Spatial Spillovers in Functional Crop Diversification and implications for productivity

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1. Introduction

Agricultural systems face the challenge of increasing productivity while ensuring resilience to environmental and economic shocks. Conventional farming strategies emphasize specialization, benefiting from economies of scale but increasing vulnerability to market volatility, pests, and climate variability. Diversification offers an alternative, enhancing stability, resource efficiency, and resilience. Functional crop diversification, which is the practice of cultivating a combination of crops with distinct and complementary ecological functions, has been shown to enhance both ecosystem services and farm economic performance (Bommarco et al., 2013; Nilsson et al., 2022).

While diversification's benefits are well studied, its spillover effects on neighbouring farms remain less explored. Research on spatial spillovers in agriculture highlights how neighbouring farms influence decision-making (Case, 1992; Conley & Udry, 2010), with studies showing significant spatial dependencies in diversification choices (Vroege et al., 2020). However, much of this work focuses on agri-tourism or on-farm sales, shaped by landscape and market factors (Walford, 2001; Pfeifer et al., 2009; Hassink et al., 2016). Less attention has been given to spillover effects in functional crop diversification, which can affect economic outcomes. Understanding whether functional diversification influences not only the farm that adopts it but also its neighbours is critical for assessing its broader impact on agricultural productivity and sustainability at the regional level

This study examines whether functionally diverse cropping practices diffuse across farms and influence farm-level TFP, with potential heterogeneity across regions with different preconditions for agriculture. Using farm-level TFP estimation and spatial econometric modelling, it identifies both direct effects of diversification and indirect effects through spatial networks. Knowledge spillovers may arise as farmers learn from neighbours adopting functionally diverse cropping systems.

The analysis uses a panel dataset of around 30,000 Swedish crop farms from 2009 to 2021, integrating farm-level crop data from the Swedish Land Parcel Identification System (LPIS), financial data from Statistics Sweden (SCB), and geospatial coordinates. TFP is estimated using a production function approach (Rovigatti & Mollisi, 2018) and in a second step the estimated TFP is used as the dependent variable in a spatial Durbin model. This allows for the identification of both direct effects from a farm's own crop diversification, and indirect effects from the diversification of neighbouring farms on productivity (Vroege et al., 2020). Following Nilsson et al. (2022), functional crop diversity is quantified using a decomposition of the Shannon diversity index where crops are categorized into nine ecological functional groups.

2. Conceptual framework

2.1 Functional diversity

The approach to measuring crop diversity is based on the framework in Nilsson et al. (2022), wherein the Shannon diversity index is decomposed into functional diversity (HF) and related diversity (HR). For this analysis, the focus is on functional diversity which is the diversity among crop groups with distinct ecological functions. This includes crops such as legumes, grasses, or forbs, which provide complementary ecosystem services (de Bello et al., 2010; Westoby and Wright, 2006). Functionally diverse cropping systems enhance key ecosystem functions by promoting ecological complementarity among crop groups with distinct traits (Bommarco et al., 2013; Gagic et al., 2015). These systems can also reduce yield variability and vulnerability to shocks (Isbell et al., 2017; Watson et al., 2017). Additionally, they can support on-farm biodiversity and ecosystem services, contributing to long term environmental sustainability of the farm (de Bello et al., 2010; Kremen and Miles, 2012). These combined ecological and economic advantages highlight the relevance of functional diversity in agricultural research and policy (Altieri et al., 2015; Bowles et al., 2020).

2.2. Farm Total Factor Productivity

The economic benefits of functional diversification are closely linked to its ability to enhance resource use efficiency and support economies of scope in crop production. By cultivating crops with complementary ecological functions, farms can leverage synergies that allow the same inputs, such as fertilizers or labour, to support multiple crops more efficiently than in less diverse systems (Chavas and Kim, 2007; de Roest et al., 2018). This reduces reliance on costly external inputs, as functionally diverse systems provide a broader range of growth factors internally, such as natural pest control and nutrient cycling (van der Ploeg et al., 2019). Moreover, functionally diverse farms can better stabilize yields and mitigate production and market risks (Altieri et al., 2015; Bowles et al., 2020). These mechanisms position functional diversity as key for farm economic performance and resource self-sufficiency.

Total Factor Productivity (TFP) offers a comprehensive measure of farm performance by capturing the efficiency from incorporating capital, labour, and intermediate inputs in the production process (Rovigatti and Mollisi, 2018). Unlike value-added-based measures, TFP reflects improvements arising from efficiency gains, technological progress, or innovative practices. This makes it particularly suited for assessing the role of functional diversity as an innovative strategy that enhances resource use efficiency. Furthermore, TFP can be decomposed to isolate efficiency improvements, allowing for a clearer identification of whether innovation is present at the individual farm level. Without such farm-level innovation, the foundation for knowledge spillovers to other farms would be absent, making TFP a critical tool for understanding both the presence and potential diffusion of innovative practices.

3. Data and Methodology

This study constructs a panel dataset covering around 30,000 Swedish crop farms from 2009 to 2021. The Swedish Land Parcel Identification System (LPIS) provides crop data, enabling the calculation of functional diversity at the farm level. Financial data from Statistics Sweden (SCB) farm financial accounts includes net sales, input use, and financial indicators, allowing for TFP estimation. Additionally, geospatial data identifying farm locations at a 1000x1000 meter resolution facilitates the spatial econometric analysis. Since financial data does not cover all farms in LPIS, the final dataset consists of medium to large-sized farms, which are more relevant for analysing productivity effects.

3.1 Measuring Functional Crop Diversification

Functional crop diversity is measured using a decomposition of the Shannon diversity index, which captures the distribution of crops among functionally distinct groups. The measure follows Nilsson et al. (2022) and is expressed as

$$\mathrm{H^F} = -\sum_{\mathrm{g}=1}^{\mathrm{k}} \mathrm{p_g} \times \ln(\mathrm{p_g})$$

Where H^F is the functional diversity index, k represents the number of functional crop groups, and p_g is the proportion of land allocated to functional group g. The index ranges from 0, indicating monoculture, to $ln(p_g)$, where all groups are equally represented. This measure emphasizes ecological complementarity rather than species count, distinguishing functional diversity from simple crop richness. Crops are categorized into nine functional groups based on ecological roles. Aggregating these classifications at the farm level provides a measure of diversification intensity and ensures that the diversity metric reflects agronomic functions rather than merely the number of species present.

3.2 Estimating Total Factor Productivity (TFP)

In this study, the TFP estimation is based on a control function approach that allows for correction of several potential sources of endogeneity, such as contemporaneous input choice, factor market frictions and firm exits. The baseline model builds on Levinsohn and Petrin (2003) in using firms' intermediate inputs to account for serial correlation between input choices and random shocks to firm productivity. The relationship between productivity, inputs and the efficiency level of farms is specified using the following Cobb-Douglas production function:

$$y_{it} = \alpha + \gamma_l l_{it} + \gamma_k k_{it} + \gamma_m m_{it} + \omega_{it} + \eta_{it} \qquad (1)$$

where y_{it} measures net sales (output) of farm i at time t, l_{it} denotes labour inputs and capital and intermediate inputs are measured by k_{it} and m_{it}. The production function is specified to relate output to inputs and the efficiency level of firms A, such that $lnA_{it} = \alpha + \epsilon_{it}$ where $\epsilon_{it} = \omega_{it} + \eta_{it}$.[1] The function, therefore, has two unobservable terms, the first is a residual η_{it} and the second is firm productivity ω_{it}, which is assumed to follow a first-order Markov process:

$$\omega_{ijt} = E(\omega_{ijt}|\omega_{ijt-1}) + \xi_{ijt} = g(\omega_{ij,t-1}) + \xi_{ijt} = g(\phi_{t-1} - \alpha - \gamma_k k_{ij,t-1}) + \xi_{ijt} \qquad (2)$$

where ξ_{ijt} represents an innovation term (Olley and Pakes, 1996). The difference between the two unobservable terms is that while the former is assumed uncorrelated with farms period t input choices, the latter can affect such choices and the fact that ω_{it} is unobservable but potentially influential leads to the well-known simultaneity bias in production function estimation (Marshak and Andrews, 1944). To address this, the control function approach is built upon and farms demand for intermediate inputs is used to define a control function for unobserved productivity.[2] Inputs are assumed to be either variable (intermediates) or quasi-

[1] The denotations in this literature is followed and lowercase letters denote the log of a variable.

[2] The alternative approach to use firms demand for investments as in Olley and Pakes (1996) is not an option for as farms in these data frequently report zero investment, which would exclude a large number of observations in

fixed (capital) and that capital accumulation follows a law of motion such that firms capital stock in t is determined by the investments made in $t-1$, making it uncorrelated with ξ_{it}. Farms demand for intermediate inputs can thus be expressed as a function of the state variables k_{it} and ω_{it} and given that demand for intermediate inputs is strictly monotonic in ω_{it}, the demand function can be inverted to obtain the following control function:

$$\omega_{it} = h_t(k_{it}, m_{it}). \tag{3}$$

Substituting equation 2 into the production function (equation 1) provides the first-stage equation in the control function estimation to obtain farm-level TFP:

$$y_{it} = \gamma_l l_{it} + \phi_t(k_{it}, m_{it}) + \varepsilon_{it} \tag{4}$$

where $\phi_t(\cdot) = \alpha + \gamma_k k_{it} + \gamma_m m_{it} + \omega_{it}(k_{it}, m_{it})$. In the empirical application, the first-stage equation is estimated using OLS and a third-order polynomial approximation followed by a generalized method of moments estimator to identify the input coefficients. Specifically, the following moment conditions are used

$$E\left[\varepsilon_{ijt} + \xi_{ijt} | k_{ijt}, m_{ijt-1}\right] = 0 \tag{5}$$

and firm total factor productivity is calculated as a residual using the production function estimates:

$$TFP_{it} = \widehat{\varepsilon_t + \xi_t} = y_{it} - \hat{\gamma}_l l_{it} - \gamma'_k k_{it} - \gamma'_m m_{it} - E\left(\omega_t \widehat{|\omega_{t-1}}\right) \tag{6}$$

where $\widehat{\omega}_{it} = \widehat{\phi}_{it} - \gamma'_k k_{it} - y'_m m_{it}$.

3.3 Second-stage spatial Econometric Model

To examine whether functional crop diversification influences not only the adopting farm's productivity but also the productivity of neighbouring farms, a spatial Durbin model (SDM) is employed. The SDM allows for the identification of both direct effects, where a farm's own diversification impacts its productivity, and indirect effects, where diversification among neighbouring farms contributes to productivity growth. The model is specified as

$$TFP_{it} = \alpha + \beta FD_{it} + \gamma WFD_{it} + \delta X_{it} + \mu_i + \lambda_t + \epsilon_{it} \tag{7}$$

Where TFP_{it} represents total factor productivity, FD_{it} captures the functional diversity intensity of farm *i*, and WFD_{it} is the spatially lagged functional diversity, which reflects the intensity of functional diversification among neighbouring farms. The coefficient γ measures the extent to which the diversification of nearby farms influences farm *i*'s productivity. The vector X_{it} includes control variables such as farm size and soil type, while μ_i and λ_t account for farm-specific and time-specific fixed effects, respectively. The spatial relationship is

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the analysis. However, since nearly all farms report positive values on intermediate I build on the approach by Levinsohn and Petrin (2003).

modelled using an inverse distance weighting matrix, where the weight assigned to a neighbouring farm j is given by

$$W_{ij} = \frac{1}{d_{ij}}$$

Where d_{ij} represents the Euclidean distance between farm i and farm j. Since raw weights may vary significantly across farms, they are row-standardized to ensure that the sum of all weights for a given farm equals one, preventing farms with many close neighbours from exerting disproportionate spillover effects.:

$$W_{ij}^{*} = \frac{W_{ij}}{\sum_j W_{ij}}$$

4. Hypotheses and Expected Contributions

This study tests three main hypotheses. First, it examines the direct effect of functional crop diversification on implied farm TFP, proposing that farms adopting higher levels of diversification experience greater productivity growth due to improved resource efficiency, soil health, and resilience to environmental shocks. Second, it investigates the spatial spillover effects of diversification, hypothesizing that the functional diversification choices of neighbouring farms positively influence a given farm's TFP, primarily through knowledge diffusion, as farmers learn and adopt best practices from their peers. Third, it examines if there exist regional heterogeneity in the effects due to varying external conditions, such as natural preconditions for agriculture, access to markets and soil quality characteristics.

This study extends the existing literature by providing empirical evidence on the role of functional crop diversification in driving farm productivity and its potential for spatial diffusion. By integrating spatial econometric modelling with a detailed panel dataset, it offers a novel perspective on how diversification influences not only the adopting farm but also its neighbours. If results indicate that diversification spillovers extend beyond the single farm, this suggests that promoting knowledge-sharing could play a crucial role in amplifying the benefits of diversification. The findings also contribute to discussions on sustainable agricultural intensification by demonstrating whether diversification strategies can be both economically viable and environmentally beneficial. By assessing whether functional diversification enhances TFP and whether its benefits extend spatially, this study can provide valuable insights for policymakers interested in promoting sustainable and resilient agricultural systems.

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