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## 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 and time 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.

# 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 Lee and Yu (2010) 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

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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 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. They are also, on average, more reliable than other nested panel sub-specifications as well as pure temporal econometric specifications. Accounting for lagged spatial dependence reduces RMSE considerably. However, when temporal cointegration is detected, the random walk specification can still be a valid alternative in some specific 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 few years of crisis during the period of analysis. On the other hand, an important finding is that the SDPD model performs better when the panel is short. This result is very important because it shed some light on 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 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. That is, working with data at a higher

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level of detail lead us to manage more information.

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. Finally, a more general contribution is related to the fact that, during the period under investigation, Italy was characterized by low GDP growth with relative stagnation until two recessions in 2008 and 2012-2013 and the recovery after 2014. This specific period may lead to new insights since, to the extent of our knowledge, the prediction performance of spatial econometric models has not been investigated in such a period yet.

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, alongside the increasing availability of regional economic data, the topic of regional economic forecasting has 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. Long et al. (2019) use an SDPD model to improve the tourism demand forecast of 341 cities in China one year ahead.

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 depen-

dent 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 preferred 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.

As mentioned in the introduction, in the period of analysis, the Italian GPD was characterized by relative stagnation until two recessions in 2008 and 2012-2013 and the recovery after 2014. This specific period may lead to non-stationarity that also reflects at the provincial level. Since the analysis of the causes of non-stationarity in the data is beyond the scope of this paper, we (i) test for stationarity for each of the 103 provinces (section 5) and (ii) define the structural model 1, the related reduced form and the forecasting procedure in time first–differencing (see section 4).

We then 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 workers. 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 workers according to three class-size $q$: 1 to 9 (q=1), 10-49 (q=2) and more than 49 (q=3) 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). 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

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

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 $\beta$ the vector of parameters, $W_n y_{n,t-1}$ is an $n$-dimensional vector of spatiotemporal lagged variables with coefficient $\gamma$, $\phi$ is the temporal

autoregressive coefficient, $\rho$ is the spatial (simultaneous) autoregressive coefficient, while $\alpha_n$ and $\delta_t$ represent individual territorial and time fixed effects, respectively. Finally, $\epsilon_{n,t}$ contain independent, normally distributed error terms with zero mean and constant variances $\sigma_\epsilon^2$.

From an economic point of view, the meaning of a global spatial spillover effect in our case is that the GVA in one province tends to rise its value due to the increased GVA values in neighboring provinces. Since GVA reflects the value generated by any unit engaged in the production of goods and services[5], it is reasonable that the increased production of goods and services in one province helps in rising neighboring production of goods and services.

$W_n$ 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, with $k = 8$. The weights matrix is then row-normalized such that $\sum_j w_{ij} = 1 \ \forall i$. The reason why we consider such a criterion is that after normalization of the weight matrix the model with normalized weights is equivalent to the structural model with non-normalized ones, since each site has the same number of neighbors, so there is a unique re-scaling factor in this case. Sometimes an alternative standardization rule based on spectral normalization could be preferable because it always guarantees the equivalence between the original spatial structural model and the model obtained from normalizing the weighting matrix, see Kelejian and Prucha (2010a).

We also supposed k as a reasonable number of neighboring provinces to choose considering the total number of Italian provinces, since the global mean of Italian provinces in each region is 5.24. We do not expect significant changes in estimation if the number of k is slightly different than 8 (LeSage and Pace, 2014), see e.g. Billé and Rogna (2020). Anyway, correlation can change if we generally used dense matrices instead of sparse matrices, please see for example Billé and Leorato (2020), and references therein.[6]

Before considering the forecasting procedure, we define the structural model (1) in time first–differencing. Defining $\Delta = (I - L)$ the time first–differencing operator such that $\Delta y_t = y_t - y_{t-1}$ with $y_t$ a variable vector at time $t$, we obtain

$$\Delta y_{n,t} = \rho W_n \Delta y_{n,t} + \phi \Delta y_{n,t-1} + \gamma W_n \Delta y_{n,t-1} + \Delta X_{n,t} \beta + \Delta \delta_t \iota_n + \Delta \epsilon_{n,t} \qquad (2)$$

where $\Delta \delta_t \iota_n$ are the transformed time fixed effects which need to be calculated from the reduced form model as follows. Starting from the model in time first–differencing in equation (2), we specify the following reduced form due to the simultaneity of the previous

model specification

$$\Delta y_{n,t} = (I - \rho W_n)^{-1} \left[ \phi \Delta y_{n,t-1} + \gamma W_n \Delta y_{n,t-1} + \Delta X_{n,t} \beta + \Delta \delta_t \iota_n + \Delta \epsilon_{n,t} \right] \qquad (3)$$

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

**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 $\rho$ in the interval $(-1/\overline{\tau}, 1/\overline{\tau})$.*

and the following two assumptions are necessary conditions for estimation

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

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

The predicted coefficients refer to the SDPD model in equation (3). We calculated the transformed time fixed effects by using the following formula from the reduced form equation (3)

$$\Delta \hat{y}_{n,t} = (I - \rho W_n)^{-1} \left[ \hat{\phi} \Delta y_{n,t-1} + \hat{\gamma} W_n \Delta y_{n,t-1} + \Delta X_{n,t} \hat{\beta} + \Delta \delta_t \iota_n \right]$$

$$\Delta \hat{y}_{n,t} = (I - \rho W_n)^{-1} \left[ \hat{\phi} \Delta y_{n,t-1} + \hat{\gamma} W_n \Delta y_{n,t-1} + \Delta X_{n,t} \hat{\beta} \right] + (I - \rho W_n)^{-1} \Delta \delta_t \iota_n$$

$$\Delta \delta_t \iota_n = (I - \rho W_n) \Delta \hat{y}_{n,t} - \left[ \hat{\phi} \Delta y_{n,t-1} + \hat{\gamma} W_n \Delta y_{n,t-1} + \Delta X_{n,t} \hat{\beta} \right] \qquad (4)$$

where $\Delta \hat{y}_{n,t}$ are the predictive values from the model in time first-differencing with transformed fixed effects.

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. We decided to focus on 1-step ahead, to skip density forecasting and for this to ignore parameter uncertainty. The main goal is to investigate whether spatial information helps in predicting regional GDPs and leave for further research these extensions. Starting from equation (3), the point forecasts are obtained using the following expression:

$$\Delta \hat{y}_{n,t+1} = (I - \hat{\rho}W_n)^{-1} \left[ \hat{\phi}\Delta y_{n,t} + \hat{\gamma}W_n\Delta y_{n,t} + \Delta X_{n,t+1}\hat{\beta} + \Delta\hat{\delta}_{t+1}\iota_n \right]. \qquad (5)$$

where $\Delta\hat{\delta}_{t+1}$ is predicted by the time effects at time $t$ $\Delta\hat{\delta}_t$, since no information is available to obtain the ones at time $t+1$. While the forecasting procedure has been made by using some algebra, the estimation procedure was implemented through the **spml** package in R. The QML estimator used in this context is consistent since a small number of neighbors have been selected for each province, see Lee (2004).

We compare the forecast accuracy of the SDPD model shown in equation (5), with three sub-specifications: (i) a static 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 $\rho = \phi = \gamma = 0$. In addition, we also use the SLX model in a panel version as follows

$$y_{n,t} = X_{n,t}\beta + W_nX_{n,t}\theta + \alpha_n + \delta_t\iota_n + \epsilon_{n,t} \quad t = 1,...,T$$
$$\epsilon_{n,t} \sim N(0, \sigma^2 I_n) \qquad (6)$$

to account for local spatial autocorrelation, and we compare these point forecasts with a univariate province-specific random-walk (RW) model, assuming zero growth in the last case[7].

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

$$(i) \quad RMSE_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_{it} - \hat{y}_{it})^2} \quad \forall i, \qquad (ii) \quad RMSE_t = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{it} - \hat{y}_{it})^2} \quad \forall t \qquad (7)$$

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

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

(8)

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 $\alpha = 0.01$. We opted for an expanding window instead of a rolling window to exploit more information from increasing sample sizes.

# 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 $\rho$. Additionally, spillover effects could last more than one period and the space-time coefficient $\gamma$ 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 vari-

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ables and improves the forecast. Thus, the empirical model becomes:

$$ln\left(\frac{GVA_{i,t}}{workers_{i,t}}\right) = \phi ln\left(\frac{GVA_{i,t-1}}{workers_{i,t-1}}\right) + \rho \sum_{j=1}^{n} w_{ij}\left(\frac{GVA_{j,t}}{workers_{j,t}}\right) +$$

$$+ \gamma \sum_{j=1}^{n} w_{ij} ln\left(\frac{GVA_{j,t-1}}{workers_{j,t-1}}\right) + \beta_{1k} ln\left(\frac{firms_{it,q}}{workers_{it,q}}\right) + \beta_2 lnIMP_{it}+$$

$$+ \beta_3 lnEXP_{it} + \beta_4 lnOVER_{it} + \beta_5 ln\left(\frac{firms}{worker}\right)_{it,q=2} \times lnEXP_{it}+$$

$$+ \beta_6 ln\left(\frac{firms}{worker}\right)_{it,q=2} \times lnIMP_{it} + \beta_7 lnIMP_{it} \times lnEXP_{it} + \delta_t \iota_n + \epsilon_{i,t}$$

$$i = 1,...,n; \quad t = 1,...,T; \quad q = 1,...,3 \tag{9}$$

As reported in section 3, the total number GVA of each province has been divided by the total number of workers. 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 9. 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 two recessions that occurred in 2008 and 2012-2013. 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 3. 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

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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 workers according to three class-size. The variable $\frac{firms_{it,q}}{workers_{it,q}}$ can be seen as an indicator of average firm size per employee with q equal to one representing micro firms, k equal to two representing small firms and k equal to three representing the remaining categories, 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 in terms of forecast performance. We first estimate our benchmark model in reduced form in equation (3) and its competitors for the entire period 2000-2016. The coefficient estimates are reported in Table 2. The spatial lag of X model, which locally incorporates explanatory variables observed on neighbouring cross-sectional units, has been included for comparative purposes among the competitors of the SDPD model. We also report the results of extending the sampling period for the SDPD model by one year at a time, see Table 3.

When the full sample is considered in Table 2, the simultaneous autoregressive coefficient $\rho$, the dynamic component $\phi$ and the spatio-temporal parameter $\gamma$ are all significant at different levels, leading to a consideration of this type of model in analyzing log(GVAs). If subspecifications are considered, we found the dynamic component $\phi$ and/or the variable $\Delta ln(firms/worker)_1$ to be highly significant, whereas the $\Delta ln(imp * exp)$ variable on the interaction between import and export is always highly significant in all model specifications. The simultaneous spatial autoregressive coefficient $\rho$ 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 $\gamma$ is significant at 5% but only in the full sample size case and in the last year of the expanding window, i.e. 2015, whereas the significance of the dynamic component $\phi$ varies from 0.1% to 10% for the last thee years of the in-sample estimation, i.e. 2013-2015. Moreover, we can occasionally find the coefficient $\Delta ln(export)$, the coefficient $\Delta ln(firms_2 * exp)$ and the coefficient $\Delta ln(imp*exp)$ to be significant at different level. This confirms the importance of foreign trade for the growth of Italian provinces. 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 as well as for the SLX specification, underlying its importance for the local economies.

More specifically, the estimated coefficient of the variable $\frac{firms_{it,q}}{workers_{it,q}}$ is negative and significant for micro enterprises, i.e. $q = 1$, when the SPD and a PD model is specified in a full sample case. This correlation is very informative about the negative relation between the relative size of micro 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 average size of micro business becomes, on average smaller, GVA per worker decreases. This is also supported by the fact that micro enterprises are less likely to invest in some crucial determinants of GVA growth, such as human capital and innovation, than larger enterprises. Considering the SLX model, we found $W \frac{firms_{it,q}}{workers_{it,q}}$ with $q = 2$ to be positive and significant. A possible explanation is that the neighbouring small enterprises lead to local economic growth through increased inter-provincial trade. The effect of $\Delta W ln(imp * exp)$ is still highly significant and positive, confirming the positive contribution to the provincial economic performance of foreign trade in also the neighbouring provinces. In general, it is reasonable to say that 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, i.e. $\frac{firms_{it,q}}{workers_{it,q}}$ when $q = 3$, 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 workers, 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[8].

### 5.1.1 Forecasting performances: a comparison of different models

Forecasting performances of the model in equation 9 are compared to the three sub-specifications as well as with the SLX model and to the RW model by computing both RMSEs (equation (7)) and population-weighted RMSEs (equation (8)). 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 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 SDPD specification, both in terms of the standard and the weighted version, i.e. $RMSE_t$ and $WRMSE_t$, respectively. Weighting for province-specific population increases the RMSEs, as we weight more errors for larger provinces. Nevertheless, it does not change the results compared to the reference model, i.e. the results are similar to the ones computed without the population weights. The average performance of the SDPD model confirms its superiority over the RW model. The SDPD models performs better in the overall 8–years mean than the other specifications. Among the other models, not considering the spatial components leads to a less accurate point forecast. The SDPD model perform slightly better than the SPD model in 2014, but the difference is relatively small. However, in general, spatial panel data models performs 5 times better over 8 years of in-sample periods, while the RW is to be preferred in only two years, i.e. the years of crisis 2009 and 2012. In 2011 we found the DPD model to be the best. 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.

Figure 1 compares forecast accuracy from another perspective, showing the differences between the forecast errors of the SDPD and the RW 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. Looking at the magnitude of the errors, one can see that when the SDPD model performs better, the differences from the RW are substantial, while when it is the RW that performs better, 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 (7), with their weighted versions (on the right), i.e. $WRMSE_i$ of equation (8), between the SDPD model and the RW 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). 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 so the RMSE differences.

### 5.1.2   A specific comparison between SDPD and RW models

These results offer empirical evidence on how the dynamic spatial model is preferable in a panel data setting, where the focus is to predict regional GDP/GVA. So far, we showed the superiority of the SDPD model over its competitors. However, it is necessary to spend some words about the low RMSE displayed by the RW model.

Intuitively, in the years of growth close to zero, the random walk is the model to be preferred. In fact, in a context of low variability, there could be cointegration among the provincial time series and the RW model is better able to capture the evolution of the economic cycle. It is then interesting to investigate which years and, in particular, for which provinces that were 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 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 SDPD model performs better in the majority of cases, regardless of the specific growth rate group. On the contrary, the RW model performs better in the 2009 year of economic crisis, where probably there is a growth close to zero for both the groups. It is also 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 A.1 in the Appendix. Moreover, we found that in the 2012 year of sovereign debt crisis the SDPD model is to be preferred for provinces with negative growth rates, while the RW performs better for provinces with positive growth rate. This fact may be due to a positive growth rate very close to zero in that year (for which a RW is to be preferred), and a higher magnitude of negative growth rate for the other provinces, which justifies the best performance of our SDPD model. Indeed, if we look at Figure 1 in 2012 there are some provinces for which the RW has lower forecast errors.

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

averaged growth rate (year by year) of each group of provinces changes according to the group's composition. 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.

In order to take into account the change in the composition of the two samples descriptive, Figure A.1 and A.2 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). It seems that when there is positive growth, the SDPD model performs better than RW. Moreover, when there is negative growth the performance of the SDPD model equals the one of the RW. Intuitively, regardless of the sign, the RW performs better only when there is zero or close to zero growth, a phenomenon that can be associated to the years of economic crisis.

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 rates at the provincial level the spillover effects between territories (from year to year) are more relevant than in the case of negative growth rates, and the SDPD model correctly captures them to improve point forecasts. On the other hand, close to 0 growth rates among territories require a RW specification which assumes zero variability in the mean part of the equation. If we look at the Table A.1 in the Appendix, 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. We leave this issue open for future research.

# 6   Conclusion

In this paper, we compare the forecasting performances of a SDPD model on the GVA of 103 Italian provinces. We consider different sub-specifications of the SDPD model

as well as the SLX panel specification and a standard set of univariate province-specific random-walk (RW) models, assuming zero growth.

We show that the SDPD model performs better, on average, than its competitors and than the simple univariate time series. However, when temporal cointegration is detected, the random walk specification is still to be preferred in two 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 specifications. The gain in forecasting accuracy comparing the SDPD and the RW model is, on average, 22 per cent. It becomes even higher when comparing 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 in the last two years, the model fails to be the most accurate one, it performs better when the panel is short. 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 characterized 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 catheterized by small and medium-size enterprises. Generally speaking, small firms are less prone to invest in human capital and are, on average, less innovative in comparison to large size firms. This could negatively affect economic growth, and it is shown in the paper. 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

# Data availability

Data and codes are available at http://francescoravazzolo.com/pages/research.html.

# Notes

[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.

[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).

[4]International Tourism Highlights, 2019 Edition.

[5]More precisely, GVA is defined by Eurostat as the value of output less the value of intermediate consumption.

[6]For a broader discussion on the different weights specifications of the matrix W, see also Giacomini and Granger (2004).

[7]We also tried an autoregressive (AR) specification. We found that our model outperforms both specifications and no substantial differences between AR and RW models. Then, we decided to drop the AR specification from the entire analysis. Results are available upon request.

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

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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 |
| $(firm/worker)_1$ | 0.653 | 0.199 | 0.452 | 2.825 | 1751 |
| $(firm/worker)_2$ | 0.046 | 0.004 | 0.033 | 0.056 | 1751 |
| $(firm/worker)_3$ | 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 in first-differences and its sub-specifications (full sample sizes)

| Coefficients | SDPD | SPD | DPD | PD | SLX |
|---|---|---|---|---|---|
| $\rho$ | 0.298 | 0.294 | | | |
| | (0.043) | (0.043) | | | |
| $\phi$ | - 0.066 | | 0.057 | | |
| | (0.015) | | (0.014) | | |
| $\gamma$ | 0.048 | | | | |
| | (0.027) | | | | |
| $\Delta ln(firms/workers)_1$ | - 0.009 | - 0.019 | - 0.009 | - 0.021 | - 0.016 |
| | (0.01) | (0.009) | (0.01) | (0.01) | (0.011) |
| $\Delta ln(firms/workers)_2$ | 0.023 | 0.010 | 0.040 | 0.027 | 0.004 |
| | (0.051) | (0.051) | (0.052) | (0.052) | (0.053) |
| $\Delta ln(firms/workers)_3$ | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| $\Delta ln(import)$ | 0.005 | 0.003 | 0.003 | 0.002 | 0.001 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.011) |
| $\Delta ln(export)$ | - 0.014 | - 0.013 | - 0.013 | - 0.013 | - 0.014 |
| | (0.01) | (0.01) | (0.01) | (0.011) | (0.011) |
| $\Delta ln(overnights)$ | 0.005 | 0.005 | 0.006 | 0.006 | 0.005 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| $\Delta ln(firms2 * imp)$ | - 0.266 | - 0.230 | - 0.262 | - 0.246 | - 0.217 |
| | (0.224) | (0.225) | (0.23) | (0.231) | (0.232) |
| $\Delta ln(firms2 * exp)$ | 0.057 | 0.041 | 0.001 | 0.004 | 0.039 |
| | (0.192) | (0.193) | (0.197) | (0.198) | (0.199) |
| $\Delta ln(imp * exp)$ | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |

*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. The spatial lag of X model (SLX) is also included for comparison purposes. Estimated standard errors are in parentheses.

Continuation of Table 2: Estimates SDPD model in first-differences and its sub-specifications (full sample sizes)

| Coefficients | SDPD | SPD | DPD | PD | SLX |
|---|---|---|---|---|---|
| $\Delta Wln(firms/workers)_1$ | | | | | 0.007 |
| | | | | | (0.022) |
| $\Delta Wln(firms/workers)_2$ | | | | | 0.393 |
| | | | | | (0.153) |
| $\Delta Wln(firms/workers)_3$ | | | | | - 0.002 |
| | | | | | (0.005) |
| $\Delta Wln(import)$ | | | | | - 0.020 |
| | | | | | (0.034) |
| $\Delta Wln(export)$ | | | | | - 0.023 |
| | | | | | (0.034) |
| $\Delta Wln(overnights)$ | | | | | 0.032 |
| | | | | | (0.016) |
| $\Delta Wln(firms2*imp)$ | | | | | - 0.539 |
| | | | | | (0.746) |
| $\Delta Wln(firms2*exp)$ | | | | | - 0.825 |
| | | | | | (0.651) |
| $\Delta Wln(imp*exp)$ | | | | | 0.008 |
| | | | | | (0.002) |

*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. The spatial lag of X model (SLX) is also included for comparison purposes. 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 |
|---|---|---|---|---|---|---|---|---|
| $\rho$ | 0.307 | 0.391 | 0.412 | 0.410 | 0.398 | 0.388 | 0.359 | 0.308 |
| | (0.06) | (0.052) | (0.048) | (0.046) | (0.045) | (0.044) | (0.043) | (0.044) |
| $\phi$ | - 0.008 | - 0.008 | - 0.023 | - 0.020 | - 0.022 | - 0.027 | - 0.032 | - 0.066 |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.016) |
| $\gamma$ | - 0.002 | 0.007 | 0.015 | 0.018 | 0.016 | 0.017 | 0.021 | 0.052 |
| | (0.024) | (0.025) | (0.025) | (0.024) | (0.025) | (0.025) | (0.026) | (0.027) |
| $\Delta ln(firms/worker)_1$ | - 0.014 | - 0.014 | - 0.013 | - 0.013 | - 0.013 | - 0.013 | - 0.012 | - 0.008 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.01) | (0.01) |
| $\Delta ln(firms/worker)_2$ | 0.009 | 0.020 | 0.012 | 0.017 | 0.021 | 0.019 | 0.020 | 0.030 |
| | (0.048) | (0.049) | (0.047) | (0.046) | (0.047) | (0.048) | (0.05) | (0.052) |
| $\Delta ln(firms/worker)_3$ | 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) | (0.001) | (0.001) | (0.002) |
| $\Delta ln(import)$ | - 0.002 | - 0.010 | - 0.011 | - 0.011 | - 0.009 | - 0.007 | 0.004 | 0.005 |
| | (0.011) | (0.011) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| $\Delta ln(export)$ | 0.026 | 0.018 | 0.008 | 0.004 | 0.000 | 0.000 | - 0.009 | - 0.014 |
| | (0.011) | (0.011) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| $\Delta ln(overnights)$ | - 0.001 | - 0.002 | 0.000 | 0.000 | 0.001 | 0.003 | 0.003 | 0.004 |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| $\Delta ln(firms2 * imp)$ | 0.238 | 0.304 | 0.197 | 0.159 | 0.061 | 0.031 | - 0.202 | - 0.289 |
| | (0.234) | (0.239) | (0.221) | (0.214) | (0.217) | (0.216) | (0.227) | (0.233) |
| $\Delta ln(firms2 * exp)$ | - 0.349 | - 0.474 | - 0.337 | - 0.270 | - 0.201 | - 0.172 | 0.023 | 0.073 |
| | (0.215) | (0.219) | (0.187) | (0.181) | (0.184) | (0.183) | (0.192) | (0.198) |
| $\Delta ln(imp * exp)$ | - 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.001 | 0.001 | 0.002 |
| | (0.001) | (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 | 8-year average |
|-------|------|------|------|------|------|------|------|------|----------------|
| *RMSE in ratio to the SDPD model* | | | | | | | | | |
| *SDPD* | *0.045* | *0.020* | *0.020* | *0.029* | *0.025* | *0.030* | *0.028* | *0.019* | *0.027* |
| SPD | 1.009 | 0.999 | 1.003 | 1.003 | 0.996 | 1.002 | 1.004 | 0.985 | 1.001 |
| DPD | 0.879 | 2.129 | 0.860 | 1.091 | 1.413 | 1.009 | 0.970 | 1.047 | 1.128 |
| PD | 0.885 | 2.129 | 0.865 | 1.091 | 1.415 | 1.016 | 0.969 | 1.030 | 1.129 |
| SLX | 0.960 | 3.300 | 1.252 | 1.040 | 1.333 | 1.019 | 0.956 | 0.998 | 1.270 |
| RW | 0.719 | 1.168 | 2.212 | 0.870 | 1.152 | 1.411 | 1.114 | 1.890 | 1.219 |
| *Weighted RMSE in ratio to the SDPD model* | | | | | | | | | |
| *SDPD* | *0.016* | *0.007* | *0.007* | *0.010* | *0.009* | *0.011* | *0.010* | *0.007* | *0.010* |
| SPD | 1.009 | 0.999 | 1.003 | 1.003 | 0.996 | 1.002 | 1.004 | 0.986 | 1.001 |
| DPD | 0.879 | 2.128 | 0.861 | 1.091 | 1.413 | 1.009 | 0.970 | 1.046 | 1.128 |
| PD | 0.885 | 2.128 | 0.866 | 1.091 | 1.415 | 1.016 | 0.969 | 1.030 | 1.129 |
| SLX | 0.960 | 3.299 | 1.253 | 1.040 | 1.333 | 1.019 | 0.956 | 0.998 | 1.269 |
| RW | 0.720 | 1.168 | 2.209 | 0.870 | 1.151 | 1.412 | 1.114 | 1.892 | 1.220 |

*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), the panel data (PD) model, and the spatial lag of X (SLX) model. $n = 103$ provinces and $T = 2009, ..., 2016$ years. For ease of comparison, values are in ratio to the SDPD model.
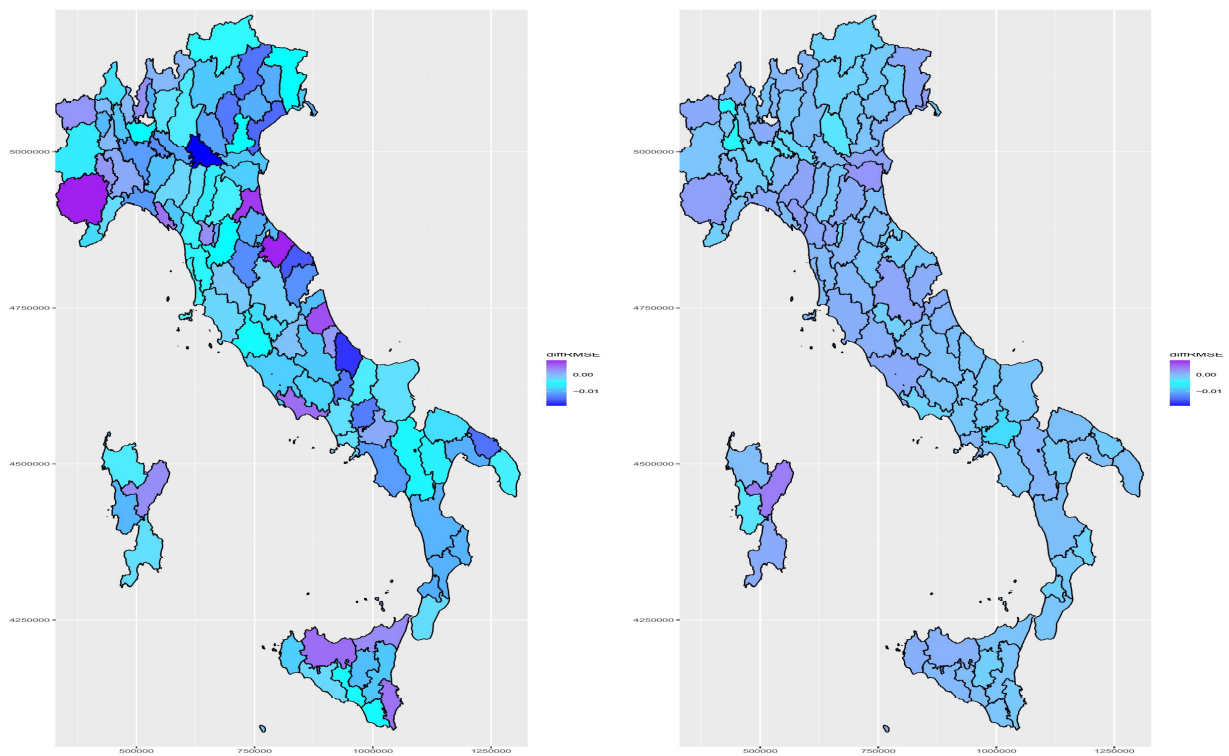
# Figures

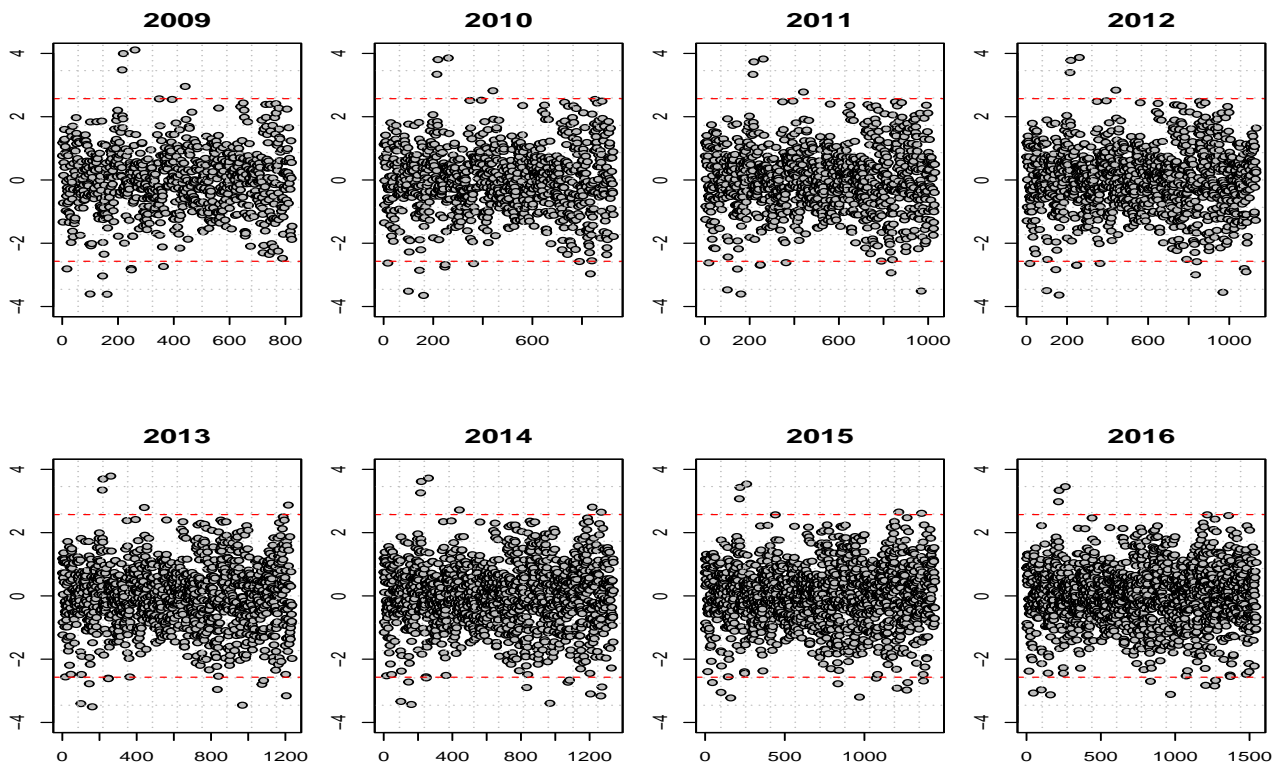Figure 1: Differences in forecast errors between SDPD and RW model by year (2009-2016)

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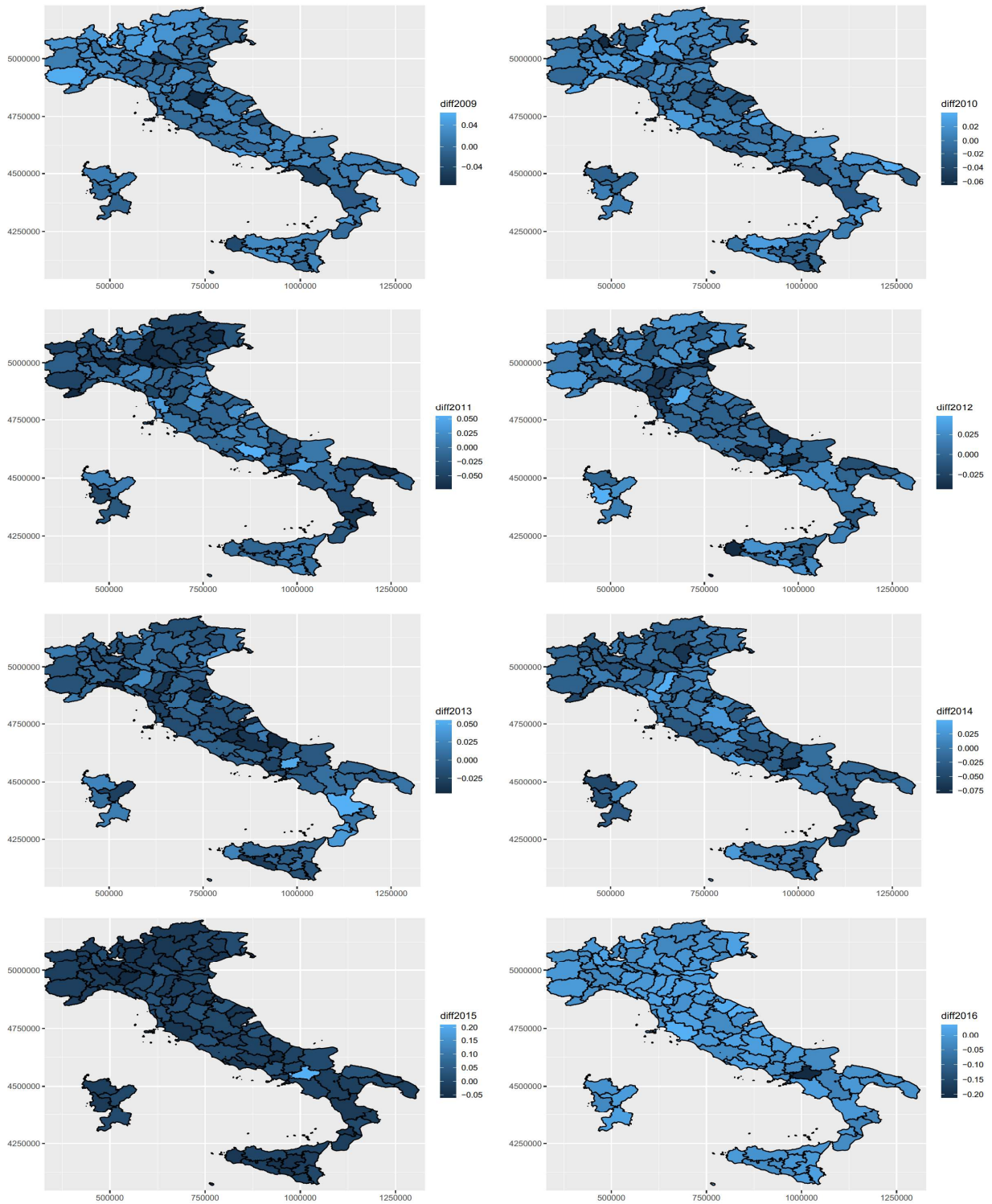


*Note:* The figure differences at the provincial level between the SDPD and the RW model in terms of temporal (on the left) and weighted temporal (on the right) provincial-specific RMSE, i.e. $RMSE_i$ and $WRMSE_i$. Each RMSE considers the total years of the forecast. Differences are attributed to a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

Figure 3: Standardized residuals to control for potential outliers

*Note:* The limits are $\pm$ 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)
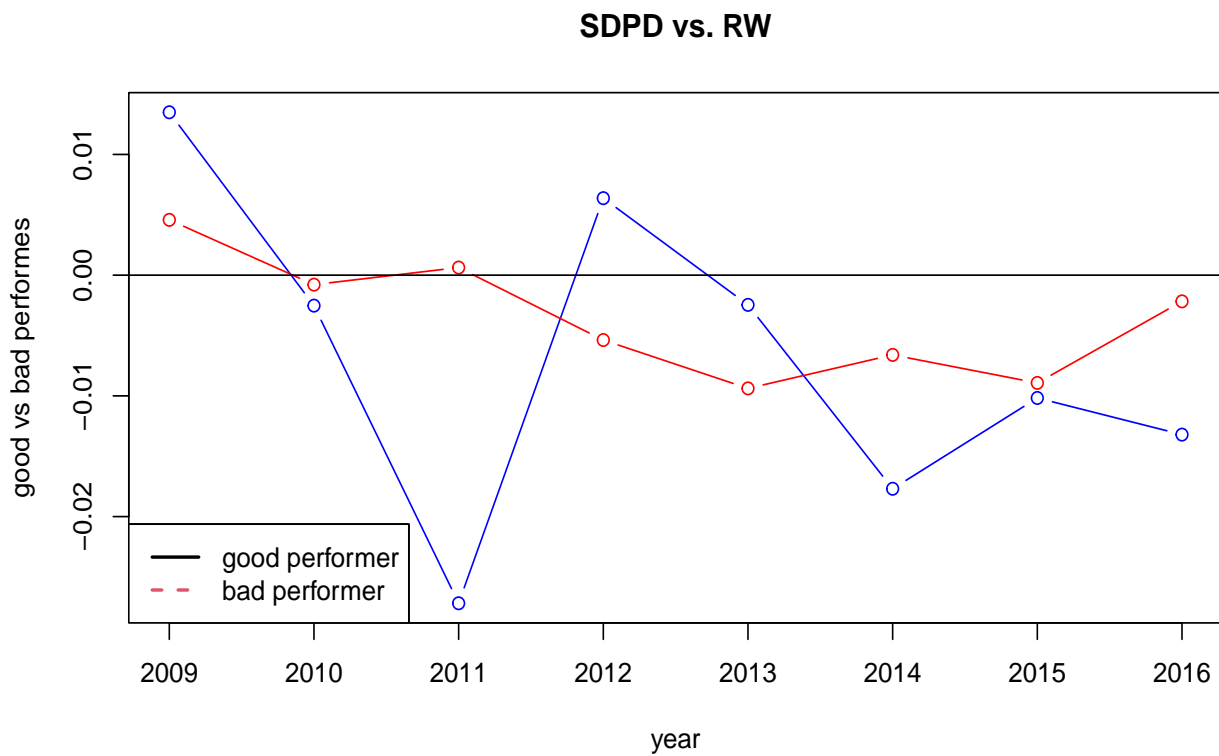


*Note:* The 23 provinces with negative growth rates (red line) over the period are Savona, Pescara, Isernia, Campobasso, Benevento, Napoli, Avellino, Matera, Cosenza, Crotone, Reggio Calabria, Trapani, Palermo, Messina, Agrigento, Caltanissetta, Enna, Catania, Ragusa, Oristano, Terni, Ascoli Piceno, 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)
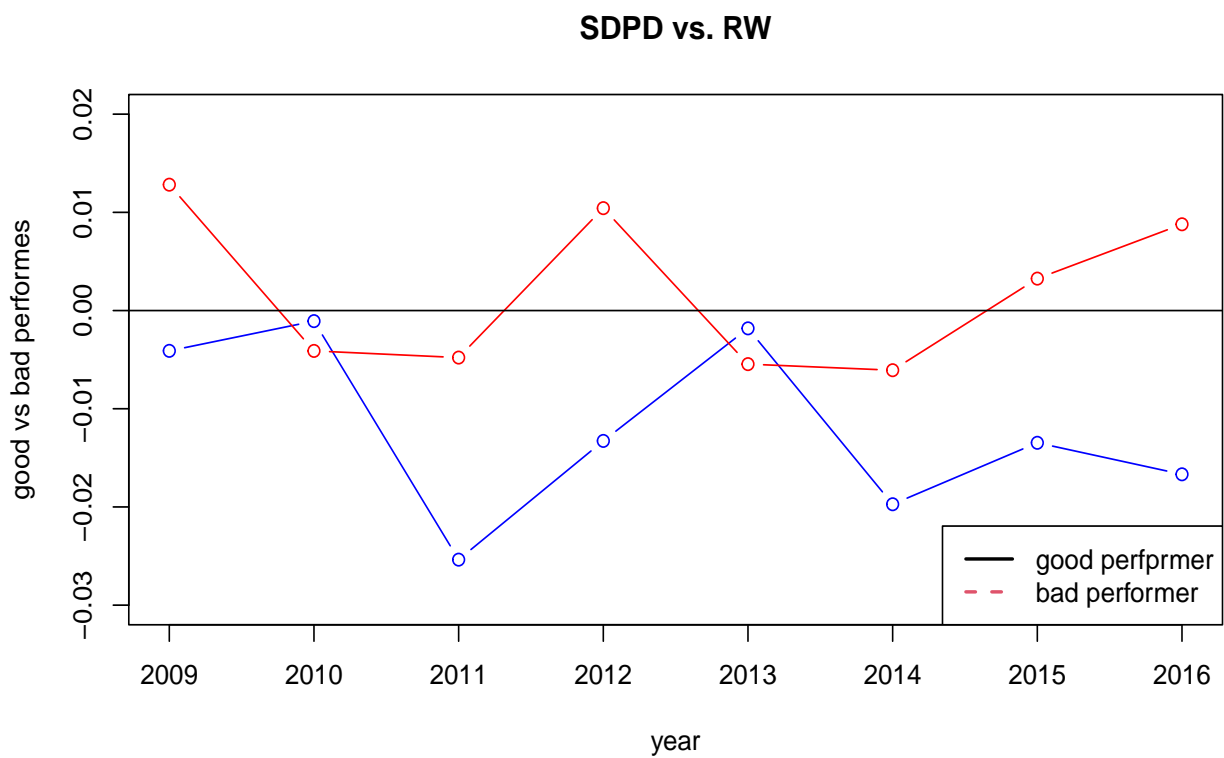


*Note:* Grouping by positive annual growth excluding 3 year-specific outliers: Verona in 2011, Catanzaro in 2014 and Lucca in 2015. Grouping by negative annual growth without an outlier Bari in 2009.