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Dynamic and spatial approaches to assess the impact of geographical indications on rural areas

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ABSTRACT

The paper explores the role of Geographical Indications (GIs) in promoting the economic development of European regions. We consider all NUTS3 regions of Italy, France, and Spain between 1993 and 2014, and 728 GIs.. Our research aims to empirically assess the impacts of GIs on labor productivity and employment, for the agricultural and industrial sectors. We rely on a dynamic panel model and considere the spatial variation of the data. The main results show that GIs generate a positive impact on employment, both in the short and the long-run. Moreover, we find that the impact of GIs is not limited to the province where they are produced, but also triggers sizable spillover effects. Our results have important policy implications for further economic research.

1. Introduction

In 1992, the European Union (EU) adopted the first Regulation (EEC) No 2081/92, defining the conditions for registering GI agricultural products and foodstuffs as protected. The policy on 'quality schemes' aims to protect, both domestically and internationally, the name of products originating in a specific place, region, or, in exceptional cases, a country, providing clear information on the value-adding attributes of the product to consumers, thus valorizing the GI products.

Undeniably, the protection and promotion of GIs in Europe has been successful. A recent study conducted by the European Commission and based on GIs across the 28 EU Member States (at the end of 2017) reports that the sales value of a product with a GI is, on average, double that for similar products without certification, a fact that gives a clear indication of the economic benefit for GI producers (European Commission, 2021).[1] Looking at the number of products registered over time, we observe a continuous mobilization of producers requesting the registration of food products characterized by a strong link with the production territory. The latter is represented by environmental and pedo-climatic factors and by a traditional process of producing, storing and transforming raw materials into products appreciated by consumers. On the other hand, the growing reputation of the PDO (Protected Designation of Origin) and PGI (Protected Geographical Indication) quality signs demonstrates consumers' appreciation of the European policy supporting quality food products through territorial labels.

One of the main objectives of GIs is fostering rural development, as the certification can benefit the production areas in terms of social and economic performance, for instance by increasing farmers' incomes or counteracting rural depopulation (Cei et al., 2021). These effects may be significant as most producers are Small and Medium Enterprises (SMEs) located in disadvantaged rural areas.

So far, the research on the socio-economic impact of GIs has been focused mainly on case studies and qualitative analysis, which, however, provide results that are not easily comparable or reproducible in other production contexts (Belletti et al., 2009, 2011; Chilla et al., 2020). Few recent works quantitatively analyze the impact of GIs on the Italian rural development (e.g., Cei et al., 2021; Crescenzi et al., 2022). Against this background, this paper aims to investigate the impact of the diffusion of GIs on socio-economic indicators at the European spatial scale by distinguishing between short- and long-run impacts and splitting their direct and indirect spatial (spillover) effects.

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[1] Note that, although GIs contributed enormously in some countries, such as Italy and Spain, there are other European countries where GI registrations did not deliver the benefits that consortium members were hoping for (Török et al., 2020; Poetschki et al., 2021; Bellassen et al., 2022).

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We carry out an empirical analysis that considers all the NUTS3 regions of three countries, Italy, France and Spain,[2] during the period 1993–2014 by relying on a dynamic panel model where the β coefficient estimated allows us to measure the difference in productivity growth among regions where the GI indicator changes by one unit, with respect to regions where there are no GIs or their number does not vary over time.

Moreover, as 'spatial dependence' prevails in many geographical datasets (as our regional data) and exemplifies Tobler's First Law of Geography - that is, things closer together are more similar than things further apart - we also rely on a dynamic model in space and time which, by describing the spatial dependence in parameters due to neighborhood relations, allows us to disentangle the direct and indirect effects of GIs, on regional productivity and employment.[3] Therefore, we apply a Dynamic Spatial Durbin Model that accounts for spatially lagged dependent and explanatory variables.

We build an original dataset starting from the European eAmbrosia database (the EU Geographical Indication Register) to connect the information of each GI with the rural area to which it refers; specifically, we consider both PDO and PGI of seven groups of products: dairy, meat, fruit and vegetable, olive oil, pasta, fish, and others. We do not consider either wines or spirit drinks. We focus on two main socio-economic variables: sectoral labor productivity and employment. Our choices fell on these outcomes as they often represent the main target of policies promoting regional/territorial growth. This is particularly true for the GI policy, which is strictly connected with the development of rural areas and the agricultural sector, which has experienced a substantial decline in the labor force and poor productivity growth over the last twenty years. Even if the promotion of rural economies has been stated as one of the main objectives of the GI policy, there is no quantitative evidence in literature dealing with the economics of GIs focusing on these outcomes in a large sample of countries and over time. As rural socio-economic development is strictly related to growth in agricultural productivity and employment, our contribution can shed some new light on the roles of the EU GI policy in this respect.

Our main results suggest that an increase in the number of GIs generates a positive socio-economic impact in the short and the long run. When considering the spatial and time variation of our data, the results show that the GI impact is not predominantly confined within a province: the 'total effect' of GIs on productivity and employment of the agricultural sector is primarily due to a significant spillover effect; for the industry sector, the GI effects on productivity are only related to neighboring regions (indirect), while direct impacts are zero.

The remainder of the paper is organized as follows. Section 2 outlines the literature review, while Section 3 reports the methodology and econometric approach; Section 4 describes the data used in the econometric analysis, and Section 5 presents and discusses the main results. The final section concludes.

2. Literature review

The GI productive system is highly fragmented, as some GIs (PDOs or PGIs) aiming at global markets have an international character. In contrast, others have a more local reach and are mainly sold in local markets. Some denominations are produced by large companies, while others by SMEs, or micro-enterprises. GIs may have supply chains limited to the agricultural phase, while others have very complex supply chains especially in the industrial phase (Vandecandelaere et al., 2009). These differences make the world of the European GIs somewhat impenetrable to researchers, and the expected effects of the European policy still need to be entirely ascertained.

Over the last two decades, the literature on the economics of GIs has analyzed in particular the link between GIs and rural areas, providing evidence of the critical role played by this EU policy in fostering the development of agricultural territories (see Török et al., 2020; Barjolle et al., 2009 for a literature review; European Commission, 2021).[4]

Most of the analyses are qualitative and focus on a small number of products or on a specific area. There are only few quantitative research works, mainly impact evaluations, that make a comparison between GIs rather than GI areas and are generally associated with one or few specific sectors, e.g. cheese and olive oil (Carbone et al., 2014) or wine (Crescenzi et al., 2022) or with a single GI producing country, e.g. Italy (Cei et al., 2018, 2021), or finding an effect of GIs on EU regions on the development of technological innovations (Stranieri et al., 2023) or on trade (Sorgho and Larue, 2018). There are also studies related to the level of sustainability of GI products at the environmental and social levels (Bellassen et al., 2022; FAO, 2023). Among these works, Poetschki et al. (2021) analyze the impact of GI adoption on farm incomes for specialized quality wine and olives producers in 2014. Using an endogenous switching regression model and FADN data, they show that GI adoption significantly improves farm incomes in these sectors, supporting the positive effect reported in the EU evaluation report of the GI policy (European Commission, 2021).

De Roest and Menghi (2000) pointed out that the production of Parmigiano Reggiano in Italy, being extremely labor intensive, positively impacts the employment rate in those regions where farms are located. Moreover, the production of Parmigiano Reggiano also has an effect from an ecological point of view due to intensive farming. The French cheese sector has also found similar results at the industry level (Bouamra-Mechemache and Chaaban, 2010). Using a unique dataset containing firm-level cost and production information on the French Brie cheese for the period 1980–2000, the authors find that due to the high costs of the raw materials and the need to operate on a large scale, farmers have little incentive to opt for a PDO certification.

Belletti et al. (2007) focus on three Italian products, PGI olive oil, PGI beef, and PDO sheep cheese. They highlight that even if direct certification costs can be quite high, this is not the main element in the firm's decision on whether or not to comply with a PDO or PGI certification. There may be additional regional benefits by attracting consumers to the producing area so that there are positive spillover effects in the local system.

Arfini and Belassen (2019) analyze the sustainability of the idea that the presence of a Local Agro-Food System (LAFS) represents a reference GI production model. In the LAFS, coordination and management actions concerning the use of resources and production strategies are developed, both formally and informally, by all stakeholders. The interaction between stakeholders governing the GIs generates, not only in the region, a virtuous effect that increases the sustainability of all the existing GIs by reducing transaction costs. Crescenzi et al. (2022) focus on Italian wine to study the differences in population and employment dynamics in rural areas with and without GIs between 1951 and 2011. The authors show that GIs attract more residents and shift the local economy toward higher value-added sectors. Cei et al. (2021) assess the effects of GIs in Italy on the NUTS3 level and find that a higher number of GI schemes causes a higher level of value-added, fostering rural development in these regions. In line with this last work, Arfini and Belassen (2019) highlight the externalities associated with public goods identified at the territorial and value chain levels for Italian and Spanish

[2] Italy, France and Spain are the most involved countries and account for more than 60% of GIs registered across the EU15 Countries.

[3] This spatial dependency violates the assumption made by ordinary regression methods that each observation is independent of other observations, which not only has the potential to render inefficient standard errors but also introduces modeling uncertainty because the effect of spatial interaction is unknown.

[4] Belletti and Marescotti (2021) carried out an operational guide on how to evaluate the impact of GIs initiatives on the improvement of economic development, social progress, and sustainability.

GI products (see also Kizos and Vakoufaris, 2011).

However, territorial elements also play a fundamental role in local dynamics, and the socioeconomic benefits of local production systems, such as GIs (Vaquero-Piñeiro, 2021; Cardoso et al., 2022).

Overall, the literature suggests that GIs play a positive role in rural areas' local development, albeit with some exceptions. While GIs contribute enormously in some countries, such as Italy, France, and Spain, the picture is more uneven in other countries, such as the Netherlands and Belgium.

To understand the importance of the possible impact of GIs on rural areas, it is worth noting that the observations in the data are dependent on space and time; therefore, spatial panel methodologies are one of the most promising tools to simultaneously analyze both the spatial and the temporal dimensions (Anselin and Griffith, 1988; Elhorst 2003, 2010, 2014a,b,c, 2017; Anselin et al., 2008). The use of spatial models would make it possible to evaluate the impact of GIs on a given territory.

Valuable applications of dynamic space-time panel data models, enabling the quantification of dynamic responses and impacts, over space and time, demonstrate that there exists a spatial relation between explanatory and dependent variables, both at the micro and macro level (see, among others, Debarsy et al., 2012; Dall'Erba, 2005; Dall'Erba and Le Gallo, 2007; Mohl and Hagen, 2010; Yang and Fik, 2014; Wang et al., 2019; Vincent and Kwadwo, 2022).

More recently, the literature has focused on spillover effects generated by various socio-economic variables related to agricultural productivity. In general, geographical proximity increases positive spillover effects in terms of knowledge diffusion (Chiffoleau and Touzard, 2014) even if there could be a possible congestion effect due to agglomeration (Rizov et al., 2012; Drucker and Feser, 2012; Eriksson, 2011).

Martínez-Victoria et al. (2019) analyze a sample of agri-food companies in Murcia (Spain) between 2005 and 2014; they find that the productivity growth of a company is spatially dependent on the productivity growth of a neighboring company, and this holds in the short and in the long run. Baldoni and Esposti (2021) focus on spatial dependence of agricultural total factor productivity by using farm-level data in Italy over the period 2008–2015 and find significant agricultural productivity spillovers, albeit over a limited area.

In general, we can argue that a change in a particular explanatory variable unit is associated with changes in the dependent variable in that unit, but also in other units as direct and indirect effects (Elhorst, 2012).

Based on the described literature, there is no clear theoretical or empirical evidence of GIs' economic and social impact on a large-scale base. In our paper, we aim to fill this gap and hypothesize that GIs may promote socioeconomic development thanks to an increase, for example, in farms' income, employment rate, or value-added. In particular, we expect an increase in employment since GIs are more labour-intensive than no-GI productions; thus, our first hypothesis is:

HP 1: GIs positively affect employment, both in the agriculture and industry sectors.

At the same time, we cannot have any prior expectations on productivity because, first, GIs producers have to comply with the traditional methodology and specific rules in line with the Regulation, and, second, GIs may lead to an increase in both the value added of the production and the employment; hence, depending on which of these two elements prevails, we can expect either positive or negative effect of GIs on productivity.

Moreover, by considering the spatial relationship existing between GIs and socioeconomic development, the second hypothesis to be tested is:

HP 2: An increase in the number of GIs in neighboring provinces impacts productivity and employment in the province.

Also for this second hypothesis, the sign of this spillover effect is expected to be positive for employment and not *a priori* defined for productivity.

Note that our hypotheses stem from the review of the empirical evidence and qualitative assessment made mainly on small-scale samples. At the same time, there is a lack of theoretical underpinning coming from this literature. Considering the three most important GIs producer countries, this contribution aims to analyze the socioeconomic impact of GI at the territorial level, using a rigorous econometric approach and ensuring the external validity of our findings.

3. Methodology and econometric approach

This section aims to adopt an empirical approach to investigate the impact of GI diffusion on socio-economic indicators, i.e. sectoral labor productivity and sectoral employment, using a System-GMM dynamic model and dynamic Spatial Durbin Model; the two approaches give us the possibility to distinguish short-and long-run impacts, as well as to split the total effect into their direct and indirect (spillover) spatial components.[5] This rigorous econometric approach allows us to analyze the socioeconomic impact of GI at the territorial level and to ascertain the external validity of our findings.

The econometric specification for sectoral labor productivity growth is derived from a standard convergence growth model in a panel data context (see Caselli et al., 1996; Rodrik, 2013).

In contrast, to study the relationship between GI diffusion on employment we consider a dynamic labor partial adjustment model (Bond and Van Reenen, 2007), first applied to the agricultural context by Petrick and Zier (2012) in a study of the labor effects of the Common Agricultural Policy (CAP).

A further step in the analysis is taken with the implementation of a spatial analysis to control the spatial relationship of the variables used. After applying Moran's-I test statistic (Moran, 1948; Cliff and Ord, 1981), the Spatial Durbin Panel Model (SDM) is run to uncover not only the mean effect of GIs on labor and employment but also to measure whether what happens in one province has a knock-on effect on neighboring provinces.

3.1. Labor productivity growth model and labor dynamic adjustment model

Our starting point is a standard productivity growth equation on panel data (Caselli et al., 1996). Formally, the growth in labor productivity, ΔY_{it}, in the territorial unit i in year t, can be represented by the following general equation:

$$\Delta Y_{i,t} \equiv \ln Y_{i,t} - \ln Y_{i,t-1} = \beta \ln Y_{i,t-1} + \gamma Z_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where the (log) lagged productivity level, $Y_{i,t-1}$, is the standard convergence term, $Z_{i,t-1}$ is a row vector of determinants of productivity, and $\varepsilon_{i,t}$ is an error term.

Crucial to our approach are the variables included in the vector $Z_{i,t-1}$. Conceptually they should depend on the particular variant of the neoclassical growth model the researcher is interested in (Caselli et al., 1996). For example, standard covariates in a neoclassic growth framework are investments in physical and human capital, indicators of the quality of institutions and size of government, trade openness and so on (e.g., Barro, 1991). However, as shown by Caselli et al. (1996), if a country or region converges to a different steady state, country/region-specific (fixed) effects should always be considered to capture differences in technology and other unobservable determinants. The fixed effects specification of the growth model is particularly useful in our context. This is because, by working at a disaggregated territorial level, we cannot control for the standard growth determinants due to the lack of available data. In addition, to capture common shocks affecting the growth process, we also include time dummies.

[5] Labor productivity is measured as value added per work considering both the agricultural and the manufacturing sectors (see Section 4 for a detailed variable description).

Thus, by including individual fixed effects (μ_i) and time fixed effects (θ_t), equation (1) can be rewritten as follows:

$$y_{i,t} = \widetilde{\beta}\, y_{i,t-1} + \varphi Z_{i,t-1} + \mu_i + \theta_t + \varepsilon_{i,t} \tag{2}$$

where $\widetilde{\beta} = (1 + \beta)$ and $y_{i,t} = \ln(Y_{i,t})$.

This new equation clearly shows that estimating the growth equation (1) is equivalent to running a dynamic panel model with the lagged-dependent variable on the right-hand-side. Equation (2) represents our basic empirical model to test the extent to which the diffusion of GIs contributes to sectoral productivity growth.

More specifically, we include in the vector $Z_{i,t-1}$, an indicator variable measuring the evolution over time of the number of GI products in each territorial unit *i*. With individual and time effects included, we can identify the GI productivity growth effect by exploiting the within-time variation in the number of GIs and productivity. The model is thus similar to a standard difference-in-difference specification, where the estimated coefficient on the GI indicator variable will measure the difference in productivity growth of the treated unit (a region where the GI indicator changes by one unit), relative to the counterfactual unit (a region where there are no GIs, or their number does not vary over time).

To study the effects of GI diffusion on employment in the agricultural and industrial sectors, we rely on a dynamic partial adjustment model adopted by Petrick and Zier (2012). The logic underpinning this model is based on a price-taking firm with convex adjustment costs of labor, induced by the existence of firing and hiring costs. By aggregating firms' behavior at the regional level, the model can be represented by the following simple equation:

$$\Delta L_{i,t} \equiv L_{i,t} - L_{i,t-1} = \gamma\left(L^*_{i,t} - L_{i,t-1}\right) \tag{3}$$

where $\Delta L_{i,t}$ is the yearly gross variation of labor stock of region *i*, $L^*_{i,t}$ is the projected long-run equilibrium level of employment in region *i* and time *t*, and $L_{i,t}$ is the current stock of labor (see Petrick and Zier, 2012). Equation (3) suggests that a regionally representative firm only partially adjusts the labor stock over time to the steady-state level, because to do so would be costly. In addition, $0 \leq \gamma \leq 1$ represents the speed of adjustment and will decrease these adjustment costs. Similarly to the discussion above concerning labor productivity growth equation, the steady-state employment level, $L^*_{i,t}$ is unobserved. As such, in the empirical application of this model it has been proxy by a vector of covariates $Z_{i,t}$, including, e.g., output, factor stocks, and so on, are assumed to be exogenous (see Bond and Van Reenen, 2007).

Concerning the impact of GIs on employment, we adopt a similar logic to Petrick and Zier (2012), assuming that GIs affect the long-run equilibrium labor demand in equation (3). This is a reasonable assumption, especially considering the level of agricultural employment. Indeed, the existence of GI production, by imposing specific constraints on production techniques, generally related to local traditions, should require more labor.[6],[7]

By adding regional and time effects to control for the unobserved steady-state labor demand, we have the following reduced-form equation of the labor dynamic:

$$\ell_{i,t} = \lambda \ell_{i,t-1} + \rho Z_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t} \tag{4}$$

with $\ell_{i,t} = \ln(L_{i,t})$, λ and ρ are the coefficients to be estimated, vector $Z_{i,t}$ includes the number of GI products and the per-capita GDP as control, μ_i and θ_t are region specific and time fixed effects, while $\varepsilon_{i,t}$ is the error term.[8]

3.2. Econometric issues

The productivity and labor equations (2) and (4) represent dynamic panel models with the lagged-dependent variable on the right-hand side, plus regional and time fixed effects. As a result, the coefficient on the GI variable (subsumed in the vector Z_i), only picks up the impact on regional productivity (employment) growth that *departs* from its growth trend.

One problem in estimating both equations (2) and (4) with a full set of fixed effects is that the lagged level of the dependent variable tends to be endogenous in a panel where the units of cross-sectional observations, *N*, are significantly higher than the yearly observations, *T* (see Arellano and Bond, 1991).[9] To avoid this inconsistency, Arellano and Bond (1991) propose a Generalised Method of Moments (GMM) estimator as an alternative to the Least Square Dummy Variable Model (LSDV). This implies transforming the model into a two-step procedure based on the first difference to eliminate the fixed effects as a first step. In the second step, the (endogenous) lagged dependent variable is instrumented using the *t* – 2, *t* – 3, and more extended lag levels of the dependent variable. In addition, as both productivity and employment display strong autocorrelation, their lagged levels tend to be weak instruments. To overcome this, we use the System GMM (SYS-GMM) estimator (Blundell and Bond, 1998, 2000) that exploits the level equation's second-moment conditions.

Formally, the SYS-GMM implementation for the labor productivity equation will be as follows:

$$\Delta y_{i,t} = \widetilde{\beta}\, \Delta y_{i,t-1} + \varphi \Delta X_{i,t-1} + \psi \Delta GI_{i,t-1} + \theta_t + \Delta\varepsilon_{i,t}$$

$$y_{i,t} = \widetilde{\beta}\, y_{i,t-1} + \varphi X_{i,t-1} + \psi GI_{i,t-1} + \theta_t + \pi_{i,t} \tag{5}$$

where $GI_{i,t-1}$ is an indicator variable measuring the number of GIs for region *i*, and represents our variable of interest, while $X_{i,t-1}$ is the per-capita GDP.

A similar system GMM model will be estimated considering the employment equation derived from equation (4):

$$\Delta \ell_{i,t} = \lambda\, \Delta \ell_{i,t-1} + \rho \Delta X_{i,t} + \omega \Delta GI_{i,t} + \theta_t + \Delta\varepsilon_{i,t}$$

$$\ell_{i,t} = \lambda \ell_{i,t-1} + \rho X_{i,t} + \omega GI_{i,t} + \theta_t + \pi_{i,t} \tag{6}$$

where all the terms are already defined above.

Using the system of equations (5) and (6), we aim to estimate unbiased GI coefficients, ψ and ω, for the productivity and employment equation, respectively. These coefficients measure the extent to which the regional diffusion of GIs exerted an effect on agricultural and industrial productivity and employment.

Our expected results are mainly based on the empirical reference literature suggesting a general positive socioeconomic effect of GIs, which the increasing number of GIs over time seems to testify. Specifically to our case, however, we must distinguish between the outcome

[6] Although not a general rule, most GIs (particularly PDOs) are based on production specifications that affect the technical and economic efficiency of the transformation process. For example, GI cheeses are mostly made from unpasteurized milk using less efficient technologies (usually vessels that work discontinuously) than the continuous cheesemakers used for industrial cheeses (Giovannetti and Bertolini, 2020). Also in the charcuterie sector, the artisan component linked to the human factor and not to machines, is dominant, mainly if carried out in small and medium-sized enterprises.

[7] Unfortunately, the dataset we use in this article does not allow to distinguish those GIs that specify more labor-intensive production techniques. It could be interesting to go through this aspect for a step forward of this research work.

[8] The estimated equations reported in the following 'Econometric issues' explicitly distinguish these two terms.

[9] This is the so-called Nickell bias, which results when panel data models with fixed effects and lagged dependent variables are estimated by the standard within (OLS) estimator and the time dimension, T, is finite. Our dataset has 265 NUTS 3 regions observed over the 1993–2014 period, thus N ≫ T.

variables, employment and labor productivity (measured as the ratio between value added and employment).

3.3. Spatial analysis

We take advantage of the dynamic spatial analysis to study the impact of GIs at the territorial level. Due to the spatial nature of our data (NUTS3 regions of Italy, France, and Spain), it is plausible that observations are not independent of one another, implying a spatial dependency within the data. In particular, since explanatory variables show a spatial pattern and these may be captured as local and global spillover effects (Elhorst, 2010), we implement a spatial Durbin Model that includes both a spatially lagged dependent variable and spatially lagged explanatory variables (LeSage and Pace, 2009). The advantage of the spatial Durbin model is that it allows the separation of the direct (within a province) and indirect (to/from neighboring provinces) impact of an independent variable on the dependent variable (LeSage and Pace 2009; Fischer and Wang, 2011). Moreover, this approach can produce unbiased coefficient estimates, regardless of the actual spatial processes underlying the observed data (Elhorst, 2010; Sabater and Graham, 2019).

Specifically, the dynamic spatial model applied can be described as follows:

$$y_t = \varphi\, y_{t-1} + \rho W y_t + \xi W y_{t-1} + \sigma Z_t + \chi W Z_t + \theta + \lambda_t \iota_N \tag{7}$$

where y_t is equal to $\ln(Y_{i,t})$ and represents the Nx1 vector for productivity (or employment) in the agricultural and industrial sectors, for every region i (with $i = 1, \ldots$N). W is the NxN spatial weighting matrix accounting for spatial connectivity and indicates how region i spatially connects to region j.[10] Z_t measures the characteristics (number of GIs) for each region in year t; WZ_t are the spatially lagged explanatory variables that capture the characteristics of neighboring regions. θ indicates individual-specific effects[11] while λ_t accounts for time-specific effects and ι_N is a Nx1 vector of ones to control for all time-specific and unit-invariant variables (Elhorst, 2010; Sabater and Graham, 2019).

It is important to notice that the parameter σ in equation (7) cannot be interpreted as simply the marginal effect of a change in the explanatory variable on the dependent variable. As in LeSage and Pace (2009) and Debarsy et al. (2012), the total marginal effect is now a combination of the direct and indirect effects, interpreted based on the partial derivatives.[12] Then, the average total effect is the average row sums of the elements of the matrix of partial derivatives; the average direct effect is the average of the diagonal elements (own derivatives); and the average indirect effect is the average row sum of the nondiagonal elements (cross-derivatives; i.e., the difference between the average of all derivatives - the average total effect - and the average own derivative - the average direct effect). Hence, the direct effect represents the expected average change across all observations for the dependent variable (productivity and employment in our case) in a particular region, due to an increase of one unit for a specific explanatory variable in this region. That is, if there is a new GI in the province, this has an impact on productivity and employment in the same province, underlining that the characteristics of the province matter. On indirect effects, the variation in the explanatory variable in the other neighboring provinces might have an impact on the dependent variable in the province (spillover effects).

In our case, results show that the presence of GIs in other neighboring provinces positively affects only agricultural employment.

4. Data and descriptive statistics

Our analysis considers the socio-economic performance of three European countries (i.e., France, Italy and Spain), and relies on data at NUTS3 territorial level over 22 years, from 1993 to 2014.[13] These three countries account for over 60% of total GIs registered by 15 European member states. The period under investigation allows us to capture the socio-economic performances before and after the entry into force of EU legislation on GIs, in 1996.

The dataset includes 265 territories at the NUTS3 level (110 in Italy, 96 in France, 59 in Spain), and 728 Geographical Indications (293 In Italy, 244 in France, 191 in Spain). Specifically, we have 237 NUTS3 regions with new GIs, 11 provinces that maintain constant the (positive) number of GIs, and 17 provinces that are always without GIs during the analyzed period.[14]

To connect the information of each GI with the territory it refers to, we built an original dataset starting from the European DOOR database, now the eAmbrosia database, which collects official information on all the registered EU geographical indications, from 1996 to 2014. Then, we analyzed the 'Code of Specification' for each 728 GI product to identify the NUTS3 regions representing the area of supply (for PDO products) and processing (for PDO and PGI products) of GIs.[15] Moreover, the GI products have been classified into seven categories and further aggregated into four product groups for the empirical analysis. Specifically, the seven groups of products are: dairy, meat, fruit and vegetable, olive oil, pasta, fish, and others (e.g. balsamic vinegar, honey, spices); when four groups are considered we maintain dairy, meat, fruit and vegetable groups, and aggregate olive oil, pasta, fish, and others in a new 'other' product group. The most important are dairy, meat and fruit & vegetables, representing 74% of the GI products of the three countries. We do not consider neither wines nor spirit drinks.

To implement the spatial dynamic analysis, we include shape files of our 2010 NUTS3 regions from EUROSTAT[16] to visualize multipart polygonal regions better. Hence, we drop islands and create the spatial contiguity matrix $W_{i,j}$ (W in equation (7)) where the ijth element of W is 1 if points i and j are neighbors, 0 otherwise.[17]

Table 1 describes our territorial dataset on GI and reports, for five different years of the period analyzed, the share of NUTS3 regions that host one (or more than one) GI product at the average level and by distinguishing among product categories and countries.

The data show that in the first year of EU legislation on GIs, 69% of the 265 regions were already involved in these productions. In contrast, at the end of the analyzed period, only a few regions were not included in any GI Code of Conduct. Those not involved regions are mainly located in Spain (10 regions), and to a lesser extent in France (7 regions), while all the 110 Italian NUTS3 present (at least) one GI product. The distinction between product categories highlights the meat sector as the category that involves the highest number of territories, reaching, in

[10] The elements on the diagonal of matrix W are set to zero.

[11] $\theta = (\theta_1, \ldots \theta_N)^T$ contains spatial specific θ_i effects and is used to control for all spatial-specific, time-invariant variables.

[12] For a formally and detailed description of the matrix behind the partial derivates, see the model specification presented in Elhorst (2010), Vitali et al. (2015) and Sabater and Graham (2019).

[13] The analysis stops in 2014 as most of the GIs registered for the three countries considered are made before this year. Between 2015 and 2020, in fact, 86 GIs were registered for Italy, France and Spain, which represent almost 10% increase of the total number of GIs in the period 1993–2014.

[14] Fig. A1 in the Appendix shows maps on the number of GIs in Italy, France and Spain at the NUTS3 level for the years 1996-2005-2014. For most of the provinces there exist an increase in the number of GIs up to the end of the period we account for, except for the 17 provinces (10 Spanish, 7 French) always without GIs.

[15] Note that the number of GIs used in all estimations is the sum of the number of PDO and PGI for each NUTS3 region in each year.

[16] Shapefile source: https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts.

[17] This matrix uses both the baseline dataset with information on GIs and other control variables, and the dataset containing the coordinates of polygons.

Table 1
Share of NUTS3 regions with Gis over the period 1996-2014

	Share of regions with GIs					NUTS3
	1996	2000	2005	2010	2014	
Dairy	0,38	0,48	0,56	0,59	0,62	265
Meat	0,24	0,51	0,63	0,71	0,74	265
Fruit&Veg	0,11	0,29	0,42	0,52	0,65	265
Oils	0,04	0,17	0,26	0,35	0,37	265
Other	0,03	0,08	0,15	0,25	0,31	265
Pasta	0,00	0,01	0,05	0,10	0,14	265
Fish	0,00	0,00	0,01	0,06	0,08	265
Tot. GIs	0,69	0,83	0,88	0,91	0,94	265
	Italy: Share of regions with GIs					
	1996	2000	2005	2010	2014	NUTS3
Dairy	0,46	0,56	0,70	0,73	0,76	110
Meat	0,14	0,52	0,69	0,74	0,75	110
Fruit&Veg	0,12	0,31	0,52	0,59	0,73	110
Oils	0,05	0,33	0,47	0,58	0,60	110
Other	0,00	0,02	0,05	0,22	0,29	110
Pasta	0,00	0,01	0,03	0,06	0,11	110
Fish	0,00	0,00	0,00	0,06	0,08	110
Tot. GIs	0,68	0,89	0,92	0,98	1,00	110
	France: Share of regions with GIs					
	1996	2000	2005	2010	2014	NUTS3
Dairy	0,39	0,55	0,61	0,76	0,80	96
Meat	0,38	0,49	0,53	0,56	0,58	96
Fruit&Veg	0,13	0,34	0,43	0,52	0,58	96
Oils	0,05	0,18	0,26	0,30	0,33	96
Other	0,03	0,05	0,07	0,13	0,15	96
Pasta	0,01	0,01	0,08	0,10	0,13	96
Fish	0,00	0,01	0,02	0,04	0,05	96
Tot. GIs	0,83	0,86	0,92	0,92	0,93	96
	Spain: Share of regions with GIs					
	1996	2000	2005	2010	2014	NUTS3
Dairy	0,22	0,31	0,36	0,37	0,39	59
Meat	0,20	0,42	0,56	0,58	0,61	59
Fruit&Veg	0,08	0,17	0,24	0,41	0,61	59
Oils	0,05	0,08	0,15	0,27	0,31	59
Other	0,03	0,05	0,14	0,22	0,29	59
Pasta	0,00	0,00	0,05	0,15	0,24	59
Fish	0,00	0,00	0,00	0,10	0,10	59
Tot. GIs	0,49	0,68	0,73	0,76	0,83	59

Source: Authors' calculations (see text).

2014, 74% of the overall 265 NUTS3 regions, and up to 80% of French NUTS3 regions.[18] GI production in the dairy sector, where we find many famous French and Italian kinds of cheese (e.g., Roquefort and Parmigiano Reggiano), involves the highest share of territories at the beginning of the period (38%), and grows to 62% by 2014. By contrast, the production of GI fruit & vegetables, which initially concerned only a small share of regions (10%), extended strongly, reaching 65% of the 265 regions in the last year of the analysis. Olive Oil, another product category that experienced a notable increase in the number of territories, passed from 4% to 37%, and up to 60% in Italy.

We use productivity and employment dimensions at the NUTS3 territorial level for the specific agricultural and industrial sectors to measure regional economic performance. The data come from the Cambridge Econometrics' Regional Database based on Eurostat.[19] A preliminary look at the agricultural data, reported in Fig. 1, allows us to see how these economic variables relate to GIs.

The graphs report the regional socio-economic dimension against the regional number of GIs, over the analyzed period and across individual countries. The correlation between GI and territories seems positive for all countries and variables, with the exception of France, where a weak, negative and non-causal relation is observed.[20] However, the strong persistence of these economic dimensions and the presence of many factors likely to influence the socio-economic development of regions reduce the pattern of this bivariate relationship. Our econometric analysis will shed some light on the role played by the GIs in determining economic regional dimensions.

The other control variables used in the econometric analysis - GDP and population - come from the Cambridge Econometrics Regional Database and are both measured at the NUTS3 level.

5. Results

5.1. System GMM dynamic model

Tables 2–4 report the results on the effects of GI production on regional productivity and employment by estimating the system of equations (5) and (6) with the system GMM estimator.[21] In all tables, columns (1) and (2) report the GI effects on the agricultural sector, while columns (3) and (4) consider effects on the industrial sector.

All standard tests used to check for the consistency of the SYS-GMM estimator (Roodman, 2009) are reported at the bottom of the tables. The Arellano-Bond tests for autocorrelation indicate the presence of first-order serial correlation but do not detect second-order autocorrelation. Hence, under this circumstance, the use of a dynamic GMM specification is correct, while the OLS estimator should be inconsistent. The standard Hansen tests for the suitability of the instruments confirm that our set of instruments is valid. As suggested by Roodman (2009), the number of instruments should not exceed the number of groups; hence, to control for instrument proliferation that could lead to a weak Hansen test, we used only 9 lags instead of all available instrument lags.

The coefficient of the lagged dependent variable ($y_{i,t-1}$) is always significant, positive, and particularly high (around 0.9), confirming the strong persistence of all our dependent variables. The level of economic development, measured as (real) GDP per capita, is always significant and positive, except when agricultural employment is considered. The latter result confirms, in line with expectations, the negative impact of development on agricultural employment, while the effect on industrial employment is always positive.

Moving to the effect of GIs, Table 2 reports the overall effect on labor productivity and employment in the agricultural and industrial sectors.

Starting from the GI productivity effect (see columns 1 and 3), the estimated coefficients are negative for both the agricultural and industrial sectors, though only in the final case is it statistically significant at 5%.

The GI coefficient is positive and statistically significant on employment for both the agricultural and the industrial sectors, albeit with different magnitudes (see columns 2 and 4). This result is in line with Hypothesis 1 where we outline that GIs have a positive effect on employment since GIs tend to be more labor-intensive. As the log of zero is undefined, we use the GI variable in level and the estimated coefficients (ψ, ω) can be interpreted as semi-elasticities. Therefore, one unit change in GI is associated with a 0.41% positive change in agricultural employment.[22] To convert our estimated coefficient in elasticity term, we multiply coefficients by the GI number sample mean equal to

[18] Note that the share concerns the number of NUTS3 regions involved in GI production, not their dimension.

[19] Productivity is measured as value added divided by employment for the two sectors: agriculture and industry. Descriptive statistics on the variables used in the empirical analysis are reported in the Appendix (see Table A1).

[20] As reported in Section 5.1, by using system-GMM econometric approach, the impact of new GIs on agricultural productivity results positive and significant only for Spain.

[21] Note that we fix the sample with the one used for spatial analysis. Thus, we exclude NUTS regions that are islands since, having no boundaries, cannot be used for spatial analysis.

[22] It is important to notice that the model manages one new unit of GI in the same way if the region gets its first GI or its 10th.

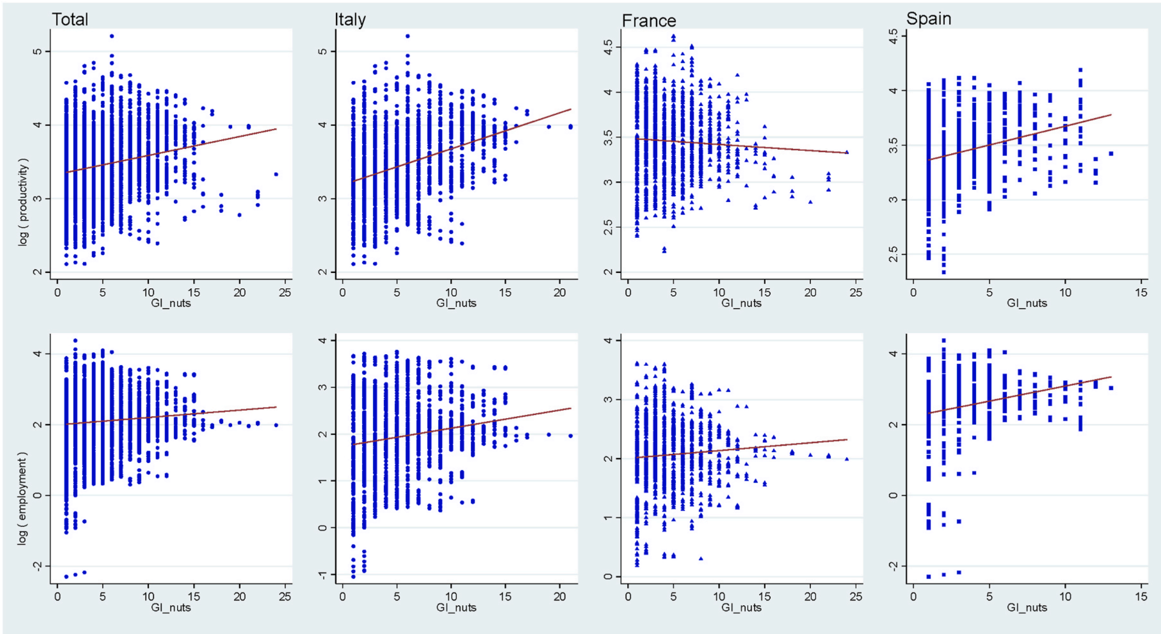

Fig. 1. Productivity, employment and GI at NUTS3 territorial level
Source: Authors' calculations. Employment data come from Cambridge Econometrics' Regional database and refer to the agricultural sector. Productivity is obtained as a ratio between (real) VA and employment. The data of GIs at the NUTS3 level has been derived by the Authors from the eAmbrosia database (see text). Lines are best fit to all data points.

Table 2
Socio-economic effects of GIs: Baseline results

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
Number of GI	−0.0006	0.0041***	−0.0012**	0.0009**
	(0.0009)	(0.0011)	(0.0005)	(0.0004)
log (GDP/POP)	0.0974***	−0.0712***	0.0466***	0.0284***
	(0.0239)	(0.0198)	(0.0085)	(0.0098)
$Y_{(t\ -1)}$	0.9060***	0.9620***	0.9652***	0.9793***
	(0.0171)	(0.0067)	(0.0121)	(0.0024)
No. of obs.	5300	5300	5300	5300
No. groups	265	265	265	265
No. instruments	259	259	259	259
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.171	0.330	0.992	0.680
Hansen (p-value)	0.115	0.103	0.134	0.104

Notes: Time dummies are included in each regression. The SYS-GMM estimator is implemented in STATA using the *xtabond2* routine. Windmeijer-corrected standard errors in parenthesis: *** <0.01; ** <0.05; * <0.1.

3.915 (see Table A1). Thus, quantitatively, the estimated (short-run) effects, when interpreted as elasticity, suggest that an increase of 10% in the number of GIs induces an employment growth of 0.16% and 0.04% in the agricultural and manufacturing sector, respectively.

However, due to the dynamic nature of our model and the persistency in employment level, in the long run a 10% growth in GIs translates into an employment growth of about 4.2% and 1.7% in the two sectors, respectively. Specifically, the long-run effect can be obtained by dividing the short-run GI estimated coefficient by (1 − λ), where λ is the coefficient of the lagged dependent variable.[23]

Table 3
Socio-economic effects of GIs: Results across countries

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
No. of GI_Italy	−0.0008	0.0043***	−0.0037***	0.0014***
	(0.0009)	(0.0010)	(0.0005)	(0.0004)
No. of GI_France	−0.0009	0.0034***	0.0013**	−0.0000
	(0.0010)	(0.0013)	(0.0005)	(0.0003)
No. of GI_Spain	0.0061***	0.0064***	0.0012*	0.0021***
	(0.0018)	(0.0019)	(0.0007)	(0.0007)
log (GDP/POP)	0.0987***	−0.0684***	0.0738***	0.0277**
	(0.0242)	(0.0196)	(0.0125)	(0.0107)
$Y_{(t\ -1)}$	0.9035***	0.9621***	0.9055***	0.9806***
	(0.0173)	(0.0069)	(0.0140)	(0.0026)
No. of obs.	5300	5300	5300	5300
No. groups	265	265	265	265
No. instruments	261	261	261	261
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.173	0.331	0.965	0.681
Hansen (p-value)	0.120	0.100	0.135	0.106

Notes: Time and NUTS3 region dummies are included in each regression. The SYS-GMM estimator is implemented in STATA using the *xtabond2* routine. Windmeijer-corrected standard errors in parenthesis. *** <0.01; ** <0.05; * <0.1.

From an economic point of view, it is essential to bear in mind that in our sample, the average growth rate of employment is negative and equal to −2.7% per year in agriculture (−0.8% industry). Thus, our results suggest that in the long run, producing GIs keeps more jobs in the agricultural and manufacturing sectors *vis-à-vis* regions without new GI producers.

[23] Note that, the larger λ the slower is the adjustment of the dependent variable (e.g. employment) to a new equilibrium, and the greater the effect in the long-run.

Table 4
Socio-economic effects of GIs: Results across product categories

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
No. of GI_Dairy	0.0001	0.0033**	−0.0020***	−0.0006
	(0.0019)	(0.0013)	(0.0008)	(0.0008)
No. of GI_Fruit&Veg	0.0007	0.0050***	0.0010	0.0016*
	(0.0022)	(0.0018)	(0.0010)	(0.0009)
No. of GI_Meat	−0.0019	0.0026*	−0.0011	0.0017**
	(0.0015)	(0.0015)	(0.0009)	(0.0007)
No. of GI_Other	−0.0018	0.0086***	−0.0025*	0.0013
	(0.0035)	(0.0026)	(0.0013)	(0.0011)
log (GDP/POP)	0.0960***	−0.0677***	0.0480***	0.0276**
	(0.0247)	(0.0194)	(0.0084)	(0.0108)
$Y_{(t-1)}$	0.9059***	0.9626***	0.9639***	0.9795***
	(0.0169)	(0.0070)	(0.0121)	(0.0026)
No. of obs.	5300	5300	5300	5300
No. groups	265	265	265	265
No. instruments	262	262	262	262
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.172	0.327	0.994	0.681
Hansen (p-value)	0.114	0.101	0.136	0.104

Notes: Time and NUTS3 region dummies are included in each regression. The SYS-GMM estimator is implemented in STATA using the *xtabond2* routine. Windmeijer-corrected standard errors in parenthesis. *** <0.01; ** <0.05; * <0.1.

Table 3 disentangles the effects across the three countries considered (i.e., Italy, France and Spain).

Results confirm the positive impact of new GIs on agricultural labor for all countries, with estimated effects higher for Spain and Italy than for France. In contrast, the GI impact on agricultural productivity, which remains close to zero for Italy and France, becomes positive and significant at 1% for Spain. Regarding the GI effect on the industry sector, the positive and significant impact on employment, previously observed at the overall effect, is confirmed for Italian and Spanish regions.

Finally, to measure whether the overall effect of a new GI changes when considering different product groups, we split the number of GIs into four product categories: Dairy, Fruit & Vegetable, Meat and Other Products. Results are reported in Table 4.[24]

Starting with the agricultural sector, the effect of GIs on productivity is still insignificant across the different products. In contrast, the effect on employment is positive and significant for all the considered products. Specifically, new GIs in the 'Other' product group (e.g., oils, fish, pasta) and the Fruit & Vegetable product group exert the highest impact on agricultural employment: one more GI increases employment by about 0.50% and 0.86% in the short-run, respectively. These effects are higher than the impacts observed for GIs in the Meat and Dairy sectors (equal to 0.26% and 0.33%, respectively). By contrast, if we consider manufacturing employment, the presence of a new GI exerts a positive and significant impact when GIs are in Meat and Fruit & Vegetable product groups. Thus, only one GI in these two product categories appears to have a spill-over effect in those 'industrial' activities directly or indirectly connected to GI productions.[25]

5.2. Dynamic Spatial Durbin Model

Due to the spatial nature of our data, there is a strong probability that the observations are not independent of one another. Spatial dependency could originate from different sources e.g., arbitrary political boundaries that split/aggregate spatial units without regard to socio-economic variables or spatial interaction. All these facts may suggest the existence of (potential) spatial dependency within the data.

A common way to illustrate the existence of spatial dependence for the dependent and independent variables under investigation is to examine the evolution of Moran's I statistic.

The results in Table 5 indicate high/moderate positive spatial correlation for all variables but industrial employment. It implies that provinces with high (low) GIs, employment, and productivity are located close to other provinces with similar high (low) values and that their outcomes tend to be similar to those of their neighbors.[26]

The results derived from the implementation of the dynamic Spatial Durbin Model (SDM) described by equation (7) show that ρ, the

[24] Although the presence of GI at NUTS3 level is generally positive and increasing over time, there are 17 provinces (10 Spanish, 7 French) always without GIs, and 11 provinces (10 French, 1 Italian) that maintain constant the (positive) number of GIs during the all period. To check the robustness of our results in absence of these observations, we estimated all regressions of Tables 2–4 using two subsamples (see Table A2 in Appendix). The first subsample, Panel A of Table A2, omits the 17 regions with no GI; the second (Panel B) excludes 28 regions, 17 provinces with no GI and 11 provinces with GI but without variation. In both cases, the results do not change, maintain sign, dimension and significance validating our main findings.

[25] Note that the choice to use the total number of GI instead of the number of only PDO, or only PGI, concerns the possibility to estimate the effect of GI policy implementation on productivity or employment, with a counterfactual that considers regions without GIs or that do not change their GI number. The use of only PDOs (or only PGI) can't offer this possibility. Indeed, the observed increase in the number of, e.g., PDO at NUTS 3 level has a counterfactual that contains regions with no PDO and regions with no new PDO but can includes regions that produce PGI. Thus, the counterfactual is not free from the effect of the GI policy when only PDO or only PGI are accounted for, and the estimations drive to less clear results. However, we estimate the impact of new GI by considering only PDO products, which registration involves products characterized by strongest link with the production territory, as further robustness check of our results. Specifically, we replicate Tables 2–4 estimations considering the number of PDOs only. The results, reported in Table A3 in Appendix, do not show consistent differences respect to the use of (total) GIs explanatory variable and confirm the general validity of previous results.

[26] Moran's I ranges between −1 and 1, indicating perfect negative and positive spatial correlation, respectively. Values close to 0 suggest a random spatial pattern.

Table 5
Moran's test

	1992	1993	1994	1995	1996
Industrial Employment	0.214	0.215	0.216	0.212	0.220
Industrial Productivity	0.219	0.230	0.236	0.254	0.270
Agricultural Employment	0.407	0.387	0.386	0.373	0.381
Agricultural Productivity	0.390	0.328	0.343	0.323	0.334
	1997	1998	1999	2000	2001
Industrial Employment	0.226	0.233	0.237	0.231	0.226
Industrial Productivity	0.289	0.301	0.292	0.267	0.242
Agricultural Employment	0.392	0.412	0.455	0.470	0.468
Agricultural Productivity	0.297	0.310	0.305	0.424	0.433
No. of GI	0.420	0.350	0.388	0.380	0.388
	2002	2003	2004	2005	2006
Industrial Employment	0.226	0.227	0.224	0.230	0.229
Industrial Productivity	0.269	0.343	0.364	0.377	0.390
Agricultural Employment	0.468	0.463	0.449	0.439	0.428
Agricultural Productivity	0.408	0.360	0.352	0.283	0.294
No. of GI	0.384	0.369	0.333	0.318	0.311
	2007	2008	2009	2010	2011
Industrial Employment	0.236	0.234	0.227	0.228	0.232
Industrial Productivity	0.382	0.394	0.523	0.533	0.575
Agricultural Employment	0.443	0.434	0.437	0.446	0.447
Agricultural Productivity	0.338	0.464	0.398	0.473	0.522
No. of GI	0.337	0.329	0.336	0.345	0.348
	2012	2013	2014		
Industrial Employment	0.238	0.235	0.237		
Industrial Productivity	0.599	0.606	0.620		
Agricultural Employment	0.446	0.448	0.446		
Agricultural Productivity	0.497	0.460	0.461		
No. of GI	0.355	0.359	0.363		

Source: Authors' calculations (see text).

Table 6
Socio-economic spillover effects of GIs: Baseline results

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
Direct effect				
No. of GI	−0.005***	0.002**	−0.000	−0.001*
	(0.002)	(0.001)	(0.001)	(0.001)
log(GDP/POP)	−0.091***	0.009	0.098***	0.052***
	(0.027)	(0.017)	(0.011)	(0.010)
Indirect effect				
No. of GI	−0.019***	0.005***	−0.004***	−0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
log(GDP/POP)	−0.040***	0.002	0.020***	0.010***
	(0.013)	(0.005)	(0.002)	(0.002)
Total effect				
No. of GI	−0.024***	0.007***	−0.004***	−0.004***
	(0.002)	(0.001)	(0.001)	(0.000)
log(GDP/POP)	−0.132***	0.011	0.118***	0.062***
	(0.039)	(0.021)	(0.013)	(0.012)
Rˆ2	0.549	0.957	0.438	0.952
No. of obs.	5300	5300	5300	5300

Notes: Short run results. *t* statistics in parenthesis and robust standard errors calculated in the model. Estimated coefficients are reported in Table A4 in the Appendix. To estimate the SDM we use the STATA command *xsmle* with time lagged dependent variable. *** <0.01; ** <0.05; * <0.1.

Table 7
Socio-economic spillover effects of GIs: Results across countries

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
Direct effect				
No. of GI_Italy	−0.011***	0.003*	−0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.001)
No. of GI_France	−0.006***	0.000	−0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
No. of GI_Spain	−0.004	0.004*	0.001	0.000
	(0.004)	(0.002)	(0.001)	(0.001)
log(GDP/POP)	−0.015	0.053**	0.134***	0.126***
	(0.034)	(0.022)	(0.013)	(0.012)
Indirect effect				
No. of GI_Italy	−0.014***	0.002	−0.003***	0.005***
	(0.003)	(0.002)	(0.001)	(0.001)
No. of GI_France	−0.036***	0.004**	−0.005***	0.021***
	(0.004)	(0.002)	(0.001)	(0.002)
No. of GI_Spain	−0.022***	−0.004	0.001	−0.010***
	(0.006)	(0.003)	(0.002)	(0.002)
log(GDP/POP)	−0.338***	−0.079**	−0.105***	−0.459***
	(0.066)	(0.032)	(0.021)	(0.032)
Total effect				
No. of GI_Italy	−0.025***	0.005***	−0.004***	0.005***
	(0.003)	(0.001)	(0.001)	(0.001)
No. of GI_France	−0.042***	0.004***	−0.005***	0.022***
	(0.004)	(0.002)	(0.001)	(0.002)
No. of GI_Spain	−0.026***	0.000	0.001	−0.009***
	(0.005)	(0.002)	(0.002)	(0.002)
log(GDP/POP)	−0.353***	−0.027	0.029	−0.333***
	(0.066)	(0.028)	(0.020)	(0.033)
Rˆ2	0.706	0.985	0.617	0.827
No. of obs.	5300	5300	5300	5300

Notes: Short run results. *t* statistics in parenthesis and robust standard errors calculated in the model. Estimated coefficients are reported in Table A5 in the Appendix. To estimate the SDM we use the STATA command *xsmle* with time lagged dependent variable. *** <0.01; ** <0.05; * <0.1.

coefficient that measures the intensity of the spatial interdependency, is always positive and statistically significant (see Tables A4-A6 in Appendix), meaning that levels of the dependent variable y depend (also) on the levels of y in neighboring provinces. Specifically, it states that spatial interaction of provincial productivity (employment) exists and that a one percent increase in the productivity (employment) of neighboring provinces increases the province productivity (employment) by 0.07 (0.05) percent in agriculture and by 0.04 (0.04) percent in manufacturing.

As parameter ρ is different from zero, the interpretation of the explanatory variables in the SDM is different from a conventional least squares interpretation (LeSage and Pace, 2009). Indeed, the spatial spillovers arise due to impacts passing through neighboring regions and back to the region itself. Thus, the sign and magnitude deriving from changes in explanatory variables are reported in Tables 6–8 as their direct, indirect and total marginal effects in the short term. The direct marginal effect provides a summary measure of the average impact arising from changes in i-region explanatory variable, taking into account feedback effects that occur from the change in the region's number of GIs on, for example, agricultural employment of neighboring regions. By contrast, the total marginal effect includes both direct and indirect impact, and measures the cumulative impact arising from typical region-j raising its GIs on the agricultural employment of all other regions (on average). Finally, the indirect marginal effect measures the impact of the GIs of all other regions on the agricultural employment of an individual region.

One of the advantages of decomposing the marginal effects into direct (own-province) and indirect (spillover) effects is that it is possible to examine which of these components prevails.

The results from Table 6 show that the average 'total effect' of GIs on agricultural productivity and employment (columns 1 and 2) is primarily due to a large spillover effect, as up to 79% and 71%, respectively, of effects are indirect.

These results are significant and, in accordance with our second

Table 8
Socio-economic spillover effects of GIs: Results across product categories

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
Direct effect				
No. of GI_Diary	−0.003	0.001	−0.002	0.002*
	(0.004)	(0.002)	(0.001)	(0.001)
No. of GI_Fruit&Veg	−0.008**	0.004**	0.002	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
No. of GI_Meat	−0.002	0.001	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)
No. of GI_Other	−0.002	−0.000	−0.002	−0.001
	(0.004)	(0.003)	(0.002)	(0.001)
log(GDP/POP)	−0.001	0.051**	0.137***	0.121***
	(0.035)	(0.022)	(0.014)	(0.012)
Indirect effect				
No. of GI_Diary	−0.023***	0.010**	−0.009***	0.019***
	(0.007)	(0.004)	(0.003)	(0.004)
No. of GI_Fruit&Veg	−0.021***	0.001	−0.003	−0.001
	(0.007)	(0.004)	(0.002)	(0.003)
No. of GI_Meat	−0.013***	0.002	−0.005***	0.017***
	(0.005)	(0.003)	(0.002)	(0.002)
No. of GI_Other	0.002	−0.004	0.002	−0.008**
	(0.008)	(0.005)	(0.003)	(0.004)
log(GDP/POP)	−0.197***	−0.102***	−0.094***	−0.477***
	(0.056)	(0.032)	(0.022)	(0.030)
Total effect				
No. of GI_Diary	−0.026***	0.011**	−0.011***	0.021***
	(0.008)	(0.004)	(0.003)	(0.004)
No. of GI_Fruit&Veg	−0.029***	0.005	−0.001	−0.001
	(0.007)	(0.003)	(0.002)	(0.003)
No. of GI_Meat	−0.015***	0.003	−0.004***	0.017***
	(0.004)	(0.002)	(0.002)	(0.002)
No. of GI_Other	0.000	−0.005	−0.001	−0.009**
	(0.008)	(0.004)	(0.003)	(0.004)
log(GDP/POP)	−0.197***	−0.051**	0.042**	−0.356***
	(0.050)	(0.025)	(0.019)	(0.029)
R^2	0.773	0.985	0.570	0.840
No. of obs.	5300	5300	5300	5300

Notes: Short run results. *t* statistics in parenthesis and robust standard errors calculated in the model. Estimated coefficients are reported in Table A6 in the Appendix. To estimate the SDM we use the STATA command *xsmle* with time lagged dependent variable. *** <0.01; ** <0.05; * <0.1.

hypothesis,[27] highlight that the impact of GIs on agriculture is not predominantly confined to a province. The signs, in line with our previous (dynamic) results, are negative for productivity and positive for employment, showing that a one-unit increase in GI is associated with the total (direct) 2.4% (0.5%) decrease in agricultural productivity and the total (direct) 0.7% (0.2%) increase in agricultural employment. Thus, compared with System-GMM results, the spatial Durbin model results reveal that the impact of GIs on agricultural productivity is significantly different from zero. For the industry sector (see columns 3 and 4) the GI impact on productivity is still negative but significant for indirect effects only. A possible underlying mechanism of why neighboring provinces producing GIs reduce, e.g., the employment in manufacturing (of the referred province), could be related to the migration process between sectors, with a consequent decrease in (manufacturing) employment of the province. The same process measured only within the province (direct effect) drives the same negative but not significant impact due to a smaller dimension of the variations that induce this migration process.[28] Using dynamic SDM, the one-unit increase of GI shows a decrease of also industry employment (−0.4%), mainly due to the indirect effects (75%).[29]

Table 7 shows different spatial results depending on the country of interest.

Only for the Italian agricultural sector is the positive impact of GI on employment (column 2) mainly a direct effect (60% of the total effect), and the (negative) impact on productivity (column 1) is almost shared between direct and spillover effects; the results show that one-unit increase in GI in the province is associated with 1.1% decrease in productivity and 0.3% increase in employment in the same province, while the total effects are, respectively, 2.5% and 0.5%. By contrast, for France and Spain, we observe a predominant spillover effect of GIs, representing more than 85% of the total GI effect on agriculture productivity and, limited to France, also on employment. Thus, only in Italy is the impact of GIs to some extent measurable in the province where it occurs, although also in this case there are additional impacts exerted by neighboring provinces as spillover effects. Indirect effects always prevail when distinguishing the main GI sectors (Table 8); the only exception concerns fruit and vegetable GIs, whose direct effects are statistically significant for the agricultural sector. Specifically, their effects on agriculture employment are mainly limited to the province in question, while the effects on productivity show that the indirect component still prevails.

6. Conclusions

The EU aims to enhance agri-food chains' competitiveness by developing quality policies, such as the one promoting rural development through GI certification. However, the socio-economic effects of GIs in EU regions are still not fully understood. In this study, we use an original data set to reduce this gap by considering the three main EU GI producers (i.e., Italy, France, and Spain), which together produce 60% of the total GIs registered by 15 European countries.

We focus, in particular, on two main socio-economic indicators, productivity, and employment, for the agriculture and industrial sectors at the European spatial scale. The System-GMM dynamic model and dynamic Spatial Durbin Model allow us to distinguish short- and long-run impacts and split the total effect into their direct and indirect (spillover) *spatial* components. Specifically, the latter enables us to disentangle the total GI effects in (direct) effects of GI, occurring within the region with GI, from (indirect) effects occurring in neighboring regions.

The results obtained through the dynamic model, show that a 10% growth in registered GIs, in the short-run, generates a 0.04% increase in agricultural employment and a 0.01% increase in industrial employment, *ceteris paribus*. In the long run, the same growth in GIs induces an employment effect of 4.2% and 1.7% for the agriculture and industry sectors, respectively, confirming our main hypothesis that GIs positively affect employment in the agriculture and industry sectors. In contrast, the overall impact of GIs on productivity is negative, with variations in both the direction and significance observed across countries, products, and industries.

The spatial analysis generally confirms the results above and highlights that the total effect is primarily due to a significant spillover: 71% of the average 'total effects' of GIs on agricultural employment are

[27] To recall, Hypothesis 2 states that an increase in the number of GIs that occurred in neighboring provinces has an impact on productivity and employment in the province.

[28] Note that the indirect effect refers to a 'diffusion effect' that can be defined in two non-exclusive ways (Elhorst, 2010). Thus, another interpretation of indirect effect could be how changes in GI in a given province influence productivity (or employment) in other provinces.

[29] When this result is split over the three countries and the four GI sectors (see Tables 7 and 8) it turns out to be positive, and this negative effect of GI on industry employment appears limited to one country (Spain) and one of the GI sectors ('other GI product').

'indirect effects'. Again, evidence supports our (second) hypothesis that GIs occurring in neighboring provinces impact productivity and employment in the province.

Thus, GIs contribute to strengthening rural areas by creating job opportunities, which are consolidated over time. This highlights the existence of connections between GI productions and the valorization of local resources that can support their economic and social sustainability within rural communities. Our results suggest that the developing 'multiplier' effect impacts all the economic sectors and services in the territory. The size of the impact depends on the GI sector. Where agricultural productions do not require complex transformation or long maturation (such as the fruit and vegetable sector), the impact in terms of employment is more significant in agriculture. In contrast, when the GIs based on meat products increase, the employment impact is greater within the manufacturing sector. This pattern emphasizes the sector-specific dynamics at play, shedding light on how GIs actively contribute to employment growth across different segments of the economy.

The results of the analysis confirm the idea that the GIs may take advantage of production and management systems that can be traced back to Local Agro-Food Systems (LAFS), where the coordination action of the value chains is developed synergistically by territorial stakeholders who interact to solve problems and generate spillovers so that the positive effect of GIs can be extended beyond the product or sector itself. This cooperative approach is often necessary to address challenges such as quality control, sustainable production practices, and marketing strategies, which are inherent to the success of GI products. LAFS favors the emergence of a bottom-up network that is well-known locally. This effect is considerably helped by the tools provided by European and national regulations for the management of GI systems based on three aspects: i) the protection of intellectual property; ii) the Open Club principle (anyone who accepts the rules of the Code of Specification can enter the system); iii) the presence of a Consortium (GI Group or Interbranch organization) that manages the GI at a collective level. Overall, the synthesis of local knowledge and awareness, regulatory tools, and collaborative efforts within LAFS and GI systems plays a fundamental role in establishing a sustainable and competitive market presence for local products.

The implications of our results for rural development concern two main aspects: territorial management and economic development. In the former case, the presence of GIs in rural areas can influence political decisions regarding resource distribution, infrastructure development, and land management (e.g., Farm to Fork policy). In the latter case, when considering the opportunity of implementing GIs in rural areas, local administrations should consider that GIs can positively impact the local economy (e.g., LAFS) even beyond the sectors strictly linked to GI production. Furthermore, it is crucial to emphasize that GIs play a dual role, as they promote employment growth in rural areas and foster a spillover effect on neighboring regions, collectively driving overall economic growth. This indicates that the policy's impact extends beyond its original intention of fostering socioeconomic growth in rural areas. From this perspective, the results of this paper are encouraging for the European Commission, which is eager to further bolster GI protection and harmonize the legal framework. The objective of the EU Commission is to boost the adoption of GIs throughout the Union, fostering advantages for the rural economy and achieving elevated protection.

Our results complement previous findings in the literature, particularly in the ex-post analysis of the socio-economic effects of GIs at the regional level. Notably, our approach encompasses a representative sample of countries over an extended period, distinguishing it from previous works. A comprehensive review by Török et al. (2020) acknowledges the scarcity of such analyses and provides valuable context for the significance of our study. Additionally, our study stands out for its focus on critical indicators such as labor productivity and employment. Moreover, the use of a rigorous econometric approach to quantitatively assess the socio-economic impact of GIs provides external validity to our results, which represents an important contribution to our analysis since previous evidence in the literature has been mainly based on qualitative analysis (e.g., Belletti et al., 2015; Bowen, 2010) or case studies. Hence, our approach provides a solid foundation for evidence-based policy decisions in this domain.

While contributing valuable insights, the study has limitations mainly due to data constraints. Ideally, for a more exact identification of the socio-economic effects of the GI policy, the use of more disaggregated NUTS3 data could provide detailed information on labor productivity and employment in the different product categories where GIs belong.

CRediT authorship contribution statement

Valentina Raimondi: Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft. **Daniele Curzi:** Data curation, Investigation, Validation, Writing – original draft. **Filippo Arfini:** Writing – review & editing. **Chiara Falco:** Data curation, Formal analysis, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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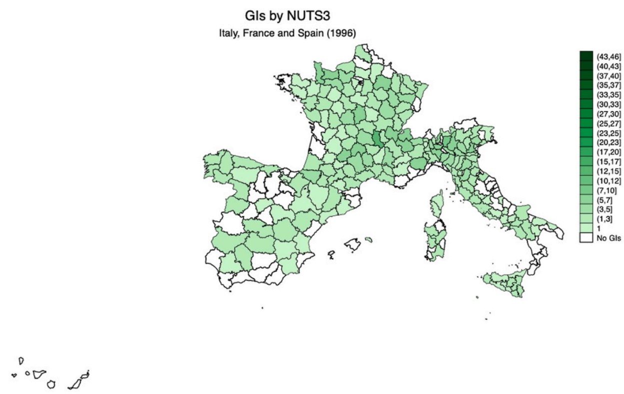
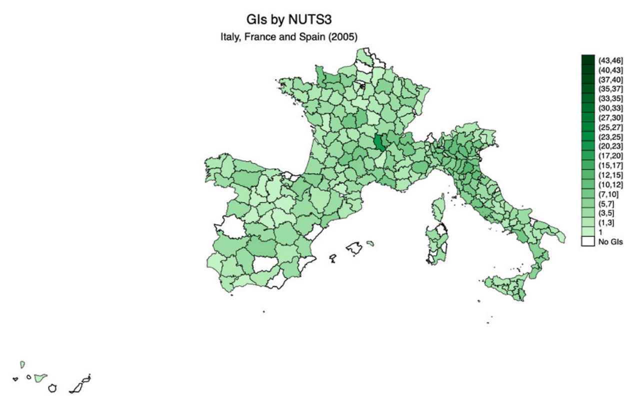
Appendix

(a)



(b)



(c)

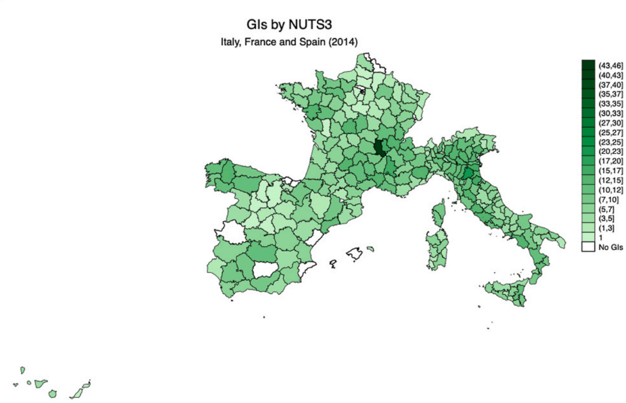


Fig. A1. Maps on the number of GIs in Italy, France and Spain at the NUTS3 level for the years 1996–2005–2014.
Sources: The data of GIs at NUTS3 level has been derived by the Authors from eAmbrosia database (see text).

Table A1
Descriptive statistics

Variables	Obs	Mean	Std.Dev.	Min	Max
log (Agr_Productivity)	5300	3.416	0.481	0.149	6.282
log (Agr_Employment)	5300	1.941	1.102	−4.135	4.381
log (Ind_Productivity)	5300	4.008	0.263	3.111	5.102
log (Ind_Employment)	5300	3.214	1.141	−3.540	6.431
log (GDP/Pop)	5300	3.063	0.272	1.998	4.423
Number of GI	5300	3.915	3.678	0	46
Number of GI - Italy	2200	4.722	3.701	0	21
Number of GI - France	1920	4.011	3.842	0	46
Number of GI - Spain	1180	2.256	2.694	0	13
Number of GI - Dairy sector	5300	1.073	1.490	0	11
Number of GI - Fruit&veg sector	5300	0.685	1.168	0	10
Number of GI - Meat sector	5300	1.377	1.786	0	23
Number of GI - Other sectors	5300	0.567	0.935	0	7

Source: Authors' calculations (see text).

Table A2
Socio-economic effects of GIs: Robustness check

	Panel A				Panel B			
	Agriculture		Industry		Agriculture		Industry	
	Productivity	Employment	Productivity	Employment	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline results								
Number of GI	−0.0011	0.0035***	−0.0010**	0.0008**	−0.0007	0.0036***	−0.0011**	0.0009**
	(0.0007)	(0.0010)	(0.0005)	(0.0004)	(0.0008)	(0.0011)	(0.0005)	(0.0004)
Results across countries								
No. of GI_Italy	−0.0014*	0.0038***	−0.0034***	0.0012***	−0.0008	0.0040***	−0.0034***	0.0013***
	(0.0008)	(0.0009)	(0.0005)	(0.0004)	(0.0008)	(0.0010)	(0.0005)	(0.0004)
No. of GI_France	−0.0013	0.0029**	0.0014***	−0.0001	−0.0012	0.0032**	0.0014**	−0.0000
	(0.0009)	(0.0012)	(0.0005)	(0.0003)	(0.0010)	(0.0013)	(0.0006)	(0.0004)
No. of GI_Spain	0.0051***	0.0060***	0.0014**	0.0020***	0.0063***	0.0060***	0.0014**	0.0020***
	(0.0016)	(0.0017)	(0.0006)	(0.0007)	(0.0018)	(0.0018)	(0.0007)	(0.0007)
Results across product categories								
No. of GI_Dairy	−0.0007	0.0028**	−0.0018**	−0.0008	−0.0004	0.0030**	−0.0017**	−0.0008
	(0.0016)	(0.0014)	(0.0007)	(0.0008)	(0.0017)	(0.0014)	(0.0007)	(0.0008)
No. of GI_Fruit&Veg	0.0006	0.0049***	0.0010	0.0016*	0.0008	0.0052***	0.0010	0.0018*
	(0.0020)	(0.0017)	(0.0009)	(0.0009)	(0.0021)	(0.0017)	(0.0009)	(0.0009)
No. of GI_Meat	−0.0027**	0.0020	−0.0011	0.0016**	−0.0021	0.0024	−0.0010	0.0017**
	(0.0013)	(0.0014)	(0.0008)	(0.0007)	(0.0014)	(0.0016)	(0.0008)	(0.0007)
No. of GI_Other	−0.0025	0.0082***	−0.0024**	0.0012	−0.0013	0.0084***	−0.0024**	0.0011
	(0.0032)	(0.0026)	(0.0012)	(0.0010)	(0.0033)	(0.0027)	(0.0012)	(0.0011)
No. of obs.	4960	4960	4960	4960	4740	4740	4740	4740

Notes: Panel A (see columns 1–4) omits the 17 regions with no GI (10 Spanish, 7 French); Panel B (see columns 5–8) excludes 28 provinces: 17 with no GIs, and 11 with GIs but not new GIs over the analyzed period (10 French, 1 Italian). The three groups of results, baseline, across countries, across products, follow the same structure of Tables 2–4 respectively. Time dummies, GDP per capita and lagged dependent variables included in all regressions. The SYS-GMM estimator is implemented in STATA using the *xtabond2* routine. Windmeijer-corrected standard errors in parenthesis: *** <0.01; ** <0.05; * <0.1.

Table A3
Socio-economic effects of PDOs: Robustness check

	GIs: PDOs			
	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
Baseline results				
Number of GI	−0.0017	0.0059***	−0.0032***	0.0014**
	(0.0012)	(0.0012)	(0.0008)	(0.0006)
Results across countries				
No. of GI_Italy	−0.0020	0.0056***	−0.0057***	0.0017***
	(0.0013)	(0.0012)	(0.0007)	(0.0005)
No. of GI_France	−0.0027	0.0049***	0.0018***	−0.0006
	(0.0019)	(0.0015)	(0.0007)	(0.0006)
No. of GI_Spain	0.0073**	0.0099***	0.0016	0.0035***
	(0.0031)	(0.0023)	(0.0014)	(0.0012)
Results across product categories				
No. of GI_Dairy	0.0031	0.0046***	−0.0026***	−0.0002
	(0.0022)	(0.0015)	(0.0009)	(0.0008)
No. of GI_Fruit&Veg	−0.0060	0.0089**	0.0027	0.0040**
	(0.0050)	(0.0038)	(0.0018)	(0.0020)
No. of GI_Meat	−0.0082**	0.0058***	−0.0056***	0.0046***
	(0.0033)	(0.0021)	(0.0016)	(0.0012)
No. of GI_Other	−0.0040	0.0072**	−0.0040**	0.0019
	(0.0041)	(0.0029)	(0.0016)	(0.0012)
No. of obs.	5300	5300	5300	5300

Notes: The three groups of results, baseline, across countries, across products, follow the same structure of Tables 2–4 respectively. Time dummies, GDP per capita and lagged dependent variables included in all regressions. The SYS-GMM estimator is implemented in STATA using the *xtabond2* routine. Windmeijer-corrected standard errors in parenthesis: *** <0.01; ** <0.05; * <0.1.

Table A4
Dynamic Models in Space and Time. Socio-economic effects of GIs: Baseline results

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
L.log(GVAagrEMP)	0.903***			
	(0.008)			
L.log(EMPagr)		0.861***		
		(0.007)		
L.log(GVAindEMP)			0.807***	
			(0.008)	
L.log(EMPind)				0.851***
				(0.007)
No. of GI	−0.004**	0.002**	0.000	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)
log(GDP/POP)	−0.092***	0.007	0.096***	0.051***
	(0.027)	(0.017)	(0.011)	(0.010)
rho	0.066***	0.047***	0.037***	0.035***
	(0.003)	(0.002)	(0.002)	(0.002)
R^2	0.549	0.957	0.438	0.952
No. of obs.	5300	5300	5300	5300

Notes: *t* statistics in parenthesis and robust standard errors calculated in the model. To estimate the SDM we use the STATA command *xsmle* with time lagged dependent variable. *** <0.01; ** <0.05; * <0.1.

Table A5
Dynamic Models in Space and Time. Socio-economic effects of GIs: Results across countries

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
L.log(GVAagrEMP)	0.914***			
	(0.008)			
L.log(EMPagr)		0.849***		
		(0.007)		
L.log(GVAindEMP)			0.804***	
			(0.008)	
L.log(EMPind)				0.856***
				(0.007)
No. of GI_Italy	−0.010***	0.003*	−0.001	0.000
	(0.003)	(0.002)	(0.001)	(0.001)
No. of GI_France	−0.004	−0.000	0.000	−0.000
	(0.002)	(0.001)	(0.001)	(0.001)
No. of GI_Spain	−0.002	0.004*	0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.001)
log(GDP/POP)	0.005	0.055**	0.138***	0.157***
	(0.037)	(0.024)	(0.015)	(0.014)
rho	0.078***	0.037***	0.043***	0.097***
	(0.003)	(0.002)	(0.002)	(0.002)
R^2	0.706	0.985	0.617	0.827
No. of obs.	5300	5300	5300	5300

Notes: *t* statistics in parenthesis and robust standard errors calculated in the model. To estimate the SDM we use the STATA command *xsmle* with time lagged dependent variable. *** <0.01; ** <0.05; * <0.1.

Table A6
Dynamic Models in Space and Time. Socio-economic effects of GIs: Results across product categories

	Agriculture		Industry	
	Productivity	Employment	Productivity	Employment
	(1)	(2)	(3)	(4)
L.log(GVAagrEMP)	0.892***			
	(0.008)			
L.log(EMPagr)		0.848***		
		(0.007)		
L.log(GVAindEMP)			0.806***	
			(0.008)	
L.log(EMPind)				0.853***
				(0.007)
No. of GI_Dairy	−0.002	0.001	−0.002	0.001
	(0.004)	(0.002)	(0.001)	(0.001)
No. of GI_Fruit&Veg	−0.007*	0.004*	0.002	−0.001
	(0.004)	(0.002)	(0.001)	(0.001)
No. of GI_Meat	−0.002	0.001	0.001	−0.001
	(0.003)	(0.002)	(0.001)	(0.001)
No. of GI_Other	−0.002	−0.000	−0.002	−0.000
	(0.005)	(0.003)	(0.002)	(0.002)
log(GDP/POP)	0.007	0.053**	0.140***	0.153***
	(0.037)	(0.024)	(0.015)	(0.014)
rho	0.059***	0.036***	0.043***	0.096***
	(0.003)	(0.002)	(0.002)	(0.002)
R^2	0.773	0.985	0.570	0.840
No. of obs.	5300	5300	5300	5300

Notes: *t* statistics in parenthesis and robust standard errors calculated in the model. To estimate the SDM we use the STATA command *xsmle* with time lagged dependent variable. *** <0.01; ** <0.05; * <0.1.

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