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Canello, Jacopo; Vidoli, Francesco

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Investigating space-time patterns of regional industrial resilience through a micro-level approach: An application to the Italian wine industry

Jacopo Canello[1] | Francesco Vidoli[2]

[1]Department of Global Economics and Management, Faculty of Economics and Business, University of Groningen, Groningen, The Netherlands

[2]Department of Political Science, University of Roma Tre, Rome, Italy

Correspondence
Francesco Vidoli, Department of Political Science, University of Roma Tre, Via G. Chiabrera, 00145, Rome, Italy.
Email: francesco.vidoli@uniroma3.it

Abstract

This paper introduces a new methodology to identify space-time patterns of regional resilience using a micro-level approach. The novel empirical tool combines geographically weighted regression with panel stochastic frontier analysis with endogenous covariates. The analysis is implemented on a panel of farm holdings operating in the Italian wine industry, focusing on the impact of a major institutional change. The results show the effectiveness of the new procedure in identifying geographical clusters of wine producers who reacted to the shock in similar ways. The responses are found to be homogeneous within specific territories and heterogeneous between regions.

KEYWORDS

endogeneity, geographically weighted regression, resilience, spatial nonstationarity, stochastic frontier

1 | INTRODUCTION

Globalization has increased uncertainty about economic and social developments in advanced and developing economies. Firms in most sectors often operate in turbulent environments, where the frequency of economic and structural shocks is increasing dramatically: both sudden events and more gradual transformations can profoundly reshape the surrounding competitive scenario, leading local actors to a continuous process of readaptation and transformation. In this evolving context, the ability to redesign the organizational structure and develop new growth paths plays a crucial role in determining firms' long-term competitiveness.

The recent literature on economic resilience has provided evidence of the existence of asymmetric territorial dynamics after economic crises or other unexpected changes (Diodato & Weterings, 2014; Fingleton, Garretsen, &

Martin, 2012, 2015; Martin, 2012), highlighting how local factors are crucial to explain the heterogeneous behavior of economic agents in such circumstances. Most of the empirical investigations on resilience focus on the macro-behavior of regions, countries or cities, while micro-level analyses on firms operating in the same industry are less diffused (Behrens, Boualam, & Martin, 2019; Duschl, 2016; Modica & Reggiani, 2015). This lack of contributions is surprising, given the essential role of firms in driving local development (Frenken & Boschma, 2007; Martin, 2012). More important, firm-level behavior might change significantly between industries, especially when shocks are sector-specific. In such cases, the adjustment process of the industry at the local level is inevitably overlooked when the analysis is implemented on the region as a whole (Urban, Pazitka, Ioannou, & Wojcik, 2019).

Given the above considerations, firm-level empirical contributions can represent an important stream for future research on economic resilience: however, the development of new empirical work must be supported by reliable methodological tools. Resilience scholars are still in the process of developing analytical methods specifically targeted at identifying and capturing the existence of asymmetric responses across local actors. Despite the presence of valuable attempts to fill the existing gap, the need to develop more rigorous statistical analyses of the reaction and recovery dynamics of regions is still pressing (Martin, 2012; Martin & Sunley, 2015; van Bergeijk, Brakman, & van Marrewijk, 2017).

The aim of this paper is to contribute to advance the current empirical literature on economic resilience by proposing a novel parametric model that allows to study local responses to disturbances and to detect the presence of specific space-time patterns of firms' performance in the data. The proposed specification combines two frameworks—the geographically weighted regression (GWR) and the endogenous panel stochastic frontier model in the style of Karakaplan and Kutlu (2017b)—to locally estimate the temporal patterns of technical efficiency in specific firm populations, overcoming the main limitations of the existing methodologies. The empirical approach presented in this paper is particularly beneficial to evaluate the resilience dynamics of firm populations affected by relevant shocks and disturbances: during these periods, when the local responses of firms are likely to be highly asymmetric, assuming the presence of a single global trend of performances and ignoring spatial factors is particularly unrealistic. The empirical investigation employs data from the Italian wine industry and is focused on the 2009–2014 period: the setting appears particularly appropriate for our goals for several reasons. First, wine production represents a strategic sector in the Italian economy: Italy is the world's leading producer of wine and is the second-largest wine exporter in the world (International Organisation of Vine and Wine (OIV), 2018). Second, Italy's wine sector is one of the major beneficiaries of funding from the European Union (EU), ranking second during the 2009–2018 period. Last but not least, this sector has been affected by a major institutional change in 2008, that is, the Common Market Organization (CMO) reform, and producers' performances are heavily dependent on context-specific and localized tangible and intangible assets (Morrison & Rabellotti, 2017).

This study contributes to the existing literature in three main ways. First, to the best of our knowledge, this is the first paper which develops a specific methodology to evaluate economic resilience using a firm-level perspective, identifying an applicable model for future contributions in this underdeveloped area of research. The focus of this analysis is on the resistance phase, as regional differences in terms of resilience mainly concern this initial phase (Fingleton et al., 2012). Second, the empirical approach provides an important advancement in the field of efficiency analysis, combining the GWR and endogenous stochastic frontier analysis (SFA) frameworks with functional mixture models in a two-step procedure: following this method, it is possible to isolate homogeneous territorial clusters of farm holdings, defined as spatial regimes.[1] This approach allows to overcome a limitation of most macro-level analyses, that is the use of territorial boundaries imposed a priori (e.g., administrative regions): given these boundaries do not necessarily mirror the territorial dynamics occurring in the locality, the use of smaller subregional scales tend to generate more robust empirical results (Di Caro & Fratesi, 2018). Third, the proposed approach is specifically designed to meet the needs of policy makers to develop place-based strategies

[1]It is worth noting that the term spatial regime should not be understood as a perfect synonym of "cluster"; more precisely, the term "regime" is linked to the production function underlying the spatial process. The identification of different spatial regimes, in a sense, is equivalent to the identification of similar growth paths after a shock.

that overcome the limitations of the traditional one-size-fits-all development policies, exploiting the potential of both the territories and the individuals that live and interact in them (Barca, 2009; Barca, McCann, & Rodriguez-Pose, 2012; OECD, 2009). According to Ali et al. (2007), taking into account spatial heterogeneity is crucial to develop effective policies: this is especially true as far as periods of crisis are concerned, given the literature has shown that the reaction of firms in different regional contexts is highly differentiated.

The remainder of the paper is structured as follows: Section 2 contains an overview of the literature on regional and sectoral resilience, focusing on the recent theoretical and empirical contributions in these fields of research and on the identification of the main gaps in the existing debate. Section 3 introduces the novel parametric frontier framework and discusses the distinctive features of the proposed estimation algorithm, explaining how the model allows to account for heterogeneous space-time patterns in the data. After having highlighted some relevant features and the recent transformations in the Italian wine industry, Section 4 presents an application to a sample of Italian wine producers. The empirical exercise shows the effectiveness of the model in capturing some important features of the data, highlighting the presence of some relevant firm-level and environmental and institutional factors associated with higher levels of resilience. Section 5 summarizes the main findings and presents some concluding remarks and possible directions for future research.

2 | THE HETEROGENEOUS RESPONSE OF LOCAL ACTORS TO SHOCKS AND DISTURBANCES: AN OVERVIEW OF THE LITERATURE ON REGIONAL AND SECTORAL RESILIENCE

Economic actors face continuous transformations associated with a wide range of unexpected circumstances, including economic recessions, environmental disasters, regulatory changes, unexpected plant closures, and the introduction of new technologies (Holm & Østergaard, 2015). In the recent past, the frequency and the impact of these events have increased dramatically, intensifying the instability of regions and cities in the global economy: the recent economic downturn that has affected most developed countries is probably the most widely used example of this changing dynamics. In such an evolving context, the increased popularity of the concept of resilience should be interpreted as a rational response to the need of advancing our understanding of an increasingly uncertain and risk-prone world (Christopherson, Michie, & Tyler, 2010; Martin, 2018).

Despite its widespread use in several academic disciplines, the notion of resilience has attracted particular attention in the field of economic geography, given its effectiveness to describe the heterogeneous reactions and recovery mechanisms of regions, cities and local communities in face of major shocks, disturbances, and perturbations. The emergence of theoretical and empirical studies on regional resilience is associated with the awareness that regional economic development is often characterized by continuous interruptions and disruptions, leading local actors to relentlessly adapt over time to various kinds of stress (Simmie & Martin, 2010). In this context, a regional economic system is defined as resilient if it is able to anticipate, prepare for, respond to, and recover from a disturbance (Foster, 2007).

Among the main approaches identified by the literature, the evolutionary view is often identified as the more effective to capture the complex and multifaceted nature of these processes: indeed, evolutionary scholars postulate the possibility for local economies to continuously move from one equilibrium to another as a result of a shock or a disturbance (Boschma, 2015; Diodato & Weterings, 2014). Such an approach assumes the existence of multiple equilibria, whereby if the previous growth path disappears after a shock, the region can still move to an alternative growth path in the recovery stage (Christopherson et al., 2010). The empirical contributions developed in the recent past seem to confirm the appropriateness of this approach, showing that the effects and the consequences of a shock or a disturbance typically vary substantially from one territory to another. Evidence of heterogeneous responses of regions to disturbances and emergence of new growth paths has been reported for Britain (Fingleton et al., 2012; Martin, 2012), the Netherlands (Diodato & Weterings, 2014), Italy (Cellini & Torrisi, 2014; Di Caro, 2017), Turkey (Eraydin, 2016), Greece (Giannakis & Bruggeman, 2017), Spain (Angulo, Mur, &

Trívez, 2018), and Sweden (Nyström, 2018). The same patterns are identified in cross-country analyses of EU regions, such as the one implemented by Brakman et al. (2015) and Fingleton et al. (2015).

The core of the empirical research on regional resilience is centered around global shocks and focuses on the macro-behavior of regions, countries, or cities. Conversely, micro-level analyses on firms affected by industry-specific shocks are less diffused (Modica & Reggiani, 2015): this lack of contributions is surprising, considering firms' strategic decisions are essential to understand resilience patterns. According to Frenken and Boschma (2007), firms ultimately drive the development of regional and national economies and are the true agents of change. Given a region is typically composed of a wide number of heterogeneous firms, a regional economy might be resilient in one sense but not in another (Gong & Hassink, 2016). More important, when the shock is sector-specific, the dynamics of the region as a whole does not provide relevant indications to disentangle the adjustment process taking place at the industry level. In such cases, restricting the focus improves the consistency of the analysis, as the path to recovery of the regional industry might differ from the recovery of the regional economy (Holm & Østergaard, 2015).

In light of this discussion, a number of recent contributions have introduced the concept of sectoral resilience (Behrens et al., 2019; Fromhold-Eisebith, 2015; Urban et al., 2019), looking at industry-specific patterns of adjustment to sectoral shocks. The main claim of this emerging strand of the literature is that sectoral shocks are often not region-specific, and the adjustment process of firms may not necessarily prioritize the recovery of any specific region. On the contrary, firms generally allocate resources and respond to economic shocks by interacting with the other actors of the global value chain, which generally operate across multiple regions (Treado & Giarratani, 2008). According to this view, sectors react through the implementation of supra-regional, often global strategies, and the resilience capacity of a region is often limited (Urban et al., 2019).

In this paper, we claim that a purely regional or purely sectoral approach toward resilience is not sufficient to interpret industry-specific shocks when the affected sector is characterized by strong territorial patterns. On the one hand, the focus on the whole region tends to mask the true local dynamics in response to the disturbance, as it includes a number of local actors that are not affected by these transformations. On the other hand, a purely sectoral perspective only focuses on cross-regional adjustments, whereas the majority of the interactions in these specific industries take place at the local level. In such circumstances, an hybrid approach is likely to be more robust, in that it allows one to restrict the analysis to the relevant subset of firms and to account for the relevant role of geography in influencing industrial dynamics.

The aim of the following section is to provide an operational solution to this issue, developing a new analytical tool that allows to identify heterogeneous local responses to sector-specific disturbances using a micro-level approach. We use this novel technique to study space-time patterns of producers' performances in a specific industry (the Italian wine sector) in response to a major regulatory change (the 2008 CMO reform). The Italian wine industry is peculiar in that production is concentrated in a number of geographical clusters and most interactions take place at the local level (De Marchi & Grandinetti, 2016): therefore, a purely sectoral approach is not appropriate to evaluate the geographical dynamics influencing producers' reactions to an industry-specific shock. The investigation is focused on the resistance phase, when local responses are expected to be more heterogeneous (Fingleton et al., 2012): using this strategy, we aim to capture both the spatial and temporal elements that are believed to influence local actors' reactions to the perturbation. The empirical model is based on the estimation of technical efficiency, defined as the difference between the actual and the maximum level of production y given a set of inputs x, and combines spatial analysis with a panel endogenous stochastic frontier framework to verify whether the dynamics of firm-level efficiency are influenced by the specific territorial context.

3 | MODELING THE HETEROGENEOUS SPACE-TIME REACTIONS OF LOCAL ACTORS TO SHOCKS: THE GEOGRAPHICALLY WEIGHTED PANEL SFA MODEL WITH ENDOGENOUS COVARIATES

The analysis of firm-level inefficiency represents a widely used empirical tool to measure the deviation of observed decision-making units from an estimated or constructed production, cost, or profit frontier. Technical efficiency is usually defined as the difference between the actual and the maximum possible level of production y given a set of inputs x (Farrell, 1957) and can be estimated using a large number of alternative models based on different assumptions. Among these alternatives, parametric models, such as the stochastic frontier approaches, are often preferred as they allow to implement inference on the conditional parameters of the model and to minimize the concerns associated with potential omitted variable bias (see e.g., Baltagi, 2001).

In the recent years, the traditional SFA framework has been modified and extended in several directions. One of the most remarkable strands of research focuses on the possibility to account for spatial effects in the estimation of technical efficiency. The first attempt to address this issue was proposed by Druska and Horrace (2004), who extended the Kelejian and Prucha (1999) specification by assuming an autoregressive specification of the error term and estimating inefficiency with the Generalized Method of Moments. Following this pioneering contribution, a number of SFA models have been developed to account for spatial dependence, with two major groups emerging in the context of cross-sectional data. The first one explains the efficiency term using a set of exogenous determinants associated with spatial heterogeneity (Brehm, 2013; Hughes, Lawson, Davidson, Jackson, & Sheng, 2011; Lavado & Barrios, 2010), while the second one accounts for spatial dependence through spatial autoregressive specifications, including the spatial lag in the dependent variable (Affuso, 2010; Glass, Kenjegalieva, & Paez-Farrell, 2013; Glass, Kenjegalieva, & Sickles, 2014), in the inputs (Adetutu, Glass, Kenjegalieva, & Sickles, 2015), or in the efficiency term (Areal, Balcombe, & Tiffin, 2010; Fusco & Vidoli, 2013; Pavlyuk, 2010, 2012, 2013; Tsionas & Michaelides, 2016).

The literature on spatial SFA has recently been extended using panel data models (Glass, Kenjegalieva, & Sickles, 2016; Gude, Álvarez, & Orea, 2018; Jeleskovic & Schwanebeck, 2012; Mastromarco, Serlenga, & Shin, 2016; Ramajo & Hewings, 2017; Tsukamoto, 2018). Despite providing significant advancements, none of the cited works have specifically accounted for the possibility of having distinct temporal patterns associated with heterogeneous local responses: as discussed in the previous section, this limitation is especially relevant when firm-level performance is evaluated after disturbances or shocks, as local actors' responses are expected to vary significantly in such circumstances. In this respect, the specifications proposed in the literature share the same limitations of the original panel data model of Battese and Coelli (1992), which tends to be restrictive as it only allows inefficiency to change over time with the same functional form (exponential) and for all productive units. Another relevant issue that has not been addressed by the existing spatial frontier frameworks is the potential endogeneity of the inputs, associated with reverse causality or omitted variable bias.[2] Despite its impact on the consistency of the estimators (Amsler, Prokhorov, & Schmidt, 2016), this important concern has been addressed only recently in the SFA literature (Karakaplan & Kutlu, 2017a, 2017b; Kutlu, 2010; Tran & Tsionas, 2013), while traditional SFA models tend to ignore this potential bias.

In an attempt to fill this gap, we propose a new spatial stochastic frontier model which addresses the two above mentioned issues and allows us to highlight the heterogeneous reactions of firms in turbulent circumstances. More specifically, the proposed specification, defined as the geographically weighted panel SFA with endogenous covariates (GWR-panel SFA), stands on two main pillars:

- A GWR algorithm which allows to locally estimate the production function for each unit i;
- A panel SFA specification that allows to overcome the potential endogeneity of inputs (Karakaplan & Kutlu, 2017b).

The GWR is a locally weighted regression in which the coefficients are nonparametric functions of longitude and latitude or the straight line distance between each observation and the target points (McMillen, 2013): it can be summarized as a moving window approach and is an effective tool to overcome the spatial homogeneity assumption. One of the main advantages of this method is that it can be used to map parameter variations over space, separating local

[2]The endogeneity issue is especially relevant when technical efficiency is estimated in the agricultural sector, given the presence of some determinants of the production process that are unobserved by the researcher, but observed by the farmer (Billé, Salvioni, & Benedetti, 2018).

spatial differences in terms of each explanatory variable (Brunsdon, Fotheringham, & Charlton, 1999). The GWR approach has also some limitations in that it is susceptible to the effects of multicollinearity (Wheeler & Tiefelsdorf, 2005), especially when the correlation between the covariates is particularly high. Furthermore, the presence of curvilinear relationships may produce false results of nonstationarity (Austin, 2007).

Despite these limitations, GWR is generally preferred over alternative techniques such as spatial filtering, which is *more prone to overfitting* and *does not produce local parameters estimates with superior properties* (Oshan & Fotheringham, 2018). Therefore, the GWR method is still considered a reliable tool to explore nonstationarity and spatial interpolation (Paez, Long, & Farber, 2008) and to accommodate more complex frameworks (Chen, Deng, Yang, & Matthews, 2012).

Locally weighted regressions are popular among regional and urban economists (Li & Mroz, 2013; Redfearn, 2009) and have been recently used to locally estimate efficiency models using cross-section data (Samaha & Kamakura, 2008; Tabak, Miranda, & Fazio, 2013). In an SFA setting, the GWR approach allows to fit specific models for each territorial location rather than fitting a global panel SFA model. This local form of regression (Brunsdon et al., 1999; Fotheringham, Brunsdon, & Charlton, 2002) allows to estimate the marginal effects of the different covariates over space.

The GWR model can be formally expressed as follows:

$$y_i = f(\mathbf{x}_i; \boldsymbol{\beta}_i(lat_i, long_i)) + \epsilon_i, i = 1, \dots, n, \tag{1}$$

where (lat$_i$, long$_i$) is the coordinates vector of the ith point in space and $\boldsymbol{\beta}_i$ (lat$_i$, long$_i$) is a realization of the continuous function β (lat, long) at point i. In this study, we combine the GWR approach with the endogenous SFA specification proposed by Karakaplan and Kutlu (2017b): this method was developed as an extension of the original model for cross-sectional data (Karakaplan & Kutlu, 2017a) to solve the endogeneity problem of inputs in an SFA panel setting through a single-stage approach. The model is expressed as follows:

$$\begin{cases} y_{it} = \mathbf{x}'_{yit}\boldsymbol{\beta} + v_{it} - su_{it}, \quad i = 1, \dots, n; t = 1, \dots, T \\ \mathbf{x}_{it} = \mathbf{Z}_{it}\boldsymbol{\delta} + \epsilon_{it} \\ \text{with} \\ u_{it} = h(\mathbf{x}'_{uit}\boldsymbol{\phi}_{\boldsymbol{u}})u_i^* \\ \begin{bmatrix} \tilde{\epsilon}_{it} \\ v_{it} \end{bmatrix} \equiv \begin{bmatrix} \Omega^{-1/2}\epsilon_{it} \\ v_{it} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I & \sigma_v\rho \\ \sigma_v\rho & \sigma_v^2 \end{bmatrix}\right) \end{cases}, \tag{2}$$

where $y_{it} \in \mathbb{R}_+$ is the output of unit i at time t, $\mathbf{x}_{it} \in \mathbb{R}_+^p$ is the vector of inputs, v_{it} is the symmetric two-sided error representing random effects, s is equal to 1 for production functions and −1 for cost functions and $u_{it} > 0$ is the one-sided error term which represents technical inefficiency.[3] The covariates are split into three groups: $\mathbf{x}_{yit}$, the exogenous and endogenous variables explaining y; $\mathbf{x}_{it}$, the endogenous variables; and $\mathbf{x}_{uit}$, the exogenous and endogenous variables explaining u. The endogeneity of $\mathbf{x}_{it}$ is corrected using $\mathbf{Z}_{it}$, the vector of all exogenous instrumental variables.

The *GWR-panelSFA* model combines Equations 1 and 2, resulting in the following specification:

$$\begin{cases} y_{it} = \mathbf{x}'_{yit} w_i \boldsymbol{\beta}_i(lat_i, long_i) + v_{it} - su_{it}, \quad i = 1, \dots, n; t = 1, \dots, T \\ \mathbf{x}_{it} = \mathbf{Z}_{it}\boldsymbol{\delta} + \epsilon_{it} \\ w_{i\cdot} = f(d_{i\cdot}) \\ \text{with} \\ u_{it} = h(\mathbf{x}'_{uit}\boldsymbol{\phi}_{\boldsymbol{u}})u_i^* \\ \begin{bmatrix} \tilde{\epsilon}_{it} \\ v_{it} \end{bmatrix} \equiv \begin{bmatrix} \Omega^{-1/2}\epsilon_{it} \\ v_{it} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I & \sigma_v\rho \\ \sigma_v\rho & \sigma_v^2 \end{bmatrix}\right) \end{cases}, \tag{3}$$

[3]The two-sided residual term is usually assumed to be normally distributed: $v \sim N(0, \sigma_v^2)$ while u is distributed as a half-normal and is always positive: $u \sim N^+(0, \sigma_u^2)$. The classical model also assumes that v and u are each identically independently distributed (*iid*) and the covariates in the model.

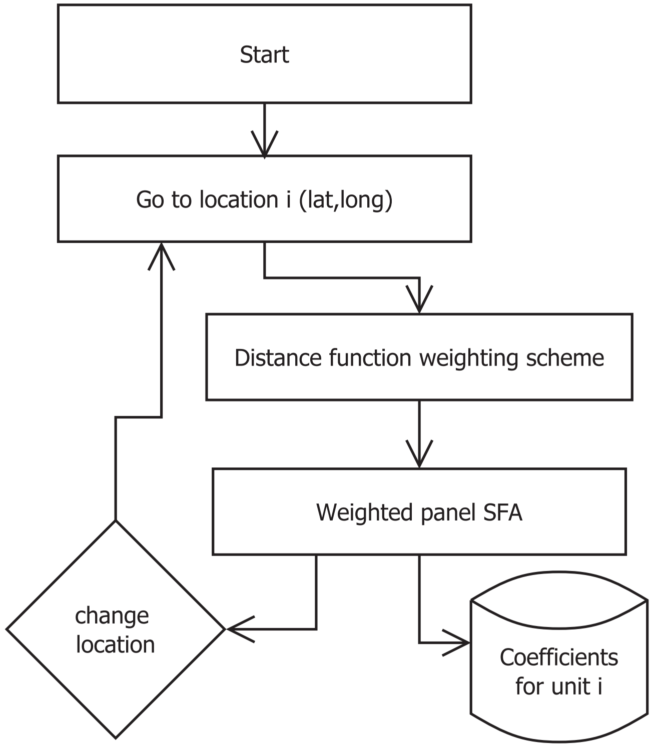

FIGURE 1 Flow diagram of the GWR-panel SFA estimation sequence. GWR, geographically weighted regression; SFA, stochastic frontier analysis

where $\boldsymbol{\beta}_i$ are the "unit specific" covariate coefficients and $w_{i.}$ are the weights depending on a distance function $d_{i.}$. The model is estimated through a single-stage approach, providing benefits in terms of modeling of the error term ϵ_{it} and the inefficiency component v_{it}: indeed, the latter can be instrumented according to the function $h(\cdot)$, $\mathbf{x}_{uit}$, and also through u_i^*, that is the producer-specific random component. Moreover, ρ is introduced in the variance-covariance matrix of ϵ_{it}, allowing to model the correlation between ϵ_{it} and v_{it}. This choice ensures u_{it} and v_{it} are conditionally independent given $\mathbf{x}_{it}$ and $\mathbf{Z}_{it}$ and addresses the potential endogeneity existing between the error term and the inefficiency component. Equation 3 can be estimated using a weighted panel SFA procedure. A flow diagram of the estimation sequence is shown in Figure 1.

The consistent local estimates of technical inefficiency obtained through the novel specification allow to move to the final stage of the process, which involves the identification of the heterogeneous responses of firms to a specific disturbance: this concluding step is critical to assess whether any detected asymmetries can be associated with specific territorial patterns and to isolate clusters of producers who perform similarly after the shock. The possibility to implement this analysis is associated with one of the strengths of the model, that is the possibility to study the local dynamics of technical efficiency for each producer over a specific period of time: following Bouveyron et al. (2015), we use the estimated temporal dummies on v_{it} to implement a functional mixture model which allows the clustering of the individual time trends in a discriminative functional subspace and the visualization of the clustered systems.[4] Using this approach, it is possible to initially obtain individual functional curves, representing individual smooth basis or single realizations of a latent functional process (Ramsay & Silverman, 2005). The data are then aggregated using clustering algorithms for finite dimensional data (Jacques &

[4]Such an approach is one of the possible alternatives to estimate clusters of functional data. Alternative methodologies have been proposed by Sugar (2003) and applied by Ieva et al. (2013).

Preda, 2014), in an attempt to identify similar spatial trends in the data. The main benefit of this procedure is that spatial boundaries are not imposed a priori by the researcher, but rather identified through a data-driven approach which captures the nonstationary nature of spatial processes. We can thus overcome one of the major limitations associated with the existing empirical contributions on resilience: indeed, regions are almost always identified using administrative boundaries, which tend to disguise the complexities of local networks.

4 | AN APPLICATION TO THE ITALIAN WINE INDUSTRY

The purpose of this section is to use the GWR-panel SFA approach to describe the recent dynamics of the Italian wine industry: as explained in the following subsection, firm-level performances in this sector have been heavily influenced by a major institutional change, generating heterogeneous responses in the different local contexts. The empirical analysis is performed using an unbalanced panel of wine producers active during the 2009–2014 period, exploiting the benefits of a detailed database, whose structure is briefly described in Section 4.2. Given the period considered in the analysis is the one immediately following a relevant regulatory change, the results will allow to evaluate the initial resistance of winemakers to this disturbance: according to the literature, it is expected to detect higher asymmetry in the reaction of local actors during the years immediately following the disruption (Fingleton et al., 2012). Moreover, the role of territorial factors is expected to be particularly relevant in explaining resilience dynamics: indeed, according to Battaglini et al. (2015), farm resilience is associable to the specific form in which the local community "reinterprets and transforms local heritage for its own use." Hence, resilience can be described as a process in which the communities settling in a place "perceive the specific nature of that place, attributing symbols to its resources and to its local peculiarities and thus reunifying, structuring and organizing it" (Paloviita & Jarvela, 2015).

Given the above mentioned factors, the GWR-panel SFA approach is expected to provide more support to interpret the efficiency trends compared to the standard SFA frameworks. The model is preliminarily estimated using the traditional panel SFA approach (Section 4.3), which assumes a global trend for technical efficiency. The analysis shows the presence of significant spatial effects that are expected to affect the estimation of the inefficiency term. To address this issue, the GWR-panel SFA model is used in Section 4.4: the results highlight the effectiveness of the alternative approach in detecting the different dynamics of technical efficiency.

4.1 | The Italian wine industry: Stylized facts and the impact of the 2008 CMO reform on producers' performances

In Italy, winemaking has a long-established tradition and is the product of a vast, heterogeneous, and articulated sector. Unlike other competing countries, Italy can rely on a large number of producers concentrated in territorial clusters and operating in a wide range of locations, including coastal plains, rolling hills, and mountainous areas. As a result, wine production is extremely diversified in terms of enological typology, production technology, and unit value of products. The above determinants contribute to explain the leading position held by this country in the global market: in 2015, Italy's share of world wine production was equal to 18.2%, generating a revenue of 12.9 billion euro (International Organisation of Vine & Wine (OIV), 2017; Mediobanca, 2017). Italy is one of the leading producers in the EU, which is itself the largest global wine-producing region and the main importer and exporter of wine, but also a highly regulated market (Meloni & Swinnen, 2013).

During the last two decades, the wine sector has witnessed profound changes in the competitive environment, driven by the emergence of New World producers (United States, Australia, Chile, Argentina, South Africa) in the global market (Cusmano, Morrison, & Rabellotti, 2010; Morrison & Rabellotti, 2017). The rise of these new competitors has often been associated with their superior ability to satisfy the emerging demand for more standardized wines, exploiting the lack of rigid regulatory constraints such as those imposed by the EU (Itçaina, Roger, & Smith, 2016). The changing competitive scenario has negatively affected the main EU wine producers, including Italy, generating the need for a major reform to regain market share. In response to these pressures, the EU implemented the CMO reform, reorganizing the way the EU wine market was managed: the new law was negotiated remarkably quickly in the autumn of 2007 and adopted in April 2008 with little opposition from the governments of producer states and growers' organizations (Itçaina et al., 2016). The reform had a major impact on the sector, removing the strict regulation of enological practices and wine labeling and fostering the emergence of a market-driven approach focused on promotion, marketing, and structural investment. The new regulation was aimed at stimulating market selection mechanisms, generating advantages for the most efficient wineries at the expense of marginal producers (Morrison & Rabellotti, 2017).

Given a prerequisite for any work on resilience is to properly identify a shock, a key question is whether the institutional change occurred in 2008 can be regarded as a significant disruption. A number of empirical methodologies have been proposed in the literature to address this issue (Balland, Rigby, & Boschma, 2015). In this paper, we formally test the presence of a shock in the Italian wine sector by implementing the Chow test (Chow, 1960) for the presence of structural breaks in a time series. Given the analysis is focused on technical efficiency, the test is implemented on labor productivity data, focusing on the Italian wine industry, as well as on the manufacturing sector and the Italian economy for the 2004–2016 period (Figure 2). The data are extracted from the Italian Bureau of Statistics (ISTAT) data warehouse (section *Enterprises—Competitiveness*). Monetary values are calculated in real terms, deflating nominal values with producer price indices. The results of the test for year 2008 confirm the presence of a structural break in the wine industry ($F = 10.28$, $p < .05$), whereas the null hypothesis of no structural break could not be rejected for the manufacturing sector ($F = 2.36$, $p = .21$) and for the entire economy ($F = 2.17$, $p = .23$). As expected, in the latter two cases the structural break is significant for year 2009 and can be associated with the global financial crisis.

In light of the above findings, it is reasonable to expect asymmetric reactions among wine producers in the years immediately following the 2008. Such asymmetry is likely to be heavily influenced by local environmental factors, considering the strong linkages existing between agricultural activities and the territory, and the key role played by soil, climatic, and morphological characteristics, but also by intangible factors, such as historical traditions and the local learning processes, in explaining the performance dynamics of most farm holdings (Beebe, Haque,

FIGURE 2 Labor productivity, wine industry, manufacturing industry and Italian economy, period 2004–2016 [Color figure can be viewed at wileyonlinelibrary.com]

Jarvis, Kenney, & Patton, 2012; Morrison & Rabellotti, 2017; Turner, 2009; Vidoli, Cardillo, Fusco, & Canello, 2016). The relevance of the place in explaining local responses after shocks can also be explained through the influence played by specific producers operating in the area: Giuliani et al. (2015) have provided evidence of the key role played by anchor firms in supporting local wine producers during sudden and unexpected adversities.

Given the above premises, a robust analysis of the performance dynamics in the winemaking sector should be supported by empirical tools which allow to account for the major influence played by spatial factors in determining economic outcomes. In this respect, the structure of the GWR-panel SFA approach seems to be particularly appropriate for the aim of the proposed investigation.

4.2 | Italian Farm Accountancy Data Network (FADN) survey: the data source used for the empirical analysis

The FADN is a yearly survey carried out by the Member States of the EU to systematically collect accountancy data on incomes and business operations of agricultural holdings in the European Economic Community. This database includes all the agricultural holdings having an economic size equal to or greater than a minimum threshold, that is, that identified to be considered commercial. The selection of the units taking part to the survey is carried out according to sampling plans defined at the national level, following the guidelines and recommendations provided by the European Commission to ensure the representativeness of the selected sample. The common methodology applied by all the Member States (Council Regulation (EC) No.: 1217/2009) aims to provide representative data along three dimensions: region, economic size, and type of farming.

The Italian section of the survey is based on the Agricultural Census, updated on a 2-year basis by the Farm Structure Survey carried out by the ISTAT: this main data source is complemented with further sources of agricultural statistics. The main benefits of this database are associated with the wide number of variables referring to physical and structural data, such as location, crop areas, livestock units, labor force, but also to the economic and financial information, such as the value of production, stocks, sales and purchases, production costs, assets, liabilities, production quotas, and subsidies. More than 1,000 variables are present in the FADN survey, allowing to harmonize information within different countries. The survey has some limitations in that it tends to over represent commercial holdings and the publication of data is significantly delayed (Hill, 2012; Keenleyside, Tucker, & McConville, 2010). Furthermore, the representativeness of the sample decreases when the focus moves from the regional to the provincial level (Gigante, Arfini, & Donati, 2014).

In this paper, an unbalanced panel of 330 wine producers was extracted from the Italian FADN database for the 2009–2014 period. The total number of observations over the 6 years is equal to 1,480, with information available for four or more years in 75% of the considered cases. The sample includes farms classified as "specialist vineyards" (code 35) according to the TF14 Grouping classification, with the great majority of producers specialized in quality winemaking (subdivision 351). Most of these farms are small businesses registered as sole proprietorship (91%) and employing an average of only 2.5 workers. As already stated, this time period is of particular interest as it allows one to evaluate the effects of the major structural transformations which have influenced the sector and affected farm holdings' performance. Using this sample, the application presented in the following sections compares the results of the traditional panel SFA approach with those of the GWR-panel SFA model, showing the benefits associated with the use of the new methodology.

4.3 | Technical efficiency estimation: Baseline model and identification

The production function of the Italian wine producers is initially estimated using a panel SFA specification with time-varying inefficiency (Battese & Coelli, 1992) as the baseline model, focusing on the relationship between output and its main inputs.

This model is the simplest yet most cited specification among the panel SFA models. Starting from the traditional specification of the panel SFA:

TABLE 1 Estimation results using the Battese and Coelli (1992) approach

	Coef.	SE	z	p > z	95% CI
Labor input (log)	0.398	0.029	13.61	.000	0.340–0.455
Machinery input (log)	0.264	0.029	8.84	.000	0.206–0.323
Land input (log)	0.384	0.025	15.41	.000	0.335–0.433
Constant	0.904	0.267	3.38	.001	0.380–1.428
μ	1.543	0.215	7.20	.000	1.123–1.963
η	−0.004	0.003	−1.04	.299	−0.010–0.003
σ^2	0.657	0.031			0.599–0.720
γ	0.642	0.018			0.605–0.677
σ_u^2	0.422	0.031			0.362–0.482
σ_v^2	0.235	0.007			0.222–0.248

Abbreviation: CI, confidence interval.

$$\ln y_{it} = \mathbf{x}'_{it}\beta + v_{it} - u_{it}, \forall\, i, \tag{4}$$

where $y_{it} \in \mathbb{R}_+$ is the output of unit i for time t, $\mathbf{x}_{it} \in \mathbb{R}_+^p$ is the vector of inputs, v_{it} is the symmetric two-sided error representing random effects and $u_{it} > 0$ is the one-sided error term which represents technical inefficiency, Battese and Coelli (1992) impose a specific pattern of temporal inefficiency variation for all producers, modeling $u_{it} = f(t)u_i$ and defining $f(t) = \exp[\eta(t - T)]$, where T is the upper limit for time and η is the unknown parameter describing how inefficiency evolves over time. When $\eta > 0$, the efficiency level increases during the considered period. In all the following sections, the production function is specified using total wine quantity produced (in tonnes) per year as the dependent variable, while the following covariates are used to define the production technology and to measure technical efficiency:

- *Labor input* = total number of hours worked per year;
- *Capital input—Machinery* = machinery power (kW);
- *Capital input—Land* = agricultural area (ha).

Table 1 reports the results of the classical Battese and Coelli (1992) specification and shows that the covariates are significantly different from zero and the signs are those expected. The values of the parameters (σ^2 and γ) confirm the appropriateness of applying a SFA model: indeed, a relevant share of the deviation from the frontier can be attributed to technical inefficiency ($\gamma = 0.64$), while only 36% or this variation is associable with noise. Furthermore, the variance of the error term (σ_u^2) is half of that of the inefficiency term (σ_v^2). Last but not least, the coefficient of the temporal pattern of efficiency η is not significant, suggesting that technical efficiency is time-invariant in the sample of farm holdings considered.

As discussed in Section 3, two major limitations are associated with this baseline specification. First, the assumption that the inputs are exogenous might be violated, given the three factors of production are possibly correlated with the output, the v term or both. In the context of agricultural production, explanatory variables can be endogenous for a number of reasons (Amsler et al., 2016), including the fact that the farmer may be aware of his v and this may affect his input choices. Second, assuming the presence of a single temporal pattern of performances might be an additional source of bias, considering the peculiarities of the sector and the presence of a major disturbance during the time period considered: given the local responses of firms are expected to be highly asymmetric, ignoring the spatial factors is likely to generate biased results. In other terms, our interpretation of the coefficient of η might be biased by the presence of spatial nonstationarity in the data.

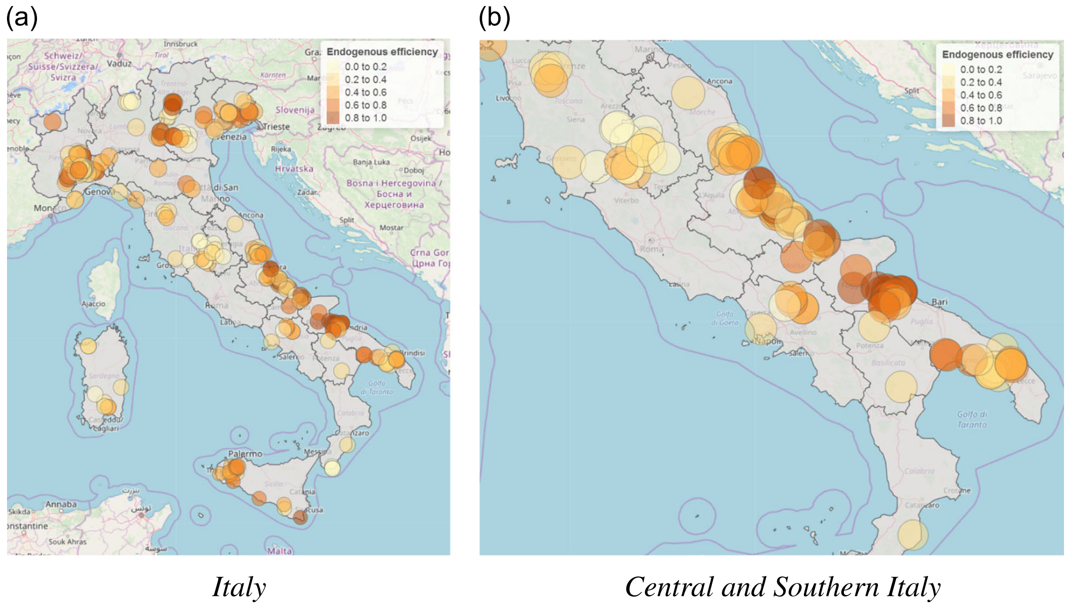

FIGURE 3 Territorial distribution of the estimated panel SFA efficiency scores. SFA, stochastic frontier analysis [Color figure can be viewed at wileyonlinelibrary.com]

Some preliminary evidence of the above issue emerges from the graphical analysis in Figure 3a, which shows the territorial distribution of the individual performances for all wine producers included in the sample. The map highlights the presence of several homogeneous areas, both in Northern and Southern Italy, characterized by similar firm-level efficiency scores: the zoom over the Central and Southern regions (Figure 3b) highlights some examples of areas characterized by significant spatial patterns, with high-efficiency scores for producers located in specific neighborhoods. The presence of spatial correlation among efficiency scores is formally evaluated using Geary *C* test[5]: the value of the statistic (0.61) suggests the presence of spatial similarities among territories and leads to reject the null hypothesis of spatial independence of farm holdings' performances.

In light of these findings, assuming the presence of a single global trend η for technical efficiency seems inappropriate to evaluate the dynamics of firm-level performances: this is particularly true considering that the time frame of the survey follows a period of relevant structural and economic transformations and that the literature has shown that local responses tend to be highly heterogeneous under these circumstances.

4.4 | Technical efficiency estimation using the geographically weighted panel SFA approach with endogenous covariates

The results of the previous subsection highlight the need to implement an alternative approach to account for both the endogeneity and the spatial nonstationarity in the data. In this respect, the GWR-Panel SFA framework outlined in Equation 3 seems particularly suitable to address the two issues emerged in the baseline model. In this subsection, we preliminarily estimate the Karakaplan and Kutlu (2017b) model (Equation 2) to embed the endogeneity problem into the SF specification and to instrument the inefficiency term u; following this, we incorporate the GWR approach to locally estimate the model and to obtain local estimates for all parameters.

[5]The value of Geary *C* lies between 0 and 2. Values lower than 1 provide evidence of increasing positive spatial autocorrelation, whereas values higher than 1 indicate increasing negative spatial autocorrelation. $C = 1$ is consistent with no spatial autocorrelation in the data.

TABLE 2 Estimation results using the endogenous panel stochastic frontier analysis approach in the style of Karakaplan and Kutlu (2017b)

	Coef.	*SE*	*z*	*p* > *z*	95% CI
Dependent variable: ln(Output)	Frontier estimation				
Labor input (log)	0.425	0.036	11.87	.000	0.355–0.495
Machinery input (log)	0.109	0.040	2.76	.006	0.032–0.187
Land input (log)	0.468	0.028	16.45	.000	0.413–0.524
Constant	0.239	0.223	1.07	.285	−0.199–0.676
Instrumental variable estimation for input: Labor					
Labor input—*lagged* ($t-1$)	0.836	0.015	57.34	.000	0.807–0.865
Machinery input—*lagged* ($t-1$)	0.025	0.013	1.93	.053	0.000–0.051
Land input—*lagged* ($t-1$)	0.069	0.011	6.12	.000	0.047–0.091
Constant	0.748	0.085	8.83	.000	0.582–0.914
Instrumental variable estimation for input: Capital—Land					
Labor input—*lagged* ($t-1$)	0.014	0.008	1.77	.077	−0.002–0.030
Machinery input—*lagged* ($t-1$)	0.000	0.007	−0.07	.946	−0.014–0.013
Land input—*lagged* ($t-1$)	0.982	0.006	166.75	.000	0.970–0.993
Constant	0.011	0.048	0.23	.817	−0.083–0.106
Instrumental variable estimation for input: Capital—Machinery					
Labor input—*lagged* ($t-1$)	0.015	0.011	1.33	.182	−0.007–0.036
Machinery input—*lagged* ($t-1$)	0.945	0.009	110.5	.000	0.928–0.962
Land input—*lagged* ($t-1$)	0.015	0.010	1.53	.126	−0.004–0.035
Constant	0.052	0.051	1.02	.309	−0.048–0.152
Dependent variable: $ln(\sigma_u^2)$	Inefficiency term				
Dummy year 2010	−0.023	0.112	−0.21	.835	−0.243–0.196
Dummy year 2011	0.017	0.102	0.16	.870	−0.184–0.217
Dummy year 2012	0.075	0.104	0.72	.469	−0.128–0.278
Dummy year 2013	0.038	0.103	0.37	.714	−0.165–0.241
Dummy year 2014	0.120	0.104	1.15	.249	−0.084–0.323
Size (revenues in million euro)	−7.399	1.372	−5.4	.000	−10.088 to −4.711
Subsidies received from the EU (% of revenues)	0.029	0.006	4.97	.000	0.017–0.040
% of land owned	−0.005	0.002	−2.11	.035	−0.009–0.000
Slope disadvantage	0.457	0.188	2.43	.015	0.088–0.826
Constant	0.402	0.245	1.64	.101	−0.079–0.882
Dependent variable: $ln(\sigma_w^2)$					
Constant	−1.845	0.046	−40.24	.000	−1.935 to −1.756

The results of the baseline endogenous model are reported in Tables 2 and 3. As shown in Table 2, this specification extends the baseline SFA model presented in the previous section in two major directions:

1. It incorporates the 1-year lags of the endogenous inputs in the instrumental frontier estimation to prevent the endogeneity bias, following a commonly used strategy in applied economics research (Reed, 2015) and in productivity and efficiency analysis (Billé et al., 2018; Bolli et al., 2016; Wooldridge, 2009);
2. It includes a set of firm-level endogenous covariates to instrument the inefficiency term using a single-step approach. This methodology removes the effect of factors linked to the individual production unit.

The analysis of the results provides some important indications in support of the validity of the model: indeed, the comparison between the standard and the corrected specification (Table 3) shows how the input coefficients

TABLE 3 Endogenous versus exogenous panel stochastic frontier analysis regression results

	Exogenous model		Endogenous model	
Dependent variable: ln(Output)		Frontier estimation		
Constant	0.819***	−0.238	0.239	−0.223
Labor input (log)	0.306***	−0.037	0.425***	−0.036
Machinery input (log)	0.142***	−0.039	0.109**	−0.04
Land input (log)	0.513***	−0.035	0.468***	−0.028
Dependent variable: $ln(\sigma_u^2)$		Inefficiency term		
Constant	0.472	−0.242	0.402	−0.245
Dummy year 2010	−0.020	−0.102	−0.023	−0.112
Dummy year 2011	0.015	−0.093	0.017	−0.102
Dummy year 2012	0.059	−0.095	0.075	−0.104
Dummy year 2013	0.015	−0.095	0.038	−0.103
Dummy year 2014	0.099	−0.095	0.120	−0.104
Size (revenues in million euro)	−6.107***	−1.122	−7.399***	−1.372
Subsidies received from the EU (% of revenues)	0.027***	−0.005	0.029***	−0.006
% of land owned	−0.004*	−0.002	−0.005*	−0.002
Slope disadvantage	0.413*	−0.183	0.457*	−0.188
Dependent variable: $ln(\sigma_v^2)$				
Constant	−1.877***	−0.046		
Dependent variable: $ln(\sigma_w^2)$				
Constant			−1.845***	−0.046
η endogeneity test			$\chi^2 = 21.01$	$p = .000$

Asterisks indicate significance at the ***0.1%, **1% and *5% levels.

change when the exogenous instruments are included. The presence of endogeneity is formally tested using the standard Durbin–Wu–Hausman test, which leads to reject the null hypothesis of no endogenous inputs: therefore, endogeneity is present in the data and correction for this bias is needed to obtain consistent estimates of the frontier. It is also worth noting that the set of firm-level covariates included in the model is significant and the signs are consistent with our expectations. The analysis of the estimated effects confirms some previous relevant findings of the literature: more specifically, a higher relative amount of EU subsidies received by the farm is associated with a lower level of technical efficiency (positive sign of the coefficient): this finding is consistent with the results of the meta-analysis implemented by Minviel and Latruffe (2017), showing that in most cases subsidies are found to be detrimental for the performances of agricultural producers. The percentage of land owned by the farmer is another relevant factor in our analysis, consistently with Amsler et al. (2016): not surprisingly, a larger share of land ownership is likely to improve the performances of wine producers, and this can be associated with a number of factors, including the higher incentives to invest (Feder & Onchan, 1987; Jacoby, Li, & Rozelle, 2002). Finally, a smaller size and the location in a disadvantaged area in terms of slope inclination and slope exposure negatively affects firm-level performances.[6]

[6]Additional estimations were conducted to evaluate the role played by two important determinants of technical efficiency. First, the organizational form chosen by the farm holding was considered, following the recent findings in the literature on the role of this factor in influencing performance in the wine industry (Brandano, Detotto, & Vannini, 2019; Maietta & Sena, 2010). Second, a proxy for climatic conditions was also considered as a possible determinant for technical efficiency. The proxy we identified was a dummy variable associated to the "climate disadvantage," defined according to a set of criteria defined by the European Commission (Jones, Reid, & Vilks, 2012). This proxy is based on four agroclimatic indicators related to the average temperatures and soil dryness (regardless of the crop type). The results of the estimations, available upon request, show that these two variables are not significant in explaining performance differences in the considered sample.

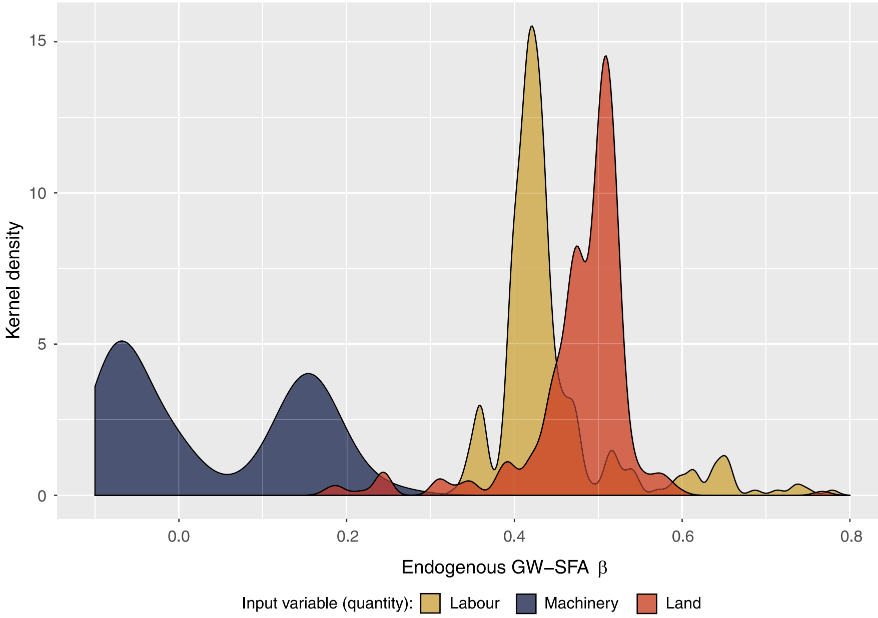

FIGURE 4 Kernel distribution of the input coefficients β varying reference unit i [Color figure can be viewed at wileyonlinelibrary.com]

Once the endogeneity issue is addressed, the following step is to integrate the GWR approach in the Karakaplan and Kutlu (2017b) model and locally estimate the coefficients according to Equation 3; as explained in Section 3, the procedure requires the preliminary identification of a vector of $n-1$ weights $w_{i\cdot}$ for each firm, which is based on the distances between unit i and the other $n-1$ producers. In this application, the spatial weights are calculated using the OpenStreetMap software, identifying the point to point time distances between the vineyards along the road network with the default maximum speed for trucks[7]: the main advantage of this approach is that it allows to account for the orography of the territory and to evaluate the actual distances between the firms that are included in the sample. The weight vector $w_{i\cdot}$ is subsequently used to estimate n weighted frontiers (one for each unit i) and to identify n different values for the coefficients of both the covariates and instrumental variables.

Figure 4 provides a first piece of evidence of the validity of the specification. The graph shows how the values of input coefficients vary significantly depending on where the model is estimated: the only exception is represented by the land input, whose elasticities appear to remain stable regardless of the area where the estimation is performed. Conversely, the elasticities of both machinery and labor inputs appear to be heavily affected by the location of the farm holding. Overall, the results highlight the presence of spatial nonstationarity that is inevitably overlooked when a global production function is estimated.

4.5 | Space-time patterns of farms' performances and the role of environmental and institutional factors

The consistent local estimates obtained through the novel approach proposed in this paper can be used to derive different temporal patterns of farm-level efficiency: in this specific application, the presence of different dynamics

[7]We would like to thank the Geodienst group of the University of Groningen for the support provided to calculate the distance matrix.

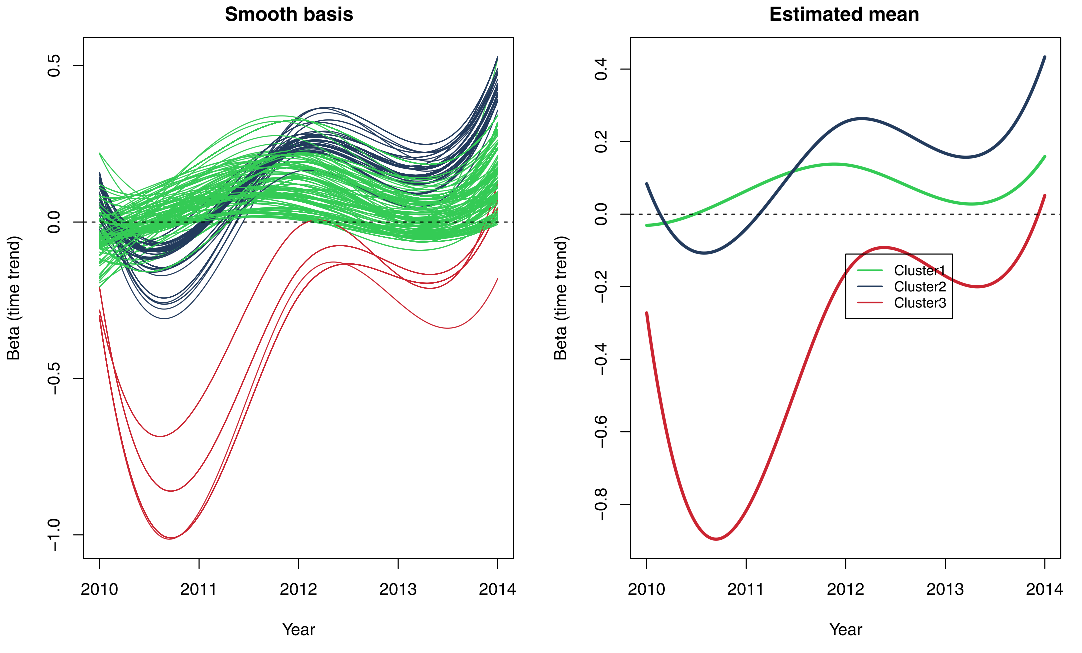

FIGURE 5 Smooth trend basis and functional clusters [Color figure can be viewed at wileyonlinelibrary.com]

mirror the heterogeneous responses of wine producers to a specific institutional change, that is, the 2008 CMO reform. To derive these heterogeneous patterns, we extract the estimated temporal dummies on v_{it} for the 2009–2014 period, using the 2009 as reference year, and we apply a functional mixture model to cluster the individual time trends in a discriminative functional subspace (Ramsay & Silverman, 2005).

Figure 5a shows the smooth basis functions for each wine producer *i* included in the sample, highlighting the presence of three groups of homogeneous temporal patterns identified through the clustering approach. The three main trends are summarized using an individual trend curve for each cluster in Figure 5b and shows the presence of three groups of farm holdings which responded differently during the period following the 2008 CMO reform. The first two homogeneous groups include the majority of wine producers and highlight the presence of some clearly distinguished territorial patterns. On the one hand, Cluster 1 is mainly populated by those farms which experienced a declining trend after the institutional transition, with negative performances especially in the period following 2011; on the other hand, Cluster 2 includes those producers who managed to achieve more stable performances after 2008, showing higher levels of resilience to the institutional shock. Finally, Cluster 3 identifies a small group of winemakers which have significantly increased their efficiency, especially in the period immediately following 2008. The geographical distribution by functional cluster (Figure 6) highlights the presence of specific territories characterized by homogeneous temporal patterns of technical efficiency: for example, producers operating in the Montepulciano (Abruzzo) and Lison Pramaggiore (Friuli) regions appear to belong almost entirely to Cluster 2, while the Marsala (Sicily), the Langhe (Piedmont), and the Collio (Friuli) regions are characterized by the widespread presence of firms belonging to Cluster 1. Figure 6 also show that farms of Cluster 3 tend to be territorially scattered throughout the country and suggest that their performances are driven by their individual strategies rather than by the influence of their local peers: however, it is also worth noting that these producers are more likely to be located in areas characterized by higher levels of resilience. An important takeaway from this analysis is that regional industrial resilience can be investigated more effectively when the territorial boundaries are identified through a data-driven approach rather than being imposed a priori: this aspect emerges distinctly for some areas such as Friuli and Veneto (Figure 6b), where the spatial patterns are found to be significantly different even within the same region.

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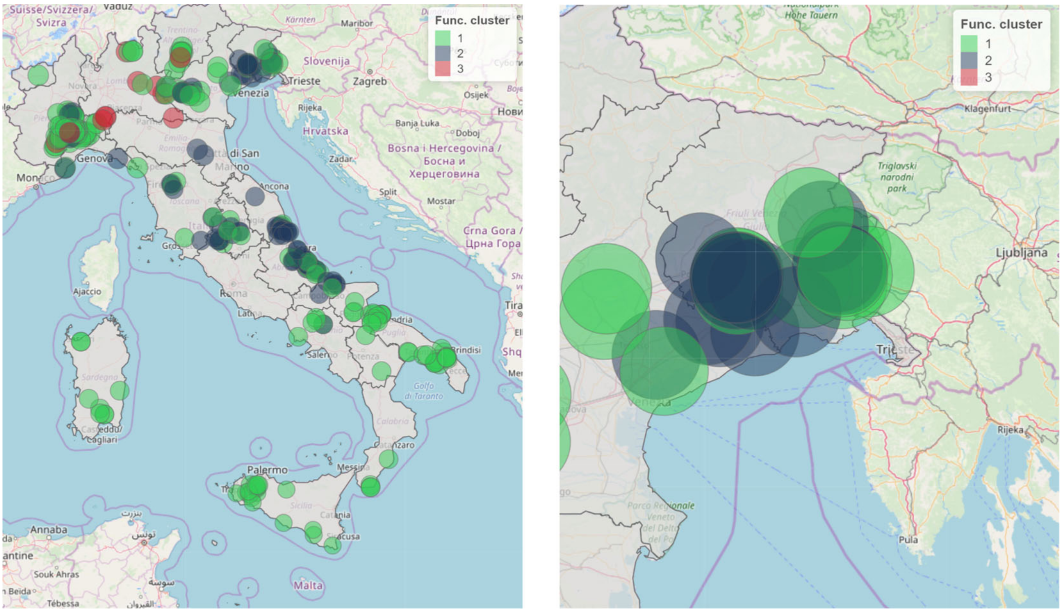
(a) (b)



Italy *Veneto and Friuli regions*

FIGURE 6 Territorial distribution of wine producers by functional cluster [Color figure can be viewed at wileyonlinelibrary.com]

As a final step of this analysis, we verify whether the heterogeneous space-time patterns identified in the data can be associated with a set of exogenous factors that are generally linked with higher levels of resilience in the literature. This exploratory evidence is provided using a simple *t* test of the difference between means in the clusters identified by the procedure. The analysis is focused on Clusters 1 and 2, that is, the two groups where the majority of farm holdings are included. The set of environmental and institutional variables selected for the analysis includes:

- *Social capital*: share of local population employed in the nonprofit sector,
- *Institutional quality*: administrative capability of local government,
- *Export propensity*: value of exports per capita in the region,
- *Value added*: value added per capita in the region,
- *Firm mortality*: share of firms that did not survive at the end of the year,
- *Innovation propensity*: number of patents registered at the European Patent Office for millions of inhabitants,
- *Risk of financing*: risk level associated with loans provided to firms in the region,
- *Unemployment rate*: people aged 15 or more looking for occupation over total labor force.

The data refer to the province where the farm is located and are extracted from the ISTAT website. Information on institutional quality is retrieved from Nifo and Vecchione (2014). The environmental and institutional variables are calculated for 2008, which is the year in which the CMO reform was adopted by all the EU member countries, including Italy.

The results of the tests, reported in Figure 7 and Table 4, show that the mean value of some of the selected variables is significantly different in the two clusters considered. More specifically, the group of relatively better performing farm holdings (Cluster 2) is located in areas characterized by higher propensity to export, lower unemployment rates and lower risk of financing, which is generally associated with more access to credit. In this

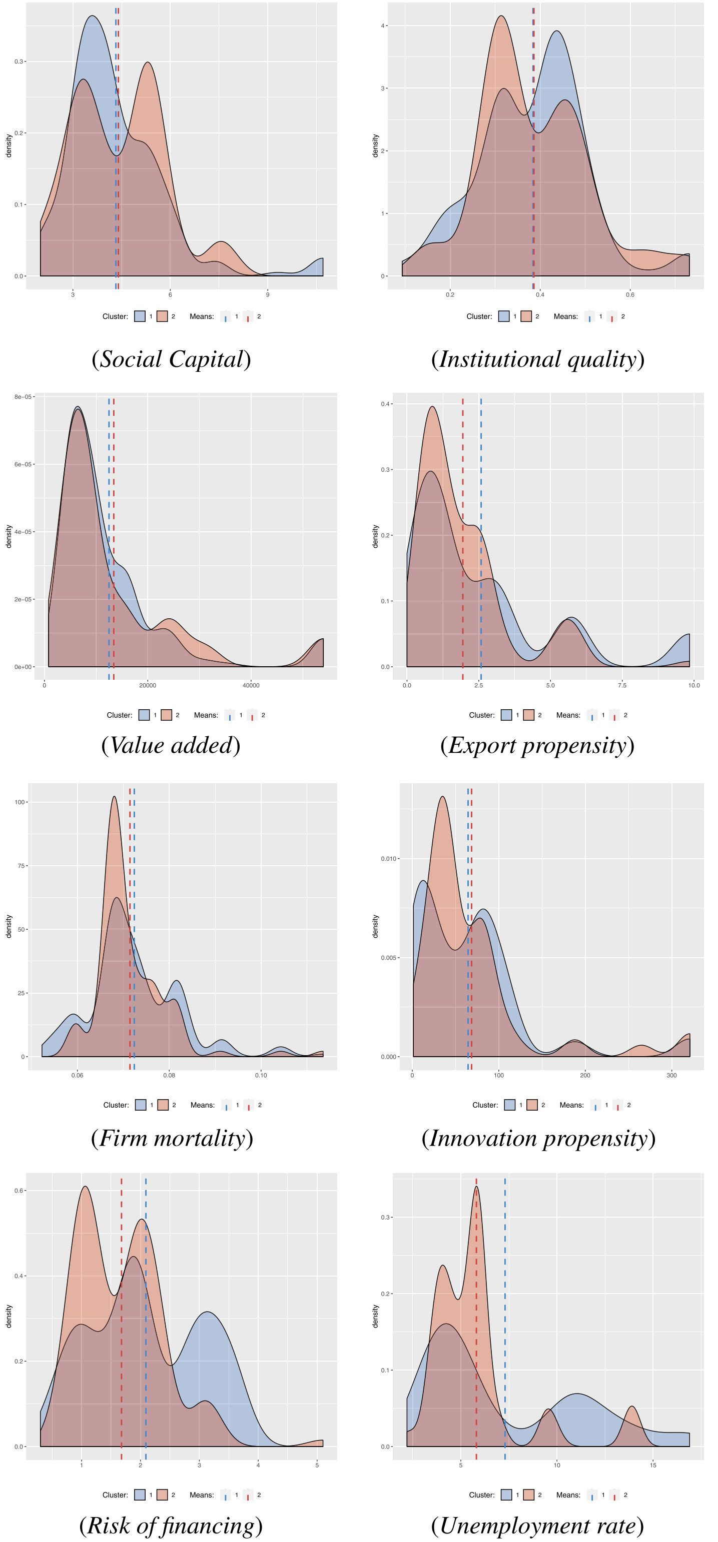


FIGURE 7 Kernel distribution and average values of environmental and institutional variables, functional cluster 1 vs 2 [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Welch two sample *t* test, functional cluster 1 versus 2

Variable by functional cluster (1 vs. 2)	*t* test	df	*p* value	Mean cluster 1	Mean cluster 2
Institutional quality	−0.130	198.82	0.895	0.384	0.386
Export propensity	−2.842	200.92	0.005	6209.295	7792.936
Firm mortality	0.868	242.66	0.386	0.072	0.071
Social capital	−0.434	219.80	0.664	4.323	4.401
Risk of financing	4.143	242.47	0.001	2.091	1.677
Innovation propensity	−0.475	193.99	0.634	64.482	68.588
Unemployment rate	3.770	276.61	0.001	7.300	5.811
Value added	−0.609	178.67	0.542	12495.18	13417.96

respect, our findings support those of previous contributions in the literature, showing that resilient firms tend to be located in areas characterized by higher competitiveness even before the shock (Fratesi & Rodríguez-Pose, 2016). Nonetheless, it is also worth highlighting that certain contextual factors generally associated with higher levels of resilience (such as social capital, institutional quality, and innovation propensity) are not found to be significantly different in the two main clusters considered. This finding suggests that the dynamics of a specific industry might not always mirror that of the entire region or of the entire economy, and that macro-environmental and institutional factors might not necessarily be sufficient to explain better performances of a specific subset of producers located in a specific subregion. In this respect, the empirical approach to be used to explain regional industrial resilience using firm-level data should be different from that proposed to interpret regional resilience from a macro perspective.

5 | FINAL REMARKS

This paper has introduced and discussed a new empirical procedure to investigate space-time patterns of regional industrial resilience using a micro-level approach. Our geographically weighted panel SFA model with endogenous covariates adds a new dimension to our current understanding of economic resilience, providing a robust empirical tool to evaluate territorial performance dynamics after a sector-specific disturbance through a firm-level perspective. The recent empirical contributions in this field of research suggest that shocks often trigger asymmetric responses among the affected actors, generating patterns that tend to be homogeneous within the same territory and heterogeneous between different regions: in this respect, the new methodology is particularly beneficial in that it allows to identify spatial regimes of firms who display similar performances after a specific disturbance, without relying on territorial boundaries imposed a priori.

The procedure has been tested on a sample of farm holdings operating in the Italian wine industry for the 2009–2014 period. This sector is relevant for the present analysis for two main reasons: first, the role of spatial factors is particularly prominent, considering the strong connections existing between agricultural activities and the local territories, as well as the key role played by climatic and morphological characteristics but also by historical traditions in explaining the performance dynamics of most wine producers (Morrison & Rabellotti, 2017). Second, the European wine industry has been affected by a major restructuring after 2008, following the CMO reform adopted by the EU to address the persisting oversupply of wine and stimulate the development of efficient practices in the sector: this institutional shock is believed to have had a major impact on most wine producers, triggering heterogeneous responses in the different regions.

The results show the effectiveness of the new procedure in identifying spatial heterogeneity, while correcting for endogeneity in the data. More specifically, the values of input coefficients for wine production are found to vary significantly depending on where the model is estimated, highlighting the presence of spatial nonstationarity that is inevitably overlooked when a global production function is estimated. In this respect, the paper also provides a methodological contribution in the field of efficiency and productivity analysis, improving the existing panel stochastic frontier specifications. Additionally, the implementation of a functional mixture model on the estimated temporal dummies allows to identify three clusters of wine producers displaying responses to the institutional shock that are homogeneous within specific territories and heterogeneous between different regions. The results show that the majority of farm holdings are concentrated in two clusters, one of which is characterized by higher ability to react to the institutional shock. The third homogeneous group identifies a small subset of producers showing a particular ability to adapt to the changing circumstances, increasing their performances during the considered period: despite being territorially scattered throughout the country, most of these producers tend to be located in areas characterized by higher levels of regional industrial resilience.

As a final exploratory test, we evaluate the heterogeneous space-time trends identified in the data through a set of exogenous factors often associated with higher levels of regional resilience. The exploratory evidence, provided using a simple *t* test of the difference between means, shows that, among the two large clusters of farm holdings, the one including relatively better performing producers is located in areas characterized by higher propensity to export, lower unemployment rates and lower risk of financing, which is generally associated with more access to credit. In this respect, our findings support those of previous contributions in the literature, showing that resilient firms tend to be located in areas characterized by higher competitiveness even before the shock (Fratesi & Rodríguez-Pose, 2016). Nonetheless, it is also worth highlighting that certain institutional factors generally associated with higher levels of resilience (such as social capital, institutional quality, and innovation propensity) are not found to be significantly different in the two main clusters considered. This finding suggests that the dynamics of a specific industry might not always mirror that of the entire region, and that environmental and institutional factors might not necessarily be sufficient to explain better performances of a specific subset of firms located in the region. In this respect, the empirical approach to be used to explain regional industrial resilience should probably be different from that proposed to interpret regional resilience from a macro perspective.

Some important policy implications stem from this analysis. In the introductory section, we have highlighted the benefits of the proposed model for policy makers willing to develop place-based strategies, overcoming the limitations of the traditional one-size-fits-all development policies. In most cases, place-based approaches tend to be more effective in that they exploit the potential of both the territories and the individuals that live and interact in them (Barca, 2009; Barca et al., 2012; OECD, 2009). However, one should also be aware of the potential pitfalls of these approaches: more specifically, the transaction costs associated with designing effective policies at the spatial cluster level could be too high, hampering their effectiveness in the long term. Moreover, such interventions might postpone necessary adjustments, as well as create dangerous dependencies at the local level (Kilkenny & Kraybill, 2003).

This investigation opens some interesting avenues for further research. More specifically, the GWR-panel SFA model can be estimated using a profit function, in an attempt to better evaluate the variations in output quality among the different producers. This aspect is extremely relevant, considering that Italian wines are highly diversified in terms of both enological typology and unit value of products, and also that one of the objectives of the 2008 reform was to reduce wine production and improve the competitiveness of wine producers. Finally, the same empirical methodology can be used to study resilience to adverse economic shocks in other sectors characterized by strong territorial patterns. In this respect, the end of the Multi Fiber Agreement (MFA) in 2005 represents an interesting example of a large and well-identified shock that has affected a specific sector (the textile-clothing industry) in several developed countries (Behrens et al., 2019). Using firm-level data from one of the affected countries and following the GWR-panel SFA approach, it would be possible to detect the heterogeneous responses of local actors to this shock in a quasiexperimental setting.

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ORCID

Jacopo Canello http://orcid.org/0000-0002-7510-7238
Francesco Vidoli http://orcid.org/0000-0003-4125-9337

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