Spezia
	Como	Lecco	Bari	Mantova	Lecco	Como	Como
	Lecco	Sondrio	Potenza	Chieti	Sondrio	Lecco	Lecco
	Sondrio	Bergamo	Agrigento	Benevento	Bergamo	Bergamo	Sondrio
	Brescia	Brescia	Ragusa	Avellino	Brescia	Brescia	Bergamo
	Pavia	Pavia	Siracusa	Foggia	Pavia	Pavia	Brescia
	Lodi	Cremona	Cagliari	Potenza	Lodi	Cremona	Lodi
	Cremona	Mantova	Oristano	Matera	Mantova	Mantova	Cremona
	Mantova	Milano	Bolzano/Bo	Trapani	Milano	Milano	Mantova
	Milano	L'Aquila	Verona	Caltanisset	Teramo	Teramo	Milano
	L'Aquila	Teramo	Piacenza	Nuoro	Chieti	Chieti	Teramo
	Teramo	Pescara	Parma	Bolzano/Bc	Isernia	Isernia	Chieti
	Chieti	Chieti	Modena	Trento	Caserta	Campobass	Campobass
	Benevento	Isernia	Massa-Carr	Verona	Napoli	Caserta	Caserta
	Taranto	Caserta	Pistoia	Vicenza	Salerno	Benevento	Napoli
	Brindisi	Benevento	Firenze	Belluno	Taranto	Napoli	Salerno
	Lecce	Salerno	Siena	Venezia	Brindisi	Avellino	Taranto
	Bari	Taranto	Rieti	Rovigo	Lecce	Salerno	Foggia
	Potenza	Brindisi	Latina	Pordenone	Catanzaro	Brindisi	Bari
	Crotone	Lecce		Udine	Messina	Lecce	Cosenza
	Catanzaro	Foggia		Gorizia	Enna	Foggia	Crotone
	Vibo Valent	Bari		Reggio nell'	Catania	Bari	Catanzaro
	Trapani	Potenza		Modena	Oristano	Potenza	Vibo Valent
	Ragusa	Matera		Bologna	Bolzano/Bc	Matera	Trapani
	Siracusa	Cosenza		Ferrara	Trento	Cosenza	Messina
	Sassari	Catanzaro		Ravenna	Verona	Vibo Valent	Catania
	Nuoro	Vibo Valent		Forlì-Cesen	Vicenza	Reggio Cala	Ragusa
	Bolzano/Bc	Messina		Prato	Belluno	Trapani	Siracusa
	Trento	Agrigento		Arezzo	Treviso	Palermo	Cagliari
...	...	...	...	...	...	...	...

Note: The table continues on the next page

Figure 7: Provinces included in the group with yearly positive growth rate (2009-2016)

...	...	...	...	...	...	...	...
	Vicenza	Ragusa		Grosseto	Venezia	Agrigento	Oristano
	Belluno	Siracusa		Latina	Padova	Siracusa	Bolzano/Bo
	Venezia	Sassari			Rovigo	Sassari	Trento
	Padova	Bolzano/Bc			Gorizia	Nuoro	Verona
	Rovigo	Trento			Trieste	Cagliari	Vicenza
	Pordenone	Verona			Piacenza	Bolzano/Bc	Belluno
	Gorizia	Vicenza			Parma	Trento	Treviso
	Trieste	Belluno			Reggio nell'	Verona	Venezia
	Parma	Treviso			Modena	Vicenza	Padova
	Modena	Venezia			Bologna	Belluno	Pordenone
	Bologna	Padova			Ferrara	Treviso	Udine
	Ravenna	Rovigo			Ravenna	Venezia	Gorizia
	Forlì-Cesen	Pordenone			Forlì-Cesen	Padova	Trieste
	Lucca	Udine			Rimini	Rovigo	Piacenza
	Pistoia	Gorizia			Massa-Carr	Pordenone	Parma
	Firenze	Trieste			Lucca	Udine	Reggio nell'
	Livorno	Piacenza			Pistoia	Gorizia	Modena
	Arezzo	Parma			Firenze	Trieste	Bologna
	Siena	Reggio nell'			Prato	Piacenza	Ferrara
	Grosseto	Modena			Livorno	Parma	Ravenna
	Perugia	Bologna			Pisa	Reggio nell	Forlì-Cesen
	Terni	Ferrara			Arezzo	Modena	Rimini
	Rimini	Ravenna			Siena	Bologna	Massa-Carr
	Macerata	Forlì-Cesen			Rimini	Ferrara	Lucca
	Viterbo	Rimini			Ancona	Ravenna	Pistoia
	Roma	Massa-Carr			Macerata	Forlì-Cesen	Firenze
	Latina	Lucca			Ascoli Picer	Rimini	Prato
	Frosinone	Pistoia			Viterbo	Lucca	Livorno
		Firenze			Roma	Pistoia	Pisa
		Prato			Latina	Firenze	Siena
		Livorno				Prato	Grosseto
		Pisa				Livorno	Perugia
		Arezzo				Pisa	Terni
		Siena				Siena	Rimini
		Perugia				Grosseto	Ancona
		Rimini				Perugia	Macerata
		Ancona				Terni	Ascoli Picer
		Macerata				Rimini	Roma
		Ascoli Picer				Ancona	Latina
		Viterbo				Roma	Frosinone
		Roma				Latina	
		Frosinone				Frosinone	
8	67	81	29	41	69	81	79

Note: Number of provinces at the end of the table.