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Diversity of research publications: relation to agricultural productivity and possible implications for STI policy

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Abstract Technologies may have significant effects on productivity in the agricultural sector as documented in the related literature. However, those impacts vary from country to country. These differences could partially reflect the distinct scientific landscapes, science technology and innovation (STI) policies and approaches to R&D. In order to explain the cross-country volatility of agricultural productivity, we aim to study issues of STI development in the agricultural sector in each country. Among other characteristics of STI in general and the scientific landscape, in particular, we looked at the diversification of research publication between subfields of agricultural science. We estimated the research diversification parameter and studied its relation to economic performance of an agricultural sector. Our main finding shows that R&D funding, if carefully balanced with the diversification of agricultural science, could improve research performance and eventually productivity in an agricultural sector.

Keywords Bibliometric analysis · Diversification of research · Research and development · STI policy · Agricultural productivity

JEL Classification Q16 · O33

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Introduction

Many researchers agree that productivity in the agricultural sector varies more than in other economic sectors across different countries (Lagakos and Waugh 2013; Gollin et al. 2014). This can be explained by inefficiencies (the cheap labor force, outdated equipment, etc.) in the agricultural sectors of developing countries (Restuccia et al. 2008; Alvarez-Cuadrado and Poschke 2011). Another reason is that over the last several decades, technological trends have had a huge impact on agricultural development all over the world and STI might play more important role in productivity growth of the agricultural sector than in the rest of the economy (Griliches 1964; Chavas and Cox 1992; Piesse and Thirtle 2010; Zouaghi and Sánchez 2016). Research policy and strategic planning play a key role in agricultural development according to several studies (including Öborn et al. 2013; Greiner et al. 2014).

There is extensive literature attempting to examine the relationship between R&D and agricultural productivity on a country level. Some researches documented lagging impact of public R&D expenditures on productivity in developed countries (Cai et al. 2017; Andersen 2015). According to other authors, the effect of R&D expenditures on productivity could be nonlinear (Huffman and Evenson 2006; Heisey et al. 2011). In the agricultural sectors of certain countries, the impact of technology may even be negative (Matulov and Cechura 2016). Approaches to agricultural STI policy differ from country to country (Vanloqueren and Baret 2009), which may result in heterogeneous patterns for productivity growth. Differences in the effects of R&D on productivity across countries can be explained by specific features of their scientific landscapes which characterizes the distribution of R&D resources.

One of the main characteristics of the country's scientific landscape is the degree of specialization in publications in certain research areas. Some authors suggest that specialization may play an important role in research and even economic performance (De Lucio et al. 2002; Yegros-Yegros et al. 2015; Urraca-Ruiz and Laguna-Molina 2016). Industry convergence, which is often closely related to convergence in research areas, forces researchers and organizations to change the specialization of their research or diversify the areas where they are attempting to innovate for better performance (Saracco et al. 2015; Caviggioli 2016).

Similar trends can be observed in agriculture. The distribution of agricultural segments in global value chains (Materia et al. 2014), new industrial technologies applied to agriculture across segments, the convergence of food production and the pharmaceutical industry, the popularity of multi-level innovation platforms in Agricultural Research for Development (AR4D) and more general agricultural innovation systems (World Bank 2012) are but a few of many factors that affect agricultural research for countries, which changes the historically and geographically determined specialization (Hansson et al. 2013; Abramo et al. 2015; Sanyang et al. 2016; Lamers et al. 2017). Demand for external sources of knowledge and corresponding emerging trends toward open innovation in agriculture (see for details in Sarkar and Costa 2008; Bigliardi and Galati 2013; Saguy and Sirotinskaya 2014; Hossain 2015) is also playing a critical role in the scientific landscape transformation. Collaboration between agricultural research centers and large multinational diversified firms, supplemented by a wide scope innovative agricultural SMEs (Small and Medium Enterprises) and farmers on domestic markets, is putting down the foundation for global diversification of agricultural research (Wood et al. 2014; Hua 2015).

But broad research diversification does not necessary imply positive economic effects. On the contrary Chen et al. (2015) discovered that R&D specialization across industries and focused Gross domestic Expenditure on R&D (GERD) positively affects the economic performance of studied countries. Authors stressed that performance might depend on the overall country level of R&D intensity. Using similar arguments, we analyzed scientific landscape and STI policies in different countries shifting from the country level perspective to the narrower level of the agricultural sector. We suggest that along with institutional factors, the choice of a country's STI objectives reflected in agricultural research diversification and corresponding GERD (Gross domestic Expenditure on Research and Development) distribution could be the key aspects of STI policy that affect economic performance of agricultural sector. The availability of the data on publication diversification allows to overcome the existing drawbacks of limited information about distribution of agricultural R&D expenditures in different countries. We consider the diversification of publications in agricultural science as an important feature of the scientific landscape and when accompanied with the overall level of agricultural R&D expenditures to be a good proxy for STI policy. Hence our research aim is to contribute to the literature on the economic effects of STI policies by studying the relationship between research diversification and productivity in the agricultural sector in selected countries.

The rest of the paper is organized as follows. We used countries' panel data to determine the relationship between research diversification and agricultural productivity controlling for other parameters of scientific landscapes and economic variables. Then we compared research diversification and GERD across selected countries to make conclusions about approaches to STI policy and R&D specialization. Finally, we studied the case of Russia more closely and presented recommendations on STI policy considerations in the agricultural sector.

Research diversification and agriculture productivity

Model and data

We study the relationship between research diversification and the productivity of the agriculture sector in different countries including other important variables in our analysis. We considered a dataset of $n = 75$ countries characterized by yearly parameters from 1996 until 2013. We developed a panel regression model and used agriculture productivity as a dependent variable.

In the related literature, there are several approaches to measuring agricultural productivity (Restuccia et al. 2008; Cincera and Ravet 2014; Gollin et al. 2014). Due to the well-documented drawbacks of Total Factor Productivity (TFP) estimation (e.g. Griliches 1964; Lyu et al. 1984), we will pick two measures of agricultural productivity: value added per worker and agricultural value added[1] per one hectare of arable land. We obtained the values of these indicators from the World Bank's database.[2] According to the World Bank's methodology: "Value added in agriculture measures the output of the agricultural sector [ISIC (International Standard Industrial Classification divisions) 1–5] less the value of intermediate inputs" and "arable land is land under temporary crops (double-cropped areas are counted once), temporary meadows for mowing or for pasture, land under market

[1] Information on Agriculture, value added (current US$) is available on the following link: http://data.worldbank.org/indicator/NV.AGR.TOTL.CD?view=chart.

[2] Information on the indicator in the World Bank database is available here: http://data.worldbank.org/indicator/EA.PRD.AGRI.KD?view=chart.

or kitchen gardens, and land temporarily fallow". According to the World Bank's methodology, agriculture includes ISIC divisions 1–5 (forestry, hunting, fishing, cultivation of crops and livestock production). The indicators are considered in constant 2010 US dollars. For our purposes, we take a natural logarithm of each indicator (AGR_VAL_AD_PER_WORK_LN, AGR_VAL_AD_PER_HECT_LN).

Research diversification in agricultural science is the key independent variable in our study. The classification of agricultural science could be provided in several ways (Bartol et al. 2016). We use the Scopus database and SciVal Benchmarking (see Colledge and Verlinde (2014) for more details)[3] analytical tool to estimate bibliometric parameters. The choice of Scopus over Web of Science and other databases was justified by its more comprehensive worldwide coverage of journals (especially in developed countries). According to the All Science Journal Classification that is used in Scopus,[4] the subject of our interest is the Agricultural and Biological Sciences category. We choose nine subareas of research related to agriculture: Agronomy and Crop Science; Animal Science and Zoology; Aquatic Science; Food Science; Horticulture; Insect Science; Plant Science; Soil Science and Veterinary Science.

We start with an introduction of a specialization parameter and then invert it to obtain a diversification parameter. There are different methods for estimating a country's research specialization (Mugabushaka et al. 2016 and references therein). The key problem when estimating a country's research specialization is that a publication refer to several research fields, which makes the sum of the percentages of papers in all subareas greater than 100%. Traditional measures of specialization would be inappropriate in such a case for cross-country analysis.

Stirling (2007) suggested a general framework for measuring science diversification. Interesting applications of Stirling's approach can be found in a number of publications (e.g. Porter and Rafols 2009; Rafols and Meyer 2010; Soós and Kampis 2011). We applied the framework and followed Zhou et al. (2012). Accounting for publications related to two research fields, we include a correlation parameter in the specialization equation. Let $\text{share}_k^i(t)$ be a share of publications of field k (one of the nine considered research fields) in the total number of publications in all nine subareas of research for country i (out of n considered countries) in year t. Then we can define correlation using the following equation:

$$\text{Corr}_{k,m}^i(t) = \frac{\sum_{i=1}^n \text{share}_k^i(t) \times \text{share}_m^i(t))}{\sqrt{\sum_{i=1}^n \left(\text{share}_k^i(t)\right)^2 \times \sum_{i=1}^n \left(\text{share}_m^i(t)\right)^2}} \tag{1}$$

According to (1), the correlation of a subarea with itself will be equal to 1. Now we would like to introduce a measure of research specialization for each country i in year t:

$$\text{Spec}_{\text{dir}}^i(t) = \sum_{k=1,m=1}^{9} \text{Corr}_{k,m}^i(t) \times \text{share}_k^i(t) \times \text{share}_m^i(t) \tag{2}$$

[3] More information about Scopus database and SciVal is available here: https://www.scopus.com/home.uri?zone=header&origin=searchbasic https://www.scival.com/benchmarking/analyse https://www.elsevier.com/solutions/scival.

[4] Information about the use of ASJC—All Science Journal Classification in Scopus is available on http://ebrp.elsevier.com/pdf/Scopus_Custom_Data_Documentation_v4.pdf.

The higher $\mathrm{Spec}^{i}_{\mathrm{dir}}(t)$ is, the more specialized is country i in year t in agricultural science. For comparability, the index of specialization could be normalized (see, for example Stare and Kejžar 2014). Since we believe that diversification is important for the development of agriculture, we introduce a normalized inverse parameter:

$$\mathrm{DIVERSIF\_ADV\_REV}^{i}_{\mathrm{dir}}(t) = 1 - \frac{\mathrm{Spec}^{i}_{\mathrm{dir}}(t)}{\mathrm{Max}_{i}\left(\mathrm{Spec}^{i}_{\mathrm{dir}}(t)\right)} \tag{3}$$

We are ready to formulate our main hypothesis.

Main Hypothesis The research diversification as expressed by (3) is related to agricultural productivity.

According to Huffman and Evenson (2006) research diversification may impact agricultural productivity nonlinearly. Narrow agricultural research specialization is not adequate to trends of globalization and collaboration mentioned in the introduction. At the same time dissipation of research resources may not be optimal for development of agricultural sector. That is why we assume that the relationship between research diversification and agricultural productivity could be nonlinear, and included the square root of the indicator (3) (DIVERSIF_ADV_REV_SQRT) in the model as well.

Clearly country's research diversification cannot explicitly explain shifts in agricultural productivity. Following extensive literature (e.g. Eberhardt and Vollrath 2016; Huang 2016) we included a list of other features of the scientific landscape as well as economic variables for each country of our analysis. To control for the quality of publications of a given country, we considered the AGRIC_PUB_FIELD_WEIGHT Field-Weighted Citation Impact (FWCI) of publications for Agricultural sciences derived from SciVal Scopus.[5] The indicator is calculated as "the ratio of citations received relative to the expected world average for the subject field, publication type and publication year" in SciVal (See "Scival metrics guidebook" for more detailed information on this indicator[6]). The higher the value of this indicator, the higher is the general level of citations of publications of a given country in comparison with the global level of citation. The FWCI indicator is actively used in bibliometric studies (see e.g. Bornmann and Leydesdorff 2013; Khor and Yu 2015; Rasolabadi et al. 2015; Halevi et al. 2016). Collaboration could be of great importance for research performance as shown by Abbasi and Jaafari (2013); Zhou et al. (2013) and Payumo and Sutton (2015). That is why we considered a parameter, AGRIC_PUB_INT_COLLAB, the share of publications written with international collaboration (i.e., at least two different countries are identified as the affiliation of the authors of a given publication). This collaboration parameter is derived from SciVal (it is called there: "The extent of international co-authorship"). The higher this indicator, the more actively a country is involved in international scientific collaboration. We calculated this parameter for the "Agricultural sciences" category as well.

To control for the country's role in global agricultural science, we included the share of the country's publications in total publications on agricultural science in the Scopus database (AGRIC_PUB_SHARE_WORLD). This parameter was calculated based on publications in all nine subfields of agricultural science.

[5] Information on all Indicators used in 'SciVal Benchmarking" is available on the following link https://www.scival.com/help/index.html.

[6] SciVal metrics guidebook is available through this link: https://www.elsevier.com/research-intelligence/resource-library/scival-metrics-guidebook.

Parameters of the scientific landscape cannot describe STI performance. Performance also depends on country-specific economic and agricultural conditions. That is why we decided to include several other variables in our analysis.

To account for differences in the fertility of soils, we included a natural logarithm of cereal yield (CEREAL_YIELD_LN) in the regression models. The indicator is obtained from the World Bank Database as well. According to the World Bank's methodology, cereal yield is measured as kilograms per hectare of harvested land.[7]

Extensive literature (Monreal-Pérez et al. 2012, Hart et al. 2015; Cirera et al. 2015) shows that trade is closely related to innovation and may impact productivity in the agricultural sector as well (Masso and Vahter 2015). We used a trade parameter (TRADE_FOOD_EXP_IMP), which is calculated based on the exports and imports of food products. The higher this indicator, the higher is the export potential of the country in the trade of food. We express the export potential of each country in each year in the following way:

$$\text{Food export potential}_{\text{year}_t}^{\text{country}\,i} = \frac{\text{Food exp}_t^i - \text{Food imp}_t^i}{\text{Food exp}_t^i + \text{Food imp}_t^i} \tag{4}$$

Countries with positive export potential indicators are net exporters of food, while countries with negative values of these indicators are net importers. Normalizing the value of (4) we obtain:

$$\begin{aligned} &\text{TRADE\_FOOD\_EXP\_IMP}_t^i \\ &\quad = \frac{\text{Food export potential}_t^i - \text{Min}_{i=1}^n\left(\text{Food export potential}_t^i\right)}{\text{Max}_{i=1}^n\left(\text{Food export potential}_t^i\right) - \text{Min}_{i=1}^n\left(\text{Food export potential}_t^i\right)} \end{aligned} \tag{5}$$

Values for exports and imports were derived from the World Bank Database. According to World Bank's methodology, "Food comprises the commodities in SITC (Standard International Trade Classification) sections: 0 (food and live animals), 1 (beverages and tobacco), and 4 (animal and vegetable oils and fats) and SITC division 22 (oil seeds, oil nuts, and oil kernels)".[8]

Bas and Strauss-Kahn (2014) considered agricultural raw materials as an important input in their model. We also used a separate parameter of trade in agricultural raw materials (TRADE_RAWMAT_EXP_IMP). It is calculated in a manner similar to (4), based on export and import values:

$$\text{Agr.raw mat.export potential}_{\text{year}_t}^{\text{country}\,i} = \frac{\text{Agr.raw mat.exp}_t^i - \text{Agr.raw mat.imp}_t^i}{\text{Agr.raw mat.exp}_t^i + \text{Agr.raw mat.imp}_t^i} \tag{6}$$

The higher the indicator, the higher is the export potential of the country in the trade of agricultural raw materials. The values for the export and import of agriculture raw

[7] Information on this indicator is available at: http://data.worldbank.org/indicator/AG.YLD.CREL.KG?view=chart.

[8] Information on the indicator "Food exports (% of merchandise exports)" is available here: http://data.worldbank.org/indicator/TX.VAL.FOOD.ZS.UN?view=chart. Information on the indicator "Food imports (% of merchandise imports)" is available here: http://data.worldbank.org/indicator/TM.VAL.FOOD.ZS.UN?view=chart.

materials were derived from the World Bank Database.[9] Countries with positive values for these indicators are net exporters of agricultural raw materials, while countries with negative values for this indicator are net importers. Similar to (5), we normalized the indicator (6) in the following way (7):

$$\begin{aligned}&\mathrm{TRADE\_RAWMAT\_EXP\_IMP}_t^i\\&=\frac{\text{Agr.raw mat.export potential}_t^i-\mathrm{Min}_{i=1}^n\left(\text{Agr.raw mat.export potential}_t^i\right)}{\mathrm{Max}_{i=1}^n\left(\text{Agr.raw mat.export potential}_t^i\right)-\mathrm{Min}_{i=1}^n\left(\text{Agr.raw mat.export potential}_t^i\right)}\end{aligned}\tag{7}$$

The diversification of agricultural production can be also an important determinant of productivity as shown by a number of studies (Barnes et al. 2015; Poláková et al. 2016). We constructed a diversification measure using production indexes to capture the growth dynamics of agricultural subsectors. The important role of production indexes for agriculture is described in Gerssen-Gondelach et al. (2015). The crop production index (PROD_IND_CROP), food production index (PROD_IND_FOOD) and livestock production index (PROD_IND_LIVESTOCK) were considered and their values were taken from the World Bank's database.[10] We used a proxy for agricultural diversification (DIVERSIF_PROD_IND), which was calculated using production indexes of all three agricultural subsectors—food, crop and livestock. The similar values of these indicators correspond to similar growth levels for all three agricultural subsectors which means that agriculture in the country is developing in several areas. The diversification proxy is measured as follows:

$$\begin{aligned}&\mathrm{DIVERSIF\_PROD\_IND}_{\mathrm{country}j}^{\mathrm{year}t}\\&=1-\sqrt{\left(\frac{\text{Prod ind crop}_j^t}{\mathrm{Max}_n\left(\text{Prod ind}_{nj}^t\right)}\right)^2+\left(\frac{\text{Prod ind food}_j^t}{\mathrm{Max}_n\left(\text{Prod ind}_{nj}^t\right)}\right)^2+\left(\frac{\text{Prod ind livestock}_j^t}{\mathrm{Max}_n\left(\text{Prod ind}_{nj}^t\right)}\right)^2}\end{aligned}\tag{8}$$

Combining all considered variables, we constructed the panel regression model for 75 countries over an 18-year period (9):

$$\begin{aligned}\text{Productivity}_{it}=&\ \text{const}+f_{it}(\text{Scientific landscape parameters})+g_{it}(\text{economic parameters})\\&+g_{it}(\text{agriculture parameters})+\text{Error\_term}_{it}\end{aligned}\tag{9}$$

Results

We start with preliminary analysis via correlation matrix of variables of the model (9). Table 1 demonstrates that the majority of the correlation coefficients are quite low.

[9] Information on the indicator "Agricultural raw materials exports (% of merchandise exports)" is available here: http://data.worldbank.org/indicator/TX.VAL.AGRI.ZS.UN?view=chart. Information on the indicator "Agricultural raw materials imports (% of merchandise imports)" is available here: http://data.worldbank.org/indicator/TM.VAL.AGRI.ZS.UN?view=chart.

[10] Information on this indicator can be found here: http://data.worldbank.org/indicator/AG.PRD.CROP.XD?view=chart.

Table 1 Correlation matrix of variables of the model (9)

Correlation matrix	AGR_VAL_AD_PER_HECT_LN	AGR_VAL_AD_PER_WORK_LN	DIVERSIF_ADV_REV_SQRT	AGRIC_PUB_FIELD_WEIGHT	AGRIC_PUB_INT_COLLAB	AGRIC_PUB_SHARE_WORLD
AGR_VAL_AD_PER_HECT_LN	1.000					
AGR_VAL_AD_PER_WORK_LN	0.354	1.000				
DIVERSIF_ADV_REV_SQRT	0.072	0.382	1.000			
AGRIC_PUB_FIELD_WEIGHT	0.232	0.491	0.196	1.000		
AGRIC_PUB_INT_COLLAB	− 0.029	− 0.345	− 0.096	0.325	1.000	
AGRIC_PUB_SHARE_WORLD	− 0.029	0.336	0.066	0.244	− 0.311	1.000
AGRIC_VAL_AD_SHARE_WORLD	0.039	− 0.108	− 0.054	− 0.075	− 0.298	0.534
TRADE_FOOD_EXP_IMP	− 0.170	− 0.125	− 0.001	0.185	0.217	0.011
TRADE_RAWMAT_EXP_IMP	− 0.196	− 0.040	− 0.015	0.204	0.248	− 0.060
CEREAL_YIELD_LN	0.518	0.559	0.302	0.373	− 0.192	0.298
DIVERSIF_PROD_IND	0.252	0.082	− 0.003	0.188	− 0.021	0.168

Correlation matrix	AGRIC_VAL_AD_SHARE_WORLD	TRADE_FOOD_EXP_IMP	TRADE_RAWMAT_EXP_IMP	CEREAL_YIELD_LN	DIVERSIF_PROD_IND
AGR_VAL_AD_PER_HECT_LN					
AGR_VAL_AD_PER_WORK_LN					
DIVERSIF_ADV_REV_SQRT					
AGRIC_PUB_FIELD_WEIGHT					
AGRIC_PUB_INT_COLLAB					
AGRIC_PUB_SHARE_WORLD					
AGRIC_VAL_AD_SHARE_WORLD	1.000				
TRADE_FOOD_EXP_IMP	0.006	1.000			
TRADE_RAWMAT_EXP_IMP	− 0.181	0.508	1.000		

Table 1 continued

Correlation matrix	AGRIC_VAL_AD_ SHARE_WORLD	TRADE_FOOD_ EXP_IMP	TRADE_RAWMAT_ EXP_IMP	CEREAL_ YIELD_LN	DIVERSIF_ PROD_IND
CEREAL_YIELD_LN	0.144	0.031	− 0.125	1.000	
DIVERSIF_PROD_IND	0.166	0.009	0.005	0.259	1.000

Correlations are calculated for the period 1996–2013 for 75 countries. Both dependent and independent variables in different specifications of the model (9) are included in correlations analysis

Table 2 Variance inflation factors of independent variables for specifications of (9) with dependent variables AGR_VAL_AD_PER_WORK_LN and AGR_VAL_AD_PER_HECT_LN

Independent variables	AGR_VAL_AD_PER_WORK_LN	AGR_VAL_AD_PER_HECT_LN
DIVERSIF_ADV_REV_SQRT	1.14	1.16
AGRIC_PUB_FIELD_WEIGHT	1.75	1.78
AGRIC_PUB_INT_COLLAB	1.57	1.57
AGRIC_PUB_SHARE_WORLD	1.78	1.91
AGRIC_VAL_AD_SHARE_WORLD	1.59	1.60
TRADE_FOOD_EXP_IMP	1.5	1.51
TRADE_RAWMAT_EXP_IMP	1.42	1.47
CEREAL_YIELD_LN	1.52	1.98
DIVERSIF_PROD_IND	1.12	1.14

For both specifications VIF is calculated for the pooled data of 75 countries for 1996–2013

We ran different specifications of the model (9) for agricultural productivity with two choices of a dependent variable: log value added per worker, log value added per hectare. Acording to the VIF test (Table 2) there are no multicollinearity issues has been detected between independent variables in specifications of the model which allows to apply empirical tests to (9) further.

Several specifications of the model (9) were included in the analysis which allow to check the robustness of the results (Table 3). According to Wald, Breusch-Pagan and Hausman tests specifications with fixed effects were preferable for the Models 1 with log value added per hectare as independent variable and for the Model 2 with log value added per worker as independent variable. The result can be explained by stability of some country specific characteristics over time.

For all specifications of the model we discovered a nonlinear relationship between the productivity and publications diversification. We obtained the high level of significance for both the diversification parameter and its square root, which resulted in the inverted U-shape form of their relationship to agricultural productivity. According to the coefficients from Table 3, we can conclude that the highest point of agricultural productivity will be reached when research diversification (DIVERSIF_ADV_REV_SQRT) equals its optimal value of approximately 0.6. When diversification grows, agricultural productivity rises to its optimal value, above which it is decreasing.

Hence the agricultural sector is less productive in both cases: when a country is extremely concentrated in one area of agricultural science and when its research is extremely diversified. Figure 1 show values of agricultural productivity against publication diversification for selected countries and reveal that diversification in many countries is much greater than optimal.

Annual diversification levels in Israel are distributed around the optimal value. The diversification of agriculture science in the USA is generally greater than 0.60, which exceeds the optimal level. US government bodies (OSTP (Office of Science and Technology Policy), DOA (Department Of Agriculture), NSF (National Science Foundation)) may support the diversification of agricultural science, this can be concluded from the high level of expenditures on innovations in agriculture, this in turn provides eventual food independence for the country and leadership on the world markets (Diakosavvas 2011).

Table 3 Panel regression of agricultural productivity according to Eq. (9)

Model type	Model 1 dependent variable AGR_VAL_AD_PER_HECT_LN			Model 2 dependent variable AGR_VAL_AD_PER_WORK_LN		
	Pooled	Fixed Eff.	Random eff.	Pooled	Fixed eff.	Random eff.
Constant	− 2.268***	− 2.940***	− 3.643***	− 4.203***	3.009***	2.734***
Scientific diversification variables						
DIVERSIF_ADV_REV	− 2.908***	− 4.519***	− 3.913***	− 0.813	− 0.600***	− 0.572***
DIVERSIF_ADV_REV_SQRT	1.919***	3.090***	2.541***	2.635***	0.453***	0.465***
Other scientific variables						
AGRIC_PUB_FIELD_WEIGHT	0.408***	0.466***	0.431***	1.968***	0.219***	0.261***
AGRIC_PUB_INT_COLLAB	0.0003	0.001	− 0.003	− 0.037***	0.005***	0.005***
AGRIC_PUB_SHARE_WORLD	− 0.090***	− 0.093***	− 0.073***	0.080***	− 0.003	0.011
Economic variables						
AGRIC_VAL_AD_SHARE_WORLD	0.029***	0.033***	0.034***	− 0.163***	0.027***	0.017***
TRADE_FOOD_EXP_IMP	− 0.826***	− 0.951***	− 1.021***	− 0.964***	0.097	0.039
TRADE_RAWMAT_EXP_IMP	− 0.260**	− 0.173*	− 0.145*	− 0.237**	− 0.267***	− 0.283***
Agriculture specific variables						
CEREAL_YIELD_LN	0.943***	0.983***	0.354***	0.722***	0.618***	0.656***
DIVERSIF_PROD_IND	1.566***	1.682***	1.574***	− 1.347***	− 0.097	− 0.116
Model specification test						
Tests	Wald test	Hausman test	Bruesch− Pagan test	Wald test	Hausman test	Bruesch− Pagan test
Test statistics	315.62	5603.26	8455.95	387.32	150.98	6145.91
P value	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Significance of independent variables is marked as follows: *significant at 10% level; **significant at 5%; ***significant at 1%. For all specifications of models: sample period is 1996- 013; 75 countries in the sample. The Wald test showed preference of the fixed effect model over the pooled model in specifications with both dependent variables (Models 1, 2). The Hausman test showed preference of fixed effect model over random effect model in specifications with both dependent variables (Models 1, 2). The Bruesch–Pagan test showed preference of random effect model over pooled model in specifications with both dependent variables (Models 1, 2). All tests were ran in Stata software

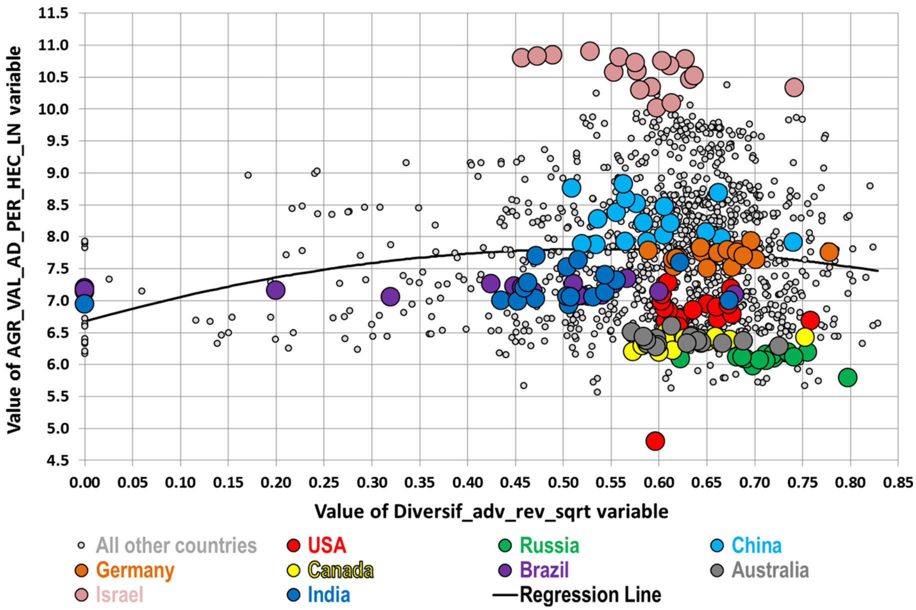

Fig. 1 The relationship between agriculture productivity (AGR_VAL_AD_PER_HECT_LN) and the diversification of agricultural science (DIVERSIF_ADV_REV and DIVERSIF_ADV_REV_SQRT). Note: each bubble represents data on agriculture productivity (AGR_VAL_AD_PER_HECT_LN) and the diversification of agricultural science (DIVERSIF_ADV_REV and DIVERSIF_ADV_REV_SQRT) in a given country for each year from 1996 to 2013 *Source*: authors' calculations from Scopus SciVal Benchmarking toolbox and World Bank data. (Color figure online)

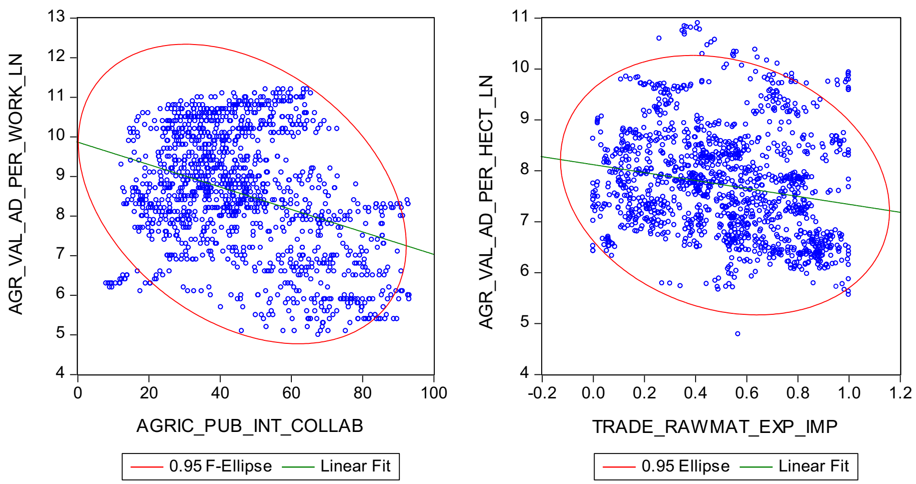

Fig. 2 Illustration of regression (9) results: relationship between agricultural productivity and the rate of research collaboration; Agricultural productivity and normalized food export potential *Source*: authors' calculations in Eviews software from scopus SciVal Benchmarking toolbox and World Bank data

Moreover, the Department of Agriculture's Cooperative State Research, Education, and Extension Service (CSREES) used to apply a portfolio approach to assess the performance of diversified research in agriculture (Ruegg 2007). It seems that since USA is a leader in science and productivity, many countries try to copy the USA's diversified scientific landscape. However, if we look at the data on diversification ("Appendix 1"), we may conclude that most countries (especially developed ones) tend to decrease their research diversification in agricultural science over time.

Other characteristics of the scientific landscape, which include research performance, play an important role in explaining agricultural productivity (see Table 3). The positive and significant regression coefficient besides AGRIC_PUB_FIELD_WEIGHT in both specifications allows us to conclude that the higher quality of publications measured by a field weighted citation index corresponds to higher productivity of the agricultural sector. The highest levels of relative citation indexes were detected in developed OECD countries like Denmark, the Netherlands, Sweden and Switzerland. A negative relationship between productivity per worker and the country's share in global agricultural publications could be an interesting characteristic of the scientific landscape. Either countries that specialize in agricultural research are lagging in other areas (for example agricultural machinery), which resulted in lower productivity levels or it is a general characteristic of overall poor countries with a low level of research expenditures.

There are two types of countries that can be highlighted in Fig. 2. For the first type of countries, international research collaboration provides a positive synergetic effect. Those countries usually have relatively high research potential and globally recognized research groups that successfully collaborate amongst themselves following open innovation and other progressive research models. However, the level of collaboration is usually limited because such research groups are generally able to produce their own high quality research publications. Observations for those countries are placed in the upper left corner of the Fig. 2. At the same time, there are countries with low levels of research financing and education that are unable to publish internationally recognized research. For these countries, extensive international collaboration could be explained by inability of country's researchers to independently provide high quality publications without help from abroad (Rivera-Huerta et al. 2011). Ecuador, Panama, Tanzania, Uganda, Burma, etc. are known to be highly dependent on collaboration with the US, China and countries of the European Union. Observations for these countries are placed in the lower right corner of Fig. 2.

As for economic control variables we can see from Table 3 that they significantly impact agricultural productivity. Figure 2 shows a negative correlation between the log of productivity and normalized net exports of raw agricultural materials in observed countries for the period. Similar conclusions follow from the negative regression coefficient in Tables 1 for normalized food exports. The result is somewhere confusing. There are countries for which low agricultural exports could be accompanied by high productivity. At the same time, observations and regression results show that some countries with higher net exports demonstrate a low level of productivity. This fact could be a result of low labour costs in the agricultural sector for those countries, which makes their food exports competitive despite the low level of productivity and possibly modest research expenditures.

Coefficients beside DIVERSIF_PROD_IND in Table 3 have more significant impact on the productivity per hectare. Countries with large arable land and low productivity per hectare could exhibit high crop production growth fuelled by technological developments along with similar growth in livestock and food production, which also results in higher values of DIVERSIF_PROD_IND. The fertility of the soil measured by cereal yield clearly has a positive relationship with the productivity of the agricultural sector.

R&D funding of agricultural science and implications for research policy in Russia

To conduct further analysis, we looked at GERD on agricultural science and compared it to the data on the diversification of agricultural science. We used the same parameter for the diversification of agricultural science as above. Regretfully we could find only a limited dataset on GERD on agricultural science in several countries and for several periods. That is why we could not run a panel regression with this parameter. Expenditure data was obtained from OECD.stat database (section “Science and technology Indicators”) and UNESCO Institute for Statistics (UIS) database (section “Science, Technology and Innovation”). The dataset depends heavily on the quality of a country’s GERD reports. Some countries publish only GERD in agricultural science for the government and educational sector while others publish this parameter for all sectors including business expenditures. We assume that the structure of expenditures directed to different areas of science in each sector is similar to that of the entire country’s spending. Based on this assumption, we decided to develop a R&D funding index that allows us to compare different countries:

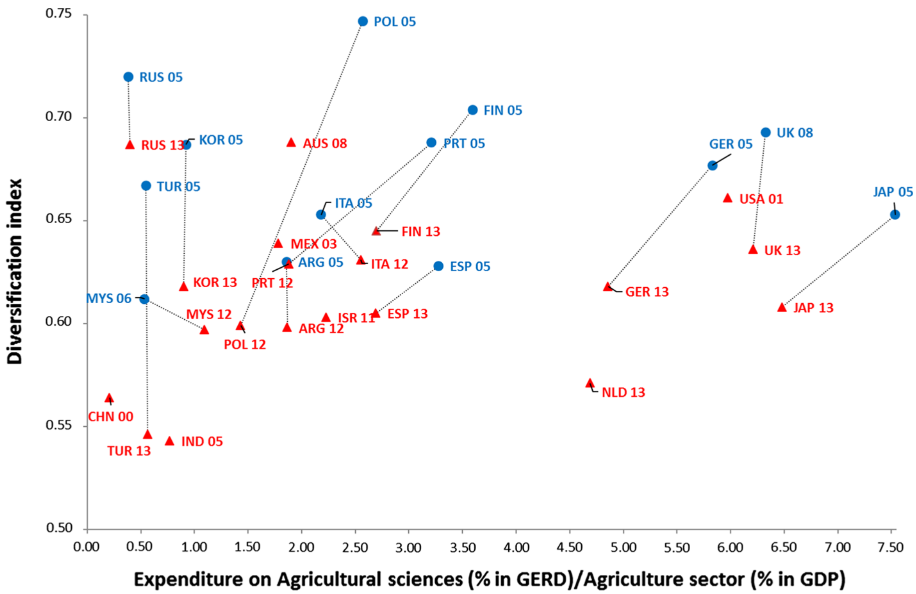

Fig. 3 Research diversification versus R&D funding index of agricultural science for selected countries and years. Note: A blue color dot denotes the earlier year’s position of the selected countries determined by research diversification and R&D funding in agricultural science. The corresponding red triangle denotes a position in later years. Because of gaps in the dataset, the illustrated values are taken for different years. Source: authors’ calculations from OECD.stat database (section “Science, Technology and Patents”) and UNESCO Institute for Statistics database (section “Science, Technology and Innovation”). (Color figure online)

$$\text{R\&D funding index} = \frac{\text{Expenditure on agricultural science as \%of countries GERD in reported sectors}}{\text{Agriculture sector in GDP in \%}} \quad (10)$$

The Fig. 3 shows the plot of research diversification and R&D funding index of agricultural science. There is evidence that research diversification in many countries has tended to decrease over last several years. R&D expenditures also decreased in many countries. Developed countries are located generally on the right side of the plot with generally higher R&D funding index values compared to developing countries. However, the trend on contracting research diversification and R&D expenditures could be even clearer for Japan and European leading economies.

We evaluated approaches to R&D using the interesting example of the Russian Federation, which plays an important role on agricultural markets and tries to catch up with research leaders. The choice of Russia was also justified by the higher diversification of agricultural research compared to other countries including the US, and at the same time, Russia has a very low level of R&D funding (Russia is in the left upper corner of Fig. 3). Such characteristics of STI policy in Russia were likely inherited from the USSR. The number of agricultural research institutes has not decreased since the USSR collapsed, and the structure of those institutions has not changed. Today, R&D financing is very low in Russia compared not only to developed countries but also to most of developing economies

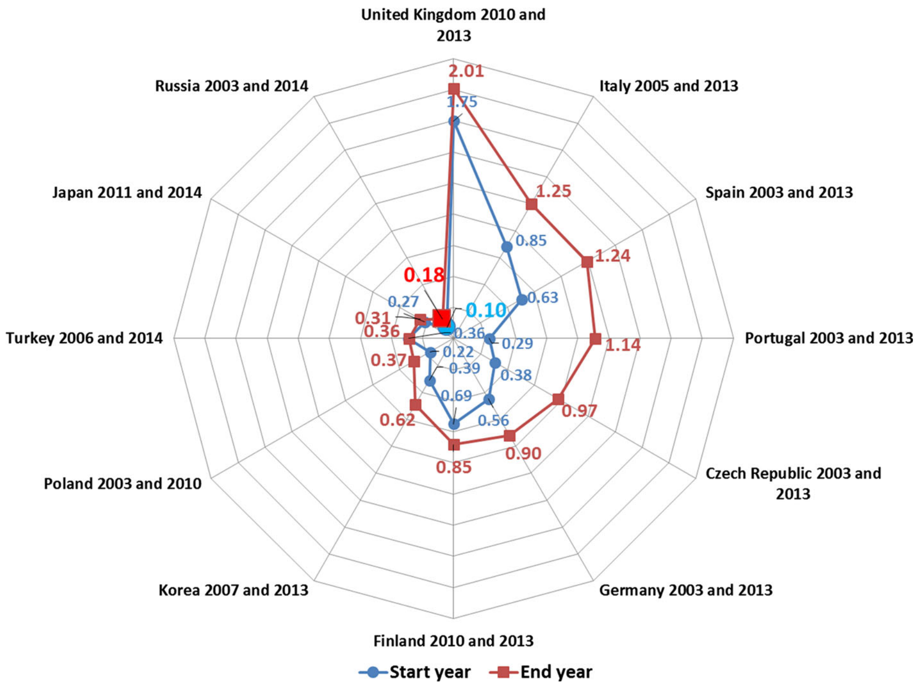

Fig. 4 Dynamics of publications in agricultural sciences per one researcher (government and higher education sectors) in selected countries and years *Source*: authors' calculations from OECD.stat database (section "Science, Technology and Patents")

("Appendix 2"). The Russian government supports the agricultural sector directing the amount equivalent to 0.3% of GDP each year toward the Agricultural Development Program[11] which is 10 times more than agricultural R&D expenditure. Extremely low R&D expenditures can be explained by the extensive import of technologies. However, despite the small R&D budget, the financing of agricultural science is very diversified according to Fig. 1, which negatively impacts agricultural productivity.

Agricultural science in Russia also suffers from high diversification. Figure 4 shows that publications per researcher in Russia remain among the lowest in the world over time. Despite low R&D funding in agricultural science, the publications per 1 mln $ of GERD PPP in the government and higher education sectors in Russia decreased over a 10-year period and stayed well below levels of many other countries (see "Appendix 3" for details).

We can observe that agricultural science in Russia is not performing well because of wide diversification, management shortcomings and a lack of funding. That is why urgent decisions in agricultural research policy are required.

Conclusion

Based on statistical inference from the panel dataset of 75 countries over 18 years, we may conclude that agricultural productivity may be also related to the level of research diversification determined by the publications in agricultural science. Moreover, the functional form of the dependence is an inverted U-shape. Using the functional form of dependence, we can determine the optimal level of research diversification. The result is robust. It is interesting that agricultural productivity also depends on other parameters of the scientific landscape in a country. Citations, research collaboration and a share in global publications in agricultural science affect agricultural productivity. The addition of economic variables to a regression and the consideration of two model specifications with productivity measured as a logarithm of value added per hectare and per worker does not detract from the significance of research diversification.

Our key finding is that countries with greatly diversified publication activity in areas of agricultural science accompanied by relatively low R&D expenditures were shown to exhibit lower productivity growth in the agricultural sector. This could be one of reasons why the diversification of agricultural science is decreasing in most countries (especially in developed ones). In Israel, the optimal balance between research specialization and diversification accompanied by relatively large R&D funding resulted in the highest values of productivity in agriculture. Hence national STI policy in agricultural sector should be coordinated carefully to avoid extensively diversified research directions setting.

Our findings are subject to certain limitations and further research is necessary to obtain definitive conclusions. The Scopus database does not cover all domestic journals, especially those published in national languages, which may bias the research diversification effect as well as the impact of other characteristics of the scientific landscape (citations and number of publications). Data limitations may cause model misspecifications and do not allow for measuring the effect of some other economic factors including GERD on productivity. Examples of such analysis on the country level can be found in Jin and Huffman (2016) or Zhang et al. (2015). Moreover, the relationship between commercial and public

[11] The program is available here http://mcx.ru/activity/state-support/programs/program-2013-2020/ (Russian version).

R&D funding was out of the scope of this paper, but this could play an important role in research and economic output (Muscio et al. 2017). The macro level study could be extended with an analysis of the performance of agricultural firms in different countries.

Despite the limitations, the study may be interesting for agricultural STI policymakers. More specifically in the Russian agricultural sector, we observed low R&D expenditures and broadly diversified research objectives. The recent performance of Russian agricultural science has been very poor and agricultural productivity remains low compared to developed countries. According to results of our study, STI policy in Russia may be adjusted to ensure more focused agricultural R&D. Our findings suggest that if carefully specialized, agricultural R&D could perform significantly better and would help continue the competitive development of Russian agricultural sector.

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Appendix 1

See Table 4.

Table 4 Diversification of agricultural science (DIVERSIF_ADV_REV and DIVERSIF_ADV_REV_SQRT) in selected countries from 2005 to 2013 *Source*: authors' calculations from Scopus SciVal Benchmarking toolbox

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013
Algeria	0.659	0.618	0.601	0.640	0.649	0.640	0.674	0.623	0.589
Argentina	0.630	0.538	0.587	0.664	0.597	0.591	0.673	0.598	0.597
Australia	0.640	0.587	0.597	0.688	0.629	0.586	0.666	0.587	0.584
Austria	0.656	0.667	0.639	0.676	0.638	0.637	0.694	0.644	0.639
Belgium	0.630	0.570	0.588	0.663	0.628	0.550	0.677	0.602	0.583
Brazil	0.540	0.319	0.000	0.000	0.000	0.200	0.448	0.457	0.425
Bulgaria	0.659	0.614	0.620	0.642	0.649	0.450	0.652	0.398	0.549
Canada	0.644	0.601	0.614	0.663	0.600	0.572	0.659	0.582	0.583
Chile	0.641	0.464	0.531	0.611	0.578	0.530	0.640	0.594	0.604
China	0.612	0.536	0.556	0.606	0.577	0.565	0.662	0.509	0.563
Colombia	0.564	0.585	0.579	0.487	0.557	0.513	0.624	0.480	0.514
Cuba	0.688	0.639	0.684	0.600	0.669	0.604	0.694	0.631	0.638
Czech Republic	0.691	0.608	0.632	0.664	0.662	0.660	0.691	0.655	0.630
Denmark	0.609	0.575	0.583	0.635	0.588	0.486	0.632	0.528	0.567
Ecuador	0.719	0.700	0.542	0.733	0.737	0.688	0.696	0.645	0.585
Egypt	0.546	0.542	0.514	0.402	0.435	0.456	0.575	0.404	0.451
Estonia	0.716	0.647	0.665	0.706	0.690	0.628	0.741	0.659	0.641
Finland	0.704	0.671	0.661	0.715	0.675	0.647	0.690	0.658	0.645
France	0.657	0.615	0.636	0.693	0.657	0.622	0.705	0.634	0.624
Germany	0.677	0.616	0.621	0.682	0.650	0.615	0.688	0.615	0.618

Table 4 continued

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013
Greece	0.614	0.604	0.619	0.663	0.625	0.578	0.664	0.594	0.549
Hungary	0.664	0.593	0.688	0.722	0.664	0.638	0.749	0.674	0.645
India	0.543	0.459	0.463	0.556	0.544	0.504	0.621	0.515	0.472
Ireland	0.607	0.532	0.547	0.589	0.605	0.585	0.657	0.613	0.592
Israel	0.628	0.558	0.575	0.611	0.528	0.457	0.603	0.489	0.473
Italy	0.653	0.612	0.639	0.684	0.679	0.591	0.678	0.615	0.631
Japan	0.653	0.607	0.635	0.685	0.627	0.602	0.676	0.623	0.608
Latvia	0.747	0.634	0.723	0.772	0.739	0.753	0.770	0.740	0.732
Malaysia	0.657	0.612	0.599	0.621	0.632	0.597	0.671	0.597	0.534
Netherlands	0.655	0.619	0.587	0.664	0.653	0.605	0.674	0.599	0.571
New Zealand	0.663	0.595	0.576	0.623	0.524	0.521	0.617	0.528	0.535
Norway	0.676	0.626	0.668	0.718	0.695	0.661	0.721	0.677	0.673
Philippines	0.538	0.479	0.451	0.447	0.464	0.217	0.510	0.349	0.292
Poland	0.747	0.724	0.699	0.710	0.622	0.593	0.642	0.599	0.609
Portugal	0.688	0.617	0.629	0.694	0.663	0.647	0.702	0.629	0.635
Romania	0.711	0.734	0.738	0.727	0.634	0.574	0.711	0.647	0.616
Russia	0.720	0.690	0.719	0.755	0.735	0.712	0.741	0.705	0.687
Slovakia	0.672	0.680	0.570	0.617	0.604	0.562	0.634	0.516	0.440
Slovenia	0.704	0.580	0.624	0.661	0.674	0.631	0.706	0.648	0.602
South Africa	0.667	0.613	0.652	0.682	0.654	0.626	0.668	0.605	0.605
South Korea	0.687	0.623	0.649	0.699	0.674	0.627	0.695	0.633	0.618
Spain	0.628	0.591	0.604	0.656	0.622	0.591	0.668	0.610	0.605
Sweden	0.677	0.608	0.648	0.691	0.653	0.621	0.696	0.635	0.624
Switzerland	0.654	0.612	0.636	0.672	0.654	0.648	0.697	0.560	0.587
Thailand	0.668	0.597	0.605	0.656	0.609	0.626	0.637	0.572	0.548
Tunisia	0.506	0.491	0.542	0.604	0.582	0.550	0.649	0.597	0.543
Turkey	0.667	0.597	0.619	0.620	0.552	0.531	0.635	0.556	0.546
Ukraine	0.640	0.607	0.708	0.712	0.752	0.703	0.757	0.680	0.692
United Kingdom	0.660	0.635	0.645	0.693	0.667	0.625	0.694	0.631	0.636
United States	0.660	0.610	0.606	0.673	0.636	0.603	0.675	0.603	0.609
Uruguay	0.713	0.506	0.587	0.630	0.527	0.512	0.652	0.563	0.579
Venezuela	0.697	0.651	0.566	0.599	0.492	0.171	0.487	0.240	0.243

Appendix 2

See Table 5.

Table 5 Expenditure on agricultural science as % of GERD in reported sectors divided by agricultural sector's share in GDP, % *Source*: authors' calculations form OECD.stat database (section "Science and technology Indicators") http://stats.oecd.org and UNESCO Institute for Statistics (UIS) Science, Technology and Innovation (full dataset) http://data.uis.unesco.org/Index.aspx?DataSetCode=EDULIT_DS

Country	Sectors for which data on R&D expenditures by fields of science is available*	2005	2006	2007	2008	2009	2010	2011	2012	2013
Argentina	All sectors	1.86	2.25	1.75	2.17	2.26	1.42	1.51	1.87	
Australia	All sectors		2.15		1.90					
Belgium	Gov and education	10.20	7.87	8.61	11.7	13.54	11.71	13.80	13.05	14.45
Canada	All sectors								1.28	1.29
Chile	All sectors			4.17	3.78	2.92	2.86	4.69	4.76	
China	Gov and education	0.44	0.47	0.48	0.48	0.50	0.50	0.50	0.50	0.50
Czech Rep.	All sectors	1.88	1.88	1.84	1.88	2.31	2.20	1.49	1.26	
Denmark	Gov, education and non profit	6.67	5.77	7.61		9.91	6.19	5.02	4.12	4.49
Estonia	All sectors	1.34	1.20	1.13	1.17	1.39	1.03	0.82	0.60	1.14
Finland	Gov and education	3.59	4.06	3.48	3.69	3.39	3.33	3.41	3.09	2.70
Germany	Gov and education	5.83	5.62	4.98	4.79	6.08	6.23	4.88	5.31	4.86
Iceland	Gov	6.03		6.46		4.35		0.53		0.76
India	All sectors	0.77								
Israel	Gov					1.85	2.12	2.23		
Italy	Gov, education, non profit	2.18	2.00	2.84	2.88	2.36	2.99	3.06	2.80	2.55
Japan	Gov, education, non profit	7.54	7.68	8.03	7.95	7.74	7.47	7.53	6.69	6.48
Latvia	All sectors	3.64	3.06	3.02	3.00	2.10	2.34	2.35		
Lithuania	All sectors	1.21	1.31	1.42	1.70	2.14	1.38	1.11	1.40	
Malaysia	All sectors		0.53		0.64	0.44	0.48	0.62	1.09	
Netherlands	All sectors							5.87	5.08	4.69
Norway	Gov and education	6.85		7.15		5.22		4.97		4.30
Poland	All sectors	2.57	2.93	2.15	2.45	2.21	2.60	2.18	1.43	
Portugal	All sectors	3.21	2.38	2.09	1.51	1.78	1.60	1.97	1.88	
Russia	All sectors	0.38	0.42	0.45	0.45	0.45	0.44	0.41	0.41	0.40
Singapore	All sectors	19.0	23.4	24.1	29.6	34.8	43.7	55.6	78.4	
South Africa	All sectors	3.08	2.64	2.30	1.74	2.31	2.47	3.06		
South Korea	All sectors	0.92	0.90	0.96	0.88	0.93	1.01	0.91	0.85	0.90
Spain	Gov, education, non profit	3.27	2.76	2.82	3.34	3.91	3.40	2.97	3.05	2.69
Sweden	Education	4.40	3.74	3.05		2.94		2.66		2.79
Switzerland	Education				2.03				3.93	
Turkey	All sectors	0.55	0.62	0.61	0.64	0.65	0.54	0.56	0.58	0.56
Ukraine	All sectors	0.57		0.86		0.80		0.67		0.56
UK	Gov and education				6.33	7.24	6.00	5.77	5.88	6.21

Table 5 continued

Country	Sectors for which data on R&D expenditures by fields of science is available*	2005	2006	2007	2008	2009	2010	2011	2012	2013
United States	Education	4.98	5.35	4.98	4.46	4.64	3.94	3.18	3.16	2.65

"All sectors" include business enterprises, government, higher education and private non-profit; "gov"—government sector; "education"—higher education sector; "non profit"—private non-profit organizations

Appendix 3

See Fig. 5.

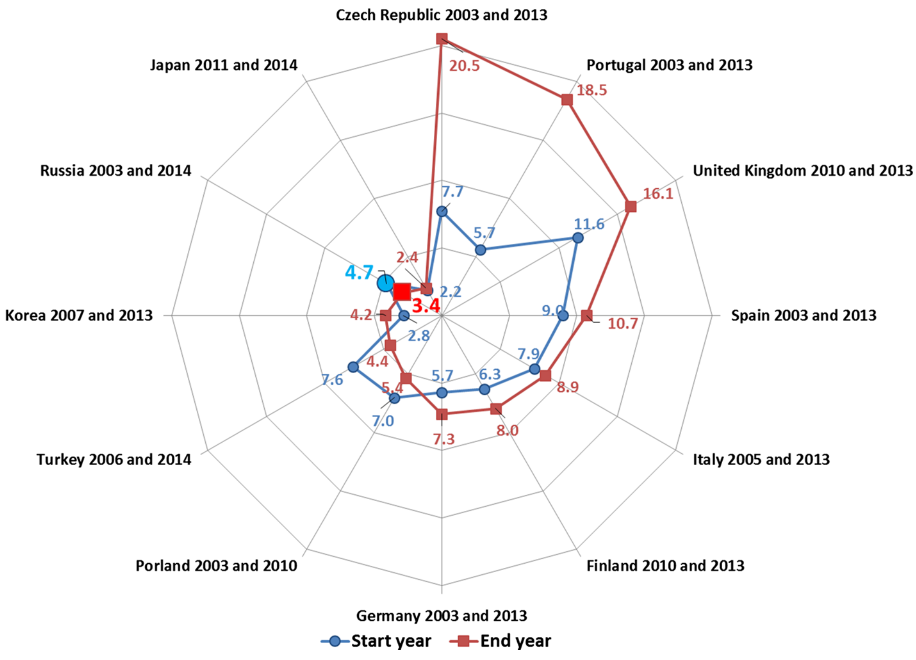

Fig. 5 Dynamics of publications on agricultural sciences per 1 mln USD of GERD PPP (government and higher education sectors) in selected countries and years *Source*: authors' calculations from OECD.stat database (section "Science, Technology and Patents")

References

Abbasi, A., & Jaafari, A. (2013). Research impact and scholars' geographical diversity. *Journal of Informetrics, 7,* 683–692. https://doi.org/10.1016/j.joi.2013.04.004.

Abramo, G., D'Angelo, C. A., & Di Costa, F. (2015). A new approach to measure the scientific strengths of territories. *Journal of the Association for Information Science and Technology, 66,* 1167–1177. https://doi.org/10.1002/asi.23257.

Alvarez-Cuadrado, F., & Poschke, M. (2011). Structural change out of agriculture: Labor push versus labor pull. *American Economic Journal: Macroeconomics, 3,* 127–158. https://doi.org/10.1257/mac.3.3.127.

Andersen, M. A. (2015). Public investment in U.S. agricultural R&D and the economic benefits. *Food Policy, 51,* 38–43. https://doi.org/10.1016/j.foodpol.2014.12.005.

Barnes, A. P., Hansson, H., Manevska-Tasevska, G., Shrestha, S. S., & Thomson, S. G. (2015). The influence of diversification on long-term viability of the agricultural sector. *Land Use Policy, 49,* 404–412. https://doi.org/10.1016/j.landusepol.2015.08.023.

Bartol, T., Budimir, G., Juznic, P., & Stopar, K. (2016). Mapping and classification of agriculture in web of science: Other subject categories and research fields may benefit. *Scientometrics, 109,* 979–996. https://doi.org/10.1007/s11192-016-2071-6.

Bas, M., & Strauss-Kahn, V. (2014). Does importing more inputs raise exports? Firm-level evidence from France. *Review of World Economics, 150*(2), 241–275.

Bigliardi, B., & Galati, F. (2013). Models of adoption of open innovation within the food industry. *Trends in Food Science & Technology, 30,* 16–26. https://doi.org/10.1016/j.tifs.2012.11.001.

Bornmann, L., & Leydesdorff, L. (2013). Macro-indicators of citation impacts of six prolific countries: Incites data and the statistical significance of trends. *PLoS ONE, 8*(2), e56768.

Cai, Y., Golub, A. A., & Hertel, T. W. (2017). Agricultural research spending must increase in light of future uncertainties. *Food Policy, 70,* 71–83.

Caviggioli, F. (2016). Technology fusion: Identification and analysis of the drivers of technology convergence using patent data. *Technovation, 55–56,* 22–32. https://doi.org/10.1016/j.technovation.2016.04.003.

Chavas, J.-P., & Cox, T. L. (1992). A nonparametric analysis of the influence of research on agricultural productivity. *American Journal of Agricultural Economics, 74*(3), 583–591.

Chen, J.-R., Chu, Y.-P., Ou, Y.-P., & Yang, C.-H. (2015). R&D specialization and manufacturing productivity growth: A cross-country study. *Japan and the World Economy, 34–35,* 33–43. https://doi.org/10.1016/j.japwor.2015.03.002.

Cincera, M., & Ravet, J. (2014). Globalisation, industrial diversification and productivity growth in large European R&D companies. *Journal of Productivity Analysis, 41,* 227–246. https://doi.org/10.1007/s11123-012-0315-x.

Cirera, X., Marin, A., & Markwald, R. (2015). Explaining export diversification through firm innovation decisions: The case of Brazil. *Research Policy, 44,* 1962–1973. https://doi.org/10.1016/j.respol.2015.06.004.

Colledge, L., & Verlinde, R. (2014). *SciVal metrics guidebook*. Amsterdam: Elsevier.

De Lucio, J. J., Herce, J. A., & Goicolea, A. (2002). The effects of externalities on productivity growth in Spanish industry. *Regional Science and Urban Economics, 32,* 241–258.

Diakosavvas, D. (2011). Evaluation of agricultural policy reforms in the United States, *OECD*. http://www.keepeek.com/Digital-Asset-Management/oecd/agriculture-and-food/evaluation-of-agricultural-policy-reforms-in-the-united-states_9789264096721-en#.WA9KwS2LSHs#page24. Accessed 6 June 2018.

Eberhardt, M., & Vollrath, D. (2016). The effect of agricultural technology on the speed of development. *World Development*. https://doi.org/10.1016/j.worlddev.2016.03.017.

Gerssen-Gondelach, S., Wicke, B., & Faaij, A. (2015). assessment of driving factors for yield and productivity developments in crop and cattle production as key to increasing sustainable biomass potentials. *Food and Energy Security, 4,* 36–75. https://doi.org/10.1002/fes3.53.

Gollin, D., Lagakos, D., & Waugh, M. E. (2014). Agricultural productivity differences across countries. *American Economic Review, 104,* 165–170. https://doi.org/10.1257/aer.104.5.165.

Greiner, R., Puig, J., Huchery, C., Collier, N., & Garnett, S. T. (2014). Scenario modelling to support industry strategic planning and decision making. *Environmental Modelling and Software, 55,* 120–131. https://doi.org/10.1016/j.envsoft.2014.01.011.

Griliches, Z. (1964). Research expenditures, education, and the aggregate agricultural production function. *The American Economic Review, 54,* 961–974.

Halevi, G., Moed, H. F., & Bar-Ilan, J. (2016). Researchers' mobility, productivity and impact: Case of top producing authors in seven disciplines. *Publishing Research Quarterly, 32*(1), 22–37.

Hansson, H., Ferguson, R., Olofsson, C., & Rantamäki-Lahtinen, L. (2013). Farmers' motives for diversifying their farm business—The influence of family. *Journal of Rural Studies, 32,* 240–250. https://doi.org/10.1016/j.jrurstud.2013.07.002.

Hart, J., Miljkovic, D., & Shaik, S. (2015). The impact of trade openness on technical efficiency in the agricultural sector of the European Union. *Applied Economics, 47,* 1230–1247. https://doi.org/10.1080/00036846.2014.993134.

Heisey, P. W., Wang, S. L., & Fuglie, K. O. (2011). *Public agricultural research spending and future US agricultural productivity growth: Scenarios for 2010–2050*. Washington: United States Department of Agriculture, Economic Research Service.

Hossain, M. (2015). A review of literature on open innovation in small and medium-sized enterprises. *Journal of Global Entrepreneurship Research, 5*(1), 1–12. https://doi.org/10.1186/s40497-015-0022-y.

Hua, Y. (2015). Influential factors of farmers' demands for agricultural science and technology in China. *Technological Forecasting and Social Change, 100,* 249–254. https://doi.org/10.1016/j.techfore.2015.07.008.

Huang, P. C. (2016). China's hidden agricultural revolution, 1980–2010, in historical and comparative perspective. *Modern China, 42,* 339–376.

Huffman, W. E., & Evenson, R. E. (2006). *Science for agriculture: A long-term perspective* (2nd ed.). Ames, Iowa: Blackwell Publ.

Jin, Y., & Huffman, W. E. (2016). Measuring public agricultural research and extension and estimating their impacts on agricultural productivity: New insights from US evidence. *Agricultural Economics, 47*(1), 15–31.

Khor, K. A., & Yu, L. G. (2015) Influence of international collaboration on the re-search citation impact of young universities. In *Proceedings of ISSI 2015 Istanbul: 15th Inter-national society of scientometrics and informetrics conference* (pp. 278–279).

Lagakos, D., & Waugh, M. E. (2013). Selection, agriculture, and cross-country productivity differences. *The American Economic Review, 103,* 948–980.

Lamers, D., Schut, M., Klerkx, L., & van Asten, P. (2017). Compositional dynamics of multilevel innovation platforms in agricultural research for development. *Science and Public Policy*. https://doi.org/10.1093/scipol/scx009. **(article in press)**.

Lyu, S.-J. L., White, F. C., & Lu, Y.-C. (1984). Estimating effects of agricultural research and extension expenditures on productivity: A translog production function approach. *Journal of Agricultural and Applied Economics, 16,* 1–8.

Masso, J., & Vahter, P. (2015). Exporting and productivity: The effects of multi-product and multi-market export entry. *Scottish Journal of Political Economy, 62,* 325–350. https://doi.org/10.1111/sjpe.12077.

Materia, V. C., Dries, L., and Pascucci, S. (2014) Innovation in agro-food supply chains–The EU policy context. *COMPETE Working paper*, 5.

Matulov, K., & Cechura, L. (2016). Technological heterogeneity, technical efficiency and subsidies in Czech agriculture. *Journal of Central European Agriculture, 17,* 447–466. https://doi.org/10.5513/jcea01/17.2.1728.

Monreal-Pérez, J., Aragón-Sánchez, A., & Sánchez-Marín, G. (2012). A longitudinal study of the relationship between export activity and innovation in the Spanish firm: The moderating role of productivity. *International Business Review, 21,* 862–877. https://doi.org/10.1016/j.ibusrev.2011.09.010.

Mugabushaka, A.-M., Kyriakou, A., & Papazoglou, T. (2016). Bibliometric indicators of interdisciplinarity: The potential of the Leinster–Cobbold diversity indices to study disciplinary diversity. *Scientometrics, 107,* 593–607. https://doi.org/10.1007/s11192-016-1865-x.

Muscio, A., Ramaciotti, L., and Rizzo, U. (2017). The complex relationship between academic engagement and research output: evidence from Italy. *Science and Public Policy, 44/2*, 235–245. scw057. https://doi.org/10.1093/scipol/scw057.

Öborn, I., Bengtsson, J., Hedenus, F., Rydhmer, L., Stenström, M., Vrede, K., et al. (2013). Scenario development as a basis for formulating a research program on future agriculture: A methodological approach. *Ambio, 42,* 823–839. https://doi.org/10.1007/s13280-013-0417-3.

Payumo, J. G., & Sutton, T. C. (2015). A bibliometric assessment of ASEAN collaboration in plant biotechnology. *Scientometrics, 103,* 1043–1059. https://doi.org/10.1007/s11192-015-1582-x.

Piesse, J., & Thirtle, C. (2010). Agricultural R&D, technology and productivity. *Philosophical Transactions of the Royal Society B: Biological Sciences, 365,* 3035–3047. https://doi.org/10.1098/rstb.2010.0140.

Poláková, J., Moulis, P., Koláčková, G., & Tichá, I. (2016). Determinants of the business model change—A case study of a farm applying diversification strategy. *Procedia - Social and Behavioral Sciences, 220,* 338–345. https://doi.org/10.1016/j.sbspro.2016.05.507.

Porter, A., & Rafols, I. (2009). Is science becoming more interdisciplinary? Measuring and mapping six research fields over time. *Scientometrics, 81*(3), 719–745.

Rafols, I., & Meyer, M. (2010). Diversity and network coherence as indicators of interdisciplinarity: Case studies in bionanoscience. *Scientometrics, 82*(2), 263–287.

Rasolabadi, M., Khaledi, S., Ardalan, M., Kalhor, M. M., Penjvini, S., & Gharib, A. (2015). Diabetes research in Iran: A scientometric analysis of publications output. *Acta Informatica Medica, 23*(3), 160–164.

Restuccia, D., Yang, D. T., & Zhu, X. (2008). Agriculture and aggregate productivity: A quantitative cross-country analysis. *Journal of Monetary Economics, 55,* 234–250. https://doi.org/10.1016/j.jmoneco.2007.11.006.

Rivera-Huerta, R., Dutrénit, G., Ekboir, J. M., Sampedro, J. L., & Vera-Cruz, A. O. (2011). Do linkages between farmers and academic researchers influence researcher productivity? The Mexican case. *Research Policy, 40,* 932–942. https://doi.org/10.1016/j.respol.2011.05.001.

Ruegg, R. T. (2007). Quantitative portfolio evaluation of US federal research and development programs. *Science and Public Policy, 34*(10), 723–730.

Saguy, I. S., & Sirotinskaya, V. (2014). Challenges in exploiting open innovation's full potential in the food industry with a focus on small and medium enterprises (SMEs). *Trends in Food Science & Technology, 38,* 136–148. https://doi.org/10.1016/j.tifs.2014.05.006.

Sanyang, S., Taonda, S. J.-B., Kuiseu, J., Coulibaly, N., & Konaté, L. (2016). A paradigm shift in African agricultural research for development: the role of innovation platforms. *International Journal of Agricultural Sustainability, 14,* 187–213. https://doi.org/10.1080/14735903.2015.1070065.

Saracco, F., Di Clemente, R., Gabrielli, A., & Pietronero, L. (2015). From innovation to diversification: A simple competitive model. *PLoS ONE, 10,* e0140420.

Sarkar, S., & Costa, A. (2008). Dynamics of open innovation in the food industry. *Trends in Food Science & Technology, 19,* 574–580. https://doi.org/10.1016/j.tifs.2008.09.006.

Soós, S., & Kampis, G. (2011). Towards a typology of research performance diversity: The case of top Hungarian players. *Scientometrics, 87*(2), 357–371.

Stare, J., & Kejžar, N. (2014). On standardization of the activity index. *Journal of Informetrics, 8,* 503–507. https://doi.org/10.1016/j.joi.2014.04.004.

Stirling, A. (2007). A general framework for analysing diversity in science, technology and society. *Journal of the Royal Society, Interface, 4*(15), 707–719.

Urraca-Ruiz, A., & Laguna-Molina, N. E. (2016). Dynamic technological specialization, aggregated convergence and growth. *International Economics and Economic Policy, 13,* 195–221. https://doi.org/10.1007/s10368-014-0297-4.

Vanloqueren, G., & Baret, P. V. (2009). How agricultural research systems shape a technological regime that develops genetic engineering but locks out agroecological innovations. *Research Policy, 38,* 971–983. https://doi.org/10.1016/j.respol.2009.02.008.

Wood, B. A., Blair, H. T., Gray, D. I., Kemp, P. D., Kenyon, P. R., Morris, S. T., et al. (2014). Agricultural science in the wild: A social network analysis of farmer knowledge exchange. *PLoS ONE, 9,* e105203. https://doi.org/10.1371/journal.pone.0105203.

World Bank. (2012). *Agricultural innovation systems: An investment sourcebook*. Washington: The World Bank. https://doi.org/10.1596/978-0-8213-8684-2.

Yegros-Yegros, A., Rafols, I., & D'Este, P. (2015). Does interdisciplinary research lead to higher citation impact? The different effect of proximal and distal interdisciplinarity. *PLoS ONE, 10,* e0135095. https://doi.org/10.1371/journal.pone.0135095.

Zhang, D., Chen, C., & Sheng, Y. (2015). Public investment in agricultural R&D and extension: An analysis of the effects on Australian broadacre farming productivity. *China Agricultural Economic Review, 7*(1), 86–101.

Zhou, Q., Rousseau, R., Yang, L., Yue, T., & Yang, G. (2012). A general framework for describing diversity within systems and similarity between systems with applications in informetrics. *Scientometrics, 93,* 787–812. https://doi.org/10.1007/s11192-012-0767-9.

Zhou, P., Zhong, Y., & Yu, M. (2013). A bibliometric investigation on China–Uk collaboration in food and agriculture. *Scientometrics, 97,* 267–285. https://doi.org/10.1007/s11192-012-0947-7.

Zouaghi, F., & Sánchez, M. (2016). Has the global financial crisis had different effects on innovation performance in the agri-food sector by comparison to the rest of the economy? *Trends in Food Science & Technology, 50,* 230–242. https://doi.org/10.1016/j.tifs.2016.01.014.