



# Modelling Spatio-Temporal Dynamics in Multi-Output Stochastic Frontiers for the European Agribusiness Industry

Silvia EMILI and Federica GALLI 

This paper introduces a maximum likelihood estimation approach for multi-output stochastic frontier models with simultaneous effects, cross-equations and temporal and spatial components to analyse the aggregate production of agricultural-related industries in European OECD countries in the period 1996–2019. The result is a comprehensive empirical assessment of input, inefficiency and shocks-related spillovers between two of the main sectors in the agribusiness industry, i.e. agriculture and food and beverage manufacturing. Our findings reveal the existence of positive spillovers in the short term from both efficiency and innovation shocks, as well as input variations, which modify into competitive pressures in the long run. Insights from this study allow policymakers to evaluate how the productive performance of each sector in the agribusiness industry influences the production output of the other, both within and between countries. Additionally, it allows for the inspection of various transmission mechanisms and contagion phenomena, aiding in the design of international support plans for the entire agribusiness industry.

**Key Words:** Multi-output stochastic frontier models; Spatial and temporal dynamics; Cross-sectoral linkages; Inefficiency spillovers; Agribusiness industry.

**JEL codes** O47 · C33 · R15

## 1. INTRODUCTION

In recent decades, industries and economic systems have undergone a significant period of economic, political, cultural and ideological globalization and liberalization (Skogstad 2000) at both the international and national levels. The globalization of productive processes, alongside the reduction of constraints, barriers or obstacles to the free exchange of goods among nations, has led to a notable increase in connectivity, collaboration and competition

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among economic entities (Badinger and Egger 2016). These dynamics, and thus the increase in the complexity of relationships between agents within national economic systems, have significantly heightened researchers' attention to production externalities across countries (Badinger and Egger 2016; Eberhardt and Teal 2013; Ertur and Koch 2007; Mitze et al. 2016), especially when international organizations act, behave and interact with countries at supranational levels (e.g. European Commission and member states of the EU). The relevance and complexity of these international linkages are particularly evident within specific contexts of study, such as the agribusiness<sup>1</sup> industry in Europe (Bonanno 2014).

At the European level, analysing the aggregate production of the different sectors within the agribusiness filière can be crucial for funds allocation, for planning country- or product-specific supporting strategies and for formulating tailored plans and programs in the context of the Common Agricultural Policy (CAP). Being Europe one of the world's biggest importers and exporters of food (European Commission, 2022), policies related to the agribusiness industry mainly aim to incentivize young individuals to venture into farming, encourage rural business start-ups, safeguard the names of specific products and promote their distinctive traits tied to their geographical origins and traditional expertise. These endeavours are crucial amidst the challenges posed by digital transformation, environmental shifts, climate fluctuations and potential economic shocks. To this end, the understanding of the dynamics characterizing the interactions within the filière, but also across countries becomes fundamental.

The agribusiness industry (or filière) comprises various sectors intricately linked through diverse channels, with both horizontal and vertical linkages characterizing their supply chains (Ciranni et al. 2021; Jambor 2014; Young and Hobbs 2002). The economic output of each sector of the filière in a given nation can be affected not just by its own policy uncertainty, input shocks, diffusion of technological advances, tastes and norms, but also by the same phenomena occurring in the rest of the world for that sector (Liu et al. 2023). As highlighted by Gheibdoust et al. (2023), the war in Ukraine caused severe disruptions in food supply both nationally and internationally, putting at risk food security and affordability worldwide. Moreover, contagion phenomena have been observed in the supply–demand imbalance of national commodity markets after the COVID-19 pandemic and subsequent geopolitical and monetary crises faced by major Western economies (Qian et al. 2023; Chen and Villoria 2022).

Besides intra-sectoral relationships, a second source of dependencies within the agribusiness filière is given by inter-sectoral connections. These vertical linkages mainly rely on input–output relationships (Vachanelidou et al. 2023). Intuitively, agriculture is a primary source of raw materials for the food and beverage industry, which in turn produces goods distributed through the wholesale and retail sectors and finally reaching consumers via restaurant-related sectors, markets and shops. Reconsidering the Ukraine situation, food disruptions not only affected agricultural production but also global trade and food manufacturing (Gheibdoust et al. 2023). In a similar manner, among possible factors determining

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<sup>1</sup> Agribusiness can be described as a series of economic activities encompassing the production, processing and commercialization of agricultural products (Rosete 2020). In this work, the terms agribusiness industry and agribusiness filières are used interchangeably to refer to the chain of vertical linkages across the different industries composing the agribusiness.

inter-sectoral dependence, we can mention supply chain integration, seasonal variability, price fluctuations and policy coordination.

However, nowadays researchers increasingly recognize that connections between industries are influenced not only by economic relationships and dependencies, such as vertical and horizontal relationships, but also by spatial proximity (Bravo-Monroy et al. 2016; Bravo-Ureta et al. 2021; Geldes et al. 2017; Rambe and Khaola 2022; Wollni and Andersson 2014). Spatial effects may stem from both neighbours in the same sector (intra-sectoral spillovers) and in other sectors within the industry (inter-sectoral spillovers), strongly shaping the productive performance of producers at different levels of geographic aggregation. At the country level, spillovers are mainly associated with import–export transactions and foreign direct investments (Coe and Helpman 1995; Eaton and Kortum 1996), technology transfers (Barro and Sala-i-Martin 1997; Howitt 2000; Ertur and Koch 2007) or human capital externalities (Lucas 1988, 1993). In the case of the agribusiness filière, being located near a major exporter of agricultural products may meet the domestic demand of neighbouring countries due to low transportation costs; foreign direct investments of multinational agribusiness companies may result in technology improvements in nearby countries (Liu and Xu 2016); technology breakthroughs in agricultural biotechnology or shocks due to adverse environmental conditions may propagate internationally (Jansson and Hofmocker 2020; Ristaino et al. 2021). Then, accounting for spatial correlation and spillover effects can be clearly recognized as a key issue in cross-country productivity and efficiency analyses of the agribusiness industry (Eberhardt and Teal 2013).

The aim of this study is to analyse the magnitude and transmission of different types of intra-sectoral, cross-sectoral and spatial spillovers within the agribusiness industry by means of methodological advances in spatial stochastic frontier literature. The result is a comprehensive empirical assessment of input, inefficiency and shocks-related spillovers between two of the main sectors in the filière, i.e. agriculture and food and beverage manufacturing, for a panel of 17 OECD countries in Europe over the period 1996–2019. To perform the analysis, in line with the multi-sectoral nature of the agribusiness industry, we merge techniques from the latest strands of advances in stochastic frontier (SF) models literature, i.e. multi-output SFs and spatial SFs.

The methodological proposal of this study consists of a maximum likelihood estimation approach for a system of stochastic frontiers for panel data models with cross-equation, temporal and spatial dependence, and simultaneous effects. Accounting for simultaneity across equations represents a source of possible identification issues besides the inclusion of spatially lagged terms, requiring adequate exploration on identification methods to address this challenge both from a modelling and policy perspective (as extensively described in the methodological section). The proposed specification is particularly suitable for investigating production processes that are interrelated through input–output linkages, spatial correlation and time dynamics, while the inefficiency processes remain uncorrelated. In general, the hypothesis of uncorrelated inefficiency mechanisms is based on the notion that inefficiency stems from the internal conversion of resources into output and it is influenced by internal factors such as available tools and techniques (e.g. knowledge, training, automation and information), thereby making it context-dependent. The reliability of this assumption can be achieved in several practical cases where the inefficiency-generating processes of the

decision-making units mainly depend on internal factors. For the agribusiness filière, this feature is discussed later on in Sect. 5, where the empirical framework, the data and results are presented.

By estimating a system of two dynamic spatial frontier equations for the agribusiness industry in Europe, this study enables policymakers to evaluate how the productive performance of each sector influences the production output of the other, both within and between countries. Additionally, it allows for the inspection of various transmission mechanisms and contagion phenomena, aiding in the design of international support plans for the entire agribusiness industry.

In the next sections, we present the methodological framework, the modelling proposal and identification conditions in Sect. 2, we introduce the estimation procedure in Sect. 3, we test the finite sample properties of our model through simulations in Sect. 4, we present the empirical application to aggregate production in Europe in Sect. 5, and in Sect. 6 we conclude.

## 2. THE MODEL

### 2.1. SPATIAL AND MULTI-OUTPUT SFs

One of the most widely employed methodological tools for productivity and efficiency analysis is represented by stochastic frontier models. This class of models was first introduced by [Aigner et al. \(1977\)](#) and [Meeusen and van Den Broeck \(1977\)](#) with the aim of investigating firms' productive efficiency by distinguishing between the inefficiency error component and random shocks. Over the subsequent decades, SFs have found widespread application in various frameworks including agricultural economics, health, tourism, labour, finance, etc. Additionally, there have been numerous methodological advances aimed at extending the baseline specification of these models ([Belotti and Ilardi 2018](#); [Glass et al. 2016](#); [Kutlu et al. 2019, 2020](#); [Liu et al. 2020](#); [Simar and Wilson 2022](#)).

First, multi-output models were developed to simultaneously consider more than one production process. One of the first contributions in this strand of literature is represented by [Fernández et al. \(2000\)](#) which aggregate the outputs of the different equations in order to model them through a single-equation frontier based on a parametric production equivalence surface. Later on, [Ferreira and Steel \(2007\)](#) specify a system of stochastic frontier equations using a multivariate skewed distribution to handle the composed error and estimate the model taking advantage of Bayesian techniques. [Carta and Steel \(2012\)](#) and [Lai and Huang \(2013\)](#) introduce and refine a copula approach to deal with the dependence of the different inefficiency error terms in multi-output production frontiers. [Liu et al. \(2020\)](#) develop a simultaneous system of SF models allowing both dependence between the random noise and inefficiency components of individual observations as well as across all equations of the model using copula functions. Recently, [Schmidt and Kneib \(2023\)](#) introduce a likelihood approach to estimate multiple-output panel data SF models utilizing smooth terms and copulas. However, to our knowledge, none of these models considers the possibility of accounting for spatial dependence within and between different frontiers.

In the last two decades, given the strong evidence of spatial phenomena such as agglomeration and clustering, authors began recognizing that the assumption of cross-sectional independence characterizing non-spatial SFs cannot be considered valid. As pointed out by [Glass et al. \(2016\)](#), we can have an omitted variable bias if spatial dependence is not taken into account and also the statistical inference can be inaccurate due to the violation of the independence assumption ([Fusco and Vidoli 2013](#)). Based on these insights, a large number of contributions modelling spatial dependence in an SF framework started spreading out in the single-equation case ([Glass et al. 2016](#); [Gude et al. 2018](#); [Orea and Alvarez 2019](#); [Areal and Pede 2021](#); [Galli 2023a,b](#)). However, to date, there are yet no works introducing spatial correlation in a multi-output SF setting, that is, considering spatial spillovers occurring between and within different frontier functions.

In this study, we extend the current literature on SF models by proposing a maximum likelihood estimation approach for a system of dynamic spatial stochastic frontier models that accounts for simultaneous effects across different frontier functions as well as time and spatial effects. In particular, our model allows differentiating between input, inefficiency and shock-related spillovers occurring inside one single production frontier and among different production processes through a standard maximum likelihood framework. This feature is achieved by assuming independence among the inefficiency error components of the different equations yielding a tractable form for the multivariate truncated distribution.

## 2.2. METHODOLOGICAL PROPOSAL

The starting point of the proposed model is the literature on systems of spatial panel data models first introduced by [Yang and Lee \(2017, 2019\)](#). The main advantage of this technique is the possibility of explicitly modelling interactions among different economic variables (each one modelled by a specific equation) with lagged, spatial and simultaneous effects. The capabilities of the system let this technique to position itself as a midpoint between spatial dynamic panel data models ([Elhorst 2014](#)), usually considered as single-equation techniques, and vector autoregressive (VAR), structural vector autoregressive (SVAR) (e.g. [Lütkepohl 2005](#)), or global vector autoregressive models (GVAR) ([Pesaran et al. 2004](#)). Indeed, if the former class of approaches has the limit of estimating homogenous parameters across units, the latter may suffer from high-dimensionality issues in estimation and assume spatial lags as weakly exogenous variables (i.e. overcoming endogeneity issues) ([Elhorst et al. 2021](#)).

The proposed multi-output SF model with spatial effects and temporal dynamics for  $m$  outputs and  $n_m$  units observed across  $T$  time periods is defined by:

$$\mathbf{B}z_t = \Psi \mathbf{W}z_t + \Phi \mathbf{W}z_{t-1} + \mathbf{P}z_{t-1} + X_t \Pi + V_t - cU_t \quad (1)$$

$$V_t \sim N_m(0, \Sigma_v) \quad (2)$$

$$U_t \sim N_m^+(0, \Sigma_u). \quad (3)$$

with  $t = 1, \dots, T$ . In particular,  $m$  is the number of equations identifying the different interdependent frontier functions and  $n_m$  is the number of units characterizing each production

process. For the sake of simplicity, in the rest of this section, we consider  $n$  constant across equations, without loss of generality.

Specifically,  $z_t = (z'_{1t}, z'_{2t}, \dots, z'_{mt})'$  is the  $nm$ -dimensional vector of outcome variables representing the production outputs, written as stacked vectors of  $m$  cross-sections, such that  $z_{\cdot t} = (z_{\cdot,1t}, z_{\cdot,2t}, \dots, z_{\cdot,nt})'$  for  $\cdot = 1, \dots, m$ .  $\mathbf{W}$  collects the spatial weight matrices for the statistical units, and it is defined by  $m^2$  possible different weighting matrices. Overall,  $\mathbf{W}$  serves as a comprehensive structure that organizes the weighting matrices associated with the various combinations of outputs in each equation<sup>2</sup>. Each spatial weight matrix contained in  $\mathbf{W}$  possesses the typical characteristics of spatial weight matrices, such as zeros on the main diagonal, symmetry, and other standard properties (LeSage and Pace 2009).  $\mathbf{B} = (B \otimes I_n)$  is an  $nm \times nm$  matrix of mutual impacts among the  $m$  dependent variables measured by the  $(m \times m)$  matrix  $B$ , where diagonal elements are equal one.  $\Psi = \Psi \otimes I_n$  is an  $(nm \times nm)$  matrix and  $\Psi$  an  $(m \times m)$  matrix of  $(m^2)$  coefficients denoting the impact of the spatially lagged dependent variables measured at time  $t$  of both own-sector spatial lags (along the diagonal of  $\Psi$ ), and of cross-sector spatial lags (off-diagonal entries). Similarly, the term  $\Phi \mathbf{W} z_{t-1}$  denotes the impact of the spatially lagged dependent variables measured at time  $t - 1$ , where the  $(nm \times nm)$  matrix  $\Phi = (\Phi \otimes I_n)$ . Moreover, the temporal dynamic is also included in the model by the term  $\mathbf{P} z_{t-1}$ , where  $\mathbf{P} = (P \otimes I_n)$  is an  $(nm \times nm)$  matrix of autoregressive coefficients. The term  $X_t \Pi = (I_m \otimes x_t) \Pi$  represents the impact of exogenous variables through the  $(km \times 1)$  vector of coefficients  $\Pi$ . In the case of production processes, in each equation,  $x_t$  is a  $(n \times k)$  matrix of  $k$  input factors. The model specification could be further enriched by including the exogenous spatial lag of  $X_t$ , i.e.  $\mathbf{W} X_t$ , in order to control for input spillovers occurring intra- and inter-equations.

The  $(nm \times 1)$  vector  $U_t$  reflects the independent and identical half-normally distributed inefficiency error component, with covariance matrix  $\Sigma_u = \Sigma_u \otimes I_n$ , where  $diag(\Sigma_u) = (\sigma_{u,1}^2, \sigma_{u,2}^2, \dots, \sigma_{u,m}^2)'$  and zero off-diagonal entries. This specification allows each equation to be characterized by its own inefficiency-generating process without considering interdependence among them. As previously anticipated, inefficiency is considered the result of the internal transformation of resources into output based on available tools and techniques such as knowledge, training, automation and information, and thus, it can be considered context-specific. In particular, in the case of a production frontier, inefficiency represents the decrease in the production level due to technical frictions, and thus, it has to be subtracted from the frontier function ( $c = 1$ ). For a cost frontier, inefficiency represents a cost increase, and thus,  $U_t$  has to be summed to the frontier ( $c = -1$ ). In both cases, since inefficiency can only take positive or at least zero values,  $U_t$  is modelled following

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<sup>2</sup>For example, if  $m=2$ , the most general structure of  $\mathbf{W}$  is given by:

$$\mathbf{W} = \begin{bmatrix} W_a & W_c \\ W_b & W_d \end{bmatrix}$$

where  $W_a$  and  $W_c$  enter in the first SF equation and  $W_b$  and  $W_d$  in the second. In particular,  $W_a$  is the spatial weight matrix representing spatial mechanisms within the first production process,  $W_d$  is the spatial weighting matrix governing the spatial behaviour of the second production process,  $W_b$  captures spatial dependence between the first and second production processes in transmission of shocks/effects from the first process to the second, and  $W_c$  is governing spillovers from the second to the first.

a half-normal distribution. Alternative positive distributions are the truncated normal, the gamma or the exponential distribution.

Finally, the  $(nm \times 1)$  vector  $V_t$  reflects the independent and identically normally distributed random error term, with zero mean and covariance matrix  $\Sigma_v = \Sigma_v \otimes I_n$ . The off-diagonal entries of this covariance matrix allow the error terms of the two equations to be correlated for each unit at the same moment in time. Indeed, a random shock affecting the first production process of the system (i.e. a natural disaster, economic crisis, war, pandemic, etc.) may also influence the productivity level of the second one due to productive interdependence. Following the classical assumptions in SF model literature,  $U_t$  and  $V_t$  are assumed to be independently distributed in order to obtain a closed form for the likelihood function (widely discussed in the next section).

Under standard regularity conditions, the model described in Eqs. (1)–(3) exhibits stability both spatially and temporally. The initial condition for ensuring the stability of the system pertains to the parameter space, which is defined by the parameters in  $B$ ,  $\Psi$ ,  $\Phi$  and  $P$ . This parameter space has to be compact to ensure that the spectral radius of the Jacobian term remains below 1, where the Jacobian is defined as  $S = (B' \otimes I_n - (\Psi' \otimes W))$ . Additionally, solutions to the equation  $|S^{-1}[(\Phi' \otimes I_n)W + P' \otimes I_n]|$  should be confined within the unit circle, ensuring stability in both spatial and temporal dimensions, respectively. Furthermore, to ensure spatial stability, assumptions on the spatial weight matrix  $W_m$  are required. First,  $W_m$  is a non-stochastic row-normalized spatial weight matrix with zero diagonal elements. Second, row and column sums of  $W_m$  are uniformly bounded in absolute value as  $N$  goes to infinity. Finally, for any possible configuration of parameters in the parameter spaces,  $S = B' \otimes I_n - (\Psi' \otimes I_n)W$  is non-singular, and  $S^{-1}$  is bounded in row and column sum norms. For a more comprehensive discussion and further details on stationarity conditions in systems of dynamic spatial panel data models, refer to [Yang and Lee \(2017, 2019\)](#).

Although the presence of the spatial autoregressive term may lead to doubts on possible identification issues, the spatial econometrics literature widely discussed the identifiability of the parameters from the reduced form of the model. In our case, parameters in Eqs. (1)–(3) are identifiable since they can be inferred from the reduced form:

$$\begin{aligned} z_t &= S^{-1} \Phi W z_{t-1} + S^{-1} P z_{t-1} + S^{-1} X_t \Pi + S^{-1} (V_t - c U_t) \\ &= \Phi^* W z_{t-1} + P^* z_{t-1} + X_t \Pi^* + (V_t^* - c U_t^*). \end{aligned} \quad (4)$$

However, due to the presence of simultaneous effects collected in  $B$ , further identification issues arise. This problem aligns with those in structural analysis of VAR models ([Amisano and Giannini 1996](#)). In this case, the objective is to identify the structural parameters in Eq. (1), with the knowledge of the reduced parameter matrices  $\Phi^*$ ,  $P^*$ ,  $\Pi^*$ ,  $\Sigma_v^* = S'^{-1} \Sigma_v S^{-1}$  in Eq. (4) and  $\Sigma_u^* = S'^{-1} \Sigma_u S^{-1}$ . In other words, we have to verify that the number of free parameters in the reduced form is at least equal to the parameters in the structural form (Eq. (1) in this paper). Formally, within a system of  $m$  equations, the sufficient and necessary condition for the identification of any particular equation is related to the rank of matrix parameters once the equation is excluded: the equation is identifiable if it is possible to construct at least one nonzero determinant of the order  $(m - 1)$  from the coefficients excluded from that particular equation but contained in other equations of the model. According to

Eq. (1), a simple solution for identification can be achieved considering exclusive restrictions. For example, for  $m = 2$ , one zero restriction is the necessary and sufficient condition for identification; in general, let  $R_j$  be a matrix of dimension  $r \times (4m + k)$  (with 4 given by the number of coefficient matrices  $B, \Psi, \Phi$  and  $P$  and  $k$  exogenous variables in each equation), which represents all exclusive restrictions for the coefficients of the  $j$ -th equation. The sufficient and necessary rank condition for identification of the  $j$ -th equation is  $\text{rank}(Rb_m) = m - 1$ , while the (necessary) order condition is given by  $r \geq m - 1$ . However, while zeros restrictions are easy to implement, they may suffer from meaningful economic justification and lead to unreliable results (e.g. [Bacchiocchi and Fanelli 2015](#), ). [Castelnuovo and Surico \(2010\)](#) found that triangular SVARs provide a misrepresented view of monetary policy shocks and their transmission, potentially leading to price puzzles and weak responses of both inflation and the output gap to monetary shocks. In the macroeconomic framework, for example, [Del Negro et al. \(2007\)](#) found that Cholesky-based SVARs produced the implausible result of output responding very quickly to a policy shock.

To overcome the limit of imposing zero restrictions, several alternative identification schemes have been proposed in the time series and SVAR literature, such as sign restrictions ([Fry and Pagan 2011](#)), structural breaks in volatility ([Lanne and Lütkepohl 2008](#)), and proxy-SVAR identification ([Stock and Watson 2012](#)). In the spatial econometrics framework, an interesting proposal is represented by [Elhorst and Emili \(2022\)](#). The authors are inspired by the possibility of differently handling the transmission channels from unemployment to output growth and vice versa, in the regional analysis of Okun's law in The Netherlands. This intuition leads to the definition of more than one spatial weighting matrix, each one accounting for different economic aspects intrinsic in the definition of the transmission channels. The result is a strategic identification scheme for their system of dynamic spatial panel equations without relying on other restrictions. Thus, according to [Elhorst and Emili \(2022\)](#) and the meaningful differences between spillover channels in our empirical setting, we consider this latter approach for our model specification.

### 3. MAXIMUM LIKELIHOOD ESTIMATION

The likelihood function associated with the model specified in Eqs. (1)–(3) can be derived from the probability density function (PDF) of the two error terms, i.e.  $U_t$  and  $V_t$ . While  $V_t$  follows a multivariate half-normal distribution with zero mean and covariance matrix  $\Sigma_v$ , the inefficiency error component  $U_t$  is distributed as a multivariate truncated normal with zero mean and diagonal covariance matrix  $\Sigma_u$ .

First, we introduce a generic multivariate truncated normal variable  $U = (U_1', \dots, U_m')'$  with mean vector  $\mu = (\mu_1, \dots, \mu_m)'$ , (full) covariance matrix  $\Sigma_u$  and vector of lower truncation points  $l = (l_1, \dots, l_m)'$ , with PDF given by

$$f_U(u, \mu_u, \Sigma_u, l) = \frac{(2\pi)^{-mn/2} |\Sigma_u|^{-\frac{1}{2}} \exp\{-\frac{1}{2}(u - \mu_u)' \Sigma_u^{-1} (u - \mu_u)\}}{(2\pi)^{-mn/2} |\Sigma_u|^{-\frac{1}{2}} \int_l^\infty \exp\{-\frac{1}{2}(u - \mu_u)' \Sigma_u^{-1} (u - \mu_u)\} du}, \quad (5)$$

where the integral in the denominator of Eq. (5) is a  $m$ -dimensional Riemann integral from  $l$  to  $\infty$ . In this generic case, the need to handle multivariate probabilities in the distribution of the inefficiency component leads to an unfeasible estimation procedure through standard maximum likelihood techniques. However, if the independence assumption of the  $U_1, \dots, U_m$  terms holds, the off-diagonal elements of the  $\Sigma_u$  matrix are all equal to zero, and the probability density function of  $U$  equals the product of all the marginals (Horrace 2005, Theorem 6).

Hence, in our case, we obtain a tractable form for the probability density function in Eq. (5) avoiding the need to handle  $m$ -dimensional integrals. In particular, the denominator is given by the product of the CDFs of  $m$  univariate half-normal distributions, which are all equal to  $\frac{1}{2}$ . Since  $l = 0_{m \times 1}$  and  $\mu = 0_{m \times 1}$ , the PDF in Eq. (5) can be rewritten as:

$$f_U(u, 0, \Sigma_u, 0) = \frac{2}{m} (2\pi)^{-mn/2} |\Sigma_u|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} u' \Sigma_u^{-1} u \right\}. \quad (6)$$

Starting from the marginal distributions of the two error terms and based on the standard independence assumption, the joint probability density function of  $V_t$  and  $U_t$  can be found as the product of the two marginal distributions as:

$$f_{U,V}(u_t, v_t) = \frac{2}{m} (2\pi)^{-mn} |\Sigma_u|^{-\frac{1}{2}} |\Sigma_v|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} v_t' \Sigma_v^{-1} v_t - \frac{1}{2} u_t' \Sigma_u^{-1} u_t \right\}. \quad (7)$$

The probability density function of the whole error term  $\varepsilon_t = V_t - cU_t$  can be obtained by substituting  $V_t = \varepsilon_t + cU_t$  in Eq. (7) and then integrating out  $U_t$  as follows:

$$\begin{aligned} f_\varepsilon(\varepsilon_t) &= \frac{2}{m} (2\pi)^{-mn} |\Sigma_u|^{-\frac{1}{2}} |\Sigma_v|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (\varepsilon_t' \Sigma_v^{-1} \varepsilon_t - \mu_t' \Sigma_\mu^{-1} \mu_t) \right\} \\ &\quad \int_0^\infty \exp \left\{ -\frac{1}{2} (u_t - \mu_t)' \Sigma_\mu^{-1} (u_t - \mu_t) \right\} du_t \\ &= \frac{2}{m} (2\pi)^{-mn/2} |\Sigma_u|^{-\frac{1}{2}} |\Sigma_v|^{-\frac{1}{2}} |\Sigma_\mu|^{\frac{1}{2}} \\ &\quad \exp \left\{ -\frac{1}{2} (\varepsilon_t' \Sigma_v^{-1} \varepsilon_t - \mu_t' \Sigma_\mu^{-1} \mu_t) \right\} \Phi(\mu_t C^{-1}), \end{aligned} \quad (8)$$

where  $\mu_t = -c\varepsilon_t \Lambda^{-1}$ ,  $\Lambda = (\Sigma_v + \Sigma_u) \Sigma_u^{-1}$ , and  $\Sigma_\mu^{-1} = (\Sigma_\mu^{-1} \otimes I_n)$  where  $\Sigma_\mu^{-1} = \Sigma_v^{-1} (\Sigma_v + \Sigma_u) \Sigma_u^{-1}$ . Moreover,  $C$  is obtained by Cholesky decomposition of  $\Sigma_\mu$ , such that  $\Sigma_\mu = CC'$  and  $\Phi(\mu_t C^{-1})$  represents the cumulative distribution function of the multivariate standard normal evaluated at  $\mu_t C^{-1}$ , over the multidimensional rectangle with lower and upper limits defined by zero and infinity.

Finally, conditionally on  $z_0$ , the log-likelihood function at time  $t$  can be written as:

$$\begin{aligned} \frac{1}{nT} \log L_t &= \frac{1}{n} \log |S| + m \log(2) - m \log(2\pi) - \frac{1}{2} \log |\Sigma_u| - \frac{1}{2} \log |\Sigma_v| + \frac{1}{2} \log |\Sigma_\mu| \\ &\quad - \frac{1}{2nT} (\varepsilon_t' \Sigma_v^{-1} \varepsilon_t - \mu_t' \Sigma_\mu^{-1} \mu_t) + \frac{m}{nT} \log \Phi(\mu_t C^{-1}), \end{aligned} \quad (9)$$

where  $\varepsilon_t = \mathbf{B}z_t - \Psi \mathbf{W}z_t - \Phi \mathbf{W}z_{t-1} - \mathbf{P}z_{t-1} - X_t \Pi$  and  $|S| = |B' \otimes I_n - (\Psi' \otimes I_n) \mathbf{W}|$  is the determinant of the Jacobian term. Consistent parameter estimates can be found by maximising the log-likelihood function using numerical maximization algorithms implemented in standard statistical software (Matlab codes are available under request).

One of the most appealing features of SF models concerns the possibility of computing technical (or cost) efficiency scores for each unit  $i = 1, \dots, n$  at time  $t$  ranging from 0 (fully inefficient) to 1 (fully efficient). After having estimated the unknown parameters, the composed prediction error can be retrieved as:  $\hat{\varepsilon}_t = \hat{\mathbf{B}}z_t - \hat{\Psi} \mathbf{W}z_t - \hat{\Phi} \mathbf{W}z_{t-1} - \hat{\mathbf{P}}z_{t-1} - X_t \hat{\Pi}$ , and then, technical efficiency scores (TE) at time  $t$  can be obtained as  $\exp(-E(\hat{u}_t | \varepsilon_t))$ . Following Jondrow et al. (1982), the mean of the distribution of  $U_t$  given  $\varepsilon_t$  can be written as:

$$E(u_t | \varepsilon_t) = -\Lambda^{-1} \varepsilon_t + \Sigma_{\mu} \left( \frac{\phi(\Lambda^{-1} \Sigma_{\mu}^{-1} \varepsilon_t)}{1 - \Phi(\Lambda^{-1} \Sigma_{\mu}^{-1} \varepsilon_t)} \right). \quad (10)$$

#### 4. SIMULATION STUDY

To evaluate the proposed estimation approach in Eq. (9), we carry out a Monte Carlo (MC) simulation experiment, with  $m = 2$ ,  $n = 20$  and  $T = 30$ , according to the characteristics of our empirical setting. The data-generating process (DGP) is defined by:

$$\begin{aligned} \begin{bmatrix} I_n & 0_{N \times N} \\ 0.100I_n & I_n \end{bmatrix} \begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} &= \begin{bmatrix} 0.250W_a & -0.300W_b \\ -0.100W_b & 0.500W_a \end{bmatrix} \begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} + \begin{bmatrix} 0.150W_a & -0.100W_b \\ 0.050W_b & 0.100W_a \end{bmatrix} \begin{bmatrix} z_{1t-1} \\ z_{2t-1} \end{bmatrix} \\ &+ \begin{bmatrix} 0.150I_n & -0.050I_n \\ -0.100I_n & 0.250I_n \end{bmatrix} \begin{bmatrix} z_{1t-1} \\ z_{2t-1} \end{bmatrix} + \begin{bmatrix} V_{1t} \\ V_{2t} \end{bmatrix} - c \begin{bmatrix} U_{1t} \\ U_{2t} \end{bmatrix} \end{aligned} \quad (11)$$

where  $z_{\cdot,t}$  is the  $(n \times 1)$  vector of the  $\cdot$ -th outcome variable observed at time  $t$ . Considering the two error components,  $V_t \sim N_2(0_2, \Sigma_v)$ ,  $vech(\Sigma_v) = (1.40, 0.30, 1.90)'$ ,  $U_t \sim N_2^+(0_2, \Sigma_u)$  with  $diag(\Sigma_u) = (0.2, 0.6)'$ , and  $c = 1$ . Moreover,  $W_a$  and  $W_b$ , respectively, represent a first-order and a second-order row-standardized binary contiguity spatial weight matrix. For the sake of simplicity, we assume one exclusive restriction on the coefficient of simultaneous effect in the first structural equation such that the coefficient  $b_{12} = 0$ . Moreover, without loss of generality, we do not include the term  $X_t \Pi$  in Eq. (1). Results for models including exogenous covariates (as well as spatially filtered exogenous covariates) are available upon request.

The MC results are reported in Table 1 based on 500 replications. For each parameter of  $\theta = (b_{21}, vec(\Psi)', vec(\Phi)', vec(P), vech(\Sigma_v)', diag(\Sigma_u)')'$ , we report its DGP value, the bias calculated as the mean of the estimates' deviation from the DGP value and the Monte Carlo standard deviation (SD) and mean-squared errors (MSE).

To ensure the robustness of the results, the MC experiment based on the maximum likelihood estimation approach is compared to one of the most commonly used alternative estimation procedures: copula-based techniques (see Lai and Huang (2013); Lai (2020); Marra and Radice (2017); Marra et al. (2017)). The baseline idea of copula-based estimation consists of writing the joint PDF of the composite errors as the product of a copula function

that models the structure of dependence among the errors of the  $m$  frontier functions and the marginal PDFs as  $f_{\varepsilon}(\varepsilon_{1it}, \dots, \varepsilon_{mit}) = c(F_1(\varepsilon_{1it}), \dots, F_m(\varepsilon_{mit}); \Omega) \times \prod_{s=1}^m f_s(\varepsilon_{sit})$ . While the second term of the product on the right-hand side of the equation considers the probability distribution functions of the  $m$  frontiers separately, the first one models the dependence among them. In particular,  $c(F_1(\varepsilon_{1it}), \dots, F_m(\varepsilon_{mit}); \Omega)$  refers to the copula function with associated  $(m \times m)$  correlation matrix  $\Omega$  where the off-diagonal elements of  $\Omega$  capture the correlation among the  $m$  equations. In our case, we consider a Gaussian copula and  $m = 2$ . Thus,  $\Omega$  is a  $2 \times 2$  correlation matrix with all ones on the main diagonal and off-diagonal elements capturing the correlation among  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$ . Since  $\Sigma_{\varepsilon_t} = (\frac{\pi-2}{\pi})\Sigma_u + \Sigma_v$  (Aigner et al. 1977), where  $\varepsilon_t$  is the vector of the stacked  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$ , and  $\text{vech}(\Sigma_{\varepsilon_t}) = (\sigma_{\varepsilon,1}^2, \sigma_{\varepsilon,12}, \sigma_{\varepsilon,2}^2)' = (\sigma_{v,1}^2 + (\frac{\pi-2}{\pi})\sigma_{u,1}^2, \sigma_{v,12}, \sigma_{v,2}^2 + (\frac{\pi-2}{\pi})\sigma_{u,2}^2)'$ , the off-diagonal elements of  $\Omega$  can be written as  $\rho_{12} = \sigma_{v,12}/\sqrt{\sigma_{\varepsilon,1}^2\sigma_{\varepsilon,2}^2}$ . Hence, the generic log-likelihood function can be derived as:

$$LL = \sum_{i=1}^n \log(c(F_1(\varepsilon_{1it}), \dots, F_m(\varepsilon_{mit}); \Omega)) + \sum_{i=1}^n \sum_{s=1}^m \log(f_s(\varepsilon_{sit})), \quad (12)$$

where the second term of the right-hand side of Eq. (12) equals the log-likelihood function in Eq. (9) in the case of null covariance among equations. For more details on the estimation of the first term in Eq. (12), see Tsay et al. (2013); Lai and Huang (2013).

To compare the likelihood-based and copula-based estimation approach, in the last two columns of Table 1 we compute the MSE ratios, calculated as the ratio of the MSEs for the ML estimates and of the MSEs obtained with the copula approach (as benchmark). Values greater than one indicate a better performance of the copula-based method compared to the ML solution. Moreover, to provide a visual representation of the MC performances of the estimator, Figures 5 and 6 of the Appendix show kernel density plots of the estimated coefficients for the 500 MC iterations, for both ML- and copula-based estimation approach.

The ML results in Table 1 show a negligible bias for all estimated parameters suggesting the satisfactory final sample performance of the proposed estimator. When comparing likelihood-based and copula-based techniques in terms of bias and standard deviation of the MC estimates, we obtain more accurate and precise results (lower bias and variability of the estimates) using the ML estimator, particularly for the simultaneous effect in  $b_{21}$  and the variance parameters. In general, the kernel density plots (Figures 5 and 6 of the Appendix) suggest that the distribution of all parameters is more bell-shaped when using ML, confirming previous insights on the dominance of the proposed approach over copula. Results are also supported by the MSE ratios, showing almost all values lower than one.

In comparing the sensitivity of two techniques, we also take into account computational time. Simulations conducted on a laptop equipped with a 12-core CPU and 32 GB of RAM, using non-optimized code, showed that for a sample size of  $n = 20$  and  $T = 30$ , the average time per iteration was 72.95 s for ML estimation and 28.41 s for copula-based estimation. Overall, while the copula-based approach proves to be less accurate than ML estimation, it offers greater advantages from a computational time perspective.

In line with findings in Table 1, the only parameter showing a notably better fit when using copula techniques is  $\sigma_{v,12}$ . In this case, the ML estimator provides a MSE value

Table 1. Monte Carlo simulation results with  $T=30$ ,  $n=20$  and  $m=2$  by using ML- and copula-based estimation techniques

DGP	ML				Copula			MSE ratio
	Bias	SD	MSE	Bias	SD	MSE		
$b_{21}$	0.100	-0.008	0.228	0.052	0.072	0.236	0.061	0.775
$\psi_{11}$	0.100	-0.001	0.042	0.002	0.003	0.042	0.002	0.966
$\psi_{21}$	-0.100	0.002	0.143	0.020	-0.041	0.154	0.025	0.773
$\psi_{12}$	-0.300	-0.003	0.058	0.003	0.011	0.061	0.004	0.855
$\psi_{22}$	0.500	0.002	0.060	0.004	0.022	0.062	0.004	0.766
$\phi_{11}$	0.150	0.003	0.051	0.003	0.006	0.048	0.002	1.093
$\phi_{21}$	0.050	-0.001	0.076	0.006	-0.003	0.080	0.006	0.875
$\phi_{12}$	-0.100	0.007	0.064	0.004	-0.001	0.067	0.005	0.910
$\phi_{22}$	0.100	-0.005	0.058	0.003	-0.002	0.062	0.004	0.855
$p_{11}$	0.150	0.006	0.045	0.002	0.003	0.042	0.002	1.163
$p_{21}$	-0.100	0.001	0.063	0.004	-0.001	0.063	0.004	0.940
$p_{12}$	-0.050	0.002	0.036	0.001	0.005	0.033	0.001	1.193
$p_{22}$	0.250	0.005	0.043	0.002	0.009	0.047	0.002	0.801
$\sigma_{v,1}^2$	1.400	0.022	0.092	0.001	0.049	0.102	0.013	0.693
$\sigma_{v,12}$	0.300	0.014	0.352	0.052	0.023	0.143	0.021	2.469
$\sigma_{v,2}^2$	1.900	-0.022	0.210	0.045	-0.046	0.216	0.049	0.774
$\sigma_{u,1}^2$	0.200	-0.016	0.117	0.014	-0.010	0.180	0.033	0.435
$\sigma_{u,2}^2$	0.600	-0.084	0.261	0.075	-0.212	0.343	0.163	0.443
Time per rep.	72.95 sec.			28.41 sec.				

double the benchmark's MSE. Considering density plots, the distribution of the  $\sigma_{v,12}$  shows a pronounced left skew when employing copula-based techniques. Therefore, to verify the absence of potential issues concerning the covariance term, in what follows we consider different DGP values for the covariance.

Results in Table 2 indicate that the advantage of copula methods in estimating the covariance parameter diminishes as  $\sigma_{v,12}$  decreases. The value  $\sigma_{v,12} = 0.3$  was chosen to test the effectiveness of the technique under conditions where external shocks propagate directly to sector's outputs and indirectly through the interactions in the error terms of other equations. In contrast, setting  $\sigma_{v,12} = 0$  represents a scenario without cross-equation transmission channels for shocks through external factors. An intermediate setting has been obtained with  $\sigma_{v,12} = 0.15$ . The results reassure us against potential issues related to  $\sigma_{v,12}$ , showing all remaining biases, MSE and MSE ratios in line with previous findings, and those for  $\sigma_{v,12}$  largely improved.

To further explore the finite sample properties of the proposed ML estimator, we perform further MC simulations modifying the temporal ( $T = 50$ ), cross-sectoral dimension ( $n = 40$ ), the number of equations in the system ( $m = 3$ ) and the spatial structure for sectoral spillovers. The estimation results, presented in Tables 6, 7 and 8 of the Appendix, demonstrate satisfactory results across all scenarios.

In particular, while we observe a substantial improvement in the goodness of results as  $T$  increases (consistent with Yang and Lee (2019) and the literature on systems of spatial dynamic panel data models), this improvement is less evident for  $n = 40$ , especially for

Table 2. Monte Carlo simulation results for different values of  $\sigma_{v,12}$  with  $T=30$ ,  $n=20$  and  $m=2$  by using ML- and copula-based estimation techniques

	ML		Copula		MSE ratio	ML		Copula		MSE ratio		
	DGP	Bias	MSE	Bias		MSE	DGP	Bias	MSE		Bias	MSE
$b_{21}$	0.100	-0.041	0.050	0.008	0.067	0.753	0.100	-0.027	0.031	0.027	0.062	0.511
$\psi_{11}$	0.250	0.001	0.001	-0.001	0.001	1.008	0.250	0.001	0.001	-0.002	0.001	1.007
$\psi_{21}$	-0.100	0.018	0.023	-0.006	0.028	0.818	-0.100	0.017	0.020	-0.017	0.026	0.791
$\psi_{12}$	-0.300	0.001	0.004	0.005	0.005	0.904	-0.300	-0.002	0.004	0.005	0.004	0.940
$\psi_{22}$	0.500	-0.002	0.003	0.009	0.004	0.825	0.500	-0.003	0.003	0.012	0.004	0.690
$\phi_{11}$	0.150	-0.004	0.003	-0.003	0.003	1.001	0.150	-0.004	0.003	-0.001	0.003	1.003
$\phi_{21}$	0.050	0.004	0.007	0.001	0.007	0.986	0.050	0.002	0.006	-0.002	0.007	0.952
$\phi_{12}$	-0.100	0.006	0.004	0.003	0.004	0.988	-0.100	0.006	0.004	0.001	0.004	1.011
$\phi_{22}$	0.100	-0.005	0.004	-0.003	0.004	0.969	0.100	-0.007	0.004	-0.003	0.004	1.004
$p_{11}$	0.150	0.012	0.002	0.011	0.002	0.996	0.150	0.009	0.002	0.009	0.002	1.006
$p_{21}$	-0.100	0.004	0.003	-0.004	0.004	0.883	-0.100	0.004	0.003	-0.007	0.004	0.820
$p_{12}$	-0.050	0.001	0.001	0.001	0.001	1.006	-0.050	0.002	0.001	0.003	0.002	1.011
$p_{22}$	0.250	-0.002	0.002	0.001	0.002	0.981	0.250	0.001	0.002	0.004	0.011	0.880
$\sigma_{v,1}^2$	1.400	0.015	0.009	0.022	0.010	0.916	1.400	0.015	0.009	0.029	0.011	0.848
$\sigma_{v,12}$	0.000	0.054	0.115	-0.015	0.148	0.779	0.150	0.012	0.081	-0.039	0.135	0.599
$\sigma_{v,2}^2$	1.900	-0.032	0.037	-0.044	0.050	0.752	1.900	0.001	0.030	-0.028	0.042	0.714
$\sigma_{u,1}^2$	0.200	-0.017	0.013	-0.033	0.018	0.742	0.200	-0.020	0.014	-0.048	0.022	0.665
$\sigma_{u,2}^2$	0.600	-0.050	0.072	-0.106	0.114	0.629	0.600	-0.049	0.079	-0.145	0.135	0.581

variances and covariance coefficients. For  $m = 3$ , we show that, as expected, the approach is highly sensitive to the number of equations and hence free parameters to be estimated (from 18 to 39, according with one zero restriction in the system with  $m = 2$  and three zeros in  $m = 3$ , where the simultaneous coefficients matrix  $B$  are specified as lower triangular). However, the results in terms of bias can be considered comparable with the ones obtained with the baseline case of  $m = 2$ . For example, in a roughly manner, the average level of bias in absolute values for the spatial lags coefficients in  $\Psi$  is equal to 0.001 for  $m = 2$  and 0.011 for  $m = 3$ ; in  $\Phi$  the average bias increases from 0.004 to 0.008; in  $\Sigma_u$  the average bias decreases with  $m = 3$ , passing from 0.050 for  $m = 2$  to 0.024.

Expanding the range of parameter settings in the MC study, the final set of simulations addresses the spatial structure and the balance between intra- and inter-sector relationships. In particular, Table 8 in the Appendix refers to the case in which we assume that intra-sectoral relationships are lower in magnitude with respect to inter-sectoral coefficients. Empirically, the aim is to verify the ability of the proposed technique to model economic and production systems with limited horizontal linkages across space. For this reason, opposite to the baseline DGP values for  $\Psi$  and  $\Phi$ , we set the coefficients belonging to the main diagonal of the two matrices close or equal zero, or at least lower than the inter-sectoral coefficients, i.e.  $\psi_{11} = 0.05$ ,  $\phi_{22} = 0$  and  $\phi_{11} = 0.05$ ,  $\phi_{22} = 0.1$ . In general, results align with those in Table 1, finding no evidence of issues related to the estimation of cross-equation spatial effects.

## 5. AGRIBUSINESS AGGREGATE PRODUCTION IN EUROPE

### 5.1. DATA, MODEL AND VARIABLES

In this section, we show the empirical application of the proposed multi-output dynamic spatial SF model with uncorrelated inefficiency term to the aggregate production of the agribusiness filière in Europe, referring to agriculture and food and beverage manufacturing sectors. For the agribusiness filière, the underlying assumption of independence among the inefficiency error components of the two production processes may be considered valid since the key elements influencing the efficiency level of the two sectors are largely distinct. While efficiency in agriculture may be heavily influenced by farms and farmers' characteristics such as farm size and ownership structure and farmer age and educational level (Latruffe 2010), efficiency in the manufacturing sector relies more on consumer preferences, distribution logistics, firm and market size and the degree of product differentiation (Green and Mayes 1991).

The starting point of the empirical model is a Cobb–Douglas function, with labour and capital inputs.<sup>3</sup> The simplicity of the chosen production function matches with the improvement in the complexity of the systems (specification and estimation) given by spatial, temporal and simultaneous dynamics. The resulting specification balances comprehensiveness with feasibility of the estimation ensuring the parsimony of the model and reliability of the results.

Aiming to capture country-level dynamics in the European agribusiness industry, we use OECD data on 17 European countries in the time period 1996–2019.<sup>4</sup> Besides OECD data, also Eurostat data are available for this kind of analysis. However, OECD dataset offer longer time series, which, besides capturing key temporal events, enhances the model's robustness, in line with the MC results of the previous section and Yang and Lee (2017, 2019)'s findings. Although the number of cross-sectional units ( $n$ ) is relatively small, the large time dimension ( $T$ ) compensates for this (Elhorst and Emili 2022). Moreover, the parameter configuration of the empirical model ( $n = 17$ ,  $T = 24$ ,  $m = 2$ ) aligns with the dimensions of those in the MC simulations, giving us confidence in the model's performance.

The output variable is proxied by the annual value added (million euros) in current PPPs, and labour and capital inputs are given by the logarithm of the annual number of employees (thousands) and fixed assets (million euros) in current PPPs. Data have been collected from the website <https://data.oecd.org><sup>5</sup> and detrended to ensure stationarity. In

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<sup>3</sup>While these inputs are informative for the complexity of intra- and inter-sectoral spillovers to some extent, they are not comprehensive. For example, for agriculture, information on cultivated land, machinery, and intermediate inputs is usually adopted as additional input factors in agriculture-related studies. Nevertheless, focusing on labour and capital as key input variables is a standard and reliable approach when estimating a Cobb-Douglas production function guaranteeing the availability of data for all sectors considered in the analysis.

<sup>4</sup>OECD data does not provide full coverage for all 17 countries in our analysis (e.g. Spain and German series present some missing observations). To address this gap, we supplemented the missing information with data from the national statistical offices' websites.

<sup>5</sup>Value added information can be retrieved from <https://lc.cx/CQb7IH>, labour from <https://lc.cx/0u-61j> and capital from <https://lc.cx/T3RhC>.

line with the overall production of the European fili re,<sup>6</sup> the relevance of the analysis for the selected sample of countries is observed in Table 9 of the Appendix, which displays the values of value added, annual employment, and fixed assets for the year 2019 across all the countries considered. While France, Italy and Spain are the primary contributors to European agricultural output, the largest shares of agricultural value added as a percentage of national GDP are observed for Hungary (6.72%), Spain (3.64%) and Czechia (3.64%). In terms of manufacturing, Spain, Germany and France are the top three countries by overall value added. However, when considering the percentage of value added to GDP, the most reliant countries are Spain, Czechia and Hungary, with percentages of 5.68%, 3.59% and 3.41% of total GDP, respectively.

Considering the spatial dimension, we preliminarily investigate the relevant role of spatial effects in the productive performance of the agribusiness industry. The univariate and bivariate global Moran's I statistics in Table 10 in Appendix suggest that different kinds of positive and significant spillovers occur among countries. In particular, spatial correlation is observed both between the two sectors and in the same sector. Moreover, Fig. 8 in Appendix locally identifies the different kinds of clusters with a 10% significance level. Overall, the figure indicates that the Mediterranean countries belong to a high–high production cluster considering both sectors while the Scandinavian countries are characterized by a low level of production, especially for the food and beverage manufacturing sector. Further details on the level of value added by country and sector can be found in the quantile map shown in Fig. 7 in Appendix.

Given the analytical complexity of the system of SFs, the model specification is defined by the following system of two Cobb–Douglas production functions due to their simplicity and flexibility.

$$\begin{aligned}
 \left( \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \otimes I_n \right) \begin{bmatrix} z_{At} \\ z_{Mt} \end{bmatrix} &= \begin{bmatrix} \psi_{11} W_a & \psi_{12} W_b \\ \psi_{21} W_b & \psi_{22} W_a \end{bmatrix} \begin{bmatrix} z_{At} \\ z_{Mt} \end{bmatrix} + \begin{bmatrix} \phi_{11} W_a & \phi_{12} W_b \\ \phi_{21} W_b & \phi_{22} W_a \end{bmatrix} \begin{bmatrix} z_{At-1} \\ z_{Mt-1} \end{bmatrix} \\
 &+ \left( \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \otimes I_n \right) \begin{bmatrix} z_{At-1} \\ z_{Mt-1} \end{bmatrix} + \left( \underbrace{\begin{bmatrix} \pi_{11}^L & \pi_{12}^L \\ \pi_{21}^L & \pi_{22}^L \end{bmatrix}}_{\Pi^L} \otimes I_n \right) \begin{bmatrix} L_{At} \\ L_{Mt} \end{bmatrix} \\
 &+ \left( \underbrace{\begin{bmatrix} \pi_{11}^K & \pi_{12}^K \\ \pi_{21}^K & \pi_{22}^K \end{bmatrix}}_{\Pi^K} \otimes I_n \right) \begin{bmatrix} K_{At} \\ K_{Mt} \end{bmatrix} + X_t \mathbf{\Pi} + \begin{bmatrix} v_{At} \\ v_{Mt} \end{bmatrix} - \begin{bmatrix} u_{At} \\ u_{Mt} \end{bmatrix} \quad (13)
 \end{aligned}$$

Specifically,  $z_{At}$  represents the logarithm of annual value added (million euros) in current PPPs for the agricultural sector for each country  $i = 1, \dots, 17$  at time  $t = 1, \dots, 25$ . Similarly,  $z_{Mt}$  refers to the logarithm of annual value added for the food and beverage manufacturing sector. Simultaneous effects across the outputs of the two sectors are captured by the off-

<sup>6</sup>Agriculture production contributes to 1.6% of the European Union's gross domestic product in 2019, while manufacturing 2.1%. Source: The World Bank <https://www.worldbank.org/en/home>.

Table 3. Estimated log-likelihood values for different combinations of spatial weight matrices:  $W_{id}$ : inverse distance;  $W_2$ : second-order binary contiguity;  $W_1$ : first-order binary contiguity

		Inter-sectoral: $W_b$		
		$W_1$	$W_2$	$W_{id}$
Intra-sectoral: $W_a$	$W_1$	–	1615.41	1722.73
	$W_2$	1752.60	–	1507.89
	$W_{id}$	1749.82	1449.71	–

diagonal elements of the  $B$  matrix. As previously anticipated, labour and capital inputs,  $L$  and  $K$ , are given by the logarithm of annual employment and fixed capital in current PPPs. The effect of the input factors on the level of output is given by the elements on the main diagonal of  $\Pi^L$  and  $\Pi^K$  within the same sector and by the off-diagonal elements for inter-sectoral effects. Spatial effects at time  $t$  and  $t - 1$  are, respectively, captured by the  $\Psi$  and  $\Phi$  matrices. In particular, the elements on the main diagonal of  $\Psi$  and  $\Phi$  measure productivity spillovers occurring between neighbours in the same sector, while those on the off-diagonal elements refer to inter-sectoral spatial effects. The temporal dynamic is captured by the parameters of the  $P$  matrix. As usual in SF models, the error term is split into two independent components,  $v_t$  and  $u_t$  measuring, respectively, random shocks and specific-sectoral inefficiencies. Finally, we include the logarithm of pro-capita GDP and land use as variables aimed to control for country-level specific characteristics ( $X_t$ ).

The spatial weight matrix  $W$  is given by a combination of two row-normalized spatial weight matrices, i.e.  $W_a$  and  $W_b$ . Beside ensuring model identification, this choice aims to stress the differences between the role of intra- and inter-sectoral effects.

## 5.2. ESTIMATION RESULTS AND SPILLOVERS

The first step in estimating the two-output dynamic spatial SF model for 17 European OECD countries concerns the definition of the spatial structure implied by  $W$ . The structure indeed can be informative of some features of the linkages characterizing the phenomenon of interest. Thus, in order to select the proper combination of spatial weight matrices, we estimated the model by using different combinations of matrices such as first-order binary contiguity matrices, second-order binary contiguity matrices and inverse distance matrices truncated at 2000 km (approximating the average level of distances among centroids).

Among the different possible configurations of spatial weight matrices, results in Table 3 indicate that the combination with a second-order contiguity matrix on the main diagonal of  $W$ , i.e.  $W_a$  (intra-sectoral), and a first-order matrix on the off-diagonal of  $W$ , i.e.  $W_b$  (inter-sectoral), maximizes the log-likelihood value, making it the preferred choice.<sup>7</sup> The greater

<sup>7</sup> For the selection and specification of spatial weight matrices, regularized estimation methods can be used to simplify the structure of  $W$ , ensuring that only the most pertinent weight matrices contribute significantly to the model (for a review, see [Otto et al. 2024](#)). However, while regularized estimation techniques have only recently been proposed in the context of stochastic frontier models ([Tsonas 2023](#); [Horrace et al. 2023](#)), further research is needed to adapt and extend penalized estimation techniques to the spatial SF framework. We thank the associate editor for this suggestion.

Table 4. Estimation results of the two-output dynamic spatial SF model for 17 European OECD countries

		Agriculture ( $z_{At}$ )		Food & beverage manufacturing ( $z_{Mt}$ )	
		Coeff.	SD	Coeff.	SD
Simultaneous	$z_{At}$	—		0.001	0.034
	$z_{Mt}$	-0.005	0.054	—	
Spatial lag	$Wz_{At}$	0.152***	0.050	0.160***	0.046
	$Wz_{Mt}$	-0.003	0.004	0.096***	0.028
Spatio-temporal lag	$Wz_{At-1}$	-0.072	0.051	-0.117**	0.047
	$Wz_{Mt-1}$	-0.091*	0.049	-0.087*	0.048
Temporal lag	$z_{At-1}$	0.120***	0.032	-0.003	0.051
	$z_{Mt-1}$	0.134*	0.081	0.286***	0.023
Labour	$L_{At}$	0.263**	0.108	0.173**	0.075
	$L_{Mt}$	0.186*	0.112	0.262***	0.092
Capital	$K_{At}$	0.307***	0.118	0.245***	0.088
	$K_{Mt}$	0.167	0.124	0.236**	0.118
$X_t$	$pcGDP_t$	0.037	0.026	-0.014	0.019
	$land_t$	0.088***	0.022	0.017	0.027

\*:  $p$ -value  $\leq 0.10$ ; \*\*:  $p$ -value  $\leq 0.05$ ; \*\*\*:  $p$ -value  $\leq 0.01$

number of neighbouring units for intra-sectoral spillovers than inter-sectoral is commuting with the idea of [Malerba et al. \(2014\)](#), assessing that spatial effects within the same sector are more likely to materialize and propagate across space compared to inter-sectoral spillovers due to the shared technological and knowledge base. Then, the estimation results with the two row-normalized spatial weight matrices are shown in [Table 4](#).

The estimates of the  $b$  parameters indicate that simultaneous effects at time  $t$  are non-significantly different from zero. Indeed, it is unlikely that countries are immediately able to adapt their production level in a given sector based on the outcome of the other. Considering spatial effects, we have evidence of positive and significant coefficients at time  $t$  both within and between sectors (except from neighbours in manufacturing to agriculture). Also, temporal effects are mostly significant, with negative values for spatial effects at time  $t - 1$ , and positive coefficients for time-lagged outputs. The estimated covariance matrices of the two error terms are  $diag(\hat{\Sigma}_u) = (0.257, 0.116)$  and  $vech(\hat{\Sigma}_v) = (0.507, 0.427, 0.359)$ , indicating a positive association (i.e.  $\hat{\sigma}_{vA,vM} = 0.427$ ) between the error components of the two sectors. Specifically, the multi-equation model that accounts for possible correlation among the error terms of the two equations provides a better fit to the data than its single-equation counterpart (assuming uncorrelated error components, i.e.  $\sigma_{vA,vM} = 0$ ) in terms of estimated likelihood values (1752.60 for our model and 1227.62 in case of uncorrelated errors). Finally, the estimates of the exogenous variables  $pcGDP$  and  $land$  are not statistically significant, a part of land use in the equation of the agricultural sector.

Since the effect of the input variables cannot be meaningfully interpreted due to the inclusion of the spatial autoregressive terms, we separately compute the short-run and long-run marginal effects of a unit change in labour and capital ([LeSage and Pace 2009](#)). Then, to derive standard errors, the covariance matrix of the estimated marginal effects is approximated by means of the delta method ([Arbia et al. 2019](#)).

Table 5. Marginal (direct and indirect) effects of the output variables to a unitary change in labour and capital

		Agriculture ( $z_{At}$ )		Food & beverage manufacturing ( $z_{Mt}$ )	
		Direct	Indirect	Direct	Indirect
Short	$K_{At}$	0.309***	0.052**	0.246**	0.025
	$L_{At}$	0.265***	0.045**	0.173*	0.018*
	$K_{Mt}$	0.168**	0.028**	0.237***	0.024
	$L_{Mt}$	0.188**	0.032**	0.263***	0.027
Long	$K_{At}$	0.035	-0.015	0.069**	-0.010
	$L_{At}$	0.030	-0.013	0.049**	-0.007
	$K_{Mt}$	0.019	-0.008	0.067***	-0.010
	$L_{Mt}$	0.021	-0.009	0.074***	-0.011

Short-run effects in the upper panel and long-run effects in the lower panel

\*:  $p$ -value  $\leq 0.10$ ; \*\*:  $p$ -value  $\leq 0.05$ ; \*\*\*:  $p$ -value  $\leq 0.01$

Table 5 reports the direct and indirect marginal effects with respect to a unitary change in labour and capital inputs differentiating among short- and long-run effects. In the short run, the direct impacts outlined in Table 5 indicate that a one-unit change in both labour and capital inputs within each sector has a positive and significant influence on the country's output for that sector. Comparing labour and capital, we find that for agriculture the effect of capital is stronger than labour, identifying this industry as a capital-intensive sector (Blanco and Raurich 2022), while manufacturing shows similar productivity levels for both input factors, with a slightly greater effect for labour compared to capital. Additionally, significant cross-sectoral relationships exist since both agriculture and the manufacturing industry are positively affected by input variations in the other sector even though with a lower intensity compared to intra-sectoral effects, as expected. Considering indirect effects, for agriculture we observe positive and significant input spillovers between neighbouring countries related to both labour and capital with higher impacts for agriculture-related input factors than for cross-sectoral ones. This result indicates that, in the short run, the agricultural sector is able to take advantage of input endowment in neighbouring countries likely due to knowledge and technology transfer, skills and labour mobility and increased trade and investment opportunities. On the other hand, the food and beverage manufacturing sector can only rely on positive spillovers occurring from neighbours' investments in the labour force of agriculture. Comparing short-run and long-run effects, we observe a reduction in the magnitude and significance of both direct and indirect impacts in time. However, only direct impacts to food and beverage manufacturing remain highly significant, indicating that intra- and inter-sectoral input effects have a positive long-lasting effect on this sector. Differently from direct effects which are still positive in the long run, we find that indirect effects turn out to be negative but non-significant indicating the existence of possible competition effects.

Besides considering how changes in the input levels in one sector may affect the outcome of the sector itself and the other interconnected sector, starting from our multi-output spatial dynamic SF model, we compute and show in Fig. 1 the response of each sector's output to a shock in a given sector in the time horizon  $t+h$  with  $h = 0, \dots, 4$ . These effects are formally defined as the first derivative of  $z_{t+h}$  in reduced form representation (Eq. (4)) with respect to

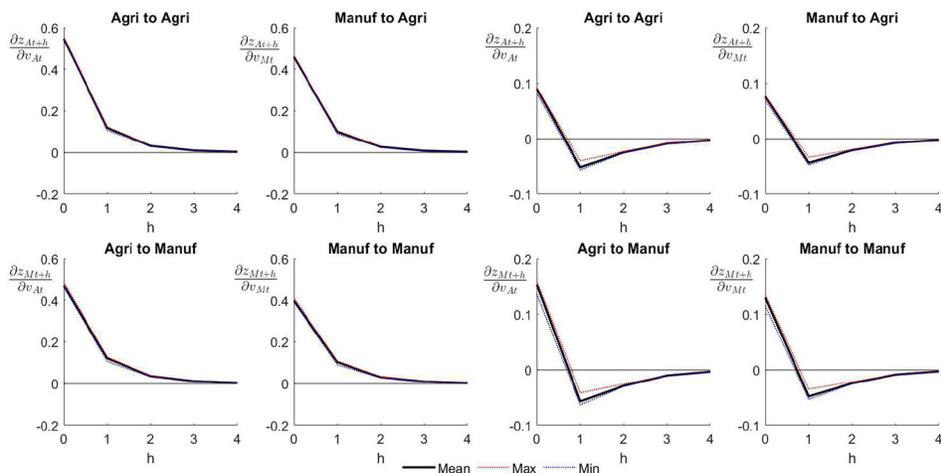


Figure 1. Direct (left  $2 \times 2$  panel) and indirect effects (right  $2 \times 2$  panel) to an innovation for  $t + h$  with  $h = 0, 1, \dots, 4$ . Mean effects in solid black lines, maximum effects in dotted red lines, minimum effects in dotted blue lines.

$v_t$  (see [Elhorst and Emili \(2022\)](#) and references therein for more details on the computation of marginal effects in multi-equation dynamic spatial panel data models). According to the standard definition of direct and indirect effects, direct and indirect impacts are, respectively, computed starting from the main and off-diagonal elements of the marginal effects matrix.

The plots on the left  $2 \times 2$  panel of Fig. 1, referring to direct effects, indicate that a shock in a sector positively affects the output of the same sector and of the other interconnected sector with an intensity that tends to vanish over time approaching zero in less than four years. This result is not new in the literature. Indeed, the structure of inter-sectoral input–output relationships can amplify sector-specific shocks, turning them into fluctuations at the aggregate level ([Acemoglu et al. 2012](#)). In particular, as demonstrated by [Joya and Rougier \(2019\)](#) shocks in sectors located in denser parts of the network tend to dissipate due to substitution effects, while those in more influential sectors trigger broader economic fluctuations through contagion. Similar findings at the country level have been observed by [Alariste Contreras and Fagiolo \(2014\)](#), showing that shocks can rapidly spread across nations and their industrial sectors, transforming sector-specific shocks in one country into global recessions that affect the broader economy. Specifically, using data on EU countries in year 2005, they find that the larger the country and the more globally central its sector within the networked input–output economy, the greater its impact. Additionally, [Giannakis et al. \(2024\)](#), examining the overall regional response to sector-specific shocks using NUTS-2 EU data, find that sectors such as agriculture, construction, electrical, optical and transport help mitigate the initial economic shock as it spreads through the broader economy. In contrast, sectors like textiles, hotels and restaurants, and financial intermediation tend to intensify the negative impact of shocks, thereby weakening regional economic stability. Further findings by [Iloskics et al. \(2021\)](#) using data on OECD countries from 1996 to 2019 reveal that certain sectors, such as food and live animals, machinery and transport equipment, and miscellaneous manufactured articles, serve as key conduits for the transmission of shocks.

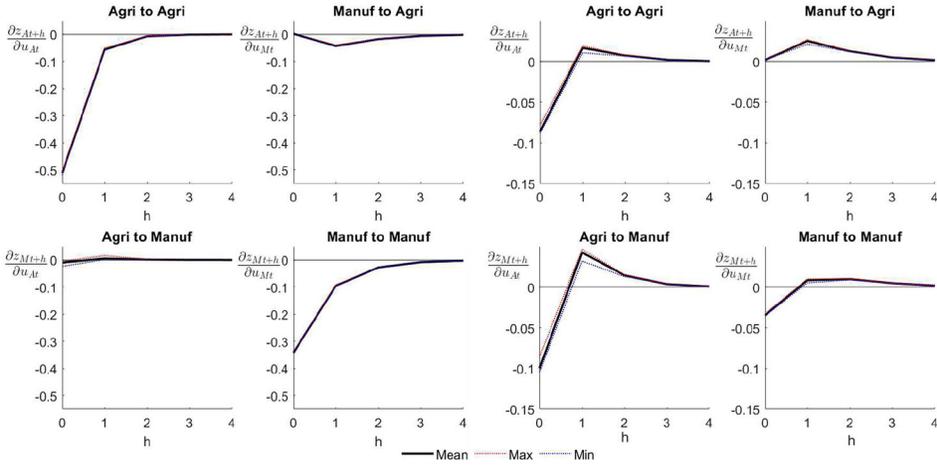


Figure 2. Direct (left  $2 \times 2$  panel) and indirect effects (right  $2 \times 2$  panel) to an inefficiency shock for  $t + h$  with  $h = 0, 1, \dots, 4$ . Mean effects in solid black lines, maximum effects in dotted red lines, minimum effects in dotted blue lines .

In contrast, chemicals and related products appear to have a stabilizing effect, playing a more prominent role in risk diversification rather than in the propagation of shocks.

Taking into account the indirect effects (as shown in the right  $2 \times 2$  panel), we observe again positive impacts at time  $t$ , but with lower magnitudes when compared to their direct counterparts. However, indirect impacts undergo a rapid swift into competitive effects after one year, ultimately approaching zero over time. Thus, as highlighted in the case of input spillovers, shocks affecting neighbours' agricultural and/or food and beverage manufacturing sectors immediately impact the productive performance of other sectors first in a positive way, and then, leaving space for competitive pressures among countries in the long run. In particular, long-term negative spillovers may arise if firms are unable to convert potential positive impacts into actual benefits (Afewerk Demena and van Bergeijk 2019). In the long run, similar negative spatial effects across countries have been found by Mitze et al. (2016) in the case of international R&D spillovers. Moreover, Chen et al. (2024), analysing data on U.S. Metropolitan Statistical Areas, find that sectoral-specific shocks in a given region negatively impact the resilience of neighbouring regions three and five years later. Finally, comparing the magnitude of direct and indirect impacts, as expected, we find that indirect effects are less effective compared to direct ones in terms of intensity, supporting the role of physical and regulatory barriers, as well as national interests in the globalization process of the European agribusiness filière. Interestingly, similar magnitudes characterize inter and intra-sectoral impacts (both for direct and indirect effects), confirming the relevant role of cross-sectoral linkages in shaping the production performance of the sectors comprising the agribusiness filière.

A notable outcome stemming from the proposed approach concerns the possibility of estimating inefficiency shocks. Specifically, the composite nature of the error term allows for disentangling the system responses to random and inefficiency shocks. Similarly to the computation of innovations' impulse response functions, the direct and indirect effects

to an inefficiency shock are defined as the partial derivatives of  $z_{t+h}$  from the reduced form in Eq. (4) with respect to  $u_t$ . The resulting impacts are shown in Fig. 2, with direct effects on the left  $2 \times 2$  panel, and indirect effects on the right  $2 \times 2$  panel. The plots for direct effects confirm the sectoral-specific nature of the inefficiency mechanisms: in fact, the magnitude of intra-sectoral effects is largely higher than the one of cross-sectoral impacts. In particular, the negative signs indicate that a shock in a sector's inefficiency level contributes to decreasing its productive performance. Similar findings were reported by [Karagiannis and Tzouvelekas \(2010\)](#), who examined the relationship between efficiency changes and inter-sectoral linkages across 14 EU countries in 1995 without identifying a clear and unique pattern. The study highlights ambiguous inter-sectoral connections, with the nature of this relationship varying based on the specific structural characteristics and unique features of each national economy. Considering indirect effects, we mainly find positive spillovers at time  $t$  (i.e. a shock in the inefficiency level of neighbours decreases the production level of neighbouring industries), which result in competitive pressures one year later. Therefore, countries can leverage the decrease in efficiency in neighbouring nations to their advantage, thereby boosting their productivity levels in the next year. However, both direct and indirect impacts to an inefficiency shock tend to vanish in a 2-year horizon.

### 5.3. EFFICIENCY SCORES

Starting from the estimation results in Table 4, it is possible to compute country-level efficiency scores for each sector. In particular, Fig. 3 shows the map of the average efficiency scores in the whole period by country and industrial sector (agriculture on the left panel and manufacturing on the right panel). Overall, European countries tend to achieve higher efficiency scores in the food and beverage manufacturing sector compared to agriculture, with much more variability for the latter sector. Indeed, the mean efficiency score in agriculture reaches 0.63 with a range of variation given by 0.33–0.82, while for the food and beverage manufacturing industry, the mean TE score is equal to 0.71, ranging from 0.52 to 0.80. Considering cross-country variations, the map indicates that Italy, the Netherlands, Portugal and Slovakia are the countries reaching higher efficiency degrees in agriculture, while Spain, UK, Germany, the Czech Republic, Norway and Sweden are the best-performing countries in the food and beverage industry in terms of efficiency.

Considering the association between the average efficiency scores of the two sectors, Fig. 4 shows that Sweden, the Czech Republic, France, Denmark and the Netherlands consistently outperform other countries, showing the highest combination of efficiency levels in the two sectors. Italy, Portugal, Slovakia and Hungary reach good efficiency levels for agriculture, but their efficiency scores for the manufacturing industry do not exceed the average level of manufacturing. On the opposite, Norway and Denmark reach the top two positions for manufacturing, but their efficiency degrees in agriculture are lower than the average score in agriculture. Finally, Ireland stands out as the worst-performing sector in agriculture, while Finland is the least efficient for manufacturing. However, they both position around the average efficiency level in the other sector. In sum, Fig. 4 indicates that reaching high efficiency levels in one sector does not imply a good efficiency degree also in the other. Indeed, despite some high-high efficiency clusters can be observed, overall the

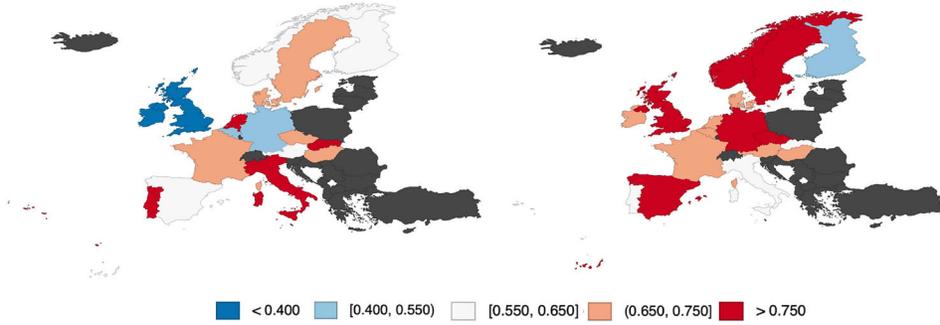


Figure 3. Map of the mean efficiency scores by sector. Agriculture in the left panel and food and beverage manufacturing in the right panel. Black areas: countries not in the estimation sample.

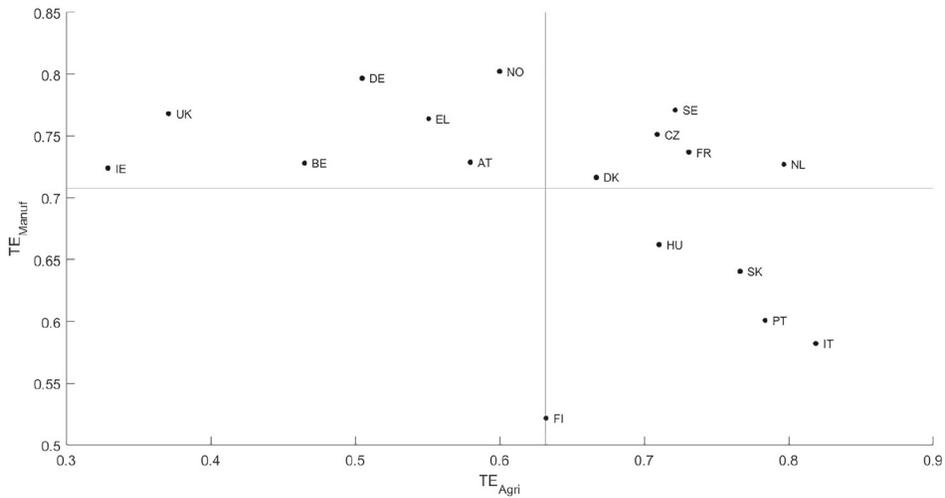


Figure 4. Scatterplot of temporal averages of efficiency scores for agriculture on the  $x$  axis and food & beverage manufacturing on the  $y$  axis. Vertical and horizontal lines are the average TE scores in the two sectors across all countries.

association is not strong enough to corroborate the idea that the efficiency mechanisms of the sectors in the agribusiness industry are characterized by intense cross-sectoral relationships. This result is fully in line with the assumption made on the zero off-diagonal elements for the covariance matrix of the inefficiency error component.

#### 5.4. ROBUSTNESS

As robustness checks, we (i) include two dummy variables ( $d_{07-09}$ ,  $d_{11-13}$ ) in the model to, respectively, control for the economic recession (2007–2009) and the crisis of the sovereign debt (2011–2013) and (ii) we estimate the model over different subsamples of countries. Specifically, we classify countries based on the weight of the agribusiness industry in the national economic accounts by computing the percentage of the output of agribusiness over total national GDP (lower-equal/greater than 4%); then, we consider GDP per capita

(lower/greater-equal than 41 thousand euros).<sup>8</sup> Note that, despite the classification being based on economic quantities, geographic contiguity is still observable among countries. The estimation results for the model with the crises dummy in Table 11 in the Appendix confirm the robustness of the estimates presented in the main results section. Moreover, the coefficients related to the dummy variables for crises are negative, although non-significant for both the agricultural and food and beverage manufacturing industries. Similarly, the estimates by group presented in Table 12 in the Appendix are overall in line with the results in Table 4. The estimates by subgroups reveal further interesting findings related to the agribusiness industry in Europe. Particularly, when the subsamples are based on the portion of GDP generated by the industry (top panel), we find that for countries highly reliant on the agribusiness industry (right-hand side), the significance of spatial effects in the agricultural sector is stronger than in the other sample of countries. Furthermore, while the coefficients for labour factors are not significant in countries with weak agribusiness-relatedness, in the highly related group, all coefficients are positive and significantly different from zero, at least at the 10% level. On the other hand, when differentiating by per capita GDP, we observe that spatial effects among agricultural sectors mainly disappear in both clusters. Conversely, spatial dynamics continue to affect manufacturing national industries, but only within the “poorer” countries cluster. These results suggest that the second partition may overlook relevant connections between neighbouring nations with related demand–supply chains in the agricultural and manufacturing sectors (as in the case of countries with a highly performing agricultural sector that fuels the manufacturing sectors of neighbouring countries).

## 6. CONCLUSION

This study aims to analyse the aggregate production of agricultural-related industries across Europe with a specific focus on inefficiency and innovation shocks, alongside variations in inputs within the agribusiness system. To reach this goal, we propose a novel approach employing maximum likelihood estimation techniques for multi-output stochastic frontier models incorporating temporal and spatial components. The model allows investigating cross-sectoral, temporal, and spatial dynamics characterizing the agricultural and food and beverage manufacturing sectors, as the two main actors of the agribusiness filière of European OECD countries from 1996 to 2019.

From a methodological point of view, this study contributes to the SF models literature by introducing a novel multi-output dynamic spatial stochastic frontier model to investigate the simultaneous relationships characterising different frontier functions. This model is designed to accommodate simultaneous effects across different frontier functions as well as time and spatial effects. This is particularly useful for investigating multi-output and

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<sup>8</sup>Countries for which the agribusiness output over GDP is greater than 4% are given by Hungary, Spain, Czech Republic, Portugal, Slovak, Italy, France and the Netherlands, while countries with a percentage less than 4% are Finland, Ireland, Austria, Belgium, Norway, Germany, Denmark, Sweden and the UK. Considering per capita GDP (pcGDP), amongst countries with higher levels of pcGDP we find Ireland, Norway, Denmark, Austria, the Netherlands, Sweden, Finland, Germany, Belgium and the UK, while in the lower pcGDP group we have France, Italy, Spain, the Czech Republic, Portugal, Slovakia and Hungary. Note that this second classification also resembles the North–South divide.

multi-input systems intertwined through input–output linkages, spatial correlation, and time dynamics such as the agribusiness filière. Noteworthy features of our model include its ability to discern productivity spillovers within a single production frontier and among diverse production processes as well as the possibility of disentangling inter- and intra-sectoral impacts to inefficiency and random shocks. The proposed specification allows to consider the correlation between random shocks affecting different frontier functions but relies on the hypothesis of independence between the inefficiency components motivated by the definition of inefficiency as context-specific.

The estimation results highlight remarkable connections between the agricultural and food and beverage manufacturing sectors both related to input variations and shocks. Considering spatial effects, significant and positive spillovers are observed both within and between sectors in the short run, mainly converting to competitive pressures one year later. These findings emphasize the importance of considering spatial spillovers and cross-sectoral effects in understanding the production dynamics of the national filières. Finally, country-level efficiency scores are computed, revealing higher and less variable efficiency degrees for the food and beverage manufacturing sector compared to agriculture. Moreover, we do not detect any particular form of association between the efficiency levels of the two sectors.

Based on our results, and in line with the strategy *Farm-to-fork* of CAP 2023–2027, policymakers should adopt an integrated approach that considers the interdependencies and synergies between the sectors comprising the agribusiness filière. In particular, given the importance of the CAP in driving agricultural trends in Europe, policymakers should acknowledge the leading role of agriculture in the agribusiness filière when formulating CAP reforms. Indeed, changes in input allocations as well as inefficiency and random shocks related to agriculture also impact downstream sectors such as food and beverage manufacturing. Moreover, policies should be designed to facilitate international collaboration and cooperation to maximize the benefits of spatial spillovers. This could involve regional development programs, infrastructure investments and cluster development initiatives aimed at fostering collaboration among firms and stakeholders across geographical boundaries.

However, while in the case of agribusiness, the assumption of uncorrelated inefficiencies may be realistic, given the distinct nature of inefficiency drivers across sectors, caution is needed when estimating the proposed model specification in other settings. Indeed, while the assumption of uncorrelated inefficiency mechanisms facilitates tractable estimation, it provides some limitations when considering its implications for policy-making and industry applications, aligning with misspecification issues in structural identification schemes of VAR processes (Castelnuovo and Surico 2010). If policymakers rely on models wrongly assuming uncorrelated inefficiency, they risk forming inaccurate expectations regarding the magnitude or timing of inefficiency shocks, potentially leading to incomplete, inappropriate or delayed recommendations. As a result, policies may fail to address the interconnected inefficiencies that span the entire filière, ultimately weakening their effectiveness. In sum, although the assumption of uncorrelated inefficiency mechanisms is methodologically convenient, it risks leading to misinformed policy recommendations and should be applied with caution evaluating its suitability case by case.

Therefore, future extensions of our model should be aimed at relaxing the assumptions of independence among inefficiency components by taking advantage of copula-based techn-

niques for the estimation. Moreover, the model could be further enriched by considering the possibility of modelling the inefficiency error term as a function of some exogenous covariates to explain the mean efficiency level in the style of Battese and Coelli (1995). Additionally, one of the main challenges in estimating the proposed model specification, as well as traditional spatial SAR models, is the need to invert a large matrix when calculating the log-determinant, which can be computationally expensive (as shown in the simulation section for the case  $m = 3$ ) and unstable when dealing with large datasets. A potential extension of this study could involve implementing a MESS-type specification (LeSage and Pace 2007), which avoids explicit matrix inversions by using the matrix exponential of the spatial weight matrix. This approach significantly reduces computational complexity, making model estimation much faster, particularly when working with large datasets. Finally, future empirical research may be devoted to further expanding our empirical analysis by considering other sectors comprising the agribusiness industry, including different spatial weighting matrices accounting for economic distances among the countries (Corrado and Fingleton 2012) and validating our results using alternative datasets, such as Eurostat data, which closely mirror OECD data in terms of the number of observations and available variables.

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**Declarations**

**Conflict of interest** none

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## APPENDIX

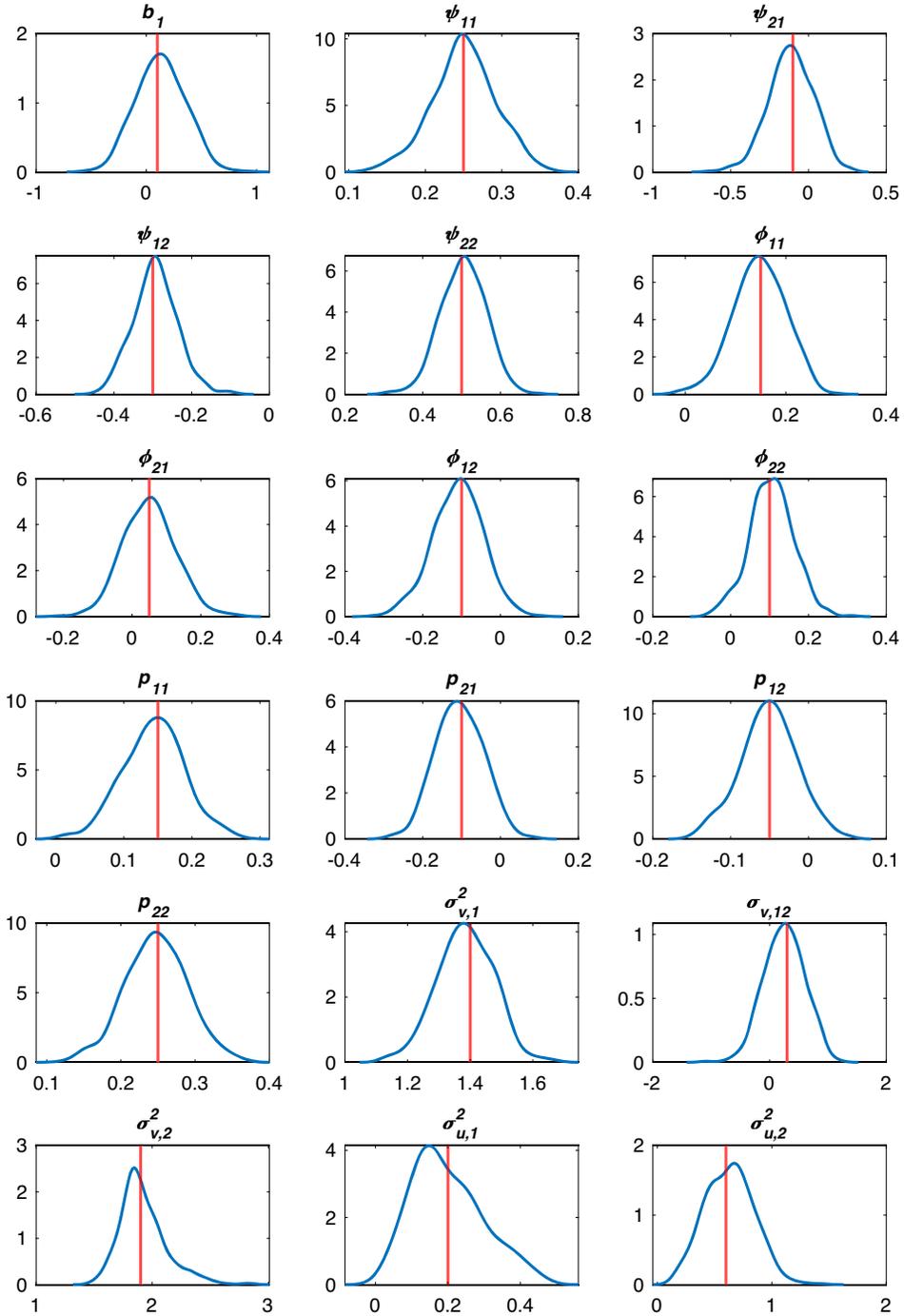


Figure 5. Kernel density plot of estimated MC parameters using a likelihood-based approach with  $N=20$  and  $T=30$ . Red line: parameter's true value.

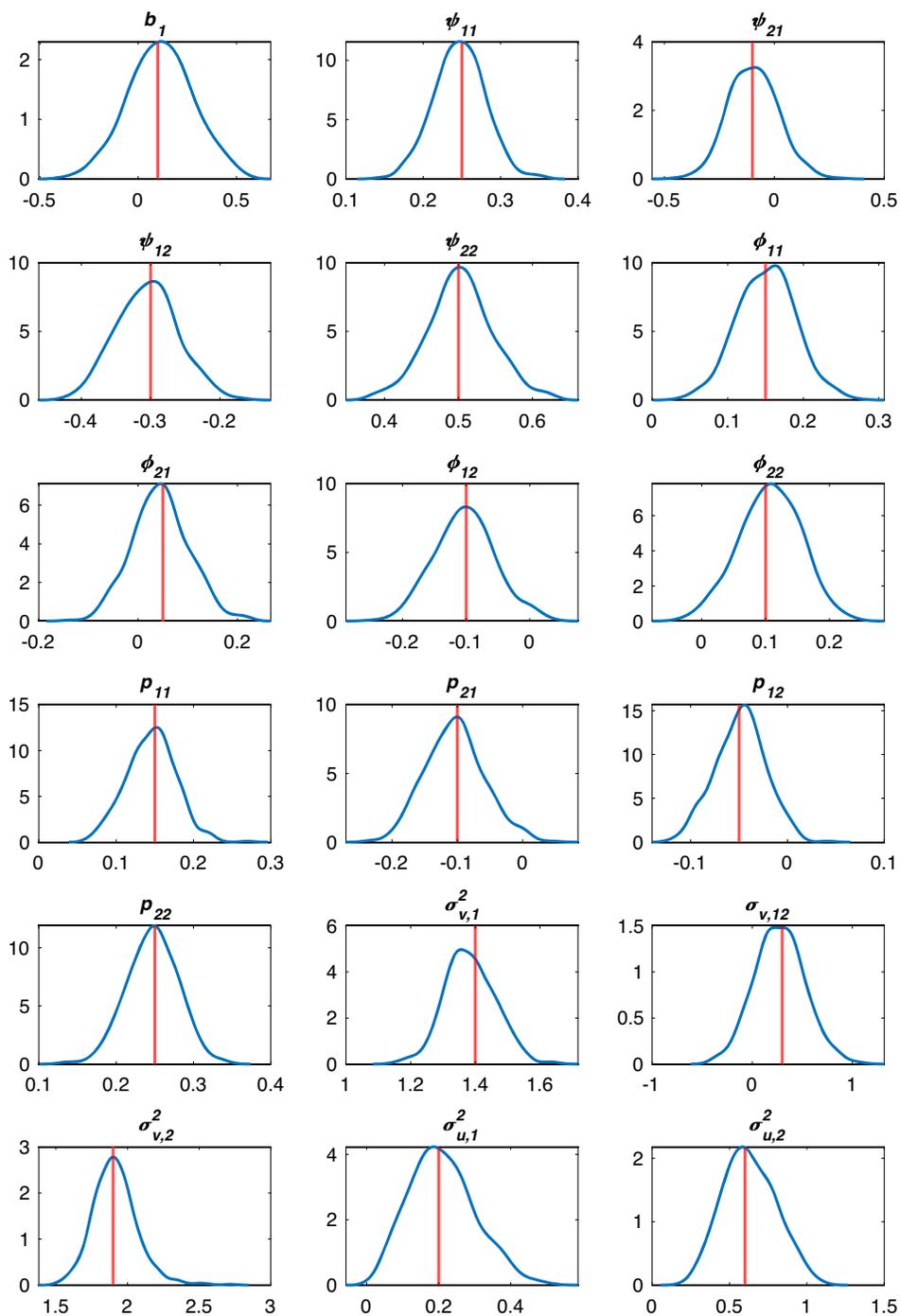


Figure 6. Kernel density plot of estimated MC parameters using a likelihood-based approach with  $N=20$  and  $T=50$ . Red line: parameter's true value.

Table 6. Monte Carlo simulation results using ML estimation for different  $T$  and  $n$  values

$DGP$		Baseline		$T=50$		$n=40$	
		Bias	SD	Bias	SD	Bias	SD
$b_{21}$	0.100	-0.008	0.228	-0.003	0.169	0.029	0.174
$\psi_{11}$	0.250	-0.001	0.042	0.004	0.034	-0.004	0.036
$\psi_{21}$	-0.100	0.002	0.143	-0.003	0.113	0.001	0.165
$\psi_{12}$	-0.300	-0.003	0.058	0.002	0.044	0.001	0.075
$\psi_{22}$	0.500	0.002	0.060	0.001	0.046	-0.002	0.039
$\phi_{11}$	0.150	0.003	0.051	0.001	0.039	0.008	0.044
$\phi_{21}$	0.050	-0.001	0.076	-0.002	0.060	-0.003	0.089
$\phi_{12}$	-0.100	0.007	0.064	0.003	0.049	0.001	0.066
$\phi_{22}$	0.100	-0.005	0.058	-0.002	0.045	0.006	0.050
$p_{11}$	0.150	0.006	0.045	0.003	0.030	0.001	0.030
$p_{21}$	-0.100	0.001	0.063	-0.002	0.045	0.006	0.044
$p_{12}$	-0.050	0.002	0.036	0.001	0.026	0.001	0.022
$p_{22}$	0.250	0.005	0.043	0.003	0.035	-0.002	0.030
$\sigma_{v,1}^2$	1.400	0.022	0.092	0.011	0.071	0.025	0.085
$\sigma_{v,12}$	0.300	0.014	0.352	0.008	0.263	0.044	0.267
$\sigma_{v,2}^2$	1.900	-0.022	0.210	-0.013	0.160	0.020	0.150
$\sigma_{u,1}^2$	0.200	-0.016	0.117	-0.012	0.089	-0.040	0.166
$\sigma_{u,2}^2$	0.600	-0.084	0.261	-0.043	0.201	-0.103	0.260
Time per rep.		72.95 sec.		137.84 sec.		170.52 sec.	

The remaining parameters are fixed to the baseline case ( $T=30, n=20, m=2$ )

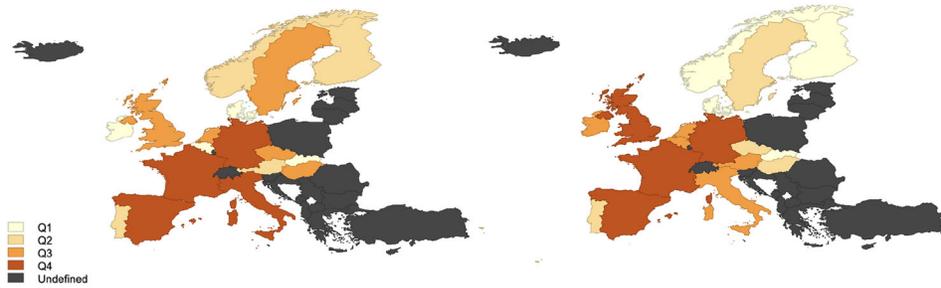


Figure 7. Quantile map of 2019 aggregate production. NB. Agricultural sector on the left panel, food and beverage industry on the right panel.

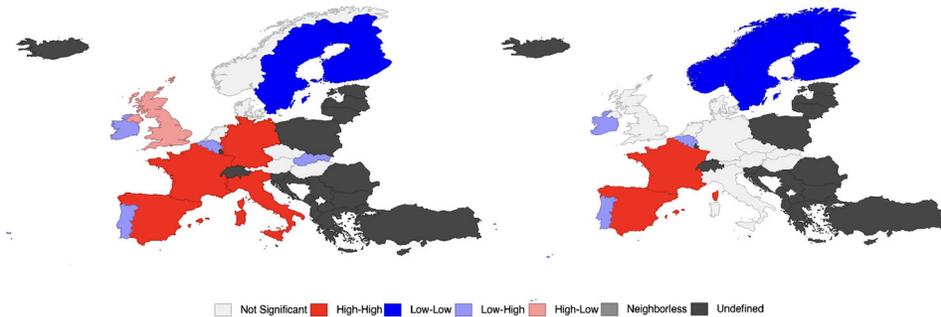


Figure 8. LISA significance cluster map for 2019 aggregate production. NB. Agricultural sector on the left panel, food and beverage industry on the right panel.

Table 7. Monte Carlo simulation results using ML estimation for  $m=3$

<i>DGP</i>		<i>m=3</i>	
		bias	SD
$b_{21}$	0.100	-0.084	0.325
$b_{31}$	0.250	-0.043	0.29
$b_{32}$	0.150	-0.013	0.238
$\psi_{11}$	0.250	-0.003	0.056
$\psi_{21}$	-0.100	0.033	0.239
$\psi_{31}$	0.050	0.006	0.140
$\psi_{12}$	-0.100	-0.014	0.114
$\psi_{22}$	0.300	-0.003	0.051
$\psi_{32}$	-0.200	-0.002	0.132
$\psi_{13}$	0.150	0.002	0.118
$\psi_{23}$	0.050	0.020	0.198
$\psi_{33}$	0.100	0.013	0.055
$\phi_{11}$	0.150	0.009	0.067
$\phi_{21}$	0.050	0.011	0.106
$\phi_{31}$	0.100	0.005	0.092
$\phi_{12}$	-0.100	0.015	0.064
$\phi_{22}$	0.100	0.004	0.067
$\phi_{32}$	-0.050	0.003	0.071
$\phi_{13}$	0.050	-0.009	0.099
$\phi_{23}$	-0.050	-0.0111	0.120
$\phi_{33}$	0.200	0.003	0.060
$p_{11}$	0.150	0.012	0.043
$p_{21}$	-0.100	0.017	0.072
$p_{31}$	0.050	-0.002	0.067
$p_{12}$	-0.050	-0.003	0.037
$p_{22}$	0.050	0.006	0.047
$p_{32}$	-0.100	-0.006	0.038
$p_{13}$	0.100	-0.003	0.043
$p_{23}$	-0.150	0.007	0.060
$p_{33}$	0.200	0.017	0.070
$\sigma_{v,1}^2$	1.400	0.025	0.097
$\sigma_{v,21}$	0.300	0.121	0.478
$\sigma_{v,31}$	0.200	0.075	0.407
$\sigma_{v,2}^2$	1.900	-0.084	0.212
$\sigma_{v,32}$	0.100	0.059	0.553
$\sigma_{v,3}^2$	1.200	-0.184	0.208
$\sigma_{u,1}^2$	0.200	-0.028	0.118
$\sigma_{u,2}^2$	0.600	-0.010	0.283
$\sigma_{u,3}^2$	0.400	-0.037	0.259

The remaining parameters are fixed to the baseline case ( $T=30, n=20$ )

Table 8. Monte Carlo simulation results using ML estimation for different true values of the spatial autoregressive parameters

	Baseline			Alternative values		
	DGP	bias	SD	DGP	bias	SD
$b_{21}$	0.100	-0.008	0.228	0.100	-0.039	0.348
$\psi_{11}$	0.100	-0.001	0.042	0.050	0.003	0.049
$\psi_{21}$	-0.100	0.002	0.143	-0.100	-0.002	0.165
$\psi_{12}$	-0.300	-0.003	0.058	-0.300	0.006	0.118
$\psi_{22}$	0.500	0.002	0.060	0.000	-0.005	0.067
$\phi_{11}$	0.150	0.003	0.051	0.050	0.002	0.062
$\phi_{21}$	0.050	-0.001	0.076	0.050	0.001	0.099
$\phi_{12}$	-0.100	0.007	0.064	-0.100	-0.002	0.073
$\phi_{22}$	0.100	-0.005	0.058	0.010	0.006	0.070
$p_{11}$	0.150	0.006	0.045	0.150	0.005	0.045
$p_{21}$	-0.100	0.001	0.063	-0.100	0.005	0.078
$p_{12}$	-0.050	0.002	0.036	-0.050	-0.001	0.037
$p_{22}$	0.250	0.005	0.043	0.250	0.004	0.048
$\sigma_{v,1}^2$	1.400	0.022	0.092	1.400	0.021	0.097
$\sigma_{v,12}$	0.300	0.014	0.352	0.300	0.059	0.522
$\sigma_{v,2}^2$	1.900	-0.022	0.210	1.900	-0.131	0.321
$\sigma_{u,1}^2$	0.200	-0.016	0.117	0.200	-0.014	0.100
$\sigma_{u,2}^2$	0.600	-0.084	0.261	0.600	-0.018	0.229

The number of observations is fixed to the baseline case ( $T=30, n=20, m=2$ )

Table 9. Descriptive statistics (year 2019)

Country	Agriculture			Food & beverage manufacturing		
	Labour (thousands)	Value added (mln euros)	Capital (mln euros)	Labour (thousands)	Value added (mln euros)	Capital (mln euros)
Austria	149	5661	3128	86	8881	1762
Belgium	59	4359	2195	101	12136	3303
Czechia	160	8909	3727	131	8867	1907
Denmark	70	4476	1391	50	4873	1039
Finland	88	6819	2038	39	3455	558
France	753	52570	16672	652	65466	10026
Germany	599	38266	13452	751	66752	9271
Hungary	187	11446	3710	128	5819	2182
Ireland	103	4065	1652	56	9507	1138
Italy	927	52939	16112	483	46742	12452
Norway	66	6762	1986	49	5477	1109
Portugal	386	8130	2135	117	7827	1755
Slovak	72	3195	1516	48	2438	585
Spain	804	50912	10025	445	79351	7712
Sweden	100	8189	3237	55	5581	862
The Netherlands	201	17333	6848	139	21678	3732
UK	399	20173	8183	434	47094	6893

Table 10. Global Moran's I (year 2019)

		Agriculture			Food & beverage manufacturing		
		Y	L	K	Y	L	K
Agri	Y	0.06*	0.09**	0.04	0.05*	0.05*	0.07**
	L	0.16***	0.19***	0.12***	0.15***	0.13***	0.15***
	K	0.00	0.03	-0.02	-0.01	-0.01	0.01
Manuf	Y	0.05*	0.09*	0.03	0.04	0.04	0.08*
	L	0.03	0.06*	-0.01	0.02	-0.01	0.03
	K	0.04	0.07**	0.02	0.04	0.03	0.05*

\*:  $p$ -value  $\leq 0.10$ ; \*\*:  $p$ -value  $\leq 0.05$ ; \*\*\*:  $p$ -value  $\leq 0.01$

Table 11. Robustness: Estimates with time dummies for crises

	Agriculture		Food & beverage manufacturing	
	Coeff.	SD	Coeff.	SD
$z_{At}$			0.002	0.16
$z_{Mt}$	-0.014	0.16		
$Wz_{At}$	0.157***	0.03	0.160***	0.02
$Wz_{Mt}$	-0.002	0.19	0.099*	0.06
$Wz_{At-1}$	-0.067***	0.02	-0.123	0.09
$Wz_{Mt-1}$	-0.090	0.14	-0.091**	0.04
$z_{At-1}$	0.124	0.20	-0.012	0.20
$z_{Mt-1}$	0.126**	0.06	0.293***	0.12
$L_{At}$	0.267*	0.17	0.168	0.21
$L_{Mt}$	0.183	0.24	0.267***	0.03
$K_{At}$	0.313***	0.05	0.247***	0.07
$K_{Mt}$	0.166	0.17	0.243**	0.11
$pcGDP_t$	0.035	0.03	-0.011	0.01
$land_t$	0.091***	0.02	0.026	0.04
$d_{2007-09}$	-0.102	0.11	-0.096	0.10
$d_{2011-13}$	-0.098	0.10	-0.103	0.09

\*:  $p$ -value  $\leq 0.10$ ; \*\*:  $p$ -value  $\leq 0.05$ ; \*\*\*:  $p$ -value  $\leq 0.01$

Table 12. Robustness: Estimates by groups of countries

	Agribusiness/GDP $\leq$ 4%				Agribusiness/GDP $>$ 4%			
	Agric.		Manuf.		Agric.		Manuf.	
	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD
$z_{At}$			0.037	0.05			0.074	0.06
$z_{Mt}$	-0.011	0.05			0.077	0.10		
$Wz_{At}$	0.119*	0.07	0.126***	0.02	0.176**	0.08	0.147***	0.03
$Wz_{Mt}$	-0.005	0.12	0.135*	0.08	0.128**	0.05	0.104	0.07
$Wz_{At-1}$	-0.071	0.08	-0.157***	0.03	-0.174**	0.07	-0.126***	0.02
$Wz_{Mt-1}$	-0.089	0.15	-0.026	0.09	-0.066	0.06	-0.160**	0.07
$z_{At-1}$	0.091	0.13	-0.001	0.06	-0.007	0.07	-0.002	0.07
$z_{Mt-1}$	0.119	0.09	0.249***	0.05	0.106**	0.05	0.187***	0.06
$L_{At}$	0.236	0.25	0.229	0.19	0.239*	0.15	0.250*	0.14
$L_{Mt}$	0.186	0.24	0.305	0.24	0.208*	0.11	0.241***	0.06
$K_{At}$	0.299***	0.09	0.235***	0.10	0.312*	0.20	0.290*	0.17
$K_{Mt}$	0.159	0.20	0.256*	0.17	0.213	0.23	0.225	0.20
$pcGDP_t$	0.156***	0.06	0.054	0.05	-0.034**	0.02	-0.169***	0.02
$land_t$	0.127	0.10	-0.052	0.06	0.076	0.08	0.086**	0.04

Table 12. (Continued)

	GDP per capita $\geq$ 41K				GDP per capita $<$ 41K			
	Agric.		Manuf.		Agric.		Manuf.	
	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD
$z_{At}$			0.022	0.02			-0.009	0.05
$z_{Mt}$	0.003	0.05			0.000	0.12		
$Wz_{At}$	0.122*	0.08	0.116	0.10	0.094	0.09	0.063***	0.01
$Wz_{Mt}$	-0.003	0.17	0.136	0.13	0.077	0.15	0.090	0.10
$Wz_{At-1}$	-0.081	0.10	-0.160**	0.08	-0.138**	0.06	-0.152***	0.05
$Wz_{Mt-1}$	-0.097	0.18	-0.025	0.14	0.030	0.10	-0.085**	0.04
$z_{At-1}$	0.115	0.13	-0.007	0.06	0.081	0.14	0.032	0.09
$z_{Mt-1}$	0.128	0.14	0.249**	0.09	0.139	0.13	0.289***	0.11
$L_{At}$	0.242	0.28	0.225	0.19	0.200	0.29	0.240	0.18
$L_{Mt}$	0.185	0.24	0.308	0.17	0.177	0.41	0.261	0.25
$K_{At}$	0.324***	0.09	0.224*	0.10	0.312	0.23	0.233*	0.15
$K_{Mt}$	0.169	0.13	0.251**	0.13	0.196	0.20	0.205	0.15
$pcGDP_t$	0.152	0.11	0.062*	0.06	0.072*	0.04	-0.094***	0.03
$land_t$	0.079	0.09	-0.027	0.05	0.051*	0.03	0.109***	0.03

\*:  $p$ -value  $\leq$  0.10; \*\*:  $p$ -value  $\leq$  0.05; \*\*\*:  $p$ -value  $\leq$  0.01

Agribusiness/GDP  $\leq$  4%: Finland, Ireland, Austria, Belgium, Norway, Germany, Denmark, Sweden, UK; Agribusiness/GDP  $>$  4%: Hungary, Spain, Czech Republic, Portugal, Slovak, Italy, France, the Netherlands; GDP per capita  $\geq$  41K: Ireland, Norway, Denmark, Austria, the Netherlands, Sweden, Finland, Germany, Belgium, UK; GDP per capita  $<$  41K: France, Italy, Spain, the Czech Republic, Portugal, Slovakia, Hungary

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