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The Impact of Chinese FDI in Africa: Evidence from Ethiopia

Riccardo Crescenzi and Nicola Limodio

Abstract

We exploit exogenous variation in China's export taxes to investigate the impact of Chinese foreign direct investment (FDI) in Ethiopia. Higher sector-specific export taxes in China lead to more Chinese FDI in Ethiopian districts specialized in those sectors and generate highly heterogeneous effects. Domestic firms competing with Chinese FDI reduce their sales, investment, inputs and prices, while firms in upstream and downstream sectors expand. We build a 20-year district panel of night lights and observe that Chinese FDI leads to no instantaneous impact on local growth, but significant and persistently positive effects after 6-12 years.

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Riccardo Crescenzi **Nicola Limodio**

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Contact details

Riccardo Crescenzi, Department of Geography and Environment,

London School of Economics and Political Science,

Houghton Street, London, WC2A 2AE, London, UK,

R.Crescenzi@lse.ac.uk

Nicola Limodio, Bocconi University,

BAFFI CAREFIN, IGIER and LEAP,

Via Roentgen 1, 20136 Milan, Italy,

nicola.limodio@unibocconi.it, www.nicolalimodio.com.

1 Introduction

China's evolution into a manufacturing giant has generated highly heterogeneous impacts across sectors, firms and localities in both developed and developing countries. Part of the "China Shock" on the world economy has materialised through trade with both advanced (Autor et al. (2013, 2014, 2016), Pierce and Schott (2016), Bloom et al. (2019), Caliendo et al. (2019)) and emerging economies (Hanson (2010)). Part of this effect can be attributed to the re-location of foreign activities by multinationals looking for low-cost locations (Amiti and Javorcik (2008), Harding and Javorcik (2011), Ebenstein et al. (2015), Alfaro et al. (2016, 2019)). More recently, the "China Shock" has started to unfold beyond the "traditional" trade channels to involve outward FDI, for example through the "Belt and Road Initiative" (Huang (2016)).

In this context, a special role has been played by African countries. Although in terms of value (both flows and stocks) Africa still accounts for a relatively small share of total global Chinese outward FDI,[1] these investments have recently attracted significant attention due to their sectoral and geographical diversification, as well as their economic and geo-political implications. A lively debate on the effect of this specific form of FDI presents a wide spectrum of views, spanning from the growth-enhancing nature of Chinese investment[2] to a more pessimistic, neo-colonialist interpretation.[3] The ongoing tensions between the USA and China have further polarised views on Chinese FDI in Africa.[4]

In this research, we offer causal evidence on the impact of Chinese FDI in Ethiopia, which constitutes a large manufacturing hub where China is heavily investing both to serve the local

[1]African countries account for 3% of outward foreign direct investment from China. Refer to Margaret McMillan, "Chinese investment in Africa" , Vox Dev, 21 July 2017, available at https://voxdev.org/topic/finance/chinese-investment-Africa.

[2]Refer to Amy Jadesimi, "How China's $60 Billion for Africa Will Drive Global Prosperity", Forbes, 14 March 2017, available at https://www.forbes.com/sites/amyjadesimi/2017/03/14/how-chinas-60-billion-for-africa-will-drive-global-prosperity/1#75f42c337ce2 and to J. Peter Pham, Abdoul Salam Bello, Boubacar-Sid Barry, "Chinese Aid and Investment Are Good for Africa", Foreign Policy, 31 August 2018 available at https://foreignpolicy.com/2018/08/31/chinese-aid-and-investment-are-good-for-Africa/.

[3]Refer to Sanou Mbaye, "Africa will not put up with a colonialist China Sanou Mbaye", The Guardian, 7 February 2011, available at https://www.theguardian.com/commentisfree/2011/feb/07/china-exploitation-Africa-industry.

[4]Refer to Emily Feng and David Pilling, "The other side of Chinese investment in Africa", Financial Times, 27 March 2019, available at https://www.ft.com/content/9f5736d8-14e1-11e9-a581-4ff78404524e.

market and to export to other African countries and beyond. In order to shed new light on the impact of this distinctive form of FDI we combine a natural experiment in FDI location choices with the universe of FDI investment in Ethiopia and the census of medium and large manufacturing firms. Beyond this detailed firm-level analysis, this research estimates the impact of Chinese FDI on the local economy by employing a night lights panel of Ethiopian districts. We exploit exogenous variation in FDI location choices in Ethiopia generated by changes in sector-specific export taxes in China. Higher export taxes in China lower Chinese exports, as shown by Gourdon et al. (2017), and induce Chinese FDI to flow toward Ethiopian districts specialized in the same sector, in line with the findings of Conconi et al. (2016). This analysis produces two main findings.

First, the increase in Chinese FDI generates mixed effects on the host economies, in line with the findings of Bloom et al. (2019). On the one hand, firms competing in the same sector and district shrink their operations (production, employment, investment, raw material) and lower their prices, in line with a competition shock induced by FDI. On the other hand, firms operating in the local upstream and downstream sectors expand their sales, investment and inputs, as the demand for their products and the quality of their inputs increases.

Second, we aggregate the effects of Chinese FDI at district level by using satellite night lights data as in Henderson et al. (2011). To follow Ethiopian districts over a 20-year horizon, we combine night lights data from two different satellites provided by the National Oceanic and Atmospheric Administration (NOAA): one offers data from 1992 until 2013, while the other from 2012 until 2019. Because these satellites employ different sensing techniques, we employ a machine-learning algorithm to make data homogeneous across sensors to produce robust estimates, as described in the data section. This paper innovatively combines machine-learning and satellite lights to produce a long-term measure of economic performance and this dataset is a key source in our analysis. In fact, our findings suggest that the positive and negative firm-level impacts of FDI offset each other in the short-run, resulting in a well-estimated instantaneous zero effect of Chinese FDI on local economic activity. However, the positive effects outweigh the negative ones in the medium-run, with an overall positive, significant and persistent impact on local growth after 6-12 years. Our findings are in line with the work of

Bau and Matray (2020), who exploit the staggered liberalization of foreign capital in India, to conclude that foreign capital (like FDI) can create positive and persistent economic effects.

By focusing on a natural experiment taking place in the FDI's country of origin, we address a fundamental identification challenge in the FDI literature: the reverse causality between local economic activity and the targets of foreign investment. China represents the ideal setting to study this research question, given the unique structure of its export taxes stemming from the non-neutrality of its value-added tax (VAT). When companies sell a product, they are liable to pay a sale tax proportional to the final price. For domestic sales, companies pay such tax only on the "added value", net of the cost of production for inputs already taxed upon purchase. Most OECD countries guarantee a VAT-neutrality: a zero VAT rate on exported goods and a full refund of the domestic VAT paid by exporters on their inputs. This systems ensures that domestic firms face identical prices when selling domestically or abroad.

However, this is not the case in China, as the government does not fully reimburse Chinese exporters for the VAT paid on their inputs, applying a partial VAT refund on inputs for exporters which varies by product. Incomplete VAT rebates are the norm in China and they are heterogeneous across sectors, generating a net export tax. As a result, sector-specific changes in both VAT and rebate rates increase the export tax. This generates a decline in Chinese exports in the corresponding sectors (Gourdon et al. (2017)) and, as we observe, an increase in sector-specific FDI. Such result is aligned with recent work by Almunia et al. (2018) showing that firms respond to local negative shocks by increasing their international exposure. We find that this de facto export tax provides the ideal instrumental variable (IV) to measure changes in the foreign direct investment of Chinese firms that leverage FDI to serve foreign markets while avoiding the export tax. This is in line with the proximity-concentration trade-off (Markusen (1984), Brainard (1997), Helpman et al. (2004), Grossman et al. (2006), Grossman and Rossi-Hansberg (2008)) and the work of Conconi et al. (2016) showing that firms actively choose between FDI and exports in their internationalization strategies.

Our research design combines this exogenous variation in FDI with two comprehensive data sources: the universe of FDI projects in Ethiopia and the local census of medium and large manufacturing firms. These data sources offer information on the sector of each project, the geographic location across Ethiopia, the investor country of origin and the local firms interacting with FDI. Through these statistical sources, we verify that, while sector-specific changes in Chinese export tax rates do not affect FDI from countries other than China, they alter FDI from China towards Ethiopian districts specialized in the same sector. This is related to work in the spatial economics literature (Allen and Arkolakis (2014), Desmet and Rossi-Hansberg (2014), Desmet et al. (2018)) and the extended gravity a la Morales et al. (2019). At the same time, having access to the census of manufacturing firms permits us to exploit the granularity of the data and study changes in firm performance within a district and across the sectors that receive new FDI.

Studies on the impact of FDI on domestic manufacturing firms in Africa find ambiguous effects. On the one hand, negative results are driven by the destruction of local businesses in response to the entry of foreign entities into local markets (Brautigam et al. (2013), Edwards and Jenkins (2015)). On the other hand, positive effects emerge due to knowledge spillovers (Haddad and Harrison (1993), Abebe et al. (2018)). Our research finds evidence in line with both effects and offers a novel interpretation of these findings. In fact, this paper goes beyond firm-level outcomes and tests the effect of Chinese FDI using satellite night lights data on a panel of Ethiopian districts. We aggregate Chinese FDI at district-level and construct a measure of district specialization for all sectors of the economy prior to the arrival of Chinese FDI. Firm-specific estimates show both negative FDI effects (as competing firms in the same sector within a district shrink) and positive effects (as firms in upstream and downstream sectors in the same district expand). However, the aggregate effects of Chinese FDI change over time. We cannot reject a zero instantaneous effect of Chinese FDI on local growth once we employ our IV strategy. At the same time, we investigate the medium run effects of Chinese FDI by regressing the current level of investment on future growth rates (after 3, 6, 9 and 12 years). This exercise leads to a positive, significant and persistent effect, which may be due to improvements in resource allocation and knowledge spillovers (Javorcik (2004), Abebe et al. (2018)).

Ethiopia offers an ideal setting to investigate the effect of Chinese FDI on firms and districts. First, the country's opening to FDI in the late 1990s largely coincides with the emergence and progressive expansion of Chinese FDI in Africa, making it possible to study the entire evolution of the Chinese FDI phenomenon and its effects on the domestic economy. Second, the emphasis of Ethiopia's Growth and Transformation Plan (GTP II) on making the country a manufacturing hub and its sustained process of growth-promoting structural transformation are well matched by the diversification of Chinese FDI away from natural resources (and natural resource-rich countries) in favour of manufacturing investments. Third, the internal geography of Chinese FDI in Ethiopia offers the opportunity to investigate the emergence of new agglomerations and hubs at the district-level, capturing more general effects on economic development and its spatial unevenness.

This paper contributes to three streams of literature. First, our results on FDI location choices (Amiti and Javorcik (2008), Harding and Javorcik (2011)) are consistent with the work of Conconi et al. (2016), which sheds new light on the choice firms have between local production and export versus direct presence in foreign markets through FDI. This is also consistent with the fact that firms strategically decide their proximity to a market against the local industry concentration (Markusen (1984), Brainard (1997), Helpman et al. (2004)). Second, this paper offers novel insights to the literature on the link between FDI and economic performance in host countries (Javorcik (2004), Haskel et al. (2007)). While from a macroeconomic perspective, Borensztein et al. (1998) and Carkovic and Levine (2005) find positive effects of FDI on domestic economic growth, the microeconomic focus indicates various transmission channels: increased demand for domestic intermediate inputs, the diffusion of firm-specific knowledge-based assets and the nature of the input-output supply-chain linkages (Rivera-Batiz and Romer (1991), Rodriguez-Clare (1996), Barrell and Pain (1997), Haaland and Wooton (1999), Markusen and Venables (1999), Haskel et al. (2007), Fons-Rosen et al. (2017), Alfaro and Charlton (2009), Antràs et al. (2012), Conconi et al. (2018)). Our paper shows that in this specific setting, the aggregate sub-national effects on districts are initially zero, but they turn positive in the medium run. In terms of FDI spillovers, our results are consistent with the literature in support of the existence of vertical spillovers (Blalock and Gertler (2004), Javorcik (2004)) and skeptical on horizontal spillovers (Aitken and Harrison (1999), Djankov and Hoekman (2000), Konings (2001)). Third, our paper contributes to the emerging literature on the distinctive impacts of Emerging Countries' FDI in developing economies (Brautigam

(2011), Brautigam et al. (2013)). Our paper offers quantitative causal evidence that suggests that the shift of Chinese FDI in Africa from natural resources to manufacturing (and services) has produced a positive impact on structural change and developmental trajectories

Section 2 describes in detail our identification strategy and datasets. Section 3 reports the empirical model and the main results. Section 4 presents robustness checks and additional specifications, while section 5 offers some concluding remarks.

2 Identification and Data

This research estimates the causal effect of Chinese FDI on Ethiopian firms and districts. Two well-known identification challenges could threaten our analysis. First, there could be reverse causality. Sectors in districts that are rapidly growing, or declining steadily, may attract FDI. This would create a spurious correlation between the measure of FDI and firm outcomes. Second, different sectors may be exposed to global sector-specific business cycles which affect both FDI flows and local firm performance, generating a correlation which is not based on a causal nexus. Alternatively, different districts may face various district-specific unobservable shocks which may lead firms in a certain district to be on a specific trajectory irrespective of FDI inflows.

We address these identification challenges by: 1) leveraging an IV estimation which exploits the exogenous variation in Chinese FDI generated by changes in Chinese export tax; 2) removing sector and district time-varying unobservables, absorbed by the presence of district-year and sector-year fixed effects. This strategy allows us to estimate the reduced-form effect of Chinese FDI on firms and districts, but does not allow us to identify all the mechanisms that are bundled into this effect. On the one hand, firms in the same sector of a district may benefit from the diffusion of knowledge spillovers and grow in response to Chinese FDI. On the other, an increase in local competition may hurt Ethiopian firms and generate negative effects. Overall, these effects cannot be separated, as such specification would require one separate instrument per effect. Our reduced-form estimates capture an aggregate effect and, given the negative effect on firms operating in the same district and sector, these are consistent with the competition shock driving local firms out of business. This is also consistent with our data on local prices, which decline when Chinese FDI enters the market.

Section 2.1 further discusses our identification strategy and provides data and institutional details on Chinese export taxes and district specialization; section 2.2 explains how we build a 20-year district panel by combining two satellite information and machine-learning; section 2.3 presents the remaining datasets in detail, an overview of Chinese FDI in Ethiopia and summary statistics.

2.1 Identification

In this section, we discuss two determinants of FDI flows: 1) export taxes across sectors in China; 2) the geographic specialization of Ethiopian districts (called *wereda* in Amharic). The interaction of these two terms will be the central feature of the IV strategy presented in detail through the empirical model.

All OECD countries offer their exporters a complete VAT rebate, which harmonizes the opportunity of selling a product domestically or internationally (Gourdon et al. (2017)). As aforementioned, China's VAT system is not neutral, and makes it less advantageous to export a product than to sell it domestically through partial rebates. The Chinese Government does not provide a complete refund on domestic VAT that exporters have paid on their inputs. This creates a net export tax, given the difference between the VAT and rebate rate. The Chinese Government aims to favour strategic domestic sectors, which in turn enables authorities to control trade surplus, government revenues and industrial policy. As a consequence, both the VAT rate and the rebate rate contribute to the attractiveness of outsourcing sector-specific production activities abroad. In particular, the higher the difference between domestic VAT rates on exported products and the relative rebate rates (i.e. the export tax), the more attractive it is for Chinese producers to outsource production abroad.

This export tax is product-specific and changes frequently and heterogeneously in response to Chinese domestic industrial policy, which constitutes strategic decisions aimed at favouring the expansion of the domestic market as well as the provision of inputs for domestic firms. The database of Gourdon et al. (2017) offers a measure of the VAT and rebate for each product in each sector and over time. To match this to the sector-specific nature of our datasets (foreign direct investment and firm-level), we take the average VAT and rebate of all products belonging to a specific sector in every year. This results in a net export tax, which is sector-specific and time-varying. Figure 1 shows the evolution of this export tax for three sectors between 2003 and 2013. While food and tobacco face a relatively constant export tax of 6%, the textile sector experiences a doubling of this tax in 2003 from 2 to 4%, a further 1% increase in 2008 and then a steep decline after 2009. On the contrary, the ceramics and glass sector faces a tripling of this tax from 4% to 12% in 2008 and then a decline to 8% in 2010. Figure 2 summarizes the overall change in export taxes over the period under analysis (2003-2013) across all sectors. Before analyzing the cross-sectional dimension of Chinese FDI in Ethiopia, we analyze the autocorrelation in the export tax. The presence of serial correlation could contaminate our identification, because this would imply that changes in the tax generate subsequent changes and, hence, makes it difficult to track the relation between the timing of the tax and the effect on FDI. For this reason, in Table 1, we regress the changes in the export tax that sector s faces at time t over its previous four lags, including sector and year fixed effects. Column (1) shows that we cannot reject the null hypothesis that changes in the previous period do not affect the following period. Beyond statistical significance, we can also see that the magnitude of this correlation is small. The next three columns present a similar exercise, in which changes in the tax are regressed on previous lags and results are in line with column (1). In Table A1 in Appendix A, we show that results are similar once sector and year fixed effects are removed.

When it comes to the foreign location of Chinese activities off-shored in response to the export tax discussed above, the literature on local economic agglomeration (Ellison and Glaeser (1999), Ellison et al. (2010), Glaeser and Xiong (2017)) suggests that firms would locate in clusters based on their sectoral specialization. For this reason, we exploit the differential sector specialization of Ethiopian districts as a measure of their exposure to an exogenous inflow of Chinese FDI induced by changes in Chinese export taxes. We measure the district specialization as the share of production of a certain sector in a given district over the total production of that sector in Ethiopia, using data from the Central Statistical Agency of Ethiopia (CSAE). Given that Chinese FDI in Ethiopia only begins in 2002, we measure average district specialization in 2000 and 2001.

This method to construct district specialization makes particular sense in the Ethiopian manufacturing context, which is characterized by a high degree of sectoral specialization across districts. For example, the Adama district (Figure 3, left panel) is highly specialized in Chemical (11% of domestic production), Food (17% of domestic production) and Paper (25% of domestic production) while the Walmera district (Figure 3, right panel) is specialized almost exclusively in the production of ceramics and glass (33% of domestic production). We verify that Chinese FDI enters Ethiopian districts with a defining sector specialization which offers necessary cross-sectional variation at district level, beyond being in line with the literature on local economic agglomeration.

2.2 Night Light Data and Machine Learning

Satellite night lights data are an important measure of economic development, particularly in low-income countries as highlighted by Henderson et al. (2011). NOAA offers a range of publicly available datasets on various satellite measurements on luminosity, as well as climate and other variables. To build a 20-year district panel, we join information from two distinct databases collected by NOAA:

- The Defense Meteorological Program Operational Linescan System (DMSP-OLS) is a set of meteorological satellites operating between 1992 and 2013. These detect visible and near-infrared (VNIR) emission sources from the earth surface at night. They present a ground swath of about 3000 km and two broad spectral bands: 1) a band covers the visible-near infrared region (0.5 - 0.9 μm); 2) another band deals with the thermal infrared region around 10 μm.[5] Measurements from this dataset have been used in most empirical applications in economics.

[5] More information is available at https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

- The Suomi National Polar-orbiting Partnership (SUOMI-NPP) is a set of weather satellites launched in 2011 and currently operating. They present innovative monitoring technologies for climate and luminosity, including an infrared imaging radiometer suite (VIIRS) sensor sending back night light images.[6] This dataset has not been used in economics despite the greater accuracy, but is common in the sensing literature.

These two datasets cannot be easily combined, as the data-gathering technologies are substantially different. For instance, both the average level and volatility of luminosity for the same city strongly differ across years. Moreover, the satellite accuracy vastly changes depending on region-specific characteristics. As a result, a naive merge of these measures would confound underlying changes in the fundamentals of an economy with differences due to sensing innovations.

For this reason, we exploit the fact that the two datasets present a two-year overlap window (2012 and 2013) during which the 75 districts are monitored under both technologies. Our conceptual exercise seeks to solve the following problem

$$Lights_{dt}^{SUOMI-NPP} = f(Lights_{dt}^{DMSP-OLS}, year_t, district_d) \tag{1}$$

in which $Lights_{dt}^{SUOMI-NPP}$ is the natural logarithm of satellite night light pixels in a district d in year t measured by the novel SUOMI-NPP satellite; $Lights_{dt}^{DMSP-OLS}$ reports the natural logarithm of satellite night light pixels in a district d in year t as reported by the old DMSP-OLS satellite and $year_t$ and $district_d$ are fixed effects for year and district (Ethiopian weredas).

We explore the overlap window to "translate" data from the old satellite in more accurate data from the new satellite. Because there is no clear functional form to convert information from the old satellite into the new one, we employ an array of machine-learning algorithms to investigate the optimal form of the function $f(.)$. As reported in greater detail in Appendix A, the following traditional models are used: 1) Linear Regression; 2) k-nearest neighbor (KNN); 3) Trees (random forest, bagging, boosting); 4) Support Vector Machine (linear kernel, radial kernel); 5) Neural Network.

[6] More information is available at https://www.nasa.gov/mission_pages/NPP/mission_overview/index.html

All of these algorithms are trained on our datasets to predict (1) and we combine two criteria in assessing the effectiveness of our exercise. First, the mean square error (MSE), which offers a simple statistic: the average squared error of our predictions. Second, we graphically compare the predictions from all algorithms to the actual values, given that a small number of outliers may reduce the information content of the MSE criterion. The combination of these two tests indicate that the Support Vector Machine with radial kernels delivers the most accurate estimates. Appendix A reports more information, statistics and figures on the methods we employed and our findings.

Figure 4 offers an example of our results for a specific district, Adwa. Between 2000 and 2011, a blue dashed line with squares reports the night lights from the old satellite (DMSP-OLS). From 2012 onward, a red line with circles displays the night lights through the new satellite (SUOMI-NPP). Finally, a red solid line with squares documents the output of our machine-learning analysis, which converts the night light data from the old into the new satellite. Our 20-year panel for the Adwa district consists of the solid line from 2000 to 2019. We offer more details on this procedure in appendix A.

We also offer an additional descriptive exercise in Figure 5 highlighting that our measure of night lights is highly correlated with GDP per capita. The left panel shows the evolution between 2000 and 2019 of our measure of night lights, in red, and the official GDP per capita, in blue. The right panel reports a scatter plot in which each year is reported as a dot in the GDP per capita - Night lights space. In both cases it is possible to see that these two measures are highly correlated, in particular the right panel highlights that this correlation exceeds 0.84 and is statistically different from zero beyond the traditional 1% threshold. This is a robust and high correlation, which differs from one where the official GDP data may present some extent of political manipulation, as highlighted by Martinez (2019).

2.3 Data and Summary Statistics

As aforementioned, our aim is to assess the impact of Chinese FDI on the economic performance of Ethiopian manufacturing firms. To do so, we rely on the record of all Chinese FDI projects active in the country provided by the Ethiopia Investment Commission (EIC) which includes detailed information on active FDI size, location, timing and country of origin for the period between 2003 and 2013. As Figure 6 illustrates, Chinese FDI has been flowing in Ethiopia since 2003, and in 2015 it accounted for 10% of all foreign investment (i.e. approximately 0.5% of Ethiopian GDP). As in virtually all developing economies, this relevant source of external finance is not evenly redistributed across Ethiopian districts and its productive sectors. Figure 7 shows that only specific areas of the country have been targeted by FDI.

The EIC dataset allowed us to match individual FDI projects to the corresponding productive sector [7] and Ethiopian district. The resulting dataset enables us to assess how Chinese FDI has influenced a set of firm-level outcomes, which we retrieve from the Ethiopian Census of Large and Medium Sized Firms. In order to capture the impact of new inward FDI on firms active in the same district and sector targeted by the investment (as well as in down/upstream sectors) we look at the following firm-level indicators: 1) value of production; 2) total employment; 3) book value of machinery, as a measure of capital investment; and 4) the use of raw materials. In addition to these measures, the Census includes firm baseline information on the sector, establishment year and location and allows us to follow a total of 8,746 establishments in the period between 2003 and 2013. Furthermore, we combine this information with data on Chinese export taxes by sector (Gourdon et al. (2017)) which forms a core component of the IV predicting Chinese FDI inflows.

In the final part of our analysis we assess the impact of Chinese FDI on total aggregate economic activity at the district level. To do so we rely on satellite night lights intensity in Ethiopian districts as a proxy for economic activity, following Henderson et al. (2011), and test whether Chinese investment has affected this variable. To go beyond a short-term analysis and assess the effects of Chinese FDI on economic activity in the medium run, we combine data from two different satellites, employing a machine-learning algorithm to make the datasets comparable as discussed in the previous section.

[7] Beverages, Building & Construction Materials, Ceramics & Glass, Chemicals, Consumer Products, Electronic Components, Food & Tobacco, Industrial Machinery, Equipment & Tools, Metals, Paper Printing & Packaging, Pharmaceuticals, Plastics, Rubber, Textiles, Wood

Table 2 reports the summary statistics for the main variables presented in this paper. Panel A describes the two key variables for our instrumental variable estimation (IV). The first row shows that the average export tax, given by the difference between the VAT and rebate rate, is 5.23% and varies between 0.59% and 15.27%. The magnitude of these changes is hard to benchmark given the uniqueness of the Chinese approach to VAT rebates. However, Gourdon et al. (2017) offer extensive evidence on the impact (and magnitude) of these variations on Chinese export decisions. These data are based on 15 sectors, followed for eleven years 2003-2013. The second row provides information on the average exposure of Ethiopian districts to all sectors, which is 4% on average with a standard deviation of 15%, a minimum of zero and a maximum of 1. Not all the 75 districts, studied in our papers, have firms for every sectors. On average a district contains firms from 7 different sectors. Panel B provides summary statistics on the inflows of Chinese FDI across all districts and sectors over time and gives evidence on the significant geographic and sectoral disparities: a low mean of 0.43 log of million Ethiopian Birr (ETB) is coupled by a high standard deviation (2.09), with a minimum of zero and maximum of 14.53. In our dataset we have a combination of 388 district-sector, observed for a time-span of eleven years. Panel C reports the summary statistics for the variables extracted from the census: output, employment, machineries and raw material. The final variable is a price index that we use to proxy effects on the output prices of Ethiopian firms. This is defined as the natural logarithm of the ratio of two variables available in the census: value of production sold and value of production. Finally, Panel D provides summary statistics on the variable used to measure district-level aggregate economic activity as in Henderson et al. (2011): the natural logarithm of the number of pixels across all 75 Ethiopian districts.

In addition to this, Figure 8 shows satellite images of night lights in Ethiopia in 2003 (left panel) and in 2013 (right panel), in order to give an indication of the year-variation of night lights level during the period of study. Ethiopia is ideal in this respect, given that it is one of the countries with the lowest levels of GDP per capita in the world and exhibits strong positive changes in brightness during our sample (2000-2019). As mentioned above, this variable will proxy local economic activity as customary in the literature on developing economies.

3 Empirical Model and Results

3.1 First Stage

We begin our analysis by assessing the relevance of our IV. In this first stage, we show that Chinese FDI inflows toward each district-sector cell depend on that district's sector specialization, and on changes in Chinese export tax to that same sector. We employ the following difference-in-difference model:

$$China\ FDI_{dst} = \gamma\ China\ Export\ Tax_{st-1} \times Exposure^{PRE}{}_{ds} + \iota_{ds} + \iota_{dt} + \iota_{st} + z_{dst} \quad (2)$$

where $China\ FDI_{dst}$ is the natural logarithm of alternative measures of Chinese FDI inflows (namely the level of Chinese investment, the number of FDI projects and the probability of receiving FDI) towards sector s in district d during year t. $China\ Export\ Tax$ is the natural logarithm of the Chinese export tax for sector s, i.e. the difference between the Chinese export VAT rate to the sector s and the corresponding rebate rate in year $t - 1$. $Exposure^{PRE}{}_{ds}$ is the natural logarithm of the share of goods sold by sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. We includes district-sector (ι_{ds}), sector-year (ι_{st}) and district-year (ι_{dt}) fixed effects. Then, we cluster two-way standard errors at the district and sector level.

Table 3 presents the estimated coefficients for the first-stage model. It proposes two different ways to deal with the zero observations: Panel A adopts an inverse hyperbolic sine transformation (IHS), while Panel B uses a simpler logarithmic transformation. As we can observe in Table 3, the interaction between our independent variables is strongly and significantly associated with Chinese investment flows to a given sector s in a district d during year t, regardless of the measure of FDI. Column (1) shows that a one percent increase in export tax in a particular sector in China leads to a 3.21% increase in Chinese FDI in Ethiopian districts that are one standard deviation more exposed to that sector. Column (2) notes that this implies a 0.42% increase in the number of FDI projects taking place in district d, sector s and year t, while Column (3) shows a 0.24% higher probability that a district-sector is targeted by a new FDI project. In our robustness checks section, we also verify that while Chinese FDI responds to changes in Chinese export VAT rebates, FDI from other countries does not. Additionally, we show that non-Chinese FDI are insensitive to the interaction between sector exposure and Chinese export tax.

As anticipated, an increase in a sector's exposure to Chinese FDI, combined with an increase in Chinese export tax, has a positive impact on the level, the number and the probability that a district-sector is targeted by Chinese FDI. These first stage results confirm that our IV strategy is valid to study the impact of Chinese FDI on firm-level and aggregate district-level productivity.

3.2 Second Stage and Reduced Form

In our second-stage analysis, we instrument the level of Chinese FDI inflows as previously presented and verify how different measures of firm-year performance react to this exogenous variation in FDI placement. This makes it possible to assess the impact of Chinese investment across different dimensions of performance. The main specification is the following:

$$x_{fdst} = \beta\, FDI_{dst} + \iota_f + \iota_{dt} + \iota_{st} + \epsilon_{fdst} \tag{3}$$

in which FDI_{dst} is instrumented using equation (2), with x_{fdst} being a set of firm-year performance indicators, namely the natural logarithm of $total\ value\ of\ production$, $total\ employment$, $book\ value\ of\ machinery$, $raw\ materials$ used in the production processes and a $price\ index$ (i.e. the difference between the production value of goods and services and their sale value). All these variables are intended to measure different dimensions of performance for firm f in sector s, district d and year t. FDI_{dst} is the instrumented level of Chinese FDI flowing to sector s in district d during year t and it is estimated using the first-stage equation presented in the previous section. We include firm (ι_f), district-sector (ι_{ds}), district-year (ι_{dt}) and sector-year (ι_{st}) fixed effects - with firm fixed effects absorbing district-sector fixed effects in the second stage. Finally, we cluster two-way standard errors at the district and sector level.

Table 4 reports the OLS estimation in Panel A, the estimated coefficients of the IV regression at the firm level in Panel B and the reduced form in Panel C. Overall, we cannot reject a zero effect in our OLS estimation, while we observe negative effects and cannot reject a zero effect in the IV and reduced-form. Hence, we conclude that Chinese FDI inflows have a negative impact on domestic firm performance.

Panel A shows that the effect of Chinese FDI on firm variables estimated via the OLS is generally very small in magnitude, mostly with a positive sign but overall never statistically different from zero. Panel B and C employ the exogenous variation in FDI induced by Chinese export taxes and indicate a different story. Panel B is based on a first-stage F statistic of 36.49 and shows that a 1 percent increase in Chinese FDI in sector s, district d, year t is associated with an approximate drop by 0.17% in firm-level value of production, a 0.30% drop in the number of employees, 0.32% drop in investment, 0.15% decline in the use of raw materials and 0.04% lower prices. While we reject that the first two coefficients are statistically different from zero below the standard 1% threshold, machinery value, raw materials and the price index present weaker statistical precision. This offers support to the hypothesis that foreign investment from China fosters competition in Ethiopian host economies at the expense of local domestic firms. Reduced-form results presented in Table 4, Panel C, are also consistent with this hypothesis. This panel indicates that a 1% increase in chinese export taxes in sector s in districts with a 1% higher exposure to sector s leads to a 0.38% lower firm output, 0.65% lower employment, 0.71% lower machinery investment, 0.34% less raw material and 0.87% lower prices.

3.3 Effects on Upstream and Downstream Sectors

Chinese FDI have a negative impact within their sector of operation through increased competitive pressure on existing firms. However, this competitive pressure could increase efficiency for surviving firms through knowledge spillovers and benefit upstream and downstream sectors through input-output linkages. Firms facing Chinese FDI in sectors which are upstream to their operations can benefit from cheaper, higher-quality inputs, which may lower their cost or increase their productivity. At the same time, firms meeting Chinese FDI in downstream sectors may benefit from the possibility to supply more efficient buyers (both new foreign subsidiaries and surviving more efficient domestic firms) through technological spillovers.

In order to verify how Chinese FDI affects firms through input-output linkages, we look at firm-level performance in response to Chinese inward FDI in upstream or downstream sectors relative to the firm's own sector of operation, following Antràs et al. (2012) and Alfaro et al. (2019). The following model is estimated:

$$\mathrm{x}_{fdst} = \beta_{UP}\, Upstream\ Export\ Tax_{st-1} \times Upstream\ Exposure^{PRE}_{ds} + \iota_f + \iota_{dt} + \iota_{st} + \epsilon_{fdst}$$

$$\mathrm{x}_{fdst} = \beta_{DOWN}\, Downstream\ Export\ Tax_{st-1} \times Downstream\ Exposure^{PRE}_{ds} + \iota_f + \iota_{dt} + \iota_{st} + \epsilon_{fdst}$$

(4)

where x_{fdst} is the usual set of sector-level performance indicators for firm f operating in sector s in district d during the year t. In the first specification, $Upstream\ Export\ Tax_{st-1}$ is the natural logarithm of the export tax in the year $t-1$ applied to the sector upstream of sector s. $Upstream\ Exposure^{PRE}{}_{ds}$ is the natural logarithm of the share of goods sold by the sector upstream of sector s in district d over the total value sold by all Ethiopian firms in the upstream sector relative to s in the pre-treatment period 2000-2001. Similarly, $Downstream\ Export\ Tax_{st-1}$ is the natural logarithm of the export tax in the year $t-1$ charged on exports from the sector downstream of sector s. $Downstream\ Exposure^{PRE}{}_{ds}$ is the natural logarithm of the share of goods sold by the sector downstream of sector s in district d over the total value sold by the same downstream sector of s in Ethiopia in the pre-treatment period 2000-2001. These new specifications now include firm (ι_f), district-year (ι_{dt}), and sector-year (ι_{st}) fixed effects. As standard in other specifications, we cluster two-way standard errors at the firm level. It is necessary to clarify that in this specification we do not separately run an IV and reduced-form estimate, as the effects of Chinese FDI on upstream and downstream firms can take place both through Chinese operations flowing in and through behavioural changes by local Ethiopian businesses. As a result, our reduced-form specification offers a succint specification combining these two effects.

Panel A of Table 5 shows the estimated coefficients of our first specification focusing on the impact of Chinese FDI on firms' upstream sectors while Panel B of Table 5 presents the same output for downstream sectors. Aggregated district-sector level analyses are included in the robustness checks section.

Panel A shows that estimates are all positive, but significant only for $total\ employment$ and $machines'\ book\ value$. These results suggest that an increase in Chinese FDI targeted to the upstream sector of sector s is associated with non-negative effects on production and significant improvements in hiring and investment of firms operating in sector s. Panel B shows that the impact on firm f from FDI in downstream sectors has a positive impact on $total\ employment$ and $price\ index$, with significant and relatively large point estimates, while other performance indicators remain positive but insignificant. Hence, firms benefit from Chinese FDI in sectors downstream of their own sector of activity, but this effect is weaker as Chinese foreign firms can source their inputs from other Chinese firms (in Ethiopia or abroad) resulting in more limited opportunities for domestic suppliers that do not increase their capital intensity and value of production.

3.4 Aggregate District Effects and Night Lights

In this part of our inquiry, we test the presence of district-level effects of Chinese FDI on Ethiopian economic performance. To do so, we conduct two separate analyses. First, we estimate the effect of Chinese FDI on districts' performance indicators, i.e. the same variables used previously to assess the impact of FDI on district-sectors and firms. Second, we use satellite data on visible night lights as a proxy for economic activity (following Henderson et al. (2011)) and check whether Chinese investment flows are associated with increased economic activity in districts targeted by Chinese FDI during the selected period. This last exercise is performed with consideration to the instantaneous effect of Chinese FDI on night lights, and the medium run effects (after 3, 6, 9 and 12 years).

In our first exercise, we aggregate our firm-level data at the district level and estimate the following model:

$$x_{dt} = \beta\, FDI_{dt} + \iota_d + \iota_t + \epsilon_{dt} \tag{5}$$

where x_{dt} is the same set of sector-level performance indicators (value of production, employment, machinery, raw material and price index) and FDI_{dt} is the instrumented level of Chinese FDI flowing to sector s in district d during year t, aggregated at the district d level. One important difference with our previous specification is that we are aggregating both our instrumented variable and our instrument to a higher aggregate level as follows:

$$FDI_{dt} = \gamma \sum_{s} Export\,Tax_{st-1} \times Exposure^{PRE}{}_{ds} + \iota_d + \iota_t + z_{dt} \tag{6}$$

the district-level FDI, FDI_{dt}, is regressed over a weighted sum of the export tax in sector s at time $t-1$ interacted with the district exposure to the specific sector. Our specification also includes district (ι_d) and year (ι_t) fixed effects. Analogously to our previous models, we cluster standard errors at the district level.

As previously presented, Table 6 reports three panels A focusing on the OLS estimates, panel B displaying the IV results and panel C that includes the reduced form coefficients. Our estimated OLS effects are in line with the previous exercises: the correlation between Chinese FDI and aggregate firm indicators is not statistically different from zero. Panel B includes the IV estimates, which present a strong first-stage F of 39.48. In this case, we can see an overall pattern of positive effects, which are however insignificantly different from zero with two exceptions: 1) prices, which are positive and statistically different from zero below the 5% threshold; 2) employment, which is negative and statistically different from zero below the 10% threshold. Panel C offers results in line with Panel B: most effects are positive, and also significant like machine value and prices, while employment is negative and significant.

In the second exercise, we use satellite data on visible night lights as a proxy for economic activity. This analysis is divided in two parts. First, we check whether Chinese investment flows are associated with increased economic activity in districts targeted by Chinese FDI during the same period in which we observe our firm data. This investigation is followed by a medium run analysis, in which we regress the future satellite night lights of a district (*t+3, t+6, t+9, t+12*) on Chinese FDI at time t.

In order to implement this analysis, we are going to match our FDI data aggregated at the district level to the brightness of districts' locations. To explore this hypothesis, we explore the following specification:

$$Nightlights_{dt} = \beta \, FDI_{dt} + \iota_d + \iota_t + \epsilon_{dt} \tag{7}$$

where $Nightlights_{dt}$ is the natural logarithm of the average recorded brightness in the location of district d during the year t and FDI_{dt} is the instrumented level of aggregate Chinese FDI flowing to district d in year t. Our specification includes district fixed effects (ι_d), year fixed effects (ι_t) and we cluster standard errors at the district level.

After studying the contemporaneous effect of Chinese FDI on satellite night lights, we study the medium run effects by replacing $Nightlights_{dt}$ with $Nightlights_{dt+k}$, with k being the number of years after the arrival of Chinese FDI. In order to study whether these effects are persistent, we study the effects with 3 year lags and set $k = 3, 6, 9, 12$.

Column (1) of Table 7 reports the OLS coefficients obtained when regressing night lights brightness on Chinese FDI. Column (2) presents the first-stage result when Chinese FDI is instrumented using our IV. Column (3) shows the coefficients of the reduced-form regression where brightness is directly regressed on the instrument. In line with the previous results, higher Chinese export taxes lead to higher Chinese FDI in districts presenting a particular sector-specialization. This high correlation generates a large first-stage F of 187.24. Finally, Column (4) presents the two-stage coefficients obtained by using the full specification of our model. Our results indicate that we cannot reject a zero effect of Chinese FDI on the local economic activity in Ethiopia during the selected period. Given that we cannot reject a zero in this specification, this leads us to reject that Chinese FDI generates any instantaneous effects.

Once we replace $Nightlights_{dt}$ with $Nightlights_{dt+k}$ and study the medium run effects of Chinese FDI on local economic activity, sizeable differences emerge. Figure 9 plots the coefficients of five separate estimates in which the pixels at year $t + k$ (with $k = 0, 3, 6, 9, 12$) are regressed over $Ln\, China\, FDI_{dt}$ through an OLS and then its IV version. The upper panel of 9 reports the OLS estimates, which show that there is a marginally positive effect after 3, 6 and 9 years and that this declines to zero after 12 years. In all of these cases, these results are not statistically different from zero.

The lower panel of 9 shows that once Chinese FDI is instrumented using export taxes and district specialization, a different picture emerges: all point estimates are positive, nearly all of them significant and persistently grow with time. The average positive effect on local economic activity is 0.02 after 3 years and climbing to 0.14 after 12 years. Beyond this, such effects become statistically different from zero after 6 years and stay persistently significant with time. These results are consistent with Chinese FDI generating no instantaneous effect on local economic activity, but leading to positive and persistent medium run effects. The reasons for this effect may be given by the fact that competition may take time to improve the resource allocation of the local economy and also that local knowledge spillovers may take time to manifest in this specific context.

4 Additional Evidence and Robustness Check

4.1 Export Taxes, Reverse Causality and Imports

This section investigates the Chinese export taxes and explores two potential threats to our identification strategy: 1) reverse causality; 2) imports.

We explictly verify the existence of reverse causality in Table 8, in which the changes in the export tax rate in sector s at time t are regressed over changes in the average value of production of Ethiopian firms in sector s and the previous period. This specification is explored without any fixed effect in column (1), with only sector fixed effects in column (2) and both sector and year fixed effects in column (3). In all of these cases, the effects are not statistically different from zero, which reassures us that the drivers of changes in Chinese export taxes are uncorrelated with preceding sectoral fluctuations in Ethiopian production. As well as the lack of statistically significant effect, it is important to note that all effects are near zero regardless of the fixed effect specification.

After this, we explore a potential threat to our identification strategy. Chinese export taxes may affect the Ethiopian economy through a different channel: inducing a decline in imports from China, which may then lead induce real effects. To verify how quantitatively relevant this channel is, we retrieve a dataset on Ethiopian imports from China by sector ($Import_{st}$) and regress these over the export taxes from China (Tax_{st}) in Table 9. Column (1) presents results without any fixed effect, Column (2) adds sector fixed effects and Column (3) introduces both sector and time fixed effects. Once again, we fail to detect an effect which is statistically different from zero. In terms of mangnitudes, we note that while column (1) presents a large coefficient, this progressively drops to zero as we introduce fixed effects.

4.2 Evidence from unconnected sectors

In the previous paragraph, we presented some evidence on partial inter-sectoral spillover effects of Chinese FDI. In this section, we investigate whether we can observe similar effects in sectors that do not operate in the supply chain of the sector in receipt of Chinese FDI. Through our IV strategy, we instrument Chinese FDI targeted at the treated sector in a given district.

After this step, we aggregate performance indicators at the district level excluding the treated sector s. Finally, we regress these aggregated variables on instrumented Chinese investment to sector s, in order to check whether these flows have broader spillover effects outside sector s' supply chain. The model we use to investigate this hypothesis is the following:

$$x_{dzt} = \beta \, FDI_{st} + \iota_d + \iota_t + \epsilon_{zt} \tag{8}$$

where FDI_{dst} is obtained from the first-stage described below:

$$FDI_{dst} = \gamma \, China \, Export \, Tax_{st-1} \times Exposure^{PRE}{}_{ds} + \iota_{ds} + \iota_{dt} + \iota_{st} + z_{dst} \tag{9}$$

where x_{dzt} is the set of performance indicators (*value of production, total employment, book value of machinery, raw materials* and *price index*) aggregated for all sectors (denoted with z) in district d except the treated sector$s$. FDI_{dst} is the instrumented level of Chinese FDI flowing to sector s (i.e. the excluded sector) in district d during year t. Our specification includes district fixed effects (ι_d) and year fixed effects (ι_t). Finally, we cluster standard errors at the district level.

Panel B of Table 10 shows the estimated coefficients for the two-stage OLS estimation,while Panel A proposes the simple OLS estimates. Panel C presents the analogous results when we perform a reduced form analysis. When we look at Panel B, we note that the two-stage coefficients are all negative and relatively large, but they remain statistically insignificant. Reduced-form results are very similar, except for the coefficient associated with total employment which becomes significant upon adopting this latter specification. We can interpret this result as suggesting that a percent increase in Chinese FDI to the treated sector s is associated with approximately a percent decrease in aggregate employment in all other sectors. However, despite this coefficient, the general lack of significance of all other estimates suggests that there is little evidence of relevant inter-sectoral spillover effects in sectors other than the treated one and its upstream and (to a lesser extent) downstream counterparts.

4.3 Placebo using Non-Chinese FDI

In our analysis, we have used Chinese export tax rates combined with district sectoral exposure in order to instrument the total level of Chinese FDI in each district in Ethiopia. In order to evaluate the reliability of our instrument, we test whether our instrument is a good predictor of FDI from countries other than China. To do so, we replicate the first-stage analysis of Section 2.4 and estimate the following model:

$$Non - China\, FDI_{dst} = \gamma\, China\, Export\, Tax_{st-1} \times Exposure^{PRE}{}_{ds} + \iota_{ds} + \iota_{dt} + \iota_{st} + z_{dst} \quad (10)$$

where $Non\ China\ FDI_{dst}$ is the natural logarithm of total FDI coming from foreign countries other than China received by sector s in district d during year t. As in the first stage, $China\ Export\ Tax$ is the natural logarithm of the Chinese export tax for sector s and $Exposure^{PRE}{}_{ds}$

is the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. As we did for previous cases, we study two alternative specifications: one that includes district-sector (ι_{ds}), and sector-year (ι_{st}) fixed effects and another also including district-year (ι_{dt}) fixed effects. Finally, we cluster two-way standard errors at the district and sector level.

Table 11 presents the estimated coefficients for the first-stage models described. As we can observe from the estimated coefficients, our IV is not significantly associated with non-Chinese investment flows to a given sector s in a district d during year t, regardless of the number of fixed effects we include in our model. These results suggest that our instrumental variable approach is indeed well suited to model the inflow of Chinese FDI into Ethiopia, and also to rule out the effect of possible confounders.

4.4 Controlling For Contemporaneous Export Tax Rates

In our first-stage analysis, we built our instrument using the interaction between district sectoral exposure to FDI and Chinese export tax rates. Specifically, we used a lagged specification for this latter term, assuming that changes in tax rates need time to generate changes in FDI inflows. In the following test, we relax this assumption and add a control in our first-stage model that takes into account the contemporaneous effect of changes in Chinese Export taxes on Chinese investments. The model we estimate is the following:

$$ChinaFDI_{dst} = \gamma ChinaExportTax_{st-1} \times Exposure^{PRE}{}_{ds} + ChinaExportTax_{st} + \iota_{ds} + \iota_{dt} + \iota_{st} + z_{dst} \tag{11}$$

where $China\ FDI_{dst}$ is the natural logarithm of alternative measures of Chinese FDI inflows (namely the level of Chinese investment, the number of FDI projects and the probability of receiving FDI) received by sector s in district d during year t. $China\ Export\ Tax_{st-1}$ is the natural logarithm of the Chinese export tax for sector s, i.e. the difference between the Chinese export VAT rate to the sector s and its relative rebate rate in the year $t-1$. Analogously, $China\ Export\ Tax_{st}$ is the natural logarithm of the Chinese export tax for sector s in the year t. $Exposure^{PRE}{}_{ds}$ is the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. As in the original first-stage analysis, we estimate this model first using district-sector (ι_{ds}) and sector-year (ι_{st}) fixed effects and then adding also district-year (ι_{dt}) fixed effects. As we can observe in both specifications (Table 12, Panel A and B), the inclusion of contemporaneous Chinese export tax does not have a substantial effect on our original estimates. As with our previous checks, these results support the original design of our instrumental variable approach.

4.5 Aggregated Effects on Upstream and Downstream Sectors

In previous paragraphs we have assessed FDI impacts on upstream and downstream sectors at the firm level. In this paragraph, we are going to see if the previous patterns hold true for data aggregated at the district-sector level. For this alternative case, we estimate a model similar to the reduced-form OLS presented above and expect to find evidence of the positive impact of Chinese FDI on upstream and downstream sectors' performance measures. The alternative specifications we adopt are the following:

$$\mathrm{x}_{dst} = \beta_{UP}\, Upstream\ Export\ Tax_{st-1} \times Upstream\ Exposure^{PRE}_{ds} + \iota_{ds} + \iota_{dt} + \iota_{st} + \epsilon_{dst}$$

$$\mathrm{x}_{dst} = \beta_{DOWN}\, Downstream\ Export\ Tax_{st-1} \times Downstream\ Exposure^{PRE}_{ds} + \iota_{ds} + \iota_{dt} + \iota_{st} + \epsilon_{dst}$$

(12)

where x_{dst} is the usual set of sector-level performance indicators for sector s in district d during the year t. In our first specification, $Upstream\ Export\ Tax_{st-1}$ is the natural logarithm of the export tax for the sector upstream of s, i.e. the difference between the Chinese export VAT rate in the sector upstream of s and its corresponding rebate rate in the year $t-1$. $Upstream\ Exposure^{PRE}{}_{ds}$ is the natural logarithm of the share of goods sold by the sector upstream of s in district d over the total value sold by all Ethiopian firms in this same sector in the pre-treatment period 2000-2001. Similarly, $Downstream\ Export\ Tax_{st-1}$ is the natural logarithm of the export tax for the sector downstream of s in the year $t-1$. $Downstream\ Exposure^{PRE}{}_{ds}$ is the natural logarithm of the share of goods sold by the sector downstream of s in district d over the total value sold by this same sector in Ethiopia in the pre-treatment period 2000-2001. Our current specifications include district-sector (ι_{ds}), district-year (ι_{dt}) and sector-year (ι_{st}) fixed effects. As previously, we cluster two-way standard errors at the district and sector level.

Panel A of Table 13 presents the estimated coefficients of our first specification focusing on the impact of Chinese FDI on upstream sectors while Panel B of Table 13 presents the same output for downstream sectors. In Panel A of Table 13, we see that our estimates are all positive, large in size and significant for all indicators of performance except for $value\ of\ production$. These results seem to support our explanation, indicating that a percent increase in Chinese FDI targeted at the upstream sector of sector s is associated with improvements in performance indicators in sector s, which approximately range from 0.7% to 1.4% gains in performance. However, the same pattern does not emerge when we consider Chinese FDI in the sector downstream of s. As Panel B of Table 13 shows, the coefficients associated with performance measures are smaller in size and statistically insignificant. From a general perspective, this outcome suggests that FDI directed to upstream sectors indeed benefits a specific sector's performance. We argue that this positive spillover originates from suppliers' increased efficiency, which translates to a downward pressure on the prices charged by suppliers and possible technological spillover effects. However, there is no evidence that this mechanism holds for downstream FDI.

4.6 Evidence at district-sector level

In this section, we repeat the first and the second stage analisys at the district-sector level. Hence, we do not control for the district-year fixed effects. This allows to retrieve a broader picture of Chinese FDI's impact.

In the first stage, we verify whether the Chinese FDI is directed toward districts specialized in specific sectors, when the Chinese export tax on these sectors vary. Thus, we propose the following model:

$$China\,FDI_{dst} = \gamma\,China\,Export\,Tax_{st-1} \times Exposure^{PRE}{}_{ds} + \iota_{ds} + \iota_{dt} + \iota_{st} + z_{dst} \qquad (13)$$

where $China\ FDI_{dst}$ is the natural logarithm of alternative measures of Chinese FDI inflows (namely the level of Chinese investment, the number of FDI projects and the probability of receiving FDI) towards sector s in district d during year t. $China\ Export\ Tax$ is the natural logarithm of the Chinese export tax for sector s, i.e. the difference between the Chinese export VAT rate to the sector s and the corresponding rebate rate in year $t-1$. $Exposure^{PRE}{}_{ds}$ is the natural logarithm of the share of goods sold by sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. We always present two specifications: one that includes district-sector (ι_{ds}) and sector-year (ι_{st}) fixed effects; clustering two-way standard errors at the district and sector level.

In Table 14, to deal with the null observations for Chinese FDI amounts and project we adopt an inverse hyperbolic since transformation (IHS) in Panel A and a logarithm transformation in Panel B. As we can observe in Panel A, the interaction between our independent variables is strongly and significantly associated with Chinese investment flows to a given sector s in a district d during year t, regardless of the measure of FDI. Column (1) shows that a one percent increase in export tax in a particular sector in China leads to a 5.82% increase in Chinese FDI in Ethiopian districts that are one standard deviation more exposed to that sector. Column (2) notes that this implies a 0.26% increase in the number of FDI projects taking place in district d, sector s and year t, while Column (3) shows a 0.08% higher probability that a district-sector is targeted by a new FDI project.

For the second stage, we adopt the same empirical strategy outlined in section 3.2. Altough, we switch from a firm prospective to a sector-district one:

$$x_{dst} = \beta\, FDI_{dst} + \iota_{ds} + \iota_{dt} + \iota_{st} + \epsilon_{dst} \quad (14)$$

in which FDI_{dst} is instrumented through:

$$FDI_{dst} = \gamma\, China\, Export\, Tax_{st-1} \times Exposure^{PRE}{}_{ds} + \iota_{ds} + \iota_{st} + z_{dst} \quad (15)$$

with x_{dst} being a set of district-sector performance indicators, namely the natural logarithm of $total\ value\ of\ production$, $total\ employment$, $book\ value\ of\ machinery$, $raw\ materials$ used in the production processes and a $price\ index$ (i.e. the difference between the production value of goods and services and their sale value). All these variables are intended to measure different dimensions of performance of sector s in the district d during the year t. FDI_{dst} is the instrumented level of Chinese FDI flowing to sector s in district d during year t and it is estimated using the first-stage equation presented in the previous section. Similarly to our first-stage regressions, our full specification includes district-sector (ι_{ds}) and sector-year (ι_{st}) fixed effects. Finally, we cluster two-way standard errors at the district and sector level.

In Table 15, Panel A, presents a simple OLS model, Panel B reports the estimated coefficients for the second-stage model, and Panel C shows the reduced-form results. Chinese FDI shows a negative and significant impact across all measures of district-sector performance except for $price\ index$. These results are consistent with the reduced-form specification. This suggests that Chinese FDI stimulates competition within the target district-sector, driving some domestic firms out of the market, which in turn leads to a decrease in production, employment, use of machinery and use of raw materials.

5 Conclusions

This paper studies the effect of Chinese FDI in Ethiopia. Our empirical analysis combines a detailed dataset at firm and district level with a natural experiment inducing exogenous variation in district-sector Chinese FDI. We exploit sector-specific export tax changes in China to show that Chinese FDI is increasingly directed to Ethiopian districts specialized in the same sectors being targeted by such export taxes domestically in China.

Our results show that firms operating in districts receiving Chinese FDI shrink their operations significantly: lowering production, employment, investment, and raw material inputs. We also observe that the prices charged by such firms report a large decline, which is in line with the hypothesis of an increase in local competition. Meanwhile, firms operating in the relevant upstream and downstream sectors in the same district benefit from Chinese FDI and expand their operations, while firms in other sectors remain unaffected.

We go beyond firm-level estimates and study the aggregate effect of Chinese FDI through a district panel of satellite night lights. This leads us to verify that the positive and negative effects of Chinese FDI cancel each other out at the aggregate level at the time of the investment, with our results reporting a well-estimated zero effect on local economic condition. However, we observe that in the medium run the positive effects of Chinese FDI outpace the negative effects.

Overall, our findings cast some doubts on the fierce and often-times ideological debate around Chinese presence in Africa. We show that the effects of Chinese FDI are highly heterogeneous, but overall positive in the medium run. We hope that this empirical contribution may offer grounds for a fruitful, evidence-based discussion, and subsequent refinement of guidance surrounding optimal trade and investment policies.

Tables

Table 1: Rebates' variation serial correlation

Variables	(1) ΔTax_{st}	(2) ΔTax_{st}	(3) ΔTax_{st}	(4) ΔTax_{st}
ΔTax_{st-1}	0.068			
	(0.062)			
ΔTax_{st-2}		-0.100		
		(0.075)		
ΔTax_{st-3}			-0.083	
			(0.056)	
ΔTax_{st-4}				-0.038
				(0.061)
Sector FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Obs.	135	120	105	90
Adj. R sq.	0.509	0.658	0.664	0.749
M.D.V.	0.113	0.040	0.043	0.032
S.D.D.V.	0.342	0.211	0.225	0.225

Notes: This table presents OLS estimates, where the unit of observation is a sector s during a year t. The dependent variable is the variation of the export tax's natural logarithm between time t and time $t-1$. This export tax is computed as the difference between the Chinese export VAT rate to sector s' and its relative rebate rate in the year $t-1$. The independent variable is the lag of the dependent one at $t-1$ in column (1), at $t-2$ in column (2), at $t-3$ in column (3) and at $t-4$ in column (4). We control for sector and year fixed effects, the standard errors are robust. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 2: Summary Statistics on Main Aggregates

Variables	(1) Observations	(2) Mean	(3) St. Dev.	(4) Minimum	(5) Maximum
	Panel A - Export Tax and District Exposure				
Chinese Export Tax	165	5.23	3.60	0.59	15.27
District-Sector Exposure	388	0.04	0.15	0	1
	Panel B - Chinese FDI across District and Sectors				
Ln FDI China	4,268	0.43	2.09	0	14.53
	Panel C - Firms Census Data				
Ln Value of Prod.	10,587	15.47	2.19	1.10	22.28
Ln Employment	10,587	3.50	1.41	0	8.98
Ln Machineries	10,587	12.20	3.61	0	20.97
Ln Raw Mat.	10,587	14.71	2.45	0	22.52
Ln Price Index	10,587	-0.019	0.39	-6.92	12.30
	Panel D - Satellite Lights				
Ln Number of Pixels	1,050	1.46	1.21	0	4.00

Notes: This table reports the summary statistics for the four datasets used in our analysis. Panel A shows the summary statistics for the Chinese Export Tax across all sectors and over time and data on the sector exposure of all districts in Ethiopia. Panel B indicates the summary statistics on Chinese FDI in Ethiopia as a natural logarithm. Panel C contains the summary statistics for the five variables extracted from the Census of Manufacturing Firms. Panel D describes data on night lights, used to measure aggregate economic activity at the district level. For each panel, the table reports the number of observations (indicated as Obs.), the mean, standard deviation (indicated as Std. Dev.), the minimum and maximum observation.

Table 3: Chinese FDI, Export Taxes and District Exposure

	(1) Ln FDI China	(2) Ln Proj. Num.	(3) Prob. of FDI
	Panel A - IHS		
$Exp._{ds} \times$	3.208***	0.419***	0.241***
Tax_{st-1}	(0.536)	(0.091)	(0.057)
District-Sector FE	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Obs.	4268	4268	4268
Adj. R sq.	0.787	0.666	0.540
M.D.V.	0.430	0.024	0.021
S.D.D.V.	2.094	0.182	0.143
	Panel B - log(1+x)		
$Exp._{ds} \times$	2.991***	0.327***	0.241***
Tax_{st-1}	(0.509)	(0.070)	(0.057)
District-Sector FE	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Obs.	4268	4268	4268
Adj. R sq.	0.789	0.666	0.540
M.D.V.	0.430	0.024	0.021
S.D.D.V.	2.094	0.182	0.143

Notes: This table presents first-stage ordinary least squares (OLS) estimates, where the unit of observation is a given sector s operating in district d during the year t. The dependent variable in column (1) is the natural logarithm of the volume of Chinese FDI targeted to sector s operating in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of projects financed by Chinese FDI projects in sector s of district d in year t. The dependent variable in column (3) is the probability of sector s of district d to receive Chinese FDI during year t. Our independent variables are alternatively regressed over an interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. the difference between the Chinese export VAT rate to the sector s and its relative rebate rate in the year $t - 1$ and 2) the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. In Panel A, we adopt an inverse hyperbolic sine transformation to deal with the null observations of Chinese FDI and the number of projects financed. In panel B, we face the same issue opting for a log(1+x) transformation. We control for district-sector, the district-year and the sector-year fixed effects. The errors are clustered at the district-sector level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 4: Evidence on Competing Firms

	(1) Ln Value of Prod.	(2) Ln Total Empl.nt	(3) Ln Book Machine Value	(4) Ln Raw Material	(5) Ln Price Index
	Panel A - OLS				
$Ln\,FDI$	0.011	-0.022*	0.038	0.022	0.001
$China$	(0.011)	(0.012)	(0.032)	(0.016)	(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year	Yes	Yes	Yes	Yes	Yes
Obs.	10587	10587	10587	10587	10587
Adj. R sq.	0.881	0.838	0.557	0.717	0.214
M.D.V.	15.47	3.499	12.20	14.71	-0.019
	Panel B - second stage				
$Ln\,FDI$	-0.172**	-0.295***	-0.325	-0.154*	-0.039*
$China$	(0.077)	(0.082)	(0.199)	(0.089)	(0.023)
Firm FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year	Yes	Yes	Yes	Yes	Yes
Obs.	10587	10587	10587	10587	10587
Adj. R sq.	0.875	0.806	0.547	0.713	0.204
M.D.V.	15.47	3.499	12.20	14.71	-0.019
F-Statistic	36.49	36.49	36.49	36.49	36.49
	Panel C - reduced form				
$Exp._{ds} \times$	-0.380**	-0.651***	-0.718*	-0.341*	-0.087*
Tax_{st}	(0.159)	(0.157)	(0.409)	(0.190)	(0.048)
Firm FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year	Yes	Yes	Yes	Yes	Yes
Obs.	10587	10587	10587	10587	10587
Adj. R sq.	0.881	0.839	0.557	0.717	0.214
M.D.V.	15.47	3.499	12.20	14.71	-0.019

Notes: This table presents simple OLS estimates (Panel A), second-stage OLS estimates (Panel B) and reduced form estimates (Panel C), where the unit of observation is a firm f belonging to sector s operating in district d during the year t . The dependent variable in column (1) is the natural logarithm of the value of production of firm f in sector s located in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of employees of firm f operating in sector s of district d in year t. The dependent variable in column (3) is the natural logarithm of the book value of machinery reported by firm f in sector s located in district d during year t. The dependent variable in column (4) is the natural logarithm of the reported value of raw materials used by firm f operating in sector s of district d in year t. Finally, the dependent variable in column (5) is the natural logarithm of a price index, calculated as the difference between the production value of goods and services produced by firm f in sector s located in district d during year t and their value at the moment of sale. In Panels A and B, our independent variable is the natural logarithm of the level of Chinese FDI targeted to sector s operating in district d during year t. In Panel B, this variable has been instrumented using our previous measure of sector exposure to Chinese FDI. In Panel C, our independent variable is the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. difference between the Chinese export VAT rate to the sector s and its relative rebate rate in the year $t-1$ and 2) the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. We include firm, district-year, district-sector and sector-year fixed effects in all columns and we cluster standard errors at the firm level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following row shows the mean of the dependent variables. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. The F-statistic for the first-stage of Panel B regressions is 36.49.

Table 5: Chinese FDI and Input-Output Linkages

	(1) Ln Value of Prod.	(2) Ln Total Empl.nt	(3) Ln Book Machine Value	(4) Ln Raw Material	(5) Ln Price Index
	Panel A - upstream firms				
$Up\,Exp._{ds} \times$	0.134	0.248**	0.573*	0.178	0.052
$Up\,Tax_{st-1}$	(0.116)	(0.103)	(0.303)	(0.142)	(0.039)
Firm FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	13701	13701	13701	13701	13701
Adj. R sq.	0.883	0.840	0.574	0.751	0.172
M.D.V.	15.44	3.431	3.431	14.67	-0.021
S.D. Dep. Var.	2.245	1.512	1.512	2.510	0.402
	Panel B - downstream firms				
$Down\,Exp._{ds} \times$	0.121	0.245**	0.085	0.078	0.120***
$Down\,Tax_{st-1}$	(0.108)	(0.110)	(0.257)	(0.134)	(0.042)
Firm FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	13701	13701	13701	13701	13701
Adj. R sq.	0.883	0.840	0.574	0.751	0.173
M.D.V.	15.44	3.431	12.30	14.67	-0.021
S.D. Dep. Var.	2.245	1.512	3.567	2.510	0.402

Notes: This table presents the OLS estimates of the reduced form, where the unit of observation is a given sector s operating in district d during the year t. The dependent variable in column (1) is the natural logarithm of the value of production of all firms in sector s located in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of employees of all firms operating in sector s of district d in year t. The dependent variable in column (3) is the natural logarithm of the book value of machinery reported by firms in sector s located in district d during year t. The dependent variable in column (4) is the natural logarithm of the reported value of raw materials used by firms operating in sector s of district d in year t. Finally, the dependent variable in column (5) is the natural logarithm of a price index, calculated as the difference between the production value of goods and services produced by sector s located in district d during year t and their value at the moment of sale. Our independent variable in Panel A (B) is the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. difference between the Chinese export VAT rate to sector s' upstream (downstream) sector and its relative rebate rate in the year t-1 and 2) the natural logarithm of the share of goods sold by the sector s' upstream (downstream) sector in district d over the aggregate value sold by all Ethiopian firms during the pre-treatment period 2000-2001. The relative upstream (downstream) sector of sector s is assigned using data from the U.S. Bureau of Economic Analysis. We include firm, district-year, district-sector and sector-year fixed effects in all columns and we cluster the standard errors at the firm level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 6: Aggregate Effects on Firms

	(1) Ln Value of Prod.	(2) Ln Total Empl.nt	(3) Ln Book Machine Value	(4) Ln Raw Material	(5) Ln Price Index
	Panel A - OLS				
$Ln\,FDI$	0.007	-0.005	0.046	-0.001	-0.004
$China$	(0.045)	(0.034)	(0.049)	(0.053)	(0.003)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	703	703	703	703	703
Adj. R sq.	0.752	0.739	0.534	0.688	0.094
M.D.V.	15.91	3.865	12.99	15.12	-0.019
S.D.D.V.	2.134	1.642	3.012	2.124	0.245
	Panel B - second stage				
$Ln\,FDI$	0.139	-0.535*	0.359	0.165	0.102**
$China$	(0.175)	(0.271)	(0.220)	(0.221)	(0.042)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	703	703	703	703	703
Adj. R sq.	0.737	0.314	0.490	0.663	-0.670
M.D.V.	15.91	3.865	12.99	15.12	-0.019
S.D.D.V.	2.134	1.642	3.012	2.124	0.245
F-Statistic	39.48	39.48	39.48	39.48	39.48
	Panel C - reduced form				
$Exp._d \times$	0.238	-0.914*	0.614**	0.283	0.174***
Tax_{dt-1}	(0.249)	(0.460)	(0.273)	(0.323)	(0.053)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	703	703	703	703	703
Adj. R sq.	0.752	0.740	0.533	0.688	0.096
M.D.V.	15.91	3.865	12.99	15.12	-0.019
S.D.D.V.	2.134	1.642	3.012	2.124	0.245

Notes: This table presents simple OLS estimates (Panel A), second-stage OLS estimates (Panel B) and reduced form estimates (Panel C), where the unit of observation is a district d during the year t. The dependent variable in column (1) is the natural logarithm of the value of production of all firms in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of employees of all firms operating in district d in year t. The dependent variable in column (3) is the natural logarithm of the book value of machinery reported by firms in district d during year t. The dependent variable in column (4) is the natural logarithm of the reported value of raw materials used by firms operating in district d in year t. Finally, the dependent variable in column (5) is the natural logarithm of a mean price index, calculated as the difference between the production value of goods and services produced by all firms operating in district d during year t and their value at the moment of sale. In Panel A and B, the predicting variable is the natural logarithm of the volume of Chinese FDI targeted to district d during year t. In Panel B, this variable is instrumented with the weighted sum of the export tax in sector s time t-1 interacted with the district exposure to the specific sector. Panel C reports the reduced-form estimates. We include district and year fixed effects in all columns and we cluster standard errors at the district level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. The F-statistic for the first-stage of Panel B regressions is 39.48.

Table 7: Chinese FDI and Local Economic Development

	(1) Ln Pixels Lights OLS	(2) Ln China FDI	(3) Ln Pixels Lights	(4) Ln Pixels Lights IV
$Ln\,China\,FDI_{dt}$	0.019			-0.017
	(0.014)			(0.026)
$Exp._{d}$		1.925***	-0.032	
$\times\,ExportTax_{dt-1}$		(0.395)	(0.046)	
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	1050	1050	1050	1050
Adj. R sq.	0.892	0.554	0.891	0.888
Mean Dep. Var.	1.455	0.786	1.455	1.455
S.D. Dep. Var.	1.206	2.854	1.206	1.206

Notes: This table presents first-stage, second-stage and reduced-form estimates, where the unit of observation is a given district d during the year t. The dependent variable in column (1) is the natural logarithm of the average brightness level at night of the location where district d is located during year t. Nightlight Brightness data is provided by NOAA and originates from US Air Force Weather Agency. The dependent variable in columns (1), (3) and (4) is the natural logarithm of the average brightness level at night of the location where district d is located during year t. In column (1), this variable is regressed of the non-instrumented level of Chinese FDI targeted to district d during year t. In column (3), nightlight brightness is regressed over our instrumental variable, which is a weighted sum of the export tax in sector s time $t-1$ interacted with the district exposure to the specific sector. In column (4), nightlight brightness is regressed over the instrumented level of Chinese FDI targeted to district d during year t. The dependent variable in column (2) is the level of Chinese FDI targeted to district d during year t, which is regressed over a weighted sum of the export tax in sector s time $t-1$ interacted with the district exposure to the specific sector. The F statistic of this first-stage OLS is F 187.24***. We include district and year fixed effects in all columns and we cluster standard errors at the district level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 8: Reverse Causality Test

Variables	(1) ΔTax_{st}	(2) ΔTax_{st}	(3) ΔTax_{st}
$\Delta Ln.\,Value$	0.00008	0.0001	-0.0004
$of\ Prod._{st-1}$	(0.0002)	(0.0005)	(0.0003)
Sector FE	NO	YES	YES
Year FE	NO	NO	YES
Obs.	150	150	150
Adj. R sq.	0.007	0.078	0.513
M.D.V.	0.102	0.102	0.102
S.D.D.V.	0.327	0.327	0.327

Notes: This table presents the OLS estimates, where the unit of observation is a given sector s during the year t. The dependent variable is the difference of the export tax's natural logarithm between year t and year t-1 for sector s. The independent variable is the difference of the logarithm of the production value of all firms in sector s, between year t-1 and year t-2. In column (1), we apply no fixed effects. In column (2), we control for sector fixed effects. In column (3), we control for year and sector fixed effects. The standard errors are clustered at the year-sector levels. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variable. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 9: Taxation's impact on import

Variables	(1) $Imports_{st}$	(2) $Imports_{st}$	(3) $Imports_{st}$
Tax_{st}	-0.415	-0.220	0.007
	(0.470)	(0.320)	(0.258)
Sector FE	No	Yes	Yes
Year FE	No	No	Yes
Obs.	165	165	165
Adj. R sq.	0.008	0.451	0.956
M.D.V.	16.70	16.70	16.70
S.D.D.V.	2.334	2.334	2.334

Notes: This table presents the OLS estimates, where the unit of observation is a given sector s during the year t. The dependent variable is logarithm of the Chinese imports' USD value for sector s and year t. The data on the imports are retrieved from the "Observatory of Economic Complexity" (https://oec.world/en/visualize/stacked/sitc/import/eth/chn/show/1962.2017/). The independent variable is the export tax's natural logarithm for year t and sector s. The natural logarithm of the export tax is computed as the difference between the Chinese export VAT rate to sector s' and its relative rebate rate in the year t-1. In column (1), we apply no fixed effects. In column (2), we control for sector fixed effects. In column (3), we control for sector and year fixed effects. The standard errors are clustered at the sector and year levels. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 10: Chinese FDI and Spillovers

	(1) Ln Value of Prod.	(2) Ln Total Empl.nt	(3) Ln Book Machine Value	(4) Ln Raw Material	(5) Ln Price Index
	Panel A - OLS				
$Ln\,China$	-0.037	-0.037***	-0.040	-0.039	0.001
FDI_{jt}	(0.024)	(0.012)	(0.028)	(0.024)	(0.001)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	3267	3267	3267	3267	3267
Adj. R sq.	0.787	0.801	0.744	0.764	0.075
M.D.V.	18.63	6.201	16.43	17.97	-0.036
S.D.D.V.	2.492	2.068	2.807	2.496	0.179
	Panel B - second stage				
$Ln\,China$	-0.506	-0.432	-0.493	-0.429	0.001
FDI_{jt}	(0.357)	(0.284)	(0.367)	(0.283)	(0.006)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	3267	3267	3267	3267	3267
Adj. R sq.	0.703	0.719	0.685	0.706	0.080
M.D.V.	18.63	6.201	16.43	17.97	-0.036
S.D.D.V.	2.492	2.068	2.807	2.496	0.179
F-Statistic	25.08	25.08	25.08	25.08	25.08
	Panel C - reduced form				
$Exp._j \times$	-0.666	-0.567	-0.649	-0.564	0.001
Tax_{st-1}	(0.501)	(0.392)	(0.515)	(0.397)	(0.007)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	3267	3267	3267	3267	3267
Adj. R sq.	0.788	0.808	0.745	0.764	0.080
M.D.V.	18.63	6.201	16.43	17.97	-0.036
S.D.D.V.	2.492	2.068	2.807	2.496	0.179

Notes: This table presents simple OLS estimates (Panel A), second-stage OLS estimates (Panel B) and reduced form estimates (Panel C), where the unit of observation is the aggregation of all sectors except sector s. operating in district d. during the year t. The dependent variable in column (1) is the natural logarithm of the value of production of all firms that do not belong to sector s, located in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of employees of all firms operating in all sectors excluding sector s in district d during year t. The dependent variable in column (3) is the natural logarithm of the book value of machinery reported by firms located in district d during year t, excluding those belonging to sector s. The dependent variable in column (4) is the natural logarithm of the reported value of raw materials used by firms operating in all sectors excluding sector s, located in district d during year t. Finally, the dependent variable in column (5) is the natural logarithm of a price index, calculated as the difference between the production value of goods and services produced by all firms not belonging to sector s, located in district d during year t and their value at the moment of sale. In Panels A and B, our independent variable is the natural logarithm of the level of Chinese FDI targeted to sector s operating in district d during year t. In Panel B, this variable has been instrumented in the first-stage using our previous measure of sector exposure to Chinese FDI. In Panel C, our independent variable is the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. difference between the Chinese export VAT rate to sector s and its relative rebate rate in the year t-1 and 2) the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms during the pre-treatment period 2000-2001. We include district and year fixed effects in all columns and we cluster standard errors at the district level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. The F-statistic for the first stage of Panel A regressions is 25.08.

Table 11: Placebo using Non-Chinese FDI

	(1) Ln FDI Non China	(2) Ln Proj. Num.	(3) Prob. of FDI
$Exp._{ds}$ $\times$	0.027	0.035	0.114
Tax_{st-1}	(0.232)	(0.079)	(0.142)
District-Sector FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
District-Year FE	No	Yes	Yes
Obs.	4628	4628	4628
Adj. R sq.	0.894	0.954	0.509
M.D.V.	1.161	0.183	0.042
S.D. Dep. Var.	3.404	0.604	0.201

Notes: This table presents first-stage OLS estimates, where the unit of observation is a given sector s operating in district d during the year t. The dependent variable in column (1) is the natural logarithm of the volume of non-Chinese FDI targeted to sector s operating in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of projects financed by non-Chinese FDIs in sector s of district d in year t. The dependent variable in column (3) is the probability of sector s of district d to receive non-Chinese FDI during year t. Our independent variables are alternatively regressed over the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. the difference between the Chinese export VAT rate to the sector s and its relative rebate rate in the year $t-1$ and 2) the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. We include district-sector and sector-year fixed effects in all columns and we cluster two-way standard errors at the district and sector level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 12: Contemporaneous Export Tax Rates

	(1) Ln FDI China	(2) Ln Proj. Num.	(3) Prob. of FDI
	Panel A - no district-year fixed effects		
$Exp._{ds} \times$	4.641***	0.310***	0.149**
Tax_{st-1}	(0.463)	(0.082)	(0.050)
$Control for Exp.Tax_{st-1}$	Yes	Yes	Yes
District-Sector FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Obs.	4268	4268	4268
Adj. R sq.	0.797	0.669	0.547
M.D.V.	0.436	0.024	0.021
S.D.D.V.	2.112	0.182	0.143
	Panel B - district-year fixed effects		
$Exp._{ds} \times$	2.442***	0.313***	0.239***
Tax_{st-1}	(0.459)	(0.076)	(0.056)
$Control for Exp.Tax_{st-1}$	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes
District-Sector FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Obs.	4268	4268	4268
Adj. R sq.	0.782	0.695	0.556
M.D.V.	0.436	0.024	0.021
S.D.D.V.	2.112	0.182	0.143

Notes: This table presents first-stage OLS estimates, where the unit of observation is a given sector s operating in district d during the year t. The dependent variable in column (1) is the natural logarithm of the volume of Chinese FDI targeted to sector s operating in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of projects financed by Chinese FDIs in sector s of district d in year t. The dependent variable in column (3) is the probability of sector s of district d to receive Chinese FDI during year t. Our independent variables are alternatively regressed over the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. the difference between the Chinese export VAT rate to the sector s and its relative rebate rate in the year $t-1$ and 2) the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. We control for contemporaneous Chinese export tax in all regressions. In Panel A, we include district-sector and sector-year fixed effects in all columns and we cluster two-way standard errors at the district and sector level. In Panel B, we also add district-year fixed effects. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 13: Chinese FDI and Upstream - Aggregated District Sector

	(1) Ln Value of Prod.	(2) Ln Total Empl.nt	(3) Ln Book Machine Value	(4) Ln Raw Material	(5) Ln Price Index
	Panel A - upstream sectors				
$Up\,Exp._{ds}$ ×	0.121	0.356**	0.728***	0.435**	0.196**
$Up\,Tax_{st-1}$	(0.151)	(0.150)	(0.188)	(0.174)	(0.086)
District-Sector FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	2529	2529	2529	2529	2529
Adj. R sq.	0.815	0.822	0.630	0.763	0.110
M.D.V.	16.88	4.650	14.01	16.11	-0.061
S.D.D.V.	2.472	1.839	3.660	2.650	0.741
	Panel B- downstream sectors				
$Down\,Exp._{ds}$ ×	0.243	0.257	0.475	0.223	-0.014
$Down\,Tax_{st-1}$	(0.188)	(0.180)	(0.279)	(0.215)	(0.075)
District-Sector FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	2529	2529	2529	2529	2529
Adj. R sq.	0.815	0.822	0.630	0.763	0.109
M.D.V.	16.88	4.650	14.01	16.11	-0.061
S.D.D.V.	2.472	1.839	3.660	2.650	0.741

Notes: This table presents second-stage OLS estimates, where the unit of observation is a given sector s operating in district d during the year t. The dependent variable in column (1) is the natural logarithm of the value of production of all firms in sector s located in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of employees of all firms operating in sector s of district d in year t. The dependent variable in column (3) is the natural logarithm of the book value of machinery reported by firms in sector s located in district d during year t. The dependent variable in column (4) is the natural logarithm of the reported value of raw materials used by firms operating in sector s of district d in year t. Finally, the dependent variable in column (5) is the natural logarithm of a price index, calculated as the difference between the production value of goods and services produced by sector s located in district d during year t and their value at the moment of sale. Our independent variable is the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. difference between the Chinese export VAT rate to sector s' upstream sector and its relative rebate rate in the year t-1 and 2) the natural logarithm of the share of goods sold by the sector s' upstream sector in district d over the aggregate value sold by all Ethiopian firms during the pre-treatment period 2000-2001. The relative upstream sector of sector s is assigned using data from the U.S. Bureau of Economic Analysis. We include district-sector, district-year and sector-year fixed effects in all columns and we cluster two-way standard errors at the district and sector level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 14: Chinese FDI, Export Taxes and District Exposure

	(1) Ln FDI China	(2) Ln Proj. Num.	(3) Prob. of FDI
	Panel A - IHS		
$Exp._{ds} \times$	5.825***	0.257***	0.076*
Tax_{st-1}	(0.511)	(0.085)	(0.042)
District-Sector FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Obs.	4268	4268	4268
Adj. R sq.	0.800	0.597	0.490
M.D.V.	0.430	0.024	0.021
S.D.D.V.	2.094	0.182	0.143
	Panel B - log(1+x)		
$Exp._{ds} \times$	5.532***	0.203***	0.076*
Tax_{st-1}	(0.488)	(0.066)	(0.042)
District-Sector FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Obs.	4268	4268	4268
Adj. R sq.	0.801	0.597	0.490
M.D.V.	0.430	0.024	0.021
S.D.D.V.	2.094	0.182	0.143

Notes: This table presents first-stage ordinary least squares (OLS) estimates, where the unit of observation is a given sector s operating in district d during the year t. The dependent variable in column (1) is the natural logarithm of the volume of Chinese FDI targeted to sector s operating in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of projects financed by Chinese FDI projects in sector s of district d in year t. The dependent variable in column (3) is the probability of sector s of district d to receive Chinese FDI during year t. Our independent variables are alternatively regressed over the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. the difference between the Chinese export VAT rate to the sector s and its relative rebate rate in the year $t-1$ and 2) the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. In Panel A, we adopt an inverse hyperbolic sine transformation to deal with the null observations of Chinese FDI and the number of projects financed. In panel B, we face the same issue opting for a log(1+x) transformation. We control for district-sector and the district-year fixed effects. The errors are clustered at the district-sector level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

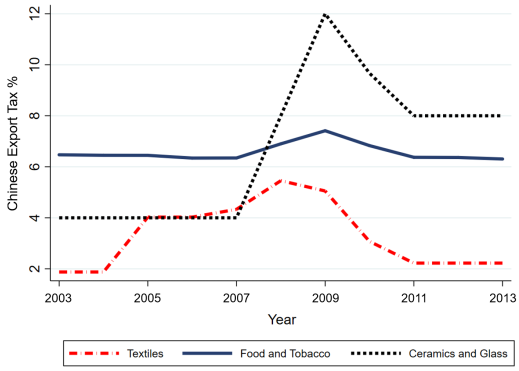
Table 15: Chinese FDI and District-Sector Aggregates

	(1) Ln Value of Prod.	(2) Ln Total Empl.nt	(3) Ln Book Machine Value	(4) Ln Raw Material	(5) Ln Price Index
			Panel A - OLS		
$Ln\,FDI$ $China$	-0.019	-0.077**	-0.022	0.014	-0.007
	(0.04)	(0.032)	(0.054)	(0.045)	(0.005)
District-Sector FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	1973	1973	1973	1973	1973
Adj. R sq.	0.804	0.804	0.632	0.747	0.046
M.D.V.	16.62	4.487	13.71	15.87	-0.004
S.D.D.V.	2.673	1.961	3.634	2.796	0.350
			Panel B - second stage		
$Ln\,FDI$ $China$	-0.170***	-0.221***	-0.099**	-0.164**	-0.007
	(0.049)	(0.039)	(0.041)	(0.058)	(0.011)
District-Sector FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	1973	1973	1973	1973	1973
Adj. R sq.	0.799	0.796	0.631	0.740	0.046
M.D.V.	16.62	4.487	13.71	15.87	-0.004
S.D.D.V.	2.673	1.961	3.634	2.796	0.350
F-Statistic	60.73	60.73	60.73	60.73	60.73
			Panel C - reduced form		
$Exp._{ds} \times$ Tax_{st}	-0.925***	-1.201***	-0.539**	-0.892***	-0.037
	(0.237)	(0.167)	(0.207)	(0.271)	(0.056)
District-Sector FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	1973	1973	1973	1973	1973
Adj. R sq.	0.805	0.806	0.632	0.748	0.046
M.D.V.	16.62	4.487	13.71	15.87	-0.004
S.D.D.V.	2.673	1.961	3.634	2.796	0.350

Notes: This table presents second-stage OLS estimates (Panel A) and reduced form estimates (Panel B), where the unit of observation is a given sector s operating in district d during the year t. The dependent variable in column (1) is the natural logarithm of the value of production of all firms in sector s located in district d during year t. The dependent variable in column (2) is the natural logarithm of the number of employees of all firms operating in sector s of district d in year t. The dependent variable in column (3) is the natural logarithm of the book value of machinery reported by firms in sector s located in district d during year t. The dependent variable in column (4) is the natural logarithm of the reported value of raw materials used by firms operating in sector s of district d in year t. Finally, the dependent variable in column (5) is the natural logarithm of a price index, calculated as the difference between the production value of goods and services produced by sector s located in district d during year t and their value at the moment of sale. In Panel A and B, our independent variable is the natural logarithm of the level of Chinese FDI targeted to sector s operating in district d during year t, which has been instrumented in the first-stage using our previous measure of sector exposure to Chinese FDI (see section 3.2). In Panel B, this variable is instrumented with the interaction between the following two terms: 1) the natural logarithm of the export tax, i.e. the difference between the Chinese export VAT rate to the sector s and its relative rebate rate in the year $t-1$ and 2) the natural logarithm of the share of goods sold by the sector s in district d over the aggregate value sold by all Ethiopian firms in sector s during the pre-treatment period 2000-2001. We include district-sector and sector-year fixed effects in all columns and we cluster two-way standard errors at the district and sector level. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. The F-statistic for the first-stage of Panel A regressions is 60.73***.

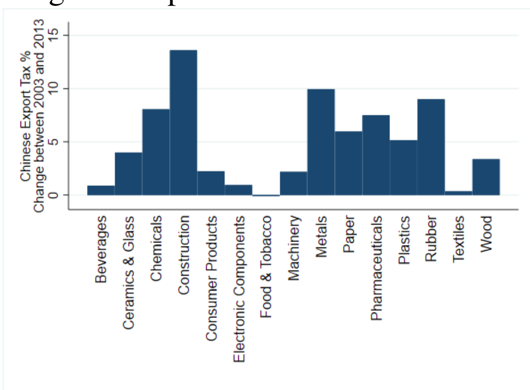
Figures

Figure 1: Export Taxes in Selected Sectors - 2003 - 2013



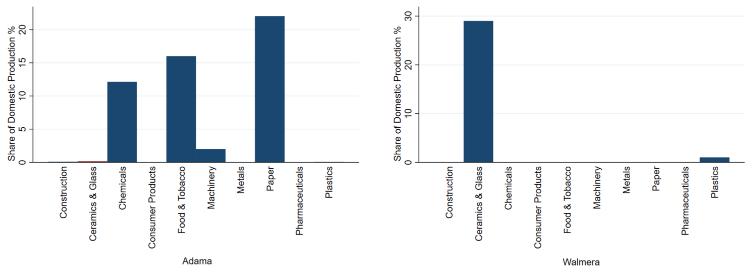
Notes: This graph shows the evolution of the wedge between sector-specific VAT rate and its relative rebate rate (i.e. the export tax) applied by Chinese authorities to selected sectors in the period between 2003 and 2013. For illustrative purposes, we only report data on the textile sector (dashed red line), the food and tobacco sector (solid blue line) and the ceramics and glass sector (dashed grey line). Data on Chinese VAT and rebate rates is obtained from Gourdon et al. (2017).

Figure 2: Changes in Export Taxes Across Sectors - 2003 - 2013



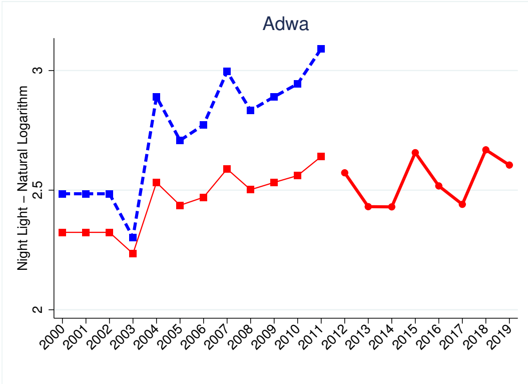
Notes: This graph shows the change of the wedge between sector-specific VAT rate and its relative rebate rate (i.e. the export tax) applied by Chinese authorities between 2003 and 2013. Data on Chinese VAT and rebate rates was obtained from Gourdon et al. (2017).

Figure 3: Sector Specialization in the Districts of Adama and Walmera



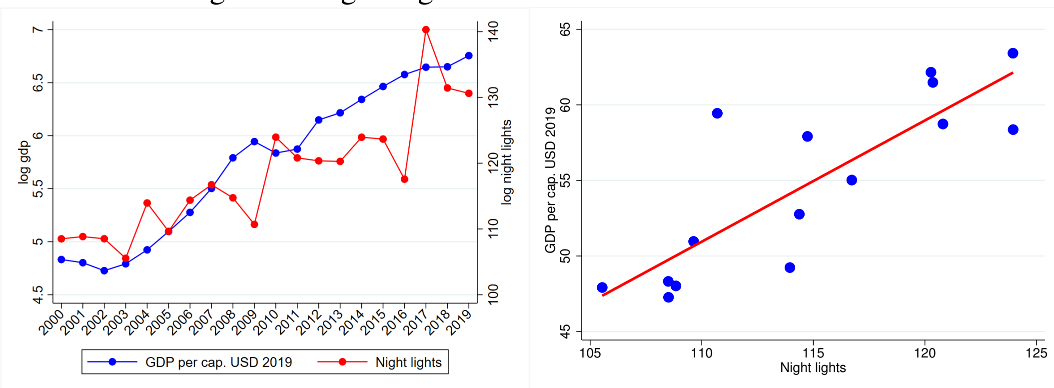
Notes: This graph shows the share of total domestic production for sectors operating in the Adama (left panel) and Walmera (right panel) districts in the period between 2000 and 2001. Data on the share of total domestic production for this district was obtained from the Central Statistical Agency of Ethiopia (CIT).

Figure 4: Night Light Satellites and Machine-Learning



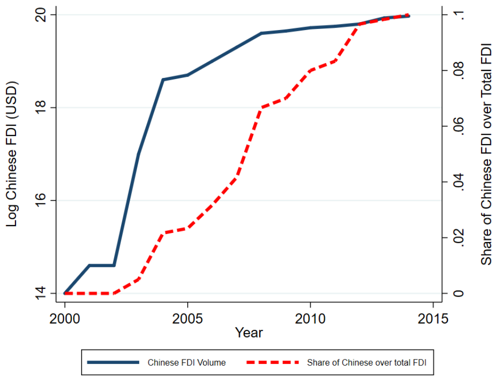
Notes: This figure reports three night light measures for the district of Adwa. A blue-line with circles displays the lights under the old satellite, the "DMSP-OLS". A solid red line with circles shows the night light measure under the new satellite, the "SUOMI-NPP"". A dashed red line with circles presents the result of our machine-learning conversion.

Figure 5: Night Light and GDP evolution - 2000-2019



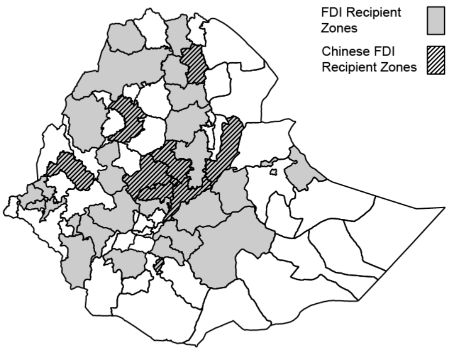
Notes: This graph displays two figures. On the left, we present the evolution of night lights and Ethiopian GDP, over the years 2000-2019. The night lights are computed summing the logarithm of the values recorded in the studied districts d, for every year t. On the right, we plot the GDP on y axis and the night lights on the x axis, for the years 2000-2019. The correlation between these two variables is 0.84 and is statistically different from zero below the 1% threshold. The night lights are computed summing the logarithm of the values recorded in the studied districts d, for every year t. The GDP is computed as the logarithm of the GDP per capita, expressed in USD (2019) billions. Data on GDP is provided by the "World Bank" (`https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=ET`).

Figure 6: Chinese FDI in Ethiopia, 2000 - 2015



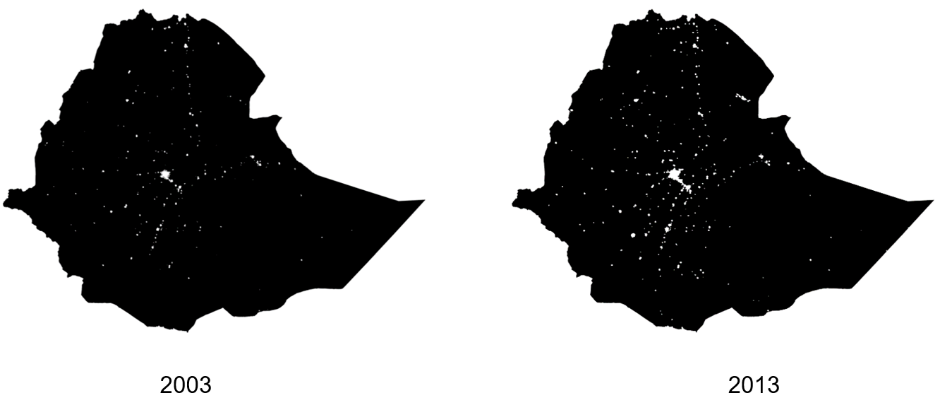
Notes: This graph shows the evolution of FDI inflows to Ethiopia in the period between 2000 and 2015. The blue line shows the yearly level of FDI entering the country, measured on a logarithmic scale. The red line shows the evolution of the share of Chinese FDI over the total FDI received by Ethiopia. The data used to plot this graph was obtained from the Ethiopia Investment Commission (World Bank, 2017).

Figure 7: The Geography of Foreign Direct Investment in Ethiopia



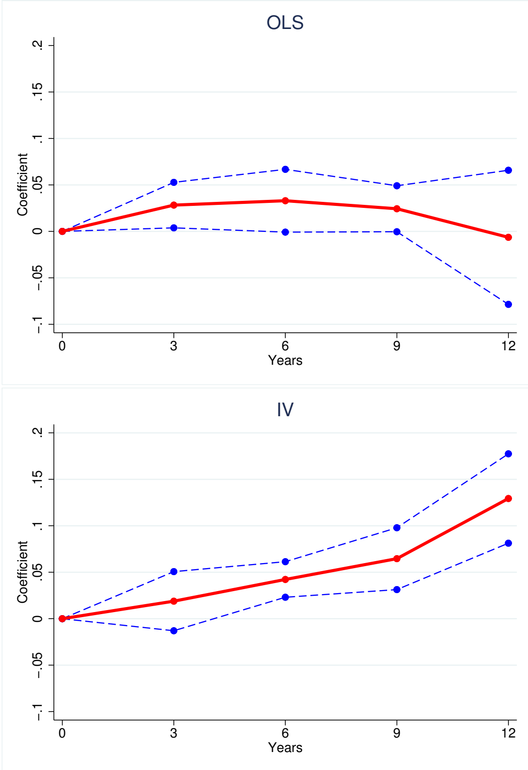
Notes: This map highlights Ethiopian Administrative Zones that have been targeted by FDI in the period between 1992 and 2015. Grey areas indicate Administrative Zones that have been recipients of FDI projects from any source, while white areas indicate those that have not. Gray areas with the diagonal pattern are recipients of Chinese FDI. Data used to draw this map was obtained from the Ethiopia Investment Commission (World Bank, 2017).

Figure 8: Night lights in Ethiopian Districts -- 2003 and 2013



Notes: This figure shows the night light brightness of Ethiopian districts in 2003 and 2013. To facilitate the interpretation of the figure, we plot night lights in white and leave dark areas in black. The data to build this picture comes from NOAA's NGDC, which provided us processed data collected by the US Air Force Weather Agency.

Figure 9: Satellite Night Lights and Chinese FDI in the Medium Run



Notes: Each figure presents OLS and IV estimates of the effect of Chinese FDI on local economic activity, where the unit of observation is a given district d during the year t. The dependent variable in both panels is the natural logarithm of the average brightness level at night of the location where district d is located during year $t + k$, with $k = 0, 3, 6, 9, 12$. Nightlight Brightness data is provided by NOAA and originates from US Air Force Weather Agency. The upper panel reports the coefficients of five separate OLS regressions in which the natural logarithm of night light brightness at time $t + k$ is regressed over the natural logarithm of Chinese FDI at time t. The lower panel reports the coefficients of five separate IV regressions in which the natural logarithm of night light brightness at time $t + k$ is regressed over the natural logarithm of Chinese FDI at time t, which is instrumented using a weighted sum of the export tax in sector s time $t - 1$ interacted with the district exposure to the specific sector. Standard errors are clustered at district level.

Online Appendix

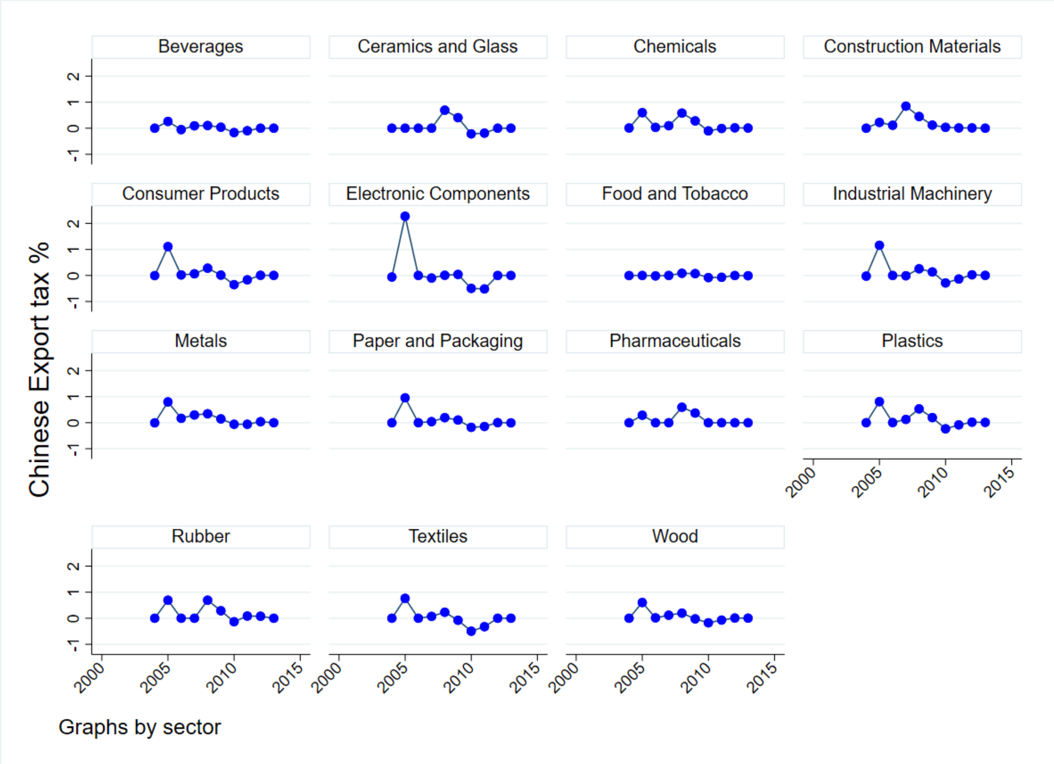
Appendix A

Table A1: Rebates' variation serial correlation

	(1)	(2)	(3)	(4)
Variables	ΔTax_{st}	ΔTax_{st}	ΔTax_{st}	ΔTax_{st}
ΔTax_{st-1}	0.04			
	(0.061)			
ΔTax_{st-2}		-0.040		
		(0.028)		
ΔTax_{st-3}			0.131**	
			(0.064)	
ΔTax_{st-4}				0.044
				(0.046)
Sector FE	NO	NO	NO	NO
Year FE	NO	NO	NO	NO
Obs.	135	120	105	90
Adj. R sq.	-0.006	-0.004	0.037	-0.006
M.D.V.	0.113	0.040	0.0428	0.032
S.D.D.V.	0.342	0.211	0.225	0.225

Notes: This table presents simple OLS estimates, where the unit of observation is a sector s during a year t. The dependent variable is the variation of the export tax's natural logarithm between time t and time $t-1$. This export tax is computed as the difference between the Chinese export VAT rate to sector s' and its relative rebate rate in the year $t-1$. The independent variable is the lag of the dependent one at $t-1$ in column(1), at $t-2$ in column(2), at $t-3$ in column(3), at $t-4$ in column(4). We do not control for fixed effects, the standard errors are robust. The row Adj. R sq. shows the adjusted R^2 of these regressions while the following two rows show the mean and standard deviation (S.D.) of the dependent variables respectively. The symbols ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Figure A1: Export Taxes - 2003-2013



Notes: This graph shows the evolution of the wedge between sector-specific VAT rate and its relative rebate rate (i.e. the export tax) applied by Chinese authorities to the studied sectors in the period between 2003 and 2013. Data on Chinese VAT and rebate rates are obtained from Gourdon et al. (2017).

Appendix B - Appendix B - Night Light Data and Machine Learning

As discussed in section 2.2, we create a 20-year panel containing the satellite night light measures for 75 districts between 2000 and 2019. A key constraint in this exercise is given by the fact that the measures for the old satellite, DMSP-OLS, only go from 2000 to 2013, while the measures for the new dataset, SUOMI-NPP, go from 2012 to 2019.

We exploit the two-year overlap between these datasets to convert the old lights in the new lights. To do this, we solve

$$Lights_{dt}^{SUOMI-NPP} = f(Lights_{dt}^{DMSP-OLS}, year_t, district_d) \tag{B1}$$

in which $Lights_{dt}^{SUOMI-NPP}$ is the natural logarithm of satellite night light pixels in a district d in year t measured by the novel SUOMI-NPP satellite; $Lights_{dt}^{DMSP-OLS}$ reports the natural logarithm of satellite night light pixels in a district d in year t as reported by the novel DMSP-OLS satellite and $year_t$ and $district_d$ are fixed effects for year and district (Ethiopian weredas).

Given the lack of a prior on the functional form of $f(.)$, various machine-learning algorithm are used to offer the most reliable 20-year panel and these are described below:

• Linear regression: This is the simplest method, expressing the equation above as a linear model, and delivering interpretable results.

• KNN: While the linear regression imposes a parametric approach implying strong assumptions about the predicted variables' distribution, KNN is a non-parametric method: for each observation it uses the K nearest ones to estimate the predictor through its mean value. The value of K regulates the bias-variance tradeoff: 1) small values of K creates models with low bias and high variance; 2) high values of K results in high bias and low variance. The optimal value of K can be found using standard iterative approaches.

• Trees: a decision tree selects the predictors generating the highest explicative power, splitting the variables according to a series of successive binary decisions and nodes. This resembles human-reasoning in event classification and provides interpretable results. We focus on three traditionally employed trees:

– Random forest: this algorithm randomly proposes only a subset of the predictors for the split at each node and focuses on those with the highest explicative power;

– Bagging: this algorithm bootstraps the data and it explores all predictors in every node. Each tree employes different observations to find the most predictive right-hand side variables;

– Boosting: this algorithm is similar to bagging, however it weights the observations at each resampling according to the outcome of the previously trained tree.

• Support vector machine (SVM): this algorithm draws hypothetical hyperplanes in the variables spaces to separate the observations into different classifications. There are two main types of hyperplanes for separating the variables:

– linear: it uses a parametric approach to separate the data;

– radial: it uses a non-linear and non-parametric approach to separate the data;

• Neural networks: this is a non-parametric learning method and requires long computations and extensive datasets. This delivers non-interpretable models.

We train all of the previous machine learning algorithms on the 2012 data and we test them on the 2013. Therefore we will have two measures of 2013 data: a) the ones predicted by each algorithm and based on the 2012 data; b) the observed 2013 data. At this stage, we can measure the performance of the algorithms and verify their accuracy.

The first performance indicator we employ is the Mean Square Error, as described in section 2.2. Table B1 shows that the least performing methods are the Linear Model, KNN and Boosting. While the SVM with radial kernels seems to be the algorithm presenting the strongest performance. The Neural Network model does not dominate the other methods, this may due to several factors including the small sample available for training.

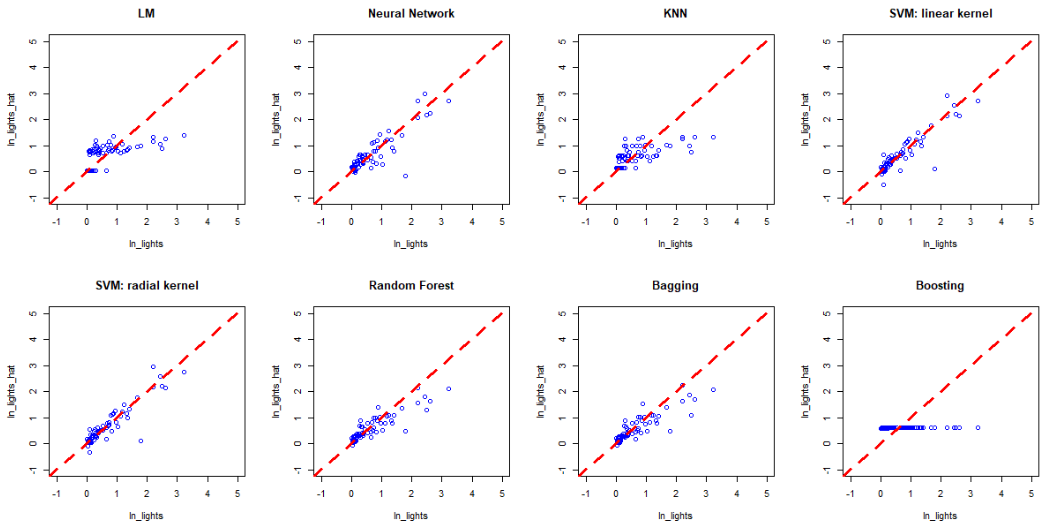
As well as verifying the MSE criterion, we also perform a graphic investigation. Given the relatively small sample of observations, this is a convenient way to inspect whether some algorithms offer a low MSE balancing over and under-fitting predictions. Figure B1 reports a panel for each method, which plots on the y-axis the predicted night lights and on the x-axis the actual lights. Most algorithms seem to be doing a good job, as most observations lie on the 45 degree line. The only exceptions are given by: 1) the linear model (top left corner, indicate with LM), which indicates that the linear model predicts lower values than the observed ones; 2) the boosting model (bottom right corner), which predicts all observations with a single value. For this reason, we use the predictions of the SVM algorithm using radial kernels.

Table B1: Algorithm Performance and Mean Square Error

(1) Algorithm	(2) Mean Square Error
Linear Model	0.294
KNN	0.281
Trees: Random Forest	0.124
Trees: Bagging	0.131
Trees: Boosting	0.511
SVM: linear kernel	0.084
SVM: radial kernel	0.079
Neural Network	0.116

Notes: This table reports the mean square error for all the algorithms used in our analysis. This measure has been computed on the test set, not used for developing the algorithm.

Figure B1: Predicted and Actual Satellite Night Lights



Notes: This figure reports a graphic representation of the performance of each algorithm. Each panel is a method and the y-axis shows the predicted night lights, while the x-axis reports the actual night lights.

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THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Institute of Global Affairs
The London School of Economics
and Political Science
Houghton Street
London WC2A 2AE

Email: iga@lse.ac.uk

lse.ac.uk/iga

Design: LSE Design Unit (lse.ac.uk/designunit)