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Impact of foreign direct investment on greenhouse gas emissions in agriculture of developing countries*

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This research analyses the impact of foreign direct investment on greenhouse gas emissions in the agriculture sector of developing countries. Panel data from 63 developing countries for the period 2005 to 2014 was used to estimate a dynamic econometric model by applying a system-generalised method of moments. The empirical results indicate a positive impact of foreign direct investment in agriculture on the carbon dioxide equivalent emission intensity in developing countries. The results provide weak support for the pollution havens hypothesis and imply the importance of coordination between foreign direct investment and environmental policies.

Key words: agriculture, CO₂ emissions, foreign direct investment, generalised method of moments, greenhouse gas emission intensity.

1. Introduction

Climate change is a growing concern, as the surface temperature of the earth increased between 0.65 and 1.06°C on average in the period from 1880 to 2012 and is likely to increase by another 1.5°C over the course of this century (IPCC 2014). Global warming could cause unprecedented climate-related extreme events (IPCC 2014; Stott 2016). This could adversely affect agricultural production through reducing crop yields and increasing risks of food insecurity and income stability for the rural population worldwide (Lobell and Gourdji 2012; Heumesser *et al.* 2013; Lipper *et al.* 2014).

Anthropogenic greenhouse gas emissions are considered to be the main drivers of climate change (Haines *et al.* 2009; IPCC 2014). The literature estimates agriculture's contribution to total greenhouse gases falls in the range from 10% to 32%, depending on the study (IPCC 2006; Friel *et al.* 2009; Gerber *et al.* 2013; Bellarby *et al.* 2014). The change in land use and deforestation make up to an additional 6–17% of total greenhouse gases emissions (Friel *et al.* 2009; Popp *et al.* 2010; World Bank 2011). With growing populations, increasing food prices and biofuel use, the emissions

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from agriculture are likely to grow further in the future (Searchinger *et al.* 2008; Popp *et al.* 2010). The majority of direct agricultural greenhouse gas emissions include land emissions, enteric fermentation, biomass burning, rice cultivation, manure management, and fuel use in agricultural production, whereas the indirect emissions are mostly caused by deforestation motivated by arable land expansion driven by a growing demand for agricultural products (Smith *et al.* 2007; Chel and Kaushik 2011; Hertel 2011). Given the relative importance of agricultural greenhouse gas emissions, understanding the drivers of the emissions are important for defining adequate climate change mitigation strategies.

The mitigation strategies are often based on implementing innovative agricultural practices which sustainably increase productivity, while simultaneously reducing greenhouse gas emissions (World Bank 2011). Some innovative practices include sustainable intensification of agricultural production, improved resource use efficiency, the use of conservation agriculture, improved livestock and grazing management, and crop development, increased energy efficiency and making available the finances needed for implementing emissions-reducing agricultural practices (World Bank 2011, Garnett *et al.* 2013; Lipper *et al.* 2014). The implementation of these practices has been followed by a global decreasing trend of the greenhouse gases emissions per 1,000 calories of food produced across all continents (Sadowski and Baer-Nawrocka 2018). However, the pace of reduction varies across countries. The implementation of these practices is particularly constrained in developing countries due to the insufficient level of technology, knowledge, and human and financial capital (IPCC 2014). Foreign direct investment could potentially alleviate these constraints, providing the necessary financing and technology for developing countries (Borensztein *et al.* 1998; Newman *et al.* 2015).

Globalisation has led to unprecedented growth in the flow of goods and capital in recent decades, which has also affected agriculture (UNCTAD 2009). Multinational companies from developing countries (especially from China and India), countries lacking arable land (such as the Gulf countries), and the developed countries, are becoming increasingly important investment sources. By investing in the agriculture of developing countries, their primary aim is to stabilise the supply of agricultural products in the uncertain economic environment of volatile prices and growing demand of agricultural products (Hallam 2011). The issue which arises is how these foreign direct investment inflows affect host countries. The environmental effects of the inflows are particularly important for agriculture, where the production and the environment are strongly interconnected (Pearson 2000; Sun *et al.* 2017). Greenhouse gas emissions are one of such possible effects. Notably, if there is an impact of foreign direct investment in agriculture on greenhouse gas emissions, that impact can, in theory, be either positive or negative.

If foreign multinational companies use technology associated with lower greenhouse gas emission intensity than local companies in host countries,

foreign direct investment could lead to positive spillover effects in host countries, reducing overall emission intensity, which is analogous to the pollution halo hypothesis (Zarsky 1999). Foreign direct investment could also lead to agricultural modernisation, which may distance the production from sound ecological principles. For instance, the increase in agricultural productivity could be attained by sacrificing the environment and favouring the economies of scale, specialisation, mechanisation, monoculture crops, capital-intensive and energy-intensive agricultural production (Koothafkan *et al.* 2012; McMichael 2014; Altieri *et al.* 2015). This could eventually increase greenhouse gas emission intensity in developing host countries. Such effect can also be explained with the pollution haven hypothesis. According to this hypothesis, the differences in environmental standards incite the relocation of production, thus creating pollution havens in developing countries (McGuire 1982). In the case of agriculture, lax greenhouse gas emissions regulation and the absence of carbon pricing could be an attracting factor for foreign direct investment. This could ultimately increase emissions intensity in the host country. In reality, both positive and negative impacts of foreign direct investment could occur simultaneously.

Most of the existing empirical literature analyses the aggregate impact of foreign direct investment on the emissions observing entire economies. Less attention has been paid to this problem in the context of agriculture (Jorgenson (2007), Paziienza (2015), and Maji *et al.* (2016) are the exceptions).

We address this gap in the literature by investigating the impact of foreign direct investment inflows on carbon dioxide equivalent emissions intensity in agriculture of developing countries. The purpose of this analysis is to examine the evidence and determine if such impact exists and, if so, to quantify it. The main hypothesis of this research is that the increase of foreign direct investment inflows into developing countries agriculture *ceteris paribus* causes an increase in the carbon dioxide equivalent emission intensity of their agriculture. This hypothesis was tested by applying a system-generalised method of moments to estimate a dynamic econometric model, using a sample from 63 developing countries for the period 2005 to 2014. The estimated results support the initial hypothesis, although not strongly.

Comparing to the wider context of the existing empirical literature, which examines the relationship between foreign direct investment and greenhouse gas emissions (which analyse the problem from the point of view of the entire economies), this research focuses on agriculture, a sector which is a major contributor to global greenhouse gas emissions. By doing this, the research addresses the problem of aggregation bias, which is present in the most of the aforementioned related literature. To the best of our knowledge, this is the first research to use dynamic panel models to describe the relationship between foreign direct investment and greenhouse gas emissions. The same applies to the use of a system-generalised method of moments to estimate the models. In this way, we account for potential endogeneity due to simultaneity and model misspecification bias not addressed in these studies. Furthermore,

this research uses the largest sample, comparing to the related literature focusing on agriculture, which allows for estimation of a model with a number of theoretically relevant variables and the extraction of net impact of foreign direct investment. Additionally, the research observes the longest time period compared to other relevant studies. Finally, the observed period is particularly interesting, as it witnessed a great expansion of international capital movement in developing countries' agriculture, driven by the growth in demand for agricultural products and price volatility (Mueller *et al.* 2011; Heumesser *et al.* 2013; Koizumi 2015).

The remainder of this paper is organised as follows. The second section provides an overview of the existing theoretical and empirical literature regarding the research problem. Section 3 describes the applied methodology. Section 4 presents the key empirical results of the research. The final section concludes the paper.

2. Literature review

2.1 Review of the theoretical literature

In previous decades, a number of theoretical models were developed with the aim to describe the relationship between international economic activity and environmental degradation. Pethig (1976) constructed one of the first models of this type, by expanding the classical Ricardian model of comparative advantage with a pollution variable.

McGuire (1982) expanded the standard Heckscher-Ohlin model by adding the third factor of production – the environment. The model shows that unilateral or uncoordinated strengthening of environmental standards, when the factors of production are mobile, leads to factor movement from a more regulated to a less regulated economy. This model is, thus, theoretical basis of pollution haven hypothesis, which can also be extended to the problem of greenhouse gas emissions in agriculture. A recent example is the rise in implementation of carbon pricing initiatives, particularly in developed countries (World Bank 2018). These initiatives increase energy and fertiliser costs, which are important inputs in agriculture (USEIA 2014; Meng 2015; USDA 2018). The increased operating costs could motivate the producers who are unable to adapt by increasing energy efficiency to relocate the production to countries without carbon pricing systems. This could, in turn, increase emission intensity in the host country, provided that the existing agricultural producers have less emission intensive production. Another possibility is that lower standards of forest protection facilitate agricultural expansion, attracting the investment while at the same time resulting in the increased emissions from land use change. Finally, favourable regulations and incentives among countries can make certain emission intensive segments of agricultural production, such as livestock production or rice cultivation, particularly attractive for foreign investors, who expand those segments in

host country ultimately increasing agricultural greenhouse gas emission intensity.

Grossman and Krueger (1991) and Copeland and Taylor (1994, 2013) established a theoretical framework for analysing the impact of foreign direct investment and trade on environmental degradation. This framework can be extended to the problem of greenhouse gas emissions and is widely used as a foundation for empirical work examining the impact of foreign direct investment and greenhouse gas emissions, which is also the case in this research. According to this framework environmental effects of foreign direct investment and trade are dependent on change in three factors: the scale of economic activity; the composition of economic activity; and the technique of production.

The scale of economic activity refers to the increased environmental degradation in the host country due to the increase in production resulting from foreign direct investment inflows. As agricultural production causes greenhouse gas emissions, this increased agricultural production increases the emissions in absolute terms, regardless of possible differences among the foreign and local producers in terms of technology and emissions intensity.

Change in the composition of economic activity refers to the effects of foreign direct investment on the expansion of the activities with heterogeneous greenhouse gas emissions intensities. For example, in agriculture, livestock production has particularly high emission intensity. Therefore, if the foreign direct investment expands livestock production, this will result in the increase of emission intensity of agriculture as a whole (even if the technology and emission intensity is exactly the same between foreign and local producers). Change in the composition of economic activity is a particularly important factor in the analysis at higher levels of aggregation. This factor affects the emissions in both absolute terms and their intensity.

Change in the technique of production refers to the acquisition of new technologies by host countries, enabled by foreign direct investment inflows, or economic development. The change in the technique of production is controversial as it can lead to both higher and lower emissions in the host country. If multinational companies apply production technologies and methods which emit less greenhouse gases than the technologies applied by their local counterparts, the overall impact on emission intensity will be negative, as suggested by Hanna (2010). Conversely, if multinational companies apply technologies associated with higher emission intensity, foreign direct investment is expected to positively affect overall emission intensity. Multinational companies are also likely to adhere to higher environmental standards than required by host country regulation in order to protect their reputation among the consumers in developed countries' markets, thus further improving overall emission intensity in host country (Abdelzaher and Newburry 2016). Finally, the presence of multinational companies can lead to spillover effects and improve ecological performances of local producers (Albornoz *et al.* 2009).

2.2 Review of the empirical literature

As the impact of foreign direct investment on greenhouse gas emissions cannot be determined a priori from theory, the literature treats this issue as an empirical problem. In the last decade, there were many empirical studies investigating this problem using different methodologies, ranging from estimating simple cross-sectional data models and time series analysis to more complex static, dynamic, spatial, and gravity panel data models.

Pioneering empirical research explicitly examining the relationship between foreign direct investment and carbon dioxide emissions showed a positive impact of foreign direct investment using the sample of developing countries (Grimes and Kentor 2003), while no relationship between the variables was found in the sample containing both developing and developed countries (Shandra *et al.* 2004).

Some recent empirical studies report not only positive or negative impacts of foreign direct investment on greenhouse gas emissions in developing countries, but also conditional impacts (both positive and negative impact, depending on the characteristics of individual countries) and no statistically significant impact. For instance, Aliyu and Ismail (2015) found a positive impact of foreign direct investment on carbon dioxide emissions for a panel of African countries, while Solarin and Al-Mulali (2018) reported similar results for a panel including both developed and developing countries. In contrast, a negative impact of foreign direct investment on greenhouse gas emissions was found by Shao (2018), who used the most comprehensive sample thus far, which included 188 countries observed over the 23-year period. Similarly, case studies focusing on China and Vietnam suggest that foreign direct investment reduces greenhouse gas emissions (Tang and Tan 2015; Sung *et al.* 2018). Some of the studies report results which imply conditional impact of foreign direct investment on greenhouse gas emissions, showing that the relationship between the two variables is dependent on absorptive capacity of the host country, approximated with human capital, corruption level and economic development (Lan *et al.* 2012; Shahbaz *et al.* 2015; Doytch and Uctum 2016). Finally, Perkins and Neumayer (2009) used a sample of 98 developing countries and did not find any statistically significant relationship between foreign direct investment and carbon dioxide emissions efficiency.

The empirical literature provides mixed and conflicting results regarding the prospective impact of foreign direct investment on greenhouse gas emissions. This can be partially attributed to differences estimation methods, countries included in the sample and the unit of observation. It is also possible that the results reflect an aggregation problem, as it was shown that idiosyncrasies of the sectors observed can affect the relationship between the variables (Dick and Jorgenson 2010; Sung *et al.* 2018). Using aggregated country-level data which refers to the entire economy, implicitly assumes

sectorial homogeneity of the prospective impact, which does not necessarily exist, and can thus bias the results.

One possibility of addressing the aggregation bias is to focus the analysis on a single sector. However, research focusing on individual sectors, such as agriculture, is lacking.

Jorgenson (2007) was among the first to analyse the impact of foreign direct investment in the primary sector on carbon dioxide equivalent emissions in agriculture. He observed 35 developing countries and discovered a robust positive relationship between the variables. One of the shortcomings of this research is the foreign direct investment data which referred to both agriculture and mining. Following this study, data on foreign direct investment in agriculture of many countries have become available. Another issue with Jorgensen's study is that carbon dioxide equivalent emission was measured in absolute terms. In this case, it is not possible to differentiate between the impacts of domestic and foreign investment on the environment. The sample they used for estimating their model was small, as nine independent variables were estimated using 35 observations. Finally, the research did not use dynamic panel models methodology, which was adequate given a lagged independent variable among the dependent variables in Jorgensen's model.

Foreign direct investment was also shown to increase carbon dioxide equivalent emissions in a Nigerian case study which used time series methodology (Maji *et al.* 2016). Using the panel data on agriculture of the members of Organisation for Economic Cooperation and Development (the majority of which are developed countries) and static econometric model, Paziienza (2015) determined that foreign direct investment reduces per capita carbon dioxide equivalent emissions in agriculture. Conversely, Almulali *et al.* (2016) could not find causality between foreign direct investment and carbon dioxide equivalent emissions in agriculture, using a sample of 15 developed countries and cointegration methodology. In conclusion, the results of empirical research focused on agriculture are mixed, which does not differ from the results of the research using more aggregated data.

3. Methodology

3.1 Model, variables, and data sources

We begin developing the empirical model with the dependent variable: carbon dioxide equivalent emission intensity. The emission intensity is used instead of absolute emissions because the growth of agricultural production is important for food security, income generation, and livelihood of rural population, so it is more meaningful to focus the analysis on emission intensity. Moreover, as the research focuses on the effects of change in production structure and technique, as defined by the theoretical framework, it is necessary to observe emission intensity. Dependent variable was

measured as emissions intensity (the ratio of absolute carbon dioxide equivalent emissions in agriculture measured in metric tons¹, to gross value of agricultural production measured in 1,000 USD at constant prices for 2004–2006), analogous to the approach of Perkins and Neumayer (2009) and Shao (2018).

Variable CO_{2it-1} represents a dependent variable with a time lag of one year. It reflects the inertia and persistence in the temporal dynamic of carbon dioxide equivalent emission intensity. Such dynamics can be theoretically explained by ecologic efficiency convergence between developed and developing countries (Perkins and Neumayer 2009).

Foreign direct investment in agriculture (FDI_{it}) is the variable in focus of this research. Since its examined impact refers to emission intensity, the parameter β_2 in Model (1) indicates average net effect of the change in production technique, as postulated by the theoretical framework of Grossman and Krueger (1991). Therefore, it is not possible to predict with certainty the sign of parameter β_2 .

Foreign direct investment was measured in terms of annual inflows, due to data considerations (Lowder *et al.* 2015). As the available data on foreign direct investment referred not only to agriculture, but also to forestry and fishery, it was adjusted using the correction factors based on the ratio of gross output value of agriculture and gross output value of agriculture, forestry and fisheries (imputing any correction factor missing values with within group averages).

The model includes a vector of control variables. One of the control variables is the export of agricultural products (EXP_{it}). Some countries, particularly the developed ones, might restrict trade with developing countries to pressure the developing countries' exporters to improve environmental standards, especially in agriculture, which is why trade openness may improve country's environmental performance (Vogel 1997; Bradford 2015; Mavragani *et al.* 2016). As the internationally comparable data on environmental standards stringency of developing countries is challenging to obtain for all the countries in the sample, and the existing bilateral agricultural trade flows data had too many missing values to calculate a comparable and consistent measurement, the variable was approximated with free on-board value of agricultural exports.

The import of capital goods (IMP_{it}) is also controlled for in the model, as it can potentially serve as a channel of technology transfer in agriculture. It is not possible to *a priori* determine its impact on emission intensity, as the

¹ Carbon dioxide equivalent emissions refer to the emissions which are the result of agricultural activities including enteric fermentation, manure management, rice cultivation, the use of synthetic fertilisers, crop residue burning, savannah burning and the use of energy in agricultural production. The use of this measurement in calculation of greenhouse gas emission intensity in agriculture was motivated by its comprehensiveness, as it entails most of the direct emission from agriculture.

imported technology is not always cleaner. The import of capital goods was approximated with the import value of machinery and transport equipment.

Gross domestic product per capita in the functional form of Kuznets environmental curve ($GDP_{it} - GDP_{it}^2$) was also used as a control variable. Apart from the usual theoretical expectation described with Kuznets environmental curve, the growth of gross domestic product per capita, which reflects the living standard of the population, can also lead to the overall increase in quantity of food consumed, and, to a lesser extent, diet change and increased meat consumption, both of which may increase carbon dioxide emission intensity in agriculture (Caro *et al.* 2014; Hawkins *et al.* 2018). Therefore, a positive sign of the parameter estimate is expected for the regressor GDP_{it} , and a negative one for its square term.

Assuming the regulation is efficiently applied, more stringent environmental regulation should decrease the emission intensity. Although there are many possibilities of measuring environmental regulations stringency (Smarzynska Javorcik and Wei 2003; Cole *et al.* 2006; Jorgenson 2007), our model uses following variables in order to maximise the sample size. Ratification of Kyoto protocol ($KYOTO_{it}$) is a dummy variable, which either takes the value 1 for the country and year in which the Kyoto protocol was ratified or zero value otherwise. Environmental regulation stringency (REG_{it}) denotes the percentage of terrestrial protected areas, observed in 2000 and 2014. As the variations of the values in the two periods were almost nonexistent, the data for the period 2005-2014 were interpolated using the linear trend.

The model controls for the composition of agricultural production (LS_{it}), following the theoretical framework of Grossman and Krueger. In agriculture, it is likely that the majority of carbon dioxide equivalent emission intensity can be explained with agricultural production structure, as the livestock sector is a major contributor to the total agricultural emissions (Friel *et al.* 2009; Gerber *et al.* 2013). The variable is hence constructed as the share of livestock production value in total agricultural production value. A positive sign of the parameter estimate for this variable is expected.

The change in oil prices could affect the producers' willingness to adjust to a more energy-efficient production, which could impact emission intensity. For this reason, the model includes the average annual free on-board world oil price (OIL) and the average annual West Texas Intermediate oil price (OILW) as control variables. The alternative measurements were used as a robustness check.

Finally, telecommunications could potentially affect emissions intensity, as their development spurs the global access to production, trade, and environmental information, which 'emancipates and democratises societies' (Mol 2006). Following the approach of Perkins and Neumayer (2008), the telecommunications variable was approximated with the share of Internet users in a country's population (INT_{it}).

Food and Agriculture Agency is the source of data for emission intensity (CO_{2it}), export (EXP_{it}) and the composition of agricultural production variables (LS_{it}), as well as for the correction factor of foreign direct investment. World Bank was the source of data for gross domestic product (GDP_{it}) and environmental regulation stringency (REG_{it}) variables. Sources of data for foreign direct investment in agriculture (FDI_{it}) include the United Nations Conference on Trade and Development and World Trade Center. Finally, the data on imports (IMP_{it}), oil prices (OIL), and telecommunications (INT_{it}) was provided by World Trade Organization, United States Energy Information Administration and International Telecommunication Union, respectively. All monetary values (EXP_{it} , FDI_{it} , IMP_{it} , GDP_{it}) are expressed in USD at constant 2005 prices.

By including the previously discussed variables on the basis of theoretical considerations, the related empirical research and idiosyncrasies of agriculture, the empirical model used in this research was specified as:

$$\begin{aligned} \log(CO_{2it}) = & \beta_0 + \beta_1 \log(CO_{2it-1}) + \beta_2 \log(FDI_{it}) + \beta_3 \log(EXP_{it}) \\ & + \beta_4 \log(IMP_{it}) + \beta_5 \log(GDP_{it}) + \beta_6 \log(GDP_{it})^2 \\ & + \beta_7 \log(REG_{it}) + \beta_8 KYOTO + \beta_9 \log(LS_{it}) \\ & + \beta_{10} \log(OIL_t) + \beta_{11} \log(INT_{it}) + \mu_i + u_{it} \end{aligned} \quad (1)$$

All of the variables in the empirical model were log-transformed. Some reasons refer to the model as a whole, while the others refer only to dependent or only to independent variables. The preliminary statistical analysis pointed to a possible nonlinear relationship between dependent variable and all continuous independent variables. The use of log-log model allowed us to account for this nonlinearity between the variables, while maintaining the linearity of the parameters and facilitating the estimation of the model.² Furthermore, log-transformation of the variables allowed us to estimate the elasticity between the dependent and independent variables, which facilitated the interpretation of the empirical results. Following the reasoning of Keene (1995) and Chinn (1996), we considered log-transformation of the dependent variable, as this variable had only positive values and their distribution was positively skewed (as evidenced by the value of Pearson's moment coefficient of skewness, which equalled to 2.28). The adequacy of log-transformation of this variable was formally confirmed with Box-Cox test (Box and Cox 1964).³ Log-transformation of the independent variables normalised the

² After examining 30 possible functional forms for the relationships between dependent and independent variables, exponential functional form was shown to be the best fit for the data and superior to linear relationship in all cases. This is why we used exponential model $CO_2 = \beta_0 CO_2^{\beta_1} FDI^{\beta_2} EXP^{\beta_3} IMP^{\beta_4} GDP^{\beta_5} REG^{\beta_6} LS^{\beta_7} OIL^{\beta_8} INT^{\beta_9}$ as the basis. Log-transformation of right and left side of the equation transformed the relationship to the one described by Model (1), allowing us to use the standard estimation methodology.

³ The value of transformation parameter maximising the maximum-likelihood estimator score was 0.17.

Table 1 List of the countries sample

Afghanistan	Colombia	Kirgizstan	Romania
Albania	Costa Rica	Laos	Russia
Algeria	Cuba	Madagascar	Salvador
Argentina	Egypt	Malawi	Saudi Arabia
Armenia	Ecuador	Malaysia	Serbia
Bangladesh	Fiji	Morocco	Tajikistan
Belize	FYR of Macedonia	Mauritius	Thailand
Belarus	Ghana	Mexico	Tanzania
Bolivia	Georgia	Myanmar	Tunisia
Bosnia and Herzegovina	Guatemala	Mozambique	Turkey
Brazil	Honduras	Nicaragua	Uganda
Bulgaria	Hungary	Panama	Uruguay
Cambodia	Indonesia	Paraguay	Vietnam
Chile	Ivory Coast	Peru	Zambia
China	Jordan	Philippines	Yemen
Cape Verde	Kazakhstan	Poland	

measurement scales which were different for each variable. Finally, the log–log model provided a better fit for the data than the level–level model, as evidenced by the adjusted coefficient of determination and Akaike information criterion values.⁴

3.2 Sample and descriptive statistics

This research uses secondary country-level panel data, with a focus on agriculture. The panel includes 63 developing countries⁵ The countries included in the sample are presented in Table 1.

Data availability dictated the choice of the observed time period 2005–2014. Our aim was to minimise the share of missing observations in the panel, while maximising the number of countries. If the years after 2014 were included in the sample, the additional data would refer only to three countries, whereas if the sample was expanded with the period 2000–2005, the additional data would, on average, refer to 35 countries, and the data prior to 2000 would refer to only 16, while the data would be missing for the other countries. Estimating the dynamic model using the GMM method for all 63 countries

⁴ Adjusted coefficient of determination for models 1–4 using log-transformed values equalled 0.9242, 0.9219, 0.9378 and 0.9449, whereas for the same models using untransformed variables they equalled: 0.4325, 0.4643, 0.4739 and 0.3915, respectively. Moreover, models 1–4 using the log-transformed values minimise Akaike information criterion (Yamaoka *et al.* 1978), which equalled 448.95, 450.21, 460.59 and 454.10 for the models using transformed values and 1,090.14, 1,090.41, 1,125.02 and 1,130.38 for the models using untransformed values, respectively.

⁵ The definition of developing countries follows the approach of International Monetary Fund (2017). International Monetary Fund classification divides all the countries into two categories: developed and developing countries, with latter including the emerging markets.

(for most of which the data would be missing in many consecutive years) would bias the results, which is why the time period 2005-2014 was chosen.

Despite the efforts to minimise missing observations in the sample, the panel is unbalanced, which is primarily a consequence of missing foreign direct investment data for the sector of agriculture, forestry, and fisheries. There are no systematically missing observations in the panel: the missing observations exist in different years and countries, across all economy sizes, development levels, and continents.

Descriptive statistics is presented in Table 2. The table shows that 368 observations were used for model estimations. The sample was greatly reduced because of limited availability of sectoral foreign direct investment data. Carbon dioxide equivalent emission intensity varies significantly across observations, indicating that the intensity of carbon dioxide equivalent emissions is heterogeneous among countries and time periods. All the other variables of the model, which simultaneously vary over countries and time, have similar characteristics.

3.3 Estimation method

One of the key characteristics of the empirical model is the introduction of the lagged dependent variable CO_{2it-1} , among the independent variables. This variable addresses potential endogeneity due to simultaneous impact between foreign direct investment and carbon dioxide equivalent emissions intensity.

Table 2 Descriptive statistics

Variable	Full variable name	Obs.	Average	St. deviation	Minimum	Maximum
CO ₂	CO ₂ eq emission intensity	378	2.76	1.79	0.53	17.47
FDI	Foreign direct investment in agriculture	378	162.73	732.09	0.05	7,042.39
EXP	Export of agricultural products	378	5,531.93	10,444.47	1.02	72,532.07
GDP	Gross domestic product per capita	378	4,824.69	4,162.84	274.82	29,562.44
IMP	Import of capital goods	378	24,482.81	65,310.65	99.86	555,828.26
INT	Share of Internet users in population	378	25.22	18.43	0.24	75.65
REG	Stringency of environmental regulation	378	14.75	10.31	0.21	40.52
LS	Share of livestock production in agricultural production	378	33.43	13.20	6.87	71.73
OILB	Oil price (Brent)	378	80.74	20.07	54.57	111.63
OILW	Oil price (WTI)	378	78.06	15.51	56.64	99.67

Note: FDI, EXP and IMP are expressed in USD millions (constant 2005 prices); INT, REG and LS are expressed as percentages; GDP, OILB and OILW are expressed in USD, and CO₂ is expressed in metric tons of CO₂eq per USD million.

Furthermore, lagged variable contains, *inter alia*, previous levels of foreign direct investment inflows. This is important, as the available data on foreign direct investment in agriculture are incomplete for many countries in the sample. Thus, using the lagged variable reduces the bias due to the missing data. Finally, the inclusion of the lagged variable reduces possible omitted-variable bias. The presence of this variable requires the use of specific dynamic panel methods for model estimation. These methods have recently gained significance in the related macrolevel research (Doytch and Uctum 2016; Kahouli and Omri 2017; Shao 2018).

Before the estimation, a correlation analysis was conducted, and the results are presented in Table 3.

The dependent variable, carbon dioxide equivalent emission intensity, is negatively correlated with all the model variables except agricultural production structure (LS) and, surprisingly, the environmental regulation stringency (REG), both of which are positively correlated with carbon dioxide equivalent emission intensity. Still, the results should be interpreted cautiously, as the model (1) inherently has an endogeneity problem, so the results of correlation analysis can be deceiving. High levels of correlation between independent variables caused the multicollinearity problem and prevented the precise isolation of the individual effects of each regressor. For this reason, the variable Internet usage (INT) was excluded from the model, as it explains the changes in carbon dioxide equivalent emissions in a similar way as the variable gross domestic product per capita. The latter variable is

Table 3 Correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Log (CO ₂)	(1) 1									
(2) Log (FDI)	(2) -0.06	1								
(3) Log (EXP)	(3) -0.08*	0.31*	1							
(4) LOG (GDP)	(4) -0.31*	0.21*	0.09*	1						
(5) Log (IMP)	(5) -0.07*	0.12*	0.77*	0.32*	1					
(6) Log (REG)	(6) 0.09*	0.23*	0.21*	0.06*	0.13*	1				
(7) Log (INT)	(7) -0.34*	0.22*	0.23*	0.78*	0.30*	0.07*	1			
(8) Log (LS)	(8) 0.38*	-0.07	0.08*	0.40*	0.22*	-0.07*	0.33*	1		
(9) Log (OILB)	(9) -0.01	0.11*	0.09*	0.11*	0.08*	0.05	0.32*	0.01	1	
(10) Log (OILW)	(10) -0.01	0.09	0.09*	0.10*	0.08*	0.04	0.30*	0.00	0.97*	1

Note: * denotes statistically significant correlation between two variables at 5% significance level.

theoretically more important, which is the reason why it was retained in the model. For the same reason, the variable import of machinery and transport vehicles (IMP) was also excluded from the model. The exclusions resulted in the following form of the model:

$$\begin{aligned}\log(\text{CO}_{2it}) = & \beta_0 + \beta_1 \log(\text{CO}_{2it-1}) + \beta_2 \log(\text{FDI}_{it}) + \beta_3 \log(\text{EXP}_{it}) \\ & + \beta_4 \log(\text{GDP}_{it}) + \beta_5 \log(\text{GDP}_{it})^2 + \beta_6 \log(\text{REG}_{it}) \\ & + \beta_7 \text{KYOTO} + \beta_8 \log(\text{LS}_{it}) + \beta_9 \log(\text{OIL}_t) + \mu_i + u_{it}\end{aligned}\quad (2)$$

The robustness of the estimates was checked afterwards by estimating alternative specifications which include the variables INT and IMP, and exclude the variables GDP, GDP², and EXP, *id est*, following models were also estimated:

$$\begin{aligned}\log(\text{CO}_{2it}) = & \beta_0 + \beta_1 \log(\text{CO}_{2it-1}) + \beta_2 \log(\text{FDI}_{it}) + \beta_3 \log(\text{EXP}_{it}) \\ & + \beta_4 \log(\text{REG}_{it}) + \beta_5 \text{KYOTO} + \beta_6 \log(\text{LS}_{it}) \\ & + \beta_7 \log(\text{OIL}_t) + \beta_8 \log(\text{INT}_{it}) + \mu_i + u_{it}\end{aligned}\quad (3)$$

and

$$\begin{aligned}\log(\text{CO}_{2it}) = & \beta_0 + \beta_1 \log(\text{CO}_{2it-1}) + \beta_2 \log(\text{FDI}_{it}) + \beta_3 \log(\text{IMP}_{it}) \\ & + \beta_4 \log(\text{REG}_{it}) + \beta_5 \text{KYOTO} + \beta_6 \log(\text{LS}_{it}) \\ & + \beta_7 \log(\text{OIL}_t) + \beta_8 \log(\text{INT}_{it}) + \mu_i + u_{it}\end{aligned}\quad (4)$$

If the models (2), (3), and (4) were estimated using the common methods such as ordinary least squares or generalised least squares, endogeneity problem would arise. This is particularly the case in the sample used in this research, where the number of countries exceeds number of time periods (Nickell 1981). Therefore, the estimation of the models in this research was conducted by applying system-generalised method of moments developed by Blundell and Bond (1998). The system method was used instead of the original differences method to achieve greater efficiency, by maximising the number of observations. Hereby, two-step procedure was employed, which is more asymptotically efficient in comparison with one-step procedure. However, the two-step procedure causes the bias in standard errors. Windmeijer's correction was hence applied to deal with this issue (Windmeijer 2005). As the panel in this research is unbalanced, the orthogonal deviations transformation was applied instead of differencing (Arellano and Bover 1995). In the choice of instruments, carbon dioxide equivalent emission intensity (CO_{2it-1}), net foreign direct investment inflows in agriculture (FDI_{it}), and the stringency of environmental regulation (REG_{it}) were considered endogenous. These variables were instrumented using the lags from 2 to 3, whereas all the other variables were considered exogenous. Hansen J-test

Table 4 Estimation results

Variable	Model (1)	Model (2)	Model (3)	Model (4)
Log(CO ₂)	0.9610*** (0.0593)	0.9617*** (0.0590)	0.9793*** (0.0422)	0.9680*** (0.0407)
Log(FDI)	0.0178** (0.0087)	0.0181** (0.0086)	0.0184** (0.0078)	0.0171** (0.0080)
Log(EXP)	0.0010 (0.0058)	0.0011 (0.0056)	−0.0031 (0.0044)	
Log(GDP)	0.0048 (0.0924)	0.0054 (0.0904)		
Log(GDP) ²	−0.0024 (0.0059)	−0.0024 (0.0057)		
Log(REG)	−0.0308 (0.0237)	−0.0321 (0.0239)	−0.0314 (0.0230)	−0.0304 (0.0234)
Kyoto	−0.0015 (0.0495)	−0.0015 (0.0504)	0.0087 (0.5100)	0.0063 (0.0516)
Log(LS)	0.0700* (0.0398)	0.0689* (0.0394)	0.0545** (0.0263)	0.0570** (0.0274)
Log(OILB)	0.0200 (0.0265)		0.0229 (0.0278)	0.0246 (0.0271)
Log(OILW)		0.0186 (0.0326)		
Log(INT)			−0.0160 (0.0155)	−0.01665 (0.0136)
Log(IMP)				−0.0051 (0.0046)
Intercept	−0.2485 (0.5802)	−0.2624 (0.5606)	−0.3783 (0.2582)	−0.3016 (0.2725)
Observations	332	332	332	332
Instruments	74	74	73	73
<i>F</i> -statistic†	507.16 (0.000)	491.24 (0.000)	716.52 (0.000)	814.77 (0.000)
Hansen test‡	0.681	0.684	0.730	0.719
AR(1)§	0.003	0.003	0.002	0.003
AR(2)	0.180	0.179	0.183	0.222

Note: Values in the parentheses indicate corrected standard errors. ***, **, and * denote coefficients which are statistically significant at 1%, 5%, and 10% level, respectively. †The row *F*-statistic shows the values of *F*-statistic, which indicate the statistical significance of the regression; *P*-values are provided in the parentheses underneath. ‡The row Hansen test refers to *P*-values of Hansen J-test. §AR(1) i AR(2) refers to *P*-values of Arellano-Bond autocorrelation test. The estimation was conducted using Roodman's (2009) procedure xtabond2 in the program Stata 13.

values suggest that the instruments used in all model specifications are adequate. Arellano-Bond autocorrelation test results indicate the adequacy of the chosen lag for the instrumental variables and correct model specification.

4. Results and discussion

The estimation results for the models (2), (3), and (4) are presented in Table 4. The first two columns refer to the alternatives of the model (2), differing in the way oil price is measured (using either OILB or OILW

variable). The other two columns refer to the estimation results of the models (3) and (4).

The results suggest a potentially positive impact of foreign direct investment inflows on carbon dioxide equivalent emission intensity in agriculture. This impact is robust to alternative specifications of model. In case of the model (2), the results indicate that the increase in foreign direct investment inflows of 10% on could lead to the increase of carbon dioxide equivalent emissions intensity in agriculture of 0.18% in the short term. The results do not differ significantly in alternative specification, which indicates that the increase of foreign direct investment inflows of 10% could increase carbon dioxide equivalent emission intensity from 0.17% to 0.18%. The impact is statistically significant at 5% level in all specifications.

The lagged dependent variable (CO_{2it-1}) is statistically significant at 1% level in all specifications with positive parameter estimate values. This justifies the inclusion of dynamics in the empirical models used in the research. The robust statistical significance of the lagged variable indicates strong persistence in the dynamics of carbon dioxide emissions in agriculture of developing countries. It also shows that carbon dioxide emission intensity is primarily determined by its past values. Finally, this result could also be interpreted as an evidence of possible convergence of carbon dioxide emission intensity in agriculture among developing countries at the rate between 2.07% and 3.90%.

Furthermore, the results show a weak positive impact of livestock production share on the emission intensity in agriculture in the case of models 1-4. The increase of livestock production share in total agricultural production by 10% potentially results in the increase in emission intensity from 0.54% to 0.70%. Other variables in all specifications are not statistically significant.

Further robustness checks were performed by estimating the model (2) for different time periods: 2005-2014; 2005-2012; 2006-2014; and 2007-2014. The results of these additional estimations are presented in Table 5.

The estimation results of model (2) for different time periods confirm the robustness of previously determined potentially positive impact of foreign direct inflows on carbon dioxide equivalent emission intensity in agriculture. The coefficients of the variable FDI are statistically significant at 5% level if the model is estimated of the period 2006-2014 and 2007-2014. The coefficients only indicate a weak correlation if the model is estimated for the period 2005-2013 and 2005-2014. The results show that the increase in foreign direct investment inflows by 10% could increase carbon dioxide equivalent emission intensity in agriculture from 0.15% to 0.20%. Such estimates do not significantly differ from the estimates determined from the results obtained from the entire sample.

The lagged dependent variable (CO_{2it-1}) remained statistically significant at 1% level in all periods, with the positive coefficient ranging from 0.97 to 0.99. According to the estimation results for the alternative time periods, the

Table 5 Robustness check

Variable	Model (5)	Model (6)	Model(7)	Model (8)
Log(CO ₂)	0.9672*** (0.0575)	0.9736*** (0.0613)	0.9669*** (0.0597)	0.9952*** (0.0463)
Log(FDI)	0.0165* (0.0092)	0.0169* (0.0097)	0.0202** (0.0098)	0.0154** (0.0073)
Log(EXP)	0.0004 (0.0052)	0.0010 (0.0063)	0.0012 (0.0057)	0.0012 (0.0067)
Log(GDP)	0.0094 (0.0867)	0.0154 (0.1001)	-0.0052 (0.1121)	0.1409 (0.1175)
Log(GDP) ²	-0.0025 (0.0056)	-0.0027 (0.0061)	-0.0019 (0.0068)	-0.0111 (0.0229)
Log(REG)	-0.0289 (0.0253)	-0.0276 (0.0236)	-0.0261 (0.0254)	-0.0171 (0.0229)
Kyoto	-0.0050 (0.0535)	-0.0084 (0.0511)	0.0272 (0.0489)	0.0440 (0.0858)
Log(LS)	0.0660* (0.0384)	0.0612 (0.0420)	0.6282* (0.0359)	0.0579* (0.0290)
Log(OILB)	0.0206 (0.0255)	0.0278 (0.0262)	-0.0123 (0.0309)	-0.0163 (0.0328)
Intercept	-0.2542 (0.4927)	-0.3426 (0.6254)	-0.1316 (0.6101)	-0.8072 (0.5576)
Observations	323	311	281	230
Instruments	71	62	72	65
F-statistic†	520.75 (0.000)	537.71 (0.000)	357.39 (0.000)	491.00 (0.000)
Hansen test‡	0.577	0.300	0.859	0.790
AR(1)§	0.003	0.002	0.003	0.003
AR(2)	0.181	0.180	0.187	0.187

Note: Values in the parentheses indicate corrected standard errors. ***, **, and * denote coefficients which are statistically significant at 1%, 5%, and 10% level, respectively. †The row *F*-statistic shows the values of *F*-statistic, which indicate the statistical significance of the regression; *P*-values are provided in the parentheses underneath. ‡The row Hansen test refers to *P*-values of Hansen J-test. §AR(1) i AR(2) refer to *P*-values of Arellano-Bond autocorrelation test. The estimation was conducted using Roodman's (2009) procedure *xtabond2* in the program Stata 13.

increase of livestock production share in total agricultural production (LS_{it}) by 10% potentially increases carbon dioxide equivalent emission intensity in agriculture between 0.58% and 0.66%. The variable is statistically significant for all the periods except 2005-2012.

Overall, the results confirm a weak positive impact of foreign direct investment on carbon dioxide equivalent emission intensity in agriculture of developing countries, which supports the pollution haven hypothesis. Such results are, *inter alia*, in line with previous findings of Jorgenson (2007), who determined a positive impact of foreign direct investment on greenhouse gas emissions in primary sector. Additionally, the results support the more general findings of Grimes and Kentor (2003), Kim and Adilov (2012), and Zugravu-Soilita (2017). However, the results differ from the findings of Pазienza (2015), who reported negative impact of foreign direct investment on greenhouse gas emissions in agriculture. This discrepancy could be

attributed to differences of economic development of the countries in the sample. Paziienza's sample consisted mostly of developed countries (25 out of 30 would be considered developed under the classification applied in this paper, with the average gross domestic product per capita for all the countries and time periods in the sample being 32,153 constant 2010 USD). Our sample consisted entirely of developing countries (having the average gross domestic product per capita of 4,676 constant 2010 USD). Therefore, it is possible that the impact of foreign direct investment on greenhouse gas emissions in agriculture depends on the level of economic development.

5. Conclusion

This research analysed the impact of foreign direct investment on carbon dioxide equivalent emission intensity in agriculture. Using the sample of 63 developing countries observed in the period 2005-2014, a dynamic panel model was estimated, employing the system-generalised method of moments. The results suggest a potentially positive relationship between foreign direct investment and agricultural greenhouse gas production, weakly supporting the pollution haven hypothesis. Such results could also be a consequence of the change in agricultural production technique which intensifies the emissions. Another possible explanation is that the presence of multinational companies increases competitive pressure on local agricultural producers. The local producers could, in turn, increase productivity, by employing more mechanisation and, generally, more energy-intensive technology in agricultural production in order to remain competitive.

Interpreted in terms of the theoretical paradigm of Grossman and Krueger (1991) and Copeland and Taylor (1994, 2013), our results suggest that capital flow liberalisation in agriculture appears to intensify greenhouse gas emissions, mainly through the change of production technique. Moreover, the results suggest a potentially significant impact of production composition on carbon dioxide equivalent emissions in agriculture.

The results imply that although foreign direct investment in agriculture in developing countries often has positive effects such as production growth, increase in food availability, improved access to water, and improved sanitary production standards (Ben Slimane *et al.* 2016), there could also be negative effects, such as intensification of greenhouse gas emissions, which should not be neglected. The increase of emission intensity, which was shown to be potentially driven *inter alia* by foreign direct investment inflows, can cause climate externalities and worsen production conditions for all agricultural producers in a host country. Depending on the concrete strategies of the host country regarding the compliance with Kyoto protocol commitments, the increased emission intensity could also increase burden on other, local agricultural producers as well as the economic subjects in other sectors. The results therefore imply that there is a need to coordinate foreign investment promotion and environmental policies

in developing countries in the case of agriculture, while taking into account potential costs of foreign direct investment.

One possibility for developing countries to fully gauge costs and benefits of foreign direct investment in agriculture is to consider the ecological parameters alongside the usual economic parameters when defining attraction and promotion policies. The selectivity in the choice of foreign investors could be warranted for the same reason, particularly if the investors are subsidised by the host country. Furthermore, greenhouse gas emission intensity could potentially be reduced by directing the investment in less emission intensive agricultural activities. For example, in agriculture, livestock production has been shown to cause carbon dioxide emissions (Appiah *et al.* 2018), so redirection of additional investments from livestock production to other agricultural activities could potentially reduce greenhouse gases emissions, as tentatively suggested by some of the results in this research. Ecological performances of the multinational companies' affiliates in host country can potentially be improved by advancing the environmental audit systems in developing countries, and improving the application of the existing environmental regulation and promoting corporate social responsibility. One practical way to achieve this is to develop and improve the metrics of emissions on company level and to introduce a public register of greenhouse gas emitters. Finally, the results of this research imply that any effort to mitigate greenhouse gas emissions in agriculture needs to be sustained and applied consistently, as the emission intensity in the sector is highly persistent.

Although the results of this research suggest a potentially significant role of the structure of agricultural production in intensifying greenhouse gas emissions, the causes of this change are out of scope of this research, which can be of interest for researchers in the future. Additionally, contrasting results regarding the relationship between foreign direct investment and greenhouse gas emissions suggest that host country characteristics, such as the level of economic development, could impact the direction and the intensity of the relationship. It could be interesting to formally test this possibility by using threshold regression methodology and a more comprehensive sample including both developing and developed countries. Finally, concrete mechanisms of foreign direct investment impact on emission intensity remains unclear and further microlevel investigation could shed light on this aspect of the problem.

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