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

Gerhard Toews[†]
Pierre-Louis Vézina[‡]

September 11, 2018

Abstract

We show that giant and unpredictable oil and gas discoveries in developing countries trigger FDI bonanzas, and we use one such episode to estimate local FDI multipliers. Across countries, we document a 58% 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 bonanza in Mozambique we combine concurrent waves of household surveys and firm censuses and estimate the local job multiplier of FDI projects. Our triple diff-in-diff and IV estimates suggest that each FDI job results in 4.4 to 6.5 additional jobs, half of which are informal.

JEL CODES: F21, F23, Q32, Q33
Key Words: FDI, local multiplier, resource discoveries.

[*]We are grateful to Fernando Aragon, Nicolas Berman, Markus Brueckner, Jim Cust, David Giles, Victoire Girard, Doug Gollin, Tarek Harchaoui, Ricardo Hausmann, Beata Javorcik, Guy Michaels, Peter Neary, Rick van der Ploeg, Steven Poelhekke, Simon Quinn, Valerie Ramey, Michael Ross, Liugang Sheng, Brock Smith, Radek Stefanksi, Kevin Tsui, Tony Venables, Wessel Vermeulen and seminar participants at the OxCarre brown bag, the 2016 CSAE Conference at Oxford, the 2016 NOVA Africa conference in Lisbon, at Paris Dauphine, at the 2016 Resource and Governance workshop in Bergen, at Harvard Kennedy School, at the 2017 IGC Workshop on Natural Resource Management and FDI in Maputo, at the 2017 Royal Economic Society Meeting in Bristol, at the Legacy of Plenty 2017 workshop at King's College London, at Dundee, at St-Andrews, at the 2017 International Economic Association meeting in Mexico City, at the 2017 DEGIT XXII conference in Paris, at the 2017 ETSG conference at EUI in Florence, at the Paris School of Economics, at Groningen, and at the 2018 Tinbergen Institute Conference for many constructive comments. We also thank James Haynes, Jorrit Oppewal and Vincenzo Salvucci for invaluable help with the data and the International Growth Centre for funding. This paper supersedes OxCarre Research Paper 177, "Resource discoveries and FDI bonanzas" and OxCarre Research Paper 199, "Resource discoveries and FDI bonanzas: An illustration from Mozambique".

[†]New Economics School, Moscow, and Oxford Centre for the Analysis of Resource Rich Economies, Dept of Economics, University of Oxford. Email: gtoews@nes.ru.

[‡]Dept of Political Economy and Dept of International Development, King's College London. Email: pierre-louis.vezina@kcl.ac.uk.

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. By doing so we highlight an unexpected and positive spillover from 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 unrelated 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 and the number of targeted sectors. 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 58%, the number of FDI projects increases by 30%, the number of sectors targeted and of source countries increase by around 19%. We find the effect to be stronger in poor countries with weak governance. 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 country's largest city while in the rest of the country the FDI effects are strongest in business services and construction, as well as in electricity and extraction.

We illustrate this mechanism using Mozambique's recent experience which we delve in to estimate the local multiplier effect of FDI projects. 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 (Arezki et al., 2017). While these fields are still under development as of September 2018, fDiMarkets data suggests that foreign firms moved in right after the first discovery in a multitude of industries, directly creating around 10,000 jobs in the following 3 years, all across the country. In 2014 alone it attracted \$9 billion worth of FDI. Our counterfactual 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 the FDI bonanza we link FDI projects from the fDiMarkets database (FT) as well as data on firms from the 2002 and 2014 firm censuses (CEMPRE) to household outcomes across districts, sectors, and periods using data from two waves of Household Budget Surveys from 2002 to 2014. This allows us to estimate FDI-job multipliers.[1] Since FDI and employment vary across these three dimensions we are able to estimate job multipliers using a triple difference-in-differences model controlling for all district-sector-, district-year- and sector-year-specific sources of variation. To fully account for any remaining endogeneity, e.g. business expectations within Mozambique driving both FDI and non-FDI business creation, we use an instrumental variable strategy to isolate the FDI shock caused by the gas discovery. Our instrument is based on the idea that the distribution of discovery-driven FDI bonanzas across sectors and cities follows a distinctive pattern across countries that is unrelated to the country specificities. We use the shares of FDI across sectors and cities ranked by population in Ghana, Ethiopia, and Tanzania as an instrument for FDI across Mozambique's cities and sectors. These three countries are the only other sub-Saharan African countries that experienced a first giant discovery and a subsequent FDI bonanza since 2003. Intuitively, one can think of other discovery countries' recent FDI experience as shaping expectations and driving FDI into Mozambique, independently of Mozambique specific factors.

Our baseline estimate suggests that for each new FDI job an extra 6.2 are

[1]Our matching of household survey data with FDI projects is akin to the methods used by Atkin et al. (2018) and Basker (2005) to study the job effects of Walmart or those used in studies of the local impact of resource extraction projects (see Cust and Poelhekke 2015).

created in the same sector, 2.9 of which are formal jobs. 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's also in line with multipliers being larger in developing countries with excess capacity. We find the FDI multiplier to operate mostly within sector with limited cross-sector spillovers on average. Since 131,486 jobs were directly associated with FDI firms in 2014, we can infer that almost 1 million jobs, out of around 9.5 million total jobs in Mozambique, are the result of the FDI multiplier. Our results suggest that around 55% of the extra jobs created are informal rather than formal, around 65% are women jobs rather than men's, and that it is only workers with at least secondary education that benefit from the wave of job creation.

The Mozambique experience suggests that FDI projects may be associated with a large multiplier. These findings add to our understanding of local multipliers (Moretti, 2010) and of the job effects of FDI in developing countries (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] Last but not least, our results shed new light on the literature linking natural resources and development. While natural resources have been found to be associated with premature deindustrialization (Rodrik, 2016), a lack of export diversification (Ross, 2017; Bahar and Santos, 2018), lower foreign investment in non-resource sectors (Poelhekke and van der Ploeg, 2013), 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), our paper points to another mechanism at play,

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

i.e. a short-run FDI effect with a potential long-run development implication. Indeed our results suggest discoveries lead to simultaneous investment in various sectors including manufacturing, possibly diversifying economies and providing a window of opportunity for a growth takeoff (Murphy et al., 1989; Sachs and Warner, 1999; Aizenman and Sushko, 2011). Our results are thus in line with natural resource discoveries driving business cycles (Arezki et al., 2017), and with discovery countries being inundated with capital much like boomtowns (Jacobsen and Parker, 2014).[3]

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 fDi Intelligence, itself part of the Financial Times Group (FT). fDiMarkets has been tracking and

[3] Our results are also 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, 2014).

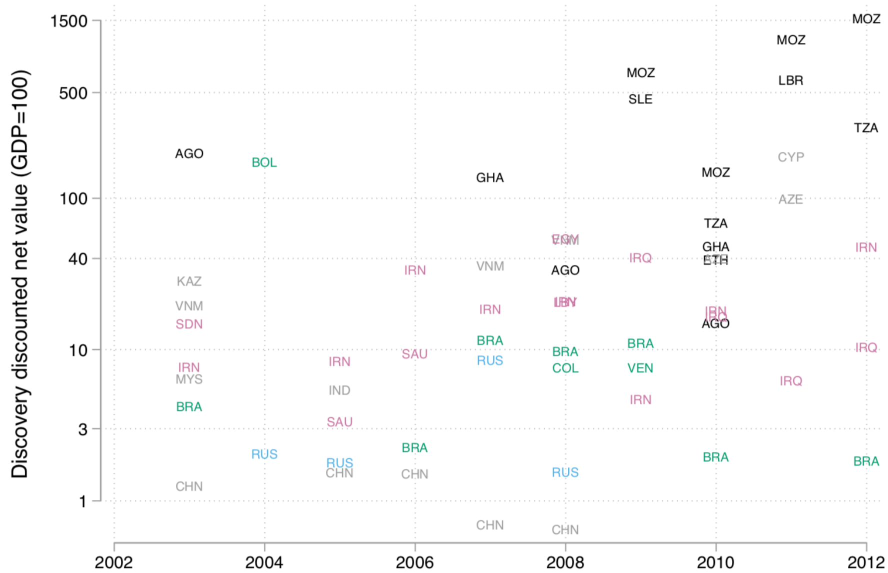
verifying individual cross-border greenfield investment projects since 2003 and is now a primary source of data for UNCTAD, the World Bank and the Economist Intelligence Unit (fDiIntelligence, 2016). The database provides information on the value of investments and the estimated number of jobs created.

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 or to other investment by oil and gas companies directly related to the giant discovery. 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 does suggest non-extraction projects create more jobs on average. While there are large differences in project size across countries, the number of jobs created by 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 and of source countries. In Figure 11 in the appendix A.1 we summarize the margins of FDI in discovery countries. Further summary statistics can be found in Table 5 of the same section.

The data on discoveries are reported by Horn (2011) in *Giant Oil and Gas Fields of the World*. Giant discoveries are defined as fields containing at least

FIGURE 1
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".

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 was around 90%. In Mozambique, the combined value of the 3 giant discoveries reaches close to 50 times its GDP.[4]

Our strategy to identify the causal effect of discoveries on FDI inflows relies on

[4]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.

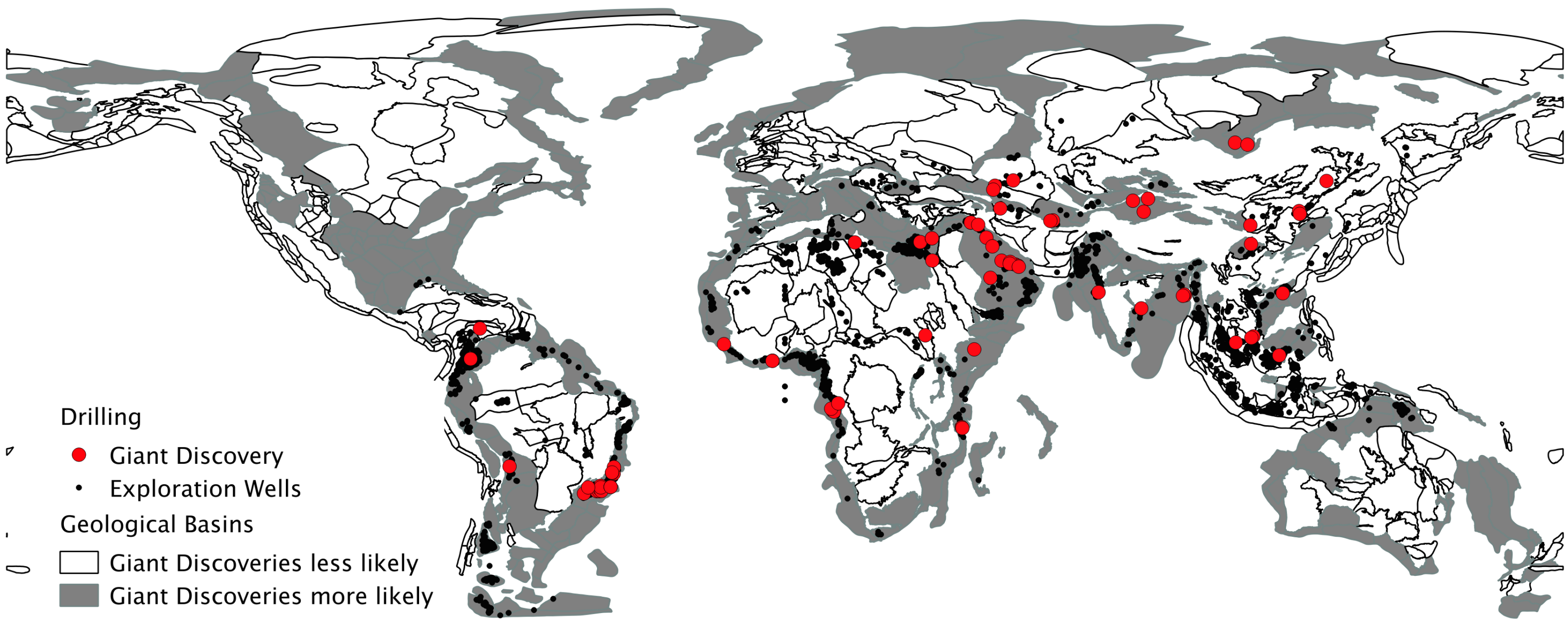
the unpredictability of giant discoveries. Previous studies have suggested that the timing of giant oil discoveries is plausibly exogenous and unpredictable due to the uncertain nature of exploration (Arezki et al., 2017; Tsui, 2011; Cotet and Tsui, 2013; Lei and Michaels, 2014; Cavalcanti et al., 2015).[5]

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 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 has still haven't found a giant field. 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.

[5] Arezki et al. (2017) argues that giant discoveries provide an ideal natural experiment to examine the effects of expectations on investment. 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.

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:

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

where FDI_{it} is a placeholder for different measures of FDI inflows in country i in year t such as the total value of FDI inflows, the number of FDI projects, the number of jobs created, the number of source countries and of target sectors. 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.[6] 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 allow to correlate arbitrarily across years within a country and across countries within a year. In alternative specifications we limit the country sample to countries with at least one exploration well, i.e. *exploration countries*, and to countries with at least one giant discovery during 2003-2014, i.e. *discovery countries*. These alternative country samples provide a more conservative counterfactual in the event exploration is endogenous.

[6] By taking the hyperbolic sine of β 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.

2.2 RESULTS

Our main results are presented in Tables 1 and 2. The Tables provide estimates of β (see equation 1) for seven different measures of FDI in three different country samples. The sample in Panel A includes all non-OECD countries, while Panel B includes only *exploration countries* and Panel C only *discovery countries*.

We find that non-extraction FDI inflows are 58% higher in the 2 years following a giant discovery. This is the lower bound estimate from Panel C, yet there is no significant difference in estimates across panels which suggests that the choice of counterfactual does not affect our main result. Using lower bound estimates, we also find that the number of FDI projects increases by 30% and the number of jobs created by 54%, while the average size of projects is not significantly affected. This suggests that the FDI effect is driven by the extensive margin rather than the intensive margin. Results in Table 2 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 and source countries increases by 19% in the 2 years following a giant discovery. These results are again very similar across panels.

The results suggest that giant discoveries attract non-extraction FDI. The FDI inflow occurs several years *before* production actually starts and, thus, precede the potential oil boom (which occurs on average 5 years after a discovery). As discussed above non-extraction FDI tends to be labor intensive and, thus, giant discoveries have indirectly the potential to create many jobs, a mechanism we explore further using Mozambique's experience in the next section. Also, this influx of FDI is driven by the extensive rather than intensive

Table 1: Non-extraction FDI

Panel A: All countries

	(1) FDI (USD million)	(2) Nb projects	(3) Avg project size	(4) Jobs created
Discovery in past 2 years	0.616**	0.300**	0.341	0.571*
	(0.263)	(0.123)	(0.217)	(0.261)
N	1992	1992	1992	1992
R-sq	0.75	0.91	0.48	0.75

Panel B: Only exploration countries

	(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 C: Only discovery countries

	(1) FDI (USD million)	(2) Nb projects	(3) Avg project size	(4) Jobs created
Discovery in past 2 years	0.551*	0.318**	0.245	0.519*
	(0.286)	(0.140)	(0.219)	(0.267)
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.

Table 2: Extensive margins

Panel A: All countries

	(1) Nb source countries	(2) Nb sub-sectors	(3) Nb sectors
Discovery in past 2 years	0.204**	0.251**	0.192**
	(0.076)	(0.082)	(0.069)
N	1992	1992	1992
R-sq	0.87	0.90	0.87

Panel B: Only exploration countries

	(1) Nb source countries	(2) Nb sub-sectors	(3) Nb sectors
Discovery in past 2 years	0.188**	0.193*	0.158**
	(0.078)	(0.088)	(0.071)
N	1080	1080	1080
R-sq	0.86	0.89	0.86

Panel C: Only discovery countries

	(1) Nb source countries	(2) Nb sub-sectors	(3) Nb sectors
Discovery in past 2 years	0.197*	0.246**	0.189**
	(0.090)	(0.095)	(0.080)
N	300	300	300
R-sq	0.81	0.88	0.82

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.

margin such that it provides a source of diversification for the economy as jobs are created across a variety of sectors. The increase in the number of source countries is also consistent with the idea that giant discoveries act as news shocks about future market size propagated across countries. Hence, giant discoveries may work as a coordination device which exogenously determine the timing of investment from different countries and sectors thereby providing a window of opportunity for a big push (Murphy et al., 1989).

Our results are in line with Arezki et al. (2017) who show that in a panel of up to 180 countries during the period 1970-2012 that aggregate investment rises robustly right after the news of a giant discovery arrives.[7] And while our results seem to go against Poelhekke and van der Ploeg (2013) it is worth noting that the latter showed that resource rents, rather than discoveries, crowded out non-resource FDI, and that was mostly in the longer run and focusing on the period 1985-2002, i.e. before the latest boom. Our results are thus complementary rather than contradicting.

We describe a battery of robustness checks to reinforce our main result in appendix A.2. 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 lags and leads around the year of the discovery, and using FDI data from UNCTAD rather than from fDiMarkets.

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 of their institutions, their distance from the discovery country, 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

[7] While Arezki et al. (2017) looked at private and public investment, 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. The latter also find that employment decreases slightly after the news while we show that the FDI bonanza created jobs in Mozambique.

Indicators.[8] We also check if the effect's size depends on the geodesic distance between the destination and the source countries.[9] The results are shown in Figure 3. 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. [10] 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).

Finally we explore the FDI response across business activities and location by re-estimating equation 1 by business activity for both, FDI to the country's metropolis and to the rest of the country.[11].

The results in Figure 4 suggest that the strongest response comes from FDI

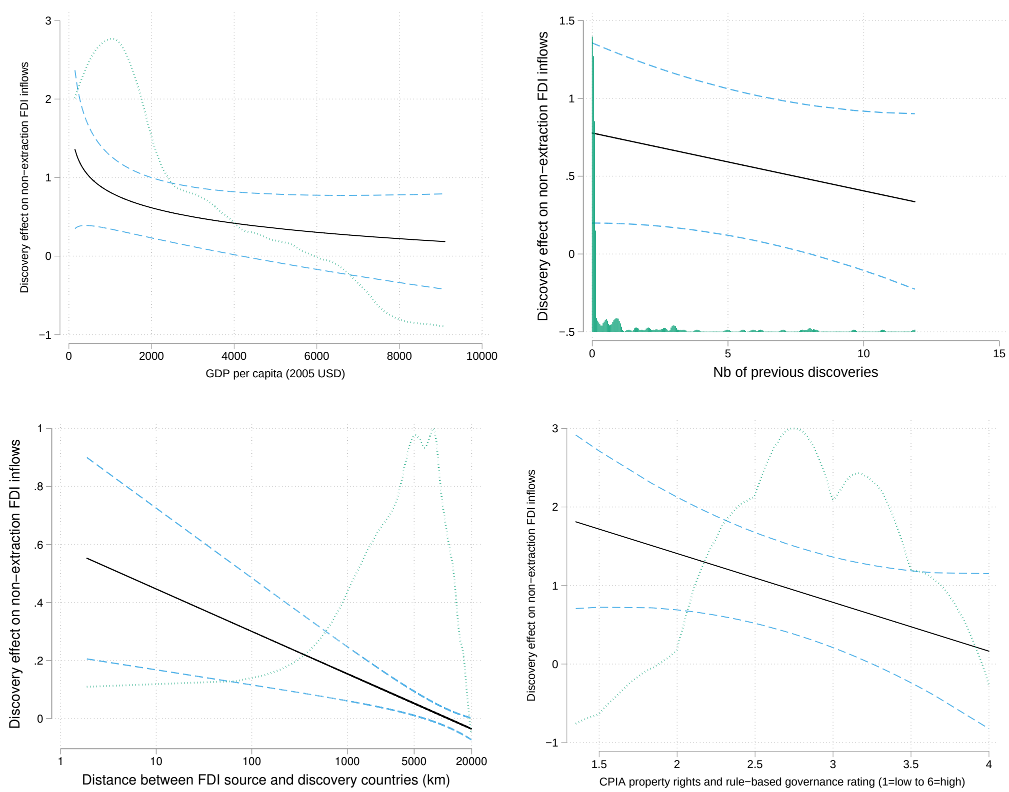
[8]CPIA stands for Country Policy and Institutional Assessment and it focuses only on low-income countries. The results also hold if we use the rule of law index from the World Bank Governance Indicators.

[9]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 aggregate them by destination county (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).

[10]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. 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.

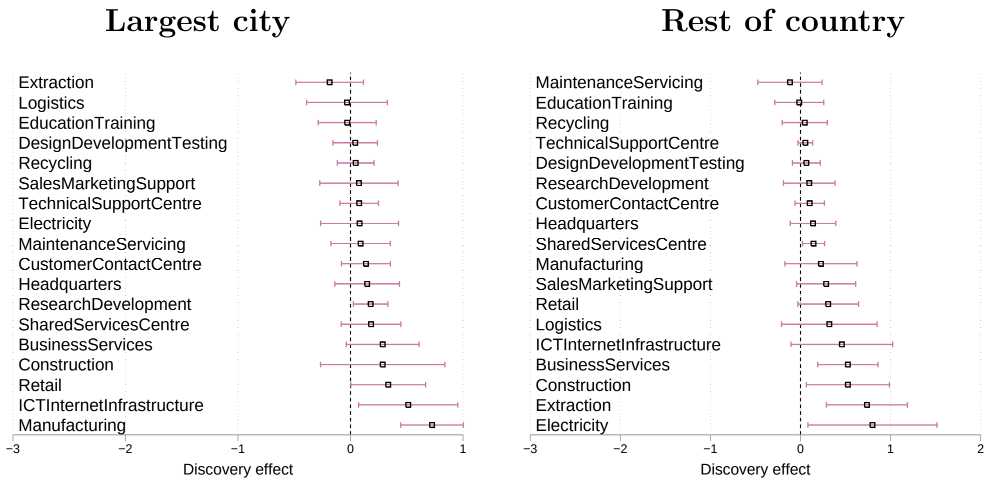
[11]We opted for business activity rather than sectors as these make a clear distinction between manufacturing and services and also because it aggregates FDI projects into 18 categories rather than 39 and thus eases the presentation of the results

FIGURE 3
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.

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.

in manufacturing, information and communication technologies, and retail in the country's largest city while in the rest of the country 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 effect 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 JOB MULTIPLIER OF AN FDI BONANZA: THE CASE OF MOZAMBIQUE

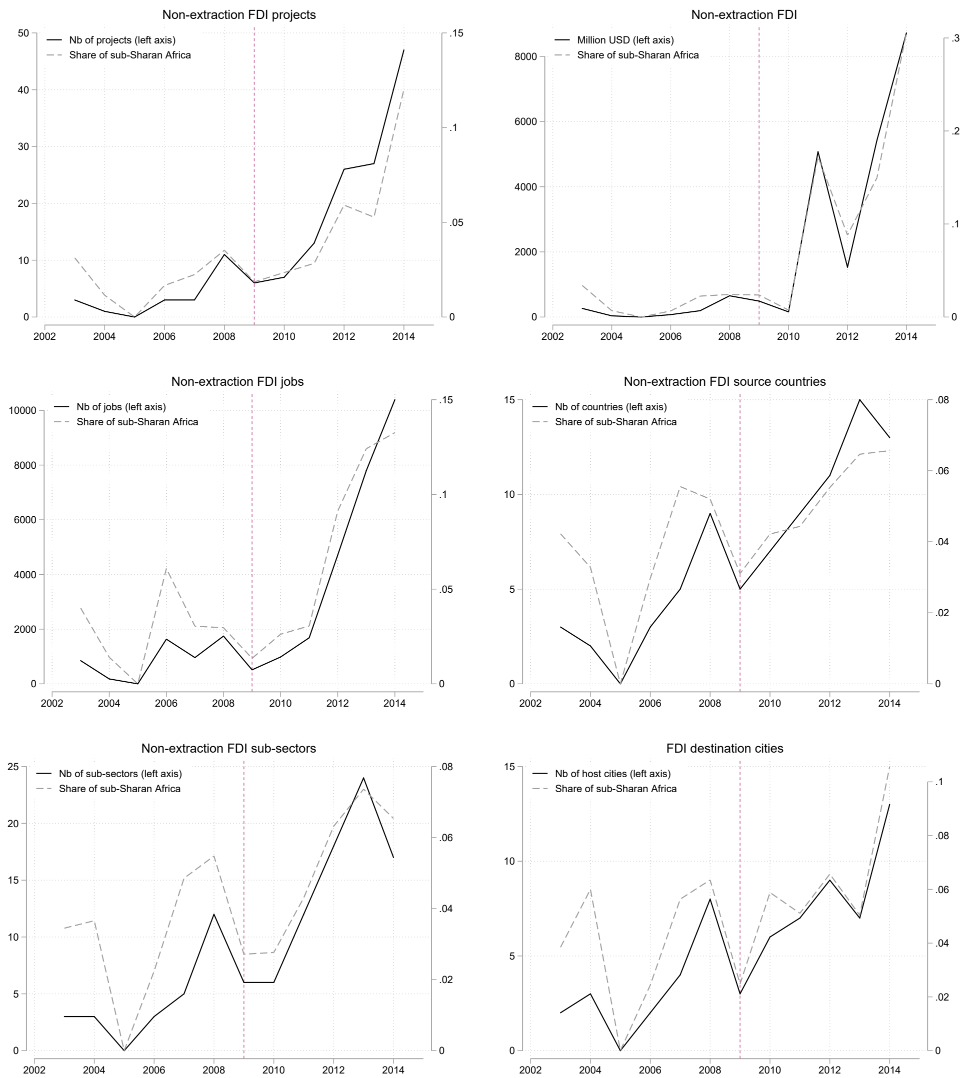
3.1 DATA AND IDENTIFICATION

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. As discoveries precede production by 5 years on average, we argue that the FDI effect is driven by expectations of higher income. The FDI bonanza (Figure 5) that followed the unprecedented giant gas discoveries off Mozambique but precedes the actual field exploitation illustrates tellingly this FDI effect. The number of yearly FDI projects quadrupled from 2010 to 2014 while the value of the investments and the number of direct jobs created increased almost 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.[12] The graphs in Figure 5 also show how the FDI boom was spread across cities and across sectors. And while most projects are from Portuguese, British and South African companies, companies from 32 countries invested in Mozambique since 2003. This FDI bonanza thus provides a unique opportunity to go one step further and evaluate the local job multiplier of the FDI projects.

Our aim here is to determine whether the FDI bonanza in Mozambique has been job creating. Our focus on employment stems from our belief that the development effect of FDI comes first and foremost from job creation. Most micro-level studies on FDI have focused on the wage or productivity

[12] 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 are based on fDiMarkets data.

effects. But the employment effects are not so obvious. In its review of the labor market effects of US 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) finds no positive effects of FDI on employment in Southern and Central and Eastern European regions while Axarloglou and Pournarakis (2007) finds that FDI inflows in manufacturing have only weak effects on local employment across US states. Last but not least, 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. Even across US States it is not clear whether the expansion of WalMart has created or destroyed jobs. Basker (2005) suggests that Wal-Mart entry 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. Hence it is surely a worthy endeavour to check whether the boom in FDI projects across Mozambique has increased household employment or not.

Our approach to gauge the job-creation effect of the Mozambique FDI bonanza is 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), as well as by empirical studies on the local employment effect of mines such as Aragon and Rud (2013) and Kotsadam and Tolonen (2016).

In our particular setting, we expect FDI jobs to have a 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, i.e. 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).[13]

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. While both mechanisms may contribute to the job multiplier, 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). On the other hand the multiplier effect operating via the increased demand for local goods and services should affect the local economy more equally across sectors.

[13]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).

To estimate such a multiplier we match the FDI projects to job numbers across districts, sectors, and periods using data from two waves of Household Surveys from 2002 to 2014. Since FDI and employment vary across three dimensions, i.e. across districts, sectors, and periods, we are 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 market potential, and district-sector fixed effects 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.

While the exogenous nature of the FDI boom, i.e. it being the result of the unexpected giant discovery, suggests that our triple diff-in-diff model will provide quasi-causal estimates, we can nonetheless be worried that its distribution across cities and sectors is driven by expectations within Mozambique that also drive non-FDI business creation. To control for such potential endogeneity we use an instrumental variable strategy based on the distribution of FDI booms across sectors and cities in three African countries that also had their first giant discovery in the late 2000s. We detail this strategy as a first robustness check after describing our baseline results.

While fDiMarkets provides yearly information on the location FDI projects at the district level, 87 of the 215 projects listed from 2003 to 2014 have unknown locations.[14] We thus also use FDI data from the 2002 and 2014 firm censuses (Censo de Empresas or CEMPRE) which was completed by the national statistics institute (INE) as an alternate source of FDI data. 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. Hence while fDiMarkets is most likely an underestimate of the number of FDI projects, our FDI flows based on CEMPRE data may be an overestimate or an underestimate. For robustness we use both FDI estimates in our regressions. We compare our two sources of data on FDI in Figure 16 in appendix A.4.

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).[15] Every survey contains information on the sector of

[14]While this may be because the investment has been announced but not realized, 128 of the projects have been confirmed by internet searches. We use these 128 projects in our regressions.

[15]The surveys were conducted by the National Statistical 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.

employment of each individual in the household. Since we are interested in the effects of FDI inflows on employment we reduce our sample to individuals between 15 and 59 years old. For a consistent matching of FDI projects 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.[16] Conveniently, the census years of 2002 and 2014 match the household survey years.

We estimate the total number of jobs using the total number of people reporting being employed in each district, sector and year and by grossing up the weights provided in the survey (see Blundell et al. (2004) for an example of grossing up weights).[17] To estimate the number of informal jobs we subtract from total jobs the number of formal local jobs as per the 2002 and 2014 firm censuses and the number of FDI jobs from either the firm censuses or fDiMarkets, depending on which source of FDI data we use in the regression. The job numbers, based on CEMPRE data are presented in Figure 6. The large majority of jobs in Mozambique are informal. Even in the capital and biggest city, Maputo, the share of formal jobs is just around 50%. And while most formal jobs are in services, FDI accounts for a larger share of formal jobs

[16]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.

[17]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 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 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 million and 25.7 millon.

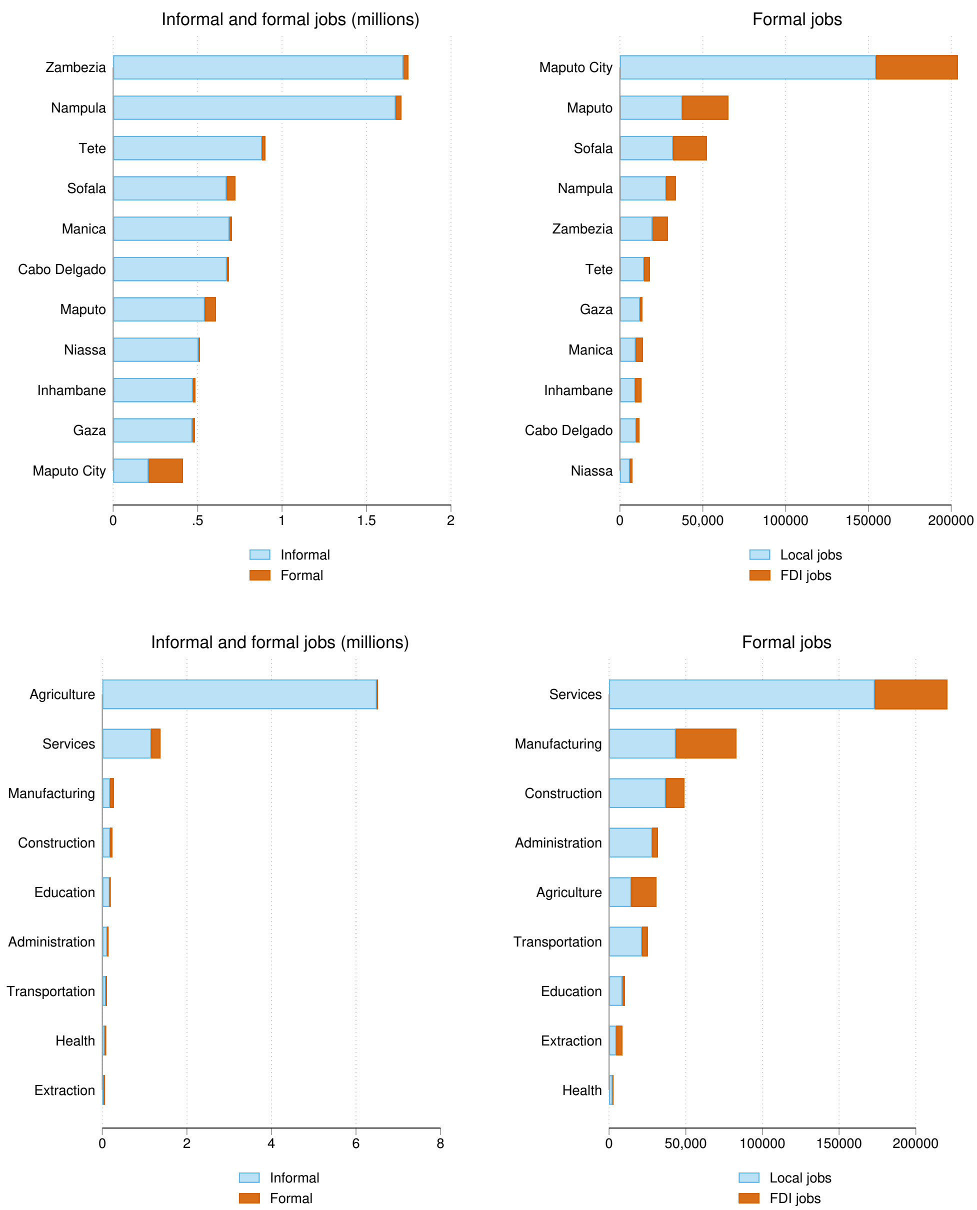
in manufacturing. Further summary statistics and a detailed description of the variables can be found in Table 7 and 8 in appendix A.3.

3.2 RESULTS

Our baseline estimates are presented in Table 3. The estimated coefficients in the top panel give us the FDI-job multiplier, i.e. the number of additional non-FDI jobs created by an extra FDI job. The bottom panel estimates are for the multiplier associated with an extra FDI project. Using FDI job numbers from the firm census (CEMPRE) suggests a multiplier of 6.2 (column 1) and the order of magnitude of this multiplier is confirmed by the fDiMarkets (FT) data which suggests a multiplier of 6.7 (column 2). Columns (3-6) break down non-FDI jobs into formal and informal jobs. It suggests that out of the 6.2 additional jobs created by an FDI job, 2.9 are formal and 3.4 are informal. Again the estimates based on fDiMarkets suggest similar numbers. These multipliers suggest large job-creation effects for FDI jobs but are nonetheless of the same magnitude as the local multipliers estimated by Moretti (2010) for high-skilled jobs, i.e. 4.9 additional nontradable jobs created for each high tech job. It's also in line with multipliers being larger in developing countries with excess capacity.

The estimates in the bottom panel of Table 3 suggest that an extra FDI project is associated with 120 non-FDI additional jobs, 50 in the formal economy and 70 in the informal sector. It confirms the larger impact of FDI on the informal sector than on the formal sector. The numbers are of a larger magnitude when using FDI data from fDiMarkets. The latter suggests that each extra FDI projects creates 1,846 additional jobs. This difference might

FIGURE 6
Jobs in Mozambique in 2014



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

Table 3: FDI job multipliers

Panel A: Job-level multipliers

	(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

Panel B: Project-level multipliers

	(1) Non-FDI jobs	(2) Non-FDI jobs	(3) Formal jobs	(4) Formal jobs	(5) Informal jobs	(6) Informal jobs
FDI projects (CEMPRE)	119.963***		50.109***		70.430***	
	(13.368)		(2.522)		(13.665)	
FDI projects (FT)		1846.264***		958.713***		891.961***
		(132.935)		(14.992)		(123.008)
N	1012	1012	1012	1012	1012	1012
R-sq	0.96	0.96	0.97	0.98	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.

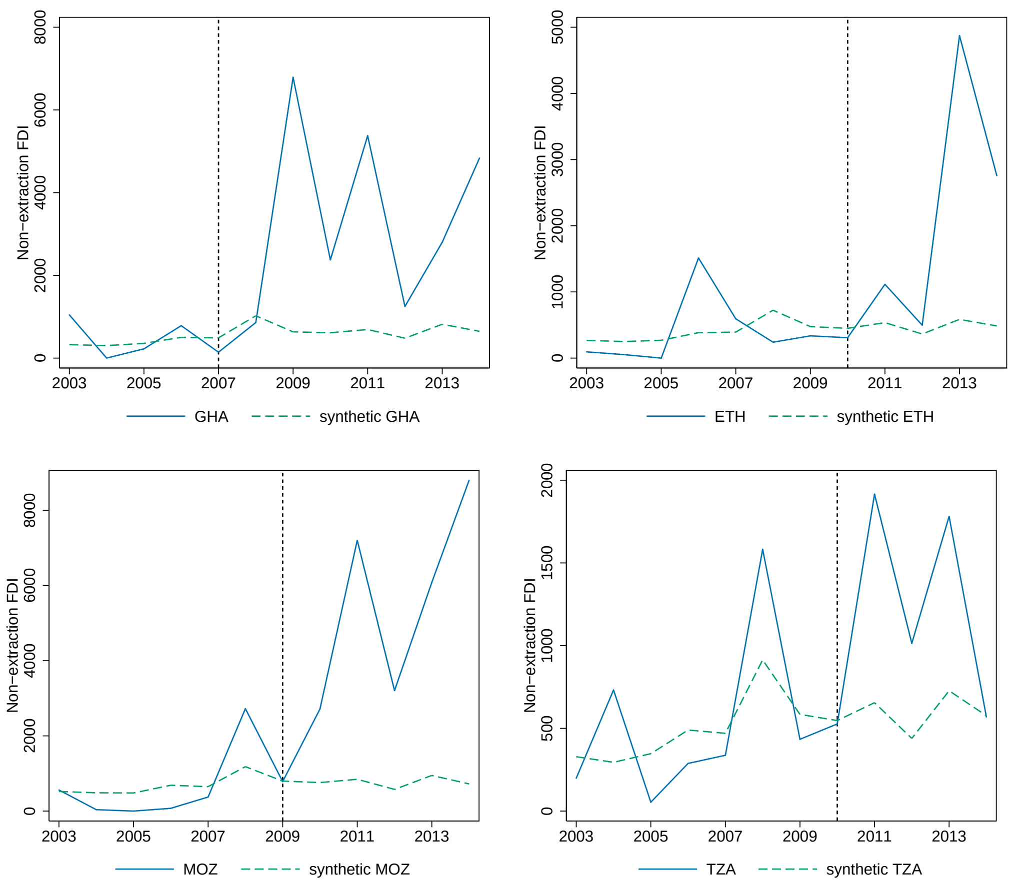
be explained by a selection of mostly large projects in the fDiMarkets data.

Robustness to potential endogeneity As mentioned earlier we can nonetheless be worried that the distribution of FDI projects and jobs across cities and sectors is driven by expectations within Mozambique that also drive non-FDI business and job creation. 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 is unrelated to the country specificities.

Figure 7 illustrates the effect of discoveries on FDI inflows for Ghana, Ethiopia, Tanzania as well as Mozambique. These four sub-Saharan African countries announced their first giant discoveries in the late 2000s. The

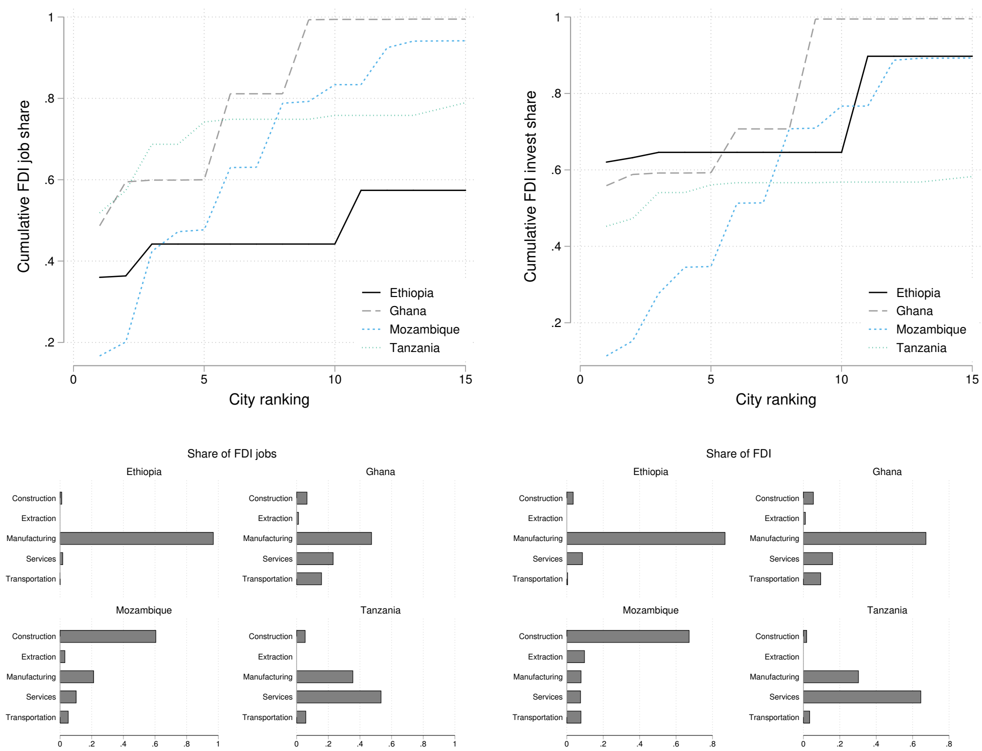
FIGURE 7

FDI: Discovery countries vs. synthetic counterfactuals



Notes: Discovery countries are defined as countries with at least one giant discovery since 2003 (shown in Figure 1). Synthetic counterfactuals are weighted averages of non-extraction FDI in other 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 8
FDI and FDI Jobs in post-discovery years



Notes: Post-discovery years are as in Figure 7. The numbers are based on fDiMarkets data.

fDiMarkets data suggests that 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.

The distribution of FDI booms, measured in FDI jobs as well as projects, across sectors and cities in these four African countries is shown in Figure 8. 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 is more random. Nonetheless, we can use the average shares of FDI jobs by sectors and city rank in the three other African countries to construct an instrument for FDI in Mozambique. The intuition is that the common distributional features of FDI in countries with similar giant discoveries provides variation across districts and sectors that is not driven by Mozambique-specific expectations but rather by the usual pull forces at play in discovery countries. We thus multiply the average of FDI shares across sectors and city rank in post-discovery years in Ghana, Ethiopia and Tanzania (we assume zero FDI jobs in 2002) and use it to instrument FDI jobs in Mozambique. Intuitively, one can think of other discovery countries' recent FDI experience as shaping expectations and driving FDI into Mozambique, independently of Mozambique specific factors.

The first stage results in column (1) of Table 4 confirm the relevance of our instruments. For both FDI jobs and FDI projects 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 (2-4) are not statistically different from our simple triple diff-in-diff estimates. The number of non-FDI jobs caused by FDI jobs is estimated at 6.52 while FDI projects are found to cause 117.4 extra jobs on average. We also confirm our previous results that the multiplier effect is slightly larger for the informal sector.

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.[18] The

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

Table 4: FDI job multipliers - Instrumental variable estimates

Panel A: Job-level multipliers

	(1) FDI jobs (CEMPRE)	(2) Non-FDI jobs	(3) Formal jobs	(4) Informal jobs
Instrument	1.492***			
	(0.068)			
FDI jobs (CEMPRE)		6.515***	1.855***	4.166***
		(1.527)	(0.153)	(1.525)
N	1012	1012	1012	1012
R-sq	0.12	0.08	0.51	0.02
F IV		476.65	476.65	476.65

Panel B: Project-level multipliers

	(1) FDI projects (CEMPRE)	(2) Non-FDI jobs	(3) Formal jobs	(4) Informal jobs
Instrument	13.044***			
	(0.238)			
FDI projects (CEMPRE)		117.408***	50.728***	66.504***
		(14.781)	(1.298)	(15.427)
N	1012	1012	1012	1012
R-sq	0.87	0.10	0.61	0.04
F IV		2996.85	2996.85	2996.85

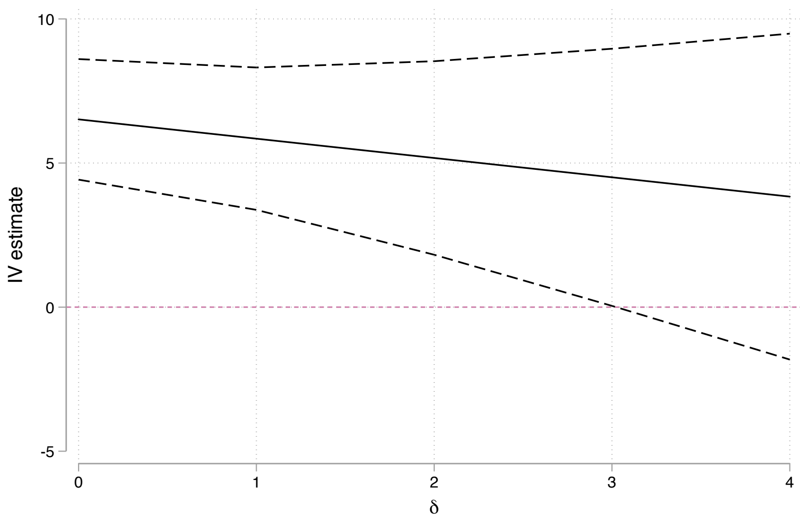
Notes: District-year, district-sector and sector-year fixed effects included in all regressions. Standard errors in parenthesis clustered by district, and * stands for statistical significance at the 10% level, ** at the 5% level and *** at the 1% percent level. The IV is the product of the average FDI job shares by sector and by ranked cities in post-discovery years in Ghana, Ethiopia, and Tanzania.

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-sector, district-period and sector-period fixed effects have been partialled out):

$$\widetilde{Jobs}_{ijt} = \alpha \widetilde{FDI}_{ijt} + \delta \widetilde{Z}_{ijt} + \epsilon_{ijt}$$
$$\widetilde{FDI}_{ijt} = \gamma \widetilde{Z}_{ijt} + e_{ijt}$$

where $Jobs_{ijt}$ is the number of individuals employed in non-FDI jobs in district i in sector j in year t; FDI_{ijt} is the number of jobs directly created by FDI

FIGURE 9
Relaxing our IV exogeneity assumption



Notes: The figure shows how our IV estimate of the FDI multiplier changes if local firms' decisions are also directly affected by our IV, i.e. the experience of foreign firms abroad. The δ captures the strength of the hypothetical relationship between our IV and non-FDI jobs. This approach was suggested by Conley et al. (2012) and the code provided by Clarke and Matta (2017). The dashed lines are 95% confidence intervals.

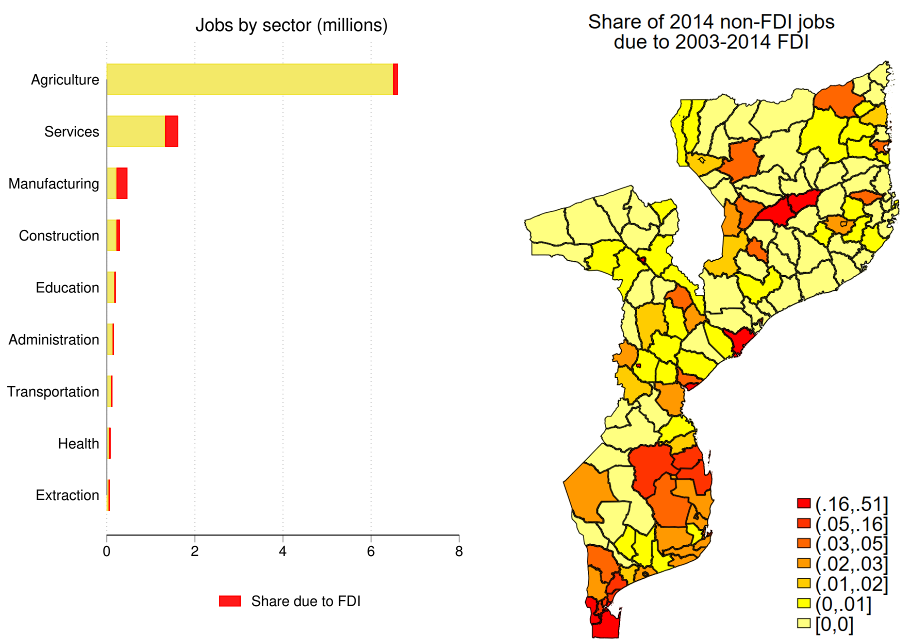
projects, and Z_{ijt} is our instrumental variable constructed using the experience of FDI bonanzas in other discovery countries. If one believes that δ is not equal to zero, and thus that local firms' decisions are also affected by the experience of foreign firms abroad, our instrument is no longer strictly excludable and our estimate of α is biased. Using the specification above we can evaluate how our IV estimate of α changes for successive increases in δ, i.e. an increasing violation of the exclusion restriction.

This sensitivity analysis is summarized in Figure 9. For δ values below 3, the IV estimate of the FDI multiplier remains statistically significant and around 6. It is only when δ is larger than 3 that our IV estimate is insignificant. In other words, our result is robust to significant violations of the exclusion restriction. It is only in the extreme scenario where local businesses would react twice as much as FDI to foreign FDI experiences that our IV estimates would not longer hold. If local firms react either as much as or less so than foreign firms, i.e. if δ is around or below $\gamma \approx 1.5$, our IV estimate remains largely stable and robust.

In appendix A.5 we include a battery of robustness checks. First we generate 100 placebo allocations of FDI jobs by reshuffling randomly the real FDI jobs within district-years and within sector-years. This falsification exercise confirms that our multiplier estimates operate within district-sector. 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. We also include regressions where we aggregate the data at the district level. Finally, we also explore the different effects across gender and skills in appendix A.6.

In order to better grasp the magnitude of our benchmark estimate of a multiplier of 6.2 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 (131,486 jobs in 2014) but also all the non-FDI jobs due to the multiplier. We simulate this drop using our benchmark multiplier and present the results by district and sector in Figure 10. We find that there would be almost 1 million less jobs, out of around 9.5 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.

FIGURE 10
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 6.228 (column (1) in Table 3). The heat map gives the share of non-FDI jobs due to the same FDI multiplier by district.

4 CONCLUSION

This paper suggests that across countries giant oil and gas discoveries lead to FDI bonanzas. FDI in non-extractive sectors increases by 58% in the 2 years following a giant discovery. This result is driven by the extensive margin, i.e. by new projects, in new sectors, 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 investment which in turn could provide an opportunity for a growth takeoff.

Our paper also argues that FDI bonanzas triggered by giant discoveries can have large job-creation effects. In the context of Mozambique, our preferred estimate of the FDI multiplier suggests that one extra FDI project creates around 120 additional non-FDI jobs in its host district and sector. Our results thus point to the importance of estimating FDI multipliers in poor countries to better gauge the role of FDI in development.

References

ABADIE, A., A. DIAMOND, AND J. HAINMUELLER (2010): "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of Californias Tobacco Control Program," *Journal of the American Statistical Association*, 105, 493–505.

ADELMAN, M. (1962): "Petroleum Production Costs in General," *Journal of Industrial Economics*, 3–24.

AIZENMAN, J. AND V. SUSHKO (2011): "Capital flows: Catalyst or Hindrance to economic takeoffs?" NBER Working Papers 17258, National Bureau of Economic Research, Inc.

ALFARO, L. AND A. CHARLTON (2013): "Growth and the Quality of Foreign Direct Investment," in *The Industrial Policy Revolution I: The Role of Government Beyond Ideology*, ed. by J. E. Stiglitz and J. Y. Lin, London: Palgrave Macmillan UK, 162–204.

ALFARO, L., S. KALEMLI-OZCAN, AND V. VOLOSOVYCH (2008): "Why Doesn't Capital Flow from Rich to Poor Countries? An Empirical Investigation," *The Review of Economics and Statistics*, 90, 347–368.

ALLCOTT, H. AND D. KENISTON (2018): "Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America," *The Review of Economic Studies*, 85, 695–731.

ARAGON, F. M. AND J. P. RUD (2013): "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine," *American Economic Journal: Economic Policy*, 5, 1–25.

Arezki, R., V. A. Ramey, and L. Sheng (2017): "News Shocks in Open Economies: Evidence from Giant Oil Discoveries*," *The Quarterly Journal of Economics*, 132, 103.

Atkin, D., B. Faber, and M. Gonzalez-Navarro (2018): "Retail Globalization and Household Welfare: Evidence from Mexico," *Journal of Political Economy*, 126, 1–73.

Axarloglou, K. and M. Pournarakis (2007): "Do All Foreign Direct Investment Inflows Benefit the Local Economy?" *The World Economy*, 30, 424–445.

Bahar, D. and M. A. Santos (2018): "One more resource curse: Dutch disease and export concentration," *Journal of Development Economics*, 132, 102 – 114.

Basker, E. (2005): "Job Creation or Destruction? Labor Market Effects of Wal-Mart Expansion," *The Review of Economics and Statistics*, 87, 174–183.

Bazzi, S. and M. A. Clemens (2013): "Blunt Instruments: Avoiding Common Pitfalls in Identifying the Causes of Economic Growth," *American Economic Journal: Macroeconomics*, 5, 152–86.

Blanas, S., A. Seric, and C. Viegelahn (2017): "Jobs, FDI and Institutions in Sub-Saharan Africa: Evidence from Firm-Level Data," Tech. rep.

Blonigen, B. A. and J. Piger (2014): "Determinants of foreign direct investment," *Canadian Journal of Economics*, 47, 775–812.

Blundell, R., M. Brewer, A. Duncan, H. Reed, and A. Shephard (2004): "The employment impact of recent labour market reforms: A Bank of England Report," .

Burbidge, J. B., L. Magee, and A. L. Robb (1988): "Alternative Transformations to Handle Extreme Values of the Dependent Variable," *Journal of the American Statistical Association*, 83, pp. 123–127.

Cavalcanti, T., D. D. Mata, and F. Toscani (2015): "Winning the Oil Lottery: The Impact of Natural Resource Extraction on Growth," Tech. rep.

Clarke, D. and B. Matta (2017): "Practical Considerations for Questionable IVs," MPRA Paper 79991, University Library of Munich, Germany.

Conley, T. G., C. B. Hansen, and P. E. Rossi (2012): "Plausibly Exogenous," *The Review of Economics and Statistics*, 94, 260–272.

Cotet, A. M. and K. K. Tsui (2013): "Oil and conflict: what does the cross country evidence really show?" *American Economic Journal: Macroeconomics*, 5, 49–80.

Cust, J. and S. Poelhekke (2015): "The Local Economic Impacts of Natural Resource Extraction," *Annual Review of Resource Economics*.

Cust, J. F. and D. Mihalyi (2017): "Evidence for a presource curse ? oil discoveries, elevated expectations, and growth disappointments," Policy Research Working Paper Series 8140, The World Bank.

Fats, A. and I. Mihov (2013): "Policy Volatility, Institutions, and Economic Growth," *The Review of Economics and Statistics*, 95, 362–376.

fDiIntelligence (2016): "THE fDi REPORT 2016: Global greenfield investment trends," Report, The Financial Times Ltd.

Gorg, H. and E. Strobl (2001): "Multinational Companies and Productivity Spillovers: A Meta-analysis," *Economic Journal*, 111, F723–39.

Gourinchas, P.-O. and O. Jeanne (2013): "Capital Flows to Developing Countries: The Allocation Puzzle," *The Review of Economic Studies*, 80, 1484.

Herger, N. and S. McCorriston (2016): "Horizontal, Vertical, and Conglomerate Cross-Border Acquisitions," *IMF Economic Review*, 64, 319–353.

Hirschman, A. O. (1957): "Investment Policies and "Dualism" in Underdeveloped Countries," *The American Economic Review*, 47, 550–570.

Horn, M. M. K. (2011): "Giant Oil and Gas Fields of the World," *http://www.datapages.com/AssociatedWebsites/GISOpenFiles/HornGiantFields.aspx*.

Jacobsen, G. D. and D. P. Parker (2014): "The economic aftermath of resource booms: evidence from boomtowns in the American West," *The Economic Journal*.

James, A. (2015): "The resource curse: A statistical mirage?" *Journal of Development Economics*, 114, 55–63.

Javorcik, B. S. (2004): "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages," *American Economic Review*, 94, 605–627.

——— (2015): "Does FDI Bring Good Jobs to Host Countries?" *World Bank Research Observer*, 30, 74–94.

Kavanagh, M. (2013): "Abandoned oil discoveries enjoy revival," *Financial Times*.

Kotsadam, A. and A. Tolonen (2016): "African Mining, Gender, and Local Employment," *World Development*, 83, 325 – 339.

Lei, Y.-H. and G. Michaels (2014): "Do giant oilfield discoveries fuel internal armed conflicts?" *Journal of Development Economics*, 110, 139–157.

Lewis, W. A. (1954): "Economic Development with Unlimited Supplies of Labour," *The Manchester School*, 22, 139–191.

Lipsey, R. E. (2004): *The labour market effects of US FDI in developing countries*, International Labour Organization.

MacKinnon, J. G. and L. Magee (1990): "Transforming the Dependent Variable in Regression Models," *International Economic Review*, 31, 315–39.

Mann, P., L. Gahagan, and M. B. Gordon (2001): "Tectonic setting of the world's giant oil fields," *World Oil*, 222, 78–84.

Marelli, E., L. Resmini, and M. Signorelli (2014): "The effects of inward FDI on regional employment in Europe," *Romanian Journal of Regional Science*, 8, 1–23.

Matsuyama, K. (1992): "Agricultural productivity, comparative advantage, and economic growth," *Journal of Economic Theory*, 58, 317–334.

Miller, R. E. and P. D. Blair (2009): *Input-output analysis: foundations and extensions*, Cambridge University Press.

Moretti, E. (2010): “Local Multipliers,” *American Economic Review*, 100, 373–377.

Murphy, K. M., A. Shleifer, and R. W. Vishny (1989): “Industrialization and the Big Push,” *Journal of Political Economy*, 97, 1003–26.

Neumark, D., J. Zhang, and S. Ciccarella (2008): “The effects of Wal-Mart on local labor markets,” *Journal of Urban Economics*, 63, 405–430.

Nunn, N. and L. Wantchekon (2011): “The Slave Trade and the Origins of Mistrust in Africa,” *American Economic Review*, 101, 3221–52.

Poelhekke, S. and F. van der Ploeg (2013): “Do Natural Resources Attract Nonresource FDI?” *The Review of Economics and Statistics*, 95, 1047–1065.

Robertson CGG (2016): “Tellus sedimentary basins of the world,” http://www.robertson-cgg.com/products/tellus/, accessed: 2016-05-03.

Rodrik, D. (2016): “Premature deindustrialization,” *Journal of Economic Growth*, 21, 1–33.

Ross, M. L. (2012): *The Oil Curse: How Petroleum Wealth Shapes the Development of Nations*, Princeton University Press.

——— (2017): “What Do We Know About Economic Diversification in Oil-Producing Countries?” Tech. rep.

Sachs, J. D. and A. M. Warner (1999): "The big push, natural resource booms and growth," *Journal of Development Economics*, 59, 43 – 76.

——— (2001): "The curse of natural resources," *European Economic Review*, 45, 827–838.

Smith, B. (2014): "Dutch Disease and the Oil and Boom and Bust," Tech. rep.

Tsui, K. K. (2011): "More Oil, Less Democracy: Evidence from Worldwide Crude Oil Discoveries," *Economic Journal*, 121, 89–115.

van der Ploeg, F. (2011): "Natural Resources: Curse or Blessing?" *Journal of Economic Literature*, 49, 366–420.

Venables, A. J. (2016): "Using Natural Resources for Development: Why Has It Proven So Difficult?" *Journal of Economic Perspectives*, 30, 161–84.

Wood Mackenzie (2015): "Upstream Data Tool," http://www.woodmac.com/, accessed: 2015-05-03.

A FOR ONLINE PUBLICATION: APPENDIX

A.1 Additional descriptive statistics - Cross country data

Table 5 summarizes the key variables of our cross country analysis. It is particularly informative to compare the means of variables calculated using all FDI projects and means of variables which are calculated using only non-extractive FDI. First, the descriptives confirm that the number of extractive projects is much smaller relative to the total number of non-extractive projects. Second, while extractive projects are larger on average, non-extractive projects have much greater potential to generate jobs. This is consistent with our prior that the resource sector is capital intensive relative to other sectors.

Table 5: Summary statistics

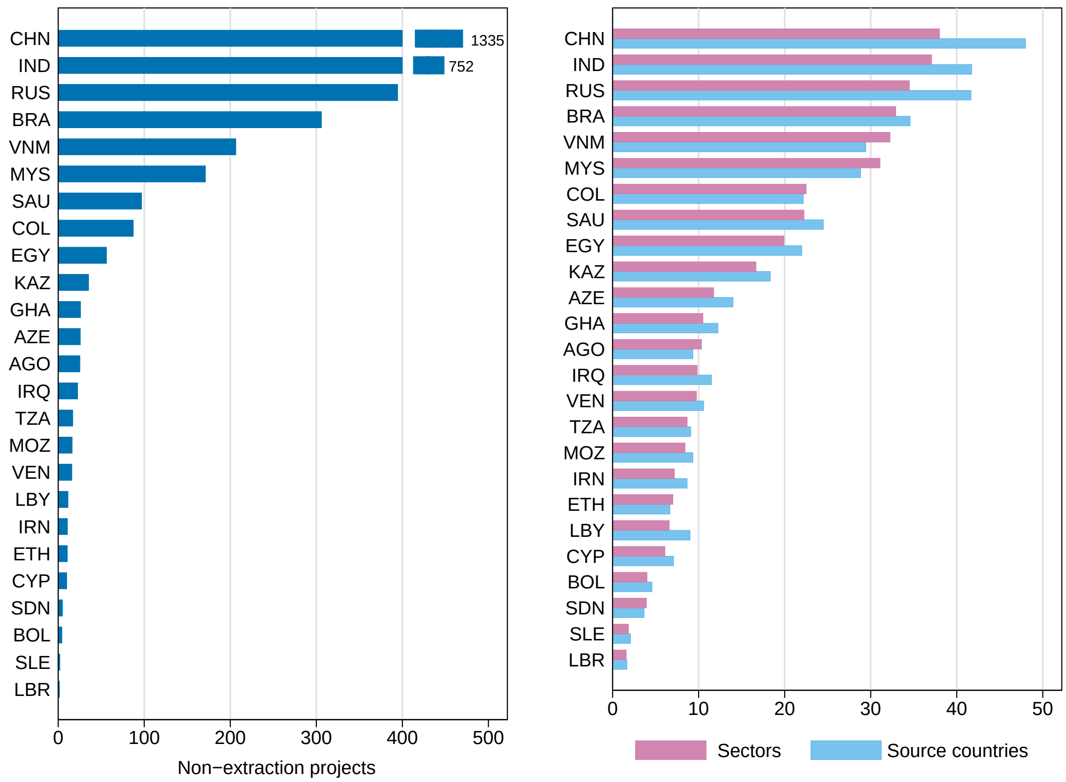
Variable	N	Mean	SD	Min	Max
Total FDI (USD million)	1992	3046	9781	0	1.28e+05
Non-extraction FDI (USD million)	1992	2713	9446	0	1.25e+05
FDI projects	1992	43	135	0	1624
Non-extraction FDI projects	1992	42	134	0	1613
Jobs created	1992	9538	35492	0	4.50e+05
Jobs created (non-extraction)	1992	9219	35267	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
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 11 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 a falsification exercise to highlight the importance of the

FIGURE 11
The extensive margins of FDI in discovery countries



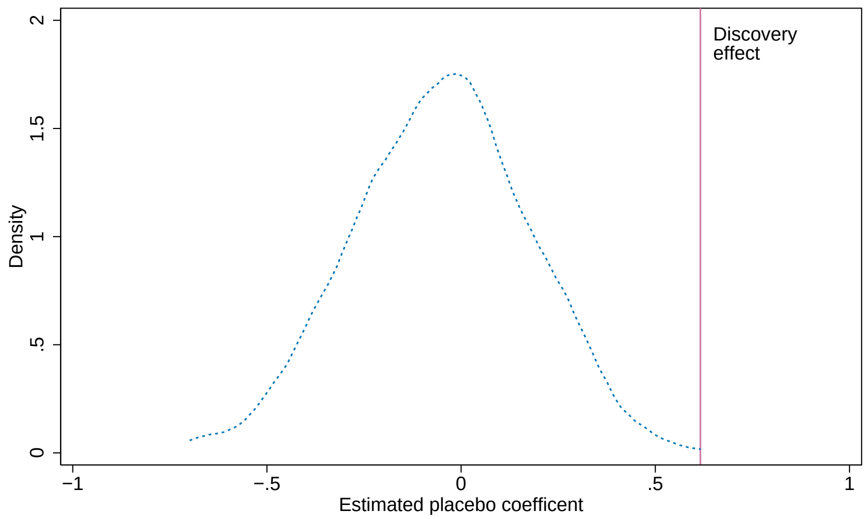
Note: The bars show the average number of projects, source countries and target sectors in discovery countries in the period 2003-2014. There are a total of 39 sectors in the fDiMarkets data.

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 equation 1 500 times on our Panel A sample. As we show in Figure 12, reshuffling the discoveries randomly does not give similar results. Indeed, the distribution 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 estimate of 0.616, 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 second robustness check we experiment with various time horizons as our 2-year cut-off may be arbitrary. We estimate our baseline regression (Panel A) 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 13, suggest that our baseline results are robust to the choice of time horizon. FDI projects

FIGURE 12

Distribution of 500 placebo discovery effects



Note: The 500 placebo discoveries were 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).

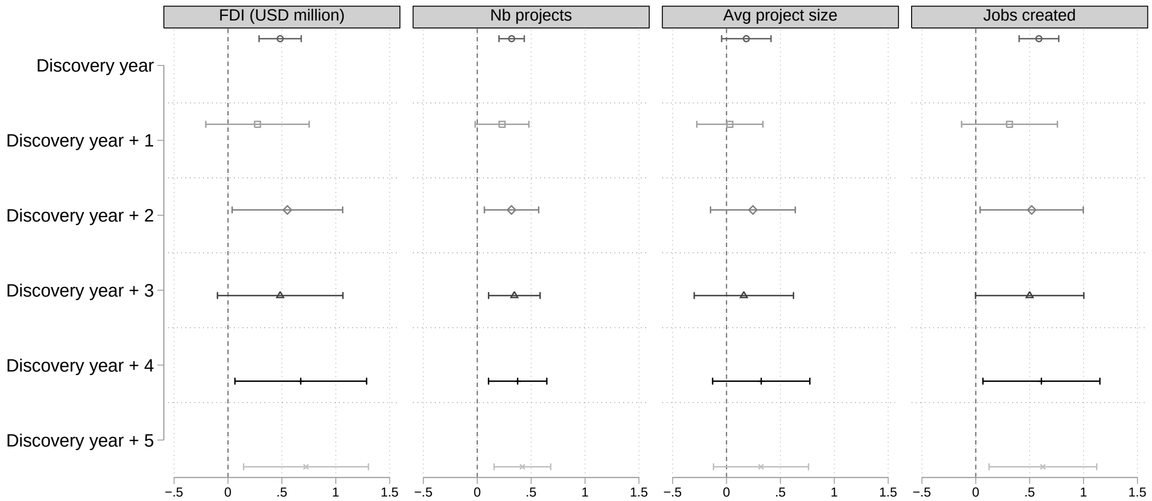
increase significantly in the year of the discovery and in the following 5 years. It is only when considering only the year of the discovery and the following year that we find less convincing effects, though the coefficients' magnitude is not statistically different. Indeed there is no significant differences across the estimates using different time horizons.

In a third robustness check we restrain our sample to the years before and the 3 years after the *first* giant discovery in each country in our sample. 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 thus estimate equation 1 but we replace D_{it} with 5 dummies (two lags, two leads and one dummy for the year of the discovery). The results of this specification are presented in Figure 14. We find a positive effect on non-extraction FDI two years after the discovery and there is no evidence of higher non-extraction FDI flows in the years preceding a discovery.

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 15 we find a high correlation of 0.6 between the two series. Their distributions suggest that none is systematically larger and plotting them against

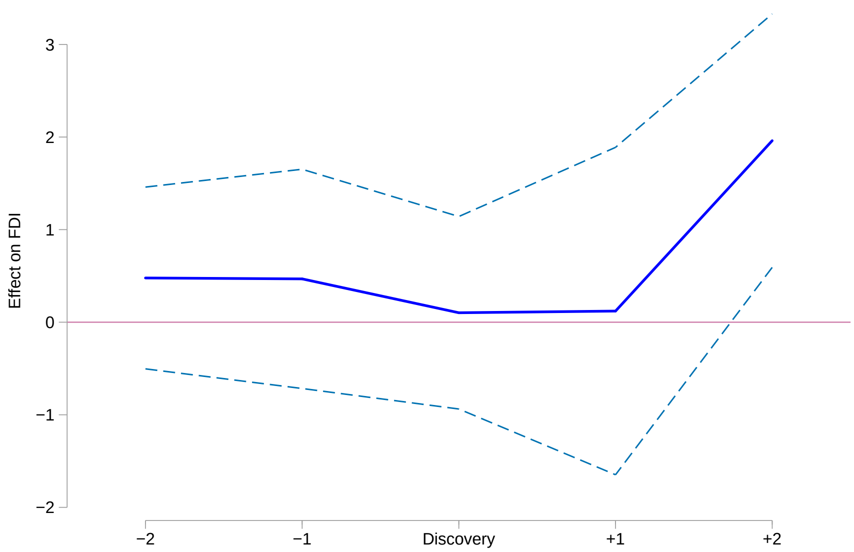
FIGURE 13

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.

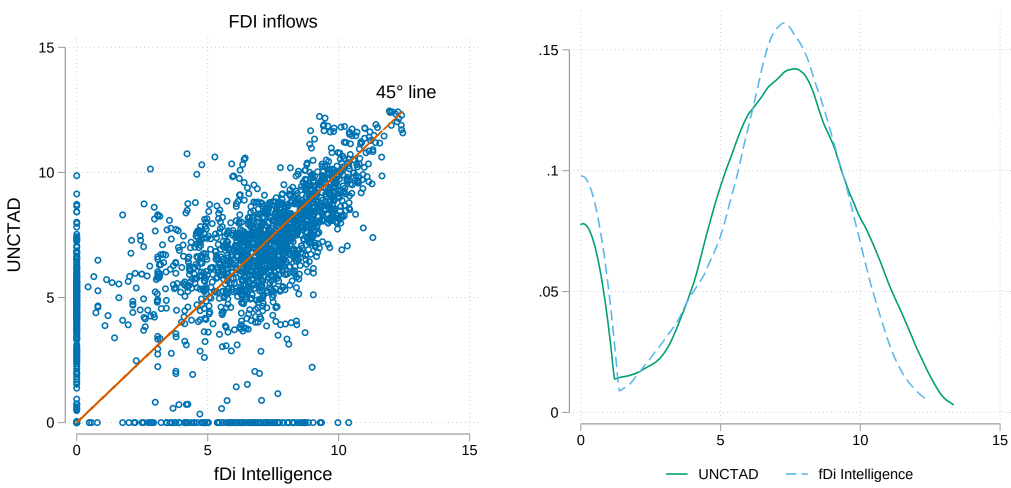
FIGURE 14



Note: The yearly effects on non-extraction FDI are estimated in a specification akin to our baseline (Table 1) where the 2-year discovery dummy is replaced with five dummies, one for each year from 2 years before to 2 years after the discovery.

each other reveals that most data points are around the 45 degree line, suggesting the difference between the two is zero on average. We continue by re-estimating our main specification 1 using the UNCTAD data. The results in Table 6 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.

FIGURE 15
FDI: UNCTAD vs fDiMarkets



Note: FDI data from UNCTAD and from fDiMarkets 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.

A.3 Additional descriptive statistics - Mozambique

Some descriptive statistics and a precise definition of the key variables are provided in Table 8 and Table 7, respectively. Focusing on the first five rows of Table 8 there are two things to note. First, 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 such that the reported values are equal to zero. 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. We discuss the discrepancies in greater detail below. Second, notice that the total number of jobs created by FDI more than doubled (when accounting for the increased number of cross sections), while the number of projects more than quadrupled. While the increase in FDI projects and employment has been substantial in absolute

Table 6: Robustness to UNCTAD data and longer time period

Period 1970-2014			
	(1)	(2)	(3)
	FDI	FDI	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)	(2)	(3)
	FDI	FDI	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: FDI 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.

terms the number of FDI jobs remained small in relative terms. Comparing the total number of FDI jobs to the total number of jobs suggests that in 2002 only 1 out of 100 workers was employed by a multinational. In 2014, the total number of FDI jobs added up to slightly more than 1%. Interestingly, our calculations suggest that the size of the informal economy is particularly large and adds up to around 95% of total employment in both years. In the subsequent four rows of Table 8 we provide descriptives on the characteristics of workers by focusing on gender and education. The data suggests that women are a substantial part of the labor force. In fact, 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 workers increased from less than 5% to around 25% in 12 years. Finally, the last four rows suggest that the labor force participation increased from 83% to 86%, and that it was accompanied by a doubling of the unemployment rate from 3.5% to 6.5%.

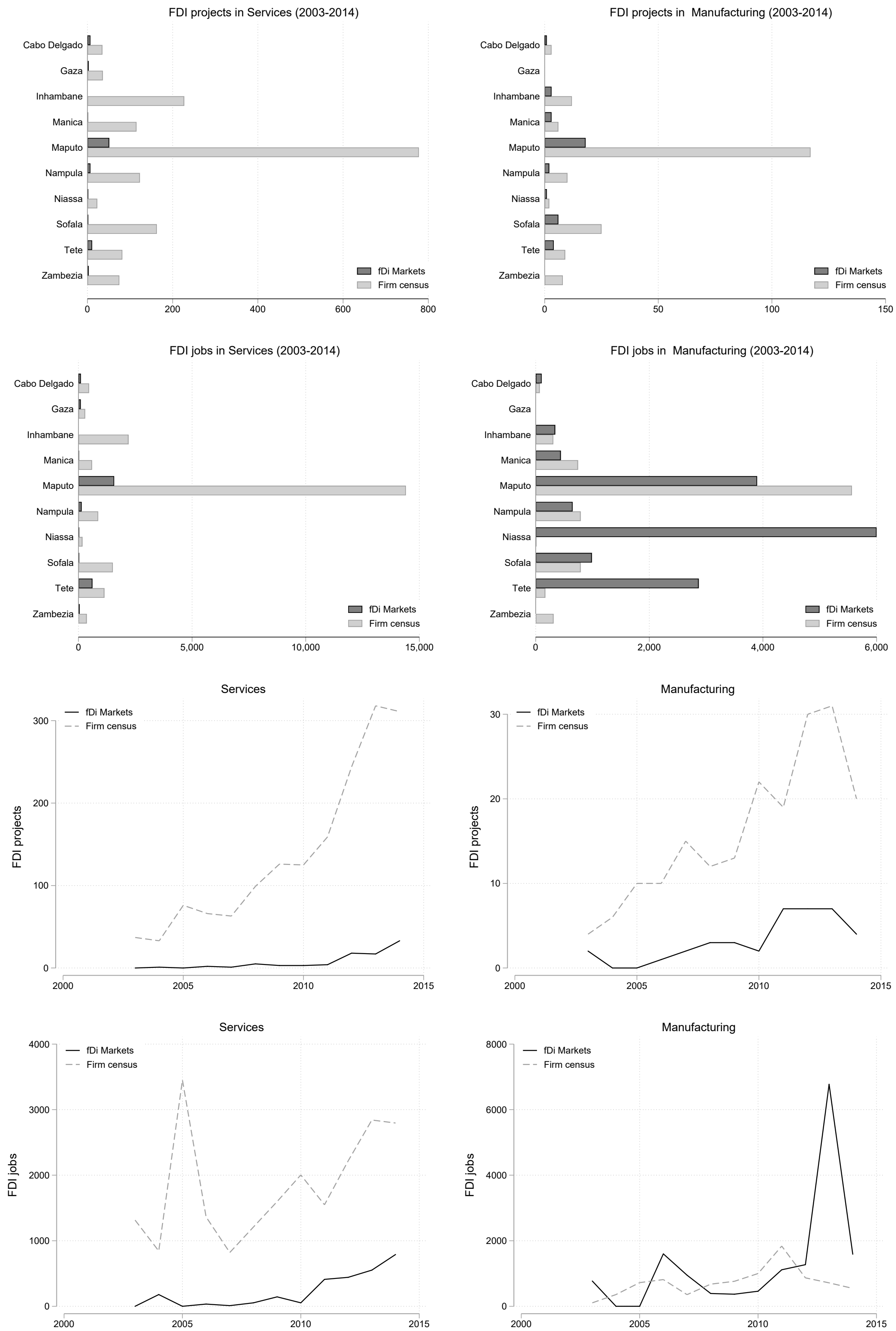
Table 7: Variables

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.
Instrument	Product of the average FDI job shares by sector and by ranked cities (biggest 15 cities) based on FDI bonanzas in Ghana, Ethiopia, and Tanzania following a resource discovery.
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 a secondary or tertiary education 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 8: Summary statistics for 2002 and 2014

	2002			2014		
	N	Mean	SD	N	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
FDI measure						
FDI projects (CEMPRE)	721	0.8	8.01	979	3.7	33.1
FDI jobs (CEMPRE)	721	88.8	898.7	979	149.2	1249.8
FDI projects (FT)	721	0	0	979	0.2	1.6
FDI jobs (FT)	721	0	0	979	19	166.6
Instrument	721	0	0	979	8.6	100.9
Jobs Measure						
Total jobs	721	11190.5	23034.3	979	10568.8	25770.4
Non-FDI jobs	721	11107.4	22793.1	979	10439.1	25342.8
Formal Jobs	721	348.1	2436.6	979	385.8	3304.5
Informal Jobs	721	10789.5	22182.6	979	10063.1	24395.8
Workers Characteristics						
Women	721	6174.10	15213.92	979	6065.49	15893.14
Men	721	5196.01	10492.63	979	5284.96	11230.43
Skilled	721	471.31	2137.58	979	2857.57	10083.75
Unskilled	721	10898.80	24038.56	979	8492.87	21208.42
City Level						
Population	135	60724.79	70813.13	135	82311.78	86494.22
Total Jobs	135	49072.45	44080.63	135	66152.53	59177.10
Unemployed	135	1775.60	9213.01	135	4654.45	12601.06
Inactive	135	9876.75	23955.87	135	11504.79	19583.24

FIGURE 16
Comparing the FDI datasets



A.4 fDiMarkets vs. CEMPRE FDI data

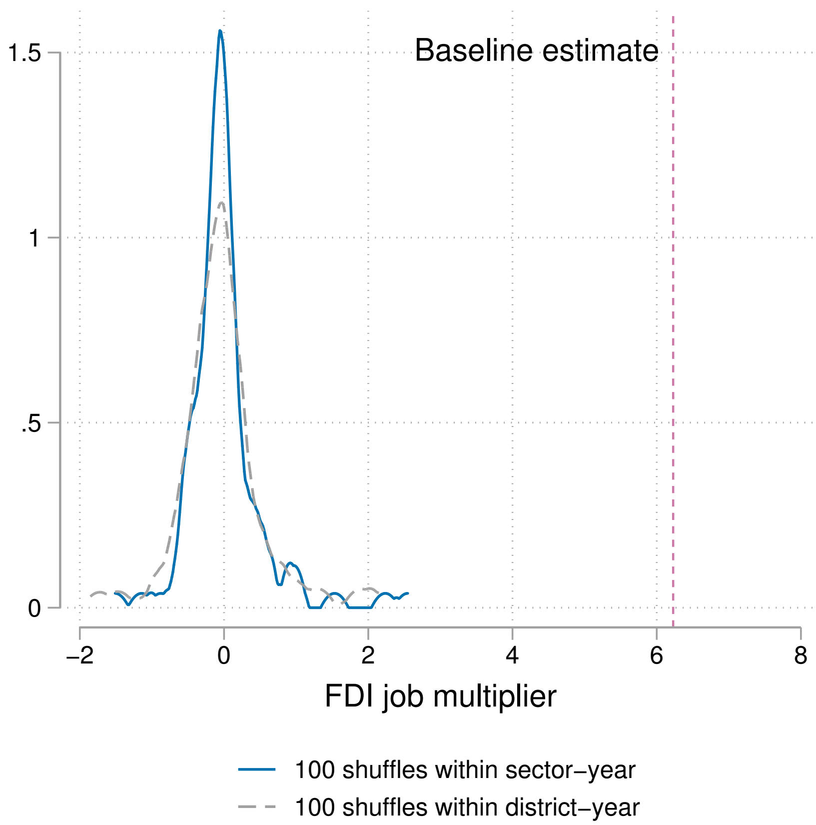
We compare our two sources of FDI data in Figure 16. The FDI stock in 2014 is much larger in the census data than in fDiMarkets. As mentioned above, this is partly because fDi markets started collecting data on FDI projects in 2003 and partly because they do not collect information on brownfield FDI. On the other hand, the firms 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 proceed by comparing the total number of FDI projects and FDI jobs created between 2003 and 2014. As expected, the results in Figure 16 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 16 that the FDI numbers are correlated across sectors, across cities and across time, we need to keep in mind that fDiMarkets systematically underestimates the total number of FDI projects and FDI jobs when interpreting the results.

A.5 Robustness of our multiplier estimate

While our triple diff-in-diff should control for most sources of endogeneity, we might still be worried that our results are driven by particularly successful cities that attracted much FDI and saw 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 17 gives the distribution of these placebo estimates. The fact that these are distributed around zero and that our estimated multiplier 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 in all districts but only in the districts where they actually take place.

To investigate whether the FDI multiplier operates mostly within-sector or if cross-sector spillovers play an important role, we estimate our baseline 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 in Table 9. They suggest that spillovers 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. We thus focus on within-sector spillovers in our paper.

FIGURE 17
Placebo FDI job multipliers



Note: The 100 placebo allocations of FDI jobs were generated by reshuffling randomly the FDI jobs within district-years and within sector-years. Their effects on non-FDI jobs were estimated using our baseline specification (Panel A of Table 3). The vertical red line gives our baseline estimate (column 1).

Table 9: 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

Panel B: Project-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 projects (CEMPRE)	119.573***		51.247***		67.702***	
	(4.857)		(1.651)		(6.537)	
FDI projects in other sectors (CEMPRE)	-0.254		0.011		-0.293	
	(1.231)		(0.104)		(1.204)	
FDI projects (FT)		1826.252***		995.159***		823.338***
		(43.612)		(0.208)		(51.891)
FDI projects in other sectors (FT)		0.743		1.886		-1.640
		(22.795)		(2.683)		(22.135)
N	1052	1052	2484	1052	1052	1052
R-sq	0.94	0.94	0.97	0.98	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.

As an additional robustness check we estimate our multipliers but at the district level rather than at the district-sector level. This relaxes the assumption that the multiplier is strongest within sectors but assumes instead that an FDI job in one sector can create spillovers in other sectors in the same district. Results are presented in Table 10. The district-level multiplier is very close to our previous estimate. The top-panel estimates based on FDI data from the firm census suggest that an extra FDI job is associated with 4.4 additional jobs, 2 formal and 2.2 informal.

In Table 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 nearly 6 total extra jobs at the district level (Column 2 in Panel B). Note that the total number of jobs created at the district level is very close to the estimate from our baseline specification in which we explore the number of jobs created within the same sector as the FDI project. This suggests that backward and forward linkages from multinationals to local firms may explain most of the multiplier effect. Moreover, one additional FDI job increases the population by approximately 3.5 individuals and pulls on average slightly more than 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 local labor force is absorbed by a large increase in local labor demand.

A.6 Additional results: Gender, education, and wages

In Table 12 we further decompose the job multiplier by gender and skills, where skilled individuals are those with at least a completed 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 multiplier in column (1) in panel A suggests that an extra FDI job is associated with 7.2 total jobs, i.e. the 6.2 additional jobs estimated above in Table 3, plus the FDI job itself. The decomposition of this multiplier by gender suggests that FDI is especially beneficial for women. It suggests a multiplier of 4.7 for women and 2.5 for men. Note that these numbers also include the FDI job itself. This gender bias is robust to using fDiMarkets (FT) data as well as to using FDI project numbers. In panel C the estimates suggest that an extra FDI project is associated with around 135 new jobs, 42 for men and 94 for women. The decomposition by skills suggest 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 7.2 total jobs created are 8.4 skilled jobs created and 1.2 unskilled jobs destroyed. This skill bias also shows up in the 3 other specifications.

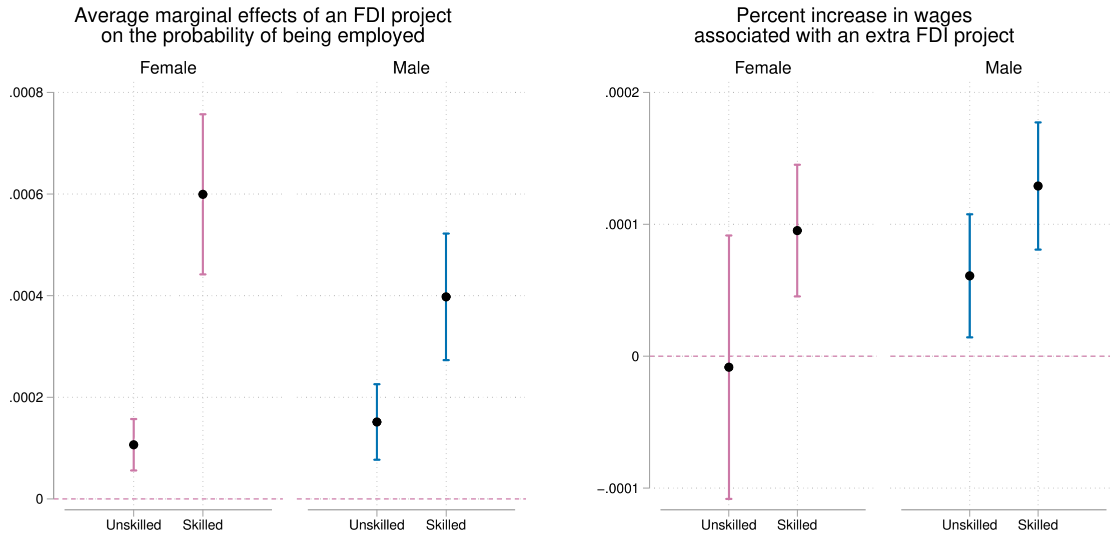
To investigate this gender and skill bias further we adjust our estimation strategy by focusing on the individual level rather than aggregated by sector. In particular, we estimate the following specification:

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

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

FIGURE 18

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.

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 is associated with 0.01% higher wages.

Table 10: FDI multipliers - District level regressions

Panel A: Job-level multipliers

	(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: Job-level multipliers - IV

	(1) FDI jobs (CEMPRE)	(2) Total jobs	(3) Non-FDI jobs	(4) Formal jobs	(5) Informal jobs
Instrument	4.459***				
	(0.245)				
FDI jobs (CEMPRE)		5.903***	4.921***	2.712***	1.976**
		(0.821)	(0.818)	(0.083)	(0.864)
N	266	266	266	266	266
R-sq	0.68	0.14	0.10	0.67	0.03
F IV		331.15	331.15	331.15	331.15

Panel C: Project-level multipliers

	(1) Total jobs	(2) Non-FDI jobs	(3) Formal jobs	(4) Informal jobs
FDI projects (CEMPRE)	133.524***	111.019***	59.646***	46.385
	(29.650)	(29.216)	(3.174)	(29.915)
N	266	266	266	266
R-sq	0.13	0.09	0.91	0.02

Panel D: Project-level multipliers - IV

	(1) FDI projects (CEMPRE)	(2) Total jobs	(3) Non-FDI jobs	(4) Formal jobs	(5) Informal jobs
Instrument	0.197***				
	(0.010)				
FDI projects (CEMPRE)		133.772***	111.508***	61.448***	44.772**
		(19.738)	(19.490)	(1.649)	(19.951)
N	266	266	266	266	266
R-sq	0.90	0.13	0.09	0.91	0.02
F IV		356.61	356.61	356.61	356.61

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.

Table 11: Additional district level regressions

Panel A: The effect of an FDI job

	(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 - IV

	(1) Pop (15-59)	(2) Employed	(3) Unemployed	(4) Inactive
FDI jobs (CEMPRE)	3.518***	5.903***	0.822***	-3.207***
	(1.207)	(0.819)	(0.261)	(0.292)
N	266	266	266	266
R-sq	0.96	0.92	0.94	0.97
F IV	332.40	332.40	332.40	332.40

Panel C: The effect of an FDI project

	(1) Pop (15-59)	(2) Employed	(3) Unemployed	(4) Inactive
FDI projects (CEMPRE)	85.569**	133.524***	22.817**	-70.772***
	(39.735)	(29.594)	(9.284)	(7.532)
N	266	266	266	266
R-sq	0.96	0.92	0.94	0.98

Panel D: The effect of an FDI project - IV

	(1) Pop (15-59)	(2) Employed	(3) Unemployed	(4) Inactive
FDI projects (CEMPRE)	79.717***	133.772***	18.625***	-72.680***
	(27.903)	(19.700)	(5.971)	(6.449)
N	266	266	266	266
R-sq	0.96	0.92	0.94	0.98
F IV	357.97	357.97	357.97	357.97

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.

Table 12: FDI job multipliers - by Gender and Education

Panel A: Job-level multipliers

	(1) Total jobs	(2) Men employed	(3) Women employed	(4) Skilled employed	(5) Unskilled employed
FDI jobs (CEMPRE)	7.229***	2.543***	4.686***	8.407***	-1.178*
	(1.002)	(0.281)	(0.764)	(0.840)	(0.554)
N	1012	1012	1012	1012	1012
R-sq	0.96	0.96	0.96	0.91	0.96

Panel B: Job-level multipliers - IV

	(1) Total jobs	(2) Men employed	(3) Women employed	(4) Skilled employed	(5) Unskilled employed
FDI jobs (CEMPRE)	7.567***	3.136***	4.430***	7.988***	-0.422
	(1.532)	(0.729)	(0.872)	(0.513)	(1.064)
N	1012	1012	1012	1012	1012
R-sq	0.10	0.07	0.10	0.58	0.00
F IV	476.65	476.65	476.65	476.65	476.65

Panel C: Project-level multipliers

	(1) Total jobs	(2) Men employed	(3) Women employed	(4) Skilled employed	(5) Unskilled employed
FDI projects (CEMPRE)	135.434***	41.864***	93.570***	160.871***	-25.436***
	(13.317)	(6.195)	(8.161)	(7.438)	(7.414)
N	1012	1012	1012	1012	1012
R-sq	0.96	0.96	0.96	0.94	0.96

Panel D: Project-level multipliers - IV

	(1) Total jobs	(2) Men employed	(3) Women employed	(4) Skilled employed	(5) Unskilled employed
FDI projects (CEMPRE)	133.858***	55.481***	78.376***	141.315***	-7.458
	(29.011)	(13.877)	(16.234)	(11.233)	(18.720)
N	1012	1012	1012	1012	1012
R-sq	0.12	0.06	0.14	0.71	0.00
F IV	659.86	659.86	659.86	659.86	659.86

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.