Quantile regression for the FDI gravity equation*†

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Abstract

Firm-level heterogeneity shapes foreign direct investment (FDI) flows, whereby a few firms are responsible for most of the world's FDI. Aggregate outcomes of FDI are highly skewed, and the estimates of FDI's antecedents vary largely depending on FDI level. The incidence of individual firms, however, varies across FDI's quantiles. To study the individual firms' effect on FDI flows, this study develops a quantile regression method for bilateral FDI panel data. This study estimates the differential incidence of individual firm-level projects on aggregate flows among 161 countries from 2003 to 2012. Results suggest that FDI's determinants vary across quantiles. In particular, the effect of individual projects on FDI flows increases in the upper quantiles. Policy-makers may use this insight to target polices on the few to benefit the many.

Keywords: Foreign direct investment; extensive margin; gravity equation; quantile regression; firm-level heterogeneity

JEL Classification: F20, F21, F23.

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1 Introduction

"Never in the field of human conflict was so much owed by so many to so few" (Churchill, 1940)

Only a few firms significantly affect investment flows, even though a single investment project may add up to several million dollars of capital investment and thousands of jobs. Few firms are also largely responsible for economic aggregate fluctuations like GDP (Gabaix, 2011) or industry sales (Giovanni et al., 2012; Giovanni & Levchenko, 2011). Mayer and Ottaviano (2008) decompose the number of foreign affiliates and average sales per affiliate for several European countries: "The happy few are leading the many." Few companies are responsible for most of the world's aggregate FDI, employment, and sales. Kleinert et al. (2012) show that foreign affiliates are responsible for variations in the business cycle. Scholars stress the role of firm-level heterogeneity on aggregate outcomes (Behar & Nelson, 2014; Helpman et al., 2004). Most empirical research on FDI's antecedents, however, does not address these empirical observations in their estimates. This study fills this gap.

The gravity equation, the most successful empirical specification for bilateral FDI, does not account for firm-level movements at the aggregate level. Firm symmetry is a key assumption of the gravity model; traditional linear estimates suffer from a firm-level over-aggregation bias. Scholars use the distinction between the extensive (how many) and the intensive margin (how much) to partially overcome this issue (Helpman et al., 2008). In the extensive margin, all firms are equal: Millionaire investments are equivalent to humble investments.

Decomposing FDI into margins helps researchers understand FDI's underlying mechanisms (Berden et al., 2014; Gil-Pareja et al., 2013; Paniagua & Sapena, 2014); nonetheless, several questions lack an answer: Do the determinants of FDI flows change with quantiles? Does the role of firm level vary across quantiles? How do individual projects affect aggregate flows? On which FDI level is the effect of the few most important? As a result, policies concerning FDI often miss their primary target.

Policymakers may target policies for the few or for the many. The identification of best-suited determinants for each level of FDI is relevant for policymakers, especially for investment promotion agencies (IPA). Policies intending to increase FDI in a particular region or country generally focus on increasing the investment leads, that is, the extensive margin (Loewendahl, 2001b; Wells & Wint, 2000). However, scholars usually measure FDI policies' success at an aggregate level (UNCTAD, 2013b). Understanding the effect of individual projects on aggregate flows is therefore essential to determine the best-suited FDI policies, especially in a context of economic crisis where credit constraints affect the number of projects but not their size (Gil-Pareja et al., 2013).

To address these research questions, this study uses quantile regression (Koenker & Bassett, 1978). Quantile regression is more adequate than other methods to understand the relationship between variables whose effects may vary with outcome levels (Huarng & Yu, 2014). Quantile regression is popular to interpret results of skewed data like wages (Buchinsky, 1994), portfolio returns (Yu et al., 2003), the Internet (Yu, 2011), business performance (Seo et al., 2014), forecasting (Huarng & Yu, 2014), and international trade (Dufrénot et al., 2010; Fidrmuc, 2009; Figueiredo et al., 2014). This study is the first to apply quantile regression to estimate bilateral FDI data in a gravity framework.

This study goes beyond previous studies in several ways. First, the study develops a quantile method to estimate the determinants of aggregate FDI flows. This study applies quantile regression for panel data (QRPD), a method that addresses fixed effects and omitted variable bias. Second, this study provides a rationale for interquantile coefficient variations. Third, this research studies the incidence of firm heterogeneity on FDI measuring the differential effect of individual projects on aggregate flows across quantiles. Results suggest that (1) FDI's determinants vary across quantiles and (2) firm heterogeneity has a greater effect in higher quantiles. This study analyzes bilateral FDI data for 161 countries between 2003 and 2012. Section 2 describes the empirical strategy, section 3 discusses the results, and finally, section 4 presents the conclusions.

2 Empirical methodology

2.1 FDI quantile gravity equation

The gravity equation is the most popular empirical tool to estimate bilateral FDI. The empirical distribution of FDI data, however, render traditional ordinary least squares (OLS) estimates of the gravity equation impractical. Standard linear regression techniques summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function $E(y|x)$ assuming this function as normal and symmetrically distributed. This procedure provides only a partial view of the relationship, especially when the data concentrate at different points in the conditional distribution of the dependent variable concentrate most of the data. Quantile regression provides that capability (Koenker & Bassett, 1978; Yu et al., 2003). In addition, quantile regression is more robust to outliers than least squares regression, and is semiparametric, avoiding assumptions about the parametric distribution of the error process (Conley & Galenson, 1998).

Applying quantile regression to the FDI gravity equation yields:

$$\ln Q_\tau[\ln(FDI)_{ijt}|x_{ijt},\alpha_{ij}] = \alpha_{ij} + x_{ijt}\beta(\tau) + v_{ij}, \tag{1}$$

where i denotes the source country and j the host country; α_{ij} are the time-invariant country-pair fixed effects; $\beta(\tau)$, are the parameters of interest which vary with quantile $\tau \in (0,1)$; the error term v_{ij} is independent and identically distributed $v_{ij} \sim iidF_v(\mu, \sigma^2)$, where F_v is an unknown continuous distribution function of v_{ij} , and; x_{ijt} are the standard set of gravity control variables observed at time t. Table 1 summarizes all variables.

The last column of Table 1 presents the expected sign change from lower to higher quantiles. Table 1 gives the hypothetical difference in the effect of FDI's determinants for low volumes and high volumes of FDI. The agglomeration phenomenon (i.e., firm proximity) gives the basis for the theoretical change of the coefficients' signs. The literature identifies firm-level advantages of agglomeration, namely increasing returns, technical externalities, knowledge spillovers, and transport costs (Chung & Song, 2004; Fujita & Thisse, 2013; Voinea & Van Kranenburg, 2011). As result, transactions costs (e.g., distance costs, language and cultural differences, and currency costs) diminish in the most crowded quantiles (i.e., the upper quantiles). Variables that favor FDI substitutes (i.e., free trade agreements, FTA) reduce their impact in higher quantiles. Variables that ease FDI (i.e., bilateral investment treaties, BIT) increase their power in higher quantiles. In addition, benefits from greater demand and supply (i.e., Gross Domestic Products, GDPs) increase with quantiles.

Anderson and Van Wincoop's (2003) study on the gravity equation includes third-country effects or multilateral resistance. Multilateral resistance represents an index of inward and outward bilateral trade costs. All bilateral trade costs in the world contribute to the bilateral trade between country pairs. Otherwise, other variables in the equation, like the border dummy, might pick up this effect. The literature advocates for the use of fixed effects procedures to address problems arising from omitted variable bias and endogeneity related to multilateral resistance (Anderson, 2011).

The fixed effects specification of the gravity equation represents an empirical

Table 1: Variable description and expected signs

Variable	Description	Expected sing	Across Quantiles
$\ln(GDP_{it} \times GDP_{jt})$	Logarithm of the gross domestic products of home and host countries respectively	(+)	↗
$\ln(D_{ij})$	Logarithm of distance in kilometers between country capitals	(−)	↘
border_{ij}	Takes the value 1 when countries share a common border, and 0 otherwise	(+)	↘
col_{ij}	Takes the value 1 if the two countries have ever had a colonial link, and 0 otherwise	(+)	↘
lang_{ij}	Takes a positive value if both countries share the same official language	(+)	↘
rel_{ij}	Is a composite index that measures the religious affinity between country pairs with values ranging from 0 to 1	(+)	↘
smctry_{ij}	Is an indicator variable that indicates if both countries were part of the same country in the past	(+)	↘
CC_{ijt}	Takes the value if both countries have the same currency in year t	(+)	↗
locked_{j}	Is 1 if the host country is landlocked	(−)	↘
BIT_{ijt}	Is a dummy that takes a value of one if the country pair has a bilateral investment treaty in force	(+)	↗
FTA_{ijt}	Is a dummy that indicates whether both countries have a free trade agreement in force	(+/−)	↘
N_{ijt}	Is the number of investment projects between home country i and host j in year t. The $\beta(\tau)$ associated to this variable is the FDI margin semi-elasticity	(+)	↗

caveat for quantile regression. Scholars have yet to reach a consensus on how to introduce fixed effects on quantile regressions. Estimate interpretation varies greatly by method (Canay, 2011; Galvao Jr, 2011; Harding & Lamarche, 2009; Koenker, 2004; Lamarche, 2010; Powell, 2013).

This study improves Canay's (2011) estimator with a quantile regression for panel data (QRPD) procedure. The fixed effects specification omits all time-invariant country pair variables (α_{ij}) because of perfect collinearity. This procedure eliminates location shift variables beforehand, making implementation computationally simple, regardless of the number of fixed effects the analysis may include. Thus, QRPD inferences follow two steps:

Step 1: Compute $\hat{\alpha}_{ij}$ as:

$$\hat{\alpha}_{ij} = \ln(FDI)_{ijt} - x_{ijt}\hat{\beta} \tag{2}$$

where $\hat{\beta}$ is an OLS estimator for β.

Step 2: Define

$$\ln F\hat{D}I_{ijt} = \ln(FDI)_{ijt} - \hat{\alpha}_{ij} \tag{3}$$

Next, estimate

$$\ln Q_{\tau}[F\hat{D}I_{ijt}|x_{ijt}, \alpha_{ij}] = x_{ijt}\beta(\tau) + u_{ij}, \tag{4}$$

considering the Koenker and Bassett's (1978) technique.

2.2 The incidence of firm heterogeneity

The literature accepts the use of different terms for extensive and intensive margin. The most common decomposition uses the number of firms and the average exports or investments per firm (Hillberry & Hummels, 2008; Mayer & Ottaviano, 2008). This method implicitly attributes an average value to each individual event. Hence, other scholars use another definition of the intensive margin: The capital value of the marginal exporter or investment (Chaney, 2008; Crozet & Koenig, 2010). As in Hillberry and Hummels (2008), the study separates the aggregate investment flows into two margins:

Like in Hillberry and Hummels (2008), the aggregate investment flows are separated into two margins:

$$FDI_{ij} = \sum_{k=1}^{N} I_{ijk} = N_{ij} \times \overline{I}_{ij} \tag{5}$$

where I_{ij} is the average quantity invested in each individual project from country i to j, N_{ij} is the number of investment projects from i to j and $\overline{I}_{ij}$ the average dollars invested per project. Therefore, the log-linear form of (5):

$$\ln(FDI_{ij}) = \ln(N_{ij}) + \ln(\overline{I}_{ij}) \tag{6}$$

According to Mayer and Ottaviano (2008), FDI is "thin" and an "exclusive club", meaning "that their distribution is highly skewed, as a handful of firms accounts for most aggregate international activity" (p.135). Therefore the number of projects is relatively small compared to the average size of those projects, meaning that $N_{ij} \ll \overline{I}_{ij}$, then

$$\ln(FDI_{ij}) = \ln(\overline{I}_{ij}) + e_{ij} \tag{7}$$

where e_{ij} is an error term which is correlated with the number of projects between i and j. The quantity invested will be implicitly affected by the number of firms which decided to invest. This information is contained in the error term e_{ij} which accounts for the extensive margin.

To leap from (6) to (7), the data must be shaped accordingly. Firstly, the number of investment projects from i to j should be low compared to the size of those projects. Secondly, the variable FDI_{ij} should be skewed with a high kurtosis. Also, $\ln(FDI_{ij})$ and $\ln(\overline{I}_{ij})$ should be highly correlated with each other and uncorrelated with N_{ij}. With these conditions, the extensive margin N_{ij} impacts aggregate flows as in independent regressor of the FDI quantile equation in (5). The coefficient $\beta(\tau)$ associated to the extensive margin N_{ij} is the FDI margin semi-elasticity. Since most firms are concentrated in the upper quantiles, the FDI margin semi-elasticity, its effect is more evident for higher levels of FDI.

2.3 Data sources

The World Bank (2013) is the source of the GDP figure (in constant year 2000 USD). Distance, common language, colony, border, and landlocked come from the CEPII (2011) database. Religion draws on data from the CIA World Factbook (2011), according to the following formula for each country pair: $\%Christian_i * \%Christian_j + *\% * + \% *$. Institutional agreements like free trade agreements (FTAs) and bilateral investment treaties (BITs) reduce the uncertainty in foreign investments (Bergstrand & Egger, 2013) BIT's construction is manual, using data from UNCTAD (2013a). The source of FTA is Head et al. (2010) complimented by UNCTAD (2013a) data. The Financial Times Ltd. cross-border investment monitor (FDI Markets, 2013) is the source of the FDI dataset. Investment count measurement is in terms of firm-level project count and capital flows in constant year 2000 USD. The dataset covers bilateral firm-level green field investments from 2003 to 2012, using an aggregation across 161 host and 120 home countries.

Table 2: Correlation matrix

Correlation	$\ln(\bar{I}_{ij})$	$\ln(FDI)_{ij}$	N_{ij}
$\ln(\bar{I}_{ij})$	1		
$\ln(FDI)_{ij}$	0.94	1	
N_{ij}	0.00	0.22	1

Table 3: Skewness/Kurtosis tests for normality

Pr(Skewness)*	Pr(Kurtosis)*	
N_{ij}	0.00	0.00
$\ln(FDI)_{ij}$	0.00	0.00

Notes: (*) p-values.

2.4 Data analysis

Several analyses on the dataset confirm the fit of the estimation method to the data. The top 10% of investors own 53% of the total projects. The total capital investment from all these companies reaches USD 1,805 billion, equating to almost one-third of the total for all companies. The top five destination countries account for more than one-third of projects. China is the top destination country accounting for one-eighth of projects this study tracks.

In the FDI database, a few projects account for most of the investment flows. Figure 1 shows the empirical cumulative distribution function of lnFDI_ijt, which shows a high skew. Note that the 10th, 50th, and 90th quantiles are roughly 6, 8, and 10 on the log scale. The correlation matrix in Table 2 shows a high correlation (0.95) between the intensive and total flows, but no correlation with the extensive margin (0.0017 and 0.2231 respectively). Table 3shows that the skewness and kurtosis test for the extensive margin (and natural aggregate flows) is highly significant, with a p = 0.0000. Table 4 presents the variables descriptive statistics.

Figure 1: Quantiles of FDI

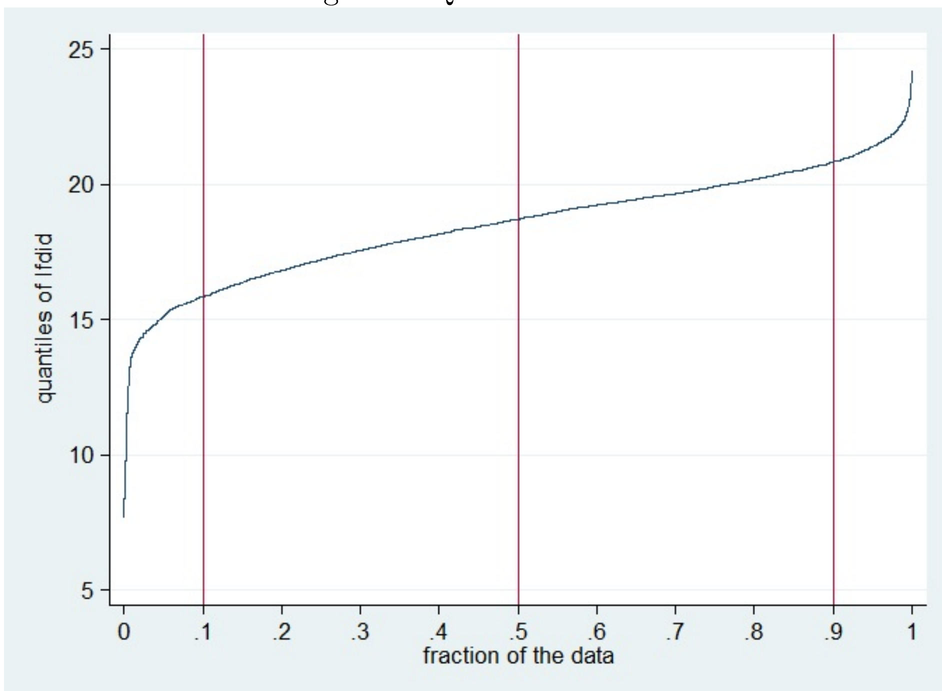


Table 4: Descriptive statistics

Variable	Mean	SD	Min	Max
$\ln(FDI_{ij}$	18.49	1.97	7.71	24.24
$\ln(GDP_{it} \times GDP_{jt})$	27.09	1.51	20.12	30.45
$\ln(D_{ij})$	8.21	1.01	4.08	9.86
col_{ij}	0.05	0.21	0	1
lang_{ij}	0.17	0.37	0	1
rel_{ij}	0.34	0.32	0	1
border_{ij}	0.06	0.25	0	1
smctry_{ij}	0.02	0.15	0	1
CC_{ijt}	0.29	0.46	0	1
locked_{j}	0.12	0.33	0	1
BIT_{ijt}	0.43	0.49	0	1
FTA_{ijt}	0.30	0.46	0	1
N_{ijt}	0.71	4.63	0	247
Observations		10338		

3 Results

3.1 Baseline estimates

The estimation results in Table 5 show baseline estimates with no fixed effects, the plain quantile regression (Koenker & Bassett, 1978). Overall, the quantile regression performs well. Most of the variables are statistically significant with expected signs that vary with quantiles. The first column shows the results using OLS and the other columns show results for the 10%, 25%, 50%, 75%, 90%, and 99% quantiles.

Figure 2 graphically shows how the coefficients vary with quantiles. The effect of GDPs (i.e., demand) increases with quantiles, that is, demand is crucial for countries with a strong FDI relationship with large FDI projects. This notion is consistent with distance effect, which diminishes (i.e., less negative) for country pairs with higher FDI quantiles. Common language has the same trend, the effect of languages wear out for the upper FDI class, like in previous estimates for trade data (Fidrmuc, 2009).

Distance's changing elasticity contributes to a popular gravity topic. Distance has a clear negative effect on trade because an increase in distance results in a surge of freight costs. Consequently, according to the proximity-concentration tradeoff, distance positively affects horizontal FDI (Markusen, 2002). Daniels and von der Ruhr (2014) find that transportation costs have a positive and statistically significant relationship with FDI, suggesting a substitute relationship between FDI and trade flows.

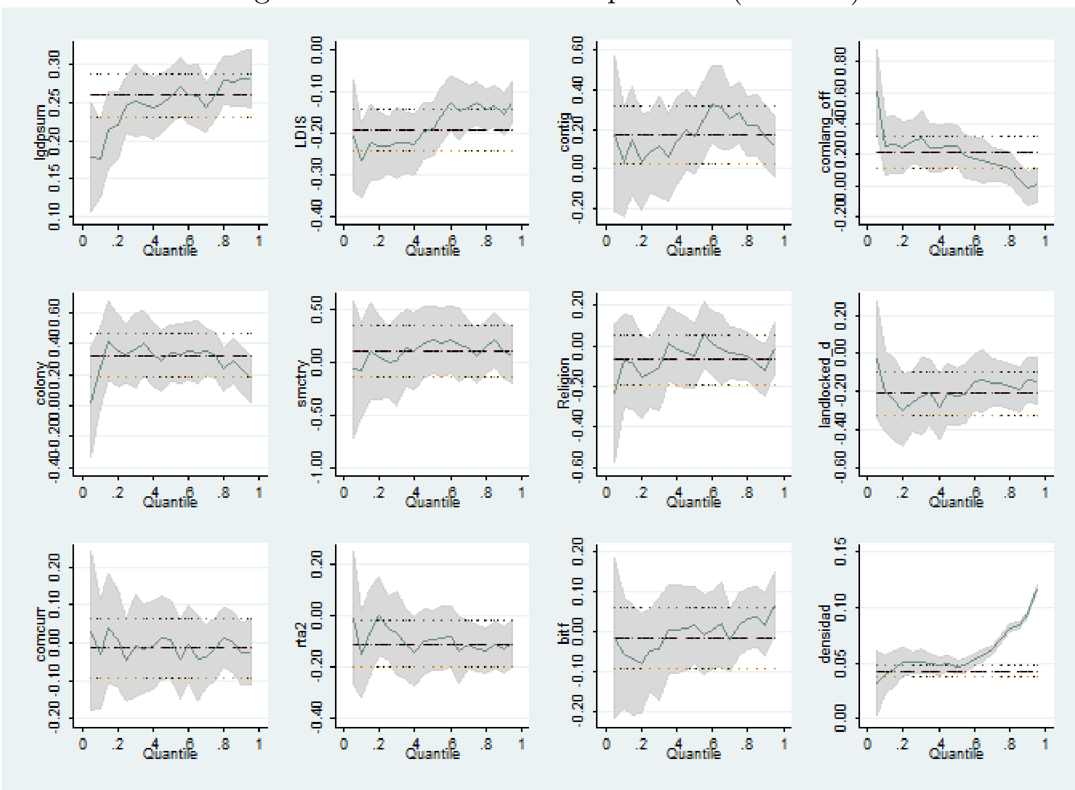
However, most empirical studies show a negative relationship between distance and FDI (Bergstrand & Egger, 2011). Therefore, distance effect on FDI accounts for more than just freight costs (i.e., reputational and governance costs), because of poor commitment between the headquarters and affiliate. Distance's varying effects suggest that freight costs are more relevant for smaller FDI projects.

Table 5: Baseline Results

	(1) OLS	(2) Q(10)	(3) Q(25)	(4) Q(50)	(5) Q(75)	(6) Q(90)	(7) Q(99)
$\ln(D_{ij})$	-0.194***	-0.267***	-0.231***	-0.191***	-0.129***	-0.153***	-0.157
	(0.02)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.11)
col_{ij}	0.324***	0.251	0.333***	0.338***	0.322***	0.234***	0.167
	(0.07)	(0.13)	(0.10)	(0.09)	(0.07)	(0.07)	(0.35)
$lang_{ij}$	0.213***	0.259***	0.285***	0.259***	0.131**	-0.018	0.028
	(0.05)	(0.09)	(0.07)	(0.06)	(0.05)	(0.05)	(0.26)
rel_{ij}	-0.066	-0.0718	-0.135	-0.0487	-0.0421	-0.122*	-0.232
	(0.06)	(0.19)	(0.08)	(0.08)	(0.06)	(0.06)	(0.29)
$border_{ij}$	0.173**	0.037	0.082	0.167*	0.288***	0.167**	-0.128
	(0.07)	(0.14)	(0.10)	(0.10)	(0.08)	(0.07)	(0.35)
$smctry_{ij}$	0.105	-0.068	-0.003	0.213	0.057	0.116	0.058
	(0.12)	(0.23)	(0.17)	(0.16)	(0.13)	(0.13)	(0.44)
$locked_j$	-0.211***	-0.200*	-0.255***	-0.227***	-0.159***	-0.141**	0.0979
	(0.05)	(0.10)	(0.08)	(0.07)	(0.06)	(0.06)	(0.19)
$\ln(GDP_{it} \times GDP_{jt})$	0.259***	0.176***	0.246***	0.259***	0.261***	0.281***	0.266***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)
CC_{ijt}	-0.0131	-0.031	-0.044	0.009	-0.013	-0.026	-0.294
	(0.04)	(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.29)
BIT_{ijt}	-0.014	-0.052	-0.045	0.016	0.018	0.018	0.110
	(0.04)	(0.06)	(0.05)	(0.04)	(0.03)	(0.039)	(0.19)
FTA_{ijt}	-0.107**	-0.148*	-0.047	-0.093	-0.126***	-0.132***	-0.243
	(0.05)	(0.08)	(0.06)	(0.06)	(0.05)	(0.05)	(0.21)
N_{ijt}	0.043***	0.040***	0.051***	0.047***	0.071***	0.094***	0.134***
	(0.01)	(0.01)	(0.01)	(0.003)	(0.001)	(0.001)	(0.004)
Elasticity $\varepsilon_{N_{ij}}$	0.03	0.03	0.04	0.03	0.05	0.07	1.00
Observations	10338	10338	10338	10338	10338	10338	10338
Fixed Year Dummies	yes	yes	yes	yes	yes	yes	yes

Notes: Standard errors in parentheses, and standard errors in brackets;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Estimates across quantiles (baseline)



Institutional agreements between country pairs (FTA and BITS) also vary with quantiles. FTA negatively affects FDI since trade costs diminish and therefore FDI is comparatively less attractive. This effect is, again, more notable in higher quantiles. BIT's effect is non-significant in the sample. However, the quantile regressions show that BIT's effect becomes slightly higher in the upper quantiles.

Of all independent variables, projects number shows the most clear upward trend, which is positive and significant in all quantiles. An increase of an individual investment project in Q(0.1) increases investment flows by 5% on average, whereas in Q(0.9), this effect is more than 9%. In the upper most quantile, Q(0.99), an individual project increases FDI flows by 13% on average.

Firm heterogeneity is more important for the upper quantiles, where a handful of firms account for most of the foreign investment. The last row of Table 5 calculates the elasticity for the different quantiles with the formula:

$$\hat{\beta}_{12} = \frac{dFDI_{ij}}{dN_{ij}} \frac{}{\overline{FDI}_{ij}} \rightarrow \varepsilon_{N_{ij}} = \hat{\beta}_{12}\overline{N}_{ij}$$

where $\varepsilon_{N_{ij}}$ is the FDI margin elasticity. An increase of 1% of the number of projects results on an average increase of 0.03% of FDI flows up to median. After this, the effect of individual firms increases; 0.05% for quantile 75th and 0.07% for quantile 90th. The effect of the extensive margin on aggregate flows is perfectly elastic for the last Q(0.99) quantile: an increase of 1% in the number of foreign projects between country pairs increases 1% the FDI flows.

3.2 Fixed effects estimates

Table 6 shows the fixed effects (QRPD) results; Figure 3 shows QRPD results corresponding graphs. Figure 4 highlights the result for the margin elasticity. Results for this variable of interest show a similar trend to the baseline results. However, QRPD corrects an overestimation of margin elasticity's effect. With fixed effects, the QRPD control for any omitted variable that might have structural effects on country pairs.

Institutional agreements (i.e., FTA and BIT) reveal that FTA positively affects FDI in the upper quantiles. This result suggests a complementarity between trade and FDI in these quantiles, compatible with vertical FDI. These quantiles may concentrate specialized vertical FDI that increase intra-industry trade.

Particularly, the results from BIT contribute to unraveling a popular topic on investment treaties' effect on FDI. Bergstrand and Egger (2013) argue that most of BIT analyses show bias because BITs and FDI may share underlying determinants. Empirical studies containing these variables report mixed empirical results ranging from non-significant (Blonigen & Davies, 2004, 2009) to positive (Neumayer & Spess, 2005) and negative (Gil-Pareja et al., 2013; Tobin & Rose-Ackerman, 2011). Pan-

Table 6: RQPD results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)	Q(99)
$\ln(GDP_{it} \times GDP_{jt})$	0.114	0.217***	0.224***	0.281***	0.338***	0.284***	0.313***
	(0.18)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.08)
CC_{ijt}	0.146	-0.045	-0.018	0.015	0.034	0.019	-0.047
	(0.23)	(0.05)	(0.04)	(0.01)	(0.03)	(0.04)	(0.26)
BIT_{ijt}	-0.038	0.202***	0.146***	0.228***	0.246***	0.189***	0.020
	(0.19)	(0.05)	(0.03)	(0.01)	(0.03)	(0.04)	(0.25)
FTA_{ijt}	0.363	-0.062	0.012	0.047***	0.084***	0.104***	0.172
	(0.25)	(0.05)	(0.03)	(0.01)	(0.03)	(0.04)	(0.4)
N_{ijt}	0.016***	0.031***	0.032***	0.040***	0.042***	0.059***	0.094***
	(0.01)	(0.01)	(0.003)	(0.001)	(0.001)	(0.001)	(0.01)
Observations	10338	10338	10338	10338	10338	10338	10338
Year fixed dummies	yes	yes	yes	yes	yes	yes	yes

Notes: Robust standard errors in parentheses, and standard errors in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3: Elasticity across quantiles (fixed effects)

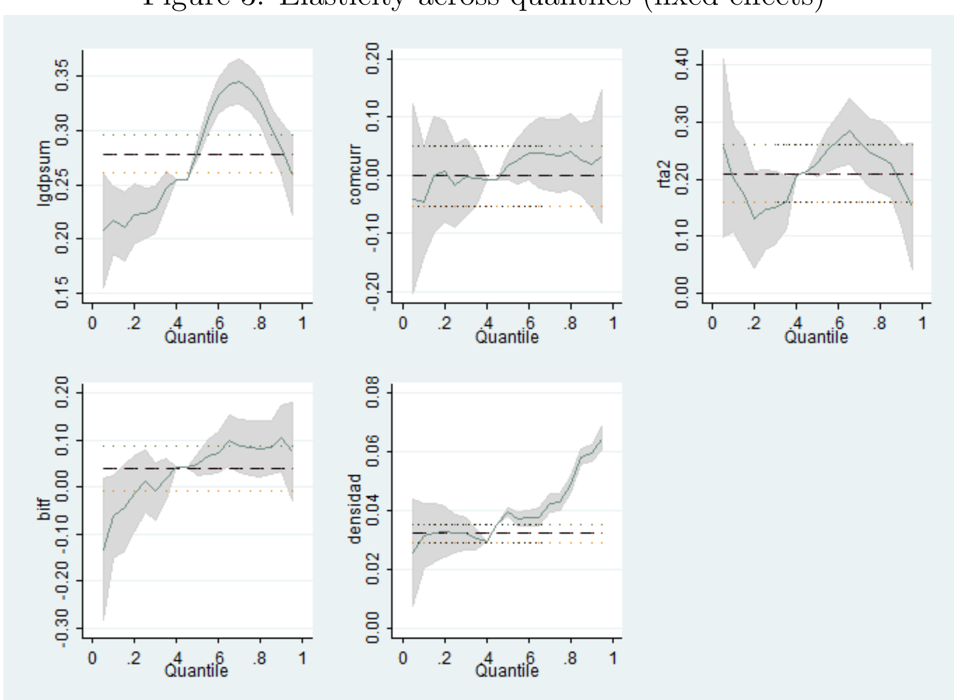
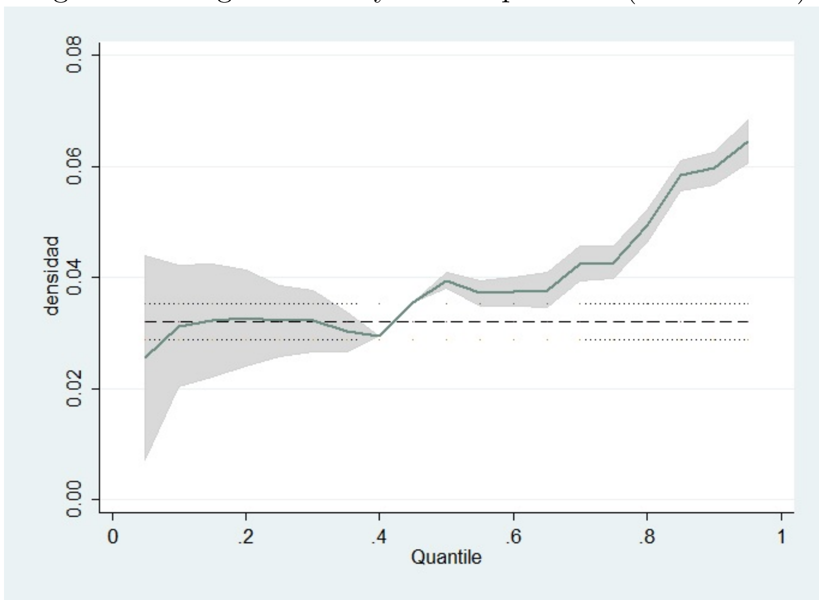


Figure 4: Margin elasticity across quantiles (fixed effects)



iagua and Sapena (2014) show that BITs are positive for developing countries and negative for developed. The results in Table 6 reveal that BIT is positive for FDI but only above the median. Institutional agreements therefore have a targeted effect on higher FDI levels.

The GDP has an upward quantile trend up to Q(0.75) where GDP stabilizes and falls toward median estimations. An increase in demand or supply capacities has a high effect on higher quantiles, but not on the upper-most quantiles. This exclusive club of firms is more resilient to variations on demand or supply.

4 Conclusions

This research offers several contributions to the FDI literature and provides useful insight regarding FDI underlying determinants. The literature highlights the role of firm heterogeneity in FDI response to country-level characteristics and institutional policies. This study applies quantile regression to study firm heterogeneity and foreign direct investment. A better understanding of these mechanisms is crucial for proper business policy and welfare. Policymakers may profit from this research in their instruments and initiatives.

The empirical findings support the argument that FDI determinants vary with FDI levels. Firm heterogeneity has a higher effect on the upper quantiles of FDI. That is, individual projects intensively shape the aggregate outlook of the superior FDI flows. This finding is consistent with the FDI literature that suggests that a few companies are responsible for most FDI flows. Results from the analysis also contribute to unraveling puzzling issues: the effect of trade and investment treaties on FDI.

This research highlights the importance of tailored policies for promoting foreign investment. Firms themselves and each firm's incidence on aggregate statistics are different. General policies may prove highly ineffective. With further research into region or sector, governments can underpin specific regulations for industries or companies responsible for most of FDI.

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