

## RESEARCH ARTICLE OPEN ACCESS

# Capturing Inter and Intra Sectoral Productivity Spillovers in Industrial *Filière*: A System of Dynamic Spatial Panel Data Models

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## ABSTRACT

Given the relevance of spatial and sectoral interactions in shaping the productivity performance of economic systems and *filières*, in this study, we suggest addressing both aspects by estimating a system of simultaneous dynamic spatial panel data models. This approach allows to consider how the production level of a specific sector is influenced by the performance of other interconnected sectors in the same area (cross-sectoral spillovers) as well as the role of productivity spillovers originating from the same or other sectors in neighbouring territories (inter and intra sectoral spatial effects). The validity of the proposed approach is confirmed through the estimation of a simultaneous system for the production process of the Italian agribusiness *filière*. The results indicate the existence of meaningful inter-dependences within and between sectors and territories that materialises in spillovers of different natures (input factors, internal and external features), offering valuable policy implications for the overall economic growth of the agriculture *filière*.

**JEL Classification:** C21, C33, L60

## 1 | Introduction

Economic systems are profoundly influenced by complex relationships and dependencies arising from multisectoral and multiproduct production processes, spatial phenomena such as agglomeration and clustering and contextual and physical factors characterising the area where production occurs (Delgado, Porter, and Stern 2016; Gereffi, Humphrey, and Sturgeon 2005; De Loecker 2011; Porter 1990). Given the high level of complexity of economic systems, comprehending the origins, nature and impact of spillovers on productivity has become increasingly challenging and is of paramount interest to scholars and economic stakeholders. This interest is driven by the informative role of productivity in understanding long-term operational trends as well as the development and growth of a system across different territorial levels.

This study aims to introduce a novel approach based on a system of equations for identifying, modelling and measuring spillover effects among interconnected industrial sectors by disentangling the impacts originating from both inter and intra sectoral relationships within a specific area and between neighbouring territories.

On one hand, spatial linkages arise because a technology shock in one area can induce changes in the productivity levels and resource allocation in neighbouring areas, leading to a complex network of production-sharing activities that impact a sector's productivity growth (Capello and Nijkamp 2009; Huggins and Thompson 2015). On the other hand, as different sectors are linked together into a common production network due to existing input-output linkages (Acemoglu and Azar 2020), it becomes crucial to identify the specific contributions of intra and inter sectoral relationships in shaping firms' production

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processes. Inter and intra-sectoral spillovers thus represent the outcomes of an ongoing process of innovation and globalisation aimed at reducing physical and political barriers to transport and trade, enhancing the diffusion of scientific knowledge, and improving the availability of high-quality data, information and communication technologies. The relevance of both spatial and sectoral spillovers in the analysis of productivity is assessed primarily due to the reading of spatial and cross-sectoral spillovers as bumping (up as well as down) factors that may affect scale economies, or in other words as 'external economies of scale in the sense that they augment (or counteract) internal scale economies by acting as shift factors, which affect the cost-output relationship and thus economic performance and competitiveness' (Cohen and Paul 2005 p. 217).

Previous literature has traditionally treated cross-sectoral spillovers and spatial transmission channels separately or focused on single-equation models often neglecting the endogenous relationships between interrelated sectors. However, the simultaneous nature of production requires a tailored modelling approach that incorporates feedback loops between different sectors. Failure to do so may result in misspecification issues, inaccurate estimation results, invalid statistical inference and unreliable empirical findings (Acemoglu and Azar 2020). Therefore, this paper contributes to the literature on cross-sectoral interdependencies by proposing a novel approach to model the endogenous relationships characterising the productive outcomes of highly interrelated sectors (e.g., composing industrial *filières*), providing a powerful tool for productivity analyses of complex production systems. This is achieved by specifying and estimating a system of production functions (one for each sector) characterised by simultaneous and lagged cross-sectoral linkages, temporal dynamics and spatial spillovers occurring within and between sectors in neighbouring territories. Each sector's output is modelled as a function of (i) production inputs, (ii) simultaneous relationships between sectors' performances, (iii) past performances of the same and related sectors, and (iv) the current and past performances of the same and related sectors in neighbouring areas. The result consists of a system of dynamic spatial panel data models (Yang and Lee 2019; Elhorst and Emili 2022) characterised by endogenous interdependencies.

In this work, spillovers are measured using different definitions for transmission channels, incorporating both geographic and economic distance measures associated with market accessibility. Unlike many previous works, we do not restrict the analysis to specific channels through which spillovers may occur (usually gathered by including in the model the spatial lags of specific covariates such as technology, foreign direct investment, and knowledge transfer), but we consider that spillovers materialise through neighbours' performance thanks to different mechanisms internal to the production process such as imitation, skill acquisition and competition, but also input factors and possible external shocks.

Specifically, the methodological tool introduced in this paper allows exploring the strength of intra and inter-industry linkages originating from input variations, reactions to factors that are external (e.g. exogenous shocks, disruptions, unpredictable events) or internal to the production system (e.g. simultaneities

in production processes). The resulting approach provides a unique framework for informing decision-makers on local and regional development policies.

In production systems highly characterised by cross-sectoral spillovers and spatial phenomena, the proposed model can be used to answer the following questions: given the input factors, how much the performance of one sector is associated with the performances of the other related sectors given the existing cross-sectoral relationships? How much of these relationships depend on spatial agglomeration phenomena? What is the role of intra sectoral and inter sectoral temporal dynamics? do sectoral performances depend more on input variations or reactions to external and internal factors?

The level of detail and comprehensiveness achieved by this novel modelling approach are depicted by an empirical analysis. In particular, given the key role of sectoral and spatial linkages among producers in the agribusiness industry, we focus on the Italian agribusiness *filière* as a case study. The agribusiness *filière*, starting from the production stage, constitutes a network of actors across various sectors that collaborate to bring the final products to consumers and, in such an interconnected system, the productive performance of one sector is closely linked to one of the others. The model is estimated using data for the time period 2013–2021, collected at the Labour Market Area (hereinafter, LMA) level of aggregation. The choice of LMA as the unit of analysis has been made aiming to account for the high level of contextual specificities, economic factors, and socio-cultural aspects in the productive processes characterising Italy, that could be overlooked at the regional or national level.

In the agricultural framework, the proposed model and theoretical questions on the origin of cross-sectoral spillovers can be translated into:

- Q1. Can a specific sector comprising the agricultural *filière* generate economic spillovers to firms belonging to the other related sectors within the same area? (*inter sectoral spillovers*)
- Q2. Can a specific sector influence the productive performance of neighbours in the sector itself? (*spatial intra sectoral spillovers*)
- Q3. Can a specific sector influence the productive performance of other sectors located in neighbouring areas? (*spatial inter sectoral spillovers*)
- Q4. Do spillovers modify considering different time horizons (i.e. short run vs long run direct and spatial effects)?
- Q5. Are spillovers more related to input variations, shock propagation or simultaneous linkages with the other sectors in the system?

The insights derived from this research can offer valuable information to policymakers, shedding light on interdependence features within diverse sectors that define complex industrial systems and *filières*. These findings are particularly pertinent for designing economic plans aimed at supporting industries, as exemplified in the case of the Italian agribusiness industry.

In the rest of the paper, we review the literature on spatial and cross-sectoral phenomena in Section 2; Section 3 describes the estimation approach, the spatial structure, and the computation of the marginal effects; we describe the data for the case of the agribusiness *filière* and provide some descriptive statistics in Section 4; in Section 5 and 6 we present and discuss the estimation results related to the case study; and in Section 7 we provide some final remarks.

## 2 | Literature

### 2.1 | Cross-Sectoral Relationships

Since the early 1990s, rapid technological advances and globalisation have transformed the structure of production in global economies. Outsourcing and offshoring have become common strategies for companies to enhance productivity and competitiveness in international markets. As a result, final goods and services are now produced through increasingly complex and fragmented processes across different sectors and countries (e.g. Baldwin 2016; Di Bernardino et al. 2023). The capacity of a sector to produce a product therefore depends on the ability of related sectors to produce similar products since their production processes are based on similar institutional requisites, infrastructures, physical factors, and technologies (Hidalgo et al. 2007).

The growing blurring of sector boundaries creates new methodological challenges for researchers in overcoming the limits of the ‘horizontal’ representation of sectors in a production system (Ciriaci and Palma 2016; Di Bernardino and Onesti 2018). Within the ‘vertically integrated’ approach (Pasinetti 1973), Acemoglu et al. (2012) differentiate between first-order and higher-order interconnections, the former referring to the direct propagation of a shock to a supplier sector to other sectors, and the latter to the way low productivity levels in one sector leads to reduced production in downstream sectors and other interconnected sectors, creating a cascade effect.

Early empirical literature has explored sectorial *interconnect*edness through the development of multisector models. These modelling approaches have primarily been employed to analyse issues related to long-term growth and structural change, development strategies, investment allocation, trade, structural adjustment to shocks, and income distribution (Robinson 1989). Most studies on these topics adopt a trade perspective, utilising input-output (I-O) tables to analyse sectoral data. Among others, Feenstra and Hanson (1996), Hummels, Ishii and Yi (2001) and Magalhães and Afonso (2017) focused on the share of imported inputs in gross output or exports at the country level; among others, Dietzenbacher et al. (2013) contributed to the world input-output tables through the World Input–Output Database project; Albrecht and Tombe (2016) and Midmore, Munday and Roberts (2006) assessed industry linkages at a higher territorial detail considering regional input–output relationships. With the availability of I-O tables at different levels of aggregation, new metrics for global value chains have emerged, leading to further research on value-added trade and the complexities of international production. Although the input-output approach remains widely used still today with

some attempts to take into account the territorial dimension of sectoral linkages (see Albrecht and Tombe 2016; Midmore, Munday, and Roberts 2006), in productivity analyses, the idea that transmission mechanisms between sectors also materialise across neighbouring areas requires an ad hoc modelling approach.

### 2.2 | An Integrated Framework for Modelling Spatial and Cross-Sectoral Interactions

Recent literature has explored transmission mechanisms among related sectors based on the concepts of clustering (e.g. Fosfuri and Rønde 2004; Delgado, Porter, and Stern 2016), agglomeration economies (e.g. Jorge and Rocha 2020; Ke 2010), or productivity spillovers (e.g. Badinger and Egger 2016; Javorcik 2004). Research in this area consistently confirms the key role of spatial mechanisms in shaping production processes, both at the firm level (Bloom, Draca, and Van Reenen 2016; Keller and Yeaple 2009; Gorg, Hijzen, and Murakozy 2009) and at the country level (Cohen and Paul 2004; Liu and Sickles 2023). In this strand of literature, the differentiation between intra and inter sectoral effects has been applied to various typologies of spatial impacts, such as knowledge spillovers (Malerba, Mancusi, and Montobbio 2014; Badinger and Egger 2016; Kekezi, Dall’Erba, and Kang 2022) and FDI spillovers (Kugler 2006; Nicolini and Resmini 2010; Orlic, Hashi, and Hisarciklilar 2018). The main idea is that technology, productivity and knowledge not only diffuse within and between industries in the same area but a shock in one sector in a specific territory can influence the performance of neighbouring economic units in the same and interconnected sectors. Evidence of sectoral interconnectedness within and between industries, both in a given area as well as across regional or international boundaries, is now well grounded, highlighting the importance of considering all these transmission channels in empirical analyses.

Despite the relevance of both the (pure-)economic and spatial dimensions in measuring cross-sectoral spillovers, to our knowledge, there are no works modelling inter and intra sectoral linkages by disentangling sectoral spillovers based on their spatial connotation. Therefore, we distinguish between sectoral linkages occurring within a certain region (pure-economic inter and intra sectoral spillovers) and sectoral interdependencies among neighbouring regions (spatial inter and intra sectoral spillovers), leading to a model for jointly explaining cross-sectoral and spatial linkages.

To date, the only papers analysing both cross-sectoral and spatial linkages in a productivity analysis framework are Emili and Galli (2023) and Badinger and Egger (2016) referring respectively to the Italian tourism industry and the manufacturing industries of 12 OECD countries. In the former, the authors investigate the overall production level of the Italian tourism industry as a function of the inputs of the different sub-sectors composing it and of input spillovers occurring across sectors. However, the analysis does not account for possible inter sectoral phenomena, either at the cross-sectional detail for a specific destination or at the spatial level, making it impossible to distinguish between sectoral output spillovers and

intra and inter sectoral productivity spillovers. Aiming to overcome these limitations, in this work we consider simultaneous relationships between sectoral outputs, by means of a system of (endogenous) interrelated production functions for an industrial *filière*.

Badinger and Egger (2016) estimate a Translog production function through a spatial panel data model to analyse the real value added of the manufacturing industry at the country level, where the spatial dimension is measured as economic distance by using information on the domestic and international use of intermediate goods. By taking advantage of input-output tables, the authors account for inter and intra sectoral spillovers generated from R&D only by means of economic-based weighting matrices that capture the interdependence of industries. In this work, we extend Badinger and Egger's (2016) approach including both geographic and economic-based spatial weighting matrices.

Similar to the approach of Badinger and Egger (2016), a common method for capturing spatial mechanisms or economic transactions between firms involves incorporating spatially lagged covariates in the model specification of the production function. Common covariates include input and capital goods transactions (Cuadros and Alguacil 2014; Foster-McGregor, Poschl, and Steerer 2016), cross-hiring of personnel (Stoyanov and Zubanov 2012), technology acquisition (Driffield, Love, and Yang 2013), patent citations (Xu and Chiang 2006), attendance to conferences, workshops and seminars (Zacchia 2020), collaborations, innovations developed by neighbours (Wieser 2005 and references therein), etc. However, since spillovers are primarily based on tacit and non-codified elements that do not leave any tangible trace (Krugman 1991), relying on specific indicators as potential sources of spillovers may hide relevant interactions between firms that contribute to the flow of information, generating effective spatial feedbacks (Gorg and Strobl 2001). In this regard, our contribution lies in simultaneously modelling cross-sectoral linkages and inter and intra-sectoral spatial spillovers coming from both observable (labour and capital inputs) and unobservable factors, disentangling the role of each sector in the same area and neighbouring areas in shaping the performances of the others.

### 2.3 | Interdependence Features of the Agribusiness Industry

Interdependence features play a crucial role in the agribusiness industry, given its complex and interconnected nature involving various sectors such as agriculture, food processing, distribution, marketing and retail, all linked together through a variety of linkages (Ciranni, Fanfani, and Gismondi 2021). The food processing sector, for instance, depends on agriculture for raw materials like fruits, vegetables, dairy products, and meat. Additionally, it is closely tied to the distribution sector for transportation, logistics and retail operations.

In addition to sectoral linkages stemming from cross-sectoral dependencies, spatial effects play a crucial role in shaping the production processes of the different sectors composing the agribusiness industry. Indeed, advances in agricultural

technology, including new knowledge and expertise, can not only benefit the farmers who adopt them but also neighbouring farmers due to technology spillovers resulting from emulation behaviours, the exchange of ideas and learning from others (Wollni and Andersson 2014; Läßle et al. 2017). Similarly, learning and knowledge spillovers can occur among food processing firms, distributors, wholesalers and retailers thanks to shared ideas, best practices, and information (Acosta, Coronado, and Romero 2015; Cardamone 2020). However, spillovers are not solely characterised by a sectoral connotation, since also inter-sectoral spatial effects may take place in the agribusiness industry (Gopinath and Roe 2000; Kekezi, Dal'Erba, and Kang 2022). For instance, the location of nearby specialised farms may impact the availability and costs of raw materials for food processors, major industry hubs in an area can grant wholesalers and retailers access to a broader variety of products, and local product specialisation may lead to the development of localised markets for locally sourced products.

In this study, to contextualise the contribution of the proposed approach, we consider how the production level of a specific sector in the agribusiness industry is shaped by the production performance of the other sectors located in the same area (i.e. inter sectoral connectivity) as well as the role of spillovers arising from neighbouring producers belonging to the same and other sectors (i.e. intra and inter sectoral spatial spillovers). In particular, the model allows inspecting different sources of inter sectoral spillovers depending on input changes and factors that are external or internal to the system.

## 3 | The Model

### 3.1 | Model Specification

The Cobb-Douglas production function is selected as the starting point for the model specification. Despite the well-known limitations of production functions within the Cobb-Douglas family, we select this specific class of functions for its flexibility and simplicity (among others see Reynès 2019). The low level of complexity of the baseline function is then highly increased by introducing cross-sectoral spillovers, spatial and temporal dynamics, as well as simultaneous relationships. In particular, to model inter and intra sectoral spillovers and inter and intra sectoral spatial effects we consider a system of dynamic spatial panel data models.

We start by considering a generic log-linearised model specification of a Cobb-Douglas production function for panel data, such as

$$\ln Q_t = f(\ln L_t, \ln K_t; \Pi_L, \Pi_K, C_n, \zeta_t, \Sigma), \quad (1)$$

$$t = 1, \dots, T$$

where  $\ln Q_t = (\ln Q'_{1,t}, \ln Q'_{2,t}, \dots, \ln Q'_{s,t})'$  is a  $(sn \times 1)$  vector collecting the logarithm of the output observed at time  $t$  for the  $s$  sectors considered;  $\ln L_t$  and  $\ln K_t$  are the logarithm of labour and fixed asset factors, both of dimension  $(sn \times 1)$ , with associated parameter matrices  $\Pi_L = (\Pi_L \otimes I_n)$  and  $\Pi_K = (\Pi_K \otimes I_n)$ , each with  $s^2$  free parameters referring to the simultaneous

effects of the input factors. The remaining parameters are given by the vector  $C_n$  of individual fixed effects,  $\zeta_t$  of time fixed effects and the covariance matrix  $\Sigma$  with  $s(s + 1)/2$  free parameters.

In the last two decades, the idea that productivity analyses can be improved by including spatial and temporal dynamics, as well as unobserved individual and time-specific fixed effects has strongly spread out (Adams 1990; Ayouba 2023; Emili and Galli 2023; Camilla, Serlenga, and Shin 2013; Yaşar and Paul 2012). This understanding is in general inspired by the awareness of largely intertwined mechanisms and factors characterising economic decisions and production processes. For example, Camilla, Serlenga and Shin (2013) examine autoregressive dynamics to study the transmission channels through which globalisation enhances the technical efficiency of 18 European countries while Kim et al. (2021) analyse the role of spatial spillover effects on the productivity level of the tourism industry in the UK. In the proposed model, these spatial and temporal dynamics as well as cross-sectoral relationships are captured including: (i) the time lag of the output variable since the performance of each spatial unit  $i$  at time  $t$  is supposed to be affected by the level of output observed in the previous time period ( $\ln Q_{it-1}$ ); (ii) the output of the other sectors observed in the same and previous time period due to possible cross-sectoral linkages; (iii) the output of the same and other sectors in the neighbouring areas as a result of agglomeration dynamics and spatial mechanisms both simultaneously ( $W \ln Q_{it}$ ) and lagged in time ( $W \ln Q_{it-1}$ ).

Following Yang and Lee (2017; 2019) and the identification strategy proposed by Elhorst and Emili (2022), the proposed model specification is then enlarged to include simultaneous, temporal and spatially lagged effects across different sectors' outputs as follows.

$$\begin{aligned} \Gamma \ln Q_t &= (I_s \otimes \ln L_t) \Pi_L + (I_s \otimes \ln K_t) \Pi_K + \Psi W \ln Q_t \\ &+ \Phi W \ln Q_{t-1} + P \ln Q_{t-1} + C_n + \zeta_t \\ &+ \varepsilon_t, \varepsilon_t \sim (0, \Sigma) \end{aligned} \quad (2)$$

In particular,  $W$  is a matrix of dimension  $sn \times sn$  summarising the assumed spatial structure of the  $s$  sectors in the  $n$  areas, and it is given by a combination of different spatial weight matrices (a wider discussion is provided in the next subsection); the matrix  $\Gamma = (\Gamma \otimes I_n)$  is the parameter matrix capturing the simultaneous effects between the outputs of the  $s$  sectors, with diagonal entries equal to one; the matrix  $P = (P \otimes I_n)$  captures the temporal dynamics of  $\ln Q_t$ . The remaining terms  $\Psi W \ln Q_t$  and  $\Phi W \ln Q_{t-1}$  are included in the model to account for simultaneous and time lagged spatial dynamics respectively by means of  $s^2$  free parameters, both in  $\Psi = (\Psi \otimes I_n)$  and in  $\Phi = (\Phi \otimes I_n)$ . The input factors are included in the model as  $(I_s \otimes \ln L_t) \Pi_L$  and  $(I_s \otimes \ln K_t) \Pi_K$  respectively for labour and capital. This specification allows to investigate not only the role of the input factors within each sector in generating its level of output, but also possible effects arising from the input factors of the other sectors of the *filière*.

Without loss of generality, to make the introduction of the model specification easier and in line with the empirical

application on the Italian agribusiness *filière* that we are going to present in the next sections, we let the number of equations  $s = 3$ . The system of (three) spatial dynamic panel data models can be explicitly rewritten in matrix form as

$$\begin{aligned} &\left( \begin{array}{ccc|c} 1 & \gamma_{12} & \gamma_{13} & \ln Q_{1t} \\ \gamma_{21} & 1 & \gamma_{23} & \ln Q_{2t} \\ \gamma_{31} & \gamma_{32} & 1 & \ln Q_{3t} \end{array} \right) \otimes I_n \\ &= (I_3 \otimes (\ln L_{1t}, \ln L_{2t}, \ln L_{3t})) \begin{array}{c} \Pi_{L1} \\ \Pi_{L2} \\ \Pi_{L3} \end{array} \\ &+ (I_3 \otimes (\ln K_{1t}, \ln K_{2t}, \ln K_{3t})) \begin{array}{c} \Pi_{K1} \\ \Pi_{K2} \\ \Pi_{K3} \end{array} + \\ &+ \begin{array}{ccc|c} \psi_{11} W_a & \psi_{12} W_b & \psi_{13} W_b & \ln Q_{1t} \\ \psi_{21} W_b & \psi_{22} W_a & \psi_{23} W_b & \ln Q_{2t} \\ \psi_{31} W_b & \psi_{32} W_b & \psi_{33} W_a & \ln Q_{3t} \end{array} \\ &+ \begin{array}{ccc|c} \phi_{11} W_a & \phi_{12} W_b & \phi_{13} W_b & \ln Q_{1t-1} \\ \phi_{21} W_b & \phi_{22} W_a & \phi_{23} W_b & \ln Q_{2t-1} \\ \phi_{31} W_b & \phi_{32} W_b & \phi_{33} W_a & \ln Q_{3t-1} \end{array} + \\ &+ \begin{array}{ccc|c} p_{11} & p_{12} & p_{13} & \ln Q_{1t-1} \\ p_{21} & p_{22} & p_{23} & \ln Q_{2t-1} \\ p_{31} & p_{32} & p_{33} & \ln Q_{3t-1} \end{array} + \begin{array}{c} C_{1n} \\ C_{2n} \\ C_{3n} \end{array} + (\zeta_t \otimes I_n) + \begin{array}{c} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{array}, \end{aligned} \quad (3)$$

with  $\Pi_1 = (\pi_{\cdot,11}, \pi_{\cdot,12}, \pi_{\cdot,1,3})'$ ,  $\Pi_2 = (\pi_{\cdot,21}, \pi_{\cdot,22}, \pi_{\cdot,2,3})'$ ,  $\Pi_3 = (\pi_{\cdot,31}, \pi_{\cdot,32}, \pi_{\cdot,3,3})'$ , where  $\cdot = \{L, K\}$  and covariance matrix of  $\varepsilon_t$  given by

$$\Sigma = \left( \begin{array}{ccc|c} \sigma_1^2 & & & \\ \sigma_{21} & \sigma_2^2 & & \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & \end{array} \right) \otimes I_n. \quad (4)$$

Each parameter matrix in the set  $\{\Pi_L, \Pi_K, \Psi, \Phi, P\}$  collects  $s^2 = 3^2$  free parameters to be estimated, where parameters with subscripts 11, 22 and 33 capture intra sectoral dynamics (in general, for  $\Psi, \Phi$  and  $P$ , the entries on the main diagonal of each matrix). The remaining parameters all relate to inter sectoral effects<sup>1</sup>. The matrix  $\Gamma$  is composed of  $s(s - 1) = 6$  free parameters collecting simultaneous impacts in the same area among the  $s = 3$  sectors. The idea is that the relationships between the production processes of the sectors are related to internal components of the process (such as R&D, social capital and financial assets), not totally captured by the two input factors.

While the estimation of the model in Eq. 3 is mainly discussed in the next subsections, the presence of simultaneous effects in the model specification requires a brief discussion of identification conditions. In particular, identification issues of the system are related to the presence of both the spatial autoregressive matrix  $\Psi$  of simultaneous effects and the matrix  $\Gamma$ . As widely discussed by Yang and Lee (2017; 2019), identification related to the spatial term is guaranteed from the “quasi-reduced” form in a standard manner. In particular, rewriting Eq. 2 as

$$\begin{aligned}
(\mathbf{\Gamma} - \mathbf{\Psi} \odot \mathbf{W}) \ln Q_t &= \mathbf{\Pi}_L \ln L_t + \mathbf{\Pi}_K \ln K_t \\
&+ \mathbf{\Phi} \odot \mathbf{W} \ln Q_{t-1} + \mathbf{P} \ln Q_{t-1} + C_n \quad (5) \\
&+ \gamma_t + \varepsilon_t
\end{aligned}$$

the reduced form of the model is obtained by pre-multiplying all the terms of Eq. 5 by the inverse of  $\mathbf{G} = (\mathbf{\Gamma} - \mathbf{\Psi} \odot \mathbf{W})$ , finally obtaining

$$\begin{aligned}
\ln Q_t &= \mathbf{\Pi}_L^* \ln L_t + \mathbf{\Pi}_K^* \ln K_t + \mathbf{\Phi}^* \odot \mathbf{W} \ln Q_{t-1} \\
&+ \mathbf{P}^* \ln Q_{t-1} + C_n^* + \zeta_t^* + \nu_t, \nu_t \sim (0, \mathbf{G}^{-1} \mathbf{\Sigma} \mathbf{G}^{-1}) \quad (6)
\end{aligned}$$

with  $\mathbf{\Pi}_L^* = \mathbf{G}^{-1} \mathbf{\Pi}_L$ ,  $\mathbf{\Pi}_K^* = \mathbf{G}^{-1} \mathbf{\Pi}_K$ ,  $\mathbf{\Phi}^* = \mathbf{G}^{-1} \mathbf{\Phi}$ ,  $\mathbf{P}^* = \mathbf{G}^{-1} \mathbf{P}$ ,  $C_n^* = \mathbf{G}^{-1} C_n$ ,  $\zeta_t^* = \mathbf{G}^{-1} \zeta_t$  and error term  $\nu_t$  with associated covariance matrix  $\mathbf{\Sigma}_\nu = (\mathbf{\Sigma}_\nu \otimes I_n) = \mathbf{G}^{-1} \mathbf{\Sigma} \mathbf{G}^{-1} = \mathbf{G}^{-1'} (\mathbf{\Sigma} \otimes I_n) \mathbf{G}^{-1}$ .

As anticipated above, a second source of identification issues is implied by the simultaneous relationships collected in  $\mathbf{\Gamma}$ , among the endogenous variables. While zero restrictions or further economic-based structural schemes can be assumed to ensure the identification of the model, we follow Elhorst and Emili (2022)'s proposal, considering more than one channel in the specification of the spatial transmission mechanisms. Specifically, we assume that while spatial effects for industries within the same sector flow through a matrix  $W_a$ , inter sectoral spatial dynamics are described by means of a different weighting matrix  $W_b$ . In the next paragraph, we provide a detailed description of the motivations driving the choice of the spatial structure assumed.

### 3.2 | Spatial Structure

Aiming at capturing the complexity of both the transmission channels and the heterogeneity of the phenomenon across the Italian territory, to analyse the productive performance of the Italian agribusiness industry the spatial structure of the model is given by a combination of “pure” and “not-pure” physical spatial weight matrices. The rationale beyond these choices is related to both geographic and phenomenon-related features of the analysed production processes.

Indeed, while “pure” physical spatial matrices such as binary contiguity and inverse distance matrices are the most common weight matrices used in empirical applications of spatial models, nowadays researchers are strongly aware of the importance and usefulness of economic-based matrices (for a comprehensive review see Corrado and Fingleton 2012). This attention results from the idea of accounting for the origins and the channels through which spatial spillovers move (e.g. migration, market mechanisms, possible relationships and interactivity between policy makers at different territorial levels).

In this study, a second-order contiguity matrix is used to account for intra sectoral spillover effects between both first and second-order neighbouring LMAs (i.e. neighbours of neighbours). Previous literature on intra-sectoral spatial spillovers suggests that they are largely linked to the territorial characteristics and configuration of the territory where production

takes place (Atkinson and Stiglitz 1969) and tend to flow globally being much less affected by distance compared to inter-sectoral spillovers (Malerba, Mancusi, and Montobbio 2014). Since in our case, LMAs strongly vary in surface area, population, physical connectivity, infrastructures, geographic location, and conformity, opting for a spatial contiguity matrix, rather than relying on the physical distance between centroids or main city centres, proves to be a more suitable and reliable approach. Likewise, in situations where territories are closely interconnected in terms of proximity, accessibility, and combination of goods and services, assuming a single-order contiguity matrix can be overly restrictive. For these reasons, a second-order binary contiguity matrix is used to account for intra-sectoral relationships between both neighbouring LMAs and neighbours of neighbours.

The matrix in charge of measuring inter-sectoral spillovers is given by a “not-pure” physical spatial matrix to capture the strength of inter-LMA relations. The idea is that smaller LMAs in terms of population may “borrow” some benefits of agglomeration economies from bigger neighbouring LMAs. This phenomenon, introduced in the literature by Alonso (1973) is known as “borrowed size” and refers to the fact that people, businessmen and labour markets in an area can respectively take advantage of facilities, warehousing, business services and demand or supply from other neighbouring areas to complement their own. Indeed, territories located in close proximity and connected through infrastructures may benefit from horizontal relationships that can create interdependencies among them. Similarly to the approach used by Otsuka (2020) to build a market accessibility index, we control for these complementarities by defining the generic time-varying spatial weight as  $w_{ij,t} = \frac{|Pop_{it} - Pop_{jt}|}{d_{ij}}$ , where  $|Pop_{it} - Pop_{jt}|$  represents the difference between the population of LMA  $i$  and LMA  $j$  at time  $t$  and  $d_{ij}$  is the distance in kilometres between the centroids of the two areas. Thus, following Camagni, Capello and Caragliu (2015), the borrowed size increases for larger neighbouring population sizes and for shorter distances to large cities according to the idea that smaller territories located near bigger ones may complement their services with those offered by bigger closest centres.

The final spatial weight matrix  $W$  included in the model is therefore defined as

$$W = \begin{bmatrix} W_{BC} & W_{MP} & W_{MP} \\ W_{MP} & W_{BC} & W_{MP} \\ W_{MP} & W_{MP} & W_{BC} \end{bmatrix} \quad (7)$$

where  $W_{BC}$  represents the second-order binary contiguity spatial weight matrix (and affects intra-sectoral relationships) and  $W_{MP}$  is the economic-based market-potential spatial weight matrix (used to model inter-sectoral spillovers). Nevertheless, in the following sections, we provide some robustness checks considering a first-order contiguity matrix as an alternative to the second-order one.

The two spatial weight matrices are doubly stochastic normalised following Le Sage and Chih (2016) recommendation. In particular, using the Sinkhorn-Knopp algorithm developed by

Knight (2008), the elements in each row and column sum to one. Some robustness checks are provided also using a standard row-normalisation approach (discussed below).

### 3.3 | Estimation and Marginal Effects

As better discussed in the next section, one of the characteristics of our empirical analysis is represented by the limited data availability over time, since AIDA data are available for a maximum of 10 years. Then, differently from Elhorst and Emili (2022), the model is estimated through Instrumental Variables (hereinafter IV). In particular, Yang and Lee (2019) argued that, in the case of small T, their proposed QML estimator is no longer consistent, and they suggest referring to IV estimation. Once individual effects have been removed by Helmet transformation, the Three Stage least square estimator (3SLS) for the system is employed. In the first stage, single equation IV estimates are obtained. Then, the parameters are used to calculate the estimated covariance matrix of the residual terms; hence, a final step is employed for the estimation of the (whole-) system parameters. The matrix of instruments suggested by Yang and Lee (2019) includes the temporal lagged values of the endogenous vector  $\ln Q_t$ , its spatial and temporal lagged observations, i.e.  $W\ln Q_{t-1}$ , the matrix of exogenous variables with removed individual effects, and spatial lagged values at the second power of  $\ln Q_{t-1}$ , i.e.  $W^2 \ln Q_{t-1}$ . See Yang and Lee (2019) and Lee and Yu (2014) for further details about variable transformation, estimation and inference issues.

After having estimated the model, we focus on the computation of spillover effects to answer Q1-Q4 distinguishing between input variations, external shocks and changes in the internal mechanisms of the system. First, to verify the existence of inter sectoral linkages related to mechanisms that are internal to the production processes, we can refer to the estimates of the simultaneous effects collected in the  $\Gamma$  matrix for sectors located in the same area, and in the  $\Psi$  matrix for spatial intra and inter sectoral linkages. Second, for input variations and external shocks, impacts have to be computed separately since the estimated parameters do not represent the marginal effects in a dynamic spatial panel data model. Following Elhorst, Gross and Tereanu (2021), we differentiate between (i) intra and inter sectoral effects originating from a one-unit shock ( $\frac{\partial \ln Q}{\partial \varepsilon} = ME_{\Delta \varepsilon}$ ) and (ii) from a unitary change in the input level  $X = L, K$  in a given sector ( $\frac{\partial \ln Q}{\partial X} = ME_{\Delta X}$ ).

Starting from the reduced form of the model, we compute the marginal effects to a unitary change in the input level as

$$\begin{aligned} \frac{\partial \ln Q}{\partial X} &= ME_{\Delta X} \\ &= \begin{bmatrix} ME_{\Delta \ln Q_1 \Delta X_1} & ME_{\Delta \ln Q_1 \Delta X_2} & ME_{\Delta \ln Q_1 \Delta X_3} \\ ME_{\Delta \ln Q_2 \Delta X_1} & ME_{\Delta \ln Q_2 \Delta X_2} & ME_{\Delta \ln Q_2 \Delta X_3} \\ ME_{\Delta \ln Q_3 \Delta X_1} & ME_{\Delta \ln Q_3 \Delta X_2} & ME_{\Delta \ln Q_3 \Delta X_3} \end{bmatrix}, \end{aligned} \quad (8)$$

where the submatrices on the main diagonal of  $ME_{\Delta X}$  contain intra sectoral effects and the submatrices on the off-diagonal represent inter sectoral effects. For both typologies of sub-

matrices of  $ME_{\Delta X}$  (i.e. diagonal and off-diagonal), the average of the diagonal elements represents direct effects (i.e. impacts occurring within a certain area) while the average of the off-diagonal elements refers to spatial effects (i.e. impacts from neighbouring units).

Specifically, aiming to answer Q1 (i.e. the occurrence of inter sectoral spillovers) in the case of input factors, direct effects can be calculated as the average of the diagonal elements of the off-block diagonal sub-matrices of  $ME_{\Delta X}$  (e.g.,  $ME_{\Delta \ln Q_1 \Delta X_2}$ ,  $ME_{\Delta \ln Q_1 \Delta X_3}$  for direct effects from manufacturing and trade to agriculture). Investigating possible spatial effects, we distinguish between intra sectoral (Q2) and inter sectoral impacts (Q3). The former can be computed based on the estimates in the block-diagonal sub-matrices while the latter from the off-block diagonal sub-matrices of  $ME_{\Delta X}$ . Moreover, given the dynamic nature of our model, we are able to compute the impacts at different points in time (Q4). In the next sections, we will refer to short-run effects for impacts happening at time  $t$  and to long-run effects for impacts at time  $t+h$ , with  $h = 1, 2, \dots$

Similar to Eq. 8, marginal effects to an innovation  $ME_{\Delta \varepsilon}$  are obtained by focusing on the first derivatives of  $\ln Q_t$  with respect to  $\varepsilon$  from the reduced form of the model. The distinction between inter and inter sectoral effects as well as between direct and spatial effects follows closely the discussion above, allowing to answer Q1-Q4 for variations originating from external shocks.

## 4 | Data

In this study, we use aggregated data at the LMA level referring to the Italian agribusiness industry in the time-period 2013–2021.

As proposed by Ciranni, Fanfani and Gismondi (2021) and references therein, the Italian agribusiness industry can be defined as composed of the agricultural sector (ATECO 1), the food and beverage industrial sector (ATECO 10-11-12), the wholesale sector (ATECO 46.17-46.2-46.3), the retail sector (ATECO 47.2-47.11) and the restaurant sector (ATECO 56). While the agricultural and food and beverage sectors refer to the production stage, the remaining three sectors concern the distribution and retail phases. In this work, we focus on the agricultural, manufacturing sector and the macro-sector of trade (both wholesale and retail), excluding the restaurant industry due to its relevant specificities. This choice is corroborated by the results of the input–output tables shown in Table A1 of Appendix A. Specifically, it can be observed that the input-output coefficients are highly relevant in magnitude among agriculture, food and beverage and the wholesale and retail sectors, while the impact from other sectors in the agribusiness industry to restaurants (which are included in the tourism industry together with the accommodation sector) is negligible (~1%).

Firm-level data on the different sectors considered in the analysis were first obtained from the AIDA-Bureau Van Dijk database, which is the only available dataset containing

georeferenced data on the consolidated accounts of Italian companies. Then, since individual information on the exact operating site is not provided, we aggregated the data by sector at the LMA aggregation level to maintain a detailed spatial level for the analysis. The LMA detail can be considered as an appropriate level of aggregation to investigate inter and intra sectoral spillovers since LMA are defined by ISTAT as 610 sub-regional geographical areas where the bulk of the labour force lives and works, and where establishments can find the main part of the labour force necessary to occupy the offered jobs. LMAs have been therefore designated for the compilation, reporting, and evaluation of employment, unemployment, work-force availability, and related tasks. Thus, they can be considered the best and finest available aggregate to define effective economies in terms of type and scope. This aggregation level also allows to encompass functional geographic regions that extend beyond the specific administrative boundaries. Due to missing information for some sectors, we ended up with a final balanced panel of 548 spatial units observed across 9 years for the three different macro-sectors considered in the analysis composing the agribusiness *filière*.

Table 1 shows some descriptive statistics on the output and input variables for the three sectors considered. Specifically, we consider value added as output and the number of employees and fixed assets as labour and capital inputs.

As preliminary spatial analysis, we compute the univariate and bivariate global Moran's I statistics for the value added in the year 2021. The results indicate that the level of global spatial dependence is positive and significant both intra and inter-sectors. Specifically, the manufacturing sector is the most characterised by spatial dependence in terms of value added (0.34) followed by agriculture (0.20) while the statistic value noticeably reduces for trade (0.12). Considering inter-sectoral spatial correlation, the most relevant dependence in terms of value added is observed across the agriculture and manufacturing sectors (0.19) and the manufacturing and trade sectors (0.19) while a smaller but still significant value characterises the agriculture and trade sectors (0.12).

Since the global Moran's I statistics can hide relevant spatial features at the local level, in Figure 1 we show the LISA significant cluster map for the value added in the year 2021. The Figure depicts that while significant high-productive clusters are located in the North of Italy and the areas around Rome and Naples for all the three sectors considered, low-productive clusters are mainly detected in the Calabria region and the two islands. Differences among sectors mainly concern the Tuscany region, which is highly shaped by high-high clusters only concerning the value added of the agricultural sector, the North-West of Italy which presents high productive clusters in the food and beverage industry alone and Southern Sicily which is mostly characterised by low-low clusters in the manufacturing sector.

## 5 | Results

The estimation results are provided in Table 2. This section separately presents the results for reactions to mechanisms internal to the system, external shocks, and input variations aiming to answer the research questions based on the three different sources of spillovers.

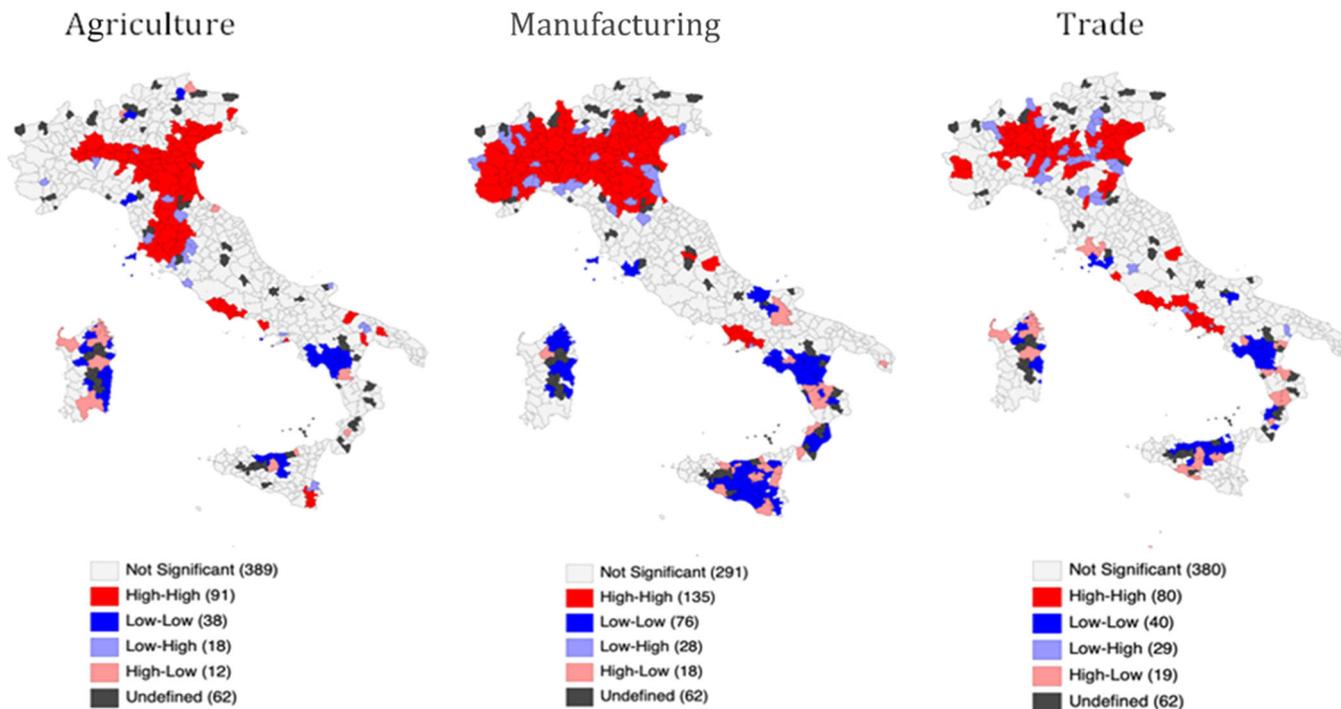
To ensure the robustness of our findings, these estimates are compared to some alternative specifications. In particular, (i) we estimate the model considering a first-order binary contiguity matrix alternatively to a second-order one for intra sectoral spillovers and (ii) we use row normalisation as an alternative standardisation method to a doubly stochastic standardisation approach. The estimation results are respectively shown in Table B1 and C1 of the Appendix. Overall, our results do not vary considerably for changes in the definition of the spatial weight matrix and using alternative standardisation methods confirming the robustness of our findings.

### 5.1 | Reactions to Mechanisms Internal to the System

The relevance of inter sectoral relationships in the Italian agribusiness *filière* is first depicted by the results in Table 2. As pointed

TABLE 1 | Descriptive statistics.

	Min	Mean	Median	Max	SD
<b>lnQ (value added)</b>					
Agriculture	0	6.90	7.52	12.50	2.75
Manufacturing	0	8.14	8.71	14.48	3.04
Trade	0	8.02	8.56	14.81	2.87
<b>lnL (labour)</b>					
Agriculture	0	3.78	4.01	10.52	1.92
Manufacturing	0	4.54	4.77	9.86	2.03
Trade	0	4.64	4.88	10.83	2.03
<b>lnK (capital)</b>					
Agriculture	0	8.44	9.16	14.02	3.08
Manufacturing	0	8.62	9.37	14.41	3.19
Trade	0	7.98	8.48	14.85	2.98



**FIGURE 1** | LISA Significance Cluster Map: Value Added, year 2021. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jors.12757)]

**TABLE 2** | Estimation results.

	Agriculture	Manufacturing	Trade
$\gamma_{Agric}$	—	-0.030	0.037
$\gamma_{Man}$	-0.074**	—	0.051
$\gamma_{Trade}$	0.134***	0.073	—
$\psi_{Agric}$	0.291***	-0.215***	-0.040***
$\psi_{Man}$	-0.067***	0.020	0.025***
$\psi_{Trade}$	0.281***	-0.182***	0.027**
$\phi_{Agric}$	-0.594***	0.158***	-0.142***
$\phi_{Man}$	0.133***	-0.046***	0.009
$\phi_{Trade}$	-0.063***	0.132***	0.065***
$\rho_{Agric}$	0.747***	0.022	-0.021
$\rho_{Man}$	0.016	0.327***	-0.003
$\rho_{Trade}$	-0.034	-0.067*	0.203***
$\pi_{LAgric}$	0.138***	0.008	0.012
$\pi_{LMan}$	0.034	0.274***	-0.009
$\pi_{LTrade}$	-0.040*	-0.015	0.174***
$\pi_{KAgric}$	0.264***	-0.019	-0.021
$\pi_{KMan}$	0.018	0.597***	-0.054
$\pi_{KTrade}$	-0.048**	-0.020	0.524***

\*\*\*:p-value < 0.01.

\*\* :p-value < 0.05.

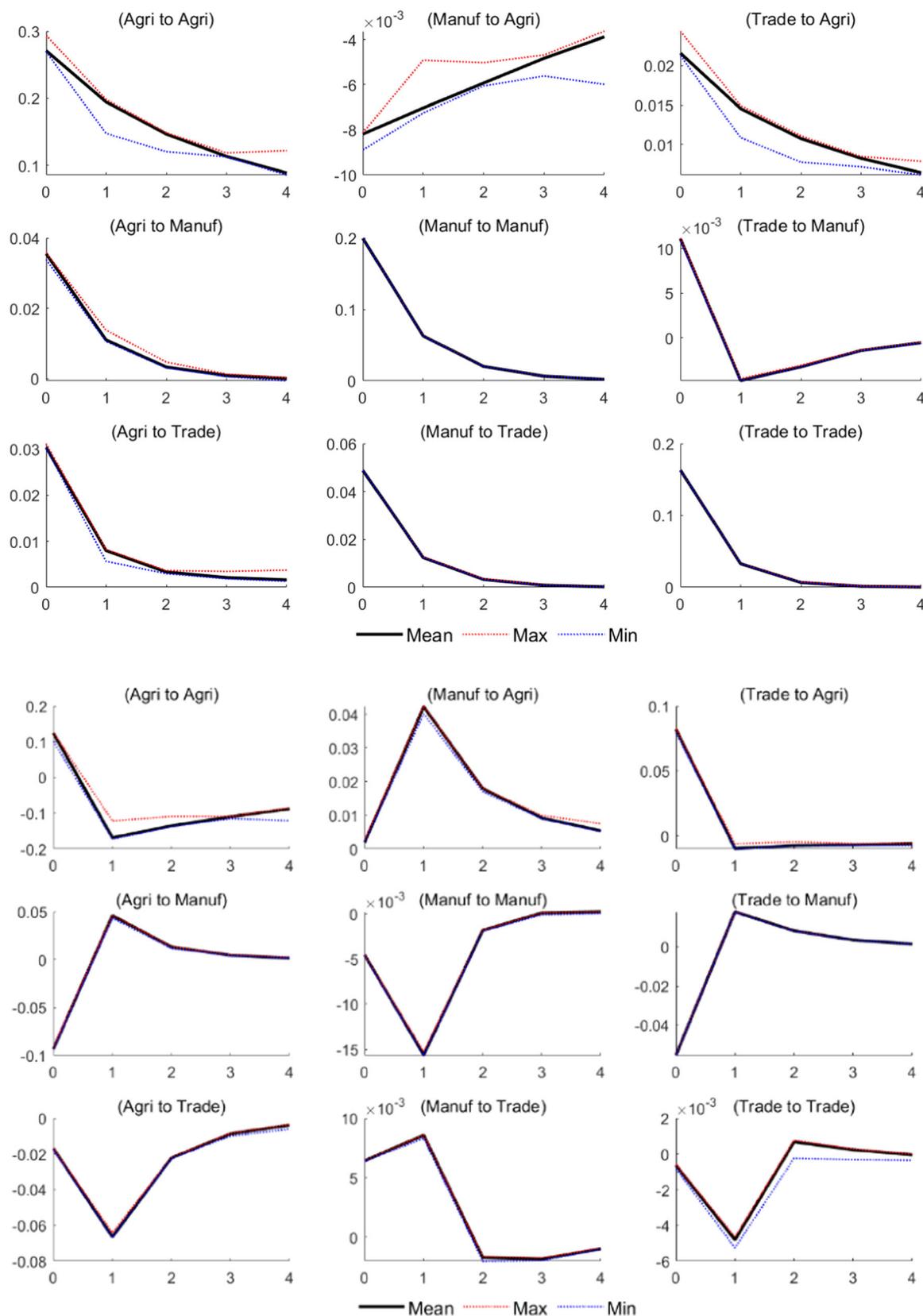
\*:p-value < 0.1.

out by the estimates of the simultaneous effects, the only sector showing a statistically significant impact of inter sectoral performances is the agricultural industry ( $\gamma_{12}$  and  $\gamma_{13}$  parameters in Eq. 3). Moreover, all sectors are characterised by spatial intra and inter sectoral spillovers since most of the  $\Psi$  entries are statistically significant (and positive). This result suggests the existence of possible positive externalities spreading out the LMA boundaries. The only exception concerns the manufacturing sector, for which we do not detect any significant intra sectoral simultaneous spatial effect. This can be related to lower flexibility both in adaptation to demand and preferences and in specialised production processes of this sector (Claassen et al. 2016).

## 5.2 | Reactions to External Shocks

The impacts of a unitary shock are summarised in Figure 2 differentiating between direct and indirect effects. The choice of a 5-year time horizon in Figure 2 is motivated by the fact that the half-life of a shock turns out to be 2.3 years, which implies that each shock has largely vanished over a period of 5 years.

The direct impacts of a unitary shock shown in the upper panel of Figure 2 indicate that innovation in a sector positively affects the productive outcome of the sector itself (intra sectoral) and of all the other sectors in an area (inter sectoral) in the short run. However, while inter sectoral effects are very weak in magnitude, intra sectoral impacts are more effective reaching a value of 0.2 in the manufacturing and trade sectors and exceeding 0.25 in agriculture. Nevertheless, in the long run, all impacts converge to zero suggesting that all sectors are capable of absorbing the shock at least after 5 years.



**FIGURE 2** | Marginal Effects: Innovations (direct effects on the upper panel and indirect effects on the lower). [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

Considering indirect effects, the lower panel of Figure 2 reports intra sectoral spillovers in the main diagonal, while off-diagonal panels show inter sectoral effects. Our results suggest that spillover effects mainly generate from agriculture, affecting

agriculture itself as well as manufacturing and trade. In particular, we find that, in the short run, a shock in the agricultural sector in one specific area positively impacts neighbours in the same sector, while firms belonging to other sectors suffer

TABLE 3 | Marginal Effects: Input Variables.

From	To	Direct		Indirect	
		Short-run	Long-run	Short-run	Long-run
<b>Labour</b>					
<b>Output</b>					
Agric	Agric	0.140***	0.102*	0.061***	-0.056
Agric	Manuf	0.035	0.025	0.015	-0.014
Agric	Trade	-0.041	-0.030	-0.018	0.016
Manuf	Agric	0.008	0.003	0.000	-0.000
Manuf	Manuf	0.276***	0.095	0.012*	-0.006
Manuf	Trade	-0.015	-0.005	-0.001	0.000
Trade	Agric	0.012	0.002	-0.000	0.001
Trade	Manuf	-0.009	-0.002	-0.000	-0.001
Trade	Trade	0.176***	0.036	-0.001	0.011
<b>Capital</b>					
<b>Output</b>					
Agric	Agric	0.269***	0.194***	0.118***	-0.108*
Agric	Manuf	0.018	0.013	0.008	-0.007
Agric	Trade	-0.048*	-0.035	-0.021*	0.019
Manuf	Agric	-0.019	-0.006	-0.001	0.000
Manuf	Manuf	0.601***	0.197**	0.027*	-0.012
Manuf	Trade	-0.020	-0.007	-0.001	0.000
Trade	Agric	-0.021	-0.004	0.000	-0.001
Trade	Manuf	-0.054	-0.011	-0.000	-0.004
Trade	Trade	0.528***	0.108	-0.002	0.033

Standard errors computed through delta method.

\*\*\*:  $p$ -value < 0.01.

\*\* :  $p$ -value < 0.05.

\* :  $p$ -value < 0.1.

negative effects. Moreover, in period  $t + 1$  positive intra-sectoral spatial spillover effects tend to become negative as well, indicating that also firms of the agricultural sector located in neighbouring territories, after a brief productivity enhancement, suffer competition effects. In addition, while in the long run, neighbours in the trade and manufacturing sectors are able to retrieve from the negative effects registered in the short run, competition effects influencing the agricultural sector of closer areas appear to be still persistent 5 years later.

Finally, other than spillovers generated from agriculture, we also detect positive spatial effects arising from innovation in manufacturing and trade influencing neighbours in the agricultural sector at time  $t + 1$  and  $t + 2$  in the former case and at time  $t$  in the latter.

### 5.3 | Reactions to Input Variations

With regard to the impact of the input variables on sectoral productive outcomes ( $\ln L$  and  $\ln K$ ), Table 3 shows the marginal direct and indirect effects related to input changes differentiating between short-run and long-run effects.

We mainly find that positive and significant direct and indirect effects occur within sectors. As for direct effects, our results suggest that all three sectors considered in the analysis are capital-intensive sectors since capital elasticity highly exceeds labour elasticity in all

cases. Moreover, they are all characterised by decreasing returns to scale since the sum of labour and capital elasticity is always less than 1 (even if we consider indirect effects). As expected, in the long run, all effects tend to be mitigated even if they mostly remain significant, especially for capital.

Considering spatial effects, in line with previous results, we find that positive input spillovers mainly occur within the agricultural sector for both labour and capital. We also have weak statistical evidence of input spillovers in the manufacturing industry while we do not detect any spatial effects related to the inputs in the trade sector. Therefore, agricultural producers and food and beverage industries located close to areas with greater availability of labour and capital inputs can enhance their productive performance likely thanks to cost reduction in transportation and increased accessibility to specific products. However, while 'input sharing' (Marshall 1890) favours the productivity level of neighbours in the short run, our results indicate that competition arises within the agricultural sector in the long run for capital inputs.

## 6 | Discussion

The estimates of the empirical model suggest that inter sectoral spillovers (Q1) mainly occur through internal mechanisms realising from food manufacturing and trade performances and

affecting agriculture. Indeed, output enhancements in the food industry and trade sectors may drive technological innovation and changes in production processes throughout the agricultural sector since innovations in food processing and trade can stimulate the demand for specific types of agricultural products that require specialised production techniques or specific varieties (Gopinath and Roe 2000). Moreover, when inter sectoral relationships are measured as responses to external shocks, we find weak cross-sectoral linkages for all productive sectors in the agribusiness *filière*. Considering input effects, the only significant spillover originates from capital in agriculture and negatively affects trade, underlying the poor role of labour and capital investments in defining cross-sectoral linkages.

Considering spatial effects within (Q2) and between (Q3) sectors, we find that impacts internal to the system emerge across all sectors except for manufacturing-to-manufacturing linkages. When evaluating responses to external shocks, our results suggest that spatial effects mainly generate from agriculture, positively affecting agriculture itself while having negative effects on the other sectors in the system. The agricultural sector can be considered the initial stage of the supply chain where raw materials for the food industry and trade are sourced. Therefore, any disruptions or improvements in the agricultural sector can propagate spatially and influence the operations and performance of the food industry and trade sectors that rely on a stable and sufficient supply of raw agricultural materials. Positive effects within agriculture may depend on the fact that when a shock occurs, businesses within the same sector share similar knowledge and expertise related to the specific challenges they face, facilitating the exchange of information, best practices, and technology, and thus production-enhancing spillovers occur (Malerba, Mancusi, and Montobbio 2014). On the other hand, a shock in the agricultural sector may lead to a shift in resource allocation towards agriculture, driven by the comparative advantage of the region in agricultural production. As a result, neighbouring trade and manufacturing sectors may face reduced competitiveness and struggle to attract investments or maintain market share (Latruffe 2010). Additionally, we observe positive spatial effects from innovations in manufacturing and trade, influencing neighbouring agricultural producers in line with direct spillovers. Regarding input spillovers, we mainly find positive intra-sectoral spatial effects related to both labour and capital within agriculture and manufacturing.

Considering time variations (Q4), our results suggest that most spillovers tend to vanish in time. However, there are a few cases of positive spatial spillovers turning to competitive effects in the long run such as spatial effects from shocks within agriculture and from input spillovers related to capital. Indeed, if neighbours are not able to adequately absorb and internalise the positive feedback arisen in the previous period, they can experience lowered local demand as consumers may prefer cheaper or better-quality products from neighbouring highly competitive territories (Porter 1990).

In conclusion, inter sectoral spillovers in the agricultural *filière* seem to be mostly related to simultaneous effects internal to the productive system (i.e. productive linkages, imitation, skill acquisition, etc.) and common reactions to shocks rather than

arising from labour and capital investments in the other inter-related sectors (Q5). Moreover, effects tend to propagate and influence also producers located in neighbouring areas with different magnitudes and signs depending on the mechanism and time horizon considered.

Based on our findings, several policy recommendations can be sketched. First, given the significant spillover effects from agriculture to manufacturing and trade, policies should prioritise stabilising the agricultural sector during shocks. This can be achieved through subsidies such as those of the Common Agricultural Policy, insurance schemes, and investments in resilient agricultural practices. In this framework, sustainable agricultural practices and investments in agricultural research and innovation should be promoted to develop new technologies that can manage disruptions and crises (i.e., Covid19 pandemic, Ukraine war, etc.) and mitigate the long-term competitive pressures within the agricultural sector. To safeguard the food and beverage manufacturing and trade from agricultural shocks, policies should encourage diversification and the development of robust supply chain networks that can face disruptions in agriculture. Moreover, regional coordination and planning are needed to establish funds that specifically target regions where multiple sectors are interlinked, ensuring that resources are allocated efficiently to areas most vulnerable to sectoral shocks. Hence, policymakers should consider spatial and cross-sectoral feedback in designing development plans and economic programs to build a more resilient and interconnected economic landscape.

## 7 | Conclusions

Given the relevance of spatial and sectoral interactions in shaping the productivity performance of economic systems, in this study, we develop an econometric approach to handle both cross-sectoral linkages and inter and intra sectoral spatial productivity spillovers. One of the main novelties of this tool concerns the possibility of distinguishing between different sources of inter sectoral linkages: impacts related to mechanisms internal to the system (direct and spatial), reactions to shocks (direct and spatial), and input variations (direct and spatial). The model developed in this paper allows conducting research on a variety of theoretical questions related to the existence of cross-sectoral spillovers, spatial phenomena, and temporal dynamics in complex economic systems with reference to input changes or external/internal factors. To show the ability of the proposed model in empirical studies, following Yang and Lee (2017; 2019) and Elhorst and Emili (2022), we estimate a system of dynamic spatial panel data models using data at the LMA level for the Italian agribusiness industry in the time period 2013-2021.

The results of the empirical application indicate that, for impacts related to simultaneous effects between sectoral performances, significant inter sectoral relationships exist, particularly from food manufacturing and trade to agriculture. Spillover effects also extend beyond local boundaries affecting neighbouring producers, except in the manufacturing sector, where no significant intra sectoral spatial effects are detected.

Concerning impacts to an innovation, our results suggest that a shock in a sector mainly affects the sector itself as well as the other sectors operating in the same area even if with a reduced impact. For spatial effects, we find that spillovers mainly generate from agriculture, influencing agriculture itself as well as manufacturing and trade. However, while in the long run trade and manufacturing sectors in neighbouring areas are able to absorb the negative impacts resulting in the short run, neighbours in agriculture are not capable of adequately exploiting the immediate positive feedback experiencing persistent competition effects in the long run. Thus, the importance of cross-sectoral linkages among the different sectors in the agribusiness *filière* is confirmed since a shock in one specific sector has an impact on most businesses in all sectors, both in the same area and in neighbouring territories.

Considering the input variables, we find that a unitary increase in labour and capital inputs in a sector mainly boosts the productive performance of the sector itself via direct effects. Moreover, also positive intra sectoral input spillovers contribute to shaping the productivity level of the agricultural and manufacturing sectors in the short run. However, in the long run, competition effects from neighbouring agricultural producers may arise within agriculture.

Insights from this study may be of interest to both academics and policymakers. Researchers interested in productivity analyses may take advantage of the flexible model developed in this work for investigating a wide range of productive systems across different countries and industries, where spillovers can flow through different transmission mechanisms, either observable or unobservable. However, one of the weaknesses of this modelling approach is its complexity, particularly due to the increasing number of parameters to estimate as the number of equations in the model increases. Therefore, this tool is particularly useful for production systems composed of a few sectors. In contrast, for very complex industries, previous techniques, such as SUR models, input-output models and the introduction of specific spatially lagged covariates, can be computationally easier to handle.

In future developments of this work, it would be interesting to expand the territorial detail of the analysis or to use this tool to evaluate productivity spillovers across countries and industries. From a methodological point of view, future extensions may concentrate on expanding the model specification to include an inefficiency error component in line with the stochastic frontier modelling framework to also consider efficiency mechanisms.

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### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available from Bureau Van Dijk. Restrictions apply to the availability of these data,

which were used under license for this study. Data are available from <https://login.bvdinfo.com/R0/AidaNeo?SetLanguage=it> with the permission of Bureau Van Dijk.

### Endnotes

<sup>1</sup>According with the aim of this study (i.e. providing a comprehensive tool for the analysis of cross-sectoral and spatial spillovers), we discuss the role of each term in Eq. 3 focusing on the first equation of the system, as an example. In this case, the parameters related to intra-sectoral dynamics are:  $\Pi_{L1}$  and  $\Pi_{K1}$  referring to the role of input factors within the first sector,  $p_{11}$  for the impact of the past performance of the first sector itself, and  $\psi_{11}W_a$  and  $\phi_{11}W_a$  for the simultaneous and past performances of neighbours in the same first sector. The remaining parameters can be considered as those related to the inter sectoral dynamics:  $\Pi_{L2}$ ,  $\Pi_{L3}$ ,  $\Pi_{K2}$  and  $\Pi_{K3}$  are related to the effect of input factors of the second and third sector on the productive performance of the first sector;  $p_{12}$  and  $p_{13}$  refer to impact of the past performances of the second and the third sector on the level of output of the first sector;  $\psi_{12}W_b$ ,  $\psi_{13}W_b$  and  $\phi_{12}W_b$ ,  $\phi_{13}W_b$  capture the role of the simultaneous and past performances of neighbours belonging to the second and third sector on the level of output of the first sector;  $\gamma_{12}$  and  $\gamma_{13}$  measure simultaneous inter-sectoral effects.

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### Supporting Information

Additional supporting information can be found online in the Supporting Information section.