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Foreign direct investment and knowledge diffusion in poor locations☆

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ABSTRACT

We use plant level census data to identify spillovers from FDI in Ethiopia's manufacturing sector. Spillovers are identified by comparing changes in total factor productivity (TFP) among domestic plants in districts where a large greenfield foreign plant produces and districts where FDI in the same industry was licensed but not yet operational. Over the four years starting with the year of the FDI opening, the TFP of domestic plants is 11 percent higher in treated districts, employment in domestic plants increases and more domestic plants open. We describe mechanisms for knowledge diffusion using a plant level technology transfer survey. One third of Ethiopian plants are linked to FDI through labor sharing, supply chains and competition. Technology upgrading is most common as a reaction to competition in output markets and observation and imitation of FDI in the same line of business. Other benefits include enhanced managerial practices and knowledge about exporting.

1. Introduction

The gaps in productivity between developed and developing countries are large; the poorer the country, the larger the gap. Foreign direct investment (FDI) could be a powerful tool for reducing these productivity gaps. Standard means of raising productivity such as investments in education and health are obviously important but they are costly and typically take a long time to bear fruit. By contrast on-the-job training and other types of learning could be less costly and have more immediate payoffs (Romer, 1992). In fact, it is now common for developing countries to include attracting FDI as an integral part of their industrialization strategies (UNCTAD, 2018).

Despite their theoretical and practical importance, the existence and magnitude of knowledge spillovers from foreign to domestic firms are considered open questions. This is especially the case for very poor countries like Ethiopia where – arguably – FDI could have the largest relative impact. In addition, most of the evidence for spillovers has been restricted to foreign firms and their suppliers. Yet, in a country like Ethiopia where supply chains are underdeveloped, the benefits of exposure to FDI are more likely to come through other channels. For example, Ethiopian plants commonly report: (i) directly adopting production techniques through observation and imitation of foreign plants in the same line of business and (ii) technology upgrading as a result of competition from FDI. In fact, we have very little systematic evidence on the mechanisms by which knowledge is transferred from foreign to domestic plants (Balsvik, 2011; Poole, 2013; Newman et al., 2015).

This paper has two objectives. First, we test for and quantify spillovers from FDI in the Ethiopian manufacturing sector by estimating how the productivity of incumbent plants changes when a large greenfield foreign plant opens in an Ethiopian district (Woreda). Focusing on spillovers at the local level has two advantages. First, it allows us to construct a plausible counterfactual. Second, the spillovers generated at the local level are likely to be of first-order importance and thus easier to identify.

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Second, we present qualitative evidence on the mechanisms by which knowledge is transferred from foreign to domestic plants. This evidence is the result of a technology-transfer survey designed by us in cooperation with Ethiopia's Central Statistical Agency (CSA) and administered as part of Ethiopia's annual census of manufacturing plants. Apart from horizontal and vertical linkages, the survey includes questions about learning by observation, labor sharing and the transfer of "soft" as opposed to technical knowledge.

Previous research typically classifies the interactions between foreign and domestic plants into horizontal or vertical linkages. Horizontal spillovers occur between plants classified in the same industry while vertical spillovers occur between foreign plants and their suppliers or their customers. While these definitions are analytically useful, they may be too restrictive. For example, Poole (2013) finds evidence of knowledge sharing through labor movements from foreign to domestic plants irrespective of industry. Moreover, recent evidence indicates that managerial skills that are not a priori industry specific are a key determinant of plant productivity (Bloom and Van Reenen, 2010). And Bloom et al. (2018) report that knowledge spillovers from large manufacturing plants in the U.S. enhance the management practices of smaller manufacturing plants in a variety of industries.[1]

The key question throughout this literature is whether knowledge from foreign plants can be assimilated by domestic plants. When put in these terms, the similarity between research that investigates knowledge diffusion between foreign and domestic plants and research on agglomeration externalities becomes evident. For example, Rosenthal and Strange (2003) and Kantor and Whalley (2014) explain that geographic proximity plays a key role in the acquisition of skills and that one of the benefits of clustering is that it facilitates learning. And Greenstone et al. (2010) quantify these agglomeration spillovers by comparing changes in total factor productivity (TFP) among plants in 'winning' counties that attracted a large manufacturing plant and 'losing' counties that were the new plant's runner-up choice.

Based on this literature, one may expect that the spillovers stemming from the presence of foreign plants would be obtained first by nearby domestic plants, and may slowly diffuse to other, more distant domestic plants. This is likely to be the case, for instance, if trained employees move from a foreign plant to a neighboring domestic plant or if the foreign plant uses a product, production process, managerial technique, organizational form, or export market formerly unknown to domestic plants.

The results from the 2013 technology transfer module confirm that domestic plants in close geographic proximity to foreign plants are three times more likely to report being linked to foreign plants (Fig. 1). The survey results also reveal that around one third of Ethiopian plants report being linked to foreign plants through labor sharing, forward and backward linkages and competition in input and output markets. These domestic plants report learning from foreign plants through supply chain interactions,[2] labor sharing, and observation and imitation. They also report that exposure to foreign plants enhances domestic plants: (i) production processes; (ii) managerial and organizational practices; and, (iii) knowledge about exporting.

The survey results provide qualitative evidence that the presence of FDI causes some domestic plants to be more productive. To formally test for and quantify the magnitude of these spillovers at the local level, we estimate augmented Cobb-Douglas production functions that allow the TFP of domestic plants to depend on the presence of a new foreign plant. We use plant-level data from Ethiopia's Annual Census of Manufacturers.

Because the foreign plant's location decision is made to maximize profits, the chosen district may differ substantially from an average or randomly chosen district, both at the time of the opening and in future periods. District characteristics that affect the foreign and domestic plants' TFP and that are difficult to measure include local transportation infrastructure, current and future costs of inputs, quality of the labor force, presence of intermediate input providers, and any other local cost shifters.

To identify the causal relationship between the opening of a foreign plant and domestic plants' productivity, we compare changes in TFP among domestic plants in 'treatment' districts to changes in TFP in 'control' districts. Treatment districts are defined as districts in which a large greenfield foreign plant operated. Using restricted-access administrative data from the Ethiopian Investment Commission, we define a control district as a location in which a foreign plant in the same industry applied for a license, got approval, but then did not produce during the period in which the foreign plant was operating in the treated district. As explained below, bureaucratic hurdles are the most cited explanation for the lag in investment translations (e.g., World Bank, 2014). The pre-trends in the treatment and control districts look quite similar; this finding is consistent with our identifying assumption that plants in the control districts form a valid counterfactual for the plants in the treated districts.

Our baseline estimates show an increase in TFP for treated domestic plants following the start of production of a greenfield foreign plant. Over the four years starting with the year in which the foreign plant opens, the average increase in the TFP of domestic plants is 11 percent. We obtain qualitatively similar results using an alternative strategy exploiting the assignment of land for FDI by the Ethiopian Government,

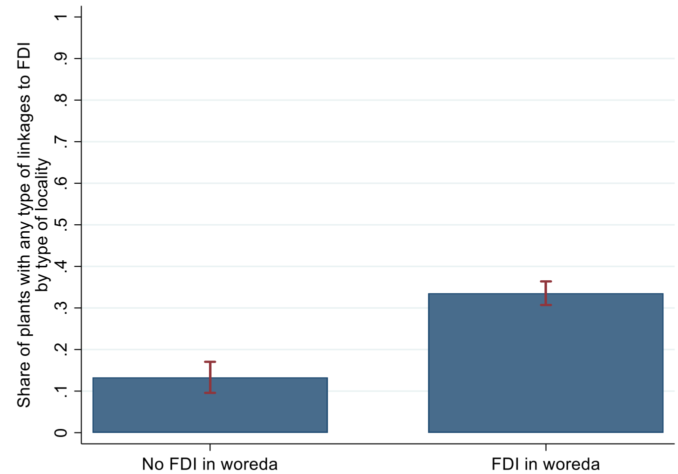

Fig. 1. Domestic Plants' Linkages by Proximity to FDI
Note: The figure shows the share of domestic manufacturing plants that reported at least one of the following linkages to FDI—i) hired employees who previously worked in FDI plant, ii) faced competition from FDI in the labor market, iii) faced competition from FDI in output market, iv) sells output to FDI plants, and v) buys inputs from FDI plant—for districts (Woredas) with manufacturing FDI presence and localities without manufacturing FDI presence.
Source: Own calculations using Ethiopia Large and Medium Scale Manufacturing (LMSM) Establishment Census, 2013 (Technology Transfer Module).

[1] Another example of spillovers that are not a-priori industry specific are corporate governance spillovers (Albuquerque et al., 2013).

[2] These findings are in line with previous survey evidence from the Czech Republic in Javorcik and Spatareanu (2009).

in combination with an event study research design.[3]

Our results are robust to alternative specifications addressing the issue of the endogeneity of inputs and do not appear to be driven by attrition of domestic plants or higher output prices.[4] A potential threat to our identification strategy is the fact that Ethiopia has been undergoing a major overhaul in its infrastructure which will impact the efficiency of domestic and foreign firms alike. To alleviate this concern, we control for government spending on capital improvements and infrastructure investment which varies by district and year and find that our results are robust to their inclusion. We have two explanations for this: (1) major developments including investments in the railway between Addis Ababa and Djibouti and the Grand Ethiopian Renaissance Dam occurred (or are ongoing) after the period we study, and (2) apart from industrial parks which did not begin to operate until 2016, to a large extent these investments are not district-specific and so are not expected to have a significant impact on location choice within Ethiopia. We explain this in greater detail in Section 2.

The productivity gains for domestic plants associated with FDI may incentivize new domestic plants to locate in districts with FDI. Thus, an indirect test of knowledge spillovers is a test for plant entry in treated districts. We find that following the entry of the foreign plant in a district there is an increase in the number of domestic plant openings. These results are consistent with the estimated increases in TFP and indicate that foreign plants attract new economic activity in the manufacturing sector to treated districts. We also document an increase in employment at treated domestic plants.

Our survey results indicate competition between FDI and domestic plants in both input and output markets. To test for competition in the labor market, we explore changes in wages in domestic plants exposed to FDI. We find little evidence of an impact of FDI entry on wages possibly due to the relative abundance of unskilled labor in Ethiopia. An important caveat is that we do not have worker characteristics or wages broken down by skill level which leaves open the possibility that wages for some skill groups might have increased.

Tests for attrition and employment changes serve as indirect tests for the relative importance of competition between FDI and domestic plants in both input and output markets. Competition could lead to relatively more attrition of domestic plants in the treatment group. It could also lead to layoffs. We find no evidence for differential attrition by treatment status. And as previously noted, instead of layoffs, we find evidence of employment expansion by plants in treated districts.

Our work contributes to the literature on knowledge spillovers from foreign direct investment in two ways. First, we overcome the identification problem that plagues much of the literature on spillovers associated with FDI by homing in on the local effects of FDI. Focusing on the local effects enables us to construct a plausible counterfactual. Moreover, as mentioned above, the local effects are likely to be of first-order importance. While our work is unlikely to settle the debate regarding the magnitude of knowledge spillovers, the evidence presented in this paper strongly supports the existence of knowledge flows from foreign to domestic plants.

Second, we present evidence based on a national census of manufacturing plants on the mechanisms by which knowledge is assimilated from foreign plants by domestic plants. Like previous work,[5] Ethiopian plants report productivity improvements associated with selling to foreign plants and hiring workers trained by foreign plants.[6] However, and unlike previous work, we find that the two most important channels through which technology upgrading occurs are through the observation and imitation of plants in the same line of business and through direct competition in the product market. These results are important because they imply that in a very poor country where domestic firms are not yet sophisticated enough to sell directly to foreign firms, exposure to FDI still has the potential to impact technology upgrading.

Our work also contributes to the empirical literature that examines the productivity advantages of agglomeration, recently reviewed by Combes and Gobillon (2015). Although there is evidence, mostly from analysis using data for developed countries, that significant agglomeration effects exist, the jury is still out over the nature of the microeconomic mechanisms that can account for these advantages (Baum-Snow, 2013; Kline and Moretti, 2014; Severnini, 2014; Cabral et al., 2018; Helm, 2020).

While the issues analyzed in this paper are of general interest, the specific case of Ethiopia is also important. Ethiopia is Africa's fastest growing country and has been for well over a decade. The government of Ethiopia has made industrialization with the help of FDI a key pillar of its growth strategy. Many on the continent of Africa view Ethiopia as an example to emulate. However, we have very little systematic evidence about how this strategy is playing out in the context of Ethiopia. Our results are generally supportive of an industrial policy that seeks to attract foreign direct investment for the purposes of upgrading domestic plants' capabilities.[7] Finally, our results underscore the importance of geographic proximity for realizing these gains. Special Economic Zones (SEZs) – a key albeit relatively recent element of Ethiopia's industrialization strategy – could limit interactions between foreign and domestic plants. This may happen if foreign plants locate in highly secure relatively remote locations or if foreign plants are given preferential access to SEZs because, for example, they export. This concern is not just relevant to African countries; SEZs are among the most popular instruments for attracting FDI and the number of SEZs has grown rapidly over the past ten years with many more planned (UNCTAD, 2019).

The remainder of this paper is organized as follows. Section 2 presents the foreign plant location decision and research design, and Section 3 describes the data and presents summary statistics. In Section 4 we outline our econometric model, we present our estimates of the magnitude of total factor productivity spillovers from FDI and discuss the validity and robustness of our estimates. The Section also presents evidence on domestic plant entry, employment and wages. Section 5 presents qualitative evidence from the technology transfer survey. Section 6 concludes.

[3] We consider as valid events the openings of foreign plants reporting that their location was allocated by the authorities—information which is reported in our technology transfer survey. Our research design then compares the TFP of domestic plants within a district before and after the opening. The regions targeted by the government are non-random; in particular the government often targets regions with higher needs in terms of investment. However, the exact geographic location within a broader region is typically determined by the availability of land. Moreover, the timing is often out of the hands of the government since there is substantial uncertainty about the exact year in which the foreign plant will start production. We estimate our econometric model with and without the never treated localities; in the latter case identification comes from the differential timing of treatment onset among the treated localities.

[4] To explore this possibility, we adopt two approaches. First, we remove domestic plants in a supply link with the new entrant, plants for which output price effects might be largest. Second, we investigate whether the TFP increase is bigger for plants that sell more locally.

[5] See for example: Javorcik (2004), Kugler (2006), Blalock and Gertler (2008), Javorcik and Spatareanu (2009), Javorcik and Spatareanu (2011), Newman et al. (2015), and Alfaro-Urena et al. (2019).

[6] See for example: Balsvik (2011), Poole (2013), and Fons-Rosen et al. (2018).

[7] The next step in this line of research would be to calculate the potential costs – both direct and indirect – of attracting foreign direct investment including foregone tax revenues and the construction of Special Economic Zones (SEZs).

2. Foreign plant location decision and research design

Our goal is to estimate the effect of FDI at the local level. Specifically, we estimate the impact of FDI on the total factor productivity (TFP) of domestic plants allowing the impact to depend on the presence of FDI in the district (Woreda). See Fig. A.1 for a map which shows Woreda boundaries. Specifically, we would like to evaluate the changes in the TFP of domestic plants when a foreign plant is added to a district. The underlying idea is that the impacts of FDI would be localized at least initially, with domestic plants in the same district more likely to be impacted by the presence of FDI.

Our primary identification challenge is that foreign companies do not select the location for their greenfield plants randomly. Like all companies, foreign companies aim to maximize profits. Thus, the location decision depends on local cost shifters (such as the quality of the labor force and transportation infrastructure), which are likely to be correlated with the TFP of domestic plants. Consequently, a simple contrast of the TFP of domestic plants in districts where a greenfield foreign plant opens with the TFP of domestic plants in districts where a foreign plant does not open is likely to produce biased estimates of FDI spillovers.

We address this empirical challenge by comparing domestic plants in districts where an FDI plant became operational (treatment districts/plants) to districts in which a foreign plant in the same industry applied for a license, got approval, but then did not produce during the period in which the foreign plant was operating in the treated district (control districts/plants). For each treatment district, at least one control district is found. The algorithm used to find control districts is described in detail in Section A.I. Here we provide a summary.

The algorithm is based on information on industry *and time of approval* of an FDI project. Let τ^{lic} denote year but be normalized so that the year when the FDI project got approved (in a treatment district) is $\tau^{lic} = 0$. For each treatment district (characterized by a given year of approval of the project and a given industry) we define the control as an FDI plant in the same industry and in the same year which got approval but then did not open during the period in which the foreign plant was operating in the treatment district. If we cannot find one, we look for a control district where the project was approved between $\tau^{lic} =$ -1 and $\tau^{lic} = 1$. And so on for $\tau^{lic} \in [-2,2]$ and $\tau^{lic} \in [-3,3]$. Notice that the year of FDI opening does *not* play a role in the algorithm.

Our identifying assumption is that the trend in domestic plants' TFP would have been identical in the absence of FDI in treatment and control districts, after conditioning on plant fixed effects, industry by year fixed effects, and other control variables. Essentially, we argue that the patterns of "conversion" from the investment stage to the operational phase are not determined by unobservable district-level characteristics that would also impact the productivity of domestic plants but rather by institutional and regulatory inefficiencies at the federal and regional levels. This argument is supported by accounts from foreign investors who report that the main obstacles to going forward with investments are: (i) trade regulations and customs clearance; and, (ii) inconsistent and frequently changing tax laws (Hailu, 2017). As Geiger and Moller (2015, p. 44) write, "Even though a One Stop Shop service is operational, its effectiveness record is mixed. Bureaucratic hurdles continue to affect project implementation."

Additionally, local governments do not appear to have the autonomy to significantly impact the investment climate in their districts. For example, Ayele and Fessha (2012, p.103) conclude that "the constitutional recognition of local government has fallen short of clearly articulating the powers and functions of local government. Unlike most other federal systems, the powers of local government are not even defined in the regional constitutions, or by way of ordinary regional legislation." Furthermore, local governments have fiscal incentives to conform to the will of regional and federal governments as they are largely financially reliant on regional and federal government grants.

As we show below, before the foreign plant started production, domestic plants in treatment and control districts were rather similar along several dimensions, and there were not statistically significant differences in TFP trends. This evidence supports the validity of our identifying assumption. Even if this assumption fails to hold, our strategy is arguably more reliable than employing regression adjustment to compare the TFP of domestic plants in districts with new entrants to the other (nearly 300) districts in our data featuring manufacturing activity, or employing a matching approach based on observables (see GHM, p. 552).

However, the federal and local governments in some cases set up worker training funds, construct new roads, and make other infrastructure investments around the time of entry of a foreign plant. It is possible that these investments benefit domestic plants in addition to the foreign plant. To examine this possibility, we control for government total capital expenditures and for government fixed assets and construction expenditures, with two measures varying at the district level over time. In addition, as noted in the introduction, the major infrastructure investments likely to affect the productivity of domestic and foreign firms have taken place after our sample period, which ends in 2013. The Industrial Park Development Corporation was established in 2015. Plans to expand the Addis Ababa airport were announced in March of 2015. And while the construction of the railroad from Addis Ababa to Djibouti started in 2011, it only began operating in 2018.

The largest of the infrastructure projects – the Grand Ethiopian Renaissance Dam (GERD) – has yet to produce any electricity. Moreover, the project is located in the remote town of Guba in the Benishangul-Gumuz Region. This region still has the lowest number and value of any form of investment in the entire country. The first filling of the dam occurred in 2020 year, and the construction of substations started in 2021. Andthe first 700 MWs of electricity generation are not expected until 2022 at the earliest. It is true that FDI would come to Ethiopia anticipating cheap electricity, but it is highly unlikely that firms can strategically choose the location within Ethiopian that would privilege access to GERD. This is because all electricity produced by GERD or any of the hydroelectric dams will be taken to the national grid.

3. Data sources and summary statistics

3.1. Data

To estimate the impact of FDI on domestic plant productivity we use two data sources: plant-level manufacturing census data for the years 1997–2013 collected by the Central Statistical Agency (CSA) and restricted-access administrative data from the Ethiopian Investment Commission. We describe these data below.

Manufacturing Census The source of manufacturing plant data is the annual Large and Medium Scale Manufacturing (LMSM) establishment census of the CSA. It consists of enterprises engaged in "the mechanical, physical, or chemical transformation of materials, substances, or components into new products and the assembling of component and parts of manufactured products" (CSA, 2015).[8] The available information includes employment, material and non-material inputs, capital stock, sales, geographic location, date of plant establishment, and asset ownership. It is worth pointing out that with these records it is possible

[8] In principle, any formal manufacturing plant in the country that employs at least 10 people and uses electricity in its production process forms part of the target population. In practice, out of the 20,711 plant-year observations, 5445 feature a number of employees smaller than 10. These are observations for plants that at some point reach 10 employees (and therefore enter the business directory that CSA compiled as a "framework" for the census) but then have a lower number of employees at the date in which they are re-surveyed. In the TFP estimation, the results are similar when we remove these plant-year observations.

to construct a genuine panel of manufacturing plants. A limitation of our data is that they do not allow us to identify the location of a plant within Addis Ababa.

We faced three main challenges trying to link plant identifiers (IDs) across years: 1) verifying that, pre-2011/12, unique IDs were consistent across years to enable us identify the same plant across the different rounds; 2) doing the same for the 2011/12 and 2012/13 rounds independently of the pre-2011/12 data, and; 3) linking plants between these two separate datasets.

To check that plant IDs were unique and consistent across years we relied on phone numbers, location of the plant (e.g. region, zone, district, etc.), the Ethiopian Electric Power Corporation (EEPCO) number of the plant, and the P.O. box number. As a further consistency check, we used the business directory that CSA compiled as a 'framework' for the census for 2008/09.[9] This list is compiled by CSA every year with data from different ministries and government agencies as a reference to identify which plants exist and should be interviewed for the survey. The list includes the name and plant number that CSA assigns to each plant during that round, as well as phone number and locational information (e.g. region, zone, district, town, etc.).

While there is typically no electronic record of the plant's name in the database, it is possible to compile this information directly from the paper questionnaires. CSA staff went through all available paper questionnaires that they had in storage, collected plant names from each paper questionnaire, and linked plants across available years using this information.[10] This effort was crucial in creating the panel identifiers for two reasons. First, it provided a link between the pre- and post-2011/12 rounds. Second, it provided us with additional information to validate unique plant IDs for rounds between 2008/09 and 2010/11.

During the final stage we evaluated the different matches obtained from all methods described above and determined which matches were valid. This was done using Stata to the extent possible but, in most cases, a visual inspection of the validity of each match was necessary to ascertain the match provided by Stata. If matches did not seem valid then, a case-by-case match was done manually. If no valid match was found, the observation was left unmatched and a new unique ID was created for the plant. Fig. A.2 shows the count of plants and the total employment by year in the matched CSA sample. Table A.2 reports descriptive statistics.

Administrative Data To implement our research design, we use restricted-access administrative data from the Ethiopian Investment Commission. This dataset contains the list of licensed FDI manufacturing investment projects during our sample period. It includes information on the date of permit, the industry, the location, and the status of the investment describing whether the plant is operational.

3.2. Summary statistics

Table 1 presents summary statistics for the 12 useable events in our dataset. Since our goal is to identify a substantial shock to a district's economy, we require a large relative increase in local employment. To qualify as a useable event, we impose the requirement that the foreign plant's labor force is at least 100 employees or constitutes at least 1 percent of total employment in local manufacturing in $\tau = 0$ or $\tau = 1$. We also require that the location is not assigned by the government. We have a total of 27 districts, 15 of which are controls. FDI plants tend to be in food and beverages (5), chemicals and chemical products (3), and other non-metallic mineral products (3).

[9] Similar lists for other rounds of the LMSM are not available. According to the Director of the Business Statistics Directorate, due to changes in management and issues with the storing of data, the lists for other years have been lost.

[10] CSA staff were only able to retrieve paper questionnaires for the last five rounds of the LMSM—it is CSA's policy to store paper questionnaires for no more than five years.

Table 1
Sample of FDI opening and districts.

FDI Openings	12
Number of control districts per treatment district:	
1 district	9
2 districts	3
Reported year of foreign plant opening:	
2004–2007	5
2008–2010	7
Foreign plant industries:	
Food & beverages	5
Chemicals and chemical products	3
Non-metallic mineral products	3
Motor vehicles	1
Foreign plant characteristics:	
Number of employees	113.71
	(187.00)
Share of local labor market (%)	9.91
	(18.48)

Note: This table displays descriptive information on the useable openings and districts used in the main research design. The algorithm used to find control districts is described in Section A.I. The values for 'Number of employees' and 'Share of local labor market' are the average between $\tau = 0$ and $\tau = 1$. Standard deviations are shown in parentheses.

Table 2 displays the means of plant-level variables across districts in $\tau = -1$ and the percentage change between $\tau = -4$ and $\tau = -1$. These means are shown for treatment and control districts in Columns 1 and 2 respectively. Column 3 reports the p-value from a test of equality between Columns 1 and 2. Column 4 reports the p-values obtained using

Table 2
Plant Characteristics by Treatment Status, Prior to the start of FDI Production.

	(1) Treatment Districts	(2) Control Districts	(3) p-value (1)–(2) (Clustered)	(4) p-value (1)–(2) (Cameron, Gelbach and Miller)
Plant Age in $\tau = -1$	15.0	13.2	0.200	0.233
Employees in $\tau = -1$	84.7	93.8	0.586	0.631
Perc. Change between $\tau = -4$ and $\tau = -1$	25.3	24.6	0.947	0.952
Capital per Worker in $\tau = -1$	75.0	63.2	0.442	0.503
Perc. Change between $\tau = -4$ and $\tau = -1$	21.1	7.0	0.240	0.370
Capital in $\tau = -1$	5032.1	6479.3	0.507	0.523
Perc. Change between $\tau = -4$ and $\tau = -1$	44.1	25.7	0.108	0.163
Plant-level Average Yearly Wage in $\tau = -1$	6.5	5.4	0.104	0.170
Perc. Change between $\tau = -4$ and $\tau = -1$	30.3	27.5	0.676	0.700

Note: P-values in Column 3 are calculated from standard errors clustered at the district level. P-values in Column 4 are obtained using the bootstrap procedure developed by Cameron et al. (2008). All monetary amounts are in 1000s of 2013 Birr. 1000 Birr are roughly equivalent to 34 USD using the 2018 exchange rate.

the procedure recommended by Cameron et al. (2008). This exercise offers a chance to evaluate the soundness of the empirical strategy, as measured by preexisting observable plant characteristics. To the extent that these observable features are balanced among treated and control districts, this lends support to the research design. The table shows that there are not significant differences in plant age, and the levels and growth rates of the following variables: employees, capital, capital per worker and plant-level average yearly wages.[11] Overall, we conclude that the covariates are balanced between plants in treatment and control districts.

4. Effects of FDI on domestic plant productivity

4.1. Econometric model

The regression equation that forms the basis of our empirical analysis on the sample of domestic plants is:

$$\begin{aligned}\ln(Y_{pidrt}) &= \beta_L \ln(L_{pidrt}) + \beta_K \ln(K_{pidrt}) + \beta_M \ln(M_{pidrt}) \\ &+ \delta 1(FDI\_PRODUCTION)_d + \varkappa 1(\tau \geq 0)_{dt} \\ &+ \varphi\left[1(FDI\_PRODUCTION)_d \cdot 1(\tau \geq 0)_{dt}\right] + \alpha_p \\ &+ \mu_{it} + Trend_{rt} + \varepsilon_{pidrt}\end{aligned} \tag{1}$$

where p references plant, i industry, d district, r region, and t calendar year; Y_{pidrt} is the value of total plant production, and we allow the total number of employees L_{pidrt}, total capital inputs K_{pidrt}, and material inputs M_{pidrt} to have separate impacts on output[12]; we also allow for permanent differences across plants α_p, industry by (calendar) year effects μ_{it} controlling for contemporaneous (calendar-year contemporaneous) shocks in the same industry in treated and control districts, and a stochastic error term ε_{pidrt}. The dummy $1(FDI\_PRODUCTION)$ is equal to one if plant p is located in a treatment district; τ denotes year, but it is normalized so that the year *when the foreign plant started production* is $\tau = 0$; the variable $Trend_{rt}$ is a region-specific trend. Notice that the year of approval of an FDI project (either in a treated or control locality) does *not* play a role in the estimation.

A concern for the validity of our interpretation of the estimates arises from the observation that the dependent variable in the econometric model is the value of output. Therefore, the estimated spillover effect may reflect higher output prices rather than higher productivity—we explore this possibility in Section 4.3. We report standard errors clustered at the district level. Given that the number of districts is equal to 27, we also report the p-values obtained using wild bootstrap (Wu, 1986) with null imposed, as recommended by Cameron et al. (2008)—we use the *boottest* Stata routine developed by Roodman (2018).

4.2. Baseline results

The yearly difference between estimated mean TFP in treatment and control districts obtained by estimating equation (1) is shown in Fig. 2 along with the 95-percent confidence intervals. The estimates are obtained from a version of equation (1). Specifically, the natural log of output is regressed on the natural log of inputs, year by two-digit industry fixed effects, plant fixed effects, and the event time indicators.[13] While the values of the point estimates increase between $\tau = -4$ and $\tau = -2$, the difference in trends between treatment and control is not

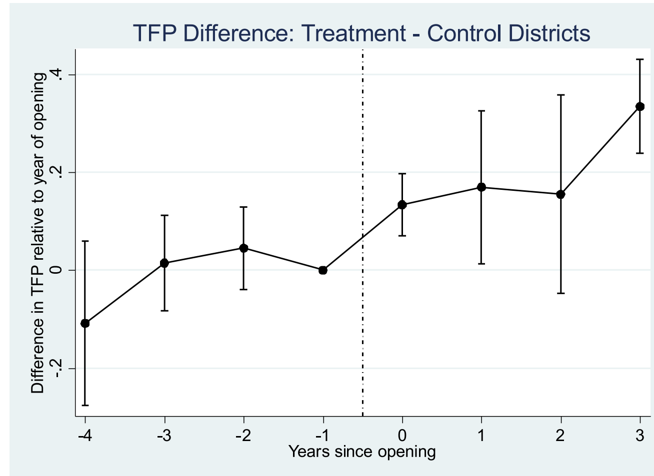

Fig. 2. Difference in Domestic Plants' Productivity in Treated vs. Control Districts, Relative to the Year of Start of FDI Production.
Note: The figure plots point estimates for leading and lagging indicators for the large foreign plant opening. The omitted category is one period prior to the large foreign plant opening. Vertical bars correspond to 95 percent confidence intervals with district-clustered standard errors.

significant in the period before the new plant starts production. Specifically, none of the pre-treatment coefficients are statistically significant. After the start of the FDI plant's production, there appears to be a change in the difference in TFP between the treatment and control districts.[14][15]

Table 3 shows the estimates of the coefficients on the event time indicators for several specifications; it also displays the estimated mean shift parameter φ in Equation (1). Column 1 reports baseline estimates, which suggest an increase in TFP of approximately 11 percent.[16] Estimates are similar when domestic plants are required to be in the data for at least 3 years prior to the event, which addresses concerns related to the endogenous opening of new plants and compositional bias (Column 2).

To put the size of the estimated impact of the FDI opening in perspective, we use a growth accounting framework in which growth in manufacturing value-added is decomposed into TFP growth and factor input accumulation (see Appendix A.II). The increase in TFP associated with FDI increases manufacturing's share in total GDP growth from .54 percent to .57 percent. Thus, when viewed from the perspective of the wider economy, these effects are quite modest. The main reason for this

[11] Conclusions are similar when plants are weighted by the inverse of their number per district.

[12] Capital stock is given by the full amount of the paid up capital of the firm including investments in asset and land in a given period. Material cost reflects expenses incurred to procure intermediate products including raw materials and inputs.

[13] The sample is restricted to include only plant by year observations within the period of interest (where τ ranges from -4 through 3).

[14] Regarding the jump in the point estimates between $\tau = 2$ and $\tau = 3$, this appears to be part of a more general pattern of dynamics of the opening effect (see e.g. Figs. A.7 and A.9): a significant coefficient for $\tau = 0$ followed by point estimates typically increasing over time. This pattern suggests that some positive effects take place shortly after the entry (i.e. within the same year) and some others take more time to materialize. It is consistent with the estimates in Greenstone, Hornbeck and Moretti (JPE, 2010; see their Fig. 1, Panel B at p. 565). It is also consistent with the qualitative evidence from our technology transfer survey; plants commonly report upgrading production technologies. Learning about and adopting new production techniques typically takes time.

[15] In Fig. A3 we report the equivalent of Fig. 2 on a balanced panel. Fig. A.4 shows estimates when in the matching algorithm we look for a control only in the same year. In other words, if we cannot find a district where an FDI plant in the same year got approval, we stop the algorithm, i.e. do not move to the next step in which we look for a control district where the project was approved between τ^{lic} = -1 and τ^{lic} = 1. The displayed coefficients on the event time dummies in Fig. A.5 indicate yearly mean TFP in treatment districts and control districts, relative to the year before the foreign plant opened.

[16] In Table A.3 we report 12 regressions; in each of them we drop one treated district, and the relative control district(s).

Table 3
Changes in Domestic plants' productivity, following the start of FDI production.

	(1)	(2)	(3)	(4)
	Baseline	At least 3 years	Materials-Capital Interactions	Materials-Capital and Materials-Labor Interactions
logK	0.053***	0.045***	…	…
	(0.017)	(0.016)		
logM	0.523***	0.506***	…	…
	(0.054)	(0.054)		
logL	0.265***	0.284***	0.228***	…
	(0.058)	(0.057)	(0.058)	
tau = −4	−0.108	−0.119	−0.098	−0.109
	(0.086)	(0.083)	(0.086)	(0.082)
tau = −3	0.015	−0.001	0.018	0.010
	(0.049)	(0.044)	(0.050)	(0.050)
tau = −2	0.045	0.047	0.040	0.035
	(0.043)	(0.044)	(0.044)	(0.044)
tau = −1	0	0	0	0
tau = 0	0.134***	0.119***	0.126***	0.123***
	(0.032)	(0.029)	(0.038)	(0.037)
tau = +1	0.169**	0.209**	0.164**	0.140*
	(0.080)	(0.087)	(0.076)	(0.078)
tau = +2	0.155	0.262***	0.162*	0.161*
	(0.103)	(0.086)	(0.093)	(0.089)
tau = +3	0.334***	0.336***	0.342***	0.335***
	(0.049)	(0.058)	(0.049)	(0.052)
Mean Shift	0.108	0.136	0.106	0.098
	(0.048)**	(0.046)**	(0.046)**	(0.045)**
	[0.050]*	[0.022]**	[0.044]**	[0.026]**
Observations	10,889	9331	10,889	10,889
Adjusted R-squared	0.905	0.906	0.908	0.91

Note: The table reports results from estimating eq. (1). It shows the estimates of the coefficients on the event time indicators for several specifications; it also displays the estimated mean shift parameter. Plant FE, industry by (calendar) year effects, region trends are always included. Standard errors clustered at district level in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. For the mean shift, we report in brackets the p-value obtained using the bootstrap procedure developed by Cameron et al. (2008). In Column 2 domestic plants in treated districts are required to be in the data for at least 3 years prior to the event. Column 3 adds to Column 1 a fourth-degree polynomial function of log capital and log materials and the interaction of both functions (see Levinsohn and Petrin 2003). Column 4 adds interactions between log materials and log labor to the controls in Column 3 (see Ackerberg et al. (2015)).

is the very low share of manufacturing value-added in Ethiopia's economywide value-added.

A significant conceptual concern is the possibility of 'transmission bias', which arises from plants' reaction to unobservable productivity shocks when making input choices. Because unobservable shocks 'transmit' to input choices, inputs should be treated as endogenous. Unlike the typical estimation of plant-level production functions, our goal is to obtain a consistent estimate of the diff-in-diff coefficient corresponding to the FDI entry, so transmission bias is important only to the extent that it causes biased estimates of this coefficient (GHM p. 583). In order to explore the significance of transmission bias in our setting we control for flexible functions of capital, materials, and labor (Levinsohn and Petrin, 2003; Ackerberg et al., 2015). The estimates (shown in Columns 3–4) also indicate an increase in TFP of domestic plants of roughly the same magnitude.

4.3. Validity and robustness

The main empirical result so far is that following the opening of a large foreign plant, the TFP of domestic plants appears to be significantly higher in treated districts. We now investigate the sensitivity of this result.

Making use of government designation of locations: As an alternative empirical strategy, we exploit the government designation of locations for greenfield foreign plants, in combination with an event study research design.

In order to implement this second empirical strategy, we asked plant managers what the most important reason for choosing the location for the production facility was. We consider as valid events for our identification strategy the openings of foreign plants reporting "Did not choose the location, was allocated by the authorities".[17]

We now provide some institutional background to the investment land allocation process. Both federal and regional offices are in many cases involved in the process. In an email interview, the General Director of Policy and Program Studies at the Ministry of Industry explained how the ministry, after receiving a request from a potential investor typically contacts a Regional office responsible for investment land administration (Ahmed Nuru, email interview, December 23, 2015). The Regional office then provides information on the land availability.

The regions targeted by the federal government for investment promotion are non-random. In particular, in order to foster equitable regional growth, the government often targets regions (outside Addis and its surrounding areas) with higher needs in terms of investment (FDRE, 2011).[18] However, during our period of analysis, the exact district within a broader region is typically determined by the timing of availability of land. As pointed out to us by the General Director of Policy and Program Studies in the same email interview, in no case is the process coercive. An investor can always refuse to carry on with the investment or choose some other location instead.[19] However, the fact that plant managers report that the location was not chosen but allocated provides support to our strategy of using government designation to obtain quasi-experimental variation in the treatment. Moreover, the timing is often out of the hands of the government since there is substantial uncertainty in which year the foreign plant will start production.

In the words of a manager at a foreign plant:

> It was not up to us to choose the location for our company. The [Federal] government gave us the location that we have now. That is usually the case. […] After asking for the land, we just waited for the responses of the [Federal] government. After a long time they gave us the location. […] The time we waited was two years. [..] This is because of the procedures that the offices of the government follow which often take time. […] I didn't think that it would take such a long period of time to get land for investment (recorded interview, Jan 10, 2017, middle manager at FDI plant with 112 employees in Sululta and Adama, Oromiya Regional State).

In general, the local TFP impact of the entry of the foreign plants may be identified provided that there are no district-specific pre-trends in the outcomes of interest, a condition that appears to be satisfied in the data. We evaluate the local impact of FDI using an "event-study" research design, as in Kline (2011). This design allows us to test for the presence of district-specific pre-trends in the outcome of interest and to recover any dynamics of the opening effect. Our main approach is to compare the "treated" districts both to districts that have not yet been treated and districts that will never be treated during our sample period. We then re-estimate our econometric model without the never treated localities, so that identification comes from the differential timing of treatment onset among the treated. In what follows we describe in detail the econometric model, descriptive statistics, and estimates. As we will

[17] The other possible answers are "Cheap labor", "Good infrastructure", "Located close to raw materials and input suppliers", "Located close to customers", "Located close to producers of similar products", "Expected that many more producers would be located in this site", and "Others (specify)".

[18] We include region trends in all our specifications.

[19] If the investor is interested in the location, negotiations take place on the price and terms of lease. Note that in Ethiopia land is publicly owned and both local and foreign plants can enter into lease-hold or rental arrangements to acquire land for investment.

explain, overall the results we obtain are qualitatively similar to the baseline ones.

The regression equation that forms the basis of our empirical analysis is:

$$\ln(Y_{pidrt}) = \beta_L \ln(L_{pidrt}) + \beta_K \ln(K_{pidrt}) + \beta_M \ln(M_{pidrt}) + \sum_\tau \beta_\tau D^\tau_{drt} + \alpha_p + \mu_{it} + Trend_{rt} + \varepsilon_{pidrt} \quad (2)$$

where D^τ_{drt} are a sequence of "event-time" dummies indicating that the foreign plant opened (in district d) τ periods ago (where τ may be negative). Formally:

$$D^\tau_{drt} \equiv I[t - e = \tau],$$

where $I[.]$ is an indicator function for the expression in brackets being true, and e is the year of the plant entry. Therefore the B_τ coefficients characterize the time path of TFP relative to the date of the foreign plant opening for treated districts.

The results are obtained by estimating equation (2) by OLS, including a series of event-time dummies along with dummies for the plant and region-specific trends. We report results with and without including industry-year fixed effects. We normalize the first lead (−1 in event time) to zero, so that all post-event coefficients can be interpreted as treatment effects. The event time indicator "-4″ is set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. The event time indicator "+3″ is set to 1 for all periods 3 periods after the event and 0 otherwise.[20] In order to qualify as a useable FDI manufacturing opening, we impose the following criteria. First, the location must be assigned by the government. In our data 36 percent of FDI manufacturing openings report the location to be assigned by the government. Second, the FDI plant's labor force is at least 100 employees or constitutes at least 1 percent of total employment in local manufacturing in $\tau = 0$ or $\tau = 1$.[21] Third, the opening is not preceded or followed by the entry of FDI whose location was chosen by the plant's owners (i.e. non "allocated by the authorities") and employing at least either 100 employees or 1 percent of the local manufacturing labor force.[22] Table A.4 displays descriptive information on the 17 useable openings. We have a total of 223 control districts of which 206 are never treated.[23] Openings tend to be in non-metallic mineral products (8), food and beverages (4), and wood, furniture and paper (3).

Fig. 3 plots the estimated β_τ coefficients based on equation (2) and has two important features. First, there is no pre-treatment trend in the coefficients. Second, there is a shift in TFP of local domestic plants after the entry of a government-assigned foreign plant. While the general pattern in Fig. 3 is quite clear, the individual β_τ coefficients are not estimated very precisely. We therefore offer more formal tests of the null hypothesis that the FDI plant entry has no impact on local plants' TFP. To increase statistical power, in Table 4, in addition to reporting the estimated β_τ coefficients for several specifications, we follow the approach in Kline (2011) and test hypotheses about the average of the β_τ coefficients over the period between $\tau = 0$ and $\tau = 2$. Column 1 reports

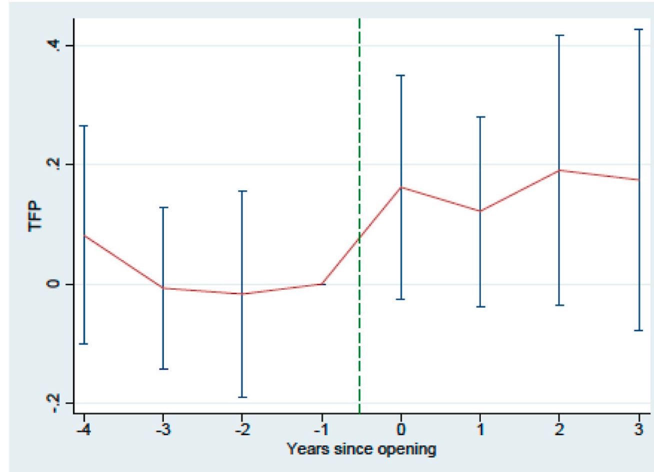

Fig. 3. Domestic Plants' Productivity, Relative to the Year of a Foreign Plant Opening (Research Design: Government Allocation).
Note: The figure plots point estimates for leading and lagging indicators for the large foreign plant opening. Event time indicator "-4″ set to 1 for periods up to and including 3 periods prior to the event and 0 otherwise. Event time indicator "+3″ set to 1 for all periods 3 periods after the event and 0 otherwise. The omitted category is one period prior to the large foreign plant opening. Vertical bars correspond to 95 percent confidence intervals with district-clustered standard errors.

baseline estimates: the estimated average increase over the three years starting with the year of the opening is 16 percent, significant at the 10 percent level. In Column 2 of Table 4 and Fig. A.6 we drop the never treated localities, and therefore identification comes from the differential timing of treatment onset among the treated localities. In Column 3 of Table 4 we require domestic plants in treated districts to be in the data for at least 3 years prior to the event. In Columns 4–5 we address the issue of transmission bias. These estimates also indicate an increase in TFP of domestic plants.

Attrition of Sample Plants: Differential attrition in the sample of domestic plants in treatment and control districts could potentially contribute to the measured gap in TFP among survivors after the FDI opening. The evidence suggests that this is unlikely to explain our finding of positive FDI effects in treatment districts. We find that comparable numbers of treatment and control plants remained in the sample at the end: 52 percent in treatment districts and 54 percent in control districts (i.e., the number of plants at $\tau = 3$ as a fraction of the number of plants at $\tau = 0$).

Government expenditures: the federal and local governments in some cases set up worker training funds, construct new roads, and make other infrastructure investments around the time of entry of a foreign plant. It is possible that these investments benefit domestic plants in addition to the foreign plant. To examine this possibility, we control for government total capital expenditures and for government fixed assets and construction expenditures. These measures vary at the district level and over time.[24] Columns 1 and 2 of Table 5 show that the main conclusions are unchanged.

Changes in the intensity of capital usage: If the capital stock in treated districts was used below capacity, then domestic plants may react to the FDI opening by growing the intensity of their capital usage and therefore increase production (GHM p. 585). To explore this possibility, we control for the ratio of the dollar value of energy usage (which is increasing in the use of the capital stock) to the capital stock. The estimates, displayed in Column 3 of Table 5, are similar to the main ones.

[20] These endpoint coefficients give different weight to districts experiencing the entry of the foreign plant early or late in the sample period, since the sample of treated districts is unbalanced in event time. Therefore, in discussing the effect of the opening, we concentrate on the event-time coefficients falling within $\tau = 0$ and $\tau = 2$ that are identified off of a nearly balanced panel of districts.

[21] In our data 39 percent of these large FDI manufacturing openings report the location to be assigned by the government.

[22] Specifically, we exclude districts that receive such openings in $\tau = (-3, 3)$.

[23] We exclude never-treated districts receiving the opening of a large foreign plant whose location was not "allocated by the authorities."

[24] We thank the Ministry of Finance and Economy for providing the data.

Table 4
Domestic plants' productivity: average of the event-study coefficients between $\tau = 0$ and $\tau = 2$ (Research Design: Government Allocation).

	(1)	(2) Treated Only	(3) At least 3 years	(4) Materials-Capital Interactions	(5) Materials-Capital and Materials-Labor Interactions
tau = −3	−0.015	−0.008	0.090	−0.001	−0.007
	(0.070)	(0.148)	(0.119)	(0.061)	(0.058)
tau = −2	−0.025	0.044	0.145	−0.012	−0.002
	(0.090)	(0.135)	(0.137)	(0.079)	(0.074)
tau = −1	0	0	0	0	0
tau = 0	0.162*	0.127	0.285	0.201	0.208*
	(0.095)	(0.115)	(0.172)	(0.125)	(0.123)
tau = +1	0.125	0.229	0.179	0.113	0.108
	(0.082)	(0.147)	(0.139)	(0.078)	(0.073)
tau = +2	0.190	0.428**	0.406*	0.155	0.159
	(0.115)	(0.184)	(0.221)	(0.119)	(0.116)
Average change	0.159	0.261	0.290	0.156	0.158
	(0.087)*	(0.135)*	(0.167)*	(0.097)	(0.093)*
		[0.051]*	[0.094]*		
Observations	4728	953	561	4728	4728
Districts	223	17	13	223	223

Note: This table reports results from fitting several versions of eq. (2). In addition to reporting the estimated β_τ coefficients for several specifications, we follow the approach in Kline (2011) and test hypotheses about the average of the β_τ coefficients over the period between τ = 0 and τ = 2. The dependent variable is Log (Output). 'Average change' refers to the average of the coefficients in periods t = 0, 1, and 2. Column 2 drops the never treated localities. Column 3 reports estimates from the specification of Column 2, but domestic plants are required to be in the data for at least 3 years prior to the event. Column 4 adds to Column 1 a fourth-degree polynomial function of log capital and log materials (see Levinsohn and Petrin 2003). Column 5 adds interactions between log materials and log labor to the controls in Column 4 (see Ackerberg et al. (2015)). For Columns 2 and 3, we report in brackets the p-value obtained using the bootstrap procedure developed by Cameron et al. (2008). Log(L), Log(K), Log (M), plant FE, industry by (calendar) year effects, and region trends are always included.

Other functional forms: We also experiment with different functional forms to test our results. In Column 4 of Table 5, inputs are modeled with a translog function form. In Column 5, we allow the effect of each production input to differ at the 2-digit industry level to account for possible differences in technology or quality of inputs across industries. Finally, in Column 6, we allow the effect of inputs to differ in treated/control districts and before/after the FDI opening. In all three cases, the estimates support our findings from the baseline specification.

Changes in the Price of Plant Output: As mentioned above, another concern for the validity of our interpretation of the estimates arises from the observation that the dependent variable in the econometric model is the value of output. The theoretically correct dependent variable in a productivity study is the quantity of output, but, due to data limitations, this study (and most of the empirical literature on productivity in a large sample of plants) uses price multiplied by quantity. Therefore, the estimated spillover effect may reflect higher output prices rather than higher productivity. To explore this possibility, we remove domestic plants in a supply link with the new entrant, plants for which output price effects might be largest. Since we observe the presence of a supply link only in the last year (see Section 5 for details), we focus on the sample that survives until the end of our sample period. These estimates (shown in Column 7 of Table 5) also indicate an increase in TFP of domestic plants.[25]

Interaction weighted estimator: FDI plants opening later may be different from those opening earlier, generating cohort-specific treatment effects (Goodman-Bacon 2021; Callaway and Sant'Anna 2021). We therefore implement the interaction weighted estimator for an event study. Sun and Abraham (2021) prove that this estimator is consistent for the average dynamic effect at a given relative time even under heterogeneous treatment effects.[26] The estimates, shown in Fig. A.7, are qualitatively similar.

4.4. *Beyond productivity: entry, employment and wages*

Entry: Do the foreign plants attract new economic activity? Baseline estimates showed positive TFP changes for local domestic plants following the opening of the new foreign plant. Thus, new manufacturing domestic plants may choose to locate in the districts receiving FDI to gain access to these productivity advantages. Motivated by this observation, we estimate:

$$Log(B)_{drt} = \delta I(FDI\_PRODUCTION)_d + \varkappa I(\tau \geq 0)_{dt} + \varphi\left[I(FDI\_PRODUCTION)_d \cdot I(\tau \geq 0)_{dt}\right] + \alpha_d + \psi_t + Trend_{rt} + \varepsilon_{drt} \tag{3}$$

where B stand for births, i.e. is the count of new domestic plants, and ψ_t is a year effect.

The estimates in Column 1 of Table 6 imply a 47 percent increase in the number of domestic plant openings. To put the size of the estimated impact of the FDI opening in perspective, a 47 percent increase corresponds to a 0.7-standard-deviation increase in the distribution of plant births.[27] The FDI openings we consider are a key occurrence for these districts, and the implied change in the relative standing of districts is arguably sizable but not improbable (GHM, p. 589). The estimated change in births is consistent with the estimated increases in TFP since it appears that the foreign plants attracted new economic activity in the manufacturing sector to the receiving districts.

Employment: In the remainder of Table 6 we study the changes in employment and wages in treated districts. The employment regression equation is:

$$ln\left(L_{pidrt}\right) = \delta I(FDI\_PRODUCTION)_d + \varkappa I(\tau \geq 0)_{dt} + \varphi^L\left[I(FDI\_PRODUCTION)_d \cdot I(\tau \geq 0)_{dt}\right] + \alpha_p + \mu_{it} + Trend_{rt} + \varepsilon_{pidrt} \tag{4}$$

where L indicates total number of employees. The estimates (shown in Column 2) imply a 24 percent increase in the total number of employees. This is equivalent to the average plant in the treatment districts adding around 20 employees to its payroll. The diff-in-diff coefficient is significant at the 5 percent level when clustering at the district level and at

[25] In addition, we follow GHM and investigate whether the TFP increase is bigger for plants that sell more locally. Specifically, in our survey we have asked domestic plants the distance to the most important customer. This allows us to estimate a version of equation (1) that interacts 1(FDI_PRODUCTION), 1(τ ≥ 0), and [1(FDI_PRODUCTION) •1 (τ ≥ 0)] with this distance. We do not find that the TFP increase is bigger for plants that sell more locally. Specifically, the coefficient of the interaction of [1(FDI_PRODUCTION) •1 (τ ≥ 0)] with this distance is equal to −0.0002 and not significant (S.E. 0.0004).

[26] We use the *eventstudyinteract* Stata routine available at https://economics.mit.edu/grad/lsun20/stata.

[27] We obtain these quantities using the cross-sectional data from the LMSM Census for 2005, the midpoint of our sample period.

Table 5
Changes in Domestic plants' productivity, following a foreign plant opening, Robustness to Different Specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Control for Gov't Capital Expend.	Control for Gov't Fixed Assets Expend.	Control for Intensity of Capital Usage	Translog Functional form	Input – Industry Interactions	Input – Treated and Input – Post interactions	Drop plants with Supply Link
tau = −4	0.242***	0.249***	−0.107	−0.107	−0.088	−0.130*	−0.196
	(0.054)	(0.065)	(0.085)	(0.087)	(0.069)	(0.067)	(0.143)
tau = −3	0.020	0.050	0.015	0.011	0.020	−0.013	−0.086
	(0.060)	(0.065)	(0.048)	(0.054)	(0.037)	(0.053)	(0.103)
tau = −2	−0.011	0.022	0.046	0.038	0.044	0.039	−0.016
	(0.068)	(0.058)	(0.043)	(0.046)	(0.037)	(0.037)	(0.120)
tau = −1	0	0	0	0	0	0	0
tau = 0	0.166**	0.153*	0.132***	0.130***	0.115***	0.101***	0.186**
	(0.077)	(0.085)	(0.034)	(0.033)	(0.031)	(0.034)	(0.081)
tau = +1	0.145	0.178*	0.165**	0.143*	0.149**	0.153**	0.437**
	(0.098)	(0.105)	(0.080)	(0.078)	(0.069)	(0.073)	(0.192)
tau = +2	0.057	0.123	0.154	0.162*	0.123	0.165	0.252
	(0.141)	(0.143)	(0.101)	(0.093)	(0.093)	(0.109)	(0.172)
tau = +3	0.299***	0.348***	0.332***	0.333***	0.279***	0.355***	0.529***
	(0.076)	(0.068)	(0.047)	(0.054)	(0.045)	(0.061)	(0.163)
Mean Shift	0.123**	0.129**	0.105**	0.102**	0.090**	0.087*	0.277**
	(0.056)	(0.062)	(0.048)	(0.047)	(0.041)	(0.046)	(0.131)
Observations	7803	7803	10,889	10,889	10,889	10,889	2419
Adjusted R-squared	0.887	0.887	0.908	0.909	0.910	0.907	0.895

Note: The dependent variable is Log (Output). The table reports results from fitting several versions of eq. (1). In Columns 1 and 2 we control for government total capital expenditures and government fixed assets and construction expenditures, respectively. In Column 3 we control for the ratio of the dollar value of energy usage (which is increasing in the use of the capital stock) to the capital stock. Column 4 uses a translog function form for inputs, Column 5 allows the effect of each input to differ by 2-digit industry, and Column 6 allows the effect of inputs to differ in treated/control districts and before/after FDI production. In Column 7 we remove domestic plants in a supply link with the new entrant. Standard errors clustered at district level in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. Log(L), Log(K), Log (M), Industry X year dummies, plant FE and region trends always included.

Table 6
Plant entry, employment, wages.

	(1)	(2)	(3)	(4)
	Log births	LogL	LogW	Log W (controlling for L)
tau = −4	−0.380	−0.152	−0.068	−0.077
	(0.428)	(0.101)	(0.071)	(0.072)
tau = −3	0.029	−0.093*	−0.005	−0.010
	(0.526)	(0.053)	(0.066)	(0.067)
tau = −2	−0.021	0.003	−0.025	−0.025
	(0.548)	(0.059)	(0.053)	(0.055)
tau = −1	0	0	0	0
tau = 0	0.499	0.223*	0.012	0.026
	(0.419)	(0.114)	(0.073)	(0.078)
tau = +1	0.290	0.230*	−0.042	−0.028
	(0.355)	(0.124)	(0.088)	(0.091)
tau = +2	0.676	0.412***	0.017	0.043
	(0.414)	(0.114)	(0.084)	(0.084)
tau = +3	0.338	0.578***	−0.057	−0.021
	(0.391)	(0.134)	(0.106)	(0.107)
Mean Shift	0.471	0.235	0.001	0.024
	(0.241)*	(0.108)**	(0.060)	(0.062)
	[0.044]**	[0.065]*	[0.859]	[0.690]
Observations	156	11,413	11,398	11,398
Adjusted R-squared	0.276	0.818	0.645	0.648

Note: Column 1 reports results from estimating eq. (3). The dependent variable is (log) count of new domestic plants. Column 2 reports results from estimating eq. (4). Dependent variable is (log) number of employees. In Column 3 we use (log) average plant-level wage as dependent variable; the rest of the regression equation is identical to eq. (4). In Column 4 we use (log) average plant-level wage as dependent variable and control for (log) number of employees. Standard errors clustered at district level in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. We report in brackets the p-value obtained using the bootstrap procedure developed by Cameron et al. (2008). The mean number of births is 6. Summary statistics for L are provided in Table 2 and Table A2.

10 percent when using the Cameron et al. (2008) procedure. In Fig. A.8 we report the equivalent of Fig. 2 for L.[28][29]

Wages: We also estimate equation (4) with wages as the dependent variable. This regression should be interpreted cautiously because we do not have individual-level wage data and we are forced to use (log) plant level average wage (constructed as total wage bill divided by the number of employees). Setting this concern aside, the estimated diff-in-diff coefficient (shown in Column 3) is positive, but small and not precisely estimated. Results are similar when controlling for the number of employees (Column 4).

4.5. External validity

In extrapolating from our results to other settings, it is important to keep in mind the following qualifications. First, the impact of our treatment is not representative of the typical FDI plant opening. The FDI plants we consider are larger (in terms of size of the workforce) than the average new foreign plant in the Ethiopian manufacturing sector. Second, the FDI plants we consider tend to be in food and beverages, and chemicals and chemical products. These sectors tend to be less export oriented than sectors such as textiles and garments. Third, the domestic firms in our dataset are larger than the average Ethiopian firm, formal, and in manufacturing. Our estimates are therefore obtained from a dataset of FDI and domestic firms for which one may anticipate larger FDI effects.

5. Technology transfer: qualitative evidence

To dig into the black box of technology transfer, we added a technology transfer module to Ethiopia's annual census of manufacturers for the year 2013 (available upon request). It is not possible to use these data in our estimates of the causal impact of FDI on domestic firm TFP

[28] In Fig. A.9 we report the equivalent of Fig. A.8 on a balanced panel.

[29] We also report the equivalent of Fig. 2 for value added per worker, Y/L, K, M (Figs. A.10–A.13).

since we only have one cross-section. But from these data, we can obtain qualitative evidence about the process of technology transfer. We also explore the extent to which being in the same location and same location and industry influence linkages controlling for firm productivity and firm size. Due to data limitations our evidence is purely descriptive.

5.1. Linkages, learning and benefits of FDI

Domestic plant managers were asked to respond to the following questions about links to foreign plants based in Ethiopia: (i) have you faced competition from foreign plants in output markets? (ii) have you ever faced competition from foreign plants in the labor market? (iii) have you ever hired labor previously employed by a foreign plant? (iv) do you purchase inputs from foreign plants? and, (v) do you sell inputs to foreign plants? A tabulation of the responses to these questions is presented in Table 7. Almost one third of all domestic plants (29.2 percent) report at least one connection to foreign plants. 16.1 percent of domestically owned plants reported facing competition from foreign plants in output markets. 5.7 percent of plants report facing competition from foreign plants in the labor market, while 6.9 percent of plants report hiring labor previously employed by foreign plants. 9.2 and 5.9 percent reported purchasing inputs from and selling inputs to foreign plants, respectively.

The results in Table 7 indicate that 15.7 percent of plants report upgrading production technologies to compete with foreign firms. Around 12.1 percent of plants report directly adopting production techniques from observing or copying foreign plants in the same four-digit industry. This suggests that domestic plants need not be in a formal relationship with a foreign plant to benefit from FDI. Around 10.1 percent of plants report licensing technology from foreign plants. A further 6.2 percent of plants report benefiting from hiring workers who previously worked in foreign plants.[30] 4.3 percent of plants reported upgrading through a relationship with foreign customer plants. These findings are in line with previous survey evidence from the Czech Republic reported by Javorcik and Spatareanu (2009). Only 1.7 percent of plants reported learning from foreign supplier plants.

Table 7
Linkages to FDI reported by domestic plants.

	Share of domestic plants
A. Reported Linkages	
(i) Faced competition from foreign plants in output markets	16.1
(ii) Faced competition from foreign plants in labor markets	5.7
(iii) Hired labor previously employed by foreign plants	6.9
(iv) Purchases inputs from foreign plants	9.2
(v) Sells inputs to foreign plants	5.9
(vi) At least one of the above	29.2
B. Reported Mechanisms for Knowledge Transfer	
(i) Competition induced technology upgrading	15.7
(ii) Observation and imitation of production techniques used by foreign firms	12.1
(iii) Licenses technology from foreign plants	10.6
(iv) Employ workers previously employed by foreign firms	6.2
(v) Customer relations required upgrading	4.3
(vi) Supplier relations required upgrading	1.7
(vii) At least one of the above	30.5
C. Reported Benefits Associated with FDI	
(i) Production technologies	66.4
(ii) Managerial practices	8.4
(iii) Organizational structure	6.9
(iv) Knowledge of how to export	8.4
(v) Others	9.9

Source: Ethiopia Large and Medium Scale Manufacturing (LMSM) Establishment Census, 2013 (Technology Transfer Module)

We next report on the benefits domestic plants attain from their linkages with foreign plants. Plant managers who reported some type of knowledge transfer were asked to report on the types of benefits obtained from the presence of foreign plants. Responses to these questions are presented in Table 7. Benefits reported are as follows: 66.4 percent of plants reported improved production technologies; 8.4 percent reported increased knowledge of how to export; 8.4 percent improved managerial practices; and, 6.9 percent improved organizational structure.[31] These results make clear that improvements to production technologies are, by far, the most common sort of benefit attained through knowledge transfers.

5.2. Location as a determinant of linkages

In this section we use data from both the manufacturing census and the technology transfer module to explore whether the extent to which linkages are affected by domestic firms' location and industry. We consider whether the plant is in the same district as a foreign plant, the same district and industry eventually adding controls for exporter status, labor productivity, plant size, and industry. To estimate the relationship between these characteristics and whether a plant is linked to FDI, we construct a dummy variable *Link* that is equal to one if the plant reported any one of the five linkages in section 5.1, and zero otherwise. The estimating equation is:

$$Link_{pid} = \alpha + \beta_1 (FDI_{PRESENCE})_d + \beta_2 (FDI_{PRESENCE})_{id} + \sigma X_{pid} + \varepsilon_{pid} \tag{5}$$

where p references plant, i industry, d district; dummy $(FDI_{PRESENCE})_d$ is equal to one if plant p is located in the same district as a foreign plant and dummy $(FDI_{PRESENCE})_{id}$ is equal to one if plant p is located in the same district and the same 4-digit ISIC industry as a foreign plant. We show the estimates in Table 8. X_{pid} denotes a set of plant characteristics that are introduced as controls, including whether the plant exports, the log of value added per worker, plant employment size measured as a categorical variable, and plant industry (2-digit ISIC).[32]

The OLS estimates reported in Column 1 of Table 8 indicate that the mean likelihood of a domestic plant reporting that they are linked to FDI is 32.3 percent for plants in districts with FDI presence and around 12.1 percent for plants in districts without any foreign plant. This is not surprising and is similar to what we show in Fig. 1. In Column 2, we separate the effect of being in the same district from the effect of being in the same district and industry; being in the same district as a foreign plant, but different industry, is associated with a 12.4 percentage point increase in the likelihood of linkages relative to domestic firms in districts without FDI – being in the same industry and same district is associated with a further 13.2 percentage point increase in the likelihood of reporting a linkage with FDI.

These results persist even after introducing additional plant-level controls, though the magnitude on the coefficients for FDI presence falls. Exporting, labor productivity (measured in value added per worker), and plant size are all positively correlated with linkages to FDI.

[30] These findings are in line with previous evidence from developed countries. Serafinelli (2019) finds evidence of labor market-based knowledge spillovers in the Veneto region of Italy. In a similar vein (Saxenian, 1994, p.37), maintains that the geographic proximity of high-tech plants in Silicon Valley is associated with a more efficient flow of new ideas.

[31] There was a fifth possible response, 'other'. We exclude this category as we do not have information about what 'other' might refer to because the very small number of plants that reported "other" did not list specific benefits for which they had been prompted.

[32] We tested additional controls such as real wages and the real capital stock; each of these enters positively on their own but including these controls along with value-added per worker leads to multicollinearity and insignificance of the controls. We therefore show only results using value-added per worker which can be thought of as a proxy for a host of controls which measure firm performance.

Table 8
Linkages to FDI by domestic plant characteristics.

VARIABLES Outcome = any linkage to FDI	(1)	(2)	(3)	(4)	(5)
FDI plant in same district (=1 if yes, 0 otherwise)	0.202*** (0.0248)	0.124*** (0.0293)	0.115*** (0.0289)	0.0765*** (0.0287)	0.0692** (0.0288)
FDI plant in same district & 4-digit ISIC sector		0.132*** (0.0303)	0.126*** (0.0300)	0.114*** (0.0293)	0.0679** (0.0294)
Firm exports production (=1 if yes, 0 otherwise)			0.309*** (0.0741)	0.192** (0.0754)	0.195** (0.0772)
Value added per worker (log)			0.0339*** (0.00996)	0.0120 (0.0101)	0.0180* (0.0102)
Plant size - 20–49 employees				0.132*** (0.0316)	0.124*** (0.0324)
Plant size - 50–99 employees				0.166*** (0.0460)	0.108** (0.0461)
Plant size - 100–499 employees				0.288*** (0.0455)	0.225*** (0.0461)
Plant size - 500+ employees				0.357*** (0.108)	0.313*** (0.101)
Constant	0.121*** (0.0195)	0.121*** (0.0195)	−0.256** (0.110)	−0.0673 (0.109)	−0.00514 (0.131)
Industry dummies?	NO	NO	NO	NO	YES
Observations	1208	1208	1208	1208	1208
R-squared	0.036	0.053	0.079	0.128	0.186

Note: Any linkage indicates that a plant reported at least one of the following linkages: i) hired employees who previously worked in FDI plant, ii) faced competition from FDI in the labor market, iii) faced competition from FDI in local output market, iv) sells output to FDI plants, and v) buys inputs from FDI plants. The reference employment size is 10–19 employees. For the 2-digit ISIC dummies included in Column 5, a test for joint significance rejects the null hypothesis that the industry dummy coefficients are equal to zero at the 1% level. We exclude sectors with fewer than 5 observations. Robust SEs in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

These results are intuitive in that larger more productive firms are more likely to have the capacity to benefit from FDI. The results are also consistent with Javorcik and Spatareanu (2011) who find that more productive firms are more likely to be in supplier relationships with FDI. Finally, as expected, adding 2-digit industry controls in Column 5 increases the fit of the model as measured by the R squared by about 50 percent.

These results are supportive of the notion that location matters for technology transfer; domestic firms in closer geographic proximity to foreign plants are more likely to report linkages to FDI. Domestic firms in the same location and same industry are roughly twice as likely to report linkages. Tables A.5–A.9 report results of estimating equation (5) for each linkage separately. The results are generally intuitive. For example, labor linkages or hiring workers who previously worked in a foreign firm is not industry specific (row 2 Table A5). By contrast, competition in the product market is influenced by domestic firms' 4-digit industry (row 2 Table A7).

6. Concluding remarks

This paper makes two main contributions. First, by comparing changes in TFP among domestic plants in 'treated' districts that attracted a large greenfield foreign plant and 'control' districts where greenfield FDI in the same industry was licensed but not yet operational, estimates of the magnitude of knowledge spillovers at the local level are identified. Over the four years starting with the year of the foreign plant opening, the TFP of domestic plants is 11 percent higher in treated districts. These estimates are comparable to estimates obtained using an alternative identification strategy that exploits the assignment of land to foreign investors by the Ethiopian government. We also find evidence that employment in these domestic plants increases, and that foreign plants attract new economic activity to recipient districts.

Second, we provide qualitative evidence on the process of technology transfer. Domestic plants report that technology upgrading occurs through: (i) learning by observation and imitation; (ii) hiring workers who previously worked at foreign plants; (iii) direct contact via customer and supplier relationships; (iv) licensing technology from foreign plants; and, (v) competitive pressures. Knowledge about production processes is the most common type of benefit associated with FDI, but domestic plants also learn from foreign plants about managerial and organizational practices and logistical aspects of the supply chain, including exporting. This evidence underscores the usefulness of an empirical strategy that moves beyond the confines of industrial classifications.

The overall evidence lends support to the idea that FDI generates positive spillovers. Moreover, domestic plants located in close geographic proximity to foreign plants appear more likely to benefit from FDI. The results also provide some support for the Ethiopian government's industrial policy although more research is needed to quantify the cost of the incentives provided to foreign plants and to compare these costs with the benefits of knowledge spillovers.

Credit author statement

Girum Abebe: Conceptualization, Methodology, Software, Validation, Writing- Reviewing and Editing. **Margaret McMillan**: Supervision, Data curation, Writing- Original draft preparation, Reviewing and Editing, Validation, Visualization, Conceptualization, Investigation, Methodology. **Michel Serafinelli**: Conceptualization, Methodology, Investigation, Software, Validation, Writing- Reviewing and Editing.

Data availability

If the editor decides for Acceptance, at that stage we will update the do files (to reflect any changes to empirical models/number of observations etc following suggestions) and share all files.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2022.102926.

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