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Food and the forest: A spatial analysis on the nexus between foreign direct investment and deforestation

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ABSTRACT

This study examines the effect of foreign direct investment (FDI) on deforestation in non-OECD countries, in consideration of the potential trade-offs between economic objectives and environmental concerns and the pollution haven hypothesis. The study applies a multilevel fixed effects estimator to an original panel dataset of more than 4500 locations that received FDI across 120 countries between 2003 and 2019 and considers the sectors and sub-sectors of investment projects to examine heterogeneous land intensity in agricultural and food activities. Three main conclusions emerge. First, the food sector is primarily responsible for FDI-driven forest loss, while FDI projects in other sectors do not seem to significantly contribute to deforestation. Second, forest loss induced by food FDI is driven by specific sub-sectors; in particular, FDI projects in the food trade and services sub-sector seem to be significant, which is likely attributable to increased demand for local agricultural production. Third, animal industry FDI has the most significant impact on forest loss where the forest land cover is dominant.

1. Introduction

Understanding the trade-offs between economic development and environmental sustainability is crucial for advancing sustainable development (e.g. Saccone and Vallino, 2022; Schulz et al., 2023). Foreign Direct Investment (FDI) can sustain recipient countries' economic development by establishing new economic activities and improving efficiency, employment, technological innovation, infrastructure development, fiscal revenue and competition (e.g. Iamsiraroj, 2016). Since the early 1980s, global FDI flow has grown rapidly and from the 1990s, developing economies recorded an impressive growth in FDI inflow, which peaked in 2015. The food sector followed a similar trend, with a first peak before the global food crisis of 2007–2008 (see Fig. A1 in Appendix A). Currently, developing economies receive more than half of global FDI inflow, while in 1990 they only represented one-sixth of global inward investment (UNCTAD, 2022).

Along with positive economic effects, FDI may also introduce negative and positive environmental impact (Doytch and Uctum, 2016; Long et al., 2017; Solarin and Al-Mulali, 2018; Huaranca et al., 2019; Doytch, 2020; Pradhan et al., 2022). On the positive side, multinational companies can indeed contribute to the dissemination of new green technologies and practices through technological transfer, knowledge sharing and preferential relationships with the most responsible local companies (*the pollution halo hypothesis applied to FDI*), particularly when a country implements strong environmental regulations (Birdsall and Wheeler, 1993; Kim and Adilov, 2012; Huynh and Hoang, 2019). However, FDI inflow can lead to environmental degradation by directing polluting activities towards developing countries that often have weaker regulatory frameworks and institutions (*pollution haven hypothesis applied to FDI*) (Kim and Adilov, 2012; Huynh and Hoang, 2019).

Among the potential negative repercussions of FDI on the local environment, the impact on host countries' forest resources in relation to agricultural and other land intensive activities requires special attention (Walker et al., 2000; Ceddia et al., 2014; Doytch and Uctum, 2016; Papworth et al., 2017; Huaranca et al., 2019; Kinda and Thiombiano, 2021; Pendrill et al., 2022; Vasconcelos et al., 2024) as an increasing proportion of FDI projects has been directed towards developing countries' agricultural sectors in previous decades (Dogan, 2022). In particular, the impact of food-related FDI on local forests must be carefully considered. Although FDI in the food sector represents a small

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percentage of total inflow, significant growth rates have emerged since the mid-1990s.

Empirical literature reveals some evidence of deforestation attributable to FDI inflow (Doytch and Uctum, 2016; Long et al., 2017; Bokpin, 2017; Assa, 2018; Lokonon and Mounirou, 2019; Doytch, 2020; Piabuo et al., 2024); however, such evidence is primarily based on macroeconomic approaches with limited geographical coverage. Moreover, it does not distinguish the impact that FDI projects in different sectors may have, although such distinction would offer important information for policymaking. Based on this, the aim of the study is to assess the relationship between forest loss and food FDI inflow in different sub-sectors at a geographically disaggregated level that covers a large number of countries. More specifically, using an original panel dataset of more than 4500 locations that received cross-border greenfield investments between 2003 and 2019 in 121 non-OECD countries, this study examines their effects on forest area change, based on satellite data, distinguishing between non-food and food FDI and further classifying food projects into sub-sectors to account for different land intensity of agricultural and food activities.

The rest of the paper is structured as follows. Section 2 describes the theoretical framework of the paper, presenting a general review of the relevant literature and our hypotheses concerning the nexus between deforestation and food FDI. Section 3 presents the methodology and data used in the empirical analysis. Section 4 reports and discusses the main findings, while the final section concludes.

2. Literature review and theoretical hypotheses

The process of deforestation and its deleterious effects on global climate change have become more and more evident in the recent decades, encouraging the investigation of this phenomenon and its causes in public debate and scientific research. These analyses largely vary in scope and methodology, but most research focuses on single case studies observing specific forested areas within countries or transnational areas (Walker et al., 2000; Godar et al., 2012; Faria and Almeida, 2016; Maji, 2017; Huaranca et al., 2019; Silva et al., 2021; Tameko, 2024) or cross-country studies (Long et al., 2017; Leblois et al., 2017; Abman and Lundberg, 2020; Xiao et al., 2022; Piabuo et al., 2024). In addition, there are literature reviews (Angelsen, 1999; Angelsen and Kaimowitz, 1999; Wehkamp et al., 2018; Pendrill et al., 2022; Busch and Ferretti-Gallon, 2023) combining these case studies to draw more general conclusions, and research adopting analytical perspectives to propose theories concerning the drivers of deforestation (Rudel and Roper, 1997; Amsberg, 1998; Miyamoto, 2020).

In particular, considerable attention is paid to economic openness and the effects of trade flow on deforestation (Niklitschek, 2007; Tsurumi and Managi, 2014; Ahmed et al., 2015; Faria and Almeida, 2016; Leblois et al., 2017; Maji, 2017; Abman and Lundberg, 2020; Ajanaku and Collins, 2021; Xiao et al., 2022; Tameko, 2024), obtaining mixed results. An inverse relationship between trade openness and deforestation is observed in Nigeria (Maji, 2017) and Chile (Niklitschek, 2007), while a positive relationship is found in Brazil (Faria and Almeida, 2016), Indonesia (Kustanto, 2021) and Congo Basin countries (Tameko, 2024). This positive relationship is also confirmed by Abman and Lundberg (2020), who find that smallholder participation in palm oil commodity markets ensured by contract farming (in which farmers receive credit, a guaranteed price and quantity for the contract duration and output pickup at the village) also contributes to deforestation in tropical developing countries. Similarly, Leblois et al. (2017) analyse a panel of 128 countries, concluding that agricultural trade is one of the major drivers of deforestation, while Ajanaku and Collins (2021) find forest product trade to be a major cause of deforestation. Conversely, no relationship between trade openness and deforestation is found in an analysis of Pakistan by Ahmed et al. (2015) or by Xiao et al. (2022) for African countries.

A limited number of studies focus on the environmental impacts of FDI on deforestation in particular. Moreover, the results are mixed, with contradictory findings. The *pollution haven hypothesis* predicts a positive impact of FDI on carbon emissions and deforestation, which is explained by the intensive use of natural resources and delocalisation of activities, with negative externalities to avoid environmental regulation. This result is found, among others, by Long et al. (2017), who demonstrate the detrimental effects of FDI on forests as well as natural resources and minerals examining a panel of 125 developing countries. A detrimental relationship is also found for African countries by Bokpin (2017), Assa (2018) and Lokonon and Mounirou (2019).

In contrast, the *pollution halo hypothesis* predicts a negative impact of FDI on CO_2 emissions and deforestation, which is explained by the introduction of better (greener) technologies along with investments. This result is found, among others, by Pradhan et al. (2022), who focus on the relationship between CO_2 emissions and FDI inflow in Brazil, Russia, India, China and South Africa (BRICS countries). However, a majority of the literature observes non-linear and more complex relationships of FDI when examining carbon footprint (Doytch and Uctum, 2016; Solarin and Al-Mulali, 2018; Doytch, 2020; Piabuo et al., 2024) or deforestation (Tsurumi and Managi, 2014; Caravaggio, 2020; Ajanaku and Collins, 2021), with positive effects prevailing in poorer countries and negative impacts in richer countries. Scholars refer to these results as an environmental Kuznets curve for deforestation and propose the forest transition theory (de Jong et al., 2017), i.e. deforestation increases in the first stages of economic growth, but at a slower pace until the process reverses with a sufficiently high level of development.

More specific causes of deforestation that emerge from the literature include land tenure regimes and sectoral specialisation. In particular, the agricultural sector (Walker et al., 2000; Mbatu, 2010; Ceddia et al., 2014; Leblois et al., 2017; Papworth et al., 2017; Huaranca et al., 2019; Caravaggio, 2020; Kinda and Thiombiano, 2021; Pendrill et al., 2022; Vasconcelos et al., 2024), extractive activities (Papworth et al., 2017; Doytch, 2020; Kinda and Thiombiano, 2021) and non-financial services (Doytch and Uctum, 2016; Doytch, 2020) are demonstrated to generate deforestation. Within the food sector, the environmental impact of animal production tends to be much larger than that of vegetable substitutes (Walker et al., 2000; Godar et al., 2012; Goldman et al., 2020; Pendrill et al., 2022). Pendrill et al. (2022) suggest that more than one-third of the deforestation induced by agricultural activities is attributable to the expansion of cattle pastures. A similar result is provided by Goldman et al. (2020), who consider seven agricultural commodities (palm oil, soy, cattle, plantation wood fibre, cocoa, coffee and plantation rubber) and identify cattle activities as the main driver of forest cover loss. Walker et al. (2000) and Godar et al. (2012) show that large scale cattle ranching is particularly deleterious in Amazonia, including large and small producers, both of which demonstrate a significantly larger influence from large-scale cattle ranching. Conversely, Silva et al. (2021) do not find any clear link between deforestation and extensive land use for cattle production. In a similar vein, agricultural activities promoted by large-scale and multinational companies have been associated with deforestation, while the evidence is more nuanced for smallholders (Huaranca et al., 2019; Müller-Hansen et al., 2019), although the impact of small farmers and rural poor on forests in still notable (Miyamoto, 2020; López-Carr, 2021).

To the best of our knowledge, of the previous research that provides sector-level detail about the environmental impact of economic activities, only two studies specifically focus on FDI (Doytch and Uctum, 2016; Doytch, 2020) and no studies examine the effects of FDI on deforestation. Therefore, although the reviewed studies provide important insights on the effect of sector specialisation on deforestation, they do not address the potentially contrasting effects of FDI in different sectors (most importantly, in the food industry) on deforestation. Moreover, most of the reviewed studies rely on macroeconomic approaches considering sector specialisation, FDI inflow and environmental impact at the country level, while the dynamics governing the relationship between these phenomena are predominantly local.

Furthermore, since the publication of Hansen et al. (2013) data about forest loss, the number of studies relying on satellite images are rapidly increasing, demonstrating the importance of assuming a local perspective (Busch and Ferretti-Gallon, 2023). Referencing Busch and Ferretti-Gallon (2017 and 2023), 320 spatially explicit econometric studies were published in peer-reviewed academic journals between 1996 and 2019 about the drivers of deforestation. These studies generally find that deforestation is associated with greater accessibility and higher economic returns (from agriculture, livestock and timber), population pressure is associated with more deforestation and only policies that directly influence allowable land-use activities are associated with less deforestation. To the best of our knowledge, no previous research investigates FDI as a potential driver of deforestation and we next provide a few examples considering other relevant drivers to better frame the findings of our research concerning agriculture, international openness and densely forested areas. Mbatu (2010) finds deforestation in Cameroon to be associated with demographic variables and agricultural production. In a cross-country analysis based on aggregated satellite data, Leblois et al. (2017) find a (weak) correlation between deforestation and international trade. Also using satellite data, Papworth et al. (2017) find that gold mining and agriculture drive forest loss in Myanmar. Baehr et al. (2021) measure the impact of rural infrastructure on deforestation, revealing a mild effect that is statistically relevant in densely forested areas.

Based on previous literature and the noted gaps, this study investigates the effect of FDI on deforestation and innovates in three directions. First, the study relies on a large and detailed database on cross-border bilateral greenfield investments (fDi Markets) and categorises them into non-food and food projects, further classifying food projects into different sub-sectors.[1] This allows us to bridge the gap between the literature on the deforestation effects of FDI and the investigation concerning the environmental impact of different sectors of economic activity. Second, unlike previous studies on the effects of FDI, this research adopts a broad geographic scope, analysing more than 4500 locations over 120 non-OECD countries situated in different regions and continents, providing globally relevant conclusions. Third, the analysis uses annual satellite data on forest cover and deforestation, which allows us to observe the phenomenon from a local perspective.

As suggested by the literature, indeed, the impact of FDI on deforestation may operate through different direct and indirect channels, and our research hypotheses address both effect types. The direct effect involves the use of land and natural resources as inputs of the production process driven by FDI, noting that investments in developing countries may intensively consume environmental resources according to the pollution haven hypothesis. More specifically, FDI projects in the agriculture and food industry (Walker et al., 2000; Mbatu, 2010; Ceddia et al., 2014; Leblois et al., 2017; Papworth et al., 2017; Huaranca et al., 2019; Caravaggio, 2020; Goldman et al., 2020; Kinda and Thiombiano, 2021; Pendrill et al., 2022; Vasconcelos et al., 2024) and in the livestock and animal industry (Walker et al., 2000; Goldman et al., 2020; Pendrill et al., 2022) are particularly expected to have negative impacts on forests. Services such as transport and non-financial services can also exert negative environmental impacts (Doytch and Uctum, 2016; Doytch, 2020), but not necessarily in terms of deforestation. Indirect effects are associated with potential increases in formal employment, diversification of economic activities and structural change that may result from FDI. For example, FDI projects that improve market access for agricultural products produced by smallholders are expected to result in forest loss (Abman and Lundberg, 2020) by providing incentives for farmers to exploit more land. In contrast, FDI projects that increase formal employment can reduce the dependency of the rural poor on local natural resources for their livelihoods (Huaranca et al., 2019; Müller-Hansen et al., 2019; Miyamoto, 2020; López-Carr, 2021). Indirect effects of FDI, particularly those foreseen by the pollution halo hypothesis, can be considered systemic, and may also have impacts that reach beyond local deforestation; for example, by introducing technologies that ensure more efficient use of raw materials such as wood or agricultural products and reduce pressure on land at the national level or by stimulating the adoption of enhanced environmental regulations. However, these systemic effects are not examined in this study, which only focuses on the effects of FDI on deforestation at the local level.

3. Data and methodology

Data concerning FDI are drawn from the fDi Markets database, which is published by the Financial Times Ltd. and provides comprehensive information on announced FDI reported in the press and cross-referenced against multiple sources, with a primary focus on direct company sources.[2] The database provides updated, comprehensive and detailed information about cross-border bilateral greenfield investments.[3] This study considers the FDI received by non-OECD (mostly developing)[4] countries between 2003 and 2019. The fDi Markets database contains information about investments' place of destination (country, state, region, town/village), its sector and sub-sector and the amount of capital invested.

We use the information about the country of destination, state, region and city to geo-reference each FDI project using the Stata 'geocode' command (Ozimek and Miles, 2011) and opencagegeo (Zeigermann, 2016). The FDI projects considered by this study include those in destination locations that were possible to geo-reference, for which the control variables are available and are located in areas (location) that were at least partially covered by forest in the year of the investment. These data include 58,650 investments in 4521 locations, which are the units of our panel dataset. Locations are defined as circular areas with 7.5 km radius around the FDI location and are relatively large and correspond to around 17,000 ha each.[5] The choice of this radius results from a trade-off between opposite considerations. On the one hand, a relatively broad area can mitigate the urban bias that is implicit to the georeferencing exercise performed, which is based on toponyms and

[1] Non-food includes industries in the primary sector such as timber and mining.

[2] Therefore, the fDi Markets dataset might include some announced investments for the most recent years that are then discarded. However, this bias only applies to recent years because discarded projects are removed from the database, ensuring the reliability of the database for less recent years. For this reason, we discarded the data from 2022, 2021 and 2020 in this study (Castellani and Pieri, 2013), considering the time period from 2003 (the beginning of the recording) to 2019.

[3] According to the fDI Markets dataset, greenfield investments correspond to the establishment of new enterprises or the substantial expansion of an existing foreign firm (Jungmittag and Marschinski, 2022).

[4] As presented in Section 4, robustness tests are also conducted excluding areas in high income countries from the sample (Appendix C, Table C5).

[5] For robustness tests, alternative 5 km and 10 km radiuses are taken, resulting in around 8000 ha and 31,500 ha, respectively.

tends to associate FDI to towns and centres, while the processes we observe are likely to be located in their surroundings. In particular, deforestation effects may even materialise beyond this area and most likely within daily commuting distance from the centre of the investment. On the other hand, a relatively narrow dimension limits the confounding effect of noise and other factors, including the overlap of other FDI locations (see Appendix C, Table C2 and Table C4, for robustness tests addressing these issues).

Investments are grouped into 37 sectors in the fDi Markets classification. The Food & Beverages sector consists of 3379 investment projects (5.76 % of the total),[6] and projects are further divided in 21 sub-sectors.[7] For the purposes of this study, the 21 sub-sectors are grouped into four categories,[8] as follows:

- Food processing: bakeries, breweries, snack, soft-drinks, sugar, seasoning, dairy;
- Food trade and services: stores, services, trade;
- Animal industry: animal food, animal production, animal processing;
- Other food: coffee and tea, crops, fishing and hunting, fruits and vegetables, grains, seafood, wineries, other.[9]

For each location i, year t and sub-sector ss, we sum the invested amount in USD (deflated to 2015 USD prices) ($FDI_{i\ t\ ss}$). We then construct the main explanatory variables by calculating these figures for each group h (i.e. non-food; food processing, food trade and services, animal industry and other food) as follows:

$$FDI_{ith} = \sum_{ss=1}^{SS} FDI_{i\ t\ ss} \forall \mathrm{ss} \in \mathrm{h} \tag{1}$$

While most investment values provided by the fDI Markets database are reportedly estimated, two main considerations support the use of these data. First, the main (only) alternative is simply using the number of investments received, which fails to reflect activities' scale. This implies the assumption that the overall dimension of FDI is proportional to the number of investment projects received, while some regions might attract a few large projects when others attract many small ones (Castellani et al., 2016). Second, recent studies increasingly use the FDI values estimated by fDI Markets, at least in robustness tests, demonstrating overall consistency (Amoroso and Muller, 2018; Jungmittag and Marschinski, 2022). Fig. 1 compares the two options, confirming general similarity.

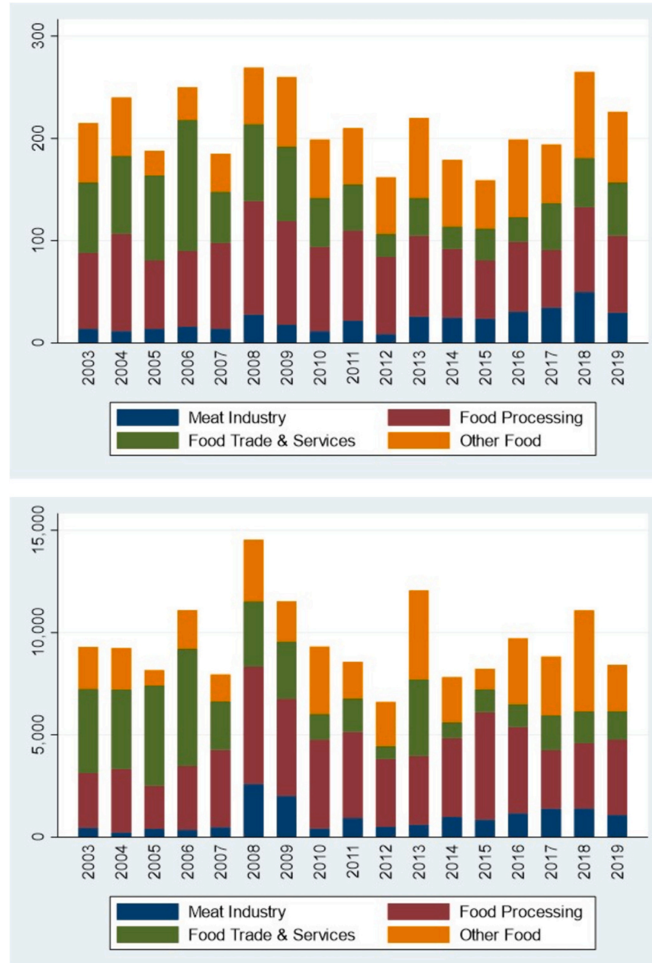

Fig. 1. Number of FDI by year and sub-sector (top panel) and value of FDI by year and sub-sector in constant 2015 USD million (bottom panel).

The dependent variable and all regressors refer to the location surrounding the FDI project. The dependent variable references data on forest loss from Hansen et al. (2013) and is constructed as the percentage of 30 m × 30 m cells that experienced deforestation in the location in a given year. Therefore, the forest loss variable does not refer to the rate of loss (i.e. the denominator is constant).[10] As an alternative dependent variable, the percentage of cells that experienced forest loss is also cumulated over 3 years (from t to $t+2$) to account for potential distribution of the effects of FDI projects over the three years following implementation.

The number of control variables is severely limited by the spatial nature of data because some potentially relevant variables are simply unavailable for the specific locations surrounding each FDI. Nevertheless, we are able to control for the main causes of deforestation identified in the literature (Angelsen and Kaimowitz, 1999; Tsurumi and Managi, 2014), and particularly for population density and development, as

6 This is after excluding Tobacco investments, which are not relevant to the food focus of this study.

7 The fDi Markets classification is generally but loosely inspired by the North American Industry Classification System (NAICS https://www.census.gov/naics/). Indeed, while the NAICS classification has a clear hierarchy in which the classification by sector (i.e. agricultural production vs processing of agricultural products) precedes the classification by nature of the product, the fDi Markets classification sometimes gives priority to the product, regardless of the value chain stage involved. For example, the grains class does not only include agricultural production of grains, but also includes processing into flour and other manufactured products.

8 In selecting the sub-sectors for each of the four groups, we prioritise internal homogeneity (i.e. all the sub-sectors included actually belong to the group) over comprehensiveness (i.e. all the FDI projects relevant to the group are included). For example, FDI projects in the sub-sectors classified as 'other food' are likely to include a mix of investments in agricultural production and food processing. Consequently, not all processing investments are included in the food processing group (no comprehensiveness), while all the investments in this group refer to processing (homogeneity). Similarly, it is not possible to identify FDI in the primary sector from the fDi Markets' classification, i.e. in agricultural production. It is also important to note that the animal industry group is cross-cutting to primary and secondary sectors and includes the animal products along the value chain, with the homogeneity given by the nature of the product.

9 As presented in Section 4, an alternative classification including the dairy sub-sector in animal industry is used for testing the robustness of main results (Appendix C, Table C5).

10 Forest loss is defined as a stand-replacement disturbance or the complete removal of tree cover canopy at the Landsat pixel scale (30 × 30 m), where forest loss is defined as occurring if pixel tree canopy cover goes from >50 % to ~0 % in a given year (Hansen, 2013). Forest pixels in 2000 are defined accordingly as those with more than 50 % forest cover (Hansen, 2013).

measured by nighttime light emissions. We quantify average population density by averaging population in a 1 sq. km grid in the location. Satellite nighttime light emissions in the 1 sq. km grid are averaged over the location and divided by the corresponding averaged population density. The resulting variable is per capita nighttime light, which is a proxy for economic development and many development-correlated factors (Elvidge et al., 1997; Chen and Nordhaus, 2011; Henderson et al., 2012, 2018; Weidmann and Schutte, 2017; Asher et al., 2021; Gibson et al., 2021).

When potential endogeneity is considered, reverse causality is not a main concern in the relationship between FDI and deforestation. A considerable body of literature examines the determinants and factors that attract FDI in developing countries (Root and Ahmed, 1979; Asiedu, 2002; Economou et al., 2017) and food FDI in particular (Ning and Reed, 1995; Walkenhorst, 2001; Makki et al., 2004; Chanegriha et al., 2017; Bailey, 2018); however, no research shows that deforestation can attract FDI. However, we contend that countries with weaker legal and policy frameworks and regulatory oversight protecting forests might attract land-intensive FDI. The deforestation impact of investments might also depend on these laws and policies, indicating the risk of omitting related control variables (Xing and Kolstad, 2002; Assa, 2018). More generally, governance and the degree of economic freedom also have an influence (Ceddia et al., 2014; Bokpin, 2017; Long et al., 2017; Assa, 2018). Additionally, other country-level variables such as logistic performance, national-level shocks, national-level conflicts, international agreements and sanctions and the degree of trade openness for specific products might affect both FDI and deforestation. For these reasons, we introduce a country–year fixed effect into our models to control for country-level variables and associated evolution over time. This is a more comprehensive approach than any proxy of the variables discussed above and any other country-level controls that we might include (for which estimation is beyond the scope of this study).[11] Moreover, by controlling for development in each location using per capita nighttime light, we mitigate the concern of omitting a variable that might contribute to cause both deforestation and FDI inflow. We select the fixed effects estimator with multiple fixed effects to strengthen identification and limit omitted variable bias by compensating for the limited number of available controls for individual locations through multiple fixed effects. This estimator allows us to control for the fixed effects of the unit of observation (i.e. location) as well as time (year) and country interaction. The model is specified as follows:

$$\mathrm{FL}_{it} = \alpha + \sum_{b=h}^{H} b_h FDI_{ith} + \gamma \mathrm{PCNL}_{it} + \delta \mathrm{POP}_{it} + \eta_i + \theta_{ct} + \varepsilon_{it} \tag{2}$$

where FL_{it} is the percentage of forest loss in each location i in year t. FDI_{ith} is the value of investments that targeted location i in year t for each group of sectors and sub-sectors (h). $PCNL_{it}$ and $\mathrm{POP}_{\mathrm{it}}$ are respectively per capita nighttime light emissions and population density in each location i in year t. η_i denotes the location fixed effect, and θ_{ct} accounts for the fixed effect of the combination of country (i.e. country of the target location) and year. The error term is ε_{it}, which is clustered by location.

In all the tables, models are first presented without any control variable (baseline), followed by the introduction of population density and models that also control for development referencing nighttime light emissions. We then estimate these same models for sub-samples of locations i that are grouped depending on the percentage of forest cover remaining in year t (forest cover residual). Information about the cover residual in each location of interest is obtained by subtracting all the forest losses experienced up to year t from the forest cover registered in $t = 2000$ (Hansen et al., 2013). We then categorise locations into more and less forested for two reasons. First, FDI might enjoy the economies of scale that are necessary to clear and initiate new production activities in remote places that local businesses and farmers are unable to exploit. Second, the same forest loss in a green area or in a more urban context is qualitatively different as deforestation in a green area has a strong impact on the environment and ecosystem and is usually a preliminary step towards further forest loss.

Robustness tests presented in Appendix C include 1) a narrower definition of the location, with a radius of 5 km from the FDI target point (Table C1); 2) a broader location definition, with a radius of 10 km from the FDI target point (Table C2); 3) an alternative construction of the dependent variable, reflecting different assumptions about the time frame of the effects and assuming that forest loss resulting from FDI might materialise in the year of the investment as well as the following two, three and four years (Table C3C3), cumulating the original forest loss values forward. Moreover, we re-estimate the models after excluding locations that include more than one FDI target point or overlap from the sample. This is done to avoid mixing the effects of different FDI in the same location (Table C4). Table C5, presents the results of alternative estimates from FDI re-grouping, including the dairy sub-sector in the animal industry and excluding high-income countries from the sample. Finally, in Table C6 we re-estimate models controlling for country-level governance.[12] Appendix B presents descriptive statistics, the list of countries in the sample, exact data sources and details regarding the variables' construction.

4. Results

Table 1 reveals that when FDI projects are simply classified into food and non-food FDI (column 1), the food component has a positive and significant coefficient, suggesting that FDI in the food sector might be associated with deforestation, which is consistent with the pollution haven hypothesis. This also holds when the model is extended by introducing population density and nighttime light emissions as control variables (columns 2 and 3). To obtain further insights on the drivers behind the observed relationship, we decompose food FDI projects into animal industry, food trade and services, food processing and other food sub-sector groups as introduced in Section 3. In baseline and extended models (columns 4–6), FDI in food trade and services exhibits a positive and significant coefficient whose dimension is above that of most other sub-sectors. This result might be explained by the peri-urban nature of retail and wholesale activities and logistic hubs, which are intensive in terms of land use and resemble what Doytch (2020) finds regarding the impact of non-financial services on the ecological footprint. Moreover, the increasingly diffused adoption of contract farming and similar solutions by investors can contribute to explaining this result. In contract farming, the production of agricultural commodities remains with small- and medium-scale farmers from the surroundings and the investor only centralises collection through collection centres and sometimes other value adding activities down the value chain (Abman and Lundberg, 2020). Indeed, contract farming is now among the preferred solutions for investors (Barrett et al., 2012; Bellemare and Bloem, 2018). Contract farming projects, which are classified as trade and services, can still promote agricultural activity.

Table 2 presents the results obtained when the sample is divided into two sub-samples, respectively including locations where the residual forest cover is lower (columns 1–3) vs more (columns 4–6) than half of the area. The rationale behind our interest in locations where forest is

[11] This large number of effects ($c \times t$, where c is the number of countries and t is the number of years) renders the estimation using common Stata commands cumbersome and slow, while the same results can be obtained with the Stata routine reghdfe by Correia (2016), which is much faster.

[12] To allow the inclusion of a country-level variable, we must exclude country–year fixed effect, which is replaced by year fixed effect in Appendix Table C6 models. We also include the same models without controlling for governance in the table as benchmarks.

Table 1
Modelling forest loss in the 7.5 radius area around the FDI (multiway fixed effects estimator).

	1	2	3	4	5	6
Non-food FDI	−0.0015	−0.0010	−0.0010	−0.0016	−0.0010	−0.0010
	(0.0038)	(0.0041)	(0.0041)	(0.0038)	(0.0041)	(0.0041)
Food FDI	0.0734	0.0772*	0.0772*			
	(0.0461)	(0.0467)	(0.0467)			
FDI in animal industry				0.3554	0.3648	0.3648
				(0.4136)	(0.4149)	(0.4149)
FDI in food trade and services				0.1427***	0.1484***	0.1484***
				(0.0323)	(0.0316)	(0.0316)
FDI in food processing				−0.0373	−0.0390	−0.0390
				(0.0323)	(0.0311)	(0.0311)
Other food FDI				0.0871	0.0972	0.0972
				(0.0626)	(0.0626)	(0.0626)
Population density		−0.0311***	−0.0311***		−0.0312***	−0.0312***
		(0.0069)	(0.0069)		(0.0069)	(0.0069)
Per capita nightlight emission			−0.0001			−0.0001
			(0.0001)			(0.0001)
Constant	0.1751***	0.2152***	0.2152***	0.1751***	0.2153***	0.2153***
	(0.0002)	(0.0089)	(0.0089)	(0.0002)	(0.0089)	(0.0089)
Observations	*72,321*	*72,321*	*72,321*	*72,321*	*72,321*	*72,321*
Locations	*4521*	*4521*	*4521*	*4521*	*4521*	*4521*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.5979*	*0.5983*	*0.5983*	*0.5979*	*0.5984*	*0.5984*

Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2
Modelling forest loss in the 7.5 radius area around the FDI in location sub-samples based on forest cover residual.

	Residual forest cover <0.5			Residual forest cover ≥ 0.5		
	1	2	3	4	5	6
Non-food FDI	0.0018	0.0021	0.0021	−0.0670**	−0.0671**	−0.0671**
	(0.0032)	(0.0032)	(0.0032)	(0.0292)	(0.0292)	(0.0292)
FDI in animal industry	−0.0567	−0.0518	−0.0518	4.0335***	4.0300***	4.0300***
	(0.0493)	(0.0478)	(0.0477)	(0.2296)	(0.2305)	(0.2305)
FDI in food trade and services	0.1231***	0.1262***	0.1262***	0.6899	0.6776	0.6776
	(0.0407)	(0.0382)	(0.0382)	(1.2230)	(1.2226)	(1.2227)
FDI in food processing	−0.0185	−0.0196	−0.0196	−0.7355	−0.7377	−0.7378
	(0.0230)	(0.0224)	(0.0224)	(0.7064)	(0.7053)	(0.7054)
Other food FDI	0.0855	0.0917	0.0917	0.3746	0.3841	0.3840
	(0.0610)	(0.0610)	(0.0610)	(0.5038)	(0.5048)	(0.5047)
Population density		−0.0170***	−0.0170***		0.0734	0.0734
		(0.0053)	(0.0053)		(0.1516)	(0.1516)
Per capita nightlight emission			−0.0001			−0.0003
			(0.0001)			(0.0090)
Constant	0.1369***	0.1611***	0.1611***	0.4748***	0.4597***	0.4598***
	(0.0002)	(0.0075)	(0.0075)	(0.0099)	(0.0312)	(0.0312)
Observations	*64,128*	*64,128*	*64,128*	*7802*	*7802*	*7802*
Locations	*4104*	*4104*	*4104*	*520*	*520*	*520*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.6281*	*0.6283*	*0.6283*	*0.6141*	*0.6141*	*0.6141*

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the dominant land cover relies on the considerations extensively introduced above (Section 3). The coefficients of FDI in food trade and services are only large, positive and significant for locations with relatively low residual forest cover (<50 %). Conversely, in locations with relatively more forest, the largest and most significant (positive) coefficients are those of the animal industry sub-sector. Similarly, when we divide the sample into quintiles of the forest cover residual distribution (Table 3), the effect of FDI in food trade and services on deforestation is confirmed for the central quintiles (columns 4–6), while animal industry drives the deforestation effect in the top quintile (columns 7–9), representing the locations that still have at least 37 % of forest cover residual in the year of the investment. Non-food FDI projects have a negative but weakly significant coefficient (columns 4–6 of Table 2; columns 7–9 of Table 3). The rationale for this result might be explained by the reduced dependency of the rural poor on natural resources (Huaranca et al., 2019; Müller-Hansen et al., 2019; Miyamoto, 2020; López-Carr, 2021); for example, an increase in labour demand in sectors other than agriculture may reduce the pressure of farming on forests.

Regarding the other regressors, population density exhibits a negative and significant coefficient in the full sample (Table 1) and in locations with relatively less forest cover residual (columns 2 and 3 of Table 2; columns 2, 3, 5 and 6 of Table 3). This is probably attributable to the low forest cover residual of urban, high-density locations, which reduces the likelihood of forest loss simply because forest is not there or is no longer there. Development, as proxied by per capita nighttime light emissions, is consistently insignificant and its inclusion does not affect

Table 3
Modelling forest loss in the 7.5 radius area around the FDI in location sub-samples based on forest cover residual quintiles.

	Bottom quintile			Central quintiles			Top quintile		
	1	2	3	4	5	6	7	8	9
Non-food FDI	0.0004	0.0005	0.0005	0.0048	0.0043	0.0043	−0.0450*	−0.0450*	−0.0450*
	(0.0004)	(0.0004)	(0.0004)	(0.0044)	(0.0044)	(0.0044)	(0.0250)	(0.0250)	(0.0250)
FDI in animal industry	−0.0154	−0.0143	−0.0143	−0.0101	−0.0078	−0.0078	3.4445***	3.4442***	3.4440***
	(0.0220)	(0.0222)	(0.0222)	(0.0362)	(0.0359)	(0.0359)	(0.5953)	(0.5957)	(0.5958)
FDI in food trade and services	0.0035	0.0048	0.0048	0.1494***	0.1467***	0.1467***	0.8083	0.8078	0.8078
	(0.0144)	(0.0145)	(0.0145)	(0.0243)	(0.0239)	(0.0239)	(0.8636)	(0.8639)	(0.8640)
FDI in food processing	0.0161	0.0162	0.0162	−0.0282	−0.0319	−0.0319	−0.3957	−0.3956	−0.3956
	(0.0279)	(0.0278)	(0.0278)	(0.0286)	(0.0276)	(0.0276)	(0.2453)	(0.2454)	(0.2453)
Other food FDI	0.0164	0.0174	0.0174	0.0252	0.0342	0.0342	0.8667	0.8664	0.8666
	(0.0241)	(0.0240)	(0.0240)	(0.0479)	(0.0477)	(0.0477)	(0.6651)	(0.6644)	(0.6645)
Population density		−0.0009**	−0.0009**		−0.0270***	−0.0270***		0.0026	0.0026
		(0.0004)	(0.0004)		(0.0081)	(0.0081)		(0.0629)	(0.0629)
Per capita nightlight emission			0.0000			−0.0000			0.0020
			(0.0000)			(0.0000)			(0.0097)
Constant	0.0103***	0.0124***	0.0124***	0.1470***	0.1808***	0.1808***	0.4188***	0.4180***	0.4177***
	(0.0000)	(0.0009)	(0.0009)	(0.0002)	(0.0102)	(0.0102)	(0.0008)	(0.0202)	(0.0203)
Observations	*14,189*	*14,189*	*14,189*	*43,137*	*43,137*	*43,137*	*14,261*	*14,261*	*14,261*
Locations	*0.6036*	*0.6037*	*0.6037*	*0.6194*	*0.6197*	*0.6197*	*0.6189*	*0.6189*	*0.6189*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.0004*	*0.0005*	*0.0005*	*0.0048*	*0.0043*	*0.0043*	*−0.0450**	*−0.0450**	*−0.0450**

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the size or significance of the other coefficients.

Robustness tests presented in Appendix Tables C1 and C2 replicate the same models considering respective radiuses of 5 km and 10 km from the centre of the location of the investment, which is typically a town. The results confirm that FDI projects in the animal industry have a tremendous detrimental effect in locations that are more than half covered by forest at the time of investment. However, some differences are revealed when the other sub-sectors are considered. The coefficients of FDI in food trade and services remain positive but are no longer significant within the 5 km radius. This provides some support for the argument that deforestation is correlated with agricultural activities induced by FDI in surrounding rural areas. FDI can create demand for agricultural production, even without directly engaging init. In such cases, deforestation effects can be found further from the centre in which the FDI project is located (radius > 5 km), as in the case of contract farming (Abman and Lundberg, 2020). FDI projects in food processing also have a significant negative effect when the forest cover residual is at least half of the area (model 3 in Table C1). This is probably attributable to the same reason that drove the significant negative coefficients of non-food FDI in the main models (i.e. work opportunities in sectors other than agriculture that reduce the pressure of farming on forests).

To account for possible delayed effects, the robustness tests presented in Table C3 consider forest loss in the year of the investment as well as the next two, three and four years (by cumulating forest losses registered over three-, four- and five-year periods). The deforestation effects of FDI in the animal industry (above 50 % of forest cover residual, columns 3, 6 and 9) and those of FDI in food trade and services (whole sample and lower half, columns 1, 2, 4, 5, 7 and 8) are both confirmed. Additionally, non-food FDI sometimes exhibits a significant deforestation effect over the three- and four-year periods (columns 1, 2 and 5). In other words, while food FDI has an immediate impact on forests by directly using the land for agriculture and livestock purposes, the deforestation effects of non-food FDI seem to take longer. This might be attributed to the fact the deforestation has an indirect effect in such cases, resulting from the growing number of people and activities attracted around the FDI location in the years following the investment.

An additional set of robustness tests presented in Appendix Table C4 excludes locations where at least another target location exists in the radius of 7.5 km from the FDI target location from the sample because of the challenges they pose in distinguishing respective effects. Our results are also confirmed in this case. Appendix Table C5 presents robustness tests performed with slightly altered classifications of food sectors and excluding high-income countries. The alternative food sector classification is obtained by grouping the FDI in the dairy industry with those in the animal value chain to encompass a broader portrayal of the industry. We modify the processing group that includes the dairy sector in the main models accordingly. The exclusion of high-income countries aims to ensure that the results, primarily focused on the development challenges and trade-offs faced by developing countries, are not driven by the few high-income countries in the sample. These tests also confirm the robustness of previous results. Finally, Table C6 not only demonstrates that our results are robust to the inclusion of the quality of governance among the regressors, but also that governance itself has a significant negative effect on forest loss, contributing to the limitation of deforestation.

5. Discussion and conclusions

By analysing the effect of cross-border greenfield investments in non-OECD countries on deforestation, this study contributes to the research concerning the environmental impacts of FDI in developing countries, with three main findings. *First*, the FDI projects that primarily drive forest loss in recipient countries are those in the food sector, while FDI in other sectors does not seem to significantly contribute to deforestation. This reinforces the potential existence of a pollution haven dynamic at play in developing countries, which aligns with most of the literature on FDI and deforestation (Long et al., 2017; Bokpin, 2017; Assa, 2018; Lokonon and Mounirou, 2019), indicating a specific connection between agrifood activities and environmental degradation (Walker et al., 2000; Mbatu, 2010; Ceddia et al., 2014; Leblois et al., 2017; Papworth et al., 2017; Huaranca et al., 2019; Caravaggio, 2020; Goldman et al., 2020; Kinda and Thiombiano, 2021; Pendrill et al., 2022; Vasconcelos et al., 2024). *Second*, forest loss induced by food FDI is driven by specific sub-sectors, while other sub-sectors do not exhibit significant correlation with deforestation. In particular, among food FDI projects, those in food trade and services seem to be the main driver of deforestation, which is likely due to increased demand for local agricultural production (Abman and Lundberg, 2020) as well as new infrastructure and logistic hubs. Our estimates indicate that a one million USD investment in food trade and services is associated with almost 300 square metres of forest loss. Considering that the average investment in this sub-sector is around 64 million USD, this corresponds to a 1.67-ha loss. While the small dimension of this impact on average does not call for urgent policy action, the significance of the effect deserves attention. Moreover, while we estimate impacts within the 7.5 km threshold, additional effects might occur beyond this radius. *Third*, contrasting dynamics are found in areas characterised by different forest land cover, and the deforestation effect of FDI in food trade and services is only confirmed for locations with relatively low residual forest cover, which is likely because such investments require relatively less land in locales that are close to pre-existing agricultural activities, which might have already consumed a relevant share of the forest. Conversely, deforestation is primarily driven by FDI in the animal industry in locations with relatively more residual forest.

More specifically, in areas where at least half of the original forest is still standing, this finding suggests that an investment of one million USD in the animal industry would result in around three-quarters of hectare of immediate forest loss and almost one hectare lost in the next two years. The average size of an investment in this sub-sector (47 million USD) corresponds to more than 33 ha of forest loss. The forest loss associated with FDI in the meat and animal industry are easily explained by the intensive land use required. Animal grazing is a clear example as well as animal feed production, which is notoriously more land intensive than the production of human food (Bender, 1994; van Zanten et al., 2016).

Interestingly, congruent with the pollution halo hypothesis, non-food FDI projects are found to have a negative but weakly significant effect in locations characterised by relatively more residual forest. The dimension of the impact implies that an average annual investment (around 300 million USD) can save around 3 ha of forest. This might be explained by the work opportunities offered in non-agricultural sectors and the beneficial effects of structural change reducing the pressure of the rural poor on land-based income sources, which aligns with Miyamoto (2020) and López-Carr (2021). However, this result is contingent on the time frame examined, wherein when deforestation is considered over a longer period following the investment, a detrimental effect is also detected for non-food FDI, which may be interpreted as an indirect effect of resulting economic and infrastructural development.

In terms of policy recommendations, this study indicates that low- and middle-income countries that seek to attract FDI should consider the potential trade-off between economic development and forest protection, particularly if FDI projects are concentrated in the food sector and in the animal food products sub-sector. Moreover, development partners should enable low- and middle-income countries to prioritise environmental sustainability to protect global forests and fight climate change, although this can conflict with legitimate development objectives (Bel and Teixidó, 2020), and develop solutions to solve this trade-off. Finally, this study reveals the need to promote global awareness (Poore and Nemecek, 2018) on food consumption habits and the sustainability of animal production, which applies to high-income countries, where the consumers of products from long value chains are often found as well as low- and middle-income countries. These countries (middle-income countries in particular) are indeed undertaking a so-called nutrition transition (Damman et al., 2008; Popkin, 2006) that is associated with increased animal product consumption, among other effects.

The scope of the analysis presented in this study was constrained by data availability at the local level. When new data are available, further research could investigate the causality mechanisms that explain the relationships demonstrated in this study to explore the country-level effects that our model aggregates into country–year fixed effects and could employ alternative methodologies such as event (Callaway and Sant'Anna, 2021) or survival analysis. Moreover, more disaggregated analyses should investigate which specific activities within the identified sub-sectors cause deforestation. Finally, policy-oriented research should examine the types of foreign investment, i.e. in terms of size and geographical origin, that should be discouraged to protect national forest resources.

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CRediT authorship contribution statement

Luca Bortolotti: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Marta Marson:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Donatella Saccone:** Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Appendix

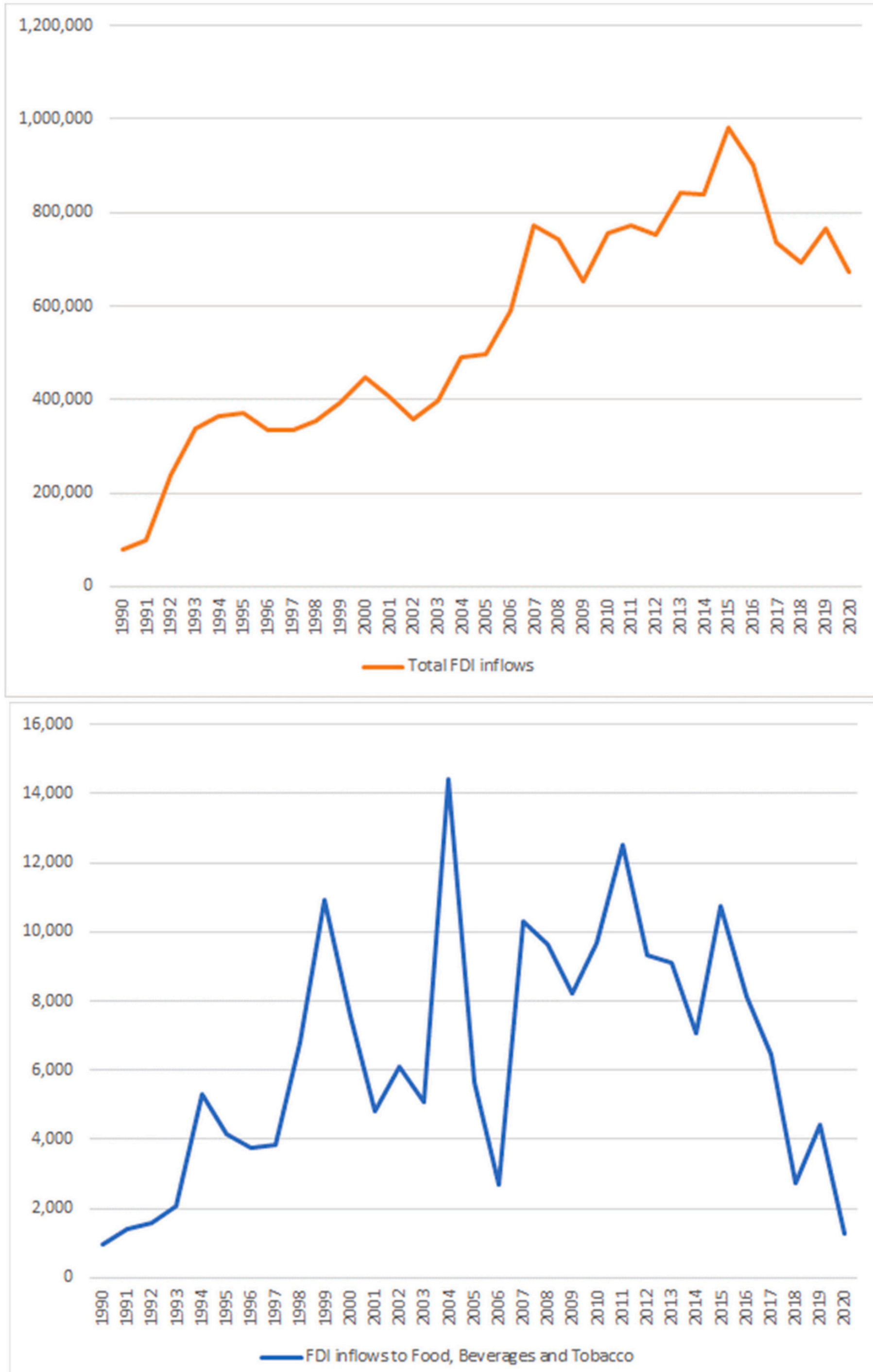

Fig. A1. FDI inflows in non-OECD economies, 1990–2020 (million USD 2015). Authors' analysis based on FAOStat 2023

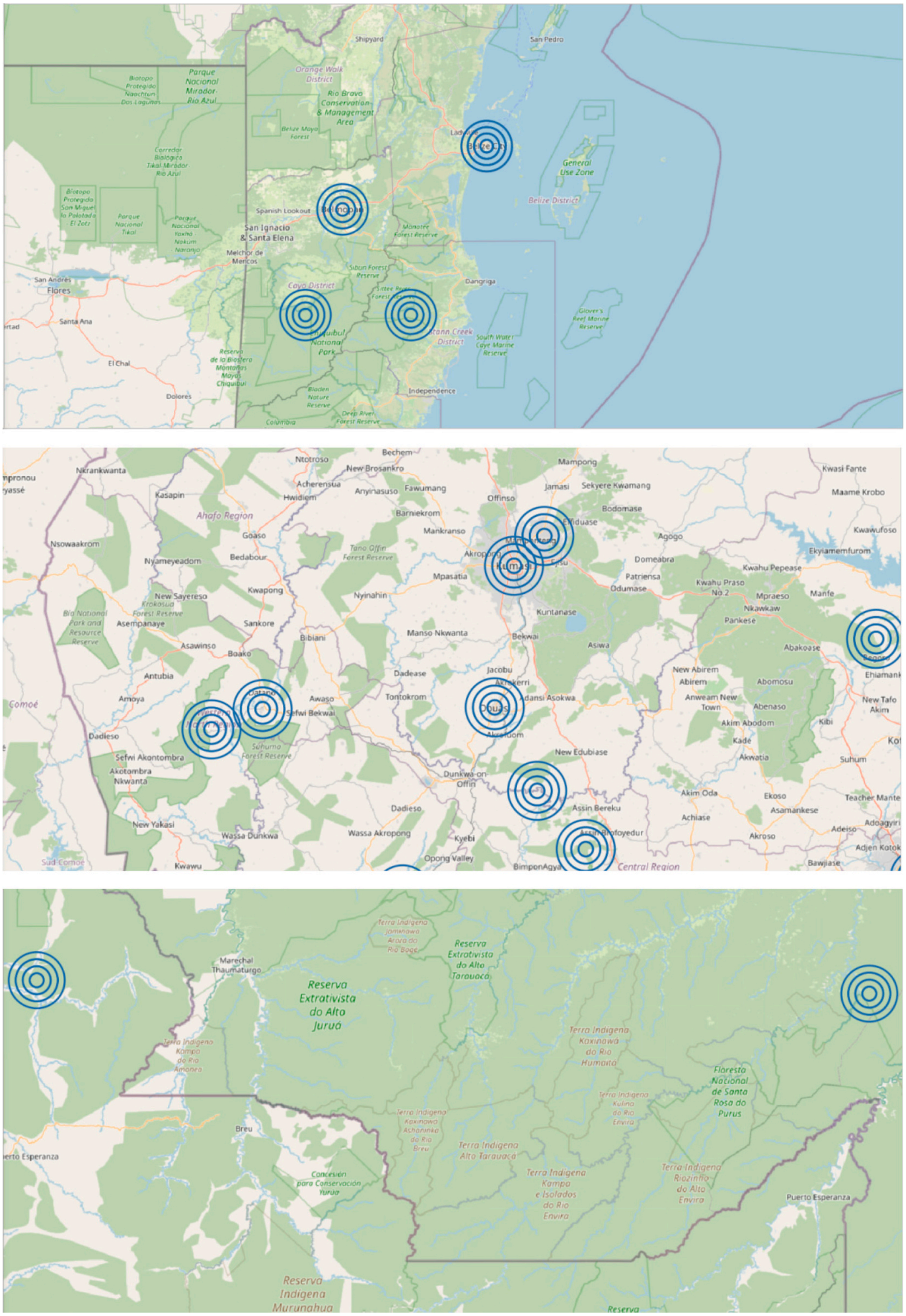

Fig. A2. Examples of FDI locations.

The blue concentric circles represent FDI locations from our sample, with the most external circle representing the 10 km radius, then the 7.5 km, the 5 km and the core. The background is from OpenStreetMap and green should not be interpreted as necessarily indicating forest land cover, but still provides an idea of the features of the location. The scale is approximately 1:1,000,000.

Appendix B. Data sources and descriptive statistics

All data are available at https://drive.google.com/file/d/1zgKD9b8B1l0GEr91MrnYitEdqi1kWno-/view?usp=drive_link

Table B1. Data sources.

Variables	Description	Construction	Source
Non-food FDI (billion USD 2015)	The value of all FDI but those in the food and beverage production chain.	All the FDI but that in the Food & Beverages sector, including investments in Tobacco.	fDi Markets
Food FDI (billion USD 2015)	The value of FDI in the food and beverage production chain.	FDI in the Food & Beverages sector with the exception of investments in Tobacco.	fDi Markets
FDI in animal industry (billion USD 2015)	The value of FDI related to the animal value chain.	All food FDI in Animal food, Animal production and Animal slaughtering & processing sub-sectors.	fDi Markets
FDI in food trade and services (billion USD 2015)	The value of FDI related to trade and services connected to food products.	All food FDI in Food & beverage stores, Food services and Wholesale trade sub-sectors.	fDi Markets
FDI in food processing (billion USD 2015)	The value of FDI related to food processing and manufacturing activities.	All food FDI in Bakeries & tortillas, Breweries & distilleries, Dairy products, Seasoning & dressing, Snack food, Soft drinks & ice and Sugar & confectionary products sub-sectors.	fDi Markets
Other food FDI (billion USD 2015)	The value of the remaining FDI in the food and beverage sector.	All food FDI in Coffee & tea, Crop production, Fishing, hunting & trapping, Fruits & vegetables & specialist foods, Grains & oilseed, Other (Food & Beverages), Seafood products and Wineries sub-sectors.	fDi Markets
Population density	Population density in 1000 persons per sq. km in a circular area surrounding the investment location (radius 5/7.5/10 km alternatively).	Average population density (Population counts at 30 arc sec resolution)/1000.	Bright, E.A., Coleman, P.R., Rose, A.N. *LandScan Global Population Database* Oak Ridge, TN 37831 Oak Ridge National Laboratory https://landscan.ornl.gov
Nighttime light emissions per capita	Nighttime light emissions per sq. km in a circular area surrounding the investment location (radius 5/7.5/10 km alternatively).	Nighttime light emissions per sq. km divided by population density averaged over a circular area surrounding the investment location (radius 5/7.5/10 km alternatively).	Li et al. (2020) https://pubmed.ncbi.nlm.nih.gov/32499523/
Governance	Quality of governance at country level (−2.5 – +2.5)	Average of the six dimensions of governance covered by Worldwide Governance Indicators, which include Voice and Accountability Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption.	Worldwide Governance Indicators - World Bank https://www.worldbank.org/en/publication/worldwide-governance-indicators
Forest loss percentage	Percentage of 30 × 30 m pixels that experienced forest loss in the reference year in a circular area surrounding the investment location (radius 5/7.5/10 km alternatively).	Number of 30 × 30 m pixels that experience forest loss in the reference year divided by number of pixels in a circular area surrounding the investment location (radius 5/7.5/10 km alternatively) x 100.	Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, *L. chini*, C. O. Justice and J. R. G. Townshend. 2013. *High-Resolution Global Maps of 21st-Century Forest Cover Change*. Science 342 (15 November): 850–53. https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.7.html
Forest loss cumulated percentage	Percentage of 30 × 30 m pixels that experienced forest loss in the reference year or in the following 2/3/4 years in a circular area surrounding the investment location (radius 5/7.5/10 km alternatively).	Number of 30 × 30 m pixels that experience forest loss in the reference year or in the following 2/3/4 years divided by number of pixels in a circular area surrounding the investment location (radius 5/7.5/10 km alternatively) x 100.	
Forest cover residual	Percentage of 30 × 30 m pixels with forest cover in 2000, which did not experience forest loss in the reference year or in any year between 2000 and the reference year in a circular area surrounding the investment location.	Number of 30 × 30 m pixels with forest cover in 2000 minus number of 30 × 30 m pixels that experienced forest loss in the reference year or in any year between 2000 and the reference year in a circular area surrounding the investment location (radius 5/7.5/10 km alternatively) x 100.	

Table B2. Descriptive statistics.

	Obs	Mean	Std. dev.	Min	Max
Non-food FDI	72,321	0.0573	0.44	0	45.36
Food FDI	72,321	0.0022	0.03	0	2.78
FDI in animal industry	72,321	0.0002	0.01	0	1.27
FDI in food trade and services	72,321	0.0006	0.01	0	2.66
FDI in food processing	72,321	0.0008	0.02	0	2.76
Other food FDI	72,321	0.0005	0.01	0	1.01
Population density in a 7.5 km radius	72,321	1.29	2.68	0	39.61
Per capita nightlight emission in a 7.5 km radius*	72,321	0.16	5.44	0	1162
Forest cover residual percentage in a 7.5 km radius	72,321	19.55	22.28	2.27E-11	100
Forest loss percentage in a 7.5 km radius	72,321	0.18	0.49	0	16.97
Governance	72,321	−0.2039	0.8762	−2.0187	1.7055
Forest loss % in the next 3 years (t, $t+1$, $t+2$) in a 7.5 km radius	64,320	0.53	1.29	0	29.06

(*continued on next page*)

(*continued*)

	Obs	Mean	Std. dev.	Min	Max
Population density in a 5 km radius	69,831	1.75	3.36	0	51.85
Per capita nightlight emission in a 5 km radius*	69,831	0.15	6.09	0	1501
Forest cover residual percentage in a 5 km radius	69,831	18.14	22.19	9.09E-13	100
Forest loss percentage in a 5 km radius	69,831	0.16	0.51	0	26.79
Forest loss % in the next 3 years (t, $t+1$, $t+2$) in a 5 km radius	62,132	0.50	1.33	0	41.55
Population density in a 10 km radius	73,463	1.04	2.25	0	32.68
Per capita nightlight emission in a 10 km radius*	73,463	0.16	6.57	0	1567
Forest cover residual percentage in a 10 km radius	73,463	20.54	22.36	2.27E-11	99.98
Forest loss percentage in a 10 km radius	73,463	0.18	0.47	0	15.14
Forest loss % in the next 3 years (t, $t+1$, $t+2$) in a 10 km radius	65,341	0.55	1.27	0	24.07

[*] maximum per capita nightlight values above the 63 are due to the presence average population densities below 0.001.

Table B3. Countries and locations in the sample.

	Obs	%		Obs	%		Obs	%		Obs	%		Obs	%
Albania	340	0.5	Cayman Is.	51	0.1	Guinea	104	0.1	Malta	272	0.4	Rwanda	166	0.2
Algeria	714	1.0	Central Af. Rep.	34	0.1	Guinea B.	14	0.0	Mauritius	85	0.1	St Lucia	51	0.1
Andorra	85	0.1	China	6174	8.5	Guyana	68	0.1	Moldova	187	0.3	Serbia	2057	2.8
Angola	279	0.4	Colombia	918	1.3	Haiti	102	0.1	Mongolia	12	0.0	Sierra Leone	153	0.2
Argentina	2486	3.4	Comoros	85	0.1	Honduras	323	0.5	Montenegro	204	0.3	South Africa	669	0.9
Armenia	446	0.6	Costa Rica	799	1.1	India	4364	6.0	Morocco	540	0.8	South Sudan	90	0.1
Azerbaijan	442	0.6	Cote d Ivoire	114	0.2	Indonesia	1938	2.7	Mozambique	301	0.4	Sri Lanka	721	1.0
Bahamas	34	0.1	Croatia	1512	2.1	Iran	78	0.1	Myanmar	294	0.4	Syria	180	0.3
Bangladesh	334	0.5	Cuba	357	0.5	Jamaica	153	0.2	Namibia	37	0.1	Taiwan	595	0.8
Barbados	51	0.1	Cyprus	119	0.2	Kazakhstan	690	1.0	Nepal	158	0.2	Tajikistan	61	0.1
Belarus	493	0.7	Dem.Rep. Congo	222	0.3	Kenya	524	0.7	New Caledonia	17	0.0	Tanzania	330	0.5
Belize	68	0.1	Dominican Rep.	425	0.6	Kyrgyzstan	151	0.2	North Korea	51	0.1	Thailand	995	1.4
Bermuda	34	0.1	Ecuador	408	0.6	Laos	330	0.5	N. Macedonia	405	0.6	Trinidad & T.	85	0.1
Bhutan	136	0.2	Egypt	232	0.3	Lebanon	224	0.3	Pakistan	208	0.3	Tunisia	517	0.7
Bolivia	202	0.3	El Salvador	374	0.5	Lesotho	10	0.0	Palestine	23	0.0	Turkmenistan	68	0.1
Bosnia-Herz.	901	1.3	Eq. Guinea	68	0.1	Liberia	119	0.2	Panama	368	0.5	Turks & C. Is.	34	0.1
Botswana	6	0.0	Eswatini	97	0.1	Libya	45	0.1	Papua N.G.	102	0.1	Uganda	380	0.5
Brazil	6429	8.9	Ethiopia	146	0.2	Liechtenstein	85	0.1	Paraguay	301	0.4	Ukraine	1577	2.2
Brunei	51	0.1	Fiji	85	0.1	Lithuania	527	0.7	Peru	587	0.8	Uruguay	544	0.8
Bulgaria	2312	3.2	Gabon	153	0.2	Macau	34	0.1	Philippines	2057	2.8	Uzbekistan	418	0.6
Burundi	22	0.0	Georgia	680	0.9	Madagascar	179	0.3	Kosovo	459	0.6	Venezuela	479	0.7
Cambodia	435	0.6	Ghana	297	0.4	Malawi	71	0.1	Rep. Congo	51	0.1	Vietnam	2278	3.2
Cameroon	204	0.3	Grenada	34	0.1	Malaysia	2295	3.2	Romania	3397	4.7	Zambia	168	0.2
Cape Verde	62	0.1	Guatemala	306	0.4	Maldives	57	0.1	Russia	6045	8.4	Zimbabwe	72	0.1

Appendix C. Robustness tests

Table C1. Alternative radius (5 km).

	Whole sample	Res. forest cover < 0.5	Res.forest cover ≥0.5	Bottom quintile	Central quintiles	Top quintile
	1	2	3	4	5	6
Non-food FDI	−0.0004	−0.0002	−0.0416*	0.0003	0.0072	−0.0247
	(0.0041)	(0.0036)	(0.0238)	(0.0002)	(0.0045)	(0.0240)
FDI in animal industry	0.9748	−0.0469	9.2054***	−0.0408	−0.0016	8.4328***
	(1.0266)	(0.0557)	(0.2551)	(0.0258)	(0.0456)	(0.7338)
FDI in food trade and services	0.0516	0.0421	−0.0071	0.0040	0.0073	1.2576
	(0.0394)	(0.0326)	(0.6566)	(0.0030)	(0.0155)	(1.6492)
FDI in food processing	−0.0413	−0.0178	−1.2655**	0.0023	−0.0075	−0.6659
	(0.0384)	(0.0266)	(0.5398)	(0.0160)	(0.0247)	(0.4216)
Other food FDI	0.1061	0.0443	0.0149	−0.0063	0.0513	0.8678
	(0.0853)	(0.0571)	(0.3400)	(0.0081)	(0.0594)	(0.9061)
Population density (ray 5 km)	−0.0184***	−0.0099***	−0.0093	−0.0002	−0.0140***	−0.0417
	(0.0032)	(0.0019)	(0.0586)	(0.0002)	(0.0036)	(0.0395)
Per capita nightlight emission (ray 5 km)	−0.0000	0.0000	−0.0032	0.0000	0.0000	−0.0042
	(0.0000)	(0.0000)	(0.0131)	(0.0000)	(0.0000)	(0.0082)
Constant	0.1961***	0.1460***	0.4960***	0.0101***	0.1526***	0.4355***
	(0.0057)	(0.0037)	(0.0137)	(0.0006)	(0.0061)	(0.0154)
Observations	*69,831*	*62,670*	*6852*	*13,680*	*41,677*	*13,777*
Locations	*4374*	*4005*	*457*	*1099*	*2608*	*867*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.5427*	*0.5724*	*0.5915*	*0.6119*	*0.5525*	*0.5737*

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C2. Alternative radius (10 km).

	Whole sample	Res. forest cover < 0.5	Res.forest cover ≥0.5	Bottom quintile	Central quintiles	Top quintile
	1	2	3	4	5	6
Non-food FDI	−0.0020	0.0026	−0.0598***	0.0003	0.0021	−0.0332
	(0.0032)	(0.0021)	(0.0222)	(0.0003)	(0.0038)	(0.0205)
FDI in animal industry	0.1290	−0.0650	2.0814***	0.0027	−0.0097	1.5016***
	(0.1844)	(0.0550)	(0.1728)	(0.0286)	(0.0398)	(0.4242)
FDI in food trade and services	0.0512***	0.0324**	0.3698	0.0071	0.0417***	0.5976
	(0.0190)	(0.0144)	(1.0362)	(0.0058)	(0.0130)	(0.5780)
FDI in food processing	−0.0086	0.0065	−0.1962	0.0284	0.0068	−0.3368
	(0.0304)	(0.0277)	(0.3244)	(0.0426)	(0.0306)	(0.2471)
Other food FDI	0.1022	0.0706	2.5508	−0.0028	0.0413	0.9401
	(0.0655)	(0.0588)	(2.6593)	(0.0125)	(0.0434)	(0.7384)
Population density (ray 10 km)	−0.0410***	−0.0283***	0.2147	−0.0027***	−0.0332***	0.2060*
	(0.0078)	(0.0069)	(0.2109)	(0.0008)	(0.0087)	(0.1054)
Per capita nightlight emission (ray 10 km)	−0.0000*	−0.0000	−0.0016	−0.0000	−0.0000**	0.0021
	(0.0000)	(0.0000)	(0.0055)	(0.0000)	(0.0000)	(0.0079)
Constant	0.2244***	0.1756***	0.4202***	0.0165***	0.1932***	0.3530***
	(0.0082)	(0.0080)	(0.0407)	(0.0014)	(0.0090)	(0.0313)
Observations	*73,463*	*64,550*	*8497*	*14,454*	*43,796*	*14,500*
Locations	*4601*	*4153*	*572*	*1170*	*2741*	*925*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.6299*	*0.6461*	*0.6522*	*0.6793*	*0.6496*	*0.6549*

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C3: Alternative lag structures (Forest loss cumulated over 3 years, 4 years and 5 years).

	Effects on forest over 3 years			Effects on forest over 4 years			Effects on forest over 5 years		
	Whole sample	Res. forest cover < 0.5	Res. forest cover ≥0.5	Whole sample	Res. forest cover < 0.5	Res. forest cover ≥0.5	Whole sample	Res. forest cover < 0.5	Res. forest cover ≥0.5
	1	2	3	4	5	6	7	8	9
Non-food FDI	0.0196**	0.0153***	−0.0584	0.0199	0.0147**	0.0225	0.0214	0.0090	0.1190
	(0.0095)	(0.0049)	(0.0816)	(0.0126)	(0.0058)	(0.1145)	(0.0164)	(0.0061)	(0.1151)
FDI in animal industry	0.3901	−0.1593	5.3907***	0.1466	−0.1485	3.2634***	0.3137	−0.0594	3.5265***
	(0.5540)	(0.1409)	(0.4904)	(0.3092)	(0.1350)	(0.4783)	(0.3730)	(0.0769)	(0.5982)
FDI in food trade and services	0.1757***	0.1379***	3.2829	0.5587***	0.5301***	1.9748	1.0696***	1.0532***	1.0328
	(0.0622)	(0.0324)	(2.7567)	(0.1147)	(0.1296)	(2.7264)	(0.2927)	(0.3118)	(3.6753)
FDI in food processing	−0.0551	−0.0356	−0.3511	−0.0804	−0.0413	−1.1844	−0.0956	−0.0605	−1.0460
	(0.0575)	(0.0464)	(0.9332)	(0.0705)	(0.0529)	(1.4161)	(0.0861)	(0.0689)	(1.3641)
Other food FDI	0.1651	0.1716	−0.0016	0.3610**	0.2908*	0.4724	0.3045	0.2418	0.4917
	(0.1141)	(0.1087)	(0.8020)	(0.1738)	(0.1628)	(1.9761)	(0.1935)	(0.1955)	(2.0475)
Population density	−0.0915***	−0.0484***	0.2520	−0.1178***	−0.0626***	0.3038	−0.1393***	−0.0748***	0.2829
	(0.0202)	(0.0153)	(0.4054)	(0.0256)	(0.0190)	(0.4831)	(0.0296)	(0.0210)	(0.5272)
PC nightlight emission	−0.0002	−0.0001	−0.0252	−0.0002	−0.0002	−0.0394	−0.0003	−0.0003	−0.0626
	(0.0002)	(0.0002)	(0.0224)	(0.0003)	(0.0002)	(0.0295)	(0.0003)	(0.0003)	(0.0437)
Constant	0.6502***	0.4753***	1.4637***	0.8593***	0.6228***	1.9931***	1.0587***	0.7617***	2.5506***
	(0.0259)	(0.0217)	(0.0833)	(0.0327)	(0.0269)	(0.0994)	(0.0377)	(0.0296)	(0.1086)
Observations	*64,320*	*56,950*	*7021*	*60,279*	*53,341*	*6611*	*56,210*	*49,708*	*6195*
Locations	*4776*	*4206*	*545*	*4776*	*4198*	*545*	*4776*	*4186*	*545*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.7562*	*0.7684*	*0.7845*	*0.7974*	*0.8027*	*0.8266*	*0.8310*	*0.8275*	*0.8621*

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C4: alternative sample (without overlapping locations).

	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5	Bottom quintile	Central quintiles	Top quintile
	1	2	3	4	5	6
Non-food FDI	−0.0004	0.0007	−0.0368	0.0008	0.0090	−0.0555**
	(0.0065)	(0.0066)	(0.0399)	(0.0006)	(0.0077)	(0.0283)
FDI in animal industry	0.5247	−0.0005	3.9866***	0.0100	0.0209	3.7976***
	(0.5408)	(0.0300)	(0.2197)	(0.0315)	(0.0295)	(0.2008)
FDI in food trade and services	0.1573***	0.1468***	0.4333	0.0117	0.1514***	0.3126
	(0.0264)	(0.0313)	(1.2015)	(0.0081)	(0.0197)	(1.0680)
FDI in food processing	−0.0835*	−0.0473	−0.6661	0.0227	−0.0664*	−0.3421
	(0.0448)	(0.0358)	(0.7455)	(0.0477)	(0.0383)	(0.2543)
Other food FDI	0.0841	0.1194	−0.8022	0.0326	−0.0118	1.0972
	(0.1006)	(0.1039)	(1.2003)	(0.0549)	(0.0633)	(1.4171)
Population density	−0.0205	−0.0104	0.0947	−0.0011	−0.0257	0.1108

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	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5	Bottom quintile	Central quintiles	Top quintile
	1	2	3	4	5	6
	(0.0171)	(0.0140)	(0.1891)	(0.0009)	(0.0245)	(0.1255)
PC nightlight emission	−0.0001	−0.0001	0.0031	0.0000	−0.0000	0.0048
	(0.0001)	(0.0001)	(0.0090)	(0.0000)	(0.0000)	(0.0104)
Constant	0.2052***	0.1516***	0.4770***	0.0126***	0.1807***	0.4220***
	(0.0131)	(0.0120)	(0.0320)	(0.0011)	(0.0188)	(0.0266)
Observations	*52,451*	*45,429*	*6610*	*10,177*	*31,276*	*10,240*
Locations	*3293*	*2933*	*437*	*830*	*1960*	*653*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.5960*	*0.6232*	*0.6139*	*0.5958*	*0.6309*	*0.6048*

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C5: alternative classification of the dairy industry and alternative sample excluding high-income countries from non-OECD countries.

	Alternative classification of the dairy industry			Excluding high income countries		
	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5
	1	2	3	4	5	6
Non-food FDI	−0.0010	0.0022	−0.0668**	−0.0010	0.0022	−0.0672**
	(0.0041)	(0.0032)	(0.0293)	(0.0041)	(0.0032)	(0.0292)
FDI in animal industry				0.3655	−0.0515	4.0301***
				(0.4149)	(0.0476)	(0.2299)
FDI in food trade and services	0.1481***	0.1263***	0.6852	0.1492***	0.1280***	0.6777
	(0.0317)	(0.0382)	(1.2267)	(0.0314)	(0.0374)	(1.2196)
FDI in food processing				−0.0390	−0.0197	−0.7376
				(0.0311)	(0.0224)	(0.7036)
Other food FDI	0.0983	0.0918	0.3806	0.0975	0.0912	0.384
	(0.0627)	(0.0610)	(0.5060)	(0.0627)	(0.0609)	(0.5035)
Population density	−0.0311***	−0.0169***	0.0729	−0.0316***	−0.0173***	0.0727
	(0.0069)	(0.0053)	(0.1518)	(0.0069)	(0.0053)	(0.1514)
PC nightlight emission	−0.0001	−0.0001	−0.0002	−0.0001	−0.0001	−0.0003
	(0.0001)	(0.0001)	(0.0090)	(0.0001)	(0.0001)	(0.0090)
FDI in the animal industry (with dairy)	0.1083	−0.0031	3.3535***			
	(0.1236)	(0.0138)	(0.7491)			
FDI in food processing (excl. dairy)	−0.1106**	−0.0632	−1.0315			
	(0.0537)	(0.0408)	(0.8617)			
Constant	0.2152***	0.1611***	0.4595***	0.2212***	0.1655***	0.4690***
	(0.0089)	(0.0075)	(0.0312)	(0.0090)	(0.0077)	(0.0313)
Observations	*72,321*	*64,128*	*7802*	*69,262*	*61,278*	*7627*
Locations	*4521*	*4104*	*520*	*4341*	*3934*	*508*
Country-year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.5984*	*0.6283*	*0.6140*	*0.5987*	*0.6301*	*0.6122*

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C6: controlling for country-level governance.

	without governace			with governance		
	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5
	1	2	3	4	5	6
Non-food FDI	0.0023	0.0037	−0.0527**	0.0023	0.0036	−0.0522**
	(0.0036)	(0.0035)	(0.0233)	(0.0036)	(0.0035)	(0.0233)
FDI in animal industry	0.3264	−0.0323	3.2249***	0.3268	−0.0322	3.2237***
	(0.3652)	(0.0345)	(0.2463)	(0.3654)	(0.0345)	(0.2459)
FDI in food trade and services	0.1504***	0.1271***	0.8028	0.1485***	0.1264***	0.7575
	(0.0297)	(0.0413)	(0.7771)	(0.0305)	(0.0417)	(0.7710)
FDI in food processing	−0.0580*	−0.0360	−0.8347**	−0.0601*	−0.0371	−0.8293**
	(0.0337)	(0.0257)	(0.4125)	(0.0339)	(0.0257)	(0.4122)
Other food FDI	0.0583	0.0611	0.1815	0.0590	0.0615	0.1716
	(0.0555)	(0.0501)	(0.5393)	(0.0558)	(0.0503)	(0.5354)
Population density	−0.0098***	−0.0057**	0.2388	−0.0099***	−0.0058**	0.2395
	(0.0031)	(0.0027)	(0.1971)	(0.0031)	(0.0027)	(0.1969)
PC nightlight emission	0.0000	−0.0000	0.0051	0.0000	−0.0000	0.0046
	(0.0001)	(0.0001)	(0.0121)	(0.0001)	(0.0001)	(0.0121)

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	without governace			with governance		
	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5	Whole sample	Residual forest cover < 0.5	Residual forest cover ≥0.5
	1	2	3	4	5	6
Governance				−0.0394***	−0.0196***	−0.1057**
				(0.0066)	(0.0038)	(0.0471)
Constant	0.1875***	0.1449***	0.4246***	0.1797***	0.1412***	0.3992***
	(0.0040)	(0.0039)	(0.0405)	(0.0042)	(0.0040)	(0.0419)
Observations	*72,321*	*64,128*	*7802*	*72,321*	*64,128*	*7802*
Locations	*4521*	*4104*	*520*	*4521*	*4104*	*520*
Year fixed effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R-squared	*0.5337*	*0.5706*	*0.5022*	*0.5339*	*0.5707*	*0.5026*

The different number of observations when splitting the sample is due to singleton observations dropped. Cluster robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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