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ANALYSIS

Farm performance and input self-sufficiency increases with functional crop diversity on Swedish farms

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ABSTRACT

Diversified crop production is a key agroecological practice that enhances ecosystem functions and reduces reliance on costly external inputs, such as for plant protection and nutrition but might also increase labour costs and lower crop yields. We investigate if functional diversification, i.e., cultivation of crop species with contrasting ecological functions, is associated with a higher growth in farm economic performance and input self-sufficiency. This is compared with increased related crop diversity i.e., the cultivation of genetically closely related crop species. We apply the system GMM dynamic panel data estimator to 35,195 medium and large Swedish farms (2001–2018), combining information on crop grown on each field and year with farm financial and individual characteristics. We find growth in farm economic performance and input self-sufficiency to respond positively to functional crop diversification and negatively to related crop diversification. The results highlight that a decomposed assessment of crop diversification provides an enhanced understanding of the build-up of resource-use efficiencies and production- and market risk reductions on Swedish farms.

1. Introduction

Crop production can be diversified in many ways, where growing multiple crops species on the farm stands out as a central practice (Hufnagel et al., 2020; Kremen and Miles, 2012). Evidence is mounting that diversified crop production and combined crop and livestock production can support a wider range of ecosystem functions while requiring less of external inputs than specialized high-input crop farming, without compromising yields (Isbell et al., 2017; Ponisio et al., 2015; Tamburini et al., 2020). Widespread adoption of diverse cropping holds the potential to contribute to food security while safeguarding biodiversity and the environment (Egli et al., 2021; Iverson et al., 2014; Kremen and Merenlender, 2018; Renard and Tilman, 2019; Tilman et al., 2006). It can also contribute to climate change mitigation and adaption (Altieri et al., 2015; Bowles et al., 2020; Marini et al., 2020).

Nevertheless, there is a continued, often policy driven, trend in major agricultural regions for more specialized and larger farms that cultivate a declining number of crops (Bennett et al., 2012; Crossley et al., 2020; Kurosaki, 2003). A possible reason for this contradiction is the perception that diversified cropping, although supplying environmental benefits, reduces crop yield and agricultural productivity and hinders the realization of scale economies (Cassman and Grassini, 2020; Fleisher and Liu, 1992; Garnett et al., 2013). Meanwhile, studies on environmental and economic effects of crop diversity show positive effects on yields (Bareille and Dupraz, 2020; Donfouet et al., 2017; Garibaldi et al., 2019), farm profits (Di Falco et al., 2010b) and food security (Di Falco et al., 2010a; Di Falco and Chavas, 2009). Crop diversity can also improve ecological functioning in agroecosystems (Di Falco and Chavas, 2008; Di Falco and Chavas, 2006; Josefsson et al., 2017; Smith et al., 2008) However, it remains to be assessed how diversified cropping affects growth in farm economic performance and input self-sufficiency, particularly over longer periods of time. This is key to understand farmers' incentives to diversify or simplify their cropping systems. This is particularly relevant in context of large-scale agricultural production, which dominates in most European countries, including Sweden.

There is increasing recognition of benefits linked to crop diversity, where farming with high ecological functional diversity enhances resource use efficiency, retention and capture within the farm ecosystem (Bommarco et al., 2013; Finney and Kaye, 2017; Gagic et al., 2015; Martin et al., 2019). An important implication for farm economic outcomes is that managing for species rich and functionally diverse cropping offers the prospect of lower reliance on costly external inputs for

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crop production, such as for plant protection and fertilisers. Crop yields can instead be maintained or even improved based on an increased reliance of locally enhanced ecosystem functions and natural resources acquired and cycled internally on the farm (Bommarco et al., 2013). Functional diversification might therefore provide farmers with the opportunity to exploit economies of scope in crop production in that the same input(s) can be used to produce two or more crops more cost-efficiently than producing them separately (Chavas and Kim, 2007; de Roest et al., 2018; Panzar and Willig, 1981). Synergies between input factors in the production system could thereby support an alternative way for enhancing farm economic performance, contrasting the economies of scale achieved in industrial farming (Ferguson and Lovell, 2019; van der Ploeg et al., 2019). However, an empirical investigation on effects of functional crop diversification on farm economic performance and resource self-sufficiency is lacking.

Farm economic and production potential of crop diversity have previously been measured as crop species richness and relative abundance (e.g., Bareille and Dupraz, 2020; Bellon et al., 2020; Di Falco et al., 2010a; Di Falco and Chavas, 2009; Di Falco and Chavas, 2008; Donfouet et al., 2017; Garibaldi et al., 2019; Smith et al., 2008). However, measures of crop species richness do not capture effects that depend on the number of functional crop groups, such as grasses, broadleaves, legumes and forbs, cultivated on a farm. Adding genetically closely related crop species that occupy similar niches and perform similar ecological functions, e.g., multiple species of cereals, has less of an effect on ecosystem functions, compared with adding functionally unrelated species that occupy disparate niches and perform additional and complementary ecological functions (Bennett et al., 2012; Finney and Kaye, 2017).

Here we examine growth in farm economic outcomes from crop diversification on Swedish farms over time 2001–2018. We use a novel empirical approach where we combine information on crop grown on each field and year from the EU Land Parcel Identification System (LPIS) (Uthes et al., 2020) with comprehensive farm financial and individual farm data from Statistics Sweden. We contribute to the literature by assessing how changes in farm crop diversity affects farm economic performance and resource self-sufficiency over a longer period of time and by decomposing the Shannon diversity into two novel crop diversity indices. The first is a measure of functional crop diversity that reflects ecological complementarity among functional groups of crop species cultivated on the farm. The second is a functional relatedness diversity index which has a higher value when multiple genetically related species in the same functional group are cultivated on the farm, e.g., multiple species of cereals. We use net value added by annual work units (VA/LU) to define farm economic performance (Reidsma et al., 2007) and the ratio of farm net value added to the gross value of production (VA/GVP) to indicate farm resource use-efficiency (van der Ploeg et al., 2019). We argue that a decomposed approach to measuring crop diversity provides an enhanced understanding of the build-up of resource capture, retention and use efficiencies on farms over time. We hypothesise that increases in functional crop diversity is associated with a higher potential for growth in farm economic performance and resource use-efficiency compared with increases in functionally related crop diversity or in overall crop species richness.

Studying average trends in Sweden (2001–2018), we find that crop species diversity has decreased with a certain rebound in later years. The sharp increase in related crop diversity and the decline in functional diversity indicate that the recent rebound in crop species richness is not likely to provide benefits to ecosystem functioning. Estimation results show that functional diversification, i.e., growing an increasing number of crop groups with contrasting ecological functionality, is associated with growth in farm economic performance and input self-sufficiency. The indicator of functional crop diversity better predicts growth in farm economic performance and relates more strongly to changes in farms input self-sufficiency compared with the diversity indicator based on crop species richness and relative abundance. An improved understanding of the economic outcomes associated with crop diversification provides valuable insights into how to design policies that support growth in farm economic performance and resource self-sufficiency, while supporting ecosystem functions and biodiversity. Results are also relevant for highlighting the extent to which farmers can expect different crop diversification strategies to be economically viable in a long-term perspective.

2. Ecology and measurement of functional crop diversity

Crop diversity on a farm, and diversity of species in general, is most often measured based on species richness and their relative abundances using the Shannon diversity index. This index is calculated from the n different crops ($c = 1, \ldots, n$) grown on a farm and their respective shares, p_c in the following:

$$H^S = -\sum_{c=1}^{n} p_c * ln(p_c) \tag{1}$$

The Shannon index can take values between 0 (in the special case where the farm only produces one crop, so that $n = 1$) and $ln(n)$ when all crops have the same share of land on the farm. This measure, focusing on the shares of the individual crops, implies a unidimensional conceptualization of diversity that ignores the functional traits between groups of crop species, which have been shown to be particularly important for agroecosystem biodiversity and multi-functionality (Finney and Kaye, 2017; Gagic et al., 2015; Martin et al., 2019). Basic ecological principles help explain why functionally diverse crop production can more effectively support ecosystem functioning, including crop yield formation. Crop species differ in how and from where they draw their resources and how they react to and handle abiotic (e.g., drought, heat) and biotic (e.g., pathogens, herbivores, weeds) interactions. Each species has evolved to occupy a particular niche in ecological space. Multiple species co-occurring in an ecosystem occupy more niches and complement each other functionally, thereby drawing resources and suppressing build-up of antagonists more efficiently. Biologically diverse ecosystems therefore have high functional integrity and resource use efficiency (Gamfeldt et al., 2013; Hooper et al., 2012; Isbell et al., 2017).

In constructing a measure of functional crop diversity, we consider that crop species have more or less similar ecological roles in the cropping ecosystem and bin crops into groups, such as legumes, grasses or forage crops based on their functional similarity. We use field- and farm-level data that from the Swedish LPIS to observe $k = 1, \ldots, 86$ crops grown on different fields for each farm over time from 2001 to 2018. Section 3 provides a detailed description of the LPIS data and the list of individual crops and the $g = 1, \ldots, 9$ functional groups are displayed in Table S1 in the supplemental file.[1] Using the crop groups, we additively decompose the Shannon diversity H^S into two components which capture (i) the functional diversity (H^F, eq. (2)) and (ii) the related diversity (H^R, eq. (3)), meaning the average diversity of crops closely related with each other, i.e. within the same functional group.

To define functional diversity (H^F), let each crop c belong to one of k functional crop groups considered in the calculation of the indices. Analogue to the calculation of H^S, the shares p_g of the crop groups $g = 1, \ldots, k$ can be used to calculate H^F as:

$$H^F = -\sum_{g=1}^{k} p_g * ln(p_g) \tag{2}$$

Here, note that $p_g = \sum_c p_c$ for all c belonging to crop group g. Similar to H^S, H^F can take values between 0 and $ln(k)$.

Based on (1), but only considering crops in crop group g, as well as

[1] Our grouping is based on assessments of ecosystem processes, crops and services via functional traits discussed in e.g., de Bello et al. (2010) and Westoby and Wright (2006).

their shares within their respective group, one also can calculate a group-specific Shannon index. If we denote this index as H_g^S, H^R can be obtained by weighting all H_g^S with the share p_g of the respective group of the total production area and calculating their sum:

$$H^R = \sum_{g=1}^{k} p_g * H_g^S \tag{3}$$

This decomposition has the appealing property that:

$$H^S = H^F + H^R \tag{4}$$

A proof with a slightly different notation can be found in Jacquemin and Berry (1979). Our decomposition of crop diversity is equivalent to that used in other contexts, for example when measuring diversity with respect to industry and education composition (e.g., Frenken et al., 2007; Wixe and Andersson, 2017). It is also formally equivalent to a special case of biodiversity measure decompositions in applied ecology (Jost, 2007).

2.1. Farm economic outcomes linked to functional crop diversity

Our main interest is to assess the influence of functional diversification (H^F) on farm economic outcomes, accounting for farm and individual factors. The economic and production potential of diverse cropping has mainly been assessed by measuring crop diversity in terms of crop species richness and abundance with the Shannon index (H^S). The prospect for improved farm profits and yields is linked to several underlying mechanisms. These include improved soil quality and ecosystem functioning on diversified farms (Bareille and Dupraz, 2020; Di Falco et al., 2010a; Smith et al., 2008), lower production- and market related risks and improved ability of diversified farms to stabilise yields in response to weather shocks and pest surges (Altieri et al., 2015; Benin et al., 2004; Bowles et al., 2020; Di Falco and Chavas, 2009; Di Falco and Perrings, 2005; Egli et al., 2021; Lin, 2011; Marini et al., 2020; McCord et al., 2015). The economic potential of crop diversity has also been examined under heterogeneous agro-ecological conditions and in rainfed marginal areas (Bellon et al., 2020; Benin et al., 2004; Di Falco and Chavas, 2009).

Functionally diverse cropping systems offer the prospect of lower reliance on costly external inputs, as a wider range of potential growth factors are available within the farm, such as for plant protection and nutrition (van der Ploeg et al., 2019). They therefore offer opportunities for farmers to recombine production inputs and exploit economies of scope in crop production (Chavas and Kim, 2007; de Roest et al., 2018). Based on this, we hypothesise that functional crop diversification (H^F) relates positively and more strongly to growth in farm economic performance and resource self-sufficiency compared with both $H^S$and H^R. We are not aware of empirical assessments of the economic potential of functional crop diversification at the farm level and over longer periods of time, which are lacking in part due to a paucity of relevant longitudinal datasets (Dyer et al., 2014).

3. Data and model

We merge data from register databases containing farm, field and individual level data to observe farmers' cropping activities, financial status and individual farmer characteristics over time. The three diversity indices eq. (1)–(3) are calculated based on information on crop grown in each field and growing season obtained from the LPIS managed by the Swedish Board of Agriculture. The Swedish LPIS identifies (1) each field (Swedish: *block*) as a spatially referenced polygon, (2) the crops grown in the field, (3) the different within-field cropped parcels (Swedish: *skifte*) in cases where multiple crops are grown in a field in a growing season, (4) the area of each field and cropped parcel, (5) agro-environmental schemes that promote organic agriculture connected to the field, and (6) the farmer who uses the field, defined by an organizational ID. The Swedish LPIS has comprehensive coverage and includes 99.7% of Swedish arable land. Only 10,900 ha are identified outside of the LPIS, most of which are part of very small land holdings (Jordbruksverket, 2021).[2] In 2018 there were 1,208,899 unique cropped parcels according to the Swedish LPIS, amounting to a total of 3,017,311 ha of agricultural land, operated by 59,004 farmers.

We calculate the crop diversity indices using the parcel-level (*skifte*) data and aggregate by farm and year. Using farm identities, we then merge the crop diversity indices with annual farm-level financial account data from Statistics Sweden (SCB). Data from SCB contain information on farm value added, gross value of production, input use (e.g., in terms of labour, fixed capital and intermediates) and individual farmer characteristics including information about age and educational attainment both by level and type of education. Data from SCB are population data in the sense that they include all active Swedish firms and all individuals in the Swedish population aged 16 or older.

Merging data from SCB with LPIS data leads to a number of unmatched farms, mainly because Swedish official statistics do not contain full financial account information for all farms, in particular smaller, part-time farms. Of the farms identified in the LPIS, 61.2% remain unmatched with farms in the SCB data. The average farm size in the sample that remains after excluding the unmatched farms is 82 ha, compared with 45 ha in the full LPIS data. Thus, our results should be interpreted with regard to this population of medium and large farms and not to the population of all Swedish farms. Although the sample does not replicate the population of Swedish farms, it contains the lion's share of the medium to large sized farms which can be expected to have the largest influence on the development of Swedish agriculture. Because the LPIS data is available from 2001 and there is a two-year lag in which SCB data become available, our panel comprises 32,503 farms and 18 years of annual data.

3.1. Economic outcome variables

We assess how the three crop diversification indices affect the farm economy using two outcome variables. The first is an indicator of farm economic performance defined as farm net value added divided by annual work units (VA/LU). We calculate farm value added in net terms and include subsidies as they comprise a significant part of farmers' incomes in a Swedish and European context (Swinnen, 2009). Using this definition, the ratio VA/LU is a proxy of farm income (van der Ploeg et al., 2019) that can be used to assess farm economic performance across farm types regardless of their family (or non-family) nature of the employed production factors (Reidsma et al., 2007).

The second outcome variable is an indicator of farm resource use-efficiency defined as the ratio of farm net value added and the gross value of production (VA/GVP). This indicator differs from our measure of farm economic performance as it signals payments for factors of production that are sourced from outside the farm at a given level of VA (van der Ploeg et al., 2019).[3] This indicator is a proxy of farm autonomy or dependence (Latruffe et al., 2016) and we consider it to assess the potential of crop diversification to influence (i.e., increase or decrease) farm input self-sufficiency. The outcome variables are defined in growth terms such that they reflect growth in farm economic performance between t and $t-1$ ($\Delta y \equiv lny_{it} - lny_{it-1}$) and growth in input self-sufficiency ($\Delta r \equiv lnr_{it} - lnr_{it-1}$). See Table 1 for detailed variable definitions.

We assess if the three measures of crop diversity relate differently in magnitude and direction to Δy and Δr with different implications for farm growth. The same direction of the relationships between crop

[2] An investigation in 2013 indicated that 85% of this "unspecified" arable land was temporary grass (*slåtter- och betesvall*) (ibid: 21).

[3] Where $GVP = VA + C + W$, where C denote the value of intermediate inputs + the consumption of fixed capital (depreciation) and W denote labor cost.

Table 1
Variable definitions and data sources.

Variable	Definition	Data source
VA/LU	Farm net value added (calculated as the value of total production (GVP) minus the value of intermediate inputs and the consumption of fixed capital (depreciation) + subsidies) divided by the number of employees in k SEK as a proxy of farm income (Reidsma et al., 2007; van der Ploeg et al., 2019).	Statistics Sweden
Δy	Dependent variable in Eq. (6) defined as $lnVA/LU_{it} - lnVA/LU_{it-1}$.	Statistics Sweden
VA/GVP	Ratio between value added and the gross value of production where ($GVP = VA + C$ where C=intermediate inputs + depreciation).	Statistics Sweden
Δr	Dependent variable in Eq. (7) defined as $lnVA/GVP_{it} - lnVA/GVP_{it-1}$.	Statistics Sweden
Shannon crop diversity (H^S)	Author's computation using Eq. (1) to indicate crop species richness using a Shannon diversity index.	LPIS
Functional crop diversity (H^F)	Author's computation using Eq. (2) to indicate functional crop diversification.	LPIS
Related crop diversity (H^R)	Author's computation using Eq. (3) to indicate related crop diversification.	LPIS
Farm size (hectares)	Land defined as the amount of land (owned and rented) in hectares divided by number of employees.	LPIS, Statistics Sweden
LU	Number of employees in full time equivalents.	Statistics Sweden
Capital	Fixed capital (the value of material and immaterial assets) in k SEK.	Statistics Sweden
Intermediate inputs	Farm net turnover minus VA in k SEK (Levinsohn and Petrin, 2003).	Statistics Sweden
Sole proprietor	Categorical variable equals one if the farm is operated as a sole proprietorship (self-employed) where the owner lacks a legal status, zero otherwise.	Statistics Sweden
Limited company	Categorical variable equals one if the farm is operated as a limited company, zero otherwise	Statistics Sweden
Trading company	Categorical variable equals one if the farm is operated as a trading company, zero otherwise	Statistics Sweden
Organic	Share of land that is certified for organic crop production and/or share of land eligible for Agri-environmental support payments for organic production.[a]	The Swedish Board of Agriculture.
Pasture	Share of land defined as pasture (crop code 89, 50, 52–56, 61).	LPIS
Higher Education	Share of employees with higher education (level of education by SUN2000 and International Standard Classification of Education code 536–640).	Statistics Sweden
Agricultural Education	Share of employees with agricultural education (subject of education by SUN2000 code 620z-623×, 629z, 640a and 640×).	Statistics Sweden
Age	Average age of employees.	Statistics Sweden
Clay content	Average clay content per farm and year from the national geodatabase of soil texture in Sweden.	(Piikki and Söderström, 2019).
Temperature	Monthly average annual June temperature.	Copernicus *E*-OBS
Precipitation	Precipitation due to wet days.	Copernicus E-OBS
Spec. crop production	Categorical variable equals one if the farm is specialized in crop production (by Swedish standard industrial identification (SNI) codes indicating its main source of business income by net turnover (>50%), zero otherwise.	Statistics Sweden
		Statistics Sweden
Spec. dairy production	Categorical variable equals one if the farm is specialized in dairy production (by Swedish standard industrial identification (SNI) codes indicating its main source of business income by net turnover (>50%), zero otherwise.	
Spec. animal production	Categorical variable equals one if the farm is specialized in animal production (by Swedish standard industrial identification (SNI) codes indicating its main source of business income by net turnover (>50%), zero otherwise.	Statistics Sweden
Spec. mixed farming	Categorical variable equals one if the farm is specialized in mixed farming (by Swedish standard industrial identification (SNI) codes indicating its main source of business income by net turnover (>50%), zero otherwise.	Statistics Sweden
CAP 2000–2006	Categorical variable equals one if year of observation falls within the CAP period 2000–2006, zero otherwise.	
CAP 2007–2013	Categorical variable equals one if year of observation falls within the CAP period 2007–2013, zero otherwise.	
CAP 2014–2020	Categorical variable equals one if year of observation falls within the CAP period 2014–2020, zero otherwise.	

[a] Certified organic farms can be observed from 2007, following the implementation of the certification scheme at the EU level. Prior to 2007, we can only observe farmers that are eligible for organic payments via the Swedish rural development programme i.e., farms in transition to becoming certified organic.

diversity and both of the outcome variables would indicate that the same strategy (functional diversification or related diversification) is functional for both outcomes. Divergent relationships indicate that the strategies are in conflict.

Our approach has some limitations as we have restricted possibilities to directly observe the underlying mechanisms that link economic outcomes with diversified cropping. The farm financial data from SCB allow us to observe the cost of externally acquired variable inputs, separated from capital investments but do not allow for separating inputs by type. It is also not possible to directly observe inputs resulting from internal resource cycling that, for instance, influence soil quality and pest regulation in diversified cropping systems. A greater availability of inputs cycled internally on the farm could influence farm economic performance and the need for farmers to acquire external inputs in subsequent periods. Hence, the use-efficiency of internal resources could modify the production function of farms that adopt cropping systems with greater functional diversity. This simultaneity bias makes the direction of the expected causal relationships ambiguous. Our identification strategy is to rely on both external and internal instruments and apply a two-system equations SYS-GMM estimator (Di Falco and Chavas, 2008). This implies that we instrument the crop diversity measures by their past levels and by local natural conditions for agriculture (see section 3.3). We also control for soil quality, on-farm organic production processes and access to pasture as they are correlated with soil enrichment and pest control (Fuglie, 2008).

3.2. Explanatory variables

We include several control variables for common production factors and account for the specifics of agricultural production in a European agricultural context (c.f. Petrick and Kloss, 2018). Production factors include capital, i.e., the size of the fixed capital stock defined as the value of both material and immaterial assets, amount of arable land, labour as number of full time employees, and intermediate inputs. We further account for natural geographically defined prerequisites for each farm linked to weather and soil quality. We use gridded data on the clay content of the soil from a detailed digital map of arable topsoil texture and soil organic matter in Sweden (Piikki and Söderström, 2019), and average annual June temperature and precipitation due to wet day available in the Copernicus *E*-OBS datasets.[4] We control for farms' organic production practices and share of land allocated to pasture as they are typically correlated with farms' overall agrobiodiversity and contribute to the farm economy by improving soil quality and pest control (Birkhofer et al., 2008; Fuglie, 2008). Both general and specific human capital are key determinants of productivity growth (Mankiw et al., 1992; Romer, 1990) and diverse cropping practices are typically more knowledge intensive compared with specialized practices (Šūmane et al., 2018; van der Ploeg et al., 2019). We therefore include controls for farmers' human capital measured both as the general educational level of the farmers and specialized education in agriculture (Baldos et al., 2019; Hayami and Ruttan, 1970). Informal and experienced-based knowledge are likely important, but data limitations prevent us from observing these sources of human capital. We include farmer age, which could reflect experience-based knowledge and/or readiness to adopt new technologies and practices (Meijer et al., 2015). We include four categorical variables to control for farm type by Swedish standard industrial identification (SNI) codes, separating between farms specialized in i) dairy production, ii) mixed crop and livestock agriculture, iii) specialized crop farms, and iv) specialized livestock farms. Following, Backman and Karlsson (2020), who find that firms differ in their growth potential depending on their legal form, we further differentiate between limited liability companies, sole proprietors, and trading companies as these three forms represent 99% of the legal forms represented in the sample. Finally, the model includes controls for the EU Common Agricultural Policy (CAP) program periods. See Table 1 for detailed variable definitions and data sources and Table 2 for sample means and standard deviations.

Table 2
Sample means and standard deviations averaged over 2001–2018.

Variable	Mean	Std. Dev.	Min.	Max.
VA/LU	475.701	562.61	0.333	50,076
VA/GVP	0.432	0.192	0.0002	1
Shannon crop diversity (H^S)	1.047	0.543	0	2.748
Related crop diversity (H^R)	0.274	0.292	0	1.630
Functional crop diversity (H^F)	0.772	0.391	0	1.978
Farm size (hectares)	83.91	107.48	0	2628.68
LU	1.95	5.44	1	815
Capital per worker	3347.75	9459.19	−3185.01	707,210
Intermediate inputs	1385.19	7145.05	0	139,164
Sole proprietorships	0.867	0.3389	0	1
Limited companies	0.105	0.307	0	1
Trading companies	0.017	0.128	0	1
Organic	0.166	0.372	0	1
Pasture	0.540	0.368	0	1
Higher Edu.	0.033	0.167	0	1
Agricultural Edu.	0.329	0.430	0	1
Age	50.02	12.51	18	85
Clay content	19.26	11.53	0	58.510
Temperature	14.48	1.42	8.249	22.096
Precipitation	342.96	92.68	116.465	922.84
Spec. crop production	0.118	0.322	0	1
Spec. dairy production	0.235	0.424	0	1
Spec. animal production	0.123	0.329	0	1
Spec. mixed farming	0.239	0.426	0	1
CAP 2000–2006	0.316	0.465	0	1
CAP 2007–2013	0.413	0.492	0	1
CAP 2014–2020	0.269	0.443	0	1

3.3. Empirical model

To estimate the effects of the crop diversity indices on the economic outcome variables, we include them as inputs in a dynamic agricultural production function (Di Falco et al., 2010a). As discussed, internal use-efficiencies associated with crop diversity are dynamic in nature as they provide the agroecosystem and the farm economy with productive responses that are transmitted to future periods (Di Falco and Chavas, 2008). We consider the presence of simultaneity bias by applying the following SYS-GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998):

$$\Delta y_{it} = \alpha + \gamma H'_{it-k} + \omega X'_{it-k} + \zeta C'_{it-k} + \tau + \mu_i + \varepsilon_{it} \tag{5}$$

$$\Delta y_{it} = lny_{it} - lny_{it-1}$$

where Δy_{it} denotes growth in farm economic performance, of farm i between t and $t-1$, H'_{it-k} denotes the diversity indices and because $H^F$and H^R are decompositions of H^S (see section 2) we estimate them in separate specifications. Moreover, γ denotes a vector of coefficient estimates of the respective crop diversity indices, X'_{it-k} denotes a vector of additional inputs (land, labour, knowledge and capital) and C'_{it-k} denotes a vector of inputs that are external to the farmer (at least in the short to medium run) in terms of weather and soil quality indicators. To account for farm specific time-invariant and temporal influences, we include year and farm fixed-effects denoted τ and μ_i and the first-difference transformation eliminates the individual effects and reduces serial correlation (Baltagi and Kao, 2001). Finally, ε_{it} denotes an idiosyncratic error term with the usual properties.

In order to assess the potential of cropping systems with varying functional diversity to influence farm input self-sufficiency, we estimate the following model:

$$\Delta r_{it} = \alpha + \gamma H'_{it-k} + \omega R'_{it-k} + \zeta C'_{it-k} + \tau + \mu_i + \varepsilon_{it} \tag{6}$$

$$\Delta r_{it} = lnr_{it} - lnr_{it-1}$$

where Δr_{it} denotes the growth in the VA/GVP ratio of farm i between t and $t-1$. The model is identical to that above in how H'_{it-k}, C'_{it-k}, τ, μ_i and the residual are defined, but differs in the definition of the vector of production inputs R'_{it-k} (X'_{it-k} above), which now exclude variable production inputs as they represent a main source of variation in the outcome variable. The estimated models in eq. (5) and (6) rely on Windmeijer's (2005) sample correction for robust variance estimation and the SYS-GMM implies instrumenting levels with differences and transforming differences, the instruments, to make them exogenous to the fixed effects. Its validity relies on the assumption that changes in any instrumental variable (I_{it}) are uncorrelated with the fixed effects ($E(I_{it}\mu_{it}) = 0$ for all i and t).

In estimating the models, we treat land, labour, capital, variable production inputs and human capital as pre-determined. We treat diversity indices as endogenous, and the inputs contained in C'_{it-k} as exogenous and use the transformed differences generated by the SYS-GMM as instruments. This implies treating temperature, precipitation and the clay content of the soil as preconditions that are unaffected by economic outcomes, at least in the short to medium term (Birthal and Hazrana, 2019; Di Falco et al., 2010a). To account for potential reverse causality we include these variables with lags and test the relevance of

[4] Detailed information on the climate indices used from the *E*-OBS dataset can be found on https://surfobs.climate.copernicus.eu/dataaccess/access_eobs_indices.php.

using different lag structures. We include one lag for both the dependent and the independent variables.[5] The clay content of the soil is time-invariant and although the SYS-GMM allows time-invariant regressors, in contrast to both a Fixed- Effects and difference GMM estimator, we have a source of variation in the clay variable coming from farmers altering their field sizes over time (as we allow for changes in parcel boundaries in creating the variable). We test the null hypothesis that instrumental variables are uncorrelated with residuals using the Sargan-Hansen test to assess the validity of the instruments.[6]

4. Results and discussion

4.1. Economic and crop diversity trends on Swedish farms 2001–2018

Mapping trends in the variables of interest, average annual net value added has increased over the studied period from 338 to 589 (k SEK) and the ratio of net value added to the gross value of production has decreased from 0.48 to 0.41 among the sampled farms. Overall crop species diversity (H^S) declined over the first 13 years of the studied period (Fig. 1), suggesting increasing farm specialization in Sweden. This is in line with trends observed in other agricultural regions (e.g., Bennett et al., 2012; Crossley et al., 2020; Kurosaki, 2003). There is also an increase in H^Sduring the last years of the dataset, albeit not rising to the level in 2001. The functional and related diversity measures give us additional information, allowing us to better characterize Swedish crop diversity trends. First, we see a decline in functional diversity (H^S) between the years 2006 and 2008, and a corresponding rise in related diversity (H^R). This coincides with a time of high grain prices, which prompted Swedish farmers to cultivate more grain. The increase in related diversity and the parallel decline in functional diversity indicate that farmers increased the cultivation of closely related cereal species at the cost of other crop categories for trends of individual crop species. Related diversity drops somewhat after 2008, but then rises again and remains elevated for the rest of the period, reaching its maximum in 2018. Functional diversity reaches its minimum in 2014, and then increases slightly. What potentially looks like the beginning of an increase in overall crop species diversity (H^S) starting in 2014, receives a more qualified interpretation when looking at the decomposed functional and related diversity measures. Functional diversity does increase somewhat, but keeping in mind the additive nature of functional and related diversity, most of the recent increase in overall diversity can be attributed to the larger increase in related diversity. The analytical benefit of decomposing the Shannon index into functional and related components is clear from Fig. 1. Examining trends of the three indices in parallel clearly tells us that exploring diversity effects using only crop species richness, as is most often the case, can lead to erroneous or incomplete conclusions.

4.2. Estimation results

Results of estimating eq. (5) are reported in Table 3 in elasticities, to allow direct comparison, and in three model specifications. Starting with the results indicating the change of the conditional mean of Δy (farm economic performance) with respect to the crop diversification indices. The coefficient of functional crop diversity (H^F) is positive and significant, and its elasticity is indicated to be almost 5.5 percentage points larger in magnitude compared with the coefficient of overall crop species diversity (H^S). The coefficient of related crop diversity (H^R) shows the opposite sign with an elasticity of about 2.2%.

The two decomposed measures of crop diversity (H^R, H^F) relate differently to both magnitude and direction of growth in farm economic performance. Although we are unable to directly observe the underlying mechanisms, these opposing effects are supportive of the theory that functionally diverse cropping systems have a wider range of ecosystem functions and potential growth factors available within the farm, compared with specialized systems (Bommarco et al., 2013; van der Ploeg et al., 2019). They should therefore have more opportunities to exploit economies of scope in production to support growth in farm performance (Ferguson and Lovell, 2019; Panzar and Willig, 1981). The lack of such complementarities and ecosystem functions could explain the negative elasticity found for increases in related diversification on farm economic performance.

The result indicating the change of the conditional mean of Δy with respect to H^F could also have resulted from combining unrelated crop species with negative yield responses to adverse weather events and environmental fluctuations (e.g., Bedoussac et al., 2015; Haughey et al., 2018; Reckling et al., 2016; Renard and Tilman, 2019; Watson et al., 2017). In contrast, the legacy of diverse crop rotations have been found to render higher yields under stressful climatic conditions (Bowles et al., 2020; Marini et al., 2020). A possible explanation for the observed response to H^F could be that, for instance, legume crops have had higher output prices and have been more profitable than grain crops. However, we consider this to be highly unlikely as a well-functioning value-chain for legume crops has is not established in Sweden. Thus, Swedish farmers are not likely to sell their benefit from price mark-ups derived from their legume production.

Growth in farm input self-sufficiency (Δr) measured with the ratio VA/GVP, as well as growth in farm performance (Δy) are positive and significant in relation to functional crop diversity (H^F). The elasticity for Δr is indicated to be larger in magnitude compared with the coefficient of related crop diversity (H^S). While farms input-use efficiency seems to benefit from employing functional diversification strategies, the opposite is found for increasing the cultivation of a few genetically related crop species. This is in line with previous findings that European cropping systems based on diversification have a higher adaptive capacity to absorb economic and environmental disturbances compared with specialized systems (de Roest et al., 2018).

Interestingly, the CAP reforms were found to influence the economic outcome variables. We can only speculate about the causes of these influences as the CAP categorical variables could also reflect other temporal trends not considered in the models. It seems like agricultural policy reforms act to support growth in farm performance. Yet, the potential of agricultural policy to support a transition to more input use-efficient farming is negative and insignificant (Table 3). This is largely in line with the view that the CAP needs to be further revised to realize environmental goals to protect biodiversity and enhance ecosystem services (European Commission, 2021; Scown et al., 2020).

We note that the estimated directions of coefficients on conventional production factors, i.e., land, labour, capital, knowledge and intermediate inputs are in line with expectations. The positive coefficients on land, labour and capital confirm their role as key input factors to improve farm economic performance (Petrick and Kloss, 2018). Human capital as a key determinant of agricultural growth is also confirmed, in particular the influence of specialized education in the agricultural sciences (Baldos et al., 2019). Growth in farm economic performance is higher in cases when capital investments and education rates are high (c. f. Gutierrez, 2002). We also note that the coefficients on organic production and the share of total land devoted to pasture are positive

[5] We apply a method of reproduction regressions to test the validity of including additional lag instruments in the system GMM (Blundell and Bond, 2000; Roodman, 2007; Windmeijer, 2005). This implies including two or more lags of each instrument, reducing the instrument count and examining the behavior of the coefficient estimates and the overid tests (Hansen J test and the difference-in-Sargan test). We find that adding more than one lag of the endogenous variables results in overfitting as the null of the overid tests cannot be rejected at usual significance levels.

[6] We use a 2SLS to validate the instruments and address overidentification. Compared with the IV-SYS-GMM, coefficients are biased (mostly) upwards and standard errors are different and in general much larger suggesting that the IV-SYS-GMM estimator is more efficient (Baum et al., 2003). These results can be obtained on request.

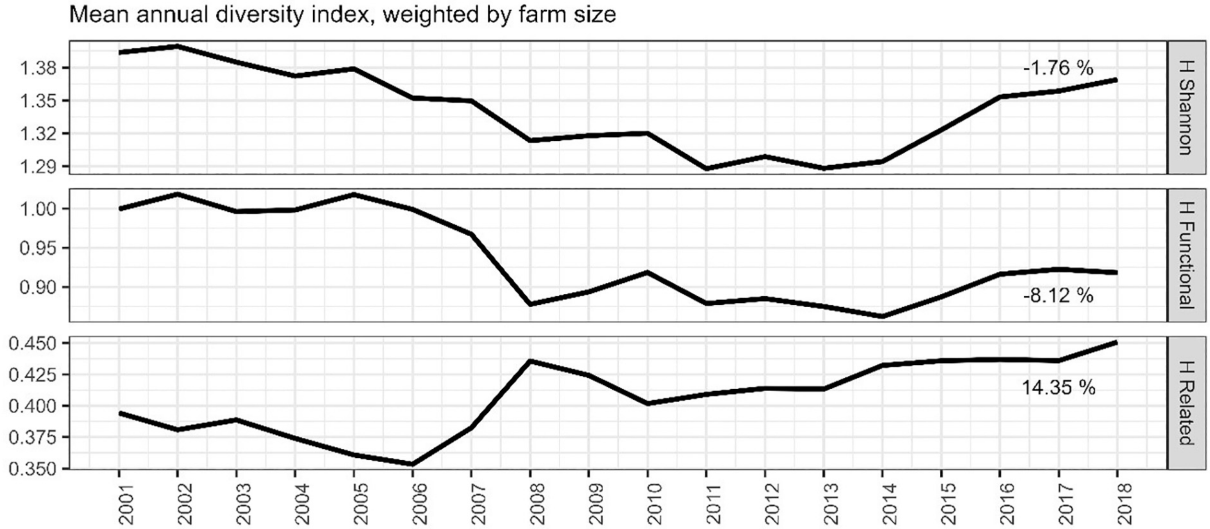

Fig. 1. Mean values of the three crop diversity indices, weighted by farm size. Percentage change between 2001 and 2018 is indicated in the figures.

throughout the estimations indicating their importance in the production process (Birkhofer et al., 2008; Fuglie, 2008).

4.3. Estimations accounting for farm specialization

The farms included in our sample are heterogeneous in terms of resource endowments and production specializations, which may influence the results. Table 2 shows that 23.9% of the farms operate as mixed farms that combine crop and animal husbandry activities, 23.5% are dairy farms and 12.3 and 11.8% are specialized crop and specialized animal producers, respectively. Estimation results (Table 3) point at significant differences in the mean outcomes with respect to all production specializations in relation to mixed farms. We therefore reestimate the models (Eq. 5 and Eq. 6) by production specialization to assess if the signs and the magnitudes of the crop diversification coefficients vary across farm types. The main results are reported in Table 4 where the last column tests equality of all coefficients across the four farm types. The full set of estimation results are reported in Table S2 and S3 in the Supplementary file.

The relationship between the outcome variables and the functional and overall diversification measures (H^F, H^S) are robust across farm types. One interesting finding applies to specialized crop farms, where we find both functional and related diversification strategies to positively affect growth in farm economic performance. This indicates that specialized crop farmers can benefit from adding both functionally unrelated and closely related crop species, e.g., adding multiple species of cereals or by introducing legumes or spring or winter wheat into their crop mix. This is in line with experimental results showing that cropping systems that mix wheat and legumes and/or combine different wheat species enhance profit (Bell et al., 2008; Noor and Sheppard, 2021). Examining coefficient estimates by farm type we find support for the hypothesis that farmers in a Swedish context benefit economically by emphasising functional diversification.

There is one specialization, horticulture, where we find that this relationship does not hold due to its more intense labour needs. However, the LPIS data, for all its richness, does not sufficiently break down vegetables or fruit into different crop codes, making it difficult to accurately measure crop diversity.[7] For this reason, farms that specialize in horticulture (around 559 farms) were removed from this sensitivity analysis as they constitute a small part of farms in Sweden.

4.4. Estimations accounting for the farm family

Given the labour- and knowledge intense character of diversified farming, farm choices with respect to different levels of diversification could potentially be different in cases abundant family work is available (Weiss and Briglauer, 2002). The “invisible hand of non-farm opportunity” and income from non-farm activities might also influence farms diversification strategies (Banerjee and Newman, 1993; Tweeten, 1969). In particular, the allocation of farm labour towards non-farm activities can influence on-farm diversity in cases when the opportunity cost of farm labour is higher/lower than rural wages (Nilsson, 2019). Based on these considerations, we employ further segmentation of the data to account for non-farm incomes and characteristics of the farm family to assess if these factors influence the main results.

In a first step, we single out farm owners in each year using each individual’s occupational status. For 86.7% of the farms, operating as sole proprietorships, the farm owner is identified by the status ‘self-employed’.[8] For these farms, we observe the civil status of the farm owners and single out identities of their married- or registered partner and their family members using the owners’ family identity code.[9] Around 12% of the farms in the sample operate as limited companies or trading companies implying that they have a more complex ownership structure where several individuals share the ownership and managerial control. Since there is no straightforward way to single out the owner or operating manager of these farms, we exclude them in this sensitivity analysis. Limited companies and trading companies constitutes a rather small part of farms in Sweden and the vast majority of Swedish farmers operate as self-employed (86.7%). We include variables to account for

[7] For example a horticulture farm whose fields are cultivated to onion, carrots, cucumbers and cabbage would have a Shannon, functional and related diversity of 0, as all those crops would receive the same crop code, 74 (vegetables), and would thus also be in the same broader crop group used for calculating functional diversity (See table S1 in the Supplemental file).

[8] Sole proprietorships are firms owned by a single person with unlimited liability.

[9] A code that assign each individual belonging to same family the same code. Family identifiers originate from the register STATIV, a longitudinal database for integration studies audited by Statistics Sweden (Statistics Sweden, 2017).

Table 3
Estimation results (SYS-GMM).

	Dependent variable Δy			Dependent variable Δr		
Shannon crop diversity(H^S)	0.047*** (0.002)	–	–	0.065*** (0.012)	–	–
Related crop diversity (H^R)	–	−0.022*** (0.006)	–	–	−0.099*** (0.001)	–
Functional crop diversity (H^F)	–	–	0.102*** (0.018)	–	–	0.145*** (0.013)
Farm size (hectares)	0.303*** (0.005)	0.373*** (0.005)	0.314*** (0.005)	−0.008** (0.004)	−0.008** (0.004)	−0.037*** (0.004)
LU	0.006** (0.003)	0.007** (0.001)	0.007** (0.001)	0.001 (0.002)	0.001 (0.001)	0.001 (0.002)
Capital per worker	0.069*** (0.001)	0.068*** (0.001)	0.061*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)
Intermediate inputs per worker	−0.054*** (0.003)	−0.043*** (0.003)	−0.042*** (0.003)	–	–	–
Sole proprietorship	−0.283*** (0.031)	−0.329*** (0.031)	−0.310*** (0.031)	−0.051** (0.022)	−0.056** (0.022)	−0.059** (0.022)
Limited company	0.327*** (0.045)	0.390*** (0.045)	0.334*** (0.044)	0.031 (0.032)	0.034 (0.034)	0.034 (0.034)
Trading company	−0.505*** (0.141)	−0.553*** (0.138)	−0.552*** (0.138)	−0.345*** (0.107)	−0.395*** (0.105)	−0.301*** (0.106)
Organic	0.084** (0.012)	0.055** (0.012)	0.076** (0.012)	0.079*** (0.009)	0.079*** (0.009)	0.078*** (0.008)
Pasture	0.440*** (0.017)	0.091*** (0.016)	0.348*** (0.014)	0.347*** (0.013)	0.301*** (0.013)	0.275*** (0.013)
Higher Education	0.039 (0.040)	0.047 (0.040)	0.037 (0.041)	0.021*** (0.003)	0.022*** (0.003)	0.012*** (0.003)
Agricultural Education	0.376*** (0.013)	0.383*** (0.013)	0.376*** (0.013)	0.065*** (0.002)	0.064*** (0.002)	0.076*** (0.002)
Age	0.644*** (0.013)	0.545*** (0.014)	0.633*** (0.014)	−0.021*** (0.010)	−0.024*** (0.012)	−0.030*** (0.012)
Clay content	−0.064*** (0.006)	−0.135*** (0.006)	−0.067*** (0.006)	0.130*** (0.005)	0.131*** (0.005)	0.133*** (0.005)
Temperature	0.288*** (0.010)	0.299*** (0.010)	0.288*** (0.010)	0.056*** (0.007)	0.056*** (0.007)	0.055** (0.006)
Precipitation	0.067*** (0.005)	0.055*** (0.005)	0.061*** (0.004)	0.055*** (0.004)	0.053*** (0.003)	0.062*** (0.003)
Spec. crop production[a]	0.096*** (0.008)	0.088*** (0.008)	0.094*** (0.008)	0.052*** (0.005)	0.051*** (0.004)	0.043*** (0.003)
Spec. animal production	−0.088*** (0.012)	−0.090*** (0.012)	−0.068*** (0.012)	−0.111*** (0.004)	−0.110*** (0.004)	−0.107*** (0.003)
Spec. dairy production	0.050*** (0.006)	0.051*** (0.006)	0.040*** (0.006)	−0.022*** (0.008)	−0.021*** (0.008)	−0.010*** (0.009)
CAP 2007-2013[b]	0.149*** (0.003)	0.130*** (0.003)	0.170*** (0.003)	−0.092*** (0.002)	−0.091*** (0.002)	−0.092*** (0.002)
CAP 2014–2020	0.102*** (0.004)	0.098*** (0.004)	0.145*** (0.004)	−0.084*** (0.003)	−0.085*** (0.003)	−0.086*** (0.003)
Intercept	−0.606*** (0.100)	−0.863*** (0.083)	−0.572*** (0.097)	−1.040*** (0.066)	−1.042*** (0.067)	−1.702*** (0.068)
Observations (groups)	274,325 (35195)	274,325 (35195)	274,325 (35195)	274,891 (35272)	274,891 (35272)	274,891 (35272)
Sargan-Hansen (*p*-value)[c]	0.1244	0.109	0.106	0.099	0.121	0.098

Notes: $^{**}p < .05$, $^{***}p < .01$. [a]The base category is Specialization in mixed farming. [b]The base category is CAP 2000–2006. [c]The Sargan-Hansen tests cannot be rejected, suggesting that the instruments are uncorrelated with the error term which is required for consistent estimation the SYS-GMM.

Table 4
Estimation results by production specialization.

	Δy		Δr		
	H^R	H^F	H^R	H^F	p-value[a]
Crop production	0.132*** (0.059)	0.032*** (0.004)	−0.022 (0.043)	0.043** (0.021)	0.002
Dairy production	−0.097*** (0.003)	0.070*** (0.032)	−0.042*** (0.004)	0.221*** (0.032)	0.021
Mixed production	−0.137*** (0.056)	0.151*** (0.032)	−0.021*** (0.006)	0.231*** (0.041)	0.073
Animal production	−0.011*** (0.002)	0.027*** (0.055)	−0.013*** (0.002)	0.067*** (0.030)	0.092

Notes: $^{**}p < .05$, $^{***}p < .01$. [a] p-value for a test for parameter equivalence; Table S2 and S2 in the Supplemental file display the full set of estimation results.

the self-employed farmers' civil status, non-farm incomes, and incomes of the spouse or the married partner. The data shows that for 89% of the farms in the sample, the farm spouse has a full-time employment outside the family farm, which limits the possibility for within family labor synergies with respect to the spouse. The one area where we believe family labor can make a difference on Swedish farms is if there is a young adult who want to eventually take over the farm. Since we cannot observe the presence of a potential successor, we include the number of children and young adults (aged 16–30) living at home (not employed in the farm) to proxy for within-family labor synergies. Variable definitions are presented in Table S4 in the Supplemental file.

The models (Eq. 5 and Eq. 6) are re-estimated including the farm family controls. Main results are reported in Table 5 and the full set of estimation results are found in Table S5 in the Supplementary file. Results show that both the magnitude and direction of the coefficients of the crop diversity measures (H^S,H^R,H^F) are in line with those presented above (Tables 3 and 4). While incomes of the spouse are functional for both economic outcomes, non-farm incomes are only positively related

Table 5
Selected estimation results including farm family characteristics (SYS-GMM).

	Dependent variable Δy			Dependent variable Δr		
Shannon crop diversity (H^S)	0.076*** (0.007)	–	–	0.054*** (0.002)	–	–
Related crop diversity (H^R)	–	−0.064** (0.028)	–	–	−0.113*** (0.004)	–
Functional crop diversity (H^F)	–	–	0.114*** (0.018)	–	–	0.110*** (0.003)
Income off-farm business activities	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)	0.034*** (0.001)	0.039*** (0.001)	0.038*** (0.001)
Income of married or registered partner	0.055*** (0.001)	0.057*** (0.001)	0.056*** (0.001)	0.120*** (0.004)	0.124*** (0.003)	0.121*** (0.004)
Teenagers and young adults living at home	0.002 (0.006)	0.001 (0.005)	0.002 (0.006)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
Civil status A	−0.054*** (0.013)	−0.053*** (0.014)	−0.060*** (0.014)	−0.003 (0.004)	−0.002 (0.006)	−0.002 (0.006)
Civil status B	−0.030*** (0.013)	−0.030*** (0.013)	−0.049*** (0.013)	0.022*** (0.002)	0.013*** (0.002)	0.012*** (0.002)
Civil status C	−0.027*** (0.012)	−0.029*** (0.013)	−0.036*** (0.013)	0.004 (0.002)	0.004 (0.002)	0.004 (0.002)
Civil status D	0.028 (0.021)	0.030 (0.021)	0.028 (0.021)	0.008*** (0.002)	0.009*** (0.002)	0.009*** (0.003)
Civil status E	0.012 (0.015)	0.013 (0.015)	0.011 (0.015)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)
Intercept (α)	−2.136*** (0.097)	−1.571*** (0.088)	−2.092*** (0.097)	0.132*** (0.014)	0.144*** (0.014)	0.145*** (0.014)
Observations (groups)	236,044 (30606)	236,044 (30606)	236,044 (30606)	236,509 (30656)	236,509 (30656)	236,509 (30656)
Sargan-Hansen (p-value)	0.142	0.137	0.140	0.098	0.097	0.099

Notes: **p < .05, ***p < .01. The full set of estimation results are reported in Table S5 in the Supplemental file.

to farm input self-sufficiency. This could indicate that farms with non-farm incomes are run in a less intensive way, possibly because the farm family is not as dependent on the farm income for their living expenses. However, leaving such income unaccounted for does not bias the main results. For the Swedish context, we cannot find support for the presence of family labour synergies with respect to children and young adults living at home.

5. Conclusions

We investigate farm economic outcomes related to crop diversification using data on Swedish farms over the period 2001–2018. We apply a novel empirical approach in combining crop field-level data from the EU LPIS with farm financial, individual and farm family information to assess how changing farm crop diversity affects farm performance and input self-sufficiency. We calculate farm-level diversity indices by decomposing the Shannon index into two indices to distinguish between the average diversity of crops grown on a farm that are functionally unrelated and functionally related. Using this approach, we assess the implications of different crop diversity measures for farm economic outcomes in a Swedish context.

Results show that growth in farm economic performance and input self-sufficiency respond differently to functional and related diversification, indicating that the two diversification strategies have very different implications for farm growth. We find the change of farm performance and input self-sufficiency to be positive with respect to changes in functional crop diversity, but negative w.r.t. changes in related crop diversity. Although we are unable to directly observe the underlying mechanisms, results are in line with the hypothesis that functionally diverse cropping systems offer farmers a wider range of potential growth factors and opportunities to exploit economies of scope in production that can improve their economic performance, compared with specialized systems (Bommarco et al., 2013; Chavas and Kim, 2007; de Roest et al., 2018; van der Ploeg et al., 2019). Ecologically, functional crop diversity strengthens ecosystem functioning such that soil fertility, nutrient use efficiency, and biological pest and weed regulation are improved (Kremen and Miles, 2012; Watson et al., 2017). These ecological processes and resources are generated on the farm.

Results could also reflect that increases in the combination of unrelated crop species have reduced Swedish farmers' market- and production risks in the face of external shocks over time. This supports the theory and empirical evidence that more diverse crop portfolios perform better in face of production risks and market price volatility (Bedoussac et al., 2015; de Roest et al., 2018; Haughey et al., 2018; Reckling et al., 2016; Watson et al., 2017). The results of this study contribute to an enhanced understanding about the relationships showing that the average large and medium sized farms in Sweden can benefit economically from a stronger emphasis on functional diversification. Results are robust across farm type and for the inclusion of farm family characteristics and controlling for within-family labour synergies.

Our findings highlight the need to separate between different types of crop diversity, and future research should carefully consider how crop species complement each other ecologically when assessing the economic impacts of crop diversification. The positive relation found between improved farm economic outcomes and functional diversification that enhance biodiversity, could entail that farmers' economic self-interest direct them towards production practices that are more beneficial for biodiversity, even in the absence of targeted public agricultural policy. This finding is useful for farmers and their advisors in planning their future crop production, by highlighting that farm economic performance and input self-sufficiency gains can be obtained from considering functional crop diversity. Although the register data on which we have based our analysis are unique in their detail and spatial and temporal coverage, the risk of endogeneity is always more or less present in observational studies. For instance, information to disentangle production inputs by type is not available in the register data. Future more detailed analysis, e.g., based on experimental case studies comparing diversified and non-diversified farms, is needed to better understand the underlying mechanisms that link functional diversification to farm economic outcomes.

Declaration of Competing Interest

We are not aware of any conflicts of interest associated with this

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2022.107465.

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