Resource discoveries, FDI bonanzas, and local multipliers: Evidence from Mozambique

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Abstract

We show that giant and unpredictable oil and gas discoveries in developing countries trigger FDI bonanzas in the short run, and we use one such episode to estimate local FDI multipliers. Across countries, we document a 56% increase in FDI in the 2 years following a giant discovery. These booms are driven by new projects in non-resource sectors such as manufacturing, retail, business services and construction. To assess the job creation effects of one such FDI bonanza in Mozambique we combine concurrent waves of household surveys and firm censuses and estimate the local job multiplier of FDI. Our estimates suggest that for each new FDI job, an additional 4.4 jobs are created locally, 2.1 of which are formal jobs.

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1 INTRODUCTION

Foreign direct investment (FDI) has long been considered a key part of economic development (Hirschman, 1957). It is associated with transfers of technology, skills, higher wages, and with backward and forward linkages with local firms (Javorcik, 2004, 2015; Gorg and Strobl, 2001). Yet poor countries with weak institutions have found it hard to attract FDI (Gourinchas and Jeanne, 2013; Alfaro et al., 2008).

In this paper we make two contributions. First we show that giant oil and gas discoveries in developing countries trigger bonanzas of new FDI projects in non-resource sectors such as manufacturing, retail, business services and construction, in the short run. By doing so we highlight an unexpected and positive effect of resource discoveries and add to our understanding of the determinants of FDI. Second, we use one such episode in Mozambique, where an FDI bonanza followed a giant offshore gas discovery in 2009, to estimate the local job multiplier of FDI projects. We find evidence for large local multipliers, highlighting the job creating potential of FDI in poor countries.

To examine the FDI response to natural resource discoveries we merge data on giant oil and gas discoveries from Horn (2011) with a project-level FDI data set compiled by fDiMarkets, part of the Financial Times Group. As the timing of giant discoveries is unpredictable due to the uncertain nature of exploration and as it precedes extraction by 5 years on average, it provides a plausibly exogenous news shock (see Arezki et al. 2017) that allows us to identify the causal effect of resource discoveries on FDI. The project-level FDI database allows us to identify FDI flows which are not directly related to the extraction of natural resources. This distinction is particularly important as the development potential of FDI is mostly associated with quality FDI in manufacturing and services rather than in extractive industries (Alfaro and Charlton, 2013). We also decompose the FDI effect into margins, i.e. the number of FDI projects, their average value, the range of source countries, the number of targeted sectors and the number of destination cities within a country. This allows us to estimate the discovery effects on the amount of FDI and on its diversification.

We find that resource discoveries in developing countries cause FDI bonanzas. Lower bound estimates suggest that in the 2 years following a large discovery, non-extraction FDI inflows increase by 56%, the number of FDI projects increases by 30%, the number of sectors targeted and of source countries increase by around 19%. When we break down FDI by business activity and by location, we find the strongest FDI effects in manufacturing, information and communication technologies, and retail in the largest cities while in other regions the FDI effects are strongest in business services and construction, as well as in electricity and extraction.

We illustrate this FDI bonanza effect using Mozambique's recent experience, which we also delve in to estimate the local multiplier effect of FDI jobs. Mozambique is a case in point as in late 2009, news of large natural gas discoveries off its coast created much fanfare as the country now had an incredible opportunity to grow out of poverty. Mozambique's offshore natural gas discoveries in the Rovuma basin since 2009 have been prolific, with a discounted net value around 50 times its GDP according to Arezki et al. (2017). While these fields are still under development as of March 2020, fDiMarkets data suggests that foreign firms moved in right after news of the first discovery in a multitude of industries, all across the country. In 2014 alone it attracted \$9 billion worth of FDI, around 15% of all FDI to sub-Saharan Africa. Our analysis suggests that none of this would have happened without the gas discovery.

To gauge the direct as well as indirect job-creation effect of FDI projects into Mozambique we link fDiMarkets' FDI data, as well as data on firms from the 2002 and 2014 firm censuses (CEMPRE), to household employment outcomes across districts, periods, and sectors using data from two waves of Household Budget Surveys from 2002 to 2014. This allows us to estimate local FDI-job multipliers, i.e. the idea that "*every time a local economy generates a new job by attracting a new business, additional jobs might also be created*" (Moretti, 2010). To isolate the causal effect of FDI jobs we first suggest that, based on our cross-country results, as well as closer inspections of post-discovery FDI booms in Ghana, Ethiopia, and Tanzania,[1] the Mozambique FDI bonanza across cities and sectors is akin to a natural experiment providing exogenous FDI shocks across the country. Second, we use an instrumental variable strategy based on a combination of push (post-discovery booms) and pull (initial sectoral composition) factors, as well as a standard shift-share instrument.

Our baseline estimate suggests that for each new FDI job an extra 2.1 formal jobs are created in the same district. If we add informal jobs we find that each new FDI job creates 4.4 jobs overall. The magnitude of this effect is in line with that of high tech firms estimated by Moretti (2010), i.e. 4.9 additional nontradable jobs created for each high tech job. It is also in line with multipliers being larger in developing countries with excess capacity. Since 126,059 jobs were directly associated with FDI firms in 2014, we can infer that almost 668,000 jobs, out of around 8.93 million total jobs in Mozambique, are the result of the FDI multiplier.

The Mozambique experience suggests that FDI projects may be associated with a large local multiplier. These findings add to our understanding of local multipliers (Moretti, 2010) and of the job effects of FDI in developing countries (e.g. Atkin et al. (2018)). Our paper also adds to our understanding of the determinants of FDI by highlighting the under-appreciated role of resource discoveries.[2] Importantly, our results shed new light on the literature linking natural resource discoveries and development in the short run. Previous research has shown that the prospect of resource wealth can unleash economic and political forces. Indeed, giant oil discoveries have been found to increase military spending in non-democracies (Cotet and Tsui, 2013) and the incidence of internal armed conflict (Lei and Michaels, 2014). Arezki et al. (2017) looked at the macroeconomic responses to giant discovery *news shocks* and found that the current account and saving rate decline right after the discovery while total

[1] These three countries are the only other sub-Saharan African countries that experienced a first giant discovery and a subsequent FDI bonanza since 2003.

[2] A recent meta analysis of FDI determinants for example does not mention resource discoveries (Blonigen and Piger, 2014).

investment increases, leaving GDP unaffected in the first 5 years after a discovery.[3] Our paper points to another mechanism at play, i.e. a short-run FDI effect.[4] Indeed our results suggest discoveries lead to simultaneous investment in various sectors including retail, services, and manufacturing, possibly diversifying economies. Our results can thus be seen as in line with natural resource discoveries driving business cycles in the short run (Arezki et al., 2017), and with discovery countries being inundated with capital much like boomtowns (Jacobsen and Parker, 2016).[5]

Importantly, our paper also adds to our understanding of the relationship between natural resources and FDI. A key paper here is Poelhekke and van der Ploeg (2013), which shows that across countries resource rents lower foreign investment in non-resource sectors. This is an important result as it constitutes an extra channel through which natural resource abundance can be a drag on economic development.[6] Their main finding is that when a country extracts natural resources for the first time, non-resource FDI from the Netherlands falls by 16% in the short run and by 68% in the long run. They also show that for countries that were already resource producers, a doubling of resource rents reduces non-resource FDI by 12.4%. While our result that giant oil and gas discoveries trigger FDI bonanzas in the short run may seem at odds with their result, it is compatible with the idea that the short-run positive FDI effects of discoveries are short-lived and reversed when resource windfalls start pouring in, around 5 years after the discovery in the case of oil and gas.[7]

[3] A recent paper by Cust and Mihalyi (2017) also shows that GDP growth following discoveries does not match IMF growth forecasts. GDP growth does pick up around 5 years after discoveries however. This is confirmed by Smith and Wills (2018) who show that economic activity in cities, measured by nighttime lights, increases around 5 years after discoveries.

[4] While Arezki et al. (2017) looked at private and public investment around giant discoveries, their data did not allow them to distinguish extractive vs. non-extractive investment. Our FDI data is thus ideal to complement our understanding of the effects of giant oil discoveries.

[5] Our results can also be seen as in line with recent evidence that suggests that resources can be associated with increased service and manufacturing activity (Allcott and Keniston, 2018; James, 2015; Smith et al., 2014), though we only look at the short-run effects of resource discoveries.

[6] Natural resources have been found to be associated with premature deindustrialization (Rodrik, 2016), a lack of export diversification (Ross, 2017; Bahar and Santos, 2018), a deterioration of democratic institutions (Tsui, 2011), and are hence often thought of as a curse (Sachs and Warner, 2001; van der Ploeg, 2011; Ross, 2012; Venables, 2016).

[7] It is important to note that our estimates are not directly comparable to those of Poelhekke and van der

The rest of our paper is structured as follows. In Section 2 we present cross-country evidence on the effect of giant discoveries on FDI. We then delve into the case of Mozambique in Section 3 where we estimate the FDI job multiplier. We conclude in Section 4.

2 THE FDI EFFECT OF DISCOVERIES: EVIDENCE ACROSS COUNTRIES

2.1 DATA AND IDENTIFICATION

To examine the FDI response to natural resource discoveries across countries we merge data on giant oil and gas discoveries with a project-level FDI data set.

The data on FDI projects is from fDiMarkets, part of the Financial Times Group (FT). fDiMarkets has been tracking and verifying individual cross-border greenfield investment projects since 2003 and is now a primary source of data for UNCTAD, the World Bank and the Economist Intelligence Unit (fDiIntelligence, 2016). The database provides information on the value of investments and the estimated number of jobs created.

Importantly, fDiMarkets provides information on the business activity of every project. We use this information to identify FDI flows which are unrelated to the extraction of natural resources. We define FDI projects that are not in the "Extraction" Business Activity as *non-extraction FDI*. This distinction is also important as it allows us to focus on the type of FDI which has been associated with productivity spillovers (Matsuyama, 1992; Gorg and Strobl, 2001) and which may have a higher capacity to create jobs than the capital-intensive extraction sector (Ross, 2012). Indeed, the FDI data suggests non-extraction projects create

Ploeg (2013) as we look at the effect of discoveries, before extraction happens, while they look at the effect of resource rents. Moreover, they focus on 1985-2002 while we look at 2003-2014, the oil-price boom years. And while we focus on developing countries they look at countries at all levels of income. Last but not least, we focus on giant oil and gas discoveries while they look at extraction of all natural resources, including oil and gas but also coal and metals and minerals. Our results should therefore not be seen as overturning their evidence.

more jobs on average. While there are large differences in project size across countries, the number of jobs in non-extraction projects is on average four times larger than in extraction projects.

The data also allows for the analysis to go beyond the country or sector FDI aggregates. It allows us to decompose FDI into extensive and intensive margins, i.e. the number of projects vs. average value of projects, as well as number of sectors, target destination cities within a country, and the number of source countries. In Figure A.1 in appendix A.1 we summarize the margins of FDI in discovery countries. Further summary statistics are in Table A.1 of the same section.

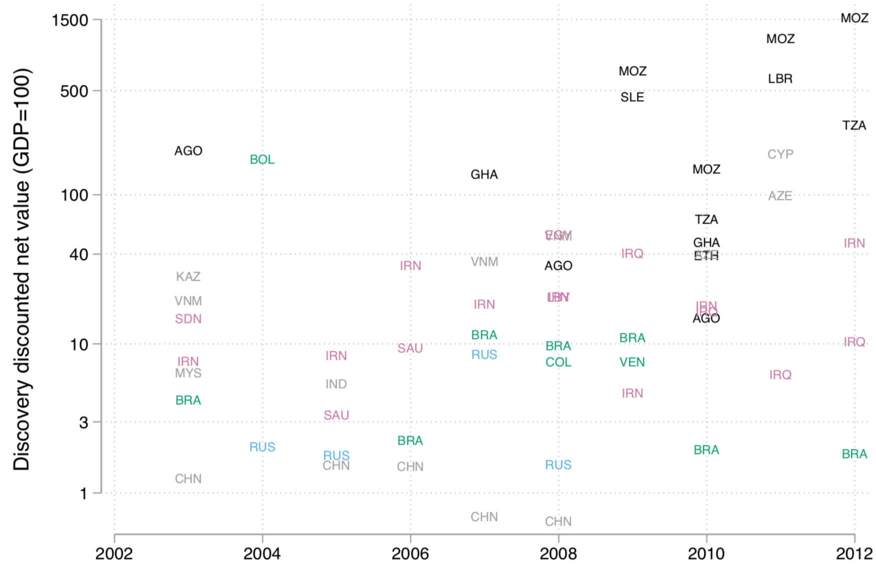
The data on discoveries is reported by Horn (2011) in *Giant Oil and Gas Fields of the World*. Giant discoveries are defined as fields containing at least 500 million barrels of ultimately recoverable oil equivalent. In total, 74 giant discoveries have been made in 29 countries between 2003 and 2014. Figure 1 graphs the net present value of giant oil and gas discoveries as a share of GDP in non-OECD countries since 2003. The average present value of discoveries relative to GDP in this period is around 90%. In Mozambique, the combined value of the 3 giant discoveries is close to 50 times its GDP.[8]

Our strategy to identify the causal effect of discoveries on FDI inflows relies on the unpredictability of giant discoveries. Previous studies have suggested that the timing of giant oil discoveries is plausibly exogenous and unpredictable due to the uncertain nature of exploration (Arezki et al., 2017; Tsui, 2011; Cotet and Tsui, 2013; Lei and Michaels, 2014; Cavalcanti et al., 2019). Also, as there is a long delay of around 5 years between discovery and extraction, giant discoveries can be thought of as news shocks affecting

[8] The the net present values are from Arezki et al. (2017) who calculated them as the "sum of gross oil revenue derived from an approximated oil production profile discounted by country-specific discounting factors, and valued at the oil price prevailing at the time of the discovery". Due to FDI data constraints our period of study is 2003-2014. The only OECD countries with giant discoveries in that period are the US and Australia. Approximately half of the countries made only one giant discovery in this period such that the remaining 59 discoveries have been made by 14 countries. This feature of discoveries, i.e. that initial discoveries tend to trigger a number of subsequent discoveries, is discussed further below.

FIGURE 1

Giant discoveries in non-OECD countries (2003-2012)



Note: The discounted net value is from Arezki et al. (2017) who calculated it as the "sum of gross oil revenue derived from an approximated oil production profile discounted by country-specific discounting factors, and valued at the oil price prevailing at the time of the discovery".

income expectations.[9]

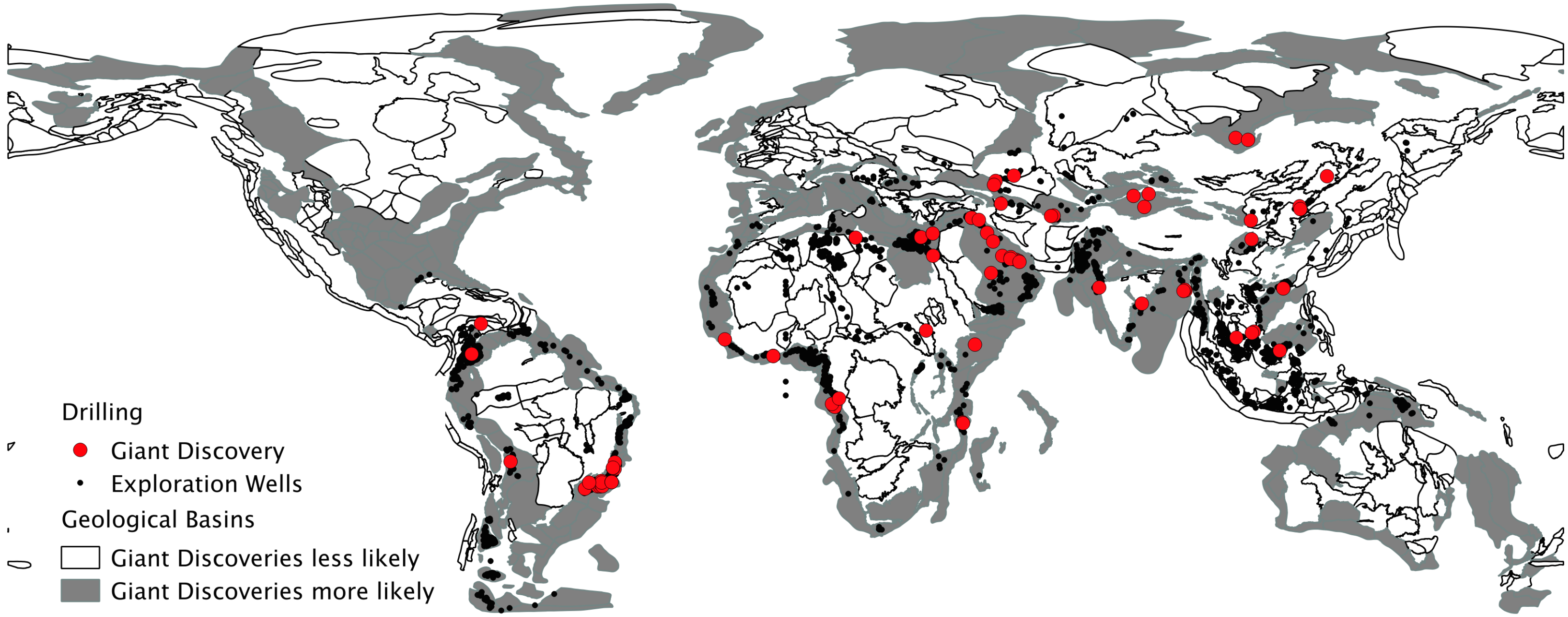
To examine the unpredictability of giant discoveries further we matched the discovery data with data on exploration wells from Wood Mackenzie (2015) and geological basins from

[9] Arezki et al. (2017) argues that giant discoveries provide an ideal natural experiment to examine the effects of expectations on the business cycle. Due to their unexpected nature and to the long-delay between discoveries and actual windfalls, giant discoveries can be thought of as news shocks that only change expectations about the discovery country. Recent research by Cust and Mihalyi (2017) suggests that, across countries, IMF growth forecasts are indeed on average 1 percentage point higher in the four years following a giant discovery, and may therefore contribute to optimistic expectations. The 5-year average delay between discovery and extraction is now commonly used in the literature. Lei and Michaels (2014) suggested that across countries during 1946-2008, oil production increased by about 35-50 percentage points within 4-10 years of a giant discovery. Wills (2014) also discussed these delays, noting that for the 400 offshore fields discovered in the UK during 1957-2011, the time between discovery and production was 4.5 years on average, while it was 2 to 9 years for US shale gas extraction around 2005-2015. Cotet and Tsui (2013) also suggests based on Laherrère (1998) that the time from discovery to first production involves a development lag ranging from about two years for onshore major fields to around ten years for offshore oilfields. Arezki et al. (2017) also provides two anecdotal graphs based on Norway wells that show delays between investment and production. Finally, in ongoing research, we have analyzed data on all of Chevron's 278 assets from 1973 to 2009 and found that on average investment starts 5 years after a discovery and production starts another 4 years after. Note also that in ongoing work David Mihalyi of the Natural Resource Governance Institute analyzed Rystad Ucube data on all oil companies and found that during 1940-2018 the global average in delays from discovery to extraction was 7.7 years.

Robertson CGG (2016) for all non-OECD countries. This data is mapped in Figure 2. Grey areas indicate basins where exploration drilling has been particularly likely to result in giant discoveries (Mann et al., 2001). While the data suggests that the probability of a giant discovery conditional on exploration drilling is around 2%, there is no deterministic relationship between exploration and discovery. Exploring for 100 years does not guarantee a giant discovery. This has already been emphasized by Adelman (1962): "There is no amount of chronological time which can be said to correspond to the exploration long run." For example, South Africa has been digging exploration wells since 1968 but news of a giant discovery only came as recently as February 2019. The Financial Times also provides a telling example of the uncertain nature of the timing of discoveries (Kavanagh, 2013). In 2010 Lundin Petroleum made the largest discovery of the year and one of the biggest ever in Norway. It was found three meters away from where Elf Aquitaine drilled but failed to find oil in 1971.

FIGURE 2

Basins, drilling, and giant discoveries in non-OECD countries (since 2003)



Note: Black dots are exploration wells (Source: Horn (2011)), red dots giant discoveries (Source: Wood Mackenzie (2015)). Grey indicate basins were exploration drilling is particularly likely to result in giant discoveries. (Source: Shapefile has been constructed by Robertson CGG (2016) while Mann et al. (2001) provide an analysis on which type of basin is particularly likely to result in a giant discovery. Drilling activity and giant discoveries in OECD countries is excluded from the Figure.

To evaluate the effect of giant discoveries on FDI flows we estimate the following specification:

$$FDI_{it} = \beta D_{it} + \alpha_i + \sigma_t + \epsilon_{it} \quad (1)$$

where FDI_{it} is a placeholder for different measures of FDI inflows in country i in year t such as the total value of non-extraction FDI inflows, the number of FDI projects, the number of FDI jobs created, the number of source countries, the number of target sectors and of destination cities within a country. To include observations where there is no FDI and thus include zeros we use an inverse hyperbolic sine transformation instead of the log transformation (Burbidge et al., 1988; MacKinnon and Magee, 1990). D_{it} is a dummy equal to 1 in the year of the discovery and the two subsequent years. The coefficient of interest is β.[10] α_i is a country fixed effect that picks up factors that do not vary over time within countries such as geography as well as variables which vary little year-on-year such as formal or informal institutions. And σ_t is a year fixed effect that controls for global factors such as global risk or FDI waves (Herger and McCorriston, 2016). ϵ_{it} represents the error term which we cluster two-way by country and year.

Importantly we limit the country sample to countries with at least one exploration well, i.e. *exploration countries*. This provides a more conservative counterfactual in the event exploration is endogenous and driving both discoveries and non-extraction FDI. It is similar to the strategy of Cavalcanti et al. (2019) who suggest that Brazilian districts with drilling but no discovery are a valid counterfactual to those that make a discovery and go on to produce oil.[11]

[10] By taking the hyperbolic sine of our estimated β coefficients we get the percentage change in FDI due to a giant discovery. We are extremely grateful to David Giles for his help in interpreting our regression coefficients.

[11] We also run robustness checks where we include all non-OECD countries in our sample or where we limit the country sample to countries with at least one giant discovery during 2003-2014, i.e. *discovery countries*.

TABLE 1
Non-Extraction FDI
Panel A: Baseline

	(1) FDI (USD million)	(2) Nb projects	(3) Avg project size	(4) Jobs created
Discovery in past 2 years	0.594**	0.303**	0.314	0.549*
	(0.264)	(0.126)	(0.211)	(0.251)
N	1080	1080	1080	1080
R-sq	0.72	0.90	0.41	0.75

Panel B: Extra results on the extensive margin of FDI

	(1) Nb source countries	(2) Nb sub-sectors	(3) Nb sectors	(4) Nb cities
Discovery in past 2 years	0.188**	0.193*	0.158**	0.184***
	(0.078)	(0.089)	(0.071)	(0.055)
N	1080	1080	1080	1080
R-sq	0.86	0.89	0.86	0.89

Notes: Sample includes only countries where oil and gas exploration took place. Country and year fixed effects included in all regressions. Non-dummy variables are in inverse-hyperbolic sines. Standard errors in parenthesis clustered by country and year. * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

2.2 RESULTS

Our main results are presented in Table 1. The Tables provide estimates of β (see equation 1) for eight different measures of FDI. The sample includes only *exploration countries*.[12]

We find that non-extraction FDI inflows are 56% higher in the 2 years following a giant discovery. We also find that the number of FDI projects increases by 30% and the number of jobs created by 52%, while the average size of projects is not significantly affected. Results in Panel B in Table 1 further confirm that the extensive margin plays a key role in the response of FDI flows to giant discoveries. We find that the number of FDI sub-sectors, source countries, and destination cities all increase by around 19% in the 2 years following a giant discovery.

The results suggest that giant discoveries attract non-extraction FDI in the short run. The

[12]Table 1 as well as Table A.2 and Table A.3 in the Appendix show the results of the same regressions but with different country samples, i.e. all non-OECD countries or only *discovery countries*. There is no significant difference in estimates across country samples.

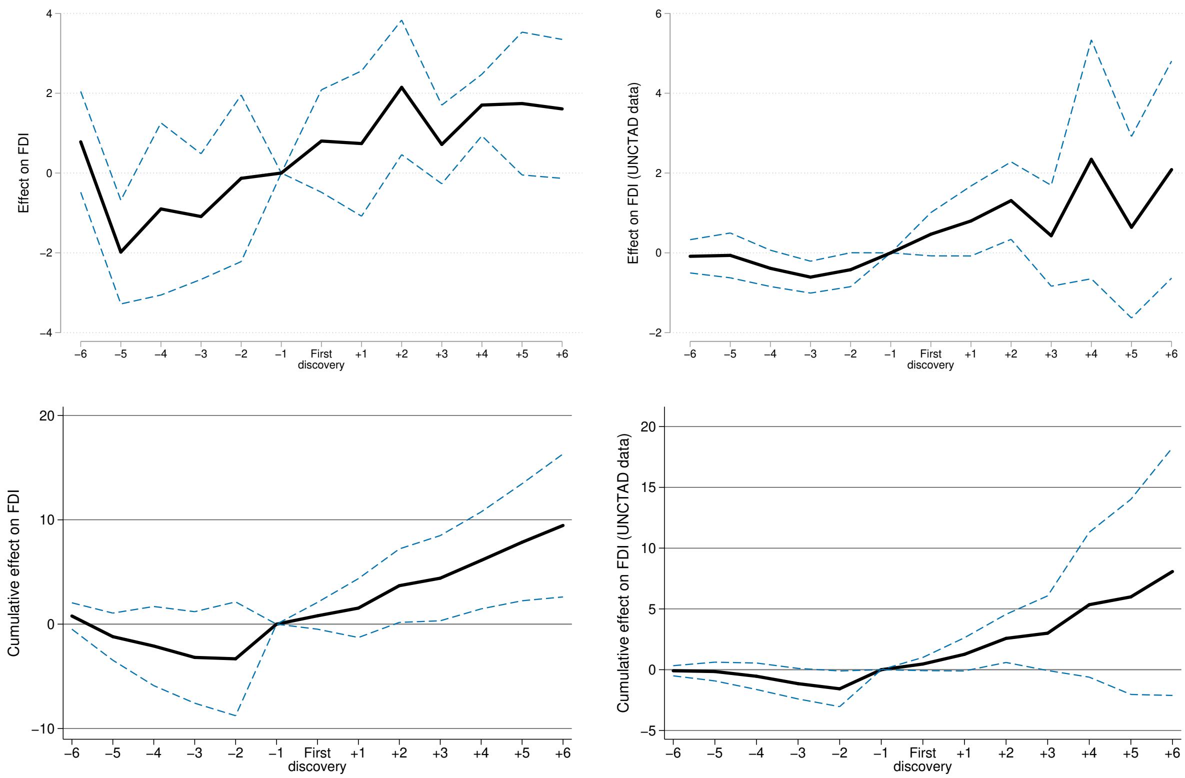
FDI inflow indeed occurs *before* production starts and hence before windfalls start pouring in, which is on average 5 years after discoveries. In many cases it even happens before the final investment decision is made by oil firms. This inflow of FDI is driven by the extensive margin such that it provides a source of diversification for the economy as jobs are created across a variety of sectors and regions. As discussed above, non-extraction FDI also has the potential to create jobs via a local multiplier, a mechanism we explore further using Mozambique's experience in the next section.

In a first robustness check we restrain our analysis to the effect of the *first* and only giant discovery. By eliminating subsequent giant discoveries from our sample we can estimate a more flexible specification which allows us to explore the dynamics of the response in non-extraction FDI in more detail while avoiding potential biases introduced by successive discoveries. We estimate equation 1 but replacing D_{it} with 12 dummies (five leads, six lags and one dummy for the year of the first discovery). The results of this specification are presented in the top-left panel of Figure 3. We find a positive and statistically significant effect on non-extraction FDI two years and four years after the first discovery, and there is no evidence of positive effects in the years preceding a first discovery. In the top-right panel of Figure 3 we reproduce this specification using data on total FDI inflows from UNCTAD, which is publicly available from 1970 to 2014 (we further compare fDiMarkets and UNCTAD FDI data in appendix A.2). The results are quantitatively and qualitatively similar, confirming sizeable increases in FDI inflows in the five years after a first giant discovery, and no positive effect in the preceding years. The bottom panels show the cumulative effects on FDI in the years before and the years after the discovery. The yearly effects, shown in the top panels, are here summed up from 6 to up to 2 years before the discovery, and from the discovery year to up to 6 years after the discovery. These cumulative results confirm the lack of pre-discovery FDI effects and the accumulation of FDI post-discovery.

We describe a battery of robustness checks to reinforce our main result in appendix A.2.

FIGURE 3

The effect of a first giant discovery on FDI inflows



Note: The top-right panel shows the yearly effects on non-extraction FDI, estimated in a specification akin to our baseline (Table 1) where the 2-year discovery dummy is replaced with 12 dummies, one for each year from 6 to 2 years before the first discovery and one for each year from the first discovery's year to 6 years later. The top-right panel shows the results of the same specification but using data on total FDI from UNCTAD. The bottom panels show the corresponding cumulative effects. Here we sum the yearly lead and lag coefficients, β_j's, such that the solid line plots $\sum_{j=-6}^{-2} \beta_j$ for the pre-discovery years and $\sum_{j=0}^{6} \beta_j$ in post-discovery years. Dashed lines show 90% confidence intervals.

FIGURE 4
Discovery effect on FDI by business activity

Notes: The bars show β coefficients estimated running regression 1 by business activity. Business activity is a level of aggregation above sectors in the fDiMarkets industry classification system.

These include a falsification exercise to highlight the importance of the timing of the discoveries; the use of various time horizons as our 2-year cut-off may be arbitrary; using different country samples, and using FDI data from UNCTAD rather than from fDiMarkets. We also look at how the discovery effect varies across destination countries based on their level of development, the quality of their institutions, their geodesic distance from the discovery country, as well as on their previous giant discoveries. Among other results, we find the effect to be stronger in poor countries with weak governance.

In Figure 4 we explore the heterogeneity of the FDI response by re-estimating equation 1 by business activity for both FDI to the country's metropolis and to the rest of the country. We find that the strongest response comes from FDI in manufacturing, information and communication technologies, and retail in the largest cities while in other regions the FDI effects are strongest in business services and construction, as well as in electricity and extraction. Note that some of those activities, in particular manufacturing, construction and retail are likely to be labor intensive and provide the potential for the creation of many jobs in developing countries. Also, the effect on business services might be linked to the deepening of retail banking and thus ease financial constraints which are frequently considered a strong impediment to development. These strong effects on manufacturing FDI to the country's largest city point to potential FDI job multiplier effects. We investigate this further in the next section on Mozambique.

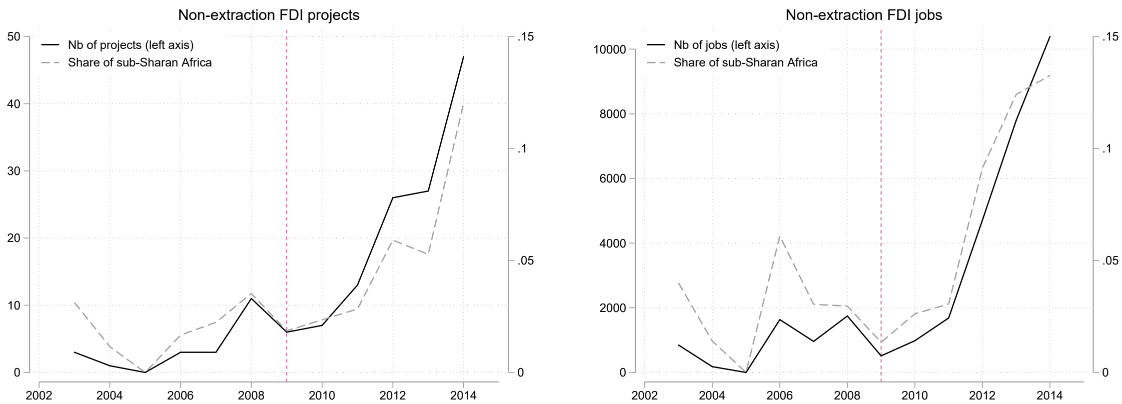
3 THE LOCAL MULTIPLIER OF FDI: THE CASE OF MOZAMBIQUE

3.1 DATA AND IDENTIFICATION

Our results so far suggest that giant oil and gas discoveries lead to FDI bonanzas of new projects, in new sectors, from new source countries, in many destination cities. As discoveries precede production by around 5 years on average, it's likely that the FDI effect is driven by expectations of higher income. The FDI bonanza (Figure 5) that followed the giant gas discoveries off Mozambique but precedes the actual field exploitation tellingly illustrates this FDI effect. The number of yearly FDI projects quadrupled from 2010 to 2014 while the number of jobs in FDI firms increased by a factor of 10. Mozambique attracted \$9 billion worth of FDI in 2014 alone, accounting for 30% of all of sub-Saharan Africa's FDI. What's more, the FDI boom was spread across cities and across sectors. Not only did the number of FDI firms increase but the number of districts with FDI also grew (see Figure 7). And while most FDI projects are by companies from Portugal, the UK and South Africa, companies from 32 countries have invested in Mozambique since 2003.[13] A synthetic counterfactual suggests this bonanza would not have happened without the giant gas discovery (Figure 6). This FDI bonanza thus provides an interesting setting to evaluate the local job multiplier of

[13] Real estate projects led the pack for the first time in 2014 and included Belgium Pyloss dozen shopping malls around the country and South Africa's Atterbury Property Developments various plans in Pemba, Beira and Nacala.

FIGURE 5
The Mozambique FDI bonanza



Notes: The numbers on the graphs are based on fDiMarkets data.

the FDI projects.

Our aim here is to estimate the employment effects of new FDI projects across Mozambique, inspired by the local multiplier literature, i.e. the idea that "every time a local economy generates a new job by attracting a new business, additional jobs might also be created" (Moretti, 2010). Most micro-level studies on FDI have focused on wage or productivity effects. Yet the employment effects are not so obvious. In its review of the labor market effects of FDI in developing countries, Lipsey (2004) suggests that affiliates, while labor-intensive relative to their parent firm, generate less employment than local firms as they are more productive and skill intensive. In the same vein, Marelli et al. (2014) find no positive effects of FDI on employment in Southern and Central and Eastern European regions while Axarloglou and Pournarakis (2007) find that FDI inflows in manufacturing have only weak effects on local employment across US states. Atkin et al. (2018) estimate the effect of foreign supermarket entry (mostly WalMart) on household welfare in Mexico and find little evidence of changes in average municipality-level employment.[14] Yet a recent paper by Setzler and Tintelnot (2019) looked at the local employment effect of foreign

[14]Even across US States it is not clear whether the expansion of WalMart has created or destroyed jobs. Basker (2005) suggests that a new WalMart increases retail employment by 100 jobs in the year of entry in a US county while Neumark et al. (2008) suggest it reduces it by about 150 workers.

multinationals in the US and found that an extra 0.42 indirect jobs are created for each new foreign multinational job in the same commuting zone. Hence it is surely a worthy endeavour to check whether FDI projects across Mozambique's districts increased employment or not.

In our particular setting we may expect FDI jobs to have a positive multiplier effect due to two distinct channels. First, the newly created FDI jobs are likely to be associated with higher salaries (Javorcik, 2015). In the context of Sub-Saharan Africa, Blanas et al. (2017) have shown that foreign-owned firms not only pay higher wages to non-production and managerial workers but they also offer more secure, less-temporary, work. These newly created jobs are likely to increase local income and in turn demand for local goods and services. For example, the multinational employees might increase the demand for local agricultural goods such as fruits and vegetables, as well as for services such as housing, restaurants and bars. Such an increase in demand will be met by local firms by adjusting production, creating more jobs and reinforcing the initial increase in demand. Hence, the increased demand for local goods and services pushes the economy to a new equilibrium by multiplying the initial number of jobs directly created by multinationals (Hirschman, 1957; Moretti, 2010).[15] Additionally, backward and forward linkages between multinationals and local firms might increase the demand for local goods and services (Javorcik, 2004). In particular, newly arrived multinationals might demand services such as catering, driving and cleaning services, as well as services from local law firms and consultancies which are more experienced with the economic and legal environment.

To estimate such a multiplier we match FDI jobs to non-FDI job numbers across districts and periods using data from two waves of Household Surveys from 2002 to 2014 with FDI data from the 2002 and 2014 firm censuses (Censo de Empresas or CEMPRE), which were completed by the National Statistics Institute (INE), as well as with fDiMarkets data. The

[15] While in Moretti (2010) the increased demand for labor is met by a spatial reallocation of labor which is determined by local differences in wages and idiosyncratic preferences for locations, in the context of a developing country, such as Mozambique, the increased demand may also be met by a reserve of surplus labor as in Lewis (1954).

CEMPRE data confirms the FDI bonanza, with the number of FDI firms increasing from 468 in 2002 to 3,151 in 2014 (see the maps in Figure A.6 and summary statistics in Table A.6).[16] To link the information on FDI projects to household-level data, we use two individual waves of the household budget survey from 2002/2003 (IAF02), and 2014/2015 (IOF14). Conveniently, the census years of 2002 and 2014 match the household survey years. Every survey contains information on the sector of employment of each individual in the household. We estimate the total number of jobs using the total number of people reporting being employed in each district and year and by grossing up the weights provided in the survey (see Blundell et al. (2004) for an example of grossing up weights). To estimate the number of informal jobs we subtract the number of formal jobs from total jobs as per the 2002 and 2014 firm censuses.[17]

The large majority of jobs in Mozambique are informal and in agriculture. Even in the capital and biggest city, Maputo, the share of formal jobs is only around 50%. And while most formal jobs are in services, FDI accounts for a larger share of formal jobs in manufacturing. Summary statistics and a detailed description of the variables can be found in Tables A.5, A.6, and A.7, and in Figure A.7 in appendix A.3.

We estimate the following specification:

[16] While fDiMarkets provides yearly information on the location of FDI projects at the district level, 87 of the 215 projects listed from 2003 to 2014 have unknown locations. We thus use FDI data from the 2002 and 2014 firm censuses as a more comprehensive source of FDI data for Mozambique. The firm census includes information on each firm's share of foreign ownership, which allows us to estimate the number of FDI firms, as well as the number of employees in those firms. This information is available only from the 2014 census and thus refers to FDI stocks rather than flows. We are nonetheless able to estimate yearly FDI flows using the registration year of the firms surveyed in 2014. This estimate includes only firms that survived until 2014 and it assumes that surviving foreign-owned firms in 2014 were foreign-owned since their registration year, i.e. not acquired. This estimate suggests more than four times more FDI projects than fDiMarkets. We compare our two sources of data on FDI in Figure A.8 in appendix A.4.

[17] The surveys were conducted by the National Statistics Institute. To collect the information, a series of interviews were conducted over a one-week period for each household. They are representative for the rural and urban zones and each of the ten provinces plus Maputo City. To make sure that our numbers add up at the country level and that survey attrition is not an issue we compared population estimates based on grossed up weights with those from the National Statistics Institute (INE). Grossing up the weights of the 2002/2003 survey gives us a population of 18.3 million. This is very close to the population estimates of INE in 2002 and 2003, at 18.1 million and 18.6 million respectively. Grossing up the weights of the 2014/2015 survey gives us a total of 25.6 million people, again in line with the INE estimates for 2014 and 2015, i.e. 25 and 25.7 million.

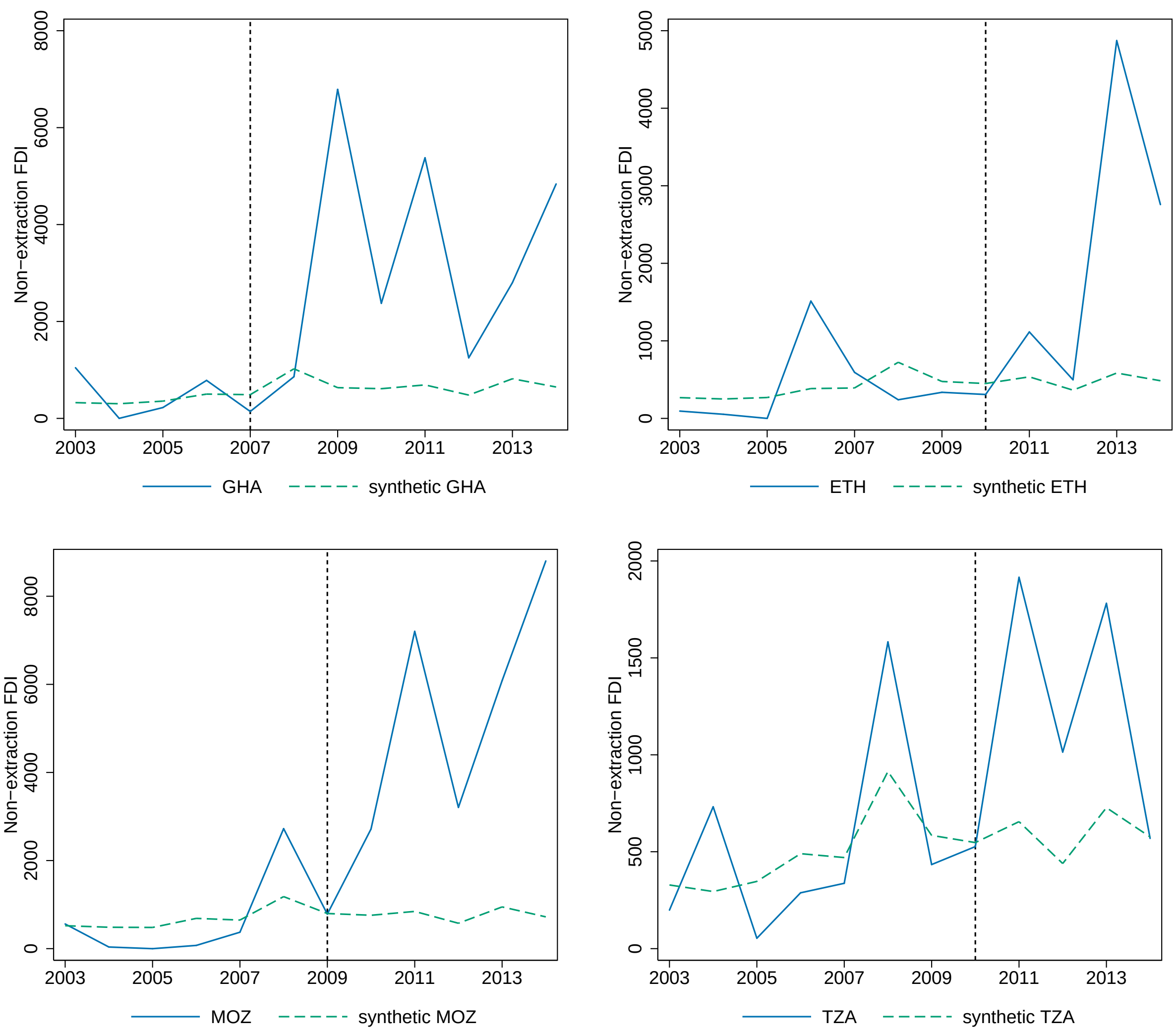
$$Jobs_{it} = \gamma FDI_{it} + \alpha_i + \Omega_t + \epsilon_{it}$$

where $Jobs_{it}$ is the number of individuals employed in non-FDI jobs, whether formal or informal, in district i in year t; FDI_{it} is the number of jobs directly created by FDI firms; α_i is a district fixed effect; Ω_t is a year fixed effect; and ϵ_{it} is the error term which is clustered by district. The coefficient on γ captures the multiplier effect of FDI jobs.

The exogenous nature of the FDI boom, i.e. it being the result of an unexpected giant discovery, suggests that our model may provide quasi-causal estimates. Indeed we can think of the Mozambique FDI bonanza across cities and sectors as akin to a natural experiment providing exogenous FDI shocks across the country. This interpretation is further confirmed by the similar experiences of Ghana, Ethiopia, and Tanzania. Like Mozambique, these three sub-Saharan African countries announced their first giant discoveries in the late 2000s. As shown in Figure 6, the fDiMarkets data suggests that in all three countries foreign firms moved in en masse in the years following the first discovery, and a counterfactual analysis suggests that this FDI wave would not have happened without the giant discovery. Indeed the size of non-extraction FDI inflows in the synthetic controls, i.e. weighted averages of non-extraction FDI in non-OECD countries with no discoveries, remains flat. What's more, FDI booms in all four countries were diversified, driven by new projects, in new cities, in many sectors (Figure 7). In Figure A.9 in appendix A.5 we also show that the distribution across sectors and cities (ranked by population) are similar. These similar patterns of FDI in other resource-discovery countries hence suggest that the Mozambique FDI bonanza can indeed be thought of as a natural experiment whereby the giant gas discovery scattered FDI projects of various kinds across the country.

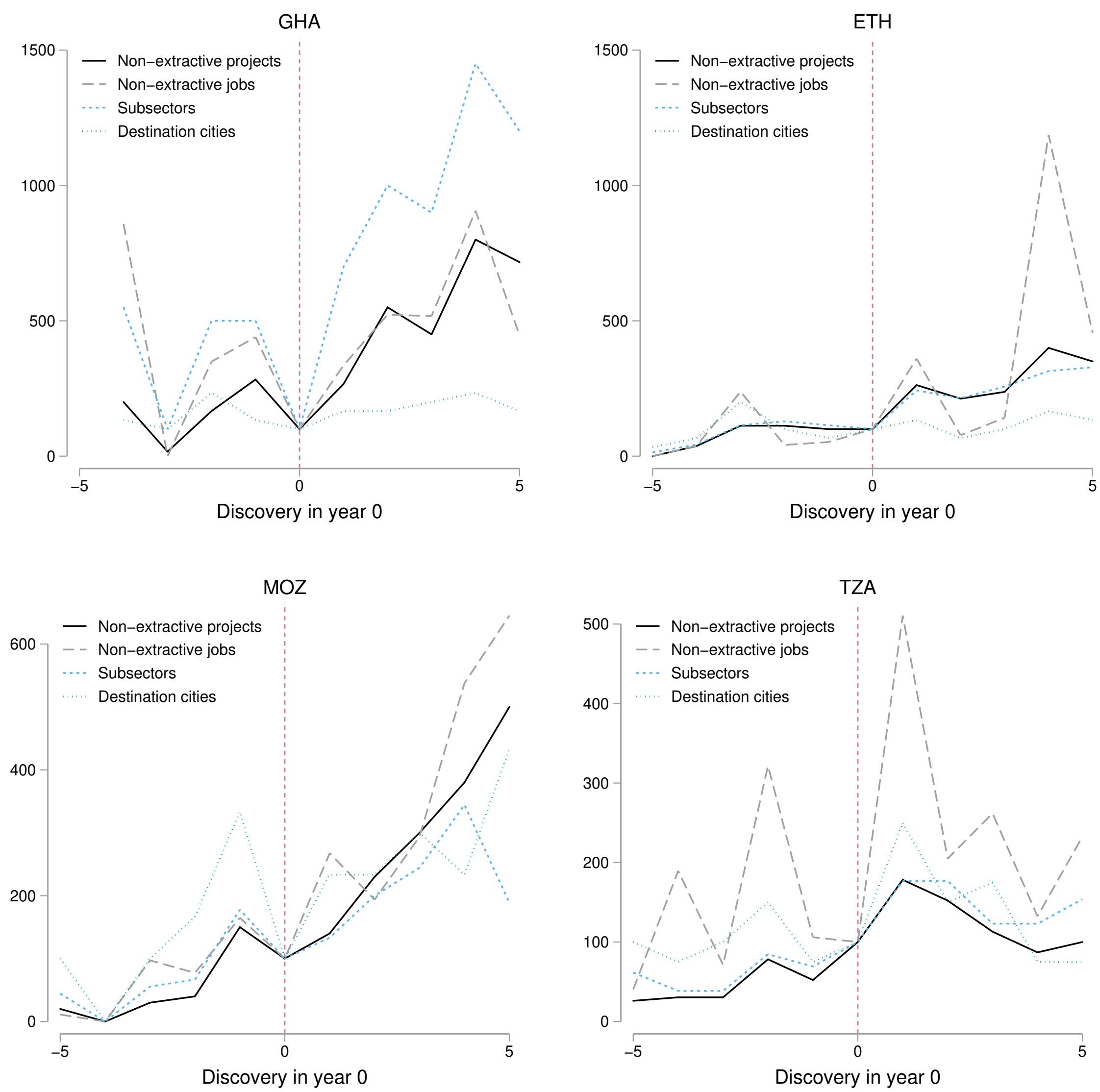
To further increase our confidence in a causal interpretation of our estimates we also use an instrumental variable strategy based on a combination of push forces (post-discovery booms in other African countries) and pull forces (initial sectoral composition), as well as a standard shift-share instrument. We detail this strategy in section A.5 in the appendix.

FIGURE 6
FDI: Discovery countries vs. synthetic counterfactuals



Notes: Synthetic counterfactuals are weighted averages of non-extraction FDI in other developing countries. The weights are generated so that the differences in FDI inflows between the country and its synthetic version are minimized prior to the discovery. Each country is thus compared to a synthetic version of itself, similar in terms of FDI inflows prior to the discovery. See Abadie et al. (2010) for details on this method.

FIGURE 7
Patterns of post-discovery FDI bonanzas



Notes: The numbers, based on fDiMarkets data, are normalized so that the series are equal to 100 in the year of the discovery.

TABLE 2
FDI multipliers

Panel A: CEMPRE DATA

	(1) Total jobs	(2) Non-FDI jobs	(3) Formal jobs	(4) Informal jobs
FDI jobs (CEMPRE)	5.278***	4.424***	2.071***	2.200*
	(1.351)	(1.287)	(0.576)	(1.271)
N	266	266	266	266
R-sq	0.14	0.10	0.74	0.03

Panel B: fDiMarkets DATA

	(1) Total jobs	(2) Non-FDI jobs	(3) Formal jobs	(4) Informal jobs
FDI jobs (FT)	6.187	4.134	5.275	-1.367
	(9.516)	(8.516)	(3.311)	(5.230)
N	266	266	266	266
R-sq	0.01	0.01	0.36	0.00

District and year fixed effects included in all regressions. Standard errors in parenthesis clustered by district and sector, and * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

3.2 RESULTS

Our baseline estimates are presented in Table 2. Using FDI job numbers from the firm census (Panel A) suggests that for each FDI job an extra 4.4 jobs are created locally. Columns 3 and 4 break down non-FDI jobs into formal and informal jobs. The disaggregation suggests that out of the 4.4 additional jobs created by an FDI job, around 2.1 are formal and 2.2 are informal. This suggests a total local job multiplier of 5.28 (column 1). If we focus on formal jobs, the multiplier is around 3.1. These multipliers suggest large job-creation effects for FDI jobs but are of the same magnitude as the local multipliers estimated by Moretti (2010) for high-skilled jobs in the US, i.e. 4.9 additional nontradable jobs created for each high tech job. It is also in line with multipliers being larger in developing countries with excess capacity (Izquierdo et al., 2019). The estimates based on fDiMarkets (Panel B) suggest a similar multiplier, with each FDI jobs creating an extra 4.1 non-FDI jobs.

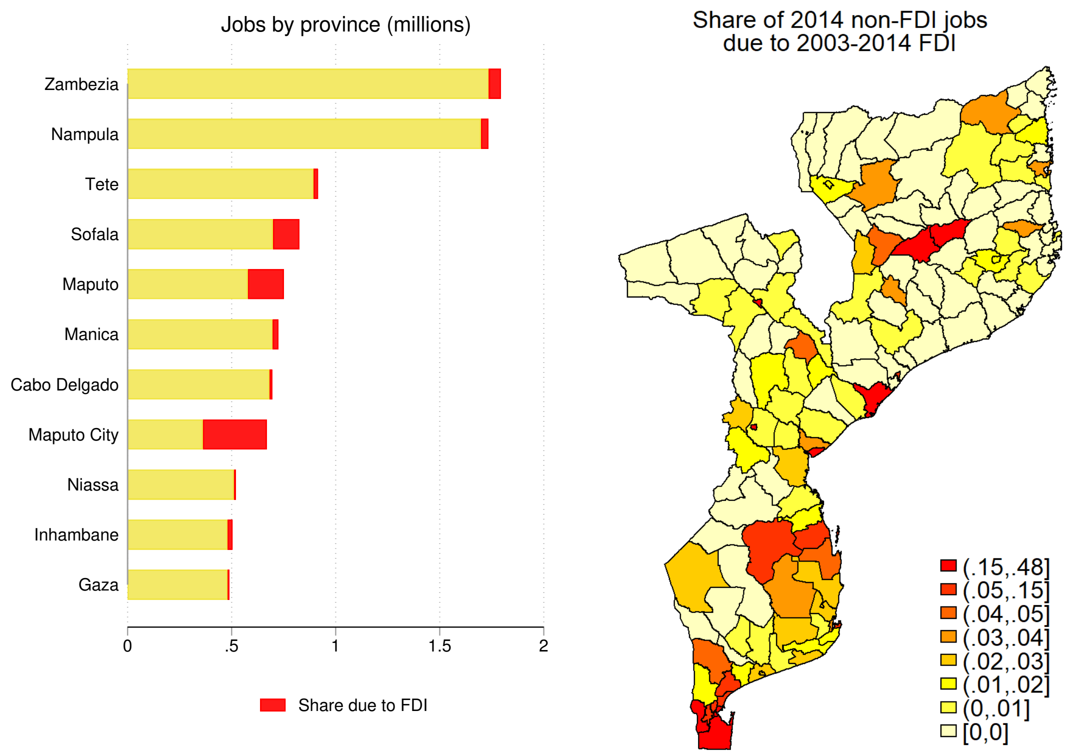
In appendix A.5 we include a battery of robustness checks. We include results using three different IVs, including a standard shift-share based on initial jobs share across sectors, as well as a stronger instrument based on districts' sectoral similarity with post-discovery FDI flows in Ghana, Ethiopia and Tanzania. The results here suggest a total job multiplier of 5.8, 6.2 or 5.3, and of around 3.1 or 3.7 on formal jobs (Table A.8). We confirm that these results are robust to a relaxation of the exclusion restriction using the plausibly exogenous approach suggested by Conley et al. (2012), recommended by Bazzi and Clemens (2013), and recently used by Nunn and Wantchekon (2011) and Fats and Mihov (2013) for example.[18]

In order to better grasp the magnitude of our benchmark estimate of a multiplier of 5.28 we proceed with a thought experiment. If we removed all FDI projects from Mozambique in 2014, how many jobs would disappear? This includes all the jobs directly associated with FDI firms (126,059 jobs in 2014) but also all the non-FDI jobs, both formal and informal, due to the multiplier. We simulate this drop using our benchmark multiplier and present the results by district and region in Figure 8. We find that there would be almost 665,591 less jobs, out of around 8.93 million total jobs in Mozambique. The drop would be especially acute in manufacturing and in Maputo (city), where more than half the jobs would disappear. In general urban districts would see the largest drops. The number of jobs in services and even agriculture would also drop substantially, given the large number of people employed in these sectors.

We also look at multipliers within district-sectors, using a 3-way fixed effect model and assuming stronger effects within district-sector. These suggests that for every FDI job an extra 2.9 formal jobs are created in the same district in the same sector (Table A.9, column 3). We then show that the FDI multiplier operates mostly within-sector rather than spilling over across sectors by including FDI in other sectors as an additional explaining variable (Table A.10). We find that spillovers across sectors seem to play no role in the multiplier effect of FDI. We also generate 100 placebo allocations of FDI jobs by randomly reshuffling the FDI jobs within district-years and within sector-years. This falsification exercise confirms that

[18] We follow the implementation procedure described in Clarke and Matta (2017).

FIGURE 8
FDI projects and job creation in 2014



Notes: The dark red part in the bar graph indicates the number of jobs due to FDI as per our multiplier estimate of 5.28 (column (1) in Table A.9). The heat map gives the share of non-FDI jobs due to the same FDI multiplier by district.

our multiplier estimates operate within district-sector and, thus, points towards the relative importance of linkages within the same sector (Figure A.11).

We also include additional regressions at the district level by looking at how FDI affects not only jobs but also the working-age population and the unemployment rate (Table A.11 in appendix A.6). We find that the number of jobs increases more than the working-age population yet the unemployment rate seems to increase as well, by less than 1 percentage point. This might be due to a larger share of the population becoming active. We also explore the different effects across gender and skills in appendix A.6. We find no statistically different effects on women and men jobs, yet it is only workers with at least secondary education that seem to benefit from the wave of job creation.

4 CONCLUSION

This paper suggests that across countries giant oil and gas discoveries lead to FDI bonanzas in the short run. FDI in non-extractive activities increases by 56% in the 2 years following such a discovery. This result is driven by new projects, in new sectors, in many cities, from new source countries. As discoveries precede production by 5 years on average, they may act as news shocks creating expectations of future income and driving an influx of diversified foreign investment. Our paper also suggests that FDI bonanzas can have large job-creation effects. In the context of Mozambique, our preferred estimate of the local FDI multiplier suggests that one extra FDI job creates around 4.4 additional non-FDI jobs in its host district. Our results point to the importance of estimating FDI multipliers in poor countries to better gauge the role of FDI in development.

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A ONLINE APPENDIX

A.1 Additional descriptive statistics - Cross country data

Table A.1 summarizes the key variables of our cross country analysis. Across 1992 country-years, the sample covering all developing countries, the average country-year received 43 FDI projects, from companies based in 8.5 different countries, in 16 sub-sectors, and worth in total around $3 billion. It is also interesting to note that non-extractive projects account for most of the FDI, wether measured in jobs, dollars, or number of projects.

TABLE A.1
Summary statistics

Variable	N	Mean	SD	Min	Max
Total FDI (USD million)	1992	3046	9781	0	1.28e+05
Non-extraction FDI (USD million)	1992	2713	9446	0	1.25e+05
FDI projects	1992	43	135	0	1624
Non-extraction FDI projects	1992	42	134	0	1613
Jobs created	1992	9538	35492	0	4.50e+05
Jobs created (non-extraction)	1992	9219	35267	0	4.49e+05
Avg project size	1992	92	211	0	4000
Avg non-extraction project size	1992	68	173	0	4000
Nb source countries	1992	8.50	10.30	0	55
Nb sub-sectors	1992	16.33	27.70	0	186
Nb sectors	1992	8.30	9.57	0	39
Nb destination cities	1992	6.76	15.51	0	149
FDI (USD Million, UNCTAD)	1992	3283	11263	0	1.29e+05
Discovery in past 2 years	1992	0.07	0.25	0	1

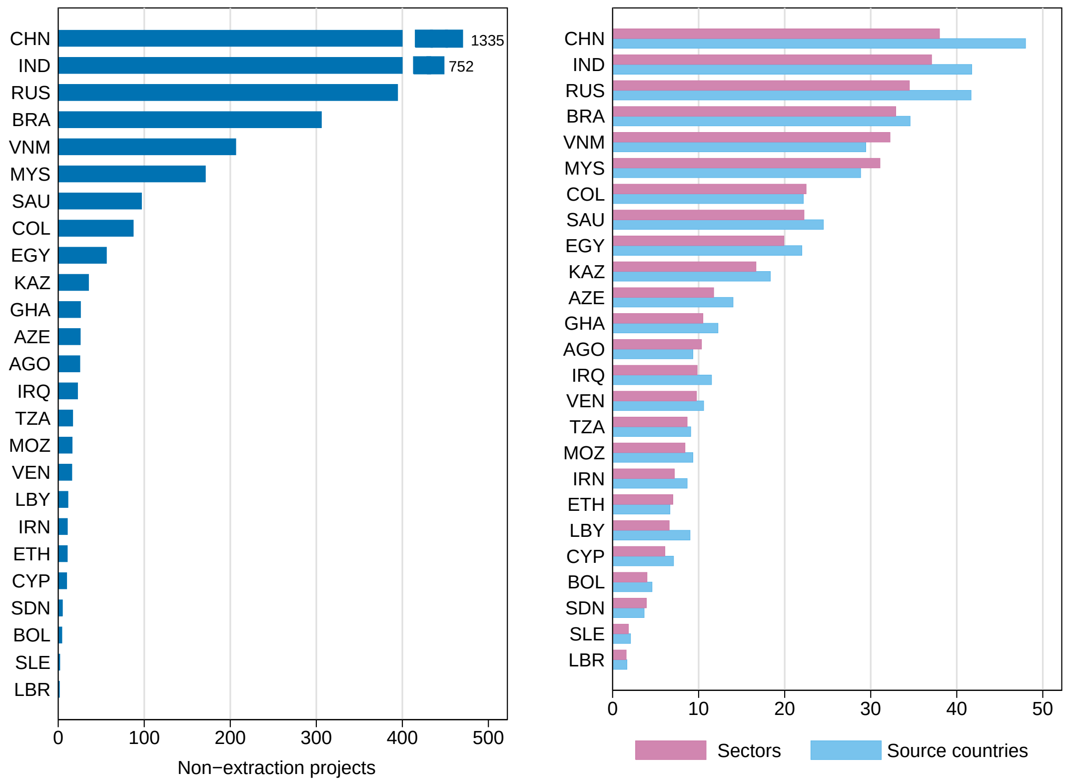
In Figure A.1 we summarize the number of FDI projects, source countries and target sectors in discovery countries. China and India received more than 500 FDI projects per year during 2003-2014 while smaller countries such as Colombia and Egypt received between 50 and 100 projects. The right panel shows that larger countries receive FDI from a larger number of countries and in more sectors. For example, Brazil and Vietnam received FDI from around 30 source countries and in 30 target sectors out of 39 possible sectors.

A.2 Robustness of our cross country results

In this section we describe a battery of robustness checks to reinforce our main cross country result. Our first check is to re-estimate our baseline results with two different

FIGURE A.1

The extensive margins of FDI in discovery countries



Note: The bars show the average number of FDI projects, source countries and target sectors in discovery countries in the period 2003-2014. There are a total of 39 sectors in the fDiMarkets data.

country samples. In our baseline we used only countries where oil and gas exploration took place. The idea is that countries with exploration but no giant discoveries are a good counterfactual to countries with giant discoveries. Here we check if the results are different when we include all non-OECD countries or when we focus only on countries with giant discoveries, in which case the treatment can be thought of as lucky years in lucky countries and the counterfactual as unlucky years in lucky countries. Results in tables A.2 and A.3 confirm that our estimates are not sensitive to our choice of counterfactual.

Our second check is a falsification exercise to highlight the importance of the timing of the discoveries across years. In this check we generated placebo discoveries by shuffling the discovery years randomly within discovery countries across years and used this "false" data to re-estimate 500 times equation 1 using our *exploration countries* sample. As we show in Figure A.2, reshuffling the discoveries randomly does not give similar results. Indeed, the distribution of the effects of 500 randomized discoveries is centred around zero, and only 19 random draws out of 500 came out positive and significant. Based on the standard error of the placebo distribution, the probability of obtaining our benchmark

TABLE A.2

Non-Extraction FDI

Panel A: All countries

	(1) FDI (USD million)	(2) Nb projects	(3) Avg project size	(4) Jobs created
Discovery year + 2	0.590**	0.288**	0.329	0.543**
	(0.238)	(0.117)	(0.205)	(0.245)
N	1992	1992	1992	1992
R-sq	0.75	0.91	0.48	0.75

Panel B: Only discovery countries

	(1) FDI (USD million)	(2) Nb projects	(3) Avg project size	(4) Jobs created
Discovery year + 2	0.525*	0.305**	0.233	0.488*
	(0.265)	(0.135)	(0.209)	(0.255)
N	300	300	300	300
R-sq	0.73	0.90	0.37	0.75

Notes: Country and year fixed effects included in all regressions. Standard errors in parenthesis clustered by country and year. Non-dummy variables are in inverse-hyperbolic sines. * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

TABLE A.3

Extensive margins

Panel A: All countries

	(1) Nb source countries	(2) Nb sub-sectors	(3) Nb sectors	(4) Nb cities
Discovery year + 2	0.197**	0.200**	0.166**	0.188***
	(0.077)	(0.085)	(0.069)	(0.054)
N	1992	1992	1992	1992
R-sq	0.87	0.90	0.87	0.87

Panel B: Only discovery countries

	(1) Nb source countries	(2) Nb sub-sectors	(3) Nb sectors	(4) Nb cities
Discovery year + 2	0.185*	0.199*	0.163*	0.183**
	(0.092)	(0.099)	(0.083)	(0.063)
N	300	300	300	300
R-sq	0.81	0.88	0.82	0.91

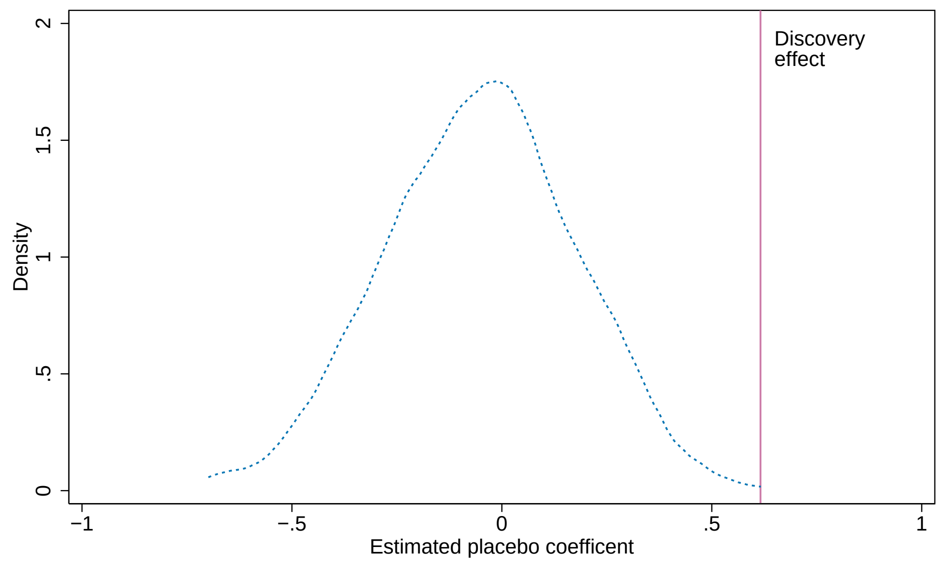
Notes: Country and year fixed effects included in all regressions. Standard errors in parenthesis clustered by country and year. Non-dummy variables are in inverse-hyperbolic sines. * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

estimate of 0.594, as shown by the vertical line, is below 0.01. This adds confidence in our identification based on the exogenous timing of the discoveries.

As a third robustness check we experiment with various time horizons as our 2-year cut-off

FIGURE A.2

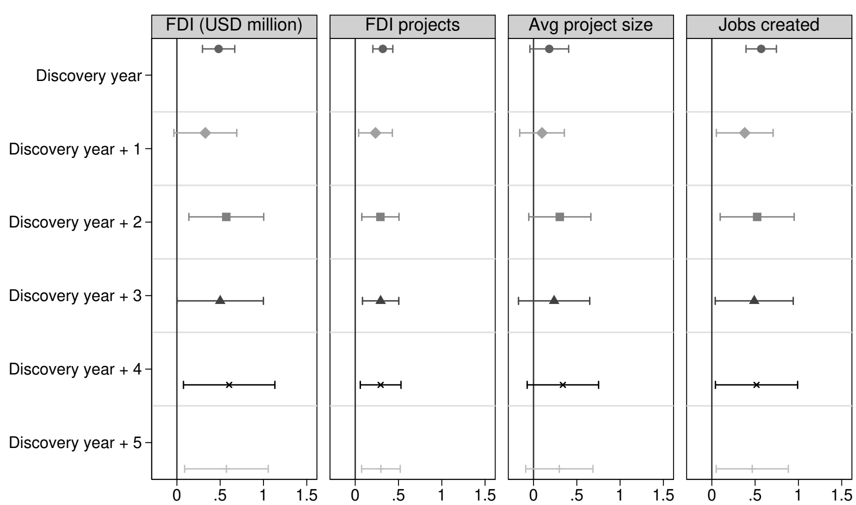
Distribution of 500 placebo discovery effects



Note: The 500 placebo discoveries are generated by reshuffling randomly the discovery years within countries across years. Their effects on non-extraction FDI were estimated using our baseline specification in equation 1. The vertical red line gives our benchmark estimate (column 1 of Table 1).

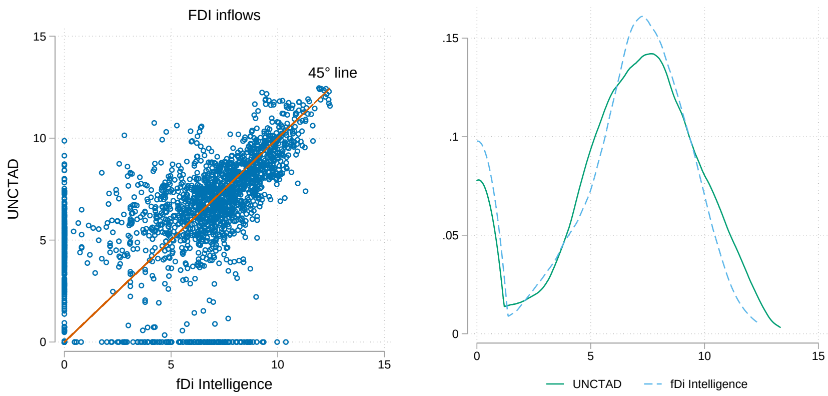
FIGURE A.3

Discovery effect on FDI: Varying time horizons



Note: The effects on non-extraction FDI are estimated in a specification akin to our baseline (Table 1) where the “Discovery in past 2 years” dummy is replaced with dummies for alternate time horizons. For example, Discovery year+4 is a dummy equal to 1 in the Discovery year and the 4 subsequent ones. The dummy Discovery year+2 is thus the same as in our baseline. The capped lines are 90% confidence intervals.

FIGURE A.4
FDI: UNCTAD vs fDiMarkets



Note: FDI data from UNCTAD and from fDiMarkets (fDi Intelligence) for our sample period (2003-2014). Observations are around the 45 degree line suggest there is no systematic difference between the two series. The right panel shows the similar distributions of the two variables.

may be arbitrary. We estimate our baseline regression but replacing our "Discovery in past 2 years" dummy with dummies for alternate time horizons, i.e. from 1 to 5 years after the discovery. For example, Discovery year+4 is a dummy equal to 1 in the Discovery year and the 4 subsequent ones. Our estimates, summarized in Figure A.3, suggest that our baseline results are robust to different time horizons. FDI projects increase significantly in the year of the discovery and in the following 5 years. There are no significant differences across the estimates using different time horizons.

Our fourth robustness check is to re-estimate equation 1 using FDI data from UNCTAD rather than from fDiMarkets. While UNCTAD is the most commonly used source of FDI across countries, it does not allow us to isolate non-extraction FDI nor to disaggregate FDI into margins. It does however allow us to expand the sample period to 1970-2014 and thus increase the external validity of our results. Comparing fDiMarkets data to UNCTAD data in Figure A.4 we find a high correlation of 0.6 across country and years between the two series. Their distributions suggest that none is systematically larger and plotting them against each other reveals that most data points are around the 45 degree line, suggesting the difference between the two is zero on average. We re-estimate our main specification 1 using the UNCTAD data. The results in Table A.4 confirm our baseline. We find that, irrespective of the counterfactual sample of countries, discoveries lead to a 55% increase in total FDI. We find similar results if we constrain the data to our main study period (2003-2014) even though the standard errors become larger.

Heterogeneity To examine further the effect of giant discoveries on FDI we look at how it varies across destination countries based on their level of development, the quality

TABLE A.4
UNCTAD data
Period 1970-2014

	(1) FDI	(2) FDI	(3) FDI
Discovery in past 2 years	0.484**	0.486**	0.434**
	(0.185)	(0.185)	(0.166)
N	8731	7523	6527
R-sq	0.73	0.74	0.75
Sample countries	Non-OECD	Exploration	Discovery

Period 2003-2014

	(1) FDI	(2) FDI	(3) FDI
Discovery in past 2 years	0.488	0.460	0.525
	(0.301)	(0.299)	(0.307)
N	1992	1080	300
R-sq	0.81	0.74	0.65
Sample countries	Non-OECD	Exploration	Discovery

Note: We take the inverse hyperbolic sine of FDI. FDI data is from UNCTAD and is in current USD. Country and year fixed effects included in all regressions. Standard errors in parenthesis clustered by country and year. * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

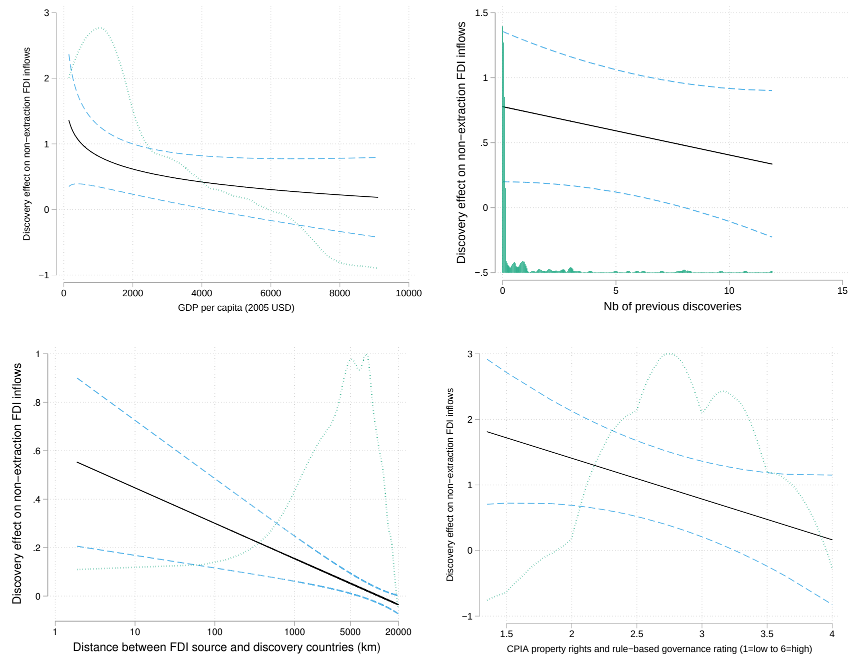
of their institutions, as well as on their previous giant discoveries. To do so we augment equation 1 by interacting the discovery dummy with real GDP per capita (in 2005 US dollars, from the World Development Indicators), with the number of previous discoveries, and with measures of institutional quality, i.e. the CPIA property rights and rule-based governance rating from the World Development Indicators.[19] We also check if the size of the effect depends on the geodesic distance between the destination and the source countries. To do so we turn our main specification into a gravity model with bilateral FDI flows, i.e. we include FDI from each source country rather than aggregating them by destination country (we include source-year and country-pair fixed effects but none for destination-year as we want to estimate the effect of the discovery dummy). The results are shown in Figure A.5. We find the effect to be stronger and statistically significant only in poor countries with an average GDP per capita below $4,000 during 2003-2014. Weak institutions do not seem to affect the relationship significantly, though if anything the resource effect is reduced by better institutions. This may reflect the fact that poor countries have weak institutions and it is in those countries that a giant discovery is a bigger deal.[20] We also find that the effect is stronger on FDI from nearer countries, maybe as the news of the discovery resonates more in neighbouring countries who also have more information about the discovery country. Finally we find that the effect is less strong when the country has had giant discoveries in the past, though this relationship is not statistically significant. This confirms that our results hold when we include the number of previous discoveries as an additional control in equation 1 as in Arezki et al. (2017).

[19]CPIA stands for Country Policy and Institutional Assessment and it focuses only on low-income countries. The results are similar if we use the rule of law index from the World Bank Governance Indicators.

[20]This result also suggests that resources may provide a missing piece to the allocation puzzle whereby low-productivity growth countries have higher FDI to GDP ratios (Gourinchas and Jeanne, 2013). While Alfaro et al. (2008) suggest that low institutional quality is the leading explanation, our results point to resources as a third variable linking FDI inflows and low productivity growth.

FIGURE A.5

Heterogeneity of the FDI effects across countries



Notes: The dark solid line is the marginal effect of a giant discovery, the dash lines are 95% confidence intervals. These are based on the specification of Table 1 where the discovery dummy is interacted with the x-axis variable. The doted line is the density estimate of the x-axis variable. The data on GDP per capita and on institutional quality is from the World Bank Development indicators.

A.3 Additional descriptive statistics - Mozambique

Descriptive statistics and definitions of key variables are provided in Table A.5 and Table A.6. According to the household survey and firm census data there were 8.93 million jobs in Mozambique in 2014, 3.65% of which are formal jobs, and 1.4% of which are jobs at FDI firms. The latter implies that FDI firms were directly responsible for roughly 40% of formal employment in 2014. Unsurprisingly the size of the informal economy is particularly large and adds up to around 95% of total employment in both years. The data also suggests that women make up more than 50% of the active labor force in both years. Comparing the number of skilled and unskilled workers in the active labor force suggests that Mozambique experienced an educational boom since the share of skilled jobs increased from less than 4% to around 19% in 12 years. Finally, the last four rows suggest that the labor force participation remained stable around 80%, and that it was accompanied by a doubling of the unemployment rate from 2.9% to 5.6%.

Focusing on the first four rows of Table A.6 one may note the discrepancies in the data on FDI jobs and FDI projects from fDiMarkets and CEMPRE in 2002 and 2014. In 2002 the discrepancy arises because fDiMarkets started collecting data in 2003 and we replaced

TABLE A.5

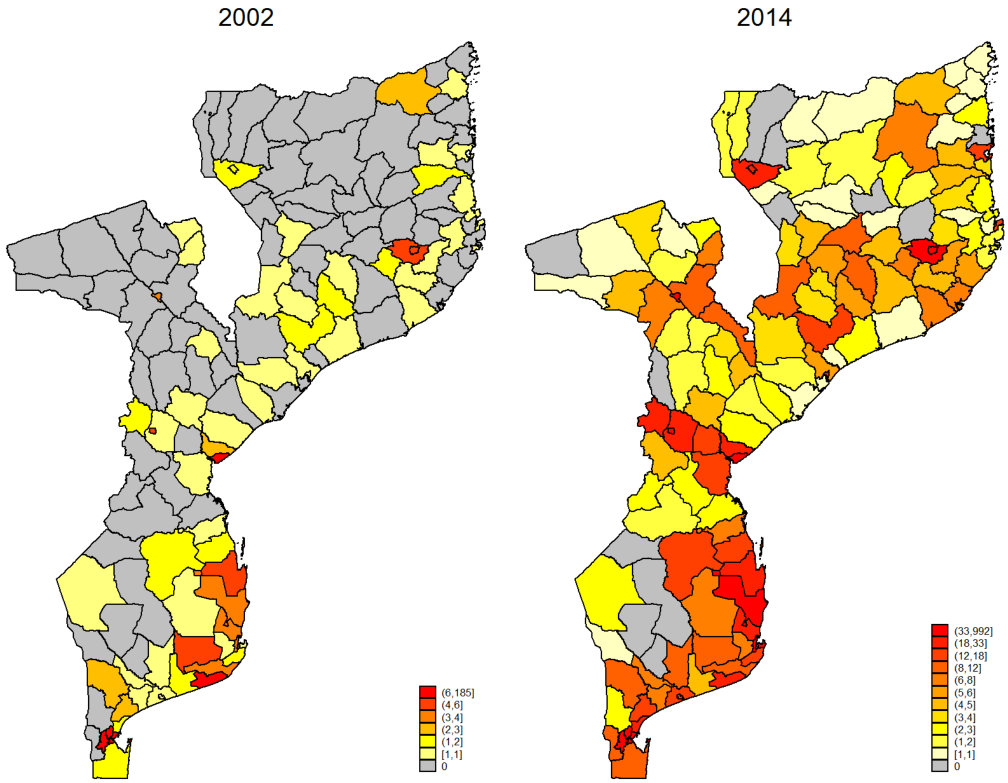
Variables

Variable	Notes
FDI projects (CEMPRE)	Sum of FDI projects in district i in sector j in period t according to firm census (CEMPRE).
FDI jobs (CEMPRE)	Sum of FDI jobs in district i in sector j in period t according to firm census (CEMPRE).
FDI projects (FT)	Sum of FDI projects in district i in sector j in period t according to fDiMarkets.
FDI jobs (FT)	Sum of FDI jobs in district i in sector j in period t according to fDiMarkets.
Total jobs	Sum of individuals between 15 and 59 employed according to the Household Survey in district i in sector j in period t.
Non-FDI jobs	Sum of individuals between 15 and 59 employed according to the Household Survey minus the sum of FDI jobs according to the census in district i in sector j in period t.
Formal Jobs	Sum of total jobs minus the sum of FDI jobs according to the census in district i in sector j in period t.
Informal Jobs	Sum of individuals between 15 and 59 employed according to the Household Survey minus sum of jobs according to the census in district i in sector j in period t.
Men employed	Sum of men employed in district i in sector j in period t according to the Household Survey.
Women employed	Sum of women employed in district i in sector j in period t according to the Household Survey.
Unskilled employed	Sum of total individuals with no or a primary education employed in district i in sector j in period t according to the Household Survey.
Skilled employed	Sum of total individuals with at least some secondary education completed (ESG1) employed in district i in sector j in period t according to the Household Survey.
Population (15-59)	Sum of individuals between 15 and 59 in location i in period t according to the Household Survey.
Unemployed	Sum of individuals between 15 and 59 reporting to be available for work but not having a job in location i in period t according to the Household Survey.
Inactive	Sum of total individuals between 15 and 59 reporting to be *not* available for work location i in period t according to the Household Survey. Individuals report to be not available for work due to studies, domestic responsibilities, permanent sickness, disabilities or age.

TABLE A.6
Summary statistics for 2002 and 2014 across 135 districts

	2002			2014		
	Sum	Mean	SD	Sum	Mean	SD
FDI projects (CEMPRE)	468	3	25	3,151	23	108
FDI projects (FT)	0	0	0	135	1	5
FDI jobs (CEMPRE)	52,578	389	2,583	126,059	934	4,562
FDI jobs (FT)	0	0	0	18,592	138	597
Total jobs	6,624,780	49,072	44,081	8,930,592	66,153	59,177
Non-FDI jobs	6,575,588	48,708	42,812	8,821,009	65,341	56,712
Informal jobs	6,387,376	47,314	39,488	8,502,673	62,983	50,625
Formal jobs	206,053	1,526	8,529	326,650	2,420	13,514
Men jobs	2,983,882	22,103	22,807	4,184,434	30,996	30,360
Women jobs	3,640,898	26,970	22,064	4,746,158	35,157	29,515
Skilled jobs	237,662	1,760	5,553	1,689,038	12,511	25,339
Unskilled jobs	6,387,118	47,312	40,507	7,241,554	53,641	42,556
Pop (15-59)	8,197,847	60,725	70,813	11,112,090	82,312	86,494
Unemployed	239,705	1,776	9,213	628,351	4,654	12,601
Inactive	1,333,362	9,877	23,956	1,553,147	11,505	19,583

FIGURE A.6
FDI firms in Mozambique: 2002 vs. 2014

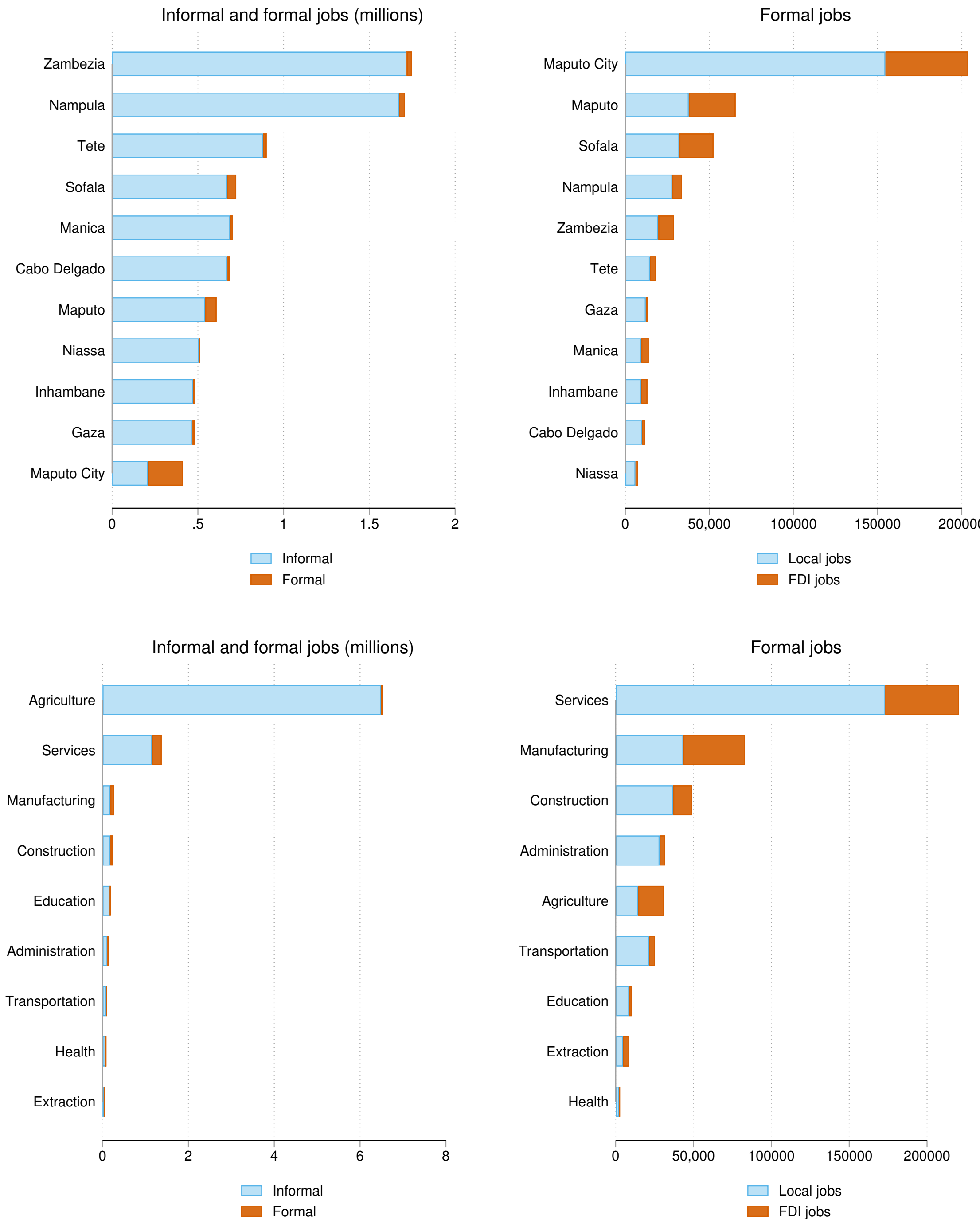


Notes: Based on CEMPRE data.

those missing values with zeros. In 2014, the discrepancy is partly because FDI projects before 2003 are not taken into account and partly due to the fact that fDiMarkets only collects information on greenfield FDI. Focusing on the CEMPRE data, Table A.6 suggests that the total number of FDI jobs more than doubled, while the number of projects went up by factor of 6.7. And, while the increase in FDI projects and employment has been substantial in absolute terms and spread across the country (Figure A.6), the share of FDI jobs out of total jobs has doubled, from 0.7% in 2002 to around 1.4% in 2014. Comparing the total number of FDI jobs to the total number of jobs suggests that in 2002 only 1 in 100 workers was employed by a multinational. In 2014, the total number of FDI jobs added up to slightly more than 1% of the 8,930,000 jobs in Mozambique.

In Table A.7 we sum the number of jobs by sector across the country. It shows that most jobs are in agriculture while most formal jobs are in services, manufacturing, and construction. The job numbers are presented by sector and by region in Figure A.7. Even in the capital and biggest city, Maputo, the share of formal jobs is only around 50%. And while most formal jobs are in services, FDI accounts for a larger share of formal jobs in manufacturing.

FIGURE A.7
Jobs in Mozambique in 2014



Notes: The numbers are based on the Household Budget Survey (IOF14) and the firm census (CEMPRE).

TABLE A.7
Jobs in 2014

	Total	Informal	Formal	FDI	Educated	No education	Women	Men
Administration	145127	115978	26399	3542	122687	22441	41041	104086
Agriculture	6522449	6491512	14512	16425	541332	5981117	3913561	2608887
Construction	231899	184391	36160	12085	90139	141760	6565	225334
Education	186712	176907	8280	1525	176591	10120	64611	122101
Extraction	44286	41507	3389	1886	10758	33528	2192	42094
Health	71636	68930	2176	530	50294	21342	39744	31892
Manufacturing	245019	183126	42832	39350	76379	168640	74283	170736
Services	1375244	1156380	171777	47087	567660	807584	600860	774384
Transportation	108219	83943	21125	3629	53197	55021	3300	104919
Total	8930592	8502673	326650	126059	1689038	7241554	4746158	4184434

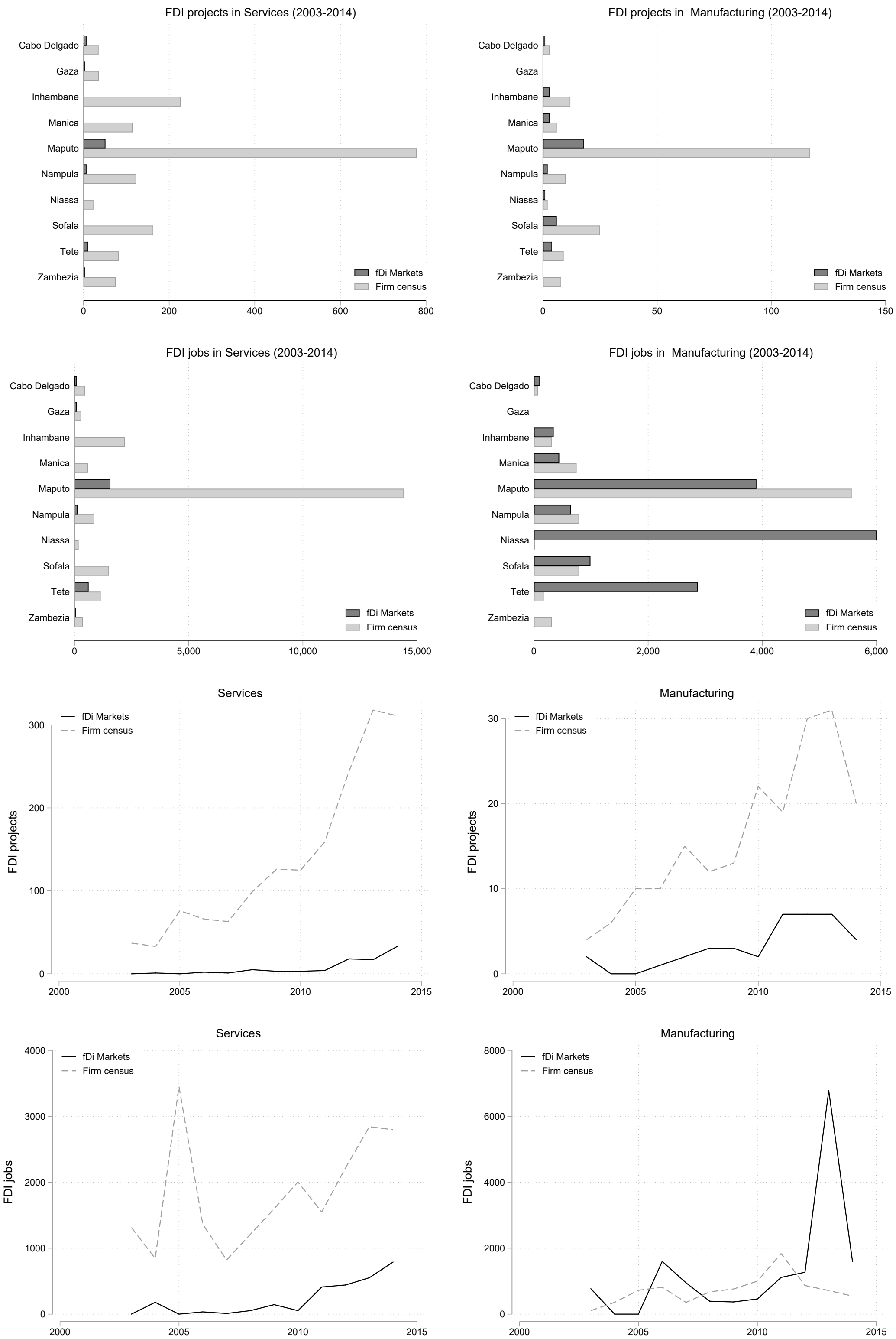
A.4 fDiMarkets vs. CEMPRE FDI data

We compare our two sources of FDI data for Mozambique in Figure A.8. The FDI stock in 2014 is much larger in the census data than in fDiMarkets. As mentioned above, this is partly because fDi markets started collecting data on FDI projects in 2003 and partly because they do not collect information on brownfield FDI. On the other hand, the firm census of 2014 includes information on each firm's share of foreign ownership, and the registration year of the surveyed firm. This allows us to estimate the number of FDI firms, as well as the number of employees in those firms in 2014 and 2002 by assuming that surviving foreign-owned firms in 2014 were foreign-owned since their registration year, i.e. not brownfield FDI. Thus, the number of FDI projects recorded by fDiMarkets is most likely an underestimate of the true number of FDI projects, while the FDI numbers based on the firm census may be an overestimate or an underestimate. Keeping these issues in mind we compare the total number of FDI projects and FDI jobs created between 2003 and 2014. As expected, the results in Figure A.8 suggest that in most cases fDiMarkets seem to underestimate the inflow of FDI, except in the case of manufacturing where fDiMarkets data suggests that more than 6,000 jobs were created in 2013. Thus, while it is apparent from Figure A.8 that the FDI numbers are correlated across sectors, across cities and across time, fDiMarkets systematically underestimates the total number of FDI projects and FDI jobs.

A.5 Robustness of our multiplier estimate

Robustness to potential endogeneity Despite our setting akin to a natural experiment and the plausibly exogenous distribution of FDI projects across localities, hard-to-measure expectations within Mozambique might be driving non-FDI business and job creation as well as FDI. To confirm that our results are robust to this potential endogeneity we use an instrumental variable strategy. The latter is based on the idea that the distribution of discovery-driven FDI bonanzas across sectors and cities follows a distinctive pattern that

FIGURE A.8
Comparing the FDI datasets



is unrelated to the country specificities but rather common across three other African countries where a giant discovery took place.[21] More precisely, our instrument is based on the idea that variation in the discovery-driven FDI bonanza across sectors and cities in Mozambique can be explained by a combination of push and pull factors. On the pull side, if districts in Mozambique had an economic structure in 2002 similar to that of discovery-driven FDI bonanzas in Ghana, Ethiopia, and Tanzania, these districts would more likely be the target of new FDI projects. On the push side we use the distribution of non-extraction FDI across cities ranked by population in the three other African countries. Intuitively, one can think of other discovery countries' recent FDI experience as isolating the non-Mozambique specific patters of the FDI bonanza across sectors and districts.

The distribution of FDI booms across sectors and cities in these three African countries and Mozambique is shown in Figure A.9. While the distributions of FDI jobs across cities ranked by population seem to follow similar power laws across countries, the distribution of FDI jobs across sectors also suggests new FDI projects in services and manufacturing in all countries. As a pull force, we can suppose that Mozambique districts that had an economic structure, measured in 2002, similar to that of post-discovery FDI booms, were more likely to attract FDI during the Mozambique FDI bonanza. In other words, the initial shares of jobs across sectors within a district, and their similarity with the sectoral composition of FDI booms in other countries, may be a good predictor of a district's FDI attractiveness. At the same time, the non-extraction FDI jobs created across cities in post-discovery countries provide a good estimate of the push in FDI Mozambique districts can expect to get. We thus use an interaction of these push and pull factors to predict FDI across Mozambique districts. To measure the similarity between the sectoral composition of foreign FDI booms and initial district jobs we use the Euclidian distance between the two vectors of sector shares.[22] Formally, our IV for post-discovery FDI_{it} can be expressed as:

$$\frac{FDI^*{}_{i't}}{\sqrt{\sum_j \left(\frac{Jobs_{ijt-1}}{\sum_j Jobs_{ijt-1}} - \frac{FDI^*{}_{jt}}{\sum_j FDI^*{}_{jt}}\right)^2}}$$

where $FDI^*{}_{i't}$ is total FDI in cities i' in the three other African countries in post-discovery period t. Cities i' are those at the same population rank as city i in Mozambique. $Jobs_{ijt-1}$ is the number of jobs in city i and sector j in 2002, and $FDI^*{}_{jt}$ is total FDI in sector j in the three other African countries in post-discovery period t. The instrument is equal

[21] Ghana, Ethiopia, and Tanzania are the only other sub-Saharan African countries that experienced a first giant discovery and a subsequent FDI bonanza since 2003.

[22] For a consistent matching of FDI jobs and households across districts and sectors we aggregate the available information into 9 sectors, namely Construction, Manufacturing, Extraction, Transportation, Services, Agriculture, Education, Health, and Administration. Services include Business Services, Retail, Maintenance and Servicing, Headquarters, ICT and Internet Infrastructure, Sales Marketing and Support, and Electricity from the fDiMarkets categories. From the CEMPRE data it includes a wide array of activities from wholesale and retail to hotels and restaurants, banking, consulting, real estate, arts and sports, as well as utilities such as water, gas and electricity. Our matching categories are available upon request.

to zero for the pre-discovery period (2002) as we use only post-discovery FDI flows as our instrument.

TABLE A.8

FDI multipliers - IV regressions

Panel A: Sector similarity to foreign FDI booms IV

	(1) FDI jobs (CEMPRE)	(2) Total jobs	(3) Non-FDI jobs	(4) Formal jobs	(5) Informal jobs
Instrument	1.285***				
	(0.050)				
FDI jobs (CEMPRE)		5.905***	4.923***	2.726***	1.962**
		(0.777)	(0.775)	(0.071)	(0.812)
N	266	266	266	266	266
R-sq	0.69	0.14	0.10	0.67	0.03
F IV		669.73	669.73	669.73	669.73

Panel B: Shift-share IV

	(1) FDI jobs (CEMPRE)	(2) Total jobs	(3) Non-FDI jobs	(4) Formal jobs	(5) Informal jobs
Instrument	3.407**				
	(1.497)				
FDI jobs (CEMPRE)		6.243**	5.317*	2.079***	3.049
		(2.951)	(2.943)	(0.452)	(3.063)
N	266	266	266	266	266
R-sq	0.31	0.13	0.10	0.74	0.02
F IV		5.18	5.18	5.18	5.18

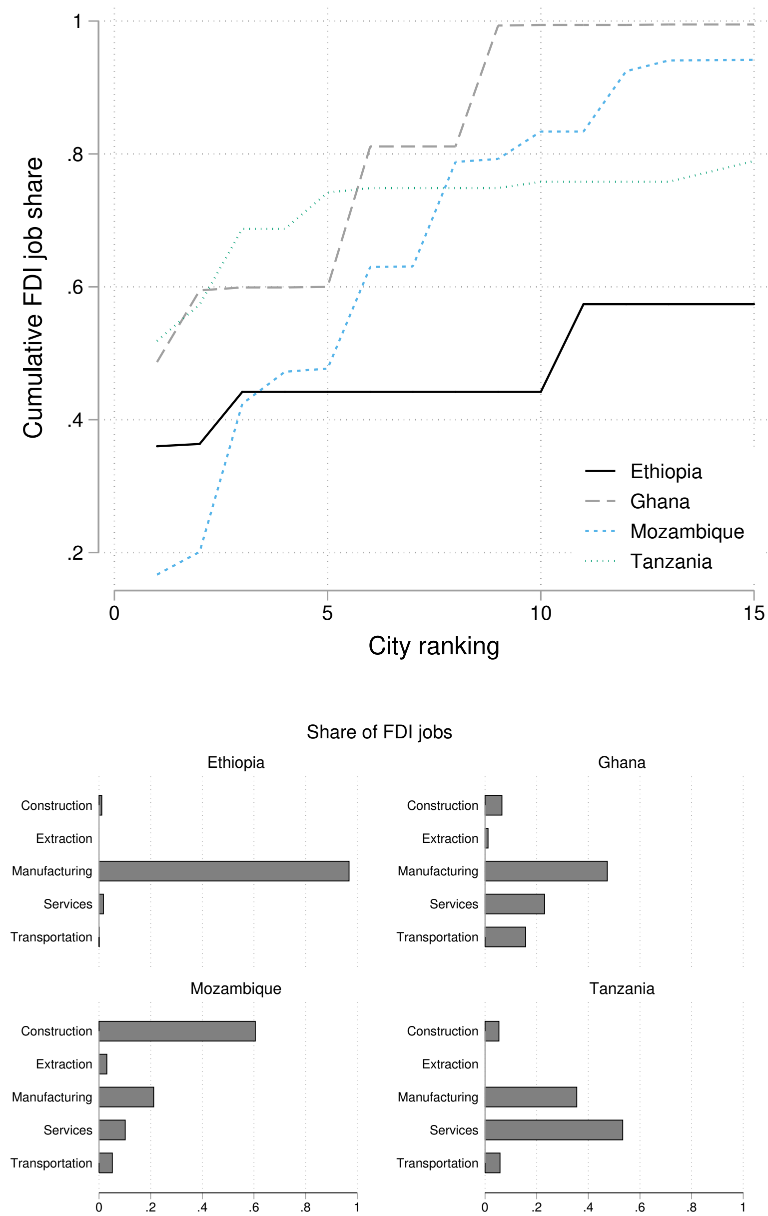
Panel C: Shift-share with foreign FDI booms IV

	(1) FDI jobs (CEMPRE)	(2) Total jobs	(3) Non-FDI jobs	(4) Formal jobs	(5) Informal jobs
Instrument	0.996**				
	(0.441)				
FDI jobs (CEMPRE)		5.322*	4.465	2.087***	2.158
		(3.015)	(2.986)	(0.461)	(3.054)
N	266	266	266	266	266
R-sq	0.32	0.14	0.10	0.74	0.03
F IV		5.11	5.11	5.11	5.11

District and year fixed effects included in all regressions. Standard errors in parenthesis clustered by district and sector, and * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

The first stage results in column (1) of Panel A of Table A.8 confirm the relevance of our instrument. The instrument effect is significant at the 1% level and its F statistic is above 10, confirming it is not weak. The second-stage results in columns 2 to 5 are not statistically different from our OLS estimates. The number of non-FDI jobs caused by FDI jobs is estimated at 4.86, of which 2.73 are formal. In Panels B and C we check if our results are robust to two different instruments. In Panel B we use a standard shift-share

FIGURE A.9
FDI and FDI Jobs in post-discovery years



Notes: Post-discovery years are as in Figure 6. The numbers are based on fDiMarkets data.

instrument, where the initial shares are the sectoral shares of jobs in each district in 2002, and the shift is the total FDI jobs in each sector in 2014. In Panel C we modify the shirt-share IV by using foreign FDI booms as a shift factor, i.e. total FDI jobs in each sector in the three African countries. Both IVs confirm the magnitude of our estimates. If we focus on formal jobs, we find that for each FDI job an extra 2.1 formal jobs are created locally (column 4). Note, however, that in Panel B and C the F statistic indicates that the IV is slightly weak.

To test for the robustness of our IV estimate to a relaxation of the exclusion restriction, we use the plausibly exogenous approach suggested by Conley et al. (2012), recommended by Bazzi and Clemens (2013), and recently used by Nunn and Wantchekon (2011) and Fats and Mihov (2013) for example. We follow the implementation procedure described in Clarke and Matta (2017). The idea is to check how our IV estimate of the FDI multiplier would change if local firms' decisions were also directly affected by the experience of foreign firms abroad. More precisely, consider the following second and first stage regressions ($\widetilde{x}$ indicates that district and period fixed effects have been partialled out):

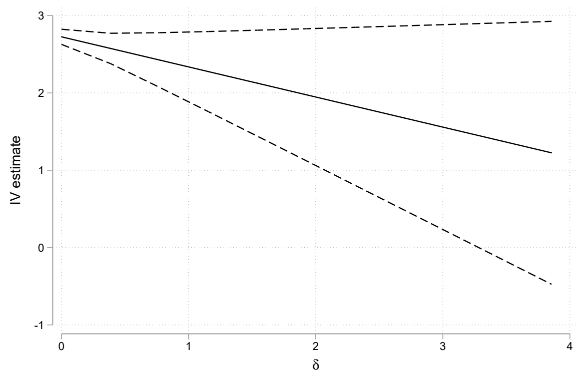
$$\widetilde{Jobs}_{it} = \alpha \widetilde{FDI}_{it} + \gamma \widetilde{Z}_{it} + \epsilon_{it}$$
$$\widetilde{FDI}_{it} = \beta \widetilde{Z}_{it} + e_{it}$$

where $Jobs_{it}$ is the number of individuals employed in non-FDI jobs in district i in year t; FDI_{it} is the number of jobs directly created by FDI projects, and Z_{it} is our instrumental variable. If γ is different from zero and local firms' decisions are also affected by the experience of foreign firms abroad, our instrument is no longer strictly excludable and our estimate of α is biased. Using the specification above we can evaluate how our IV estimate of α changes as γ increases, i.e. as an increasing violation of the exclusion restriction. We treat the uncertainty surrounding γ as being normally distributed, with the mean and variance of a U(0,δ) variable.

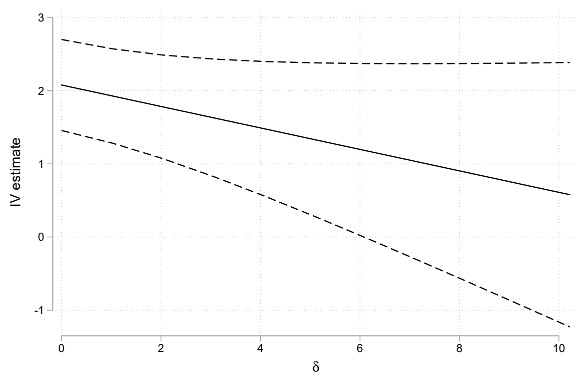
This sensitivity analysis is summarized in Figure A.10. The top panel illustrates the sensitivity of our estimate of the multiplier effect on formal jobs using our preferred IV (column 4 in Panel A of Table A.8). If local firms react either as much as or less than foreign firms to our IV, i.e. if δ is around or below $\beta \approx 1.28$, our IV estimate remains stable around 2. And as long as δ does not exceed β by a factor of 2, our IV estimate remains statistically significant and above 1. It is only in the extreme scenario where local businesses would react more than twice as much as FDI to our IV ($2 > 3.3/1.28$) that our estimates would no longer be positive and statistically significant. In other words, our IV estimate is robust to significant violations of the exclusion restriction. The two bottom panels of Figure A.10 illustrate the sensitivity of two additional IV estimates of the FDI multiplier on formal jobs, i.e. those in column 4 in Panels B and C of Table A.8. These IV estimates are also robust to fair violations of the exclusion restriction and confirm the magnitude of our estimate of the FDI multiplier on formal jobs.

FIGURE A.10
Relaxing our IV exogeneity assumption

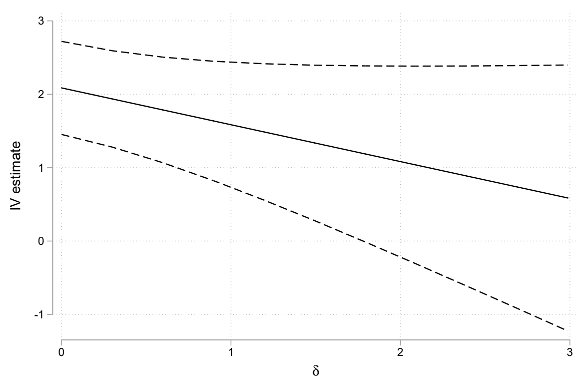
Sectoral-similarity IV



Shift-share IV



Shift-share with foreign FDI booms IV



Notes: The figure shows how our IV estimate of the FDI multiplier changes if local firms' decisions are also directly affected by our IV. We treat the uncertainty surrounding γ, the strength of the hypothetical relationship between our IV and non-FDI jobs, as being normally distributed, with the mean and variance of a U(0,δ) variable. The dashed lines are 95% confidence intervals. This approach was suggested by Conley et al. (2012) and the code provided by Clarke and Matta (2017).

TABLE A.9
FDI job multipliers at the district-sector level

	(1) Non-FDI jobs	(2) Non-FDI jobs	(3) Formal jobs	(4) Formal jobs	(5) Informal jobs	(6) Informal jobs
FDI jobs (CEMPRE)	6.228***		2.861***		3.417***	
	(1.000)		(0.331)		(0.838)	
FDI jobs (FT)		6.681		2.199		4.252
		(5.532)		(3.003)		(2.760)
N	1012	1012	1012	1012	1012	1012
R-sq	0.96	0.96	0.97	0.94	0.96	0.96

Notes: District-year and district-sector and sector-year fixed effects included in all regressions. Standard errors in parenthesis clustered by district and sector, and * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

Robustness to within district-sector effects Since FDI and employment vary across three dimensions, i.e. across districts, sectors, and periods, we are also able to estimate a triple difference-in-differences model controlling for all district-sector-, district-year- and sector-year-specific sources of endogeneity. Sector-year fixed effects allow us to control for country-level trends such as the servicification of the economy, district-year fixed effects capture local market potential, and district-sector fixed effects capture geographic factors that may influence FDI in some sectors over others. More formally, we estimate the following specification:

$$Jobs_{ijt} = \gamma FDI_{ijt} + \alpha_{ij} + \Omega_{it} + \lambda_{jt} + \epsilon_{ijt}$$

where $Jobs_{ijt}$ is the number of individuals employed in non-FDI jobs, whether formal or informal, in district i in sector j in year t; FDI_{ijt} is the number of jobs directly created by FDI projects, or the number of FDI projects; α_{ij} is a sector-district fixed effect; Ω_{it} is a sector-year fixed effect; λ_{jt} is a district-year fixed effect and ϵ_{ijt} is the error term which is clustered by district and sector. The coefficient on γ captures the multiplier effect of FDI jobs. It's important to note that the multiplier within-sector might be an overestimate of the local multiplier, as it includes re-allocation from one sector to another within a locality. On the other hand, the FDI multiplier within-sector does not necessarily take into account the effect operating via the increased demand for local goods and services. Results from the above regression are presented in Table A.9.

While the job multiplier operates across all sectors at the local level, we expect linkages to be strongest within the sector of investment. Indeed, previous work on Input-Output tables documents that linkages across firms are predominantly formed within the same sector (Miller and Blair, 2009). To investigate whether the FDI multiplier operates mostly within-sector or if cross-sector spillovers play an important role, we estimate the previous regression but including *FDI in other sectors* as an additional explaining variable. The coefficient on this variable captures the cross-sector spillovers associated with the FDI multiplier. Results are presented in Table A.10. They suggest that spillovers across sectors play no role in the multiplier effect of FDI. While this alternate specification gives very similar multipliers as above from FDI to non-FDI jobs within the same sector, the coefficient associated with FDI in other sectors is close to zero.

TABLE A.10
FDI job multipliers - with spillovers

Panel A: Job-level multipliers and spillovers

	(1) Non-FDI jobs	(2) Non-FDI jobs	(3) Formal jobs	(4) Formal jobs	(5) Informal jobs	(6) Informal jobs
FDI jobs (CEMPRE)	5.862***		2.692***		3.111***	
	(1.196)		(0.448)		(0.896)	
FDI jobs in other sectors (CEMPRE)	-0.016		-0.005		-0.012	
	(0.049)		(0.005)		(0.048)	
FDI jobs (FT)		5.903		2.948		2.787
		(5.933)		(3.307)		(2.555)
FDI jobs in other sectors (FT)		0.123		0.079*		0.041
		(0.214)		(0.038)		(0.190)
N	1052	1052	2484	1052	1052	1052
R-sq	0.94	0.94	0.96	0.93	0.94	0.94

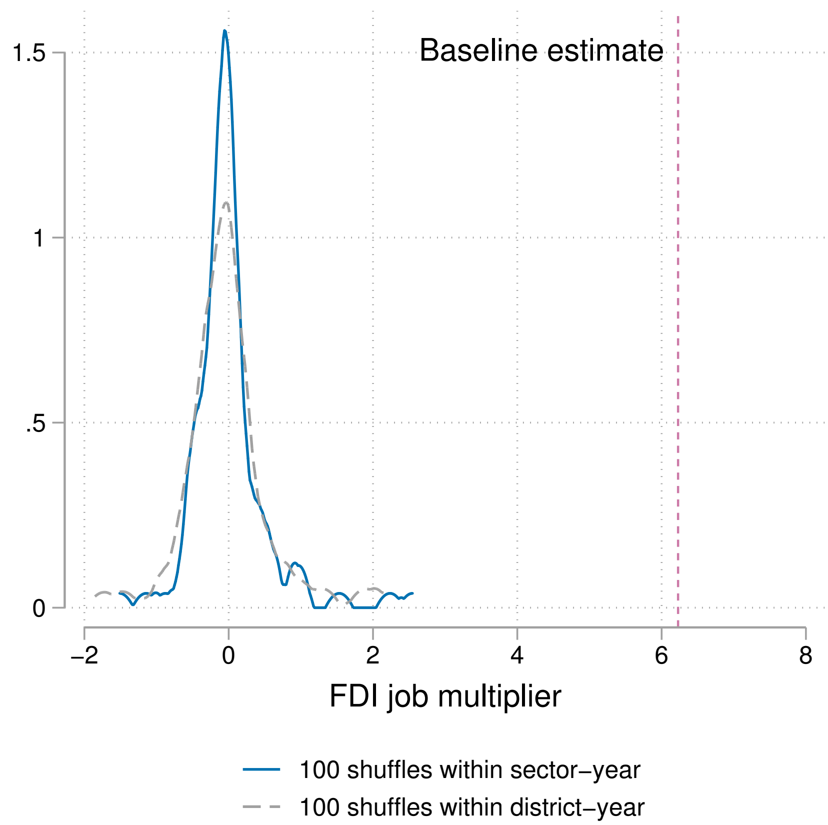
Note: District-sector and sector-year fixed effects included in all regressions. District-year fixed effects are not included as they are collinear with the sum of the two explaining variables. Standard errors in parenthesis clustered by district and sector, and * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.

While our triple diff-in-diff should control for most sources of endogeneity, we might still be worried that these results are driven by particularly successful cities that attracted much FDI and experienced local business growth or by general trends like the servicification of the economy. To test for this possibility we create 100 placebo FDI projects by shuffling existing projects within sector-year (as well as within district-year). Figure A.11 gives the distribution of these placebo estimates. The fact that these are distributed around zero and that our estimate of 6.2 is far to the right of the distribution's right tail increase our confidence that our estimates are not picking up general city or sector effects. It suggests that the FDI projects are not correlated with local jobs across sectors in all districts but only in those districts where FDI projects take place.

A.6 Additional results: Population, unemployment, gender, education, and wages

In Table A.11 we explore the relationship between the FDI bonanza and labor market outcomes at the district level. Consistent with our previous results we find that one additional FDI job is associated with 5.2 total jobs at the district level (column 2 in Panel A). Moreover, one additional FDI job increases the population by approximately 3.7 individuals and pulls on average slightly more than 2.3 individuals into the labor force. At the same time, the number of unemployed increases by less than 1 implying a decrease in the unemployment rate. Thus, our results suggest that most of the increase in the

FIGURE A.11
Placebo FDI job multipliers at the district-sector level



Note: The 100 placebo allocations of FDI jobs are generated by reshuffling randomly the FDI jobs within district-years and within sector-years. Their effects on non-FDI jobs are estimated using our baseline specification (Panel A of Table A.9). The vertical red line gives our baseline estimate (column 1).

local labor force is absorbed by a large increase in local labor demand. Differentiating between the rural and the urban population in Panel B, we see that these results are predominantly driven by an increased urbanisation in districts which have been affected by the FDI bonanza.

We further decompose the job multiplier by gender and skills, where skilled individuals are those who have at least completed some secondary education. Since this information is only available in the household survey, and not in the firm census, we can only divide total jobs by gender and skills, rather than strictly non-FDI jobs. The decomposition of this multiplier by gender suggests that FDI is slightly more beneficial for women. It suggests a multiplier of 3.0 for women and 2.3 for men. Note that these numbers also include the FDI job itself. The decomposition by skills suggests a skill-biased multiplier, with FDI jobs being associated with a reduction in unskilled employment and a large increase in skilled employment. The baseline numbers suggest that the total jobs created are 7.2 extra skilled jobs and 2.0 fewer unskilled jobs. If we take the skilled-jobs multiplier at face value, it would suggest that as many as 907,625 (=7.2 × 126,059) skilled jobs may be due to the FDI multiplier (assuming all FDI jobs are also skilled ones). This would suggest that around 53% of all skilled jobs in Mozambique are linked to FDI (according to the household survey data there are around 1,689,038 skilled jobs in Mozambique in 2014 (see Table (A.7)).

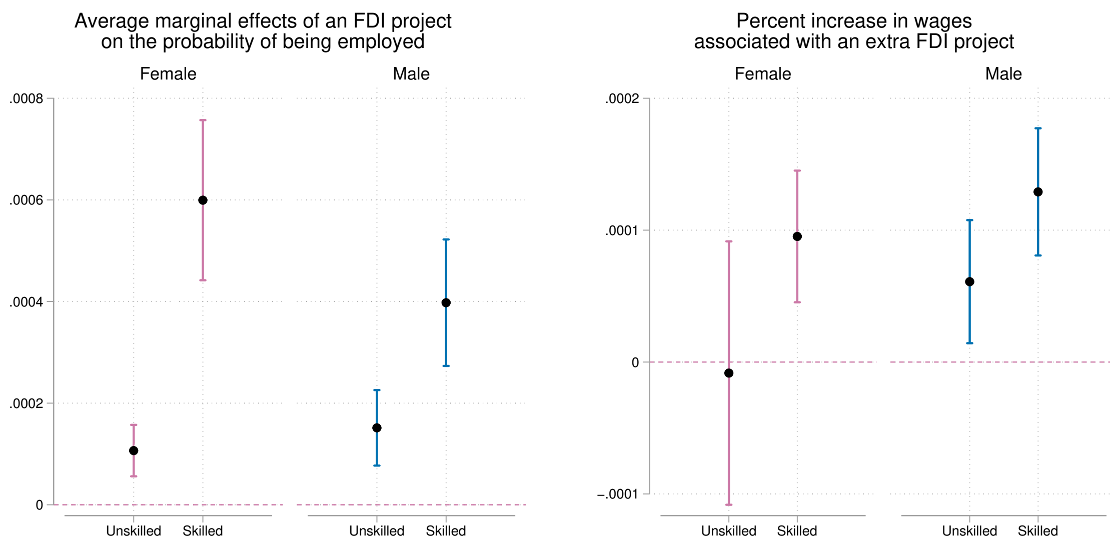
To investigate this gender and skill bias further we adjust our estimation strategy by focusing on the individual level rather than aggregated by sector. In particular, we estimate the following specification:

$$y_{il} = c + FDI_l + E_i + G_i + \alpha(E_i \times G_i) + \beta(FDI_l \times G_i) + \gamma(FDI_l \times E_i) + \mathbf{X}'\lambda_{\mathbf{il}} + \epsilon_{\mathbf{il}}$$

y_{il} is a placeholder for the logged wage of individual i in location l or a dummy which is equal to 1 if individual i reports to be employed and 0 otherwise. FDI_l is our usual measure for FDI in location l, while G and E are gender and post-primary education dummies, respectively. Depending on the specification X just contains age and age squared of individual i or additionally includes sector fixed effects, which are not used in the employment specification. This specification allows us to estimate how the probability of an individual being employed in 2014, as well as how its wage, depend on its gender, skills, and on how much FDI flowed to its district and sector since 2002. These estimates confirm the gender and skill bias of the FDI multiplier. Not only are skilled individuals more likely to be employed when there are more FDI projects in their district, but they also see their wages rise more. This is true for both men and women and points to FDI increasing wage inequality between the skilled and unskilled. The marginal effects suggest that 10 extra FDI projects in a district-sector increase the probability of skilled women to be employed by 0.6 percentage points, while it increases the probability for unskilled men by less than 0.2 (the average probability of being employed is 73%, whether formally or informally). The wage regression on the other hand suggest that 100 extra FDI projects in your district and sector are associated with 0.01% higher wages.

FIGURE A.12

The role of education and gender - 2014 individual level regressions



Note: The left figure shows the estimated marginal effects based on an individual-level linear probability model. The left-hand side variable is a dummy equal to one if the individual is employed, and zero otherwise. The right hand side includes interactions between the individual's education and skills with FDI in its district controlling for its age and age squared. We use the provided survey weights and cluster standard errors by district. The right figure shows the semi-elasticities of a similar regression with ln(wage) on the left-hand side and where district and sector fixed effects are included.

TABLE A.11

Additional district level regressions

Panel A: The effect of an FDI job on district labor markets

	(1) Pop (15-59)	(2) Employed	(3) Unemployed	(4) Inactive
FDI jobs (CEMPRE)	3.726**	5.278***	0.761***	-2.312**
	(1.587)	(1.348)	(0.245)	(0.916)
N	266	266	266	266
R-sq	0.96	0.92	0.94	0.97

Panel B: The effect of an FDI job on urban and rural jobs

	(1) Urban pop (15-59)	(2) Rural pop (15-59)	(3) Urban jobs	(4) Rural jobs
FDI jobs (CEMPRE)	4.237**	-0.511	5.759***	-0.481
	(1.649)	(0.420)	(1.525)	(0.383)
N	266	266	266	266
R-sq	0.98	0.88	0.96	0.89

Panel C: The effect of an FDI job on jobs by gender and education

	(1) Men jobs	(2) Women jobs	(3) Skilled jobs	(4) Unskilled jobs
FDI jobs (CEMPRE)	2.285***	2.993***	7.245***	-1.967**
	(0.620)	(0.773)	(1.585)	(0.917)
N	266	266	266	266
R-sq	0.94	0.91	0.89	0.90

District and year fixed effects included in all regressions. Standard errors in parenthesis clustered by district and sector, and * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level.