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Geographical Indications and Innovation: Evidence from EU regions

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ABSTRACT

Understanding the relationship between the diffusion of geographical indications (GIs) and innovation in the agri-food sector represents a relevant research area not yet properly addressed by the current literature. Our contribution aims to fill this gap by investigating the extent to which the diffusion of GIs across EU regions affects technological innovation. We investigate this issue through a Neo-Schumpeterian 'distance-to-the-frontier' model, according to which the relation between the diffusion of GIs and innovations is non-monotonic and depends on the distance of firms and local systems from the technological frontier. To test this prediction, we build an original longitudinal dataset that includes information on GIs and agri-food patents in 265 EU regions over the period 1996–2014. Using different estimators and different proxies for innovative activities, we show that the diffusion of GIs affects innovative activities, conditional on the region's distance from the technological frontier. That is to say, the spread of GIs slightly reduces innovation and growth in regions close to the technological frontier but spurs them on in laggard regions. These findings have important policy implications.

1. Introduction

With 1,367 designations and a total sales value of approximately €77.15 billion in 2017, GIs represent one of the strategic pillars of the agri-food economy in the European Union (EU) (European Commission, 2019). Since the introduction of this policy tool by Regulation 2081/92 (modified by Regulation 510/2006 and 1151/2012), a steady increase in the number of product registrations has been observed. From 2005 to 2017, there was a growth of 84 % and 69 % in GI sales value and volume, respectively. Such increase was largely driven by an impressive development in the number of protected geographical indications (PGIs), which, together with protected designations of origins (PDOs), accounted for 98 % of total GIs in 2020 (European Commission, 2020).[1]

Explanations for the success of this policy measure relate mainly to i) its capacity to act as differentiation tool and create a premium price for the certified product quality attributes (Moschini et al., 2008; Langinier and Babcock, 2008); ii) its ability to protect, both domestically and internationally, the names of specific agricultural and food products (Pouliot and Sumner, 2014); iii) the positive impact of this policy tool on regional economies in terms of the preservation of local skills, the promotion of tourism and the conservation of jobs in rural areas (Rachão et al., 2019); and iv) the improvement in the organisation of economic activities through more coordinated forms of transactions, such as consortia or cooperatives, that allow firms to share the costs of strategic investments and reduce the transaction uncertainties associated with information asymmetries (Russo et al., 2000; Stranieri et al., 2017).

One critical issue of the GI policy, which has been insufficiently investigated by the literature to date, is understanding the extent to which they encourage long-term innovation-based strategies at regional level. This is a key policy issue in general, and especially today in relation to the achievement of the European Green Deal targets, which emphasise the necessity of including sustainable economic growth

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[1] The GIs comprise PDOs, PGIs and traditional specialty guaranteed (TSG) designations. They all protect food with specific quality characteristics that are strictly linked to specific geographical areas or to the reputation of a production territory. PDOs and PGIs protect the names of food from specific geographical areas. The PDO certification guarantees that all stages of the production, processing and preparation are located within the geographical area that is identified in the product specification. The PGI certification relates to products whose quality characteristics and reputations are linked to the territory where they are produced, which is identified in the product specification. However, unlike PDOs, the ingredients used can come from other geographical areas or even from a different country. TSGs do not need to have a link with a specific production area but protect traditional food production methods.

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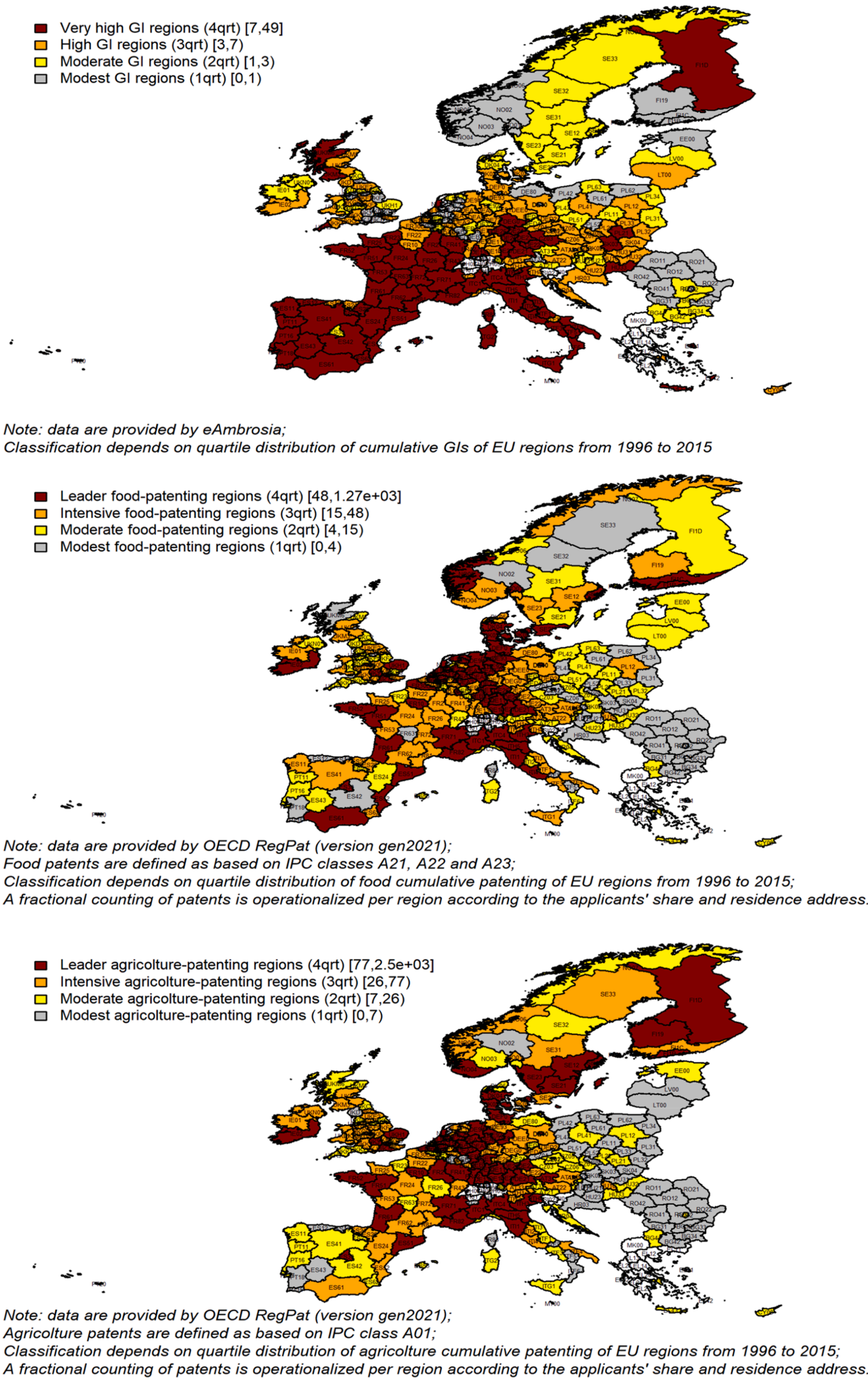

Fig. 1. Distribution of GIs (a), food patents (b), and agricultural patents (c) in European regions.

within the innovation paradigm (Ciaian, 2021). Indeed, understanding the capacity of GIs to produce spill-over effects by stimulating innovation is fundamental to evaluating its success in achieving a sustainable and competitive food system responsive to changing consumer preferences and the critical global challenges facing the food system, such as climate change, increasing loss of biodiversity, the existing bias along global value chains in favour of large firms and the awning gap between rural and urban areas (Bellassen et al., 2022; Rocchetta et al., 2022; Gocci et al., 2020).

The literature on GIs and innovation is quite controversial, with little evidence of a shared quantitative assessment of their possible interaction. The territorial distribution of GIs and agri-food innovations (proxied by patents in this paper), seems to suggest that there is a polarisation between EU regions in the adoption of GIs and engagement with innovative activities (see Fig. 1). GIs are mostly present in southern Mediterranean regions (Huysmans and Swinnen, 2019). On the other hand, agri-food inventions are mainly concentrated in central and northern regions. A few notable exceptions exist, particularly in Northern Italy (Lombardy and Emilia Romagna) and Southern France (Rhône-Alpes and Provence-Cote d'Azur), where a high degree of GI diffusion and significant innovation appear to coexist.

This polarisation of the distribution of GIs and innovation across EU regions and the contrasting view concerning the potential role of GIs in stimulating (Ruiz et al., 2018; Mancini et al., 2019) or discouraging (Moerland, 2019; Josling, 2006) innovations raises the following question: Do GIs play a role in stimulating or dampening the adoption of innovation at the regional level?

To investigate this question, we rely on the neoSchumpeterian strand of the literature, which links competition, regulation, and innovation, focusing on the "distance-to-the-frontier" model developed by Aghion et al. (2005, 2009). The model argues that the adoption of innovation by firms and territories depends on the level of market competition (which is also determined by the presence of anti-competitive normative measures) and the characteristics of the sector in which firms operate. Specifically, it predicts that under certain market conditions the relation between the level of competition and innovation is conditional on the distance from the technological frontier.

In our analysis, we explore an original longitudinal dataset that includes information on GIs and agri-food patents from 265 EU regions as defined by the second level of the Nomenclature of Territorial Units for Statistics (NUTS2) between 1996 and 2014. Using both standard regression tools and instrumental variable estimators to account for endogeneity, we find a robust, non-monotonic relationship between the diffusion of GIs and innovative activities (proxied by patents) in the agri-food sector. Consistently with the logic of the distance-to-the-frontier model, we show that GIs tend to reduce innovation in regions close to the technological frontier but encourage them in laggard regions.

Our paper contributes to this strand of the literature in several ways. First, to our knowledge, this study represents the first quantitative attempt to analyse the relationship between GIs and innovative activities across EU countries and regions. Our findings reconcile the controversy regarding the impact of GIs on innovation by using a well-established theoretical framework. Second, our analysis represents one of the few studies investigating the extent to which GI policies contribute to the prosperity and growth of rural areas at the EU regional level. With some caveats, mainly relating to data limitations, our findings support the notion that the EU's GI policy has contributed to innovation and thereby, to regional growth, particularly in laggard regions. Our final contribution concerns the large body of literature investigating the economics of GIs. Within this corpus, several authors identify possible collusion and even anti-trade bias associated with the implementation of the EU's GI policy.[2] Indirectly, our results give some support to this concern, because within the logic of the distance-to-the-frontier framework, the diffusion of GIs at regional level appears to reduce market competition, even if their overall contribution to regional development tends to be positive.

The paper is organised as follows. The next section discusses the theoretical background and empirical framework. In Section 3, we present the data and variables used in the empirical model. Next, in Section 4, the main results are presented and discussed. Finally, Section 5 discusses the results and provides some concluding remarks, focusing on the policy implications and limitations of the study.

2. Theoretical background and identification

This section starts by discussing the literature on the interaction between GIs and innovation. It then summarises the literature on market competition and innovation, aiming to justify the choice of studying the relation between the adoption of GIs and innovative activities using the 'distance-to-the-frontier' model. In the third part, we introduce the empirical strategy employed to identify the key theoretical predictions econometrically.

2.1. GIs and innovation

Existing knowledge on the relationship between GIs and innovation is somewhat patchy and mostly qualitative; furthermore, the results are contradictory. Moerland (2019) and Josling (2006) claim that GIs and innovative activities may not fit well together, although their arguments lack empirical evidence. Kuhne and Gellynck (2009) stress that innovation may not fit well with traditional food preparation because it could go against local identities and the *savoir faire* of traditional production methods. The case study of Bowen and Zapata (2009) on Mexican tequila also confirms that the introduction of innovation leads to negative firm performance, revealing that innovation needs to be well balanced with traditional production methods and product characteristics to be successful.

On the other hand, Ruiz et al. (2018) point out that firms working with GIs combine innovation with traditional methods of production to manage changing markets and to become more competitive. More precisely, in their analysis of GI amendments, they conclude that PDO/PGI certifications must be understood as evolving institutions that aim at increasing efficiency at firm and local level. Moreover, they find that most amendments relate specifically to old certifications and to foods processed through methods that are more affected by technological developments. Guerrero et al. (2009) and Linnemann et al. (2006) add to the existing debate by specifying that the adoption of innovation by firms producing traditional products is strictly related to the type of product considered. Moreover, Mancini et al. (2019) find that innovation is closely related to existing supply chain networks and that its impact on GI competitiveness is tightly bounded to the degree of collaboration among certified producers and their willingness to share knowledge and resources.

The above discussion clearly shows that it may be possible to balance the introduction of innovation and the preservation of the essential characteristics and reputation of GIs, but the evidence is still scarce and based mainly on qualitative considerations.

2.2. Theoretical background

To analyse the relationships between GIs and innovation within the European agri-food sector we referred to the theoretical frameworks which link competition, regulation and innovation (Schumpeter, 1943; Arrow 1962; Aghion and Howitt, 1992; Aghion et al., 2005).

There is a long-standing debate about this relationship. Starting from Schumpeterian growth models (Schumpeter, 1943; Aghion and Howitt, 1992) which predict a negative relationship between innovation and market competition, several theoretical approaches and the empirical evidence have been used to examine the conditions under which firms have more incentive to innovate. A part of such literature contradicts the Schumpeterian hypothesis of a positive correlation between innovation and market competition. For example, Arrow's reasoning on the 'replacement effect' shows that high market competition fosters

[2] In recent decades there has been several antitrust cases around GIs and consortia collusion. The most famous is likely the decision of the Italian Antitrust Authority about the market conduit between the Consortia of Parmigiano Reggiano and Grana Padano, notably the largest and most famous Italian PDO cheeses. See Braga and Nardella (2003) for a discussion.

innovation because of the absence of pre-innovation rents; on the other hand, monopolists and firms operating in highly concentrated markets have little incentive to innovate because such activities substitute ex-ante with ex-post rents, resulting in a reduction of ex-post profits (Arrow, 1962). Subsequent empirical works have also confirmed this positive correlation (Geroski, 1995; Blundell et al., 1999).

A convincing attempt to reconcile this dispute was introduced by the 'inverted U-shape relationship' (Aghion et al., 2005; Aghion et al. 2009). In this theoretical model, when competition increases, the reaction of incumbent firms towards innovation depends on the market structure and on their distance to the technology frontier of the sector in which they operate. In other words, this model predicts a different behaviour of firms towards innovation based on their distance from the technological frontier and of the market structure itself.

The logic of the 'inverted U-shape relationship' is that when market competition is low, neck-and-neck firms – i.e., firms which have similar production costs operating at the same technological level and close to the technology frontier – have little incentive to innovate. Otherwise, laggards in unlevelled sectors – i.e., sectors where firms have higher production costs than market leaders – have a greater incentive to innovate in order to compete at the same technological level as the market leader, and, moreover, an increase in competition will result in a faster innovation rate. On the other side, when market competition is high, neck-and-neck firms do have an incentive to innovate because of the 'escape-competition effect', i.e., firms will innovate only when competitors innovate and they gain an incremental profit from innovating compared to the pre-innovation rent. On the contrary, laggard firms in unlevelled sectors undergo a Schumpeterian effect. Specifically, laggards suffer the so-called 'discouragement effect' i.e., they have no incentive to innovate to catch up with the leader because of the reduction of post-innovation rents due to an increase of market competition. The Aghion et al. (2005; 2009) theoretical model fits well with the market structure of the agri-food sectors, which are almost all unlevelled (Grau and Reig, 2021; Mattas et al., 2021). In the EU, it is possible to observe the presence of firms close to the technological frontier and laggard firms both in agriculture and the food industry. However, the dynamic of innovation in such a different economic context is unknown.

The Aghion et al. (2005; 2009) argument goes on to deal with competition and regulation. The normative framework and market regulation measures have been recognized as factors impacting competition and in turn, innovation (Blind, 2016). Consistently with the empirical findings of the Aghion et al. (2005; 2009) theoretical model and Amable et al. (2010), anti-competitive regulations could lower innovative activities for firms close to the technological frontier and foster innovation in laggard industries. However, empirical analysis into the impact of normative measures on innovation is still at an early stage and, to the best of our knowledge, no studies have so far explored the impact of agri-food policies within this context.

Based on the above considerations, we investigate the relationship between market regulation, such as GI policy, and the innovation in agriculture and the food industry within EU regions, considering the 'distance-to-the-frontier' theoretical framework. More precisely, we apply the model proposed by Aghion et al. (2005; 2009) to test the relationship between the adoption of GI measures and innovation. More formally, in our analysis we test the following general relationship:

$$Y = f(P, D, X)$$

where Y is a measure of domestic firms' innovative activities or performance, P is a measure of market regulation (or competition), that in our specific framework is the level of GI policy adoption, and X is a vector of other covariates that affect innovation.

The logic behind this model is that the impact of P on Y is non-monotonic and switches from positive to negative depending on the distance from the technological frontier, D. Consistently with the inverted U-shape relationship discussed above, in the case of regions and markets with a low presence of P (i.e., low diffusion of GIs), laggard firms or regions will innovate less because of the discouragement effect, and market leaders will innovate more because of the escape competition effect. On the contrary, in the case of unlevelled regions and markets with a high P (i.e., high diffusion of GIs), it is expected that laggard firms will innovate at a faster rate than those close to the technological frontier.

A critical reason for the use of Aghion's theoretical framework is the consideration that GI policy in the EU can be considered, among other things, a policy measure that can alter competition for several reasons.

First, GIs increase the level of product differentiation in markets by labelling the geographical origin of raw materials and the traditional expertise of production processes. According to Scarpa et al. (2005) geographical origin plays an important role in consumer purchasing decisions. Most consumers associate PDO/PGIs label with high quality and are willing to pay a premium price for such labelled product information (Moschini et al., 2008). Therefore, GIs can be a source of market power, and they lead to a decrease of head-to-head product price competition in the market. By recognizing the important role of GI certification in performing an effective product differentiation strategy, several attempts to estimate consumers' willingness to pay for GIs have been made but most of the current literature is product-specific, and does not allow a generalization of the real level of price differentiation offered by these certifications (Sampalean et al., 2020; Menapace et al., 2011; van Ittersum et al. 2007). Moreover, several authors have also stressed the important role of different food cultures and traditions in shaping a price premium of PDO and PGI products on the market (Deselnicu et al., 2013). Notwithstanding the difficulty of estimating the precise level of price differentiation offered by such labelled products, these policy measures can potentially decrease market competition by increasing the level of product differentiation.

Second, a strand of literature acknowledges the role of GIs also in acting as a trade-reducing measure. For example, the analysis conducted by Pouliot and Sumner (2014) econometrically confirms that the introduction of a label of origin, such as the country of origin labelling (COOL) standard, lead to a decrease in the imports of cattle raised in Canada into the American market. Similarly, Marette et al. (2008) stress the role of GIs as trade barriers against competition when GI certification systems differ from one country to another. Raimondi et al. (2020) also support this perspective, finding empirical evidence that GI regulation can reduce product market competition to the EU.

Third, also the literature analysing the welfare implications of GIs considers this policy instrument as impacting on a given sector's competition because of the collusion among producers through the formation of consortia and cooperatives that may implement supply control strategies, even though the importance of improved information provided by the labels for a better functioning of the markets is recognized, as demonstrated by Akerlof (1970). Within this stream of literature, however, there is still a lively debate on the overall welfare impact of this policy, which cannot be taken for granted, as it heavily depends on the hypotheses and approaches used (Teuber, 2011). For example, Marette and Crespi (2003) demonstrate that even if GI producers collude to decrease competition, the certification may increase overall welfare due to the reduction of information asymmetry surrounding food quality attributes. These arguments are confirmed also by Lence et al. (2007), Mérel (2009) and Mérel et al. (2021), who consider GIs as socially preferable forms of collusions even though such normative measures limit production. However, Zago and Pick (2004) draw the opposite conclusion in their study, nonwithstanding the potential gain provided to consumers from improved information. They illustrate the negative effects that labelling policies have on welfare when there are no significant quality differences across products and when the administrative costs are high.

Based on the above discussion, it is evident that even though GI policy is a measure that has an impact on competition, its overall economic implications are still a matter of debate and need further investigation. The present analysis aims to contribute to this debate by considering effect of GIs on innovation within EU agri-food supply chains.

2.3. Econometric model and identification issues

The empirical strategy is in the spirit of the literature that tested the distance-to-the-frontier model, wherein an outcome variable measuring technological innovation, such as patenting, is regressed on a market competition variable (e.g. firm entry, market regulation, barriers to entry, tariffs or import competition) and its interaction with a distance-to-the-frontier term (see Aghion et al., 2009; Amable et al., 2010; Bourlès et al., 2013; Amiti and Khandelwal, 2013; Curzi et al., 2015). Empirically, we take the diffusion of GIs at the NUTS2 level as our variable that could affect the level of competition for the reasons discussed in the previous section. We thus test the relation between the regional adoption of GIs and innovative activities as measured by agri-food patents. Note, we are aware that, a priori, the anti-competitive effect induced by the diffusion of a GI is an empirical question. From this perspective, therefore, our specification can also be viewed as an indirect way to learn something about the role of GIs on the competitive environment, *ceteris paribus*.

Let $D_{i,t}$ be the distance to the frontier of region *i* at year *t*, measured as the ratio of its labour productivity (*LP*) to the highest regional labour productivity level, i.e., $D_{i,t} = \frac{LP_{i,t}}{\max(LP_t)}$, with $D_{i,t}\rightarrow 0$ for laggard regions and $D_{i,t}\rightarrow 1$ for regions close to the frontier. Formally, our strategy is to run regressions with the following empirical structure:

$$y_{i,t} = \alpha_i + \alpha_t + \beta_1 \left(D_{i,t-1} {}^{*} GI_{i,t-1}\right) + \beta_2 GI_{i,t-1} + \beta_3 D_{i,t-1} + X_{i,t-1}\gamma + \varepsilon_{cht} \tag{1}$$

The dependent variable, $y_{i,t}$, takes the number of patents in region *i* at year *t* as our main proxy of a region's innovation performance to check directly whether our results are picking up changes in regional innovative activity. The explanatory variables are all in levels for period $t-1$ to reduce endogeneity concerns. Thus, patents are explained by the lagged distance to the frontier ($D_{i,t-1}$), the lagged adoption of geographical indications ($GI_{i,t-1}$) and the interaction of these two variables $\left(D_{i,t-1}{}^{*}GI_{i,t-1}\right)$, plus a vector of controls ($X_{i,t-1}$). The interaction term should support the idea that the impact of GI diffusion on innovation is eventually conditional on the region's distance from the technological frontier (Aghion et al., 2005; 2009). To control for different permanent levels of patents across regions, we include region fixed effects, α_i, while common shocks are captured by time fixed effects, α_t.

Because there is a fraction of region–year observations with zero patents and there is overdispersion in the patent data, our main regressions are estimated by means of a negative binomial model.[3] However, as a robustness check we also run OLS equations by transforming the dependent variable in the log of (1 + patents) to retain all the available information.

We expect that $\beta_1 < 0$ and $\beta_2 > 0$, with $|\beta_2| < |\beta_1|$. To interpret this expectation in our framework, it is important to keep in mind that, in the observed period, several EU regions have experienced an increase in the adoption of GIs and hence, a reduction in market competition. The term β_2 captures the effect of GIs in regions far from the technological frontier (i.e., $D_{i,t}\rightarrow 0$). In these regions, we should expect that new barriers to entry presented by the diffusion of GIs result in an increase in rent appropriability from the innovative activities of laggard firms and regions. The $\beta_1 + \beta_2$ term should be negative, capturing the impact of the diffusion of GIs on firms' innovative activities in regions close to the technological frontier (i.e., $D_{i,t}\rightarrow 1$). In these regions, less competition induced by the diffusion of GIs should be detrimental to innovation, because incumbent producers should have less incentive to innovate in subsequent periods. Finally, the sign of the parameter β_3 on the distance to the frontier term is expected to be positive, given path dependency and spill-over effects from innovative activities (see, e.g., Etro, 2008).

The key identification issue in estimating Eq. (1) is the fact that the diffusion of GIs can be endogenous to innovative activities. As already suggested in the introduction, and better discussed in the data section, there is evidence that the territorial diffusion of GIs and agri-food patents tends to be sharply polarised across EU countries and regions (see Fig. 1). GIs are predominant in southern Mediterranean regions, while inventions, as proxied by patents, are mainly concentrated in the central and northern regions. Endogeneity due to selection can also be the result of the peculiarity of the EU's GI policy, as it aims, among other things, to spur economic growth and occupation in rural regions, areas that are often characterised by a lower level of development.

Addressing GI diffusion endogeneity is problematic in our framework due to the difficulty to find reliable instruments. Indeed, unlike Aghion et al. (2009), we cannot use market (de-)regulation policy variables as instruments for the change in market competition.[4] For this reason, in our main patenting regressions, GI diffusion, and its interaction with distance, enter lagged by one year to reduce simultaneity problems. Above all, we are mainly concerned with omitted variables bias by introducing a set of specific regional controls ($X_{i,t-1}$ in Eq. (1), suggested by the patenting literature, and by controlling also for region-specific time trends and the dynamic in the diffusion of patents.

Next, in the robustness check section some IV regressions are presented, where GI entry and its interaction with distance to the frontier is instrumented by the respective average value taken from four neighbouring regions. In this section, we also present additional results where the innovative activities are proxied by sectoral labour productivity growth, instead of patents.

3. Data and variables

3.1. Data and sample

In our analysis we took into consideration several databases: the Organisation for Economic Co-operation and Development (OECD) RegPat database (January 2021), which provides patent data for measuring regional innovation capacity in the agri-food sector and avoids the bias caused by different rules or laws in patent applications, involving several national patent offices. Moreover, we used the ARDECO database[5] to collect data on regional populations, sectoral gross value added (GVA) at constant prices and employment in the agriculture and manufacturing sectors for the operationalization of the distance to the frontier variable. We also referred to the eAmbrosia repository, that provides information identifying and localising GIs across EU regions.[6] Finally, we used the Eurostat and European Tertiary Education Register (ETER) for controls discussed below.[7]

[3] Results using standard Poisson or quasi-Poisson estimators are qualitatively and quantitatively similar.

[4] In Aghion et al. (2009) foreign firm' entry in the U.K. market, their proxy for market competition, has been instrumented by using the formation of the EU Single Market Program and U.K. sectoral market deregulation policy under the Thatcher government.

[5] The ARDECO database is the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy, maintained and updated by the Joint Research Centre.

[6] eAmbrosia is the legal repository of the names of foodstuffs and agricultural goods, wine and spirits that are registered and protected in all EU states.

[7] The European Tertiary Education Register is a database collecting information on higher education institutions (HEIs) in Europe with data on their basic characteristics and geographical positions, educational activities, staff, finances and research.

Table 1
Summary Statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Geographical Indications (#)	5,091	3.530	5.976	0	49
Agricultural Patents (#)	5,091	4.969	13.407	0	235
Food Patents (#)	5,091	3.279	7.922	0	103
Agri-food Patents (#)	5,091	8.248	18.539	0	270
Agricultural productivity growth	4,823	0.023	0.207	−3.438	2.239
Food value added growth	4,769	0.015	0.076	−0.876	0.682
Manufacturing productivity growth	4,823	0.026	0.078	−0.914	0.708
Distance to the frontier (Agriculture)	5,091	0.642	0.210	0.011	1
Distance to the frontier (Manufacturing)	5,091	0.641	0.132	0.128	1
Population density (0.000/km_sq)	5,091	0.342	0.851	0.003	10.550
Industry employment (share)	5,091	0.179	0.072	0.024	0.419
Scientific university (#)	5,091	2.034	3.872	0	25
Public university (#)	5,091	3.472	3.558	0	27
Gross fixed capital formation (log)	5,091	7.039	1.097	−0.136	9.908

Notes: For variables description and sources see Section 3.

3.2. Variables

Patents. We considered patents in both the food industry and agriculture. Despite the limitations[10] of measuring technological knowledge through patents (Alcacer and Gittelman, 2006), they remain a good proxy for calculating innovation performance at regional level (Aghion et al., 2009; Marrocu et al., 2013; Paci et al., 2014; De Noni et al., 2018). Because of the need to regionalise patent data (Maraut et al., 2008), only patents involving at least one applicant from an EU region were considered.[11] The region to which a patent is assigned was determined by the applicant's address. Patents with no applicant registered in a relevant region were excluded, as were patents involving applicants from regions listed as 'not classified'. We applied an applicant share when the patent involved multiple applicants. More precisely, if the multiple applicants were based in the same region, the patent was fully assigned to that region; if they were based in different regions, the patent was proportionally assigned to the regions involved. The share of any applicant whose address was not in the EU-28 or Norway was excluded. The 'priority year' (i.e., the date of the first patent

Table 2
Geographical Indications and Agri-food Patents: Negative Binomial Regressions.

	(1) Agriculture NegBin	(2) Agriculture NegBin	(3) Food NegBin	(4) Total NegBin	(5) Agriculture NegBin	(6) Agriculture NegBin	(7) Food NegBin	(8) Total NegBin
Dependent variable		*Number of Patents*				*Number of Patents*		
Distance ($t-1$) × GI ($t-1$)	−0.104**	−0.463***	−0.337***	−0.436***	−0.117***	−0.437***	−0.340***	−0.419***
	(0.042)	(0.110)	(0.103)	(0.089)	(0.041)	(0.118)	(0.106)	(0.088)
GI ($t-1$)	0.083**	0.320***	0.241***	0.303***	0.099***	0.308***	0.240***	0.293***
	(0.035)	(0.074)	(0.070)	(0.060)	(0.035)	(0.079)	(0.071)	(0.060)
Distance to the frontier ($t-1$)	0.358	3.012***	0.027	1.846*	0.214	2.380***	0.862	1.667**
	(0.316)	(1.139)	(1.213)	(0.999)	(0.219)	(0.848)	(0.918)	(0.660)
Pop density ($t-1$)	−0.788***	−0.720***	−0.038	−0.376***				
	(0.254)	(0.278)	(0.109)	(0.123)				
Employment share ($t-1$)	2.118	2.989*	−3.790*	0.304				
	(1.711)	(1.766)	(2.156)	(1.603)				
Scientific university ($t-1$)	−0.057**	−0.062***	0.009	−0.035*				
	(0.023)	(0.023)	(0.015)	(0.018)				
Public university ($t-1$)	0.099**	0.110**	0.001	0.074**				
	(0.043)	(0.043)	(0.032)	(0.034)				
Gross fixed cap formation ($t-1$)	0.106	0.102	0.163*	0.110				
	(0.114)	(0.115)	(0.087)	(0.088)				
Region fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Time fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Region specific time trends					Yes	Yes	Yes	Yes
Pseudo Rsq	0.336	0.338	0.343	0.333	0.334	0.336	0.340	0.332
Obs.	5091	5091	5091	5091	5225	5225	5225	5225

Notes: The table displays Poisson Negative Binomial (NegBin) estimates of patents count models; in columns 1 and 5 distance to the frontier is measured by agricultural labour productivity; in columns 2–4 and 6–8 distance to the frontier is measured through labour productivity in the manufacturing sector.
Robust standard errors clustered by NUTS2 regions, in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The final dataset encompasses approximately 1,600 GI products,[8] 18,000 patents in the food industry and 27,000 patents in agriculture across 265 NUTS2 EU-28 regions plus Norway from 1996 to 2014. The selection of the timeframe covered by this analysis (1996–2014) depends on data availability and the entry into force of Regulation 2081/92 and Regulation 2082/92. The GI legal framework was introduced in 1992 but the first registrations began in 1996. Moreover, completely reliable regional data regarding patents are available up to 2014.[9]

[8] A GI can be attributed to more than one NUTS2 region when the area of the GI is spread over two or more neighbouring regions; this operation leads to a higher number of GIs than the number reported in the introduction.

[9] The OECD RegPat database (January 2021) covers patent applications to the European Patent Office (derived from PATSTAT, Autumn 2020) and international Patent Cooperation Treaty (PCT) patents until the end of 2014.

[10] While patents are generally regarded as good indicators of innovative output, they are also usually considered to be intermediate outcomes along the value chain and International Patent Classification, albeit adequate and clear, has been created and developed for purposes other than providing researchers with a picture of the knowledge bases of industry and firms.

[11] A patent applicant refers to a company, organisation or individual who has the right to apply for the patent. Moreover, in the most common situation where an employee's invention is owned by the employer/company/organisation, the employer would be identified as the applicant and the employee as the inventor. If there is no property rights transfer to a company or an organisation, then the original inventor(s) will also be the applicant. We used applicants instead of inventors to regionalise patents to better link the economic effects of inventions to the territory in which the invention has been produced and used.

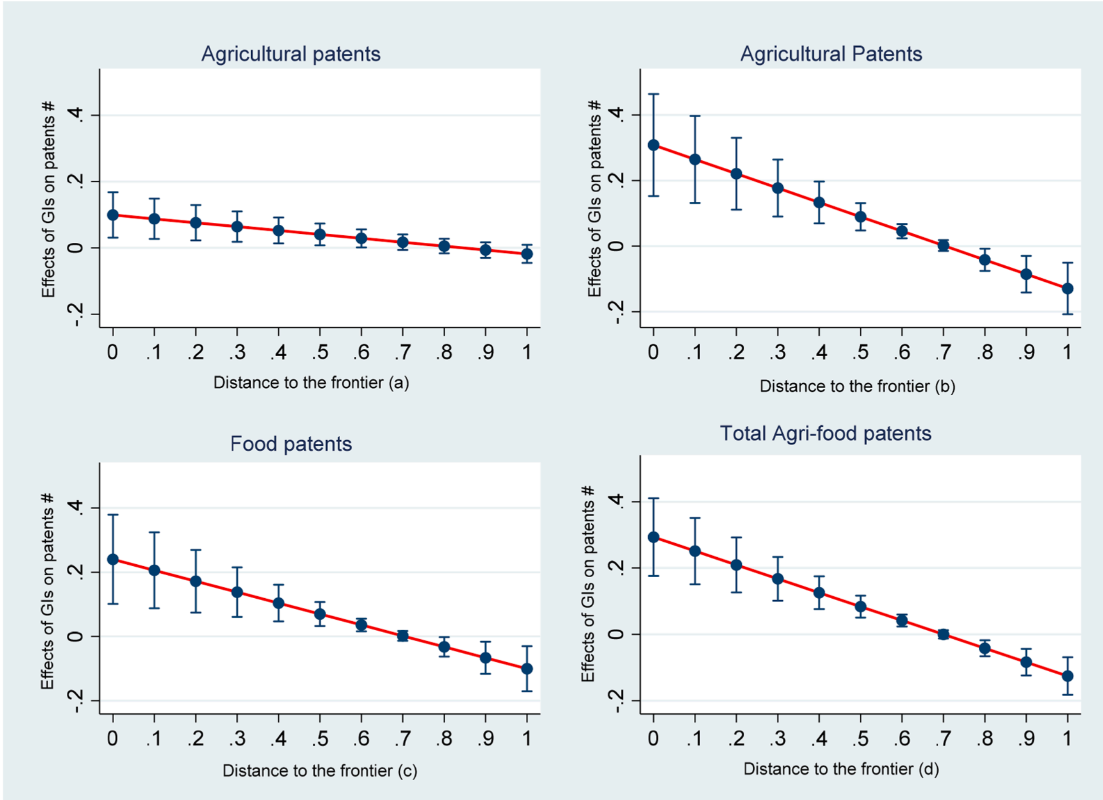

Fig. 2. Marginal Effect of GIs on Patents and Distance to the Frontier. *Notes*: The figure reports plots of the estimated marginal effects (with their 95% CI) of GIs on the number of patents conditional to distance to the frontier. Marginal effects are based on Negative Binomial regressions of Table 2 (columns 1–4). Plot (a) considers Agricultural patents and distance to the frontier based on agricultural labor productivity; Plot (b) considers Agricultural patents and distance to the frontier based on manufacturing labor productivity; Plots (c) and (d) consider Food patents and total Agri-food patents, respectively, with distance to the frontier based on manufacturing labor productivity.

Table 3
Geographical Indications and Agri-food Patents: OLS regressions.

	(1) Agriculture	(2) Agriculture	(3) Food	(4) Total	(5) Agriculture	(6) Agriculture	(7) Food	(8) Total
	OLS Regressions				Dynamic Panel Model			
Dependent variable		*Log (1 + Number of Patents)*				*Log (1 + Number of Patents)*		
Distance $(t-1) \times$ GI $(t-1)$	−0.044***	−0.136**	−0.147***	−0.197***	−0.040***	−0.120**	−0.138***	−0.177***
	(0.014)	(0.059)	(0.033)	(0.036)	(0.014)	(0.052)	(0.033)	(0.035)
GI $(t-1)$	0.038***	0.096**	0.107***	0.141***	0.035***	0.086***	0.099***	0.126***
	(0.011)	(0.037)	(0.022)	(0.024)	(0.011)	(0.033)	(0.022)	(0.024)
Distance to the frontier $(t-1)$	0.204*	0.540	−0.193	0.495*	0.184	0.532	−0.169	0.491*
	(0.118)	(0.374)	(0.270)	(0.293)	(0.118)	(0.339)	(0.268)	(0.289)
Pop density $(t-1)$	−0.746***	−0.730***	0.026	−0.373***	−0.643***	−0.628***	0.015	−0.333***
	(0.167)	(0.218)	(0.137)	(0.088)	(0.161)	(0.200)	(0.136)	(0.088)
Employment share $(t-1)$	0.515	0.603	−1.477***	−0.302	0.502	0.602	−1.314***	−0.192
	(0.472)	(0.656)	(0.448)	(0.505)	(0.469)	(0.591)	(0.444)	(0.504)
Scientific university $(t-1)$	−0.024***	−0.024**	0.005	−0.015	−0.021**	−0.022**	0.005	−0.013
	(0.009)	(0.012)	(0.008)	(0.009)	(0.008)	(0.010)	(0.008)	(0.009)
Public university $(t-1)$	0.051***	0.052***	0.013	0.053***	0.045***	0.046***	0.012	0.048***
	(0.013)	(0.020)	(0.013)	(0.014)	(0.013)	(0.017)	(0.013)	(0.014)
Gross fixed cap formation $(t-1)$	0.016	0.013	0.037**	0.041*	0.014	0.010	0.034*	0.035
	(0.019)	(0.029)	(0.019)	(0.022)	(0.018)	(0.026)	(0.019)	(0.022)
Log (1 + patents) $(t-1)$					0.119***	0.118***	0.090***	0.112***
					(0.017)	(0.024)	(0.017)	(0.017)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.834	0.834	0.816	0.869	0.836	0.836	0.818	0.871
Obs.	5091	5091	5091	5091	5091	5091	5091	5091

Notes: The table displays OLS (columns 1–4) and dynamic (5–8) panel models of patents data; in columns 1 and 5 distance to the frontier is measured by agricultural labour productivity; in columns 2–4 and 6–8 distance to the frontier is measured through labour productivity in the manufacturing sector.
Robust standard errors clustered by NUTS2 in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

application) available in the RegPat database determined the year to which a patent was assigned.

Patents in the food industry were calculated according to the number of registered patents granted by the European Patent Office per region and the year on the basis of the International Patent Classification in the following technological classes: A21—baking, equipment for making or processing doughs, doughs for baking; A22—butchering, meat treatment, processing poultry or fish; A23—foods or foodstuffs and their treatment not covered by other classes. Fig. 1(b) shows the cumulative distribution of food patents across regions.

As regards technology, the distribution of food patents reveals that most patents registered in the A21 class (more than 20 %) refer to the treatment and preservation of flour or dough for baking through the addition of organic or inorganic substances. Most of the patents in the A22 class relate to the shirring of sausage casings (18 %). Moreover, the A23 class is dominated by patents for the preservation of foods or foodstuffs through pasteurising, sterilising or otherwise preserving foods or foodstuffs through packaging (16 %).

Agricultural patents were calculated with the number of registered patents granted by the European Patent Office per region and year on the basis of the International Patent Classification: A01—agriculture, forestry, animal husbandry, hunting, trapping, fishing. Fig. 1(c) shows the cumulative distribution of agricultural patents across regions. Several agricultural patents are linked to processes for growing more robust and efficient plants, including disease resistance, cold/heat resistance, and rapid growth (6 %) or equipment for animal husbandry or the obtaining of their products (4 %).

Productivity growth. As a proxy for innovative activity, we also used labour productivity growth in the agriculture and manufacturing sectors as a robustness check. This variable represents a key measure of regional performance. Due to the lack of data, we were forced to proxy the food industry's labour productivity growth with productivity growth in the manufacturing sector, on the grounds that these variables are positively correlated. This is clearly a limitation of our analysis, even if investigating the impact of GIs on the productivity growth of the manufacturing sector may be of interest *per se*. Labour productivity (LP) has been measured according to the growth rate in constant gross value added (GVA) per worker for each NUTS2 region. We collected data from ARDECO database to operationalize both GVA growth rate (ARDECO domestic product) and workers in agriculture and the manufacturing sector (ARDECO Labour Market). We also tested a derived measure of the food industry GVA, based on the GVA of the manufacturing sector in millions of euros (at the 2015 price), weighted by the average ratio between the number of employees in the food industry and the number of employees in the manufacturing sector.[12] Data on the number of employees in the food industry were collected from the Eurostat database using the 2-digit NACE Rev.2 codes C10 (manufacture of food products) and C11 (manufacture of beverages) for the years 2008–2014, since the NACE Rev.2 classification was introduced in 2008.

Key explanatory variables. GIs were operationalised as the cumulative number of GIs registered in each NUTS2 region for each year of the time frame considered. To link the information on each GI with its geographical origin, we downloaded the code of conduct for each GI present in the repository eAmbrosia and we extracted the NUTS2 regions involved within each certification. Wine and spirits were excluded from our sample because the harmonisation of the wine legislation with GI policy is relatively new.[13] TSG-certified products were left out, as they are not linked to any territory and they only regulate the method of production. The year of registration of GIs was the year to which each product was assigned. In the database, if a GI product corresponded to more than one region, it was listed once for each of these regions. The average cumulative number of GIs per region is equal to 3.4.

The countries with the highest number of GIs are France (371), Italy (351), Spain (198), Germany (165) and Portugal (157), respectively. At the regional level, the areas with the higher number of GIs are Rhône-Alpes, Alentejo and Emilia Romagna (49 GIs), Norte (46), Centro (37), Veneto (36), Andalucía (35), Midi-Pyrénées (30), Lombardia (30), and Sicilia (30) (see Fig. 1(a)).

The distance to the technological frontier was measured as the distance in the log value of each region to the top EU region in terms of agricultural and manufacturing labour productivity (*LP*) levels, respectively. We used the maximum value of (log) labour productivity in EU regions for each year as a proxy of the technological frontier, measuring the corresponding distance according to $D_{i,t} = \frac{LP_{i,t}}{\max(LP_t)}$, where i is the NUTS2 region and t is the year from 1996 to 2014.[14] If the labour productivity of the region i at time t is equal or near the technological frontier ($\max(LP_t)$) we obtain value equal or near 1 ($D_{i,t}\rightarrow 1$); otherwise, for more distant regions we obtain values lower than 1. The closer the regions are to 0 ($D_{i,t}\rightarrow 0$), the more their distance from the technological frontier increases.

Other controls. We used population density as a proxy for urbanisation externalities, which are traditionally and positively related to economic growth and innovation (Frenken et al., 2007; Marrocu et al., 2013). Population density is the population per 1,000 inhabitants per square kilometre (population divided by one square kilometre of land) for each region and each year. To proxy the industrial structure of the regional economy, which is a relevant dimension linked to innovation activities (Hipp and Grupp, 2005), we used employment share in the manufacturing industry. In addition, we controlled for the territorial presence of research and development activities by using the number of universities in each region, disentangling the contribution of scientific institutions in which we included both private and public universities and public academic institutions supporting and developing innovative processes for business (Lee et al., 2010). Finally, we controlled for gross fixed capital formation, which is related to the fixed assets that are used repeatedly or continuously in production processes and expected to have a positive impact on regional economic innovation and performance (Darma, 2020). Gross fixed capital formation was measured as the log of the value (in millions euros) of acquisitions of new or existing fixed assets by the business sector, governments, and households minus the disposal of fixed assets in a given region and year.

Table 1 reports summary statistics of the aforementioned variables, while Table B.1 in Appendix B shows the overall, between and within variation in the sample of the main variables of interest.

4. Econometric results

In this section, we first discuss econometric results from our main patenting regression (Eq. (1)) for agricultural and food patents. This is, admittedly, the most direct way to test the relationship between GI diffusion and innovation, i.e., our key research question. Next, in the robustness check section, we briefly discuss additional econometric results to verify the extent to which our results and main conclusions are robust to endogeneity issues and to another proxy for innovative activities (i.e., the sectoral productivity growth).

[12] The ratio between the number of employees in the food sector and the number of employees in the manufacturing sector in a given region is an average calculated over the period 2008–2014, which refers to the available reliable data about regional food industry employees. Formally we have: $Food\,GVA_{i,t} = Manufact\,GVA_{i,t} * \frac{\#\text{ employees food sector}_{i,2008-2014}}{\#\text{ employees manufacturing sector}_{i,2008-2014}}$, where I is the NUTS2 region and t is the year from 1996 to 2014.

[13] Harmonization of the GIs for wines and spirts with those for foodstuff products entered into force with EC Regulation 1308/2013.

[14] To calculate the log of labour productivity in agriculture we used the agriculture GVA divided by the workers in agriculture while to measure the manufacturing labour productivity in log we used the GVA per workers in manufacture $LP_{i,t} = \log\left(\frac{GVA}{employees}\right)_{i,t}$. To measure the maximum value of (log) labour productivity we used the following formula $max(log(GVA/employees))_t$.

4.1. Regression results

In Table 2 we present the econometric results from the fixed effects negative binomial models with robust standards errors corrected for heteroskedasticity and autocorrelation of unknown forms, to control for both overdispersion and correlation over time for a given region (Cameron and Trivedi, 2010). All regressions include the lagged GI level, lagged distance to the frontier and the interaction between these two variables, plus a set of controls.[15]

In column 1, the dependent variable is agricultural patents and the distance to the frontier is measured by agricultural labour productivity. The estimated coefficient of the linear GI term is positive while the coefficient of the interaction term between GIs and distance to the frontier is negative. Both coefficients are statistically significant at the 5 % level. Importantly, the (absolute) magnitude of coefficient of the interaction term, $|\beta_1|$, is larger in magnitude than the GI linear coefficient, $|\beta_2|$, a result in line with the 'distance-to-the-frontier' prediction (see Section 2.3). In column 2, the distance to the frontier is measured through manufacturing labour productivity. The estimated coefficients of the GI linear term and its interaction with the distance term have the expected sign, and are statistically significant at the 1 % level. Further, the (absolute) magnitude of the estimated linear and interaction terms increases, which adds support to the idea that, by measuring the frontier using labour productivity in manufacturing, we can better identify leader vs laggard regions.[16] A positive linear GI and a negative interaction suggests that the diffusion of GIs tends to spur innovative activities in regions distant from the frontier ($D_{i,t}\rightarrow 0$), an effect that becomes negative in regions close to the frontier ($D_{i,t}\rightarrow 1$). The negative interaction effect thus counteracts the positive effect of GI entry in more advanced regions, as predicted by the logic of Aghion et al.'s theoretical framework.

In column 3, the dependent variable is food patents and the distance to the frontier is based on manufacturing labour productivity. Again, we find a positive linear GI term and a negative interaction between GI and the distance to the frontier, with both coefficients statistically significant at the 1 % level. Column 4 confirms the previous model's findings using the sum of agricultural and food patents.

The estimated effect of the linear distance to the frontier term, β_3, is positive in every specification, suggesting that regions already close to the technological frontier tend to be more active in patenting, although the effect is statistically significant only in columns 2 and 4. Considering control variables, lagged population density exerts a negative and significant effect on innovation,[17] while the share of employment in the industry does not. The effects of the number of scientific institutes and public universities are negative and positive respectively, and both are statistically significant.[18] Finally, the lagged (log) gross fixed capital formation has, in line with our expectations, a positive effect on patents, albeit significant at the 10 % level only in the food patenting equation (column 3).

Columns 5 to 8 try to provide a better account of omitted variables bias by including in the specification region-specific time trends instead of the set of region-specific control variables.[19] Note, in this specification, we are unable to retain year fixed effects, due to convergence problems of the negative binomial estimator, but this shortcoming need not be a major problem. The results are very close to the one reported in columns 1–4, suggesting that omitted variable bias does not seem a major issue in our estimations.

For illustrative purposes, Fig. 2 plots the marginal effects of GIs on patents with the respective 95 % confidence intervals. The Figure is based on the negative binomial regressions from Table 2 (columns 1–4). Panels (a) and (b) refer to agricultural patents. When the distance to the frontier is measured according to agricultural labour productivity (Panel a), the impact of GIs on innovation becomes significant and positive when the distance to the frontier is lower than 0.7. In regions far from the frontier ($D_{i,t}\rightarrow 0$), one additional GI increases the number of patents by 0.1. The same effect rises to 0.3 patents when the distance to the frontier is measured with industry labour productivity (Panel b). From an economic point of view this effect is quantitatively significant, particularly when we take into consideration that, on average, these laggard regions have fewer agricultural patents. For example, the average number of agricultural patents in regions that lie in the first percentile of the distance to the frontier distribution (i.e., $D \leq 0.25$) is equal to 2.3 patents. As a result, in these laggard regions an increase in the number of patents of around 0.2 ÷ 0.3 (for one additional GI) correspond to a 10 % increase. Furthermore, the GI marginal effect becomes negative and significant for distance values higher than 0.8. It is worth noting, however, that the negative GI entry effect on patents close to the frontier ($D_{i,t}\rightarrow 1$) is about 1/3 of the absolute magnitude of the impact far from the frontier; in other words, the positive GI effect quantitatively dominates the negative effect in our sample. The GI marginal effects of food (Panel c) and total agri-food patents (Panel d) display a very similar pattern. Thus, the above quantitative analysis of the marginal effect of GI diffusion on patenting strongly confirms the distance to the frontier model, although it would be wise to avoid putting too much emphasis on these extreme points, which are largely based on extrapolations, as there are too few observations with zero (or one) distance to the frontier values.

Table 3 displays results from Ordinary Least Squares (OLS) regressions by using the logarithm of one plus the number of patents as the dependent variable. One advantage of this specification is that it also provides the possibility to run a dynamic equation to control for omitted variables bias more effectively. First, in columns 1–4 we run static regressions. The GI linear term is positive and its interaction with distance to the frontier is negative, with both coefficients estimated with high precision and magnitude consistent with the prediction. As a further check, Columns 5–8 display a dynamic version of the respective OLS equations by adding the lagged dependent variable on the right-hand side of the equation. This specification is useful when accounting for

[15] Running a naïve specification that excludes the interaction term between lagged GIs and distance to the frontier, the estimated GI coefficient is always positive, very small in magnitude, and never statistically significant at the conventional level. These additional results are available from the authors upon request.

[16] The change in the magnitude of the estimated coefficients, aside from being a better characterization of the technological frontier using manufacturing productivity, can be also attributed to the fact that labour productivity in agriculture is systematically measured with errors (see Herendorf and Schoellman, 2015), an issue that tends to bias the estimates toward zero in a fixed effects model.

[17] Surprisingly, but in line with other studies on regional innovation systems (Dijkstra et al., 2013; Marrocu et al., 2013; McCann, 2013, Dijkstra et al., 2015) population density is negative and significant. Even though urbanisation economies are expected to leverage regional innovative performances, largely populated areas show an increase of negative externalities due to congestion costs, unskilled workers, labour oversupply, higher cost of living and insufficient infrastructure investments that can negatively affect innovation and growth (Dijkstra et al., 2013). Moreover, we used only agri-food patents at NUTS2 level to define our dependent variables, thus we expect that this type of innovation is more widespread in rural and less densely populated areas.

[18] An interpretation of the different effects of public and scientific universities is that, in scientific universities, private institutions do not usually implement agricultural and/or food science master degree programmes; such scientific competences are frequently covered by public universities. The simple correlation between public and scientific universities is 0.49, suggesting that within this university group, several could be private institutions. However, using the available information, we cannot disentangle this hypothesis.

[19] When these specifications were run including the vector of controls used in columns 1–4, the results were virtually the same.

Table A.1
Geographical Indications and Agri-food Patents: Negative Binomial Regressions with Control Function (CF).

	(1) Agriculture NegBin-CF	(2) Agriculture NegBin-CF	(3) Food NegBin-CF	(4) Total NegBin-CF
Dependent variable		*Number of Patents*		
Distance ($t-1$) × GI ($t-1$)	−0.121**	−0.496***	−0.389***	−0.494***
	(0.049)	(0.119)	(0.150)	(0.094)
GI ($t-1$)	0.117***	0.351***	0.268***	0.343***
	(0.039)	(0.075)	(0.094)	(0.058)
Distance to the frontier ($t-1$)	0.298	2.515**	−0.275	1.393
	(0.308)	(1.154)	(1.203)	(0.986)
Pop density ($t-1$)	−0.985***	−0.954***	−0.020	−0.407***
	(0.258)	(0.284)	(0.170)	(0.092)
Emplyment share ($t-1$)	2.159	2.767	−3.997*	0.027
	(1.625)	(1.722)	(2.362)	(1.585)
Scientific university ($t-1$)	−0.054**	−0.057**	0.009	−0.033
	(0.025)	(0.026)	(0.016)	(0.020)
Public university ($t-1$)	0.099**	0.105**	0.006	0.073**
	(0.045)	(0.045)	(0.032)	(0.034)
Gross fixed capital formation ($t-1$)	0.172	0.160	0.172**	0.146
	(0.123)	(0.124)	(0.087)	(0.094)
Region fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Control function	Yes	Yes	Yes	Yes
χ^2 test of first stage residuals (p-value)	0.102	0.173	0.201	0.074
Pseudo Rsq	0.341	0.343	0.347	0.338
Obs.	4823	4823	4823	4823

Notes: The table displays Poisson Negative Binomial (NegBin) estimates of patents count model that allow for GIs endogeneity in the linear and interacted entry terms by including the respective first-stage residuals as control function (see Wooldridge, 2010); the instruments in the first stage are GIs and GI interacted distance of the four neighbors' regions (see text); in column 1 distance to the frontier is measured by agricultural labour productivity; in columns 2 to 4 distance to the frontier is measured through labour productivity in the manufacturing sector.
Robust standard errors clustered by NUTS2 regions, in parentheses: * $p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

the dynamics whereby past innovations help to explain current ones; importantly, it also addresses residual omitted variables bias.[20] The lagged dependent variable is significant and positive in every specification, suggesting that past innovation stimulates current innovation. However, the autoregressive coefficient, equal to around 0.1, is quite small, suggesting that the path dependency in patenting is not so relevant. Overall, results from these dynamic specifications strongly confirm our hypotheses and are very close to those derived from the static model.[21]

To sum up, we find robust evidence of heterogeneity in the effects of the diffusion of GIs on subsequent patenting activities in agriculture and the food industry. As predicted by the 'distance-to-the-frontier' framework, GI diffusion appears to discourage subsequent patenting activities in regions close to the technological frontier and stimulate patenting in more distant ones, a result which is consistent with the 'escape competition' and 'discouragement effect' predicted by the theoretical model. Quantitatively, our empirical evidence also shows that the positive marginal effect of GIs far from the frontier is about two or three times larger in (absolute) value than the negative marginal effect close to the frontier, i.e., overall, GI diffusion stimulates innovation.

4.2. Robustness check and extension

The key identification issue of the above results is the fact that GI diffusion can be endogenous to innovation activities (Aghion et al, 2009). For example, when considering entry, potential GI firms are likely to take into consideration the competitiveness and innovative activity of local firms. It is difficult to predict, *a priori*, the covariance between actual GI entry and the error term, also because in our specific context problems of selection in the adoption of GIs are probably at work. Indeed, GI policy is largely directed to rural areas and thus GI diffusion is expected to be stronger in laggard regions, *ceteris paribus*.

We try to attenuate this endogeneity problem by instrumental variable (IV). More precisely we account for the endogeneity of the linear and interaction terms in the negative binomial estimator using the residuals from the first-stage regressions for GI entry and the GI–distance interaction as control function corrections. The instruments are the GIs and the distance to the frontier variables, averaged across the four neighbouring regions and their relative interaction. We are aware of the limit of this strategy, because it is clear from the maps in Fig. 1, that neighbouring regions will likely suffer from the same selection issues, although this approach should at least partially attenuate endogeneity concerns.

Table A.1 in the Appendix reports regression results. Overall, the pattern of these estimates is very close to the results reported in Table 2, in terms of both the magnitude of the estimated coefficients and their significance level. Thus, endogeneity concerns regarding GI entry do not appear a major problem for our results and conclusions. Further discussion of these additional results is reported in Appendix A.

As an additional robustness, we run regressions using sectoral labour productivity growth as a proxy of innovative activities. Even if such a variable is an indirect measure of innovation and may also reflect other dynamics associated with the labour force (for example growth due to labour reallocation), the effect of GIs on the regional productivity growth is interesting *per se*, because it is among the objectives of the EU's GI policy. Overall, we find a pattern of GI entry effects on sectoral growth, which is very similar to patent results, i.e., the interaction of GIs with distance to the frontier is always negative and displays an absolute magnitude higher than the positive linear GI term, with both coefficients statistically significant at conventional level. These additional findings and their discussion can be found in Appendix A, Table A.2.

[20] As is well known, the within-group estimator of the autoregressive coefficient tends to be biased downward in a panel model when T is small due to the so-called Nickel bias (see Bond, 2002). However, with an almost perfectly balanced panel and $T = 19$, this bias has become negligible in our context.

[21] The magnitude of the GI entry linear and interaction terms is, as expected, slightly smaller than the static version reported in columns 1–4, simply because now these coefficients capture short-term effects.

Table A.2
Geographical Indications and Sectoral Growth: OLS and IV regressions.

	(1) Agriculture OLS	(2) Food OLS	(3) Manuf OLS	(4) Agriculture OLS	(5) Food OLS	(6) Manuf OLS	(7) Agriculture IV	(8) Food IV	(9) Manuf IV
Dependent variable					*Sectoral Growth Rate*				
Distance ($t-1$) × GI ($t-1$)	−0.011**	−0.026***	−0.024***	−0.013***	−0.020***	−0.024***	−0.016**	−0.038***	−0.038***
	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)	(0.008)	(0.007)	(0.012)	(0.012)
GI ($t-1$)	0.008**	0.016***	0.016***	0.010**	0.012***	0.016***	0.014**	0.021***	0.024***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)	(0.008)
Distance to the frontier ($t-1$)	−1.529***	−0.688***	−0.960***	−1.469***	−0.535***	−0.899***	−1.521***	−0.703***	−0.967***
	(0.112)	(0.094)	(0.076)	(0.122)	(0.091)	(0.075)	(0.113)	(0.093)	(0.075)
Pop density ($t-1$)	0.088	−0.029*	−0.019				0.095	−0.036**	−0.023*
	(0.116)	(0.017)	(0.013)				(0.116)	(0.017)	(0.013)
Employment share ($t-1$)	0.424*	−0.565***	0.013				0.414*	−0.585***	−0.010
	(0.244)	(0.120)	(0.110)				(0.244)	(0.119)	(0.111)
Scientific university ($t-1$)	−0.003	0.000	0.001				−0.003	−0.000	0.000
	(0.004)	(0.002)	(0.001)				(0.004)	(0.002)	(0.001)
Public university ($t-1$)	0.015*	0.000	−0.000				0.015*	0.001	−0.000
	(0.008)	(0.003)	(0.003)				(0.008)	(0.003)	(0.003)
Gross fixed cap formation ($t-1$)	−0.009	0.011**	0.014***				−0.008	0.009*	0.013**
	(0.014)	(0.005)	(0.005)				(0.014)	(0.005)	(0.005)
Region fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region specific time trends	No	No	No	Yes	Yes	Yes			
Endogeneity Test (Ho = exogenous)							12.35	22.82	6.62
(p-value)							(0.006)	(0.000)	(0.036)
F-test all excluded instruments							18.71	21.84	21.68
(p-value)							(0.000)	(0.000)	(0.000)
Rsq	0.227	0.255	0.217	0.232	0.289	0.251	n.a.	n.a.	n.a.
Obs.	4824	4770	4824	4824	4770	4824	4824	4770	4824

Notes: The table displays OLS and IV regressions of labor productivity growth models (value added growth for the food industry); in columns 1, 4 and 7 distance to the frontier is measured by agricultural labour productivity; in columns 2–3, 5–6 and 8–9 distance to the frontier is measured through labour productivity in the manufacturing sector; in columns 7 to 9 we allow for GIs endogeneity in the linear and distance interacted entry terms using GIs (and GI interacted distance to the frontier) of the four neighbors regions; distance to the frontier is instead instrumented by the second lagged value (see text).
Robust standard errors clustered by NUTS2 regions in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, Fig. A.1 in Appendix A, plots the GI marginal effects on productivity growth with confidence intervals based on the results from Table A.2 (columns 1–3). As with patents, the negative slope of the schedule indicates that GI may have a positive effect on growth when regions are far from the frontier, though this effect becomes gradually negative as regions approach it. Importantly, and similarly to patenting regressions, our empirical evidence also shows that the positive marginal effect of GIs on growth far from the frontier is larger in (absolute) magnitude than the negative one close to the frontier, i.e., there is clear evidence supporting the distance-to-the-frontier model's assertions about the effect of GI entry on innovation and productivity growth.

5. Discussion, implications and concluding remarks

The present paper contributes to the existing debate on the interaction between the diffusion of GIs and innovation. Using different outcome variables and different estimators, we uncover strong empirical support for the 'distance-to-the-frontier' theoretical framework, i.e., the effect of GIs diffusion on innovations is conditional on the region's distance to the technological frontier. Our results support the idea that GI entry positively affects innovation and growth in regions far from the technological frontier, a relation that turns negative in regions closer to the frontier. This finding, in fact, is fully consistent with the prediction of a Neo-Schumpeterian distance-to-the-frontier model, linking market competition with innovative activities.

With regard to the research question addressed in this paper—Do GIs play a role in the knowledge adoption at regional level? — the present findings highlight clearly the important role of GIs in spurring innovation, especially in laggard EU regions. Even if the effect of GIs becomes negative in regions approaching the technological frontier, our quantitative evidence also shows that the positive marginal effect of GIs far from the frontier is about two/three times larger in (absolute) value than the negative marginal effect, and, more importantly, the latter is not always statistically significant. Thus, our results suggest that, overall, GIs foster innovation and growth. They also provide empirical support for the insight of Huysmans and Swinnen (2019), that the high concentration of GIs in southern Europe relates to the fact that the agri-food industry in these regions is less productive than in the North.

Our findings also contribute to the discussions of Moerland (2019) and Josling (2006) by demonstrating that the negative effect of GI diffusion on innovation activities does not entirely depend on the configuration of GI policy and on the strict rules associated with the valorisation of traditional production and cultural heritage; but can also depend on the characteristics of the regional economy in which the GIs are developed. Indeed, our analysis highlights that in technologically advanced regions, the role of GIs contributes only marginally to regional sectoral growth. These results must also be contextualised with the considerations of Mancini et al. (2019), who argue that innovations in GIs often relate to product or organisational improvements, which are not detected by patenting. This understanding could soften the negative relationship found in the present analysis and, to some extent, explain the presence of a high number of GIs in certain regions close to the technological frontier, such as Lombardy and Emilia Romagna in Italy and Rhône-Alpes in France. As Knickel et al. (2009) suggest, when the production of GIs is well developed and labelled products have high market recognition, innovation is mostly considered endogenous to the related network of production—that is, it is the result of collaborative activities and learning processes along the supply chain. Even though such arguments do not contradict our results, it is important to recognise that theories that focus on the role of knowledge spill-overs instead of innovation incentives could offer additional insights into the present findings (see Griffith et al., 2004).

Table B.1
Summary Statistics: Between and Within Variation in the Sample.

Variable	Variation	Mean	Std. Dev.	Min	Max	Obs.
Geographical Indications (#)	overall	3.651	6.107	0	49	N = 5500
	between		5.599	0	36.75	n = 275
	within		2.462	−19.10	24.90	T = 20
Agricultural Patents (#)	overall	4.855	13.204	0	234.50	N = 5580
	between		12.149	0	125.27	n = 279
	within		5.220	−70.58	114.09	T = 20
Food Patents (#)	overall	3.173	7.758	0	103.17	N = 5580
	between		7.189	0	63.49	n = 279
	within		2.947	−26.49	42.85	T = 20
Agri-food Patents (#)	overall	8.028	18.223	0	269.50	N = 5580
	between		17.145	0	143.64	n = 279
	within		6.256	−65.95	133.89	T = 20
Agricultural productivity growth	overall	0.022	0.208	−3.438	2.239	N = 4950
	between		0.028	−0.097	0.104	n = 275
	within		0.206	−3.420	2.306	T = 18
Food value added growth	overall	0.015	0.076	−0.876	0.682	N = 4896
	between		0.020	−0.045	0.085	n = 272
	within		0.074	−0.845	0.713	T = 18
Manufacturing productivity growth	overall	0.025	0.079	−0.914	0.708	N = 4950
	between		0.019	−0.039	0.082	n = 275
	within		0.077	−0.882	0.740	T = 18
Distance to the frontier (Agriculture)	overall	0.644	0.209	−0.170	1	N = 5225
	between		0.195	−0.024	0.915	n = 275
	within		0.075	−0.072	0.985	T = 19
Distance to the frontier (Manufacturing)	overall	0.642	0.131	0.128	1	N = 5225
	between		0.128	0.240	0.991	n = 275
	within		0.030	0.444	0.744	T = 19

Notes: For variables description and sources see Section 3.

A second important implication of our analysis involves the impact of GI diffusion on the competitive environment. If we take for granted our empirical results within the distance-to-the-frontier model, then one can conclude that GI diffusion does affect the agri-food competitive environment, a conclusion that fits with several papers investigating the possible collusion effect of the GI policy (Pouliot and Sumner, 2014; Mérel, 2009; Marette et al., 2008). Such evidence is surely indirect, and more detailed quantitative micro-studies are needed to confirm this hypothesis. Moreover, if we consider that the adoption of GIs fosters regional value creation, especially in less developed EU regions, it can be argued that such policy measures influence opposing firm dynamics, such as competition and cooperation among supply chain partners throughout integrated forms of vertical relationships. These opposing strategic behaviours could foster a 'cooperative system of value creation' (Dagnino, 2009). However, whether this kind of coopetition strategy contributes to innovation and value creation is still a point to be addressed.

Our analysis has limitations. The use of patents as proxy for innovation activities where the agri-food sector is concerned is perhaps not the best way to capture what really happens in the agri-food sector because many firms do not invest directly in research and development, and many (incremental) innovations at the farm or firm level are not detected by patenting. Moreover, our analysis has had to overcome the lack of official regional data on value added in the food industry in order to measure labour productivity in that sector. Although it is plausible that labour productivity in the food industry is correlated with that of the manufacturing sector, most GI products are sold by firms in the secondary sector. As a result, it is not possible to estimate accurately the growth rate in food industry productivity in relation to the distance to the frontier logic. Therefore, improvements in how innovation activities are measured and the use of better proxies that account for food industry performance through total factor productivity and firm level data, represent important priorities for future research. Another relevant outlet for future research is the development of more qualitative studies through in-depth interviews. Such an approach will allow scholars to better capture direct and indirect links between GIs and innovative outputs of agri-food firms within EU regions in terms of patents, trademarks, and new products.

CRediT authorship contribution statement

Stefanella Stranieri: Conceptualization, Writing – original draft, Writing – review & editing, Supervision. **Luigi Orsi:** Data curation, Methodology, Writing – original draft, Writing – review & editing. **Ivan De Noni:** Data curation, Methodology, Writing – original draft. **Alessandro Olper:** Conceptualization, Methodology, Software, Formal analysis, Writing – review & editing, Supervision.

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.

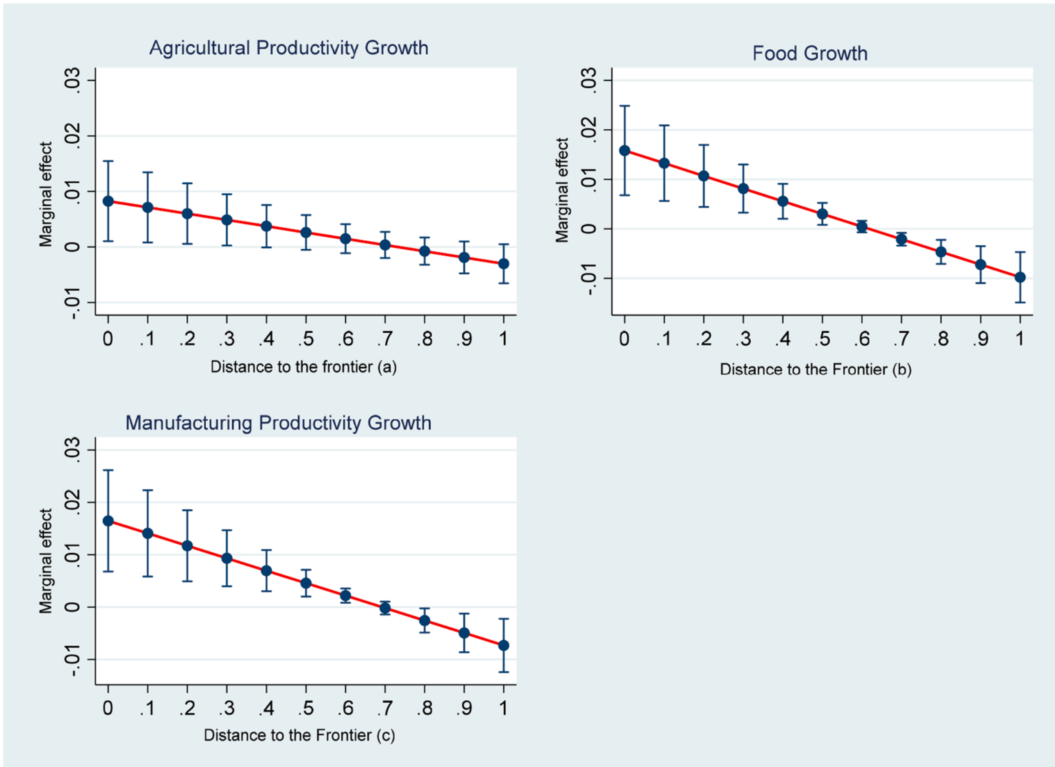

Fig. A1. Marginal Effects of GIs on Sectoral Growth and Distance to the Frontier. *Notes*: The figure reports plots of the estimated marginal effect (with their 95% CI) of GIs on sectoral labor productivity growth conditional to distance to the frontier. Marginal effects are based on OLS regressions where the dependent variable is sectoral labor productivity growth (Food growth in the case of panel b) with specifications as in columns 1–3 of Table A.2 (see Appendix); Panel (a) labor productivity growth and distance to the frontier based on agricultural labor productivity; (b) Food growth and distance to the frontier based on manufacturing labor productivity; (c) Labor productivity growth and distance to the frontier based on manufacturing labor productivity.

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Appendix A

Robustness check and extension

As discussed in the main text the key identification issue of our results is related to the fact that GI diffusion can be endogenous to innovation. We try to attenuate this endogeneity problem by an instrumental variable (IV) estimator, accounting for the endogeneity of the linear and interaction terms in the negative binomial estimator, using the residuals from the first-stage regressions for GI entry and the GI–distance interaction as control function corrections. The instruments are the GIs and the distance to the frontier variables, averaged across the four neighbouring regions and their relative interaction.

Table A.1 reports regression results. Overall, the pattern of these estimates is very close to the results reported in Table 2. The bottom of the table reports the *p*-value of the statistical test of the control function—that is, the two residuals from the first stage equations. This test is equivalent to an exogeneity Hausman test (see Wooldridge, 2010). Since these residuals are (jointly) not statistically significant at 5 % level in the second stage, endogeneity does not appear to be a major concern in these patenting regressions, *ceteris paribus*.

See Table A.1.

As an additional robustness check of our results, we run regressions using sectoral labour productivity growth as a proxy of innovative activities. Results from these additional regressions are summarised in Table A.2.[22] Overall, they strongly support the patenting regressions discussed in the

[22] Formally, the productivity growth regressions have the following empirical specification: $\Delta LP_{i,t} = \alpha_i + \alpha_t + \beta_1 \left(D_{i,t-1} * GI_{i,t-1}\right) + \beta_2 GI_{i,t-1} + \beta_3 D_{i,t-1} + X_{i,t-1}\gamma + \varepsilon_{cht}$, with $\Delta LP_{i,t}$ the annual growth rate of sectoral labour productivity.

main text. Columns 1–3 reports results of a fixed effects regression where the dependent variable is agricultural labour productivity growth and the distance to the frontier is measured accordingly. The interaction of GIs with distance to the frontier is negative and displays an absolute magnitude higher than the positive linear GI term, with both coefficients statistically significant at the 5 % level. Interestingly, the linear distance to the frontier estimated coefficient (β_3) enters negatively with a very low standard error suggesting a convergence in the productivity level across EU regions. In column 2, the dependent variable is the growth rate of value added in the food industry, but now the distance to the frontier is measured using labour productivity in the manufacturing sector. The results are striking, showing again a positive linear effect and a negative GI interaction term, both statistically significant at the 1 % level. In column 3, we use industry labour productivity growth as the dependent variable to proxy for the lack of food industry labour productivity. The results are virtually identical to those in column 2.

Columns 4–6 of Table A.2 address omitted variables bias by including a full set of region-specific trends. Results are similar both in terms of estimated magnitude and statistical level. Finally, columns 7–9 addresses the issue of entry endogeneity in the linear and interaction GI terms, illustrating our fixed effects IV regressions where the GI variable and its interaction with distance are instrumented with the average of the four neighbouring regions. In this productivity growth specification also the linear distance term is potentially endogenous and so instrumented by using its second lag term. The endogeneity tests are reported at the bottom of the Table. For both food and industry growth regressions (columns 7 and 8)—albeit less so for the agricultural one (column 9)—the null hypothesis that GI entry and its interaction with distance can be considered exogenous to growth is rejected at the 1 % level. In addition, the Kleibergen-Paap F-statistic of the instruments in the first-stage equation is higher than the Stock and Yogo (2005) critical value of 10, suggesting that our instruments are valid. All three IV regressions show negative and significant interaction effects, as well as positive and significant GI linear effects, thus confirming the main conclusion of the OLS results. Unlike the patenting regressions, when we ran IV regressions, the (absolute) magnitude of the estimated GIs' linear and interaction terms are slightly larger, suggesting that, if anything, the OLS regressions tend to be slightly biased downward from the true estimated effects.

See Table A.2.

Fig. A.1 plots the GI marginal effects on productivity growth with confidence intervals based on the results from Table A.2 (columns 1–3).[23] Like patents, the negative slope of the schedule indicates that GI may have a positive effect on growth when regions are far from the frontier, though this effect becomes gradually negative as regions approach the frontier. Importantly, and similarly to patenting regressions, our empirical evidence also shows that the positive marginal effect of GIs on growth far from the frontier is larger in (absolute) magnitude than the negative one close to the frontier. In addition, for the intermediate values of the distance to the frontier—those equal to around 0.64 (see Table 1) — the marginal effect of GI tends to be insignificant. Therefore, there is clear evidence supporting the distance-to-the-frontier model.

See Fig. A1.

Appendix B

See Table B.1.

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[23] Our marginal effect plots are based on OLS regressions for two main reasons. First, OLS results are more conservative than IV results, at least when they move in a similar direction, as our results show. Second, and most importantly, IV estimator measure local average treatment effect (LATE), and so is less representative of the overall average impact in our sample (see Angrist and Pischke, 2009).

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